Bio-based and Applied Economics

Article

Estimating a global MAIDADS demand system considering demography, climate and norms

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This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record.

Please cite this article as:

Britz, W. (2021). Estimating a global MAIDADS demand system considering demography, climate and norms. Bio-based and Applied Economics, Just Accepted.

DOI: 10.13128/bae-10488

Abstract

Based on data mainly from the International Comparison Program for 156 countries, we conduct a global cross-sectional estimation of an extended rank-3 MAIDADS demand system for nineteen commodity groups including agri-food detail for integration in a Computable General Equilibrium model. We render both marginal budget shares and commitment terms depending on the implicit utility level and consider age shares on the population, the Gini-Coefficient, the share of Islamic population, a sea access indicator and mean temperatures as further explanatory variables. We find that especially demographic factors, the share of Islamic population and mean temperature considerably improve model selection statistics and the fit of commodity groups with a low fit in a variant where prices and income only are used. Graphics of the estimated Engel curves, with details for agro-food commodity groups, highlight income dynamics of budget shares.

Keywords: Demand system estimation, AIDADS, General Equilibrium Modelling.

JEL Codes: D12, C33, C68.

1 Introduction

Partial and Computable General Equilibrium Models (CGE) are widely used tools for policy impact assessments, but simulated outcomes depend on model structure and parameterization. In their review of how final demand is modelled in long-term analysis, Ho et al. 2020 underline the importance of the choice of functional form for final demand. They find differences in baseline results for 2050 for an otherwise identical CGE model of up to factor two between a Linear Expenditure System (LES), a Constant-Difference-in-Elasticity (CDE) demand system[1] and an AIDADS specification for single sectors, and still for up to 11% in total global aggregated output, all calibrated against the same data and own and income elasticities. Similarly, Britz and Van der Mensbrugghe 2018 compare outcomes of different model configurations and find sizeable differences in comparative-static analysis under a trade liberalisation shock between variants using different functional forms, calibrated against the same data and elasticities. But besides moving to more flexible functional forms, especially with regard to Engel curves, also the parameterization of the demand systems in equilibrium model can certainly be improved. The widely used GTAP model, for instance, depicts up to 65 sectors, but its demand system is parameterized drawing on an estimation with ten aggregated sectors, only (Hertel and Van der Mensbrugghe 2019), such that elasticities for many sectors are identical.

This paper focuses on improved representation of final demand in equilibrium models for long-run analysis, specifically on the GTAP model and its variants, as the most widely used CGE models globally. The GTAP Data Base covers in its latest version 10 141 single countries or group of countries for which consistent long-term time series on final demand, related price and income are not available. A country specific estimation of parameters is therefore not feasible, such that the established practise estimates generic demand systems at global level, based on cross-sectional analysis, such as in Seale et al. 2006, Reimer and Hertel 2004, Preckel et al. 2010, Roson and Van der Mensbrugghe 2018, Britz and Roson 2019.

Given the large differences in per capita income across countries at global level and high projected income dynamics for current low and middle income countries, flexibility in Engel curves is deemed important during estimation and simulation. Here, an AIDADS system with its exponential Engel curves is often found as a sensible choice (cf. Rimmer and Powell 1996) and also used to estimate the current GTAP parameter (Hertel and Van der Mensbrugghe 2019). Ho et al. 2020 stress additionally in their review that demography, income distribution and other factors such as religious norms are found as important drivers of consumption choices in many micro-level studies, but are basically not considered as consumption drivers in any of the global CGE models.

Against this background, we aim at an improved final demand representation in CGE models in several directions, by (1) extending the sectoral detail in the global cross-sectional estimation of the AIDADS system, by (2) moving to a more flexible MAIDADS specification where also the commitment terms change with income, and by (3) controlling for additional factors which are likely to shape preferences such as religious norms. The resulting demand system is then integrated in the G-RDEM model (Roson and Britz 2019) for construction of long-run baseline, as a module of the flexible platform for CGE modelling CGEBox (Britz and Van der Mensbrugghe 2018). But the findings in here are also of relevance of partial equilibrium models focusing on specific sectors, or more generally of interest to economists interested in income dynamics of demand.

The paper is organized as follows. We first motivate the use and detail the extended MAIDADS demand system and the estimation approach before we present key results. Next,

[1] The CDE demand system underlies the widely used GTAP Standard model.

we discuss key findings with a focus on differences across variants which consider additional drivers such as demography or income distribution. Finally, we summarize and conclude.

2 Methodology

2.1 Extended MAIDADS demand system

We empirically estimate an extended AIDADS (An Implicit Additive Demand System, Rimmer and Powell 1996) demand system for nineteen product groups: ten broader non-food groups and nine food categories, where the extension refers to utility depending commitment terms. Detail for food is introduced as income effects are here especially relevant such as expressed, for instance, by Bennet's law (Bennet 1941). The AIDADS system can be understood as a generalization of a LES demand system where marginal budget shares are not fixed, a property also described as a rank three demand system with regard to income effects. Other rank three candidates are, for instance, the Quadratic Expenditure System (QES, Pollak and Wales 1978) and the quadratic AIDS (QUAIDS, Banks et al. 1997). Cranfield et al. 2003 estimated all three demand systems based an version of the data set employed in here with less demand categories, and compared them against the rank-two systems LES and AIDS from which they are derived. In their comparison, AIDADS and QUAIDS performed best and they recommend AIDADS if the income differences in the estimation or later simulations are high. One reason for this recommendation is the global regularity of AIDADS. Specifically, compared to QUAIDS, it ensures that marginal budget shares stay between zero and unity. Moreover, compared to the quadratic marginal budget shares of for instance a QUAIDS or QES specification, the exponential marginal budget shares of an AIDADS system might be considered more appropriate when covering a data set with extreme per-capita differences (Rimmer and Powell 1996).

In the AIDADS demand system, the marginal budget shares are a linear combination of two vectors, depicting the marginal budget structure at very low and very high utility (income) levels. A logistic function depending on the implicit utility level determines the linear combination. Given that the marginal budget shares in each of the two vectors fulfil the adding up condition to unity, any linear combination of the two also leads to regular budget shares. We follow Preckel et al. 2010 who extend the original Cranfield approach by rendering also the commitment terms depending on income, to what they call the MAIDADS for modified AIDADS demand system. With regard to the estimation strategy we follow Cranfield et al., 2000 who improve on the original Rimmer and Powell 1996 approach by developing an estimation method that does not rely on an approximation of utility. As usual, the independent data in the equations below are the per capita incomes Y and consumer prices p for countries c and commodity groups i,j, and the dependents the budget shares w. Equation (1) determines the estimated budget shares $w^*_{c,i}$. It is identical to a LES specification with the exception that the marginal budget shares δ and commitment terms γ are not fixed, but depend on the endogenously determined utility level.

The marginal budget shares δ_i are expressed in (2) as a linear combination of two vectors δ^{lo} and δ^{hi} driven by a logistic function depending on the utility level u, implicitly defined by (5):

$$w^*_{c,i} = \frac{x^*_{c,i} p_{c,i}}{Y_c} = \frac{\gamma_{c,i} p_{c,i}}{Y_c} + \delta_{c,i}\left[1 - \sum_j \frac{\gamma_{c,j} p_{c,j}}{Y_c}\right] = w_{c,i} - e_{c,i} \tag{1}$$

$$\delta_{c,i} = \frac{\delta_i^{lo} + \delta_i^{hi} \exp(\omega_\delta u_c - \kappa_\partial)}{1 + \exp(\omega_\delta u_c - \kappa_\partial)} \tag{2}$$

δ_i^{lo} can be interpreted as the marginal budget share at minimum utility level, i.e. very low per capita income, while δ_i^{hi} is the share at very high incomes. The utility level u_c is calculated at the given $\delta_{c,i}$ and $\gamma_{c,i}$ in (5). It drives in (2) a logistic function with the parameters ω_δ >0 and κ_∂ which in turn determines the marginal budget share; this shows the implicit utility definition. At the point where the expression $\omega_\delta u_c - \kappa_\partial$ is zero, the average between the two marginal budget share vectors is chosen, based on (5), that point is defined by κ_∂. For larger negative $\omega_\delta u_c - \kappa_\partial$, the exponent term approaches zero and the lower $\delta_{c,i}$ share is chosen; for larger positive ones, the exponent term approaches infinity such that δ_i^{hi} is selected. In opposite to the original Rimmer and Powell 1996 proposal and subsequent work, we also consider a multiplicative factor ω_δ.

Different from previous work with AIDADS or MAIDADS specifications we are aware off, the two vectors δ^{lo} and δ^{hi} are country specific in here as they depend on a set *f* of further country specific attributes *a* as detailed below, see equation (3).

$$\begin{aligned} \alpha_{c,i} &= \alpha_{i,0} + \sum_f \alpha_{i,f} \bar{a}_f \\ \beta_{c,i} &= \beta_{i,0} + \sum_f \beta_{i,f} \bar{a}_f \end{aligned} \tag{3}$$

γ are the constant terms, typically termed commitments. As suggested by Preckel et al. 2010, we render also the commitment terms an exponential function of utility, see equation (4). This allows especially better differentiating price sensitivity across income differences.

$$\gamma_{c,i} = \frac{\gamma_i^{lo} + \gamma_i^{hi} \exp(\omega_\gamma u_c - \kappa_\gamma)}{1 + \exp(\omega_\gamma u_c - \kappa_\gamma)} \tag{4}$$

Equation (5) defines the additive utility from the consumption bundle and is identical to the LES definition[2]:

$$u_c = \sum_i \delta_{c,i} \ln\left(x_{c,i} - \gamma_{c,i}\right) \tag{5}$$

Besides considering additional factors in the determination of the marginal budget shares, our approach is therefore slightly more general compared to Preckel et al. 2010 who, first, have κ identical in determining δ and γ, and, second, introduce ω into (4), only.

