Journal of Global Economic Analysis, Volume 5 (2020), No. 1, pp. 63-108.

Modelling Consumption and Constructing Long-Term Baselines in Final Demand

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Modelling and projecting consumption, investment and government demand by detailed commodities in CGE models poses many data and methodological challenges. We review the state of knowledge of modelling consumption of commodities (price and income elasticities and demographics), as well as the historical trends that we should be able to explain. We then discuss the current approaches taken in CGE models to project the trends in demand at various levels of commodity disaggregation. We examine the pros and cons of the various approaches to adjust parameters over time or using functions of time and suggest a research agenda to improve modelling and projection. We compare projections out to 2050 using LES, CES and AIDADS functions in the same CGE model to illustrate the size of the differences. In addition, we briefly discuss the allocation of total investment and government demand to individual commodities.

JEL codes: D12, D58.

Keywords: Consumption demand systems; Long-term baseline; CGE models.

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1. Introduction

Personal consumption expenditure is by far the largest component of final demand in most countries and changes in its commodity composition are an important driver of structural change. An appropriate representation of household consumption is therefore essential for models focused on long-run dynamics, either covering the whole economy such as Computable General Equilibrium (CGE) models or detailing specific sectors such as Partial Equilibrium models for the energy or agri-food sectors.

Micro-analysis of household behavior has highlighted that apart from the main drivers of prices and income, factors such as cultural and religious norms, and household demographic and location characteristics determine consumption behavior. Aggregate consumption is further affected by population composition. Disentangling these drivers from income and price dynamics in long-run analysis using aggregate demand functions is challenging. The evidence from many studies shows non-monotonic income effects; for example, certain types of food or gasoline are normal goods at low incomes, but inferior ones at high incomes. Implementing functions with well-founded price and income elasticities that can represent the observed income dynamics is therefore the focus of improving the representation of long-run baseline consumption in CGE models.

Comprehensive modelling of household demand over a long horizon, however, remains challenging, as highlighted by a workshop jointly organized by GTAP and OECD in January 2018. As a follow-up to this workshop, we first review here how household consumption is modeled in a broad range of CGE models and discuss the merits and deficiencies of these approaches. We focus on dynamic multi-country CGE models, myopic or with foresight, with varying detail of industry disaggregation, including CGE models with a focus on agri-food, land use and energy. We touch only briefly on modelling leisure demand, labor supply and savings and devote the bulk of the paper on the allocation of household expenditures for final consumption. We concentrate on the single aggregate household representation which ignores different preferences of household members[1]. We also neglect further attributes in the utility function such as an index of environmental quality as found in certain environmental models.

In section 2, we first discuss historical consumption behavior before reviewing modelling approaches used by CGE models in section 3. We believe it would be useful for modelers to consider alternatives to the common CES and LES

[1] Those interested in household models would find the survey by Chiappori and Mazzocco (2017) helpful.

functions and thus discuss the pros and cons of various approaches in some detail. Section 4 then describes how base paths of consumption function parameters are projected by various models, including extensions to approaches that overcome some of their limitations. We then turn to other determinants of final demand. We summarize the current approaches to modelling investment commodity demands and construction of their base paths in section 5. Modelling the commodity composition of government final demand is also briefly discussed in Section 5. Section 6 then summarizes our recommendations on the best practices in making such projections and discusses a research agenda to fill in the gaps in knowledge of specifying and implementing consumption models.

2. Observed consumption behavior and elasticities

In order to establish a final demand pathway in baseline construction that can be widely accepted, models need to be able to emulate the observed consumption behavior of households. The first step in constructing demand functions with well-founded price and income elasticities that can account for current and future consumption trends is thus to establish the historical record of consumption behavior. The work on consumption is huge, but we only focus here on the parts relevant for use in large global simulation models with highly aggregated sectors and households.

Textbook models of individual consumption give us functions of income and prices and there is a large empirical literature estimating such functions based on individual or household level data. The study of consumption is one of the earliest empirical studies by economists, starting with Engel's Law (Chai and Moneta, 2010), and we thus have a wealth of knowledge compared to other issues in CGE modelling. In the 3-sector model tradition of Fisher, Clark and Fourastié we may say that, as income rises, individual households, or entire economies, allocate an increasing share of consumption expenditure to manufactured goods and, at even higher incomes, an increasing share to services. This is especially pronounced for countries projected to undergo a period of fast per capita income growth in the time horizon of the baseline. In addition, certain disaggregated commodity groups such as food and energy are particularly affected by income changes and need to be carefully modeled when analyzing the bioeconomy or impacts of climate change.

This section reviews past and current consumption trends as well as the empirical work estimating demand elasticities for modeling these trends. We discuss data sources and the problems of aggregation of commodities and households.

2.1 General consumption trends and income elasticities

We first give a representative view of rich-country consumption by summarizing the results for the U.S. in Jorgenson et al. (2013, Fig. 3.1) and updated to 2016 for Figure 1. They model a full-consumption function with leisure and three bundles of consumption commodities at the top tier, namely nondurables, capital, and services. These three bundles are disaggregated to 35 commodities in lower tiers. The first feature to note is that aggregate expenditure shares change significantly over time, changes that do not correspond entirely to price movements as illustrated in Figure 1. The leisure share is large in their approach, but the downward trend after 1970 holds for other methods of defining time endowment, which is due to the rapid rise in the female labor force participation rate in the U.S. The falling share of nondurables (including food) and the rising share for services is a common feature of rising incomes. Capital services is an annualized flow from durables and housing,, and the relatively flat share hides different trends in component prices – rapidly falling electronic equipment prices and slowly rising housing prices.

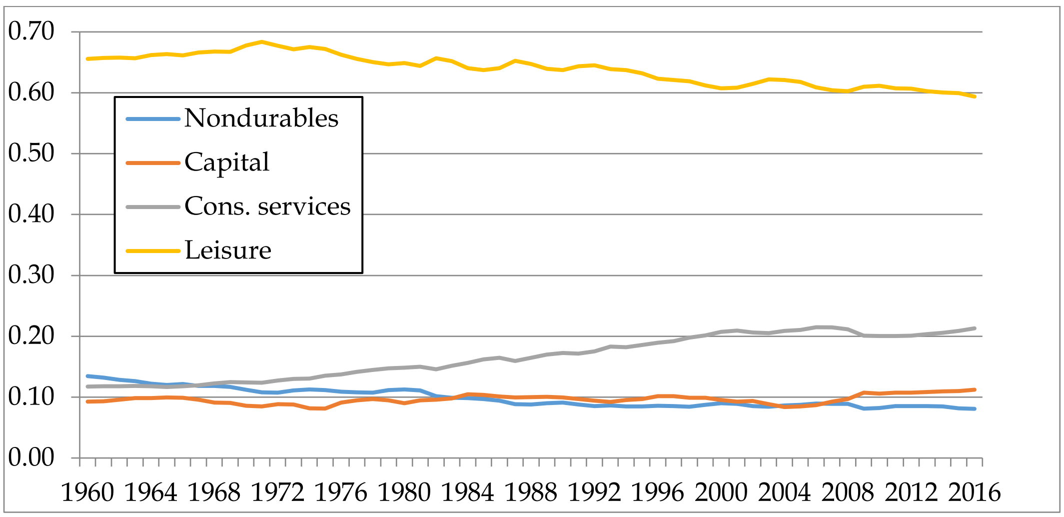

Figure 1. Consumption shares of the U.S. between 1960 and 2008: Nondurables, annualized capital services, consumer services, leisure.

Source: Authors' calculations based on Jorgenson et al. (2013, Fig. 3.1).

To have a broader global coverage, Table 1 from Muhammad et al. (2011), gives the budget shares for 9 major consumption bundles in 2005 for low-, medium- and high-income countries. Food is a major portion (48%) of poor household budgets around the world today, while richer households spend more on transport, communication and other commodities.

Table 1: Budget shares of aggregate commodity types in different countries in 2005

Commodity type	Country type		
	Low-income	Middle-income	High-income
Food, beverages and tobacco	0.485	0.311	0.204
Clothing & footwear	0.061	0.055	0.051
Housing	0.135	0.183	0.187
House furnishing	0.052	0.056	0.06
Medical care	0.045	0.059	0.089
Education	0.034	0.033	0.031
Transport & communication	0.102	0.155	0.149
Recreation	0.031	0.061	0.095
Other	0.054	0.087	0.134

Source: Muhammad et al. (2011).

The impact of rising incomes on aggregated demand is demonstrated in more detail by Britz and Roson (2019), who use national data from the International Comparison Project (ICP) to estimate an AIDADS demand system for the world economy. Their results for aggregate spending categories are illustrated in Figure 2 and show that at low income levels around 50% is spent on food, following by housing expenditures. At high income levels, food expenditures account for only around 15%, while the share of the cost of housing tends to a constant.