[2] The usual definition of the implicit utility definition in the (M)AIADS is $\sum_i \delta_{c,i} \ln\left(x_{c,i} - \gamma_{c,i}\right) - \ln(A) - u_c = 1$ with δ and γ expressed by (2) and (4). Our formulation is equivalent as the term (-ln(A)-1) could be recalculated from the expressions $\omega_\gamma u_c - \kappa_\gamma$ and $\omega_\delta u_c - \kappa_\delta$.

2.2 Estimation approach

We follow closely Cranfield et al. (2000) and Preckel et al (2010) in our estimation by performing a log-likelihood estimation on cross-sectional data from the International Comparison Program (ICP) referring to the year 2011[3] which provides a harmonized data set on expenditures (2), consumer prices and purchasing power parities. However, we don't use the publicly available data, only, but based on an agreement with the ICP, add more detail for food.

As Preckel et al. (2010) we define a quadratic covariance matrix E of dimension $(n-1)\times(n-1)$ comprising the error terms $e_{c,i}$ from (1). Dropping the last column and row reflects that budgets shares and their error terms are linear dependent due to adding up. Assuming normally distributed error terms *e*, their concentrated log-likelihood function becomes $-\frac{1}{2}\ln\left|E^*\right|$ which elements defined as

$$E^*_{ij} = \frac{1}{C}\sum_c e_{i,c}e_{jc} \wedge i \neq n,\, j \neq n \tag{6}$$

Where C is the number of countries observed. In order to improve estimation speed, we follow Preckel et al. 2010 and apply a Cholesky decomposition $E^* = R'R$ which eases defining the log of the determinant of E due to $\ln|E| = 2\ln|R|$. The decomposition does not itself constrain the estimation outcome as the (reduced) covariance matrix E^* is by definition positive definite. The decomposition is defined as:

$$E^*_{i,j} = \sum_k^{n-1} r_{ki}r_{kj} \;\forall i \neq n,\, j \neq n \tag{7}$$

The Cholesky matrix R as an upper triangular matrix comprises with $(n-1)(n-1+1)/2$ elements far less elements than E^*. The lower triangular part of the matrix R with elements $r_{kl} = 0 \;\forall k > l$ must be set to zero while for the diagonal elements non-negativity is required to guarantee finiteness. This requires small positive bounds, here chosen as 1.E-8 which turned out to not become binding (this would imply perfect fit). The overall concentrated log-likelihood to maximize is derived from the diagonal elements of R:

$$-C\,\tfrac{1}{2}\ln\prod_{i=1}^{n-1} r_{ii}^2 = -C\,\mathrm{n}\prod_{i=1}^{n-1} r_{ii} \tag{8}$$

Exhaustion of income requires adding up of the marginal budgets to unity. This leads to the following adding up restrictions during estimation:

[3] The current GTAP Data Base versions in use are Version 9 for 2011 and Version 10 for 2014, which fits to the year of the ICP data. Long-run baseline construction with recursive-dynamic CGE models projects decades into the future. With regard to consumption behaviour, this is only defendable if one assumes that observed differences in consumption patterns across countries with different per capita income level provide guidance of how pattern might change in future under stronger income dynamics. If using data from 2014 instead of 2011 would lead to distinct differences in the estimated parameters, the assumption would be challenged. But as we don't have access to newer data, we leave such evaluations to other scholars.

$$\sum_i \alpha_{c,i} \equiv 1 \Leftrightarrow \sum_i \alpha_{i,0} \equiv 1, \sum_i \alpha_{i,f} \equiv 0 \qquad (9)$$
$$\sum_i \beta_{c,i} \equiv 1 \Leftrightarrow \sum_i \beta_{i,0} \equiv 1, \sum_i \beta_{i,f} \equiv 0$$

As seen from equation (9), the regression coefficients $\alpha_{i,f}$ and $\beta_{i,f}$, must add up to zero to maintain the adding up condition as they update marginal budget shares at low and high utility depending on country specific additional factors in equation (3). As some of these regressions coefficients are therefore necessarily negative, we restrict all estimated marginal budget shares to be non-zero. In order to prevent negative estimates in later simulations with the CGE model, we introduce two artificial observations at 75% of the lowest income and 125% of the highest one. These two observations do not impact the estimated log-likelihood directly as there are no error terms attached to them, but the estimator needs to ensure that the estimated budget shares for these two observations are between zero and unity. Moreover, we ensure that the estimated commitment terms γ don't exceed 95% of the estimated demand that the minimum and maximum observations additionally introduced, beside an observation at the mean income of the sample. This provides additional safeguards against implausible outcomes when simulating with the system in later applications. These details clearly reflect the specific aims of the exercise[4].

The use of the *exp* function can provoke mathematical overflows during estimation and simulation. We therefore replace is with the following smooth quadratic exponential function:

$$\text{sqexp}(x,S) = \begin{cases} e^x & x < S \\ e^x\left(1+[x-S]+\frac{1}{2}[x-S]^2\right) & x \geq S \end{cases} \qquad (10)$$

Where S is a smoothing factor chosen here as S=10. The usefulness of this smoothing approach becomes obvious if we consider the point x = 100. The exponential function will yield ~2.7E+43 while the smoothed one results in ~1.E+8. For the resulting linear combination of the estimated parameters in (2) and (4), differences in values of this dimension are irrelevant for any reasonable estimate. This becomes visible if we consider their bounds. The marginal budget shares δ are bounded by [0,1] and the $\gamma_{lo,i}$ by $[0, Y_{\min}]$ where the minimum yearly per capita income $Y_{\min}$ is around 250 USD. This acts as a maximal bound for commitment terms as utility in (5) is only defined if $x_{c,i} > \gamma_{c,i}$ such that even with a budget share of 100%, $\gamma_{lo,i}$ can never exceed the minimum income level observed. Setting $\gamma_{up,i}$ to its lowest possible value of zero and $\gamma_{lo,i}$ at its possible maximum yields an commitment parameter of $\gamma_{c,i} = \frac{\gamma_i^{lo}}{1+\text{sqexp}(x)}$ driven by utility based on x = $\omega_\gamma u_c - \kappa_\partial$. That means that if $1+\text{sqexp}(x) >> \gamma_i^{lo}$ for larger values of *u*, the resulting marginal budget share will be, as desired, almost zero. As exp(10) ~ 5.5E4, that is already given at the point where the smoothing starts to make a difference with the $\gamma_{lo,i}$ and $\gamma_{up,i}$ at their most critical values for the approximation. More generally, one could define demand systems similar to the

[4] For the selected model, none of these additional safeguards became active during estimation and impacted the estimates.

(M)AIDADS based on any function returning values on the domain [0,1] for any value of utility *u*.

We estimate different variants of the model by considering besides price levels and income further country specific attributes related to income distribution, religious norms, climate, access to sea and demography, separately or jointly. Such additional controls are often found in demand system estimations drawing on household samples, where the attribute refer to individual households and not, as in here, to a country.

Adding these controls aims at insights if and to what extent these drivers systematically improve the fit, both with respect to the overall model and to individual categories, and reflects that these attributes have been found in micro studies as relevant to explain differences in demand behaviour (Ho et al. 2020). The usefulness of integrating further explanatory factors might deserve some discussion. In our and similar exercises, the utility structure of the representative household of any country is assumed to be identical. This implies, for instance, that consumers in a country with a mainly Islamic population would spend as much on beverages and tobacco as the ones in a country dominated by Christians when facing the same prices and enjoying the same income level. This is not very likely as consuming alcohol is often forbidden in countries where the Islamic belief dominates. Such impacts might be only partially captured by price differences in goods. Similarly, a larger share of older people might imply different expenditures on health at the same prices and identical average per capita income, motivating the use of demographic factors.

Demand system estimations based on a cross-section of country data set might face collinearity issues. First, price levels for some of the aggregated commodities are likely related in a systematic way to income levels, while we miss variability over time as found in a panel data set to dampen this effect. For instance, the so-called “Beaumol”-disease stipulates that labour-capital substitution is harder in certain service sectors, such that in countries with higher wages (and income levels), some services are systematically more expensive, the costs of a hair-cut serve often as an archetypical example. Indeed, we find R^2 values for a simple regression of prices on the logarithm of per capita income (see Table 3) for non-food groups in the range of 50-60% with the exemption of communication (~30%). For agri-food groups, the correlation between income and prices is still high (>40% R^2) for meats, fish and other food, and otherwise quite small. Any estimation using cross-country data with larger income differences will likely face these issues. In our estimation, some additional factors are also correlated to income, especially demographic factors with R^2 values of 60% and 70%, using again logarithms of income levels as explanatory factors. The problem is hence of a similar magnitude as for prices and will hinder a clear separation of demographic factors from income level effects. The R^2 for other factors are below 25% and give little reason for concern. Still, if additional factors systematically improve model selection criteria despite collinearity issues, they contribute to a better explanation, but collinearity will make it harder to tell income and price effects apart from the influence of these additional factors. We will come back to that point when discussing which of the different model variants to use for actual simulation purposes with the CGE.

Technically, we implement the estimator in GAMS, updating and improving the codes by Britz and Roson 2019 which draws on the ones originally used by Reimer and Hertel 2004. The use of GAMs is motivated by an estimation which comprises highly-nonlinear equations and constraints, such as the endogenous Cholesky-Decomposition in (7). This asks for robust non-linear programming solvers such as CONOPT4 employed in here which are not available in statistical packages.