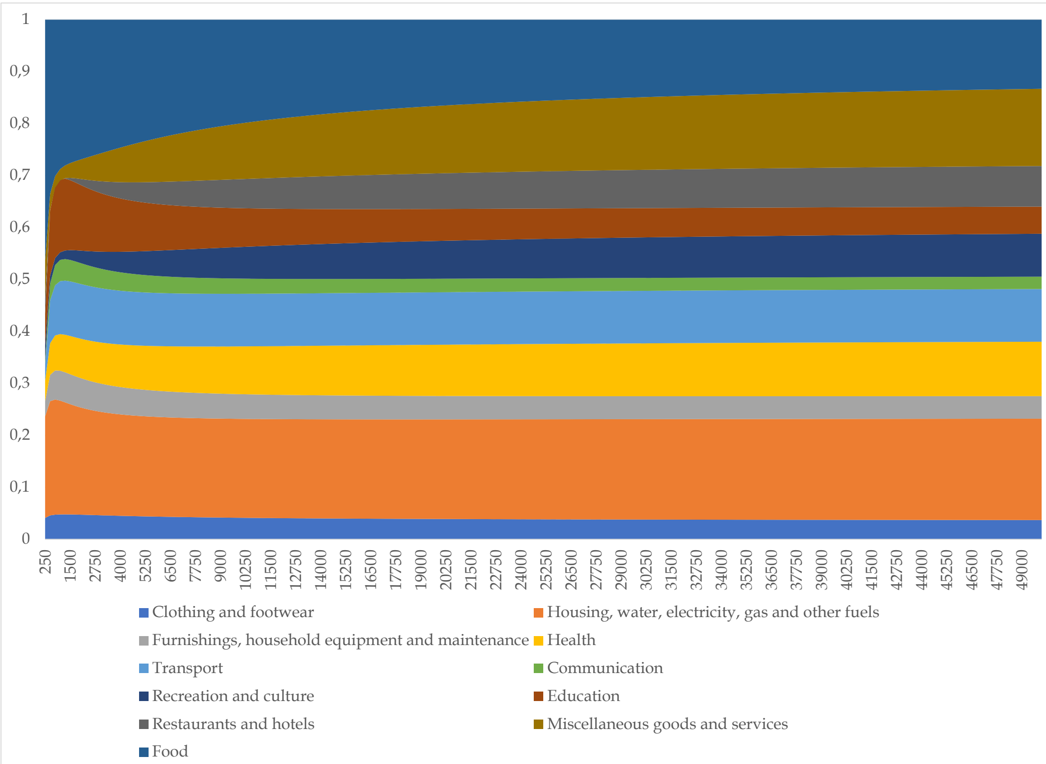

Figure 2. Consumption shares with raising per-capita income in US$ as estimated by Britz and Roson (2019), AIDADS.

Note: Simulated of budget shares with estimated parameters at mean sample price, not CGE model results.

Source: Britz and Roson 2019.

2.1.1 Food demand

Figure 2 has emphasized the large impact of income changes on food demand. The study of food demand is one of the earliest empirical economics work and Engel's Law was named in honor of his 1857 paper on this subject. He found that with rising income the share of food in total expenditure diminishes, leading to lower marginal budget shares of food (Chaudri and Timmer, 1986). In addition, Bennett's law looks at the composition of food demand and states that income growth leads to an increasing share of livestock products and a reduction in the share of staple foods in total food expenditure (Bennett, 1941). Both laws have been empirically proven across time and countries at different development stages and presently describe part of the food demand dynamics in emerging economies such as China and India.

In more recent decades, the global composition of food demand has been changing rapidly due to income changes through higher economic growth (Yu et al., 2004), structural change, urbanization and globalization. Supply side factors such as the expansion of supermarkets in developing regions are also major determinants of dietary change (Hawkes et al., 2017). As a result, dietary patterns in emerging and developing economies are diversifying and converging to the diet of Western countries that is rich in livestock products (including both meat and dairy) as well as highly processed foods consisting of refined carbohydrates, fats and sugar (Pingali, 2006; Popkin et al, 2012). Table 2 shows food budget shares of countries grouped by income as reported in Muhammad et al. (2011) and demonstrates both Bennett's law when comparing the food budget shares between low- and middle-income countries as well as the tendency of high-income countries to consume higher shares of processed food ("other food"). This is also confirmed by Britz and Roson (2019) who estimated an AIDADS demand system with detailed aggregation of food types which are mapped into the GTAP sectors. Their estimates are shown in Figure 3 and highlight that food expenditure at very low incomes comprises a high share of cereals while processed food, including convenience products, dominates food demand at high incomes.

Engel's law on its own implies that income elasticities for food commodities decrease with rising income. When we treat food as an aggregated commodity this means that the income elasticity becomes less than one when household income exceeds some threshold. At the disaggregated level, Bennett's law implies that income elasticities for some commodities such as livestock products are larger than for staples. Food commodities can be both normal goods with positive income elasticities as well as inferior goods with negative income elasticities depending on the country's and household's level of income. While staple foods are usually necessity goods, they can also turn into inferior goods at higher levels of income. For poorer households and in lower income countries, livestock products are luxury goods with an income elasticity above unity so that their consumption increases more than proportionally with income (Cirera and Masset, 2010). As income elasticities for all food types fall with income, Engel curves show a tendency to flatten out over time, and reach a saturation level at least for aggregate food demand (Chai and Moneta, 2010b). Estimates of income elasticities over time show a decrease in elasticities for all commodity groups as expected (Yu et al., 2004) and hit a saturation point where income elasticities cease to fall (Cirera and Masset, 2010). Table A2 in the supplementary materials gives income elasticities for food items for selected countries.

Table 2: Conditional food budget shares types in different countries in 2005

Food type	Country type		
	Low-income	Middle-income	High-income
Cereals	0.23	0.12	0.09
Meats	0.13	0.17	0.12
Fish	0.06	0.04	0.04
Dairy	0.08	0.10	0.07
Oils & Fats	0.05	0.03	0.01
Fruits & Vegetables	0.18	0.15	0.10
Other Food	0.15	0.21	0.37
Beverage & Tobacco	0.12	0.19	0.21

Source: Muhammad et al. (2011).

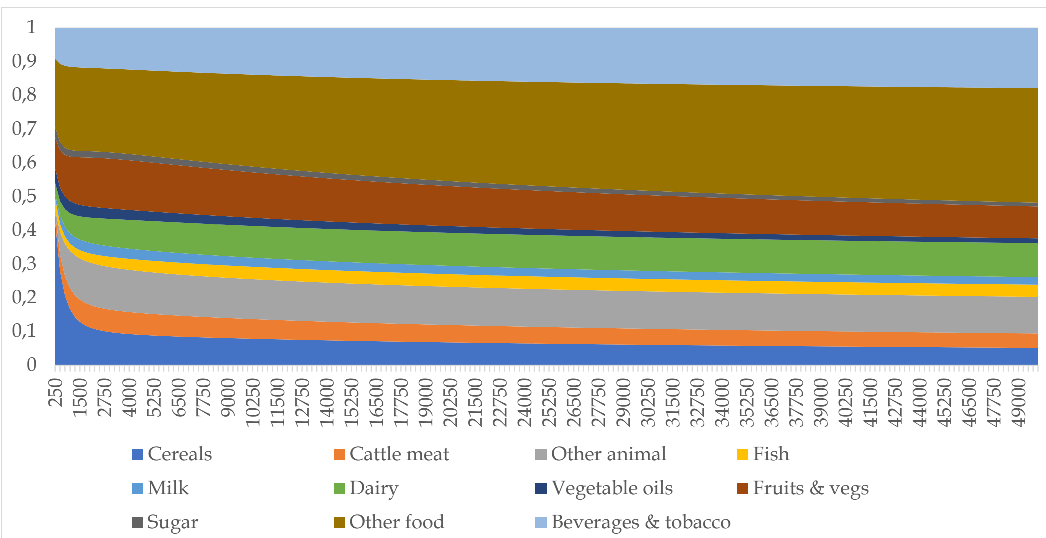

Figure 3. Consumption shares for food commodities with raising per-capita income in US$ in GTAP-sector definition by Britz and Roson (2019), AIDADS.

Note: Simulated of budget shares with estimated parameters at mean sample price, not CGE model results.

Source: Britz and Roson 2019.

2.1.2 Demand for energy services

More complex models of energy demand do not represent the demand for fuels or electricity symmetrically with the other commodities, but instead construct a household production model for energy services, e.g. transportation services as a function of vehicles and fuel. The modelling of the demand for energy services is thus even more challenging compared to food, as there could be technical change effects in these household production functions, in addition to income effects. An example of this is the introduction of electric vehicles which may change the demand for electricity even if incomes remain unchanged. In section 3.3 below we describe some examples of energy service demand models which highlights the complex income effects in energy consumption and some estimated elasticities.