GAMS is not a specialized statistical package which implies that any statistics and tests need to be programmed manually. Beside these technical issues, we see several reasons why we don’t develop code to estimate p-values for the individual parameters. First, in our demand system estimation, dropping prices or income as independents is impossible, due to constraints, the same holds for dropping additional factors in individual equations. Even for additional factors, single p-values can therefore not guide the selection of these controls. Second, even in the models with many additional factors, we still have thousands of degrees of freedoms. This renders it likely that p-values always suggest most parameters significantly different from zero, even if their relevance might be low. Moreover, the interpretation of p-values is challenging in the context of parameter restrictions. We instead carefully discuss the trade-off between considering more additional factors and model selection statistics such as the Akaike’s Information Criterion when deciding which of the model variants to choose for simulation.

2.3 Data

As other global exercises, we draw on data by the ICP as it provides standardized and consistent observations on many countries with different per capita income levels. This should help to find a robust representation of global, country-wide Engel curves. As our ultimate aim is to integrate the estimates into the GTAP derived G-RDEM model, we aggregate detailed ICP data on food expenditures covering 34 items to (aggregates of) GTAP sectors and keeping otherwise the ICP classification for non-food as shown in Table 1 below. Per capita demands are real expenditures in U.S. dollars, the prices are derived from these and nominal expenditure per capita in U.S. dollars.

Table 1: Commodity groups in estimation and ICP detail

Commodity group	ICP
Identical	Clothing and footwear Housing, water, electricity, gas and other fuels Furnishings, household equipment and maintenance Health Communication Recreation and culture Education Restaurants and hotels Miscellaneous goods and services
Cereals	Rice; Other cereals; Flour and other products
Meats and eggs	Beef and veal; Lamb, mutton and goat; Pork; Poultry; Other meats and meat preparations; Eggs and egg-based products
Fish	Fresh, chilled or frozen fish and seafood
Dairy	Fresh milk; Preserved milk and other milk products; Cheese; Butter and margarine
Vegetable oil and cakes	Other edible oils and fats
Fruits and vegetables	Fresh or chilled fruit; Fresh or chilled vegetables other than potatoes; Fresh or chilled potatoes
Sugar	Sugar
Beverages and tobacco	Spirits; Wine; Beer; Mineral waters, soft drinks, fruit and vegetable juices; Coffee, tea and cocoa; Tobacco
Other food processing	Food products nec; Narcotics; Preserved or processed fish and seafood; Frozen, preserved or processed vegetables and vegetable-based products; Frozen, preserved or processed fruit and fruit-based products; bread; Other bakery products; Pasta products; Jams, marmalades and honey; Confectionery, chocolate and ice cream

The GTAP data base differentiates between wheat, paddy rice and other coarse grains which are potential substitutes in consumption. Keeping here more detail likely violates the assumption of additive utility such that we rather aggregate here to a category “cereals”. The same holds for the two GTAP sectors ruminant meat and other animal products, the latter comprising pig and poultry meat and eggs. Moreover, the “Other meats and meat preparations“ reported by the ICP might comprise both ruminant and non-ruminant meat and can therefore not clearly be linked to individual GTAP sectors. The reader might wonder why we don’t consider bread and pasta under the cereals product aggregate. The reason is that in the GTAP SAM, cereals refer to primary production and thus the farm scale, while bread or pasta as processed product are reported under the other food industry sector which comprises many more products such as ready-to-eat menus etc.. Britz and Roson 2019 therefor argue that the input coefficients of this food processing industry aggregate are likely depending on per capita income, as empirical analysis consistently shows that bulk calorie products such as cereals, bread or potatoes are inferior goods while convenience food is a rather a luxury good. We aim with the aggregation shown in Table 1 above to get a good match between the definitions in the ICP data set and the GTAP data base which motivates this specific aggregation scheme.

Table 2: Statistics on budget shares derived from ICP data

	Mean	Min	Max	Std.Dev	R^2 on log(Y)[1]
Clothing and footwear	0,047	0,010	0,145	0,023	0,11
Housing, water, electricity, gas and other fuels	0,153	0,049	0,389	0,057	0,11
Furnishings, household equipment and maintenance	0,049	0,009	0,132	0,020	0,00
Health	0,076	0,009	0,197	0,035	0,22
Transport	0,092	0,014	0,183	0,034	0,02
Communication	0,028	0,001	0,098	0,015	0,16
Recreation and culture	0,045	0,004	0,112	0,028	0,29
Education	0,072	0,013	0,178	0,028	0,05
Restaurants and hotels	0,045	0,000	0,141	0,032	0,18
Rest	0,077	0,015	0,194	0,044	0,08
Cereals	0,049	0,001	0,311	0,063	0,33
Meats, eggs	0,053	0,006	0,239	0,035	0,03
Fish	0,013	0,000	0,103	0,016	0,14
Dairy	0,026	0,001	0,108	0,019	0,14
Vegetable oils	0,011	0,000	0,047	0,010	0,20
Fruit & veg	0,049	0,006	0,210	0,037	0,28
Sugar	0,008	0,000	0,038	0,008	0,20
Other food	0,060	0,020	0,159	0,031	0,10
Beverages and tobacco	0,048	0,009	0,149	0,023	0,00

Source: ICP 2011, aggregated according to Table 1

Notes: [1] Linear regression with log of income per capita as independent

An overview on key metrics of the budget shares as the dependent variables provides Table 2 above. We observe that for the non-food items shown in the upper part, with the exemption of costs related to housing, the minimum shares are all below 1.5%. The maxima reveal that the categorisation of non-food items is rather balanced, with the exemption of housing, they are all in the 10-20% range. The same holds, with the exemption of vegetables oils and sugar for the food categories, also. Here, all minima are with the exemption of the other food category all close to zero. The R^2 of a simple regression on log of income reaches up to 33% of cereals, but is in most case in the 10-20% range which leaves ample room for improvement by a demand system estimation.

Table 3 report key metrics for the prices and income levels as key independents. The spread of prices is astonishingly high which can also seen from their standard deviation. There is also a stronger impact of the income level on the prices, a point touched upon before. When moving from the lowest income of around 250 USD to the maxima of around 55.000 USD, the regressions suggest that price of non-food items would increase by 0.36 to 0.45 (note that the US price is set to unity and serves for normalization).

Table 3: Statistics on income and prices

	Mean	Min	Max	Std.Dev	R^2 on log(Y)[1]
Income	9.030	220	55.835	12.196	
Clothing and footwear	0,771	0,229	2,053	0,368	0,61
Housing, water, electricity, gas and other fuels	0,540	0,074	2,400	0,413	0,55
Furnishings, household equipment and maintenance	0,853	0,422	1,778	0,288	0,63
Health	0,439	0,098	1,678	0,328	0,65
Transport	0,943	0,385	2,349	0,380	0,54
Communication	0,678	0,101	1,742	0,288	0,31
Recreation and culture	0,768	0,330	1,948	0,323	0,59
Education	0,313	0,037	1,905	0,320	0,55
Restaurants and hotels	0,799	0,265	2,240	0,341	0,55
Rest	0,640	0,233	1,993	0,333	0,69
Cereals	0,916	0,258	3,588	0,395	0,15
Meats, eggs	0,994	0,277	3,313	0,467	0,51
Fish	0,593	0,155	1,723	0,289	0,53
Dairy	1,080	0,412	2,159	0,293	0,02
Vegetable oils	1,386	0,719	2,331	0,325	0,04
Fruit & veg	0,732	0,234	2,614	0,356	0,39
Sugar	0,915	0,239	2,329	0,304	0,06
Other food	0,844	0,268	1,902	0,297	0,33
Beverages and tobacco	0,716	0,128	2,289	0,329	0,33

Source: ICP 2011, aggregated according to Table 1

Notes: Price of United States = 1, [1] Linear regression with log of income per capita as independent

Data on demography are taken from the IASSA data repository[5] for the Socio-Economic Pathways which ensures that the same data can be used in model applications for long-run analysis. We use the shares of two age groups as additional factors which can be expected to be not part of the working population (<15 and > 65 years). Not only are these age groups likely to show consumption patterns different from other age groups, they also might (indirectly) control for differences in household sizes, especially the share of <15 years old. As some household expenditures comprise a fix-cost share, household size at the same average per capita income of the household members is likely to change budget shares (Deaton and Paxson 1998). We took access to sea into account especially in the hope to better control for spending on hotels and restaurants, and to explain fish consumption. Mean temperature as the climatic variable chosen not only could impact the food consumption bundle, for instance with regard to dairy, but also impact housing and clothing expenditures (Sheth 2017). To check for the influence of different income distributions, we use Gini coefficients taken mostly from the CIA factbooks, a few missing observations were filled by data from Liberati 2009. Data on the share of Islamic population were taken from a study by the Pew center, 2011 (Pew center 2011).

[5] https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about

Table 4: Additional factors considered

Factor	Variable(s)
Income distribution	Gini Coefficient
Religious norms	Share of islamic population
Climate	Mean temperature
Sea access	Coast line relative to country size [m/skm], in log
Demography	Share of persons < 15 year Share of persons > 65 years

In total, we observed for C=156 countries budget shares, prices and additional factors. The 19 commodity groups lead to 2,964 observations. The extended AIDADS model where also the commitment terms depend on the utility level has four vectors of parameters (α, β, γ^{lo}, γ^{hi}), two utility multiplier κ and two exponents ω, considering the adding up conditions, this implies m = (2*n + 2*(n-1) + 4) = 78 parameters for the MAIDADS variant without additional factors. Each additional explanatory variable adds two additional vectors of marginal budget shares at low and high income, again considering adding up, that means for each factor 2*(n-1) = 36 additional parameters to estimate. For the model considering all six additional independents, we hence estimate 294 parameters. This reduces the degrees of freedom more than a QUAIDS system which would estimate m = (3 * (n-1) + (n-1)*(n-1)/2 = 192 parameters. But the full model is not used for simulation in here, but rather serves as a benchmark to select a suitable set of additional factors beyond per capita income and price levels.