Here we give a illustrative historical record of energy use. Figure 4, taken from Jorgenson et al. (2013, Fig. 3.3), shows the energy consumption share in total U.S. personal consumption expenditures, which rose during the oil shocks of the 1970s, then fell rapidly in the 1980s and increased again in the mid-2000s. Although these changing shares are mostly driven by price effects, there are also non-price effects that are due to technical change, income effects and demography. In most demand systems, changes that are not price related are attributed to income effects instead of a change in preferences that would be analogous with the biases of technical change in production functions.

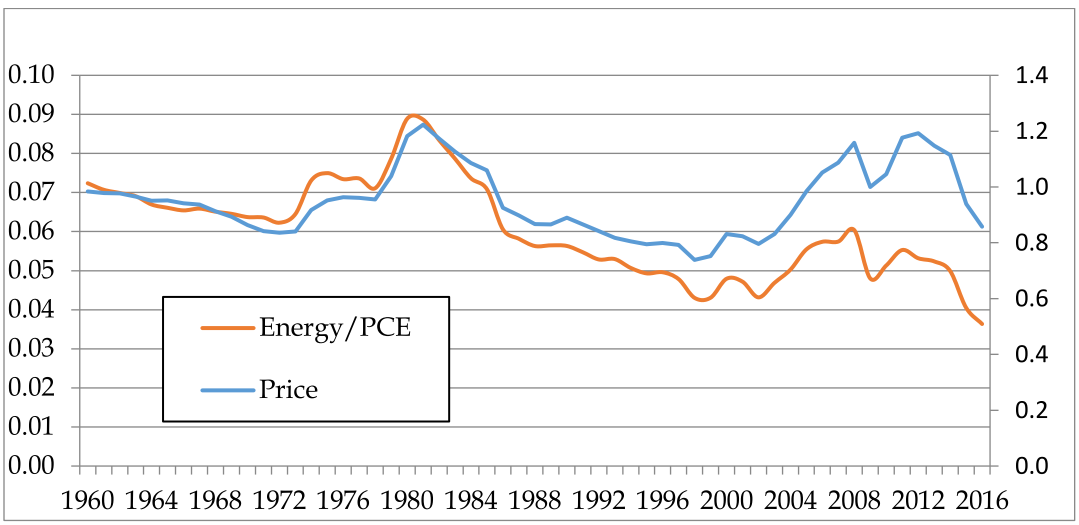

Figure 4. U.S. energy expenditure share of Personal Consumption Expenditures and relative price of energy

Source: Authors' calculations based on Jorgenson et al. (2013, Fig. 3.3).

2.1.3 Comment on necessities and luxuries

While the income elasticity below unity is well documented for food, there are surprisingly few other categories where such an Engel's law holds. Kaus (2013) and Seale and Regmi (2006) estimate income elasticities for 9 consumption bundles using a sample of countries across a broad spectrum of development.[2] Table 3 shows income elasticity estimates for selected countries over aggregate commodity types and at two points in time, 1996 and 2005. The only two categories that were found to be necessities are clothing and footwear, and to some extent, education. Still, at a range between 0.8 and 1.0, the income elasticities for these categories are much higher than for food.

Goods with income elasticities greater than unity are often referred to as luxury goods. This is misleading as income elasticities greater than unity are observed for the majority of goods and services. The highest income elasticities can be observed for services and recreation (Kaus, 2013; Seale and Regmi 2006). Furthermore, as mentioned above, even for food, the income elasticity can exceed one for some income ranges. On the other hand, Seale and Regmi (2006) report declining income elasticities for all broad categories in their study. The strongest decline in income elasticities with income can be observed for categories with high initial values, i.e. recreation and other services.

This heterogeneity of goods within broad categories of consumption among different countries can make comparisons difficult and results hard to interpret. At the same time, aggregation of commodity groups also hides the heterogeneity of expenditure behavior between different income groups, although this is less of a problem for models working with single representative households. In addition, reporting of consumption expenditures can be problematic in the case of consumption from own production (see section on food above) or public provision of services (e.g. education and health), which vary significantly across countries. We should also note that functions that obey the axioms of consumer theory impose restrictions on the income elasticity parameters in terms of the Engel aggregation where the weighted sum of the income elasticities (marginal budget shares) must be equal to 1. If there are some necessities then there must also be some income elastic commodities.

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[2] In both studies, energy is not a separate category, but included in housing or transport categories. Caron, Karplus and Schwarz (2017) estimate Engel Curves for detailed household energy commodities in China.

Table 3: Income elasticities of aggregated commodity groups for selected countries and different years

Commodity type	Malawi[a]	Vietnam		Mexico		United States	
	2005	1996	2005	1996	2005	1996	2005
Food, beverages and tobacco	0.82[b]	0.74	0.78[b]	0.59	0.65[b]	0.09	0.35[b]
Clothing & footwear	0.97	0.88	0.97	0.85	0.97	0.82	0.96
Housing	1.08	1.25	1.07	1.19	1.07	1.15	1.06
House furnishing	1.06	1.18	1.05	1.14	1.05	1.12	1.05
Medical care	2.42	1.67	1.60	1.35	1.29	1.24	1.21
Education	0.93	1.01	0.93	1.01	0.92	1.01	0.91
Transport & communication	1.25	1.22	1.20	1.17	1.15	1.14	1.13
Recreation	1.33	2.20	2.11	1.45	1.38	1.28	1.25
Other	2.50	1.73	1.62	1.36	1.30	1.25	1.21

Notes: [a]No data available for Malawi for 1996. [b]Unlike the 1996 data, the 2005 aggregated "food, beverages and tobacco" category includes restaurant and catering expenditures as well and therefore leads to higher income elasticities with respect to food than in 1996 (Muhammad et al., 2011).

Source: Seale and Regmi (2006); Muhammad et al. (2011).

2.2 Sources of data and elasticity estimates

A good estimate of demand parameters requires a large amount of data. Most current income and price elasticity estimations based on international data rely either on national aggregate data from the International Comparison Project (ICP) (as shown in Table 3 and A2) or are estimated directly through GTAP national data. The ICP is led by the World Bank and, since 1968, collects global price and expenditure data, which are then made comparable across countries using purchasing power parities (Seale and Regmi, 2006). The latest collection period in 2011 includes data for 199 countries (World Bank, 2015).

2.2.1 Income elasticities

Reimer and Hertel (2004) find that estimating income elasticities from GTAP national data leads to very similar results compared to ICP-based estimates when looking at a classification that divides total consumption into ten commodity groups with only a single aggregate food group. Therefore, for the standard GTAP model, income elasticities are directly estimated from GTAP data (and not ICP data) by first estimating an AIDADS demand system for 10 commodities, whose parameters are then used as targets to calibrate the CDE demand system of the standard GTAP model (Hertel and van der Mensbrugghe, 2016).

Yu et al. (2004) estimate income elasticities separately for cereals, livestock products, fish, horticulture and vegetables, and other food using ICP data for 1985. Both Seale and Regmi (2006) and Muhammad et al. (2011) estimate income elasticities for the same food groups as well as oils and fats, beverages and tobacco, and additionally disaggregate livestock products into meat, dairy, and eggs, using more recent ICP data for 1996 and 2005, respectively. The ICP data have some general well-known problems when used to estimate consumption functions, including data quality issues in low-income countries as well as underreported home-produced food (Seale and Regmi, 2006). Moreover, typical Western African staple foods, such as cassava, are recorded in the vegetable food commodity group, which can lead to wrong conclusions regarding the budget share and demand elasticities of vegetables (Muhammad et al., 2011).

2.2.2 Price elasticities

There is no systematic, global disaggregated dataset of price elasticities, similar to the problem for income elasticities. Muhammed et al. (2011) and Seale and Regmi (2006) estimated own-price elasticities simultaneously with income elasticities, using ICP data. Table 4 gives their uncompensated own-price elasticities, which show that the richer the country, the smaller the reaction to price changes. Food is the most inelastic commodity group across all countries and years but, in general, the own-price elasticities fall with rising income. Note that medical care remains very price elastic in low-income countries, that is, it has features of a luxury good, indicating access barriers for poorer people.

When econometric estimates of price elasticities are not available, they could be derived through simple calibration. Muhammad et al. (2011) give an overview about different ways to calculate either the uncompensated or the compensated price elasticity from income elasticity and data on consumption expenditures. These calculations often make use of the dependency between price and income elasticities in the linear expenditure system developed by Frisch (1959) (see section 3). The uncompensated own-price elasticities in the GTAP model for example are calculated based on GTAP data with the estimated income elasticities discussed above, average budget shares and the Frisch index (see Hertel and van der Mensbrugghe (2016) for the formula; see section 3 and also in the Appendix, eq. 6b, for more information on the Frisch index). Together with the estimated income elasticities, these calculated price elasticities are then used to calibrated the CDE demand system of the standard GTAP model.

Table 4: Uncompensated own-price elasticities of aggregated commodity groups for selected countries and different years

Commodity type	Malawi	Vietnam		Mexico		United States	
	2005	1996	2005	1996	2005	1996	2005
Food, beverages and tobacco	-0.601**	-0.62	-0.573**	-0.49	-0.474**	-0.07	-0.254**
Clothing & footwear	-0.71	-0.74	-0.71	-0.72	-0.708	-0.69	-0.707
Housing	-0.792	-1.05	-0.787	-1	-0.781	-0.97	-0.778
House furnishing	-0.775	-0.99	-0.773	-0.96	-0.77	-0.94	-0.768
Medical care	-1.78	-1.4	-1.175	-1.13	-0.949	-1.04	-0.89
Education	-0.685	-0.85	-0.682	-0.85	-0.675	-0.85	-0.668
Transport & communication	-0.92	-1.02	-0.883	-0.98	-0.844	-0.95	-0.826
Recreation	-0.97	-1.84	-1.551	-1.22	-1.011	-1.08	-0.92
Other	-1.83	-1.45	-1.184	-1.14	-0.951	-1.04	-0.891

Source: Seale and Regmi (2006); Muhammad et al. (2011).

There are many econometric estimates of demand functions for specific products or groups. There is, for example, a big set of studies for electricity and gasoline income and price elasticities (e.g. those reviewed in Cao et al. 2016). Unfortunately, there has been no systematic collection and processing of these estimates for use in CGE models.

2.3 Aggregation of commodity groups and households

The variety of analyses undertaken with CGE models call for demand systems with flexibles aggregation structures. This may include having different number of commodities in the demand systems compared to the supply side. Models that adhere closely to both the National Accounts and Input-Output accounts have to reconcile their different classifications within the model.

An example of the latter is Jorgenson et al. (2013, section 2.3.6) where the consumption function is based on household surveys and scaled to the classification in the U.S. Personal Consumption Expenditures (PCE) in the National Accounts while the production functions are based on Input-Output commodities[3]. National Accounts are based on purchaser prices that include

[3] There are two levels of reconciliation. One is that the PCE in the National Accounts is a comprehensive measure that includes imputations and owner-occupied housing whereas household surveys are limited to out-of-pocket expenditures. The second is that each

trade and transportation, while IO data is at factory gate prices. A bridge matrix provided in the official benchmark IO tables is used to link the two categories. For example, expenditure on "Clothing" given by the consumption function is associated with the commodity output of Apparel manufacturing, Trade, Transportation and Personal Services. Motor vehicles purchased is supplied by these industries: Motor Vehicle manufacturing, Used goods, Trade and Transportation. We observe that these bridge matrices change over time in the historical data but this is not addressed in any CGE model we know of.

Whether or not different classifications are used, one might wish to have more disaggregated commodity groups for industrial sectors than for households, and this requires the use of transition or bridge matrices. The ENVISAGE and GEM-E3 models, for example, use a bridge matrix to link consumption categories to a broader number of produced commodities (van der Mensbrugghe, 2018; Capros et al. 2013). For example, transportation demand would be allocated to fuels, vehicle maintenance, purchased transportation services – categories that may be identified on the production side of the model. (More examples of energy services demand are given in Section 3.3.) One may use an explicitly nested function, like in iPETS (see Section 3.3), or simply use a constant bridge matrix, implying no substitution between commodities within a consumption category.

A different kind of problem arises because of the aggregation of households into a single representative agent, as it is usually done in most CGE models. Indeed, aggregate consumption depends on many factors beyond aggregate income and prices, such as demographics (e.g., age structure or family composition), level of urbanization and cultural traditions (e.g., preference for or against consuming certain types of food), as discussed by Pollack and Wales (1981), Lahiri et al. (2000), and O'Neill et al. (2012).

There are two distinct channels, through which population affects the economy: one is the scale and the other is the composition. The effects of population size on the scale of consumption demand are considered by many models using an aggregate consumption function, and many would also incorporate projections of labor supply accounting for the age structure. These representative agent functions ignore the variance between individuals and households. Only a few models explicitly link the composition of consumption demand to the demographic composition of the population (e.g. iPETS, O'Neill et al., 2012, Jorgenson et al. 2013).

A simple method to disaggregate total consumption is "household downscaling" (Melnikov et al., 2017). Other authors have used household level

item in the PCE is composed of a few input-output commodities. For the U.S., one may find this bridge for the 2002 benchmark in the *Survey of Current Business* (Oct 2007, page 40).

data to disaggregate the endogenous aggregated consumption to different household types and income groups in a post-simulation calculation (Rausch et al., 2011). Jorgenson et al. (2013) use an aggregate demand function that explicitly includes variables for demographic composition and income distribution in each year of their projection. A more detailed representation of different household income groups is clearly desirable if modelers are interested in the welfare effects of policy measures or other exogenous shocks such as climate change, since not only expenditure patterns but also the heterogeneity in production factor ownership determines the distributional impacts (Hertel et al., 2010; Rausch et al., 2011).

3. Modelling of consumption in current CGE models

Implementing a model that recognizes the full complexity of household consumption behavior has proved challenging. The tractable demand systems used in many CGE models capture some essential price and income effects but cannot completely depict the non-monotonic dynamics and the full range of cross-price elasticities. We surveyed 28 CGE models and their choice of consumption functions. The results are summarized in Figure 5 (full details in Appendix Table A1). The bars in the figure represent a count of demand systems, where some models are included more than once if they allow for more than one demand system. Ten models employ the (nested) constant elasticity of substitution (CES) formulation, 9 use the linear expenditure system (LES), and 6 the constant difference in elasticity (CDE). Only 3 models use the more flexible AIDADS, while two single region models use a translog or AIDS.

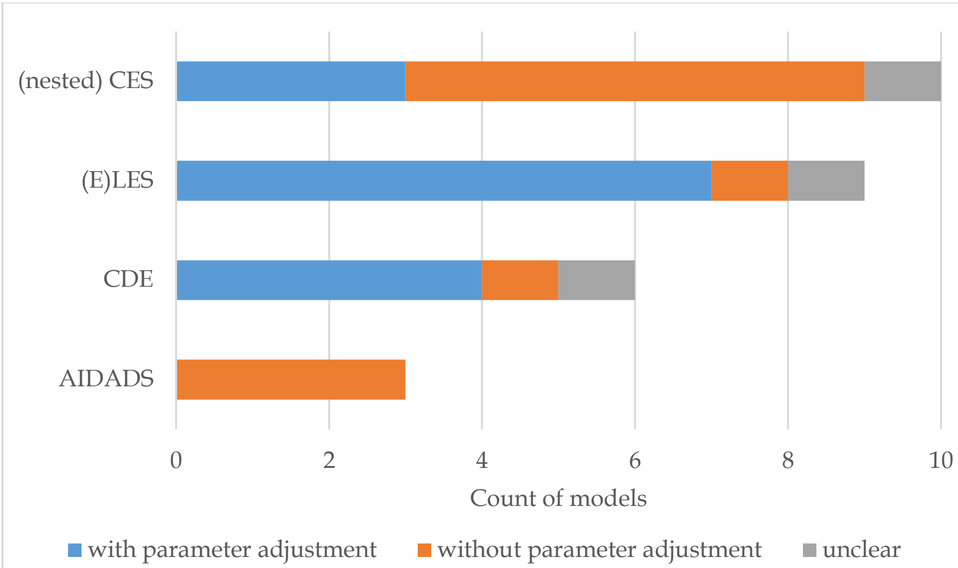

Figure 5. Demand systems used in surveyed CGE models

Source: Model documentation and responses to survey of participants of the 2018 OECD/GTAP workshop.

In practice, income effects can be flexibly modelled in two ways: (1) through a flexible functional form, or (2) by varying the parameters of a simpler demand system over time. Updating parameters allows any change in income elasticity but amounts to exogenous shifts in preferences such that a welfare analysis across time is no longer possible. Similarly, flexibility with regard to price effects can be achieved either through the functional form directly, or by introducing nested structures (usually CES nests). Figure 5 reports the share of models that use a demand system with adjustments to the parameters when calibrating a baseline (such as adjusting share parameters, subsistence level consumption, income elasticities).

3.1 Review of common consumption functions

In this section, we summarize the main functional forms used so that we can be explicit about which parameters are estimated or calibrated, and about which ones are being adjusted dynamically. We discuss the trade-offs between desirable features of a demand system – non-homotheticity, flexibility (more cross-substitution possibilities), aggregability (over household types), conformability (valid over the whole domain of possible prices), ease of disaggregation into sub-groups, and parsimony. We hope modelers will consider trying alternative approaches and, to this end, we discuss some features in greater detail in the Appendix. In Figure 6, we group models by their properties and the number of parameters, as a function of the number of commodities identified (*n*). This simple count does not report the loss of free parameters due to constraints such as shares adding to unity. Homothetic functions are those with unit income elasticities.