2.4 Integration in the CGE

Using the estimation results for benchmarking of a CGE model is far from straightforward as observed budget shares for a country or country aggregate might deviate considerably from what the econometric model suggests. Additionally, with the exemption of the agri-food sector, the commodity groups are still rather aggregated compared to, for instance, the 57 sector resolution of the GTAP 9 data base or the 65 sectors of GTAP 10.

During estimation and later simulation, the utility is implicitly driven by the demands which depend on the marginal budget shares and commitment levels which are functions of utility. In order to ease benchmarking, we follow therefore the approach of Britz and Roson 2019 which perform a regression of the estimated utility levels from (5) on per capita income and add here as further independents the additional factors. The estimate of the utility level allows deriving an estimate of the country and sector specific $\delta_{c,i}$ and $\gamma_{c,i}$ for benchmarking. We cannot introduce the error term in the simulation model directly. Instead, we have, as usual for benchmarking with CGE models, to correct some of the parameters in order to line up the observed data with the estimated ones. The errors cannot be simply added to the commitment terms $\gamma_{c,i}$ as this changes non-committed income as well. Doing so also runs the risk to introduce rather curious elasticities in the model. This becomes visible from the Marshallian demands in equation (11).

$$x_{c,i} = \gamma_{c,i} + \frac{\delta_{c,i}}{p_{c,i}}\left[Y_c - \sum_j \gamma_{c,j}\, p_{c,j}\right] \tag{11}$$

If, for instance, the observed x is large compared to what the estimations suggests as x^*, simply increasing the related commitment term γ will mean that income and price effects are considerably dampened compared to the estimation. Increasing the marginal budget shares δ at unchanged γ will instead increase price and income responsiveness.

We therefore suggest first scaling both vectors of estimated parameters δ and γ by the relation between the observed and the estimates, next scale the δ such that they add up to unity and finally penalize squared deviations from δ and γ under adding up conditions.

3 Results

3.1 Fit of different model variants

In order to assess the different model variants, we compare the value of the likelihood function, the Akaike's Information Criterion, the information inaccuracy, the Schwartz's Criterion and the system wide Root Mean Squared Error. The calculation of the statistics follows Cranfield et al. 2003, i.e. the Root Mean Squared Error for the estimation of the budget shares w for the products i is calculated as $RMSE_i = \left[1/C \sum_c \left(w_{ic} - w_{ic}^* \right)^2 \right]^{0.5}$ with C being the number of countries and the system wide RMSE by using the mean budget share as weights, i.e. $SMRSE = \sum_i \overline{w_i} RMSE_i$. The value of the likelihood function is defined as $LLF = -1/2\, C \ln\left|E^*\right|$, the information inaccuracy as $IIA = 1/C \sum_{c,i} w_{c,i} \left(\frac{w_{c,i}}{w_{c,i}^*} \right)$, Akaike's Information Criterion as $AIC = 2/C\, m + \ln\left|E^*\right|$ and the Schwartz's Criterion as $SC = 1/C \ln(T) m + \ln\left|E^*\right|$. We calculate a system wide R² by weighting the individual R² with the budget shares.

The full model which uses all additional explicatory factors clearly has the best fit with a likelihood function value of 11.472 and a system R wide ² of 54,2%, see Table 5. It shows also the best IIA value, but the AIC and SC statistics suggests that it might be over specified when compared to other variants. Specifically, it adds 6 times 2 parameter vectors to the base model, such that we estimate (around) ten parameters for each commodity from 156 observations. Both in the groups of model variants using one factor or two factors, the religious norm and the demographic variables tend show the best values for the model selection statistics.

Overall, the three factor model using the religious norm, the climate factor and demographic gives the best AIC criterion. Its LLF and the system wide R² are close to the full model, but its AIC and SC selection criteria are considerably better. We therefore consider it the most suitable candidate based on the model selection statistics. The SC criterion would favour the model without any additional factors. But, as expected, the System wide R² and the value of the likelihood function put it on the last position.

Table 5: Model selection statistics

	LLF	System R²	SRMSE	AIC	IIA	SC
Base	11.219	45,3	2,86	-142,9	9,47	**-141,4**
Norms	11.295	48,6	**2,75**	**-143,4**	9,01	**-141,3**
Demography	**11.326**	**49,5**	**2,75**	-143,3	**8,83**	**-140,5**
Sea access	11.252	46,5	2,82	-142,8	9,22	-140,7
Climate	11.275	47,7	2,80	-143,1	9,07	-141,0
Gini	11.260	47,1	2,82	-143,0	9,26	-140,8
Norms + Demography	**11.379**	**51,3**	**2,68**	**-143,6**	**8,53**	-140,0
Norms + Sea acess	11.328	49,7	2,72	-143,4	8,74	-140,5
Norms + Climate	11.345	50,5	2,71	**-143,6**	8,68	**-140,7**
Norms + Gini	11.328	50,0	2,73	-143,4	8,82	-140,5
Demography + Sea acess	11.360	50,5	2,72	-143,3	8,60	-139,7
Demography + Climate	11.367	50,8	2,72	-143,4	8,54	-139,8
Demography + Gini	11.359	50,6	2,72	-143,3	8,62	-139,7
Sea acess + Climate	11.302	48,7	2,77	-143,0	8,86	-140,2
Sea acess + Gini	11.290	48,2	2,79	-142,9	9,04	-140,0
Climate + Gini	11.300	48,6	2,78	-143,0	9,12	-140,1
Norms + Demography + Sea acess	11.413	52,4	2,66	-143,5	8,28	-139,3
Norms + Demography + Climate	**11.425**	**52,6**	**2,65**	**-143,7**	**8,25**	**-139,4**
Norms + Demography + Gini	11.405	52,2	2,66	-143,4	8,34	-139,2
Demography + Sea acess + Climate	11.395	51,6	2,70	-143,3	8,39	-139,0
Demography + Sea acess + Gini	11.390	51,5	2,70	-143,2	8,40	-139,0
Sea acess + Climate + Gini	11.327	49,6	2,75	-142,9	8,78	-139,3
Full	11.472	54,2	2,62	-143,4	7,99	-137,7

Source: Own estimation

Notes: Numbers in bold indicate the best statistic in the group of models and red ones the overall best model.

While the overall model statistics are reported in Table 5, the tables shown in the following report the R^2 for the individual equations as a widely used and easy to interpret statistics to compare the fit, here both across estimated equations in the systems and across competing model variant. For comparison, we add always the system wide R^2.

Table 6 reports in the column "Base" a model using prices and income levels only as independent variables, i.e. the slightly extended MAIDADS model as proposed by Preckel et al. 2010. The best fit is found for "Recreation and culture" with 81% as a clear luxury good, followed by "Fruits and vegetables" by 76%. As seen from Table 6, these product groups also include staple food such as potatoes or root and tubers as classical examples of Barnett's law. This might explain the relatively high fit for that category. Disappointing is the fact that "Furnishings, household equipment and maintenance" even has a negative R^2 while for "Beverages and Tobacco", 8% only of the variance are explained. Similar low fits are also reported in Britz and Roson 2019.

The low explanatory power of the base model for some of the categories motivates considering additional factors which might drive consumption patterns. In order to assess how the additional factors impact results, we estimate versions where each factor is considered without the others, any combination of two or three factors and a full model comprising all of them. Note here that we always consider the two demographic variables jointly.

We first find that adding any additional factor to the base model improves the fit as seen from Table 5. Demography gives the best results of the models with single factors, but is actually introducing two additional dependents variables in the model. While it improves the fit for each single product group compared to the base model, it is not always better than model variants using another additional factor. The best results for any model variant considering on additional factor only are shown in bold in Table 6. This highlights that for eleven out of the nineteen product groups, the two demographic factors give jointly the highest R^2. The share of Islamic population follows with seven groups. Sea, access, climate and the Gini coefficients trail both with regard of the overall fit and with regard to categories where they provide the best fit. However, one needs to consider that demography is based on two additional dependents.

Table 6: Fit of different model variants by commodity group, single factors

	Base	Norms	Demography	Sea access	Climate	Gini
System wide R^2	45,3	48,6	**49,5**	46,5	47,7	47,1
Clothing and footwear	13,4	18,2	**18,4**	13,7	14,8	17,3
Housing, water, electricity, gas and other fuels	45,4	**51,3**	48,7	46,7	46,8	45,7
Furnishings, household equipment and maintenance	-0,5	1,5	**9,9**	0,3	4,8	3,1
Health	65,7	71,5	**71,6**	66,1	70,2	66,5
Transport	32,5	33,7	**38,2**	33,4	36,0	36,5
Communication	26,4	**30,6**	30,2	27,4	30,4	30,3
Recreation and culture	80,9	**85,3**	84,1	81,2	81,5	81,3
Education	29,9	33,6	**35,8**	30,0	31,6	31,7
Restaurants and hotels	34,4	**38,3**	35,5	37,2	37,9	35,7
Rest	74,4	76,0	**76,4**	74,5	75,1	74,5
Cereals	73,1	74,4	**74,6**	**73,4**	73,5	73,2
Meats, eggs	49,4	**49,6**	**49,5**	52,6	49,5	**49,6**
Fish	33,2	34,0	34,4	**38,7**	**37,6**	35,0
Dairy	34,7	38,9	36,0	36,7	39,9	**40,6**
Vegetable oils	63,0	**63,7**	**63,1**	63,2	63,3	63,2
Fruit & veg	63,7	**65,2**	64,8	63,9	65,1	64,2
Sugar	60,9	61,2	**65,2**	62,3	61,3	60,9
Other food	61,6	61,8	64,1	63,6	62,5	**65,6**
Beverages and tobacco	8,5	16,5	**23,5**	14,2	16,5	14,1

Source: Own estimation

Notes: Numbers in bold indicate the best fit in the group of models.