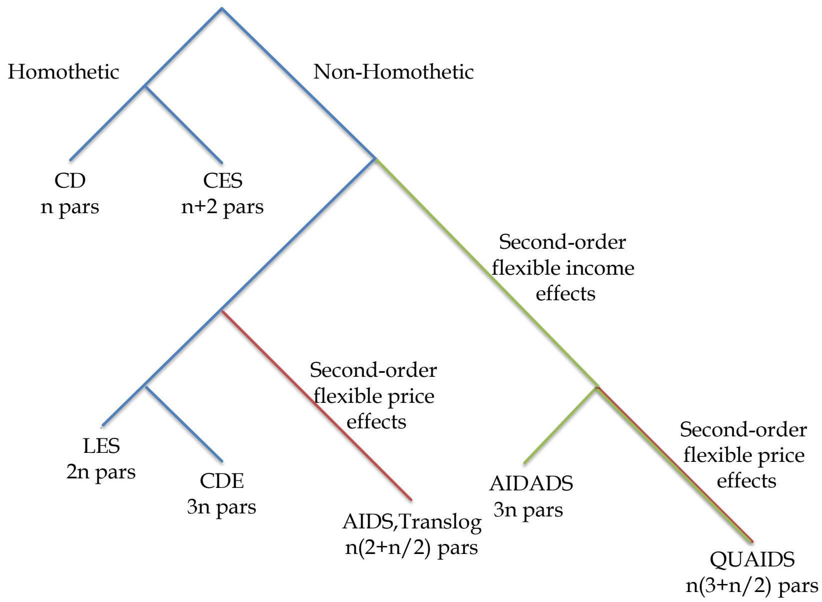

Figure 6. Overview of functional forms with n goods.

Note: "pars" denote number of parameters in a demand system without considering restrictions.

Source: Authors construction.

The main equations of the functional forms indicated in Figure 6 are summarized below. We use the following notation:

U = utility; $E(p,U)$ = expenditure function

c_i = consumption of good i

p_i = price of good i; p=vector of prices

$M = \sum_i p_i c_i$ = total expenditure

w_i = expenditure share of good i

np = number of parameters

η_i^M = income elasticity

η_i = own price elasticity

ε_{ij} = uncompensated cross-price elasticities.

A more detailed discussion of the various functions, and the models which use them, can be found in the Supplementary Material Appendix A1.

1 Constant elasticity of substitution (CES)

$$U_t = \left[\alpha_{1t} c_{1t}^{\frac{\sigma-1}{\sigma}} + \alpha_{2t} c_{2t}^{\frac{\sigma-1}{\sigma}} + .. \ + \ \alpha_{nt} c_{nt}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

σ = elasticity of substitution, α_i share parameter

$$\eta_i^M = 1 \tag{2}$$

$$\eta_i = -\sigma + \frac{\alpha_i^\sigma (\sigma - 1) p_i^{1-\sigma}}{\sum \alpha_j^\sigma p_j^{1-\sigma}}$$

$np = 2n - 2$ (for a nested structure)

2. Linear Expenditure System (LES) or Stone-Geary

$$u = \sum_i \alpha_i \ln(c_i - \gamma_i); \quad \sum_i \alpha_i = 1 \tag{3}$$

γ_i = commitment (subsistence) consumption, α_i share parameter

$$c_i = \gamma_i + \frac{\alpha_i}{p_i}(M - \sum\nolimits_j p_j \gamma_j)$$

$$\eta_i = -1 + \frac{(1-\alpha_i) p_i \gamma_i}{p_i c_i}$$

$$\eta_i^M = \frac{\alpha_i M}{p_i c_i} \to 1 \tag{4}$$

$$\phi = -\frac{M}{M - \sum\nolimits_j p_j \gamma_j}$$

$np = 2n - 1$

3. Constant differences of elasticities (CDE)

$$\sum_i B_i U^{\beta_i \gamma_i} \left[\frac{p_i}{E(p,U)} \right]^{\beta_i} = 1 \tag{5}$$

γ_i = the expansion parameter

$\alpha_i = 1 - \beta_i$ = substitution parameter

$$\eta_i^M = \frac{\sum_k w_k \gamma_k \alpha_k + \gamma_i (1-\alpha_i)}{\sum_k w_k \gamma_k} + \alpha_i - \sum_k w_k \alpha_k$$

$$\varepsilon_{ij} = w_j [\alpha_i + \sum_k w_k (1-\alpha_k) - (1-\alpha_i)] - \delta_{ij} \alpha_i \tag{6}$$

$$np = 3n$$

4. An Implicitly Directly Additive Demand System (AIDADS)

$$\sum_i \frac{\alpha_i + \beta_i e^u}{1+e^u} \ln \left[\frac{c_i - \gamma_i}{A e^u} \right] = 1 \tag{7}$$

γ_i = commitment (subsistence) consumption, α_i, β_i are parameters

$$c_i = \frac{\phi_i (M - \gamma' p)}{p_i} + \gamma_i$$

$$\phi_i = \frac{\alpha_i + \beta_i e^u}{1+e^u} \tag{8}$$

$$np = 3n - 1$$

5. Basic Translog

$$w_k = \frac{1}{D(p)} (\alpha + B \ln p - B_M \ln M_k + B_A A_k) \tag{9}$$

w_k = vector of expenditure shares of household type k

A_k = vector of 0-1 demographic indicators of k

B = matrix of cross-price share elasticities; B_M = income coefficients

B_A = matrix of demographic coefficients

$D(p) = -1 + B_M \ln p$; $\quad B_M = B\iota$

$np \sim \frac{1}{2} n(n+3)$

6. EASI (Exact Affine Stone Index)

$$w_i^k = \sum_r b_{ri} y_k^r + \sum_k (C_{ki} A_k + D_{ki} A_k y_k) + \sum_{k,j} \Gamma_{kji} A_k \ln p_j + \sum_j B_{ji} \ln p_j y_k \tag{10}$$

w_i^k = expenditure share of good i for household k

A_k = vector of 0-1 demographic indicators of k

$y_k = \ln M_k - \ln p' w$ = real total expenditures

$b_{ri}, C_{ki}, D_{ki}, \Gamma_{ki}, B_{ji}$ are parameters to be estimated

The Cobb-Douglas (CD) function has just *n* parameters to be estimated and is often used to depict investment and government demand in CGEs (see section 5 below), but none of the models reviewed here use it for household consumption. The most common formulation is the nested CES, which, excluding the common substitution elasticity, has *n* parameters set in the process of calibration to expenditure values. This is because CES is a homothetic function (with unit income elasticity). Therefore, if more complex income dynamics needs to be modelled, some share parameters have to be varied exogenously, for example, to reproduce income elasticities estimated empirically.

The LES is characterized by 2*n* parameters and implies fixed *marginal* budget shares. Its γ_i parameters express commitment (also often termed subsistence) consumption. The parameter values needed for benchmarking can be calibrated either on the basis of income or on own price elasticities. Constant (γ_i) and slope (α_i) terms can be estimated simultaneously during calibration. Some modelers also use the Frisch index (the ratio of total to discretionary income) (as discussed in the Appendix, eq. 6b). Schuenemann and Delzeit (2019), however, caution that simply using Frisch parameter values from the literature could lead to unrealistically high commitment shares. On the other hand, if the γ_i parameters are small, the behavior of a LES is not substantially different from that of a Cobb-Douglas with income and own-price elasticities close to unity. To improve the modelling of the non-commitment consumption, LES can be combined with CES sub-nests.

In order to ensure plausible behavior when the population is changing, the commitment terms need to be defined on a per-capita basis. With growing income, the progressively lower incidence of the commitment term leads to increasing income and price elasticities, at least if the constant term is positive. In order to better capture the non-linear Engel curves found empirically, the LES parameters should then be adjusted. While some models scale up the commitment term with population, some other models opt for not updating the marginal budget shares.

The CDE has *3n* parameters to estimate, so that both income and own price effects can be determined during calibration. However, as we can see from the elasticity formulas (6), calibrating the parameters to empirical elasticities is not a trivial process. For example, the CDE in the GTAP model is calibrated to estimated income elasticities, but not to empirical own-price elasticities (Hertel and van der Mensbrugghe, 2016). The own-price elasticities used to calibrate the substitution parameter are calculated using estimated income elasticities following Zeitsch et al. (1991), which rely on the direct additivity of the LES (equation 3). In the CDE, like in the LES, income elasticities stay constant for given parameters. Modelers could then adjust the expansion parameters (γ_i in eqs. 5 and 6) so as to make income elasticities change over time.

Without additional adjustments to the parameters, the above three most commonly used forms cannot capture non-linear Engel curves, which motivated the adoption of more general functional forms, among which the AIDADS, which can be conceived as a generalization of the LES. AIDADS offers second order flexibility with regard to income effects. In the form in eq. (8), the income elasticity vary logistically. Calibration for a large set of commodities is not easy, as the system is either underdetermined (if it is only calibrated to income elasticities) or overdetermined (if calibrated simultaneously to income and price elasticities). Reimer and Hertel (2004) suggest that a maximum of ten commodities might be the practical limit for AIDADS, because of computational complexity and the need to preserve a property of implicit additivity. However, Britz and Roson (2019) have shown that, under certain conditions, and with some adjustments to reconcile consumption categories, this limit can be overcome.