The bad performance of the Gini coefficient - we also tested a variant using logs instead of the linear model for which results are reported – might come as a surprise. One might have assumed that, for instance, higher income inequality at low income levels might increase the observed budget share of luxury goods. A potential explanation why the Gini coefficient does not improve the fit strongly might be that the impact of, for instance a small group of rich households, on average spending shares of the aggregate might still be rather limited.[6]

Results for individual commodity groups of the models which consider two factors jointly are shown in Table 7. Here, combining the two demographic variables with the share of Islamic population gives the best fit based on the system wide R^2, closely followed by adding the mean temperature to them. Here, the best fit found for any of the different product groups is more equally distributed over the different model variants. While the best model considering

[6] We also tested with gini coefficient provided by UN- with quite similar results.

one of the factors adds around 4% to the overall R2 of the base model (see Table 6), considering two jointly improves at best by around 6%.

Table 7: Fit of different model variants by commodity group, two factors

	Norms Demog	Norms Sea acc	Norms Climate	Norms Gini	Demog Sea acc	Demog Climate	Demog Gini	Sea acc Climate	Sea acc Gini	Climate Gini
System wide R^2	**51,3**	49,7	50,5	50,0	50,5	50,8	50,6	48,7	48,2	48,6
Clothing and footwear	18,7	18,4	18,7	19,9	19,3	**20,6**	19,9	15,3	18,0	17,7
Housing, water, electricity, gas and other fuels	**51,9**	51,7	51,5	50,9	49,0	49,0	48,9	47,4	46,9	46,9
Furnishings, household equipment and maintenance	10,4	2,0	6,7	4,2	10,4	**12,0**	11,4	5,9	3,6	6,0
Health	**73,1**	71,4	72,9	71,1	71,8	72,5	71,9	70,4	66,6	70,1
Transport	**40,3**	34,5	37,6	37,3	38,8	38,9	39,0	38,3	37,5	37,7
Communication	31,4	32,1	**33,4**	32,8	30,9	33,2	32,0	30,3	30,9	32,0
Recreation and culture	**86,4**	85,6	85,4	85,3	84,3	84,2	84,2	81,8	81,6	81,6
Education	**37,2**	34,1	34,9	35,4	35,9	36,7	36,8	32,4	31,8	32,4
Restaurants and hotels	38,6	42,0	**44,6**	39,8	39,5	43,9	39,0	39,3	37,8	38,1
Rest	**76,9**	76,0	76,2	75,8	76,3	76,3	76,5	75,3	74,7	75,0
Cereals	**76,6**	75,0	74,8	74,7	75,5	75,5	75,4	74,1	73,5	73,9
Meats, eggs	50,2	**52,7**	49,9	49,8	52,5	50,2	50,7	52,1	52,6	49,7
Fish	35,2	**40,1**	38,5	35,5	39,4	39,5	37,0	**40,1**	39,7	38,3
Dairy	**42,9**	41,0	45,1	42,2	37,6	39,5	41,9	40,2	41,5	42,8
Vegetable oils	64,2	63,7	64,1	**64,3**	63,1	63,4	63,2	63,8	63,3	63,8
Fruit & veg	**67,6**	65,6	66,3	66,3	65,3	66,0	65,9	64,8	64,6	65,8
Sugar	66,0	62,6	61,5	61,4	66,3	**66,6**	65,5	62,2	62,4	61,5
Other food	64,4	64,1	62,6	66,0	67,1	64,7	**67,2**	64,2	67,0	65,8
Beverages and tobacco	25,2	20,6	21,5	21,4	**26,9**	24,7	24,3	19,6	18,4	17,9

Source: Own estimation

Notes: Numbers in bold indicate the best fit in the group of models.

Results for the models which consider three factors jointly are shown in Table 8. Perhaps as expected from the results found for single additional factors, combining the share of the Islamic population with the two demographic variables and the mean temperature to control for climate effects gives the best fit. It misses the fit of the model will all factors (i.e. adding the Gini coefficient and the sea access indicator as well) by less than just 2%. This full model performs considerably better for "Clothing and footware" (+5%), "beverages and tobacco" (+4%) and "Meat and eggs" (+4%) compared to this best candidate model with three additional factors. It is interesting to see that simpler models give a better fit compared in two cases to the full specification, for which the fit is shown in bold if it is better than any other specification.

Table 8: Fit of different model variants by commodity group, three and all factors

	Norms Demog Sea acc	Norms Demog Climate	Norms Demog Gini	Demog Sea acc Climate	Demog Sea acc Gini	Sea acc Climate Gini	Full
System wide R^2	52,4	52,6	52,2	51,6	51,5	49,6	**54,2**
Clothing and footwear	20,4	20,6	20,4	22,9	21,5	18,3	**25,2**
Housing, water, electricity, gas and other fuels	52,0	**52,5**	52,3	48,9	49,2	47,4	**52,5**
Furnishings, household equipment and maintenance	10,9	12,8	12,6	12,4	12,0	7,3	**15,8**
Health	73,1	74,1	73,2	72,8	72,2	70,4	**74,5**
Transport	40,8	41,6	40,5	40,7	39,7	40,1	**43,2**
Communication	32,3	34,2	32,5	33,4	32,4	31,9	**35,1**
Recreation and culture	86,4	**86,5**	86,3	84,4	84,4	81,8	86,4
Education	37,7	37,9	38,5	36,6	36,8	33,1	**39,4**
Restaurants and hotels	43,0	46,5	40,4	45,0	41,8	39,5	**47,9**
Rest	76,9	76,7	**77,0**	76,1	76,4	75,2	76,6
Cereals	77,0	77,3	76,8	76,2	75,9	74,5	**78,0**
Meats, eggs	53,7	50,6	51,1	52,9	53,3	52,2	**54,6**
Fish	40,6	40,4	37,3	41,0	41,4	41,0	**42,9**
Dairy	45,5	47,0	46,0	39,4	42,8	43,1	**49,2**
Vegetable oils	64,3	64,7	64,9	64,1	63,3	64,4	**66,1**
Fruit & veg	67,8	68,3	67,9	66,0	66,4	65,7	**68,4**
Sugar	67,0	67,5	66,3	67,4	66,5	62,4	**68,4**
Other food	67,4	65,1	68,1	67,4	69,4	67,6	**70,3**
Beverages and tobacco	28,3	26,8	26,5	28,4	28,0	20,8	**30,7**

Source: Own estimation

Notes: Numbers in red indicate the best fit in the group of models. Results in bold indicate best value including the full model.

Besides considering the model selection statistics from Table 5 and considerations of the fit for individual model groups, the choice of a suitable model variant depends also on how its estimates can be integrated into long-run simulations with a CGE. Suitable variants comprise factors which are likely rather stable over time or are explicitly controlled by dynamic updates. As the IASSA data base reports projections of the demographic composition of the population for all countries and the different SSPs, the two demographic factors are obvious candidates. They also have shown to improve considerably the fit either alone or combined with others. The share of the Islamic population in a country could clearly change when simulating over multiple decades into future, but cultural habits related to current or former shares of Islamic population are properly more stable. It seems therefore defendable to use the share of Islamic population as well as an additional control. Finally, mean temperatures can be either considered stable or updated according to climate change projections. Considering both factors besides the demographic ones clearly could improve the model selection satistis and fit of most commodity groups. While in some cases, considering the Gini coefficients gave best results for certain categories, the Gini coefficient is likely to change if average per capita income increase considerably over the projection period and is therefore here excluded. Sea access seems mostly to impact fish consumption and it is likely that the benchmarking process will address outliers here anyhow.

Based on these arguments and the model statistics, we opt for the model specification with uses the two demographic factors, the share of Islamic population and the climate variable as additional explanatory variables.

Table 9: Estimated base coefficients for selected model

	Alpha	Beta	Gamma, lo	Gamma, high
Clothing and footwear	4%	5%	6	136
Housing, water, electricity, gas and other fuels	1,00E-07	20%	121	1.354
Furnishings, household equipment and maintenance	5%	6%	1	158
Health	4%	9%		781
Transport	2%	13%	3	423
Communication	2%	3%		290
Recreation and culture	1,00E-07	6%		133
Education	7%	5%	39	2.037
Restaurants and hotels	0%	6%	5	181
Miscellaneous goods and services	1,00E-07	12%		252
Cereals	10%	1,00E-07	19	
Meats, eggs	12%	3%		203
Fish	3%	1%	1	
Dairy	8%	2%		84
Vegetable oils	4%	0%		
Fruit & veg	15%	1%		131
Sugar	2%	1%		
Other food	13%	3%	7	209
Beverages and tobacco	9%	3%	10	301
Food (sum of the categories above)	76%	15%	37	928

Source: Own estimation

Note: Model considers two demographic factors and temperature as additional explanatory variables. The gamma parameters are expressed on a per capita basis.