The above functions are not suitable for depicting close substitutes such as different energy carriers or different types of meats. Currently, introducing CES sub-nests seems to be the preferred option. For example, one solution is extending the LES with a nested CES demand system for the non-subsistence consumption (e.g. in the OECD’s ENV-Linkages model). The AIDADS in Britz and Roson (2019) also uses CES sub-nests.

Consumption price elasticities have received less attention from the CGE modelling community, compared to income elasticities. One reason might be that, at the high sectoral resolution of CGE models, the long-term baseline is dominated by income effects, and price effects play a minor role. This might also be reflected in the common choice of the LES and CDE, which give no or limited space to cross-price effects. However, one should note that many policy impacts are driven primarily by price effects. This point is discussed further below.

Second order flexible functional forms with regard to price effects, but with only first order income effects, such as the translog or AIDS, are used in econometric analysis but are uncommon in CGE models. As can be seen in Table A1, they are nonetheless used in a few single-country models. The *B* matrix in eq. 9 gives the full set of cross-price elasticities. However, this means there is a large number of parameters ($\frac{1}{2}n(n+3)$ in the specification of (9), which does not include demographic terms), meaning that the number of commodities which could realistically be taken into account during the estimation process is somewhat limited. The element B_A in (9) allows for the existence of different household types having different consumption patterns even when facing identical prices and having the same income levels. The aggregate share demand vector, derived by summing over all household types, allows a natural way to include demographic projections (Sup. Appendix eq. 12). A major drawback for these flexible functions is that one must either impose global concavity on the *B* matrix, or be aware that the function may not be conformable for prices that substantially deviate from those of the sample period (because, e.g., they generate shares outside the (0,1) range). In practice, these functions are combined with sub-nests and, for consistent aggregation, the sub-nests must be specified in terms of homothetic functions.

QUAIDS is another type of function, which would give full flexibility with regard to both price and income effects, but has not been used in any reviewed CGE model considered here. The EASI has also not been used in any CGE model directly, but has been used by Caron et al. (2017) to calibrate the dynamic income effects in their LES function.

3.2 Special features of food demand in CGE models

In Section 2.1, we noted how diets in developing countries are converging towards patterns of rich countries – greater variety and more meat and dairy products. Modelling this convergence process will be key for establishing the baseline paths for global food consumption.

While the desirable features of demand systems such as non-homotheticity apply to all types of commodities, modelling the dynamics of food demand requires an even greater flexibility in terms of reaction to income and prices. This is because food is a true "necessity" and not the typical aggregate normal good. It may be both a normal and an inferior good, income elastic and inelastic, and thus it needs to be modeled such that a rich set of income and price elasticities could be reproduced. Long-term baselines of food consumption should also include the impact of various specific drivers such as the introduction of supermarkets and refrigeration.

The first challenge when modelling food demand dynamics in aggregate models is the reaction to income changes. Income elasticities differ not only between countries at different development stages, but also between households at different income levels and between different types of food as noted in section 2. This means that the aggregation of food demand is problematic as food demand is not only a function of aggregate income, but also of income distribution (Cirera and Masset, 2010). The typical regional household in CGE models is an aggregation of all (richer and poorer) households within a region that in some cases can even be a whole continent. Blundell and Stoker (2005) show that demand of individual households can only be correctly aggregated in the case of linear Engel curves, which would imply asymptotically homothetic preferences and contradicts both Engel's and Bennett's laws.

Furthermore, most demand systems used in CGE models cannot simulate saturation of food demand, that is, when income elasticities for food approach zero as people become richer. Indeed, many of the common demand systems cannot accommodate for changing income elasticities. AIDADS has endogenously varying income elasticities, but saturation effects are limited.

The construction of a realistic baseline for food consumption thus requires: (1) a detailed set of income and price elasticities for different food commodities, and (2) a demand system and utility function flexible enough to be calibrated to these elasticities and to allow for sufficient Engel flexibility.

The most commonly used demand systems in CGE models only partly consider the specific features of food demand. The LES, for instance, can be calibrated to varying income elasticities of different food types and for different household groups in the base year, but cannot reflect changing preferences and consumer behavior in the dynamic case. The fact that the implicit income elasticities eventually approach unity is especially problematic in the case of staple food and inferior goods. Indeed, Yu et al. (2004) find that the LES leads to an over-estimation of household food demand growth in regions where incomes are rising rapidly but remains quite accurate in regions where income is growing modestly. Our comparison of the unadjusted LES and CDE demand systems with the AIDADS in Section 4 below illustrates the magnitude of this over-estimation bias.

To avoid these problems, some modelers calibrate food demand patterns to a predetermined path such as a convergence to high-income diets. In the EPPA model, for example, household demand is calibrated in a way that developing countries' consumption patterns converge to those of industrial countries through a reduction in aggregate food consumption, as well as dietary patterns changing according to Bennett's law (Lahiri et al., 2000). This is done by progressively changing the substitution elasticities between food and non-food commodities and making the food consumption share dependent on per-capita income growth between periods (Paltsev et al., 2005). While this form of calibration allows for capturing food demand dynamics related to income changes, price induced changes are sometimes neglected, but could be considered alongside income effects by iterating over the baseline path (Lahiri et al., 2000)[4].

In a nested system, the substitution elasticities in the different nests determine the implicit price elasticities of food demand (Valin et al., 2014). Sometimes, however, this can lead to implausible price behavior. Some models combine the LES and CES formulations. For example, the Future Agricultural Resources Model (FARM) by the USDA, has a top nest for aggregated food categories

[4] Models that allow TFP rates to differ by industry, or have limited resource factors, will generate paths of relative prices that change significantly over time; these would have price effects on consumption demand that should be taken into account when calibrating to targeted shares.

expressed as a LES, and use CES functions for the lower nests. The model is linked to FAO Food Balance Sheets (FBS) by updating the food commodity rows in the SAM with FBS projections. The calibration of parameters in both LES and CDE models must obey the adding up condition and unless they are adjusted over time, they cannot reflect the potential saturation of food demand.

In the G-RDEM model, Britz and Roson (2019) estimate an AIDADS system with nine non-food sectors and eleven food categories using detailed ICP data for food. For the latter, they map the 34 original ICP food categories to the GTAP agri-food sectors. The parameters of these functions are not adjusted over time and the performance of this system is illustrated in section 4.2. So far, only the modified AIDADS (MAIDADS[5]) has been employed to generate saturation of food demand for regions with high income levels (Gouel and Guimbard, 2018). However the system does not appear to have been adopted in CGE models so far (Corong et al., 2017).

3.3 Special features of Energy Demand

Energy demand can be modelled like demand for other goods, and this is indeed the case of most models listed in Table A1. More than half of these models use nested CES, while others use alternative formulations (LES, CDE or flexible functions) and some models use a combination of different functions (AIM and Imaclim-R).

Some authors, however, have argued that the demand for energy is not driven by the desire to consume it directly, but rather indirectly, through the consumption of the services it provides. This calls for a different modelling approach. Based on historical data for the UK, Fouquet (2014) highlights two stylized facts regarding various energy services (lighting, passenger transport, domestic heating, etc.): (1) the income elasticities follow an inverse U-shaped curve through time, while (2) the price elasticity is normally U-shaped. This suggests a saturation effect in per capita energy consumption, which is challenging to model using simple functional forms. Whether or not developing countries will replicate this inverse-U pattern and the date at which the saturation will occur are still major uncertainties. As depicted in Figure 2, energy consumption in rich countries has become income inelastic (like food), meaning that demand systems with homothetic preferences will likely overstate future energy consumption (O'Neill et al., 2012; Caron et al., 2017).

Regardless of the chosen demand system (LES, CES, etc.), a nested approach allows us to represent the consumption of energy services provided by fuels and associated durable goods, in contrast to assuming that utility increases with

[5] The modified form replaces the subsistence term (γ) in eq. (9) by a function that depends on utility.

direct fuel and electricity consumption. We discuss below four modelling approaches, selected from models listed in Table A.1 for their methods to derive energy demand from the consumption of energy services, and were sufficiently documented. The different approaches described here are not alternatives, but rather complementary, each one of them having its pros and cons. Some models specify the links between energy consumption and the stock of durable goods providing the energy services, while other models introduce a saturation effect by imposing a budget constraint related to energy consumption. Faehn et al. (this issue) provide a more exhaustive description of methods to model household transportation, buildings, industry energy demand and the role of technology, while this section discusses the link between the final demand for energy and the modelling of the consumption of other goods.

We first give an example with the EPPA model (Paltsev et al., 2005b) which is based on a nested series of CES functions (Figure 7). Aggregate consumption is a CES function of non-transportation consumption and transportation in the top tier. Non-transportation consumption is an aggregate of energy and non-energy bundles. Transportation is an aggregate of purchased transportation and own transportation (OWNTRN); OWNTRN is an aggregate of vehicle fuels (T_{ROIL}) and other_own; other_own is an aggregate of vehicles (T_{OTHER}) and operating costs (T_{SERV}, which includes vehicle maintenance, insurance, etc.). In this representation, transportation consumption is further determined by two budget constraints: households expenditures on own-supplied transport is set as a share of total expenditure, while expenditure on fuels for vehicles is set to a share of total expenditure on refined oil products.

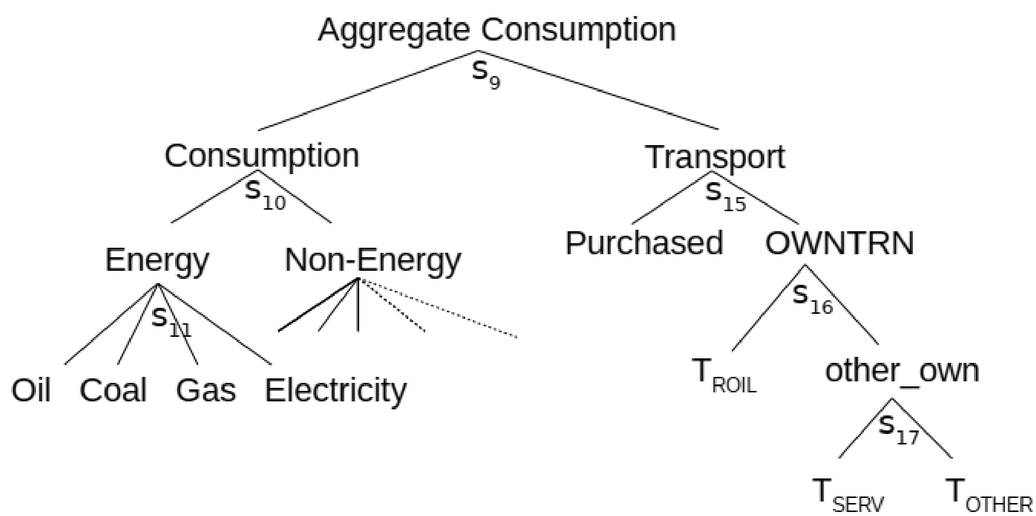

Figure 7: CES nested structure of the EPPA model.

Source: Authors own construction.

Cars sales (T_{OTHER}) are calibrated with data of the GTAP motor vehicle sector, which is a part of a non-energy intensive manufacturing sector in EPPA. The shares of expenditure on own-transportation and vehicle fuels are calibrated using various national surveys. Vehicle operating costs are supplied by a service sector, aggregating the following GTAP sectors: sales maintenance and repair, insurance and business services.

The elasticities reported in Paltsev et al., (2005b, tables 4 and 5) are: 0.5 between aggregate consumption and transport; 0.4 between the consumption of various energy goods; [0.3;0.7] between liquid fuels and other inputs; 0.5 between services and car sales for own-transport.

A second example of linking energy consumption to other goods is to be found in the GEM-E3 model, in which private energy consumption for transportation and buildings are linked to a stock of durable goods (Capros et al. 2013). Private consumption is expressed through a LES (eq. 11), with a distinction between consumption of nondurables *HCFV* (set nd), and a stock of durables *SHINV* (set dg). The stocks of durables for transportation and heating are linked with non-durable goods, needed to operate the stocks (fuels and services for maintenance). The variable *D* represents the usage of the stock and is determined by the cost of operating the stock (P^{HCFV} is an index of fuel, maintenance and other costs) relative to the consumer price index *PCI*. The consumption of the linked energy good is thus determined by the multiplication of the stock and its usage rate (subject to a minimum usage rate). The demand for the stock of durable goods depends on the price of the durable good itself as well as the (expected) user costs.

$$U_c = \prod_{i \in nd} (HCFV_i - \gamma_i)^{\sigma_i} \prod_{i \in dg} (SHINV_i - \gamma_i)^{\sigma_i} \tag{11}$$

$$D_{nd,dg} = \alpha_{nd,dg} \left(\frac{PCI}{P^{HCFV}_{nd,dg}} \right)^{\eta_{nd,dg}} \tag{12}$$

Nesting durable goods with the energy requirement makes the substitution between capital and energy sources explicit. The determination of energy efficiency of durable goods through specific rules or bottom-up models allow for a separate accounting of the services provided and their energy content. In the EPPA model, an increase in cars sales (T_{OTHER}) can bring about more energy efficient vehicles. In the GEM-E3 model, households can invest in energy saving technologies, to decrease the *D* ratio linking durables to fuel consumption.

Alternatively, a saturation effect in consuming energy services can be modelled by the introduction of dedicated budget constraints. In our third example, the Imaclim-R model (Waisman et al., 2013) uses a LES function, where one of the C_i consumption items is mobility services, S_{mob}, as shown in eq. 13. Mobility services are a CES function of four modes: air transport, terrestrial public transport, private transport by cars and non-motorized transport. The energy content of each modes is derived from reduced form of bottom-up models.

$$U_c = \prod_i (C_i - \gamma_i)^{\varepsilon_i} (S_{mob} - \gamma_{mob})^{\varepsilon_{mob}} \tag{13}$$

$$S_{mob} = CES(pkm_{air}, pkm_{public}, pkm_{car}, pkm_{nonmotor}) \tag{14}$$

Besides the budget constraint for consumption expenditures, there is a time travel constraint, which sets a ceiling on average daily travel time as estimated by some empirical studies (Zahavi and Talvitie, 1980). Each transportation mode is then associated with a travel time efficiency parameter, which influences the degree of substitutability within the CES function. This parameter depends on the average speed of each mode and the gap between mobility demand and the capacity of the network, so that congestion effects can be taken into account.

Whether or not energy consumption is represented through the services it provides, the parameters of the demand system can be adjusted over time, to make projections more realistic and consistent with given scenarios. For example, Schafer and Jacoby (2003) calibrated the elasticities of the EPPA model on the basis of a detailed transport model, considering vehicles as stocks. In the Imaclim-R model, alternative settings for the income elasticities of the demand for vehicles influence the travel time of road transport. The AIM/CGE model illustrates how an explicit representation of technology allows us to improve long-term energy demand projections. In this model, household energy demand can be represented in two ways. In the first, a generic LES differentiates the use of private cars from other sources of energy consumption, with fuels demand nested into a logit function. In the second way, energy consumption is driven by a set of technologies, selected from among hundreds (Fujimori et al., 2014). In this latter approach, the share ($SHDV_{j,l}$) of each technology l providing an energy service j is expressed as a logit of annualized investment and O&M costs ($CDV_{j,l}$), with elasticities $\sigma_{j,l}$ and shares $b_{j,l}$:

$$SHDV_{j,l} = \frac{b_{j,l} CDV_{j,l}^{\sigma_{j,l}}}{\sum_k b_{j,k} CDV_{j,k}^{\sigma_{j,k}}} \tag{15}$$

Each technology l is associated with an energy content per unit of the services it provides. The share parameters $b_{j,l}$ are updated yearly, so as to reflect the availability of technologies for different time horizons and in different scenarios.

4. Projection of consumption demand and model comparisons

We reviewed the commonly used consumption functions in section 3, all of which have terms for price and income effects, with some functions having terms for demographic and household composition effects. We next discuss how the parameters of these functions are set and possibly modified over time in the base path by various modelling groups. In section 4.2, we compare how different demand functions in the same CGE model can lead to different baseline paths.

4.1 Setting parameters and adjusting over time

We may divide the approaches for setting parameters into two groups. One is to keep the price and income parameters unchanged and only allow exogenous variables for demographic effects to change over time. This could be referred to as a "complete demand system approach" where changes in demand shares over time are delivered by endogenous income and price effects. The second approach changes the demand system parameters exogenously over time, which we call the "exogenous parameter adjustment approach." Different modelling teams use different levels of sophistication for parameter adjustments.

A complete demand system that endogenously projects demand with rising incomes is preferable from a theoretical point of view, as it provides consistent effects for small and large shocks to income. The rapidly rising incomes over decades affects consumption demand in the same function as it would do for small income changes, possibly due to policy shocks. If these are rank-1 functions, then it is the same elasticity. Rank 2 or rank 3 functions would provide more flexibility but still assume that the functional form and parameter values observed for the sample period is valid for much higher income levels. There are serious barriers to using flexible demand systems such as AIDS or translog – difficult data requirements and effort to estimate them for a large set of countries or a large set of commodities, in addition to the challenges discussed in Section 3.

A potential limitation of such complete demand systems is that stable preferences are assumed. However, one may think that preferences change over time in a way that cannot be ascribed to income effects, for example, changes in diet or vehicle use due to environmental concerns. If the demand system does not explicitly capture demographic effects (e.g. aging, urbanization), unlike the example in eq. 9, then one also needs additional flexibility. In such cases, one may explicitly prefer not to use a demand system with fixed parameters, but this then requires one to explicitly address preference changes.

Given the difficulties in specifying and calibrating a flexible demand system that give reasonable consumption demands for large changes in incomes, many modelers have resorted to the second approach of exogenous parameter adjustments to create a dynamic baseline. There are two distinct modifications under the heading of "parameter adjustments": those accounting for population changes and those accounting for growth in per-capita income.

Accounting for population growth is undertaken in many models. We illustrate this with an example from the dynamic recursive DART model. Here the commitment minima of the LES are recalibrated after each time step according to population growth. This adjustment can lead to smaller or larger commitment minima with respect to the base year. This is especially evident in Sub-Saharan Africa, because of its fast population growth. For other regions, the changes required are generally small as illustrated in Figure 8 (taken from Schuenemann and Delzeit, 2019) which compares the impact of this recalibration for a period of 23 years and three selected regions. For each region a pair of lines show the decreasing subsistence minima shares in total consumption as incomes rise. One line refers to a fixed commitment term, whereas the other line refers to a recalibrated one. While the differences are quite large for Sub-Sahara Africa, such that the recalibration prevents a fast convergence to homothetic preferences, in regions with fast income growth like China, and regions with low initial commitments, the impact of the recalibration method is relatively small.

Few models take into account other demographic aspects beyond population size, but in the iPETS model (O'Neill et al., 2012), household surveys for representative countries are used to derive relationships between consumption and characteristics such as urbanization and household size. Their share parameters in the CES functions (α in equation 1) are adjusted exogenously, on the basis of income and demographic projections. Implementing this effect into higher order demand systems might be more challenging.

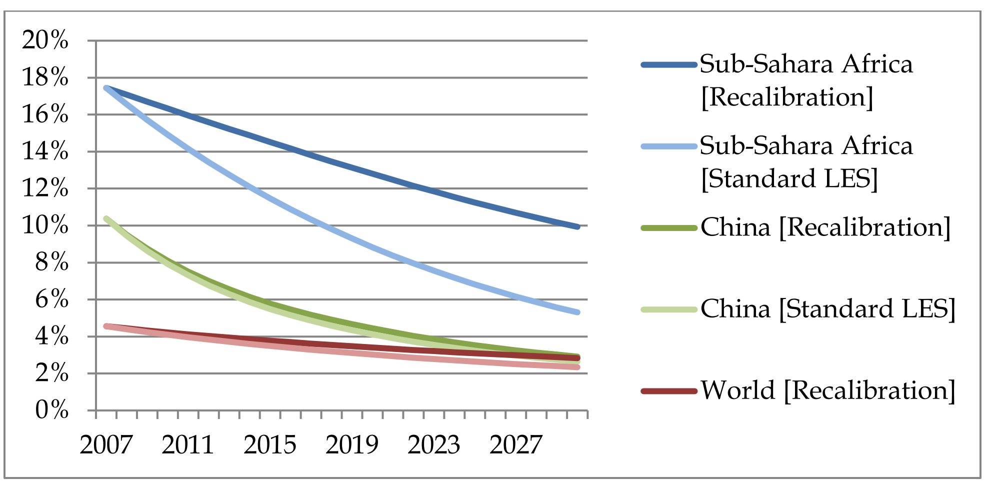

Figure 8. Share of subsistence consumption in total consumption in standard LES and with recalibration according to population growth for selected regions between 2007-2030 in the DART model

Source: Authors' calculations using DART-BIO

The second type of parameter modification considers income effects. It involves changing parameters of the consumption function, such that, for instance, the expenditure shares are adjusted such that the consumption patterns align with what are judged to be reasonable shares for future income levels. In practice, this can be achieved by iterating share parameters and income levels from a baseline, or calibrating to exogenous GDP projections (e.g. iPETS, Ren et al, 2018 and GEM-E3, Rey Los Santos et al., 2018; see also Fouré et al. in this volume for GDP calibration in long-term baselines). In iPETS, this is done by iterating over the baseline path. Starting with a guess path of per capita income, preference parameters are adjusted in each period and the model is solved, which generates a different path of income. As the underlying within-period utility function is a CES, this implies homothetic preferences within a period. That is, the consumption impact of policy changes or other shocks are captured by a function that has a unit income elasticity. [6]

Chen et al. (2015) implement a recalibration method for commitment consumption shares in the LES demand of EPPA. After each time step in the recursive-dynamic model, they are recalculated so that the regional income elasticities match the observed values and do not converge to one (see Appendix eq. 6). As the authors note, this procedure implies that welfare indexes can only be computed within each period, and present values cannot be estimated.

Caron et al. (2017) use a similar method to update parameters of a LES demand system for China, based on household survey data. In a first step, values in an econometric model that resembles the flexible Exact Affine Stone Index (EASI) are estimated, providing variable income elasticities (in contrast to Chen et al. 2015, where constant income elasticities are used for the recalibration of the EPPA model). These variable elasticities are then used to update the LES preference parameters for a baseline in C-REM, a global model with sub-national detail for China. As the baseline with updated preferences implies a different income, this updating strategy is repeated until convergence, as in O'Neill et al. (2012). Caron et al. (2017) notice that assuming homothetic preferences significantly overestimates energy demand and emissions in the baseline.

One advantage of the method of adjusted parameters is an easier integration of demand estimates for specific sectors when they are modelled in greater detail. For example, Keramidas et al. (2020) split the motor vehicle sector into electric and conventional vehicles. Demand for electric vehicles can barely be observed

[6] In principle, an adjustment of preference parameters can also be made in the counterfactual scenarios if the modellers are willing to specify an alternative income effect exogenously. One may wish to do that if the main aim is to quantify, say, household energy use. However, changing the utility function between baseline and counterfactual scenarios prevents meaningful welfare analysis.

in historical data, yet electric vehicles are expected to increase their market share in the future, so calibrating to historic data could be misleading. Adjusting parameters of less complex demand systems might therefore be a good option to integrate more realistic data, possibly based on expert judgement or detailed partial equilibrium modelling.

While the adjustments above correct for the homothetic assumption, the WTO's GTM model also allows income elasticities to change along the baseline in their CDE demand system (WTO 2018, Appendix C3). The CDE expansion parameters for ten aggregate sectors (γ in eq. 6) are adjusted on the basis of the growth in GDP per capita. To do this, the estimated expansion parameters provided in the GTAP database are first regressed against GDP per capita, using a spline regression. The expansion parameters are then adjusted in the baseline such that they converge to their fitted values. Similarly, the MAGNET model, which also uses a CDE demand system, also allows for adjustments of CDE parameters to avoid unrealistically high levels of food consumption (Woltjer et al., 2014).

Let us summarize the advantages of making the exogenous adjustments. One can use simple homothetic functions such as the CES and make adjustments to get expected baseline shares, and this would be reasonable for simulations involving small shocks to income. The non-homothetic LES system involves slightly more complex adjustments to get desired baseline shares but allows for a richer set of income elasticities. The AIDADS function is flexible and does not impose a fixed income elasticity. It has been implemented in G-RDEM (Britz and Roson, 2019) and ENVISAGE (van der Mensbrugghe, 2018). (The MAIDADS has a commitment term that is a function of utility, but that model has only been used in partial equilibrium models to date.)

There seems to be no commonly accepted guidelines on how to generate expenditure shares that can be used for exogenous adjustments of consumption parameters. We noted the example in the GTM model of an estimation across countries to determine expenditure shares, assuming that poorer countries will follow consumption patterns in developed countries (also Britz and Roson 2019 and Roson and van der Mensbrugghe 2018). There are observed differences between countries at similar incomes, variation that might be due to cultural differences. Such differences could persist and should be recognized when making projections of baselines based on these income adjustments.

4.2 A comparison of the performance of 4 different consumption functions in a 2050 baseline: CDE, LES, AIDADS and AIDADS with CES-sub-nests

We show here how projections of the commodity composition of consumption differs when using three different functional forms (CDE, LES, AIDADS) for household demand in the same model, G-RDEM (Britz and Roson, 2019). For the LES and AIDADS, commitment terms are defined on a per-capita basis and therefore scale automatically with population changes, but no adjustments to the parameters are made with respect to income, as discussed in section 4.1.

The default G-RDEM setup uses an AIDADS with sub-nests for energy (as in GTAP-E) and agri-food. These CES-sub-nests define the aggregate demand for clusters and allow us to model higher substitution between products within the nest. All baselines are based on identical GDP and population projections, from the Shared Socio-Economic Pathway 2 (Riahi et al. 2017) until 2050. G-RDEM is implemented in the CGEBox modeling platform (Britz and Van der Mensbrugghe, 2018) and includes a specific variant of the GTAP-AEZ model drawing on GTAP-AGR (Lee, 2005 and Keeney and Hertel, 2005) and GTAP-E (McDougall and Golub, 2007). A further difference from the GTAP standard model (Hertel and Tsigas