Table 9 reports the estimated parameters. Quantities during the estimation are expressed in USD dollars per capita and corrected for differences in prices, setting the US price to unity. The commitment terms γ are all modest to low, when considering that income reaches up to around 55,000 USD in the sample. Generally, the reader should keep in mind the difference between expenditure levels and budget shares. Let us take education as an example: the expenditure at low income levels (250 USD) is based on budget share of around 7%, plus forty dollars committed, i.e. around sixty dollars. At 50,000 USD, the about 5% marginal budget share implies an expenditure of 2,500 USD plus 2,000 USD of committed income, i.e. 4,500 USD. But, production costs and thus prices for educational services are also generally higher in high income countries.

Scatter plots are shown in Figure 1 for non-food and in Figure 2 for food-items. jointly with logarithmic regression lines dependent on income. Note that the income axis is logarithmic. The plots highlight two observations. First, the variation in the observed budget shares in countries of the same income range can be rather large, as seen for instance from the panel for the housing costs. There are some observations in the 500 USD range where just 5% are spent on housing, whereas the average household in others countries spends 30%. At the same time, estimates also scatter around the simple logarithmic regression line which reflects the impact of price differences across countries, but also of the other explanatory factors. The diagrams also highlight the usefulness of the using the exponential marginal budget lines of the

AIDADS system to capture, for instance, the clear saturation effect seen for cereals in Figure 2. For meats and eggs as well as dairy, the plots suggest that budget shares first increase up to around 2000 USD to drop afterwards.

Figure 1: Scatter plots, Non-Food items

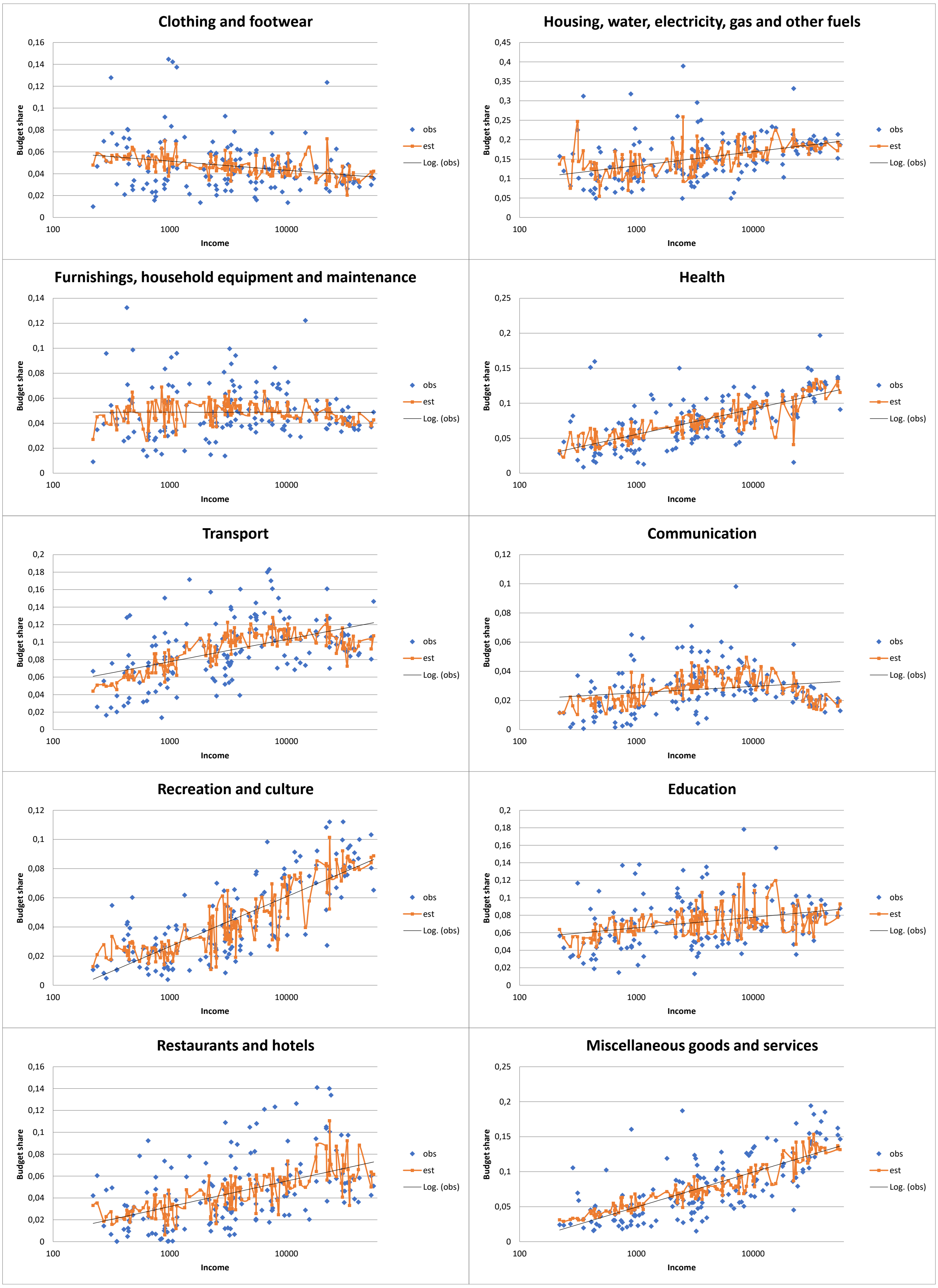


Figure 2: Scatter plots, Food items

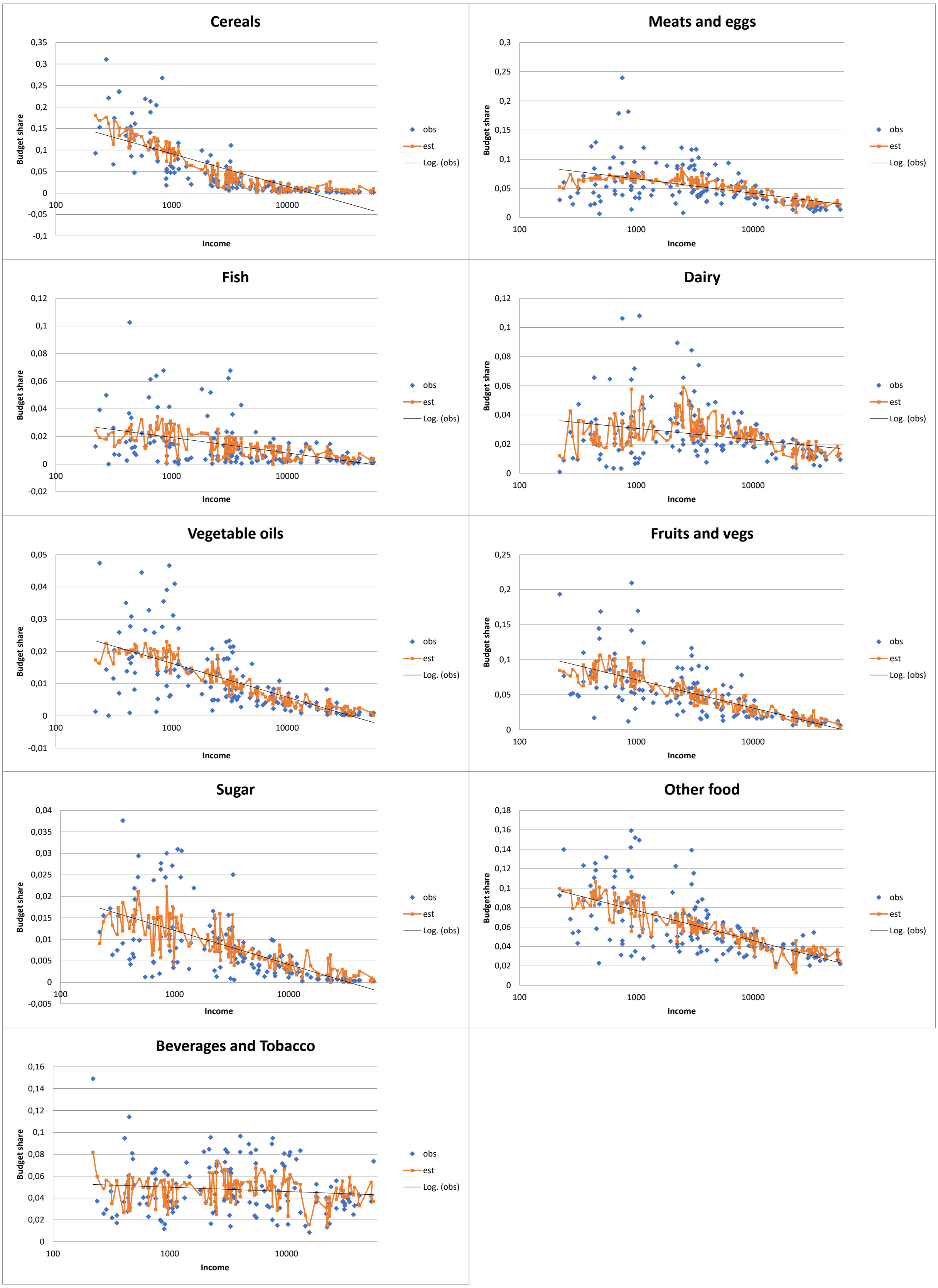
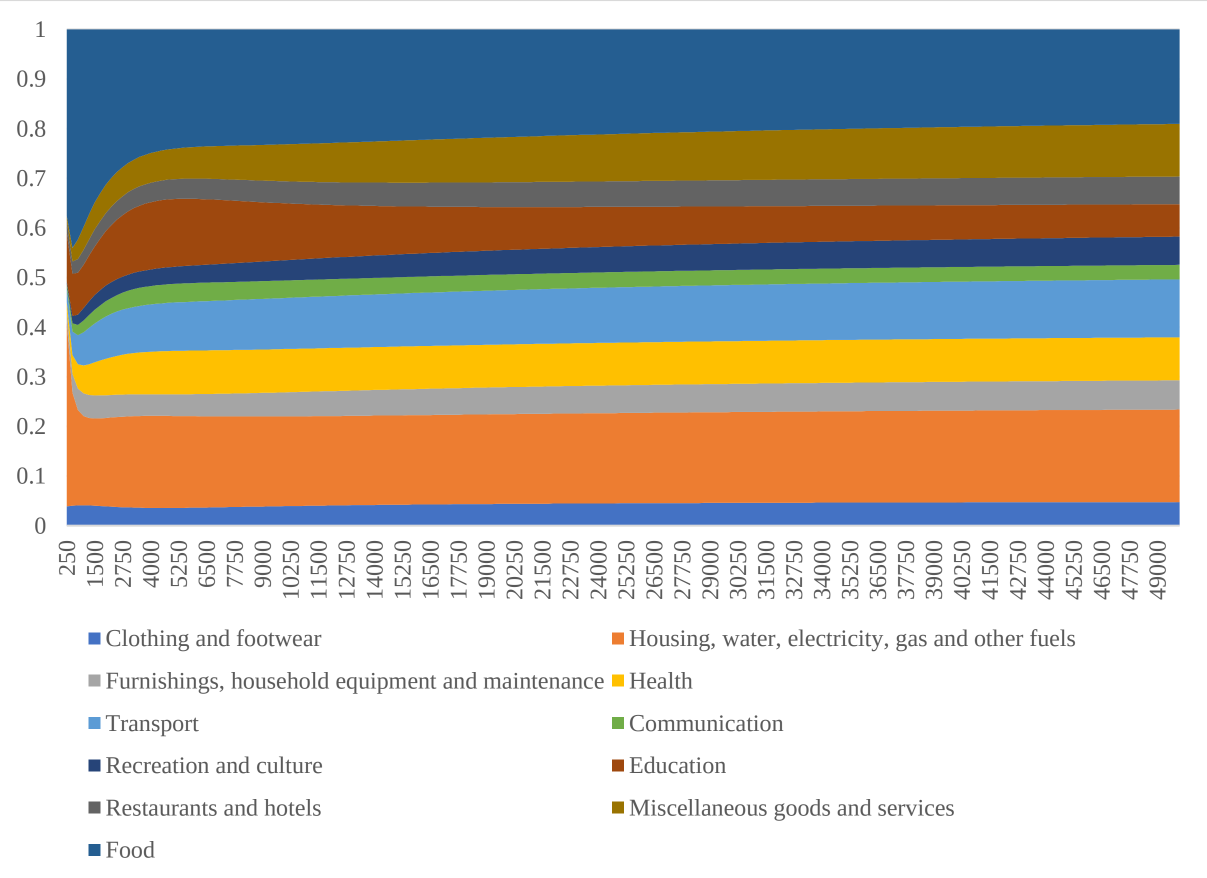


Figure 3 shows the expenditure shares resulting from the AIDADS estimation, for income levels between 250 and 50,000 USD evaluated at mean prices and mean explanatory factors. At very low income levels, more than a third of the income is dedicated to food (37%), around 13% is spent on housing and 8% on transport, 5% on Furnishing, household equipment and maintenance and 2% on health. At very high expenditure levels, the share for food drops to about 17%, while shares for housing increase moderately to around 16%. Shares for health care are more than tripling, reaching 11%, whereas for restaurants and hotels they increase by a factor five, from 1.7% up to 7%. A similar large increment is observed for "Recreation and culture" growing from less than 1.6% to over 7%.

An interesting observation is the rather drastic change in budget shares for some product groups when moving from 250 USD to 1000 USD per capita and year. Housing cost half from 37% to 18%, while expenditures for food change only slightly. Instead, budget shares for health (1.7% versus 5.6%), communication (0.08% to 2.3%), Furnishings (2.2% to 4.3%), Transport (2.8% to 6.7%), Recreation and culture (0.5% to 2.3%) and other items (0.9% to 4.6%) increase substantially. That underlines that at very low incomes, expenditures are concentrated on food, shelter and utilities, where the later might serve also as input into, for instance, food preparation in the household, which is outsourced at higher income levels.

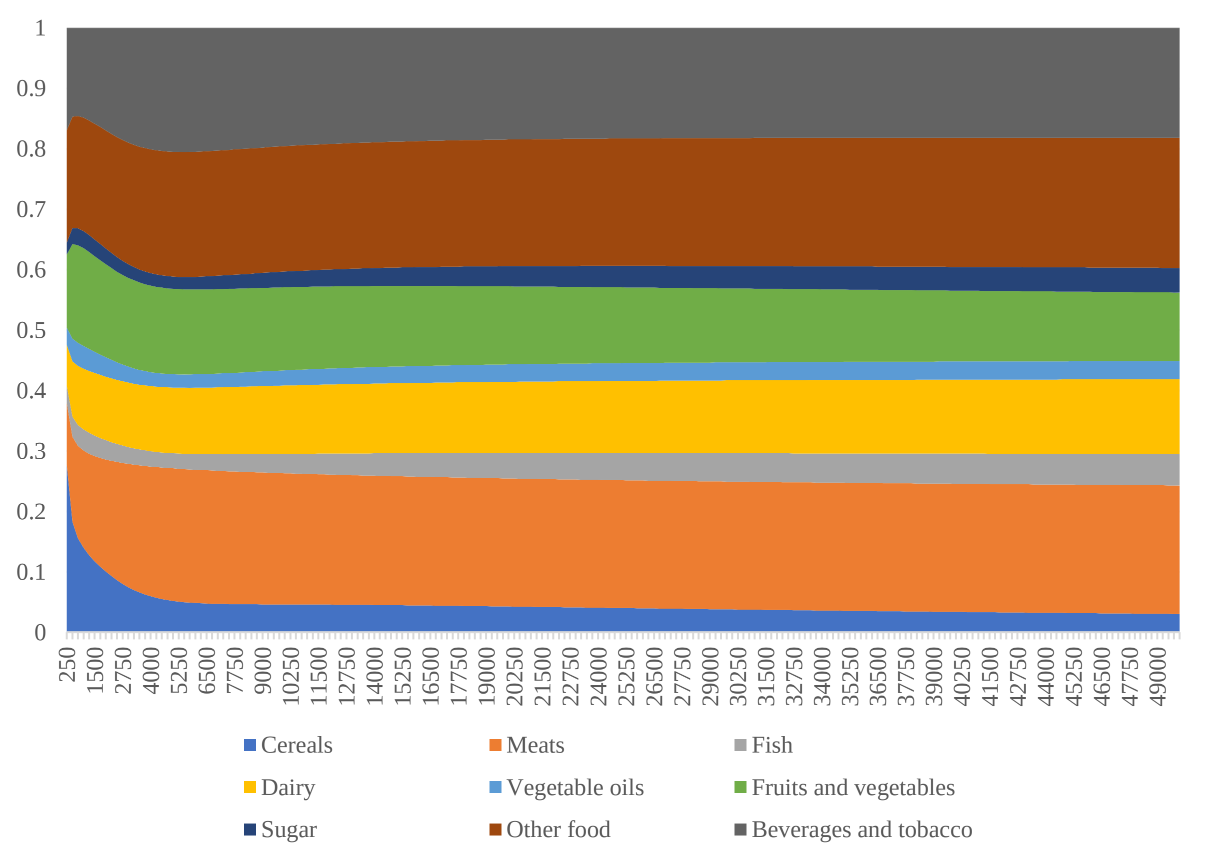
Figure 3: Simulated expenditure shares, non-food items and total for food



Note: Calculated at mean sample prices and mean sample values of the additional factors

Figure 4 below provides more detail for food categories in the AIDADS system by reporting shares on total food expenditure. At very low income levels, cereals have the highest shares with around 28%, followed by the other food category (19%) which comprises, for instance, bread, and 12 % are spent on fruits and vegetables. Expenditures on meat in total food consumption are estimated at 10%, while dairy accounts for 7% at such low income levels. There is again a distinct difference between the 250 USD to the 1000 USD consumption pattern, as the cereals share is halved to 14%, while the share of meat (+6% to 16%) and dairy (+3% to 10%) increase considerably. At very high incomes, other food (22%) followed by meat (18%) and beverages and tobacco (18%) are the largest expenditure groups inside the food bundle. The cereal shares on total food expenditure is still 3%, but the overall drop of the budget share of food implies that a very high income levels, less than 1% of the income is spent on cereals.

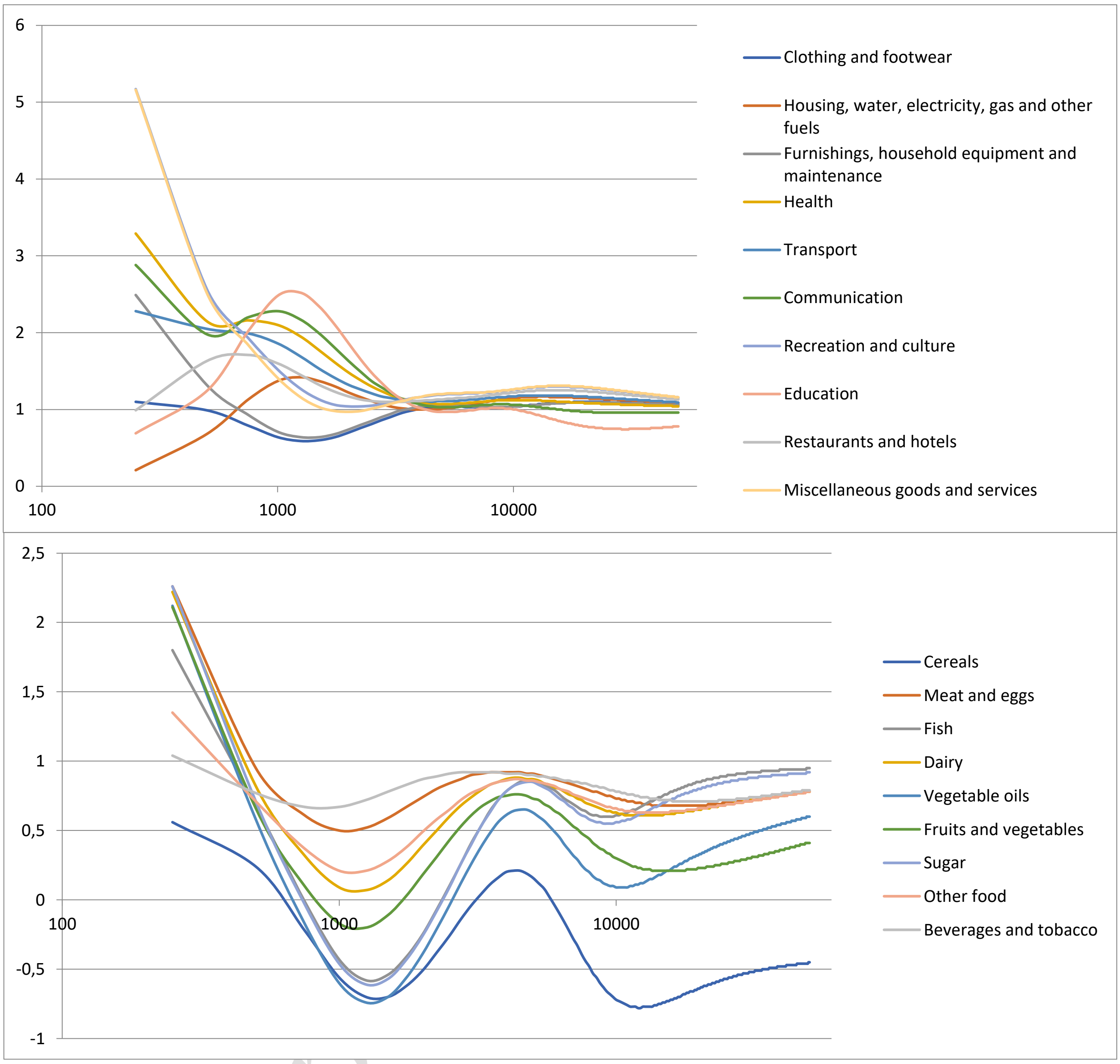
Figure 4: Expenditure shares for food categories



Note: Calculated at mean sample prices and mean sample values of the additional factors

The income dynamics become also visible from the Engel curves shown in Figure 5. Recreation and culture as well as the other service category show very high Engel elasticities at low income in the range of five. Interestingly, at high income levels, education and communication have elasticities below unity, different from all other non-food items.

Figure 5: Estimated Engel elasticities at mean prices



Note: Calculated at mean sample prices and mean sample values of the additional factors. Formula based on Preckel et al. 2010

For the food items, cereals show negative Engel elasticities over a wider ranger of the income variation. Below 100 USD, basically all food items besides cereals are luxury goods, as indicated above, this becomes possible by a quite low income elasticity for housing expenditure, also visible from the upper panel. But food item elasticities drop rapidly below 0.5 around 1000 USD, with the exemption of beverages and tobacco as well as meat and eggs, and increase slightly again up to income levels around 5.000 USD. A potential reason is the falling elasticity for housing costs suggested by the upper panel. Above 1000 USD yearly per capita income, none of the food items is a luxury good any longer and the crop based food items with the exemption of sugar have elasticities below 0.5. The reader should keep in mind that these estimates also capture the effect of compositional changes, for instance, the average household in a rich country spent income on imported fresh fruits and vegetables, while in poor countries, this product group might mainly comprise locally available roots and tubers.

6 Discussion

A suitable specification for aggregate household demand in a CGE needs to reflect the targeted applications. For detailed policy analysis such as changing subsidies and/or taxes differentiated across energy carriers, income changes are mostly limited and the focus is rather on own and cross price effects. This motivates the use of nested demand systems e.g. in the GTAP-E (McDougal and Golub 2007) model to capture in detail substitution effects between different energy carries. We focus instead on long-run analysis with large income dynamics which motivates the use of MAIDADS functional form.

Stronger Hicksian substitution effects between the commodity groups considered in here are not very likely such that second-order flexibility with regard to prices is probably not needed to identify the Engel curves. This motivates also the use of a simpler additive utility function. In this respect, we don't follow the argumentation line of Reimer and Hertel 2004 who consider the AIADS as not appropriate for more than ten product categories in estimation, an argument which would also apply to an LES or CD specification. As the G-RDEM model as our main application target also uses CES nests to substitute between different cereals and between different meats, we deliberately aggregate here beyond the individual GTAP sectors in the estimation as discussed above. Differentiating to individual cereals or meats would indeed render the use of an additive demand system dubious. An estimation exercise of an MAIDADS system for food only by Gouel and Guimbard 2019 estimates calorie demands for seven food categories, introducing hence similar detail for food as in our exercise, however estimating demands based on producer prices.

We opted in here to render marginal budget shares depending on additional factors besides prices and income. Alternatively, the commitment terms could be updated. Using the marginal budget shares has the advantage that additivity can be imposed on the impact of these additional factors. This at least prevents that more unusual observations for the additional factors can provoke e.g. negative consumption quantity estimates, or that the non-committed income overshoots the observed one when commitment terms are increased. The estimates for the commitment terms (see Table 9) suggest that they are all mostly small compared to income levels. At least for the vector at low utility, that is not an astonishing outcome as estimation of negative budget shares is not allowed even at the quite low minimal per capita income levels in the estimation. Here, neither larger increases of the commitment terms nor larger decreases are able without violating the non-negativity condition, while updates to the marginal budget share cannot provoke problems in that respect.

Switching to, for instance, a QUAIDS to better capture cross-price effects while also considering some additional factors would introduce many new parameters in the estimator. The review of Ho et. al. 2020 of demand systems in CGEs mentions only one example (Jorgenson et al. 2013, a dynamic single country CGE for the US) where a rank 3 Translog demand system is used which gives also flexibility for coss-price effects, however for four aggregate expenditure groups, only, which are further dis-aggregated to more detail based on homothetic functions. Given the non-homothetic character of e.g. food expenditure groups above, a nested approach where the lower nests assume homotheticy is probably less appropriate for our exercise. Vigani et al. 2019 estimate a QUAIDS for Kenya with detail for food, but only mention that this can improve economic models without discussing how. It is also interesting to see that in their estimation, the QUAIDS gives for most product and product groups income elasticities quite close to unity. Their hierarchical demand system layout might render it hard to link their results into CGE models, especially if flexible aggregation with regard to commodity is maintained, as in case of the GTAP family of CGE models. Furthermore, given the often high correlation between prices and income levels in our cross-sectional data where time variability of prices is missing, it could be challenging to introduce a non-additive demand system with full flexibility for price effects

Several statistic packages allow estimation of a (non-linear) system with parameter restrictions. For highly non-linear specifications such as in here, convergence and feasibility issues with the solvers inbuilt in these packages are not uncommon. It is therefore not astonishing that all authors estimating (M)AIDADS systems (Reimer and Hertel 2004, Preckel et al. 2010, Roson and Van der Mensbrugghe 2018, Britz and Roson 2019) rather use GAMS to access robust NLP solvers such as CONOPT. Estimating one of the more detailed systems in here requires up to 10 minutes of computing time using the parallelism of CONOPT4 on a fast four core machine. We consider a larger-scale bootstrapping exercise to determine the distribution of the parameters and p-values as not feasible. Arata and Britz 2019 propose instead to construct a Fisher information matrix by simulating the error terms at changed parameters. While this would be computationally feasible, we don't consider that the additional coding efforts would help us in better assessing the choice of models.

Summary and conclusion

We present an estimation of an extended MAIDADS demand system from global cross-sectional data. Existing literature in this field is extended in multiple dimensions. Compared to Britz and Roson 2019 who use the same data set, we integrate the extension proposed by Preckel et al. 2010 to render the commitment terms depending on utility. In both Britz and Roson 2019 and Preckel et al. 2010, only prices and income are used as independents while we now also consider demographic factors, the share of Islamic population to control for religious norms and cultural habits, mean temperature to check for climatic influences and test if access to sea and the Gini coefficients have a systematic impact on consumption shares. According to our knowledge, this is the first time that the (M)AIDADS specification is extended in these respects. Compared to Reimer and Hertel 2003 or Preckel et al 2010, we also introduce more detail for food expenditure and render the functional form somewhat more flexible. We find that especially demography, religious norms and temperature considerably improve the fit in our global cross-sectional analysis. We compare different model variants, considering only one, two or three factors in combination compared to the base model and a variant with all factors. Considering model selection statistics and the need to integrate estimates into long-run dynamic long run analysis with a CGE, we opt for a version where demography, religious norms and mean temperatures are maintained as additional factors. Data selection and definition of food categories in here reflects our aim to integrate the estimates in a global dynamic CGE. We deliberately removed some detail for food available from the underlying data set to render Hicksian substitution effects between groups less likely, to better motivate the use of an additive demand system. Substitution effects are instead considered by CES nests in our simulation model. Our estimation has the potential to improve the representation of demand dynamics in global long-run analysis. Further work could introduce more detail in so far more aggregated consumption categories such as the costs of housing.

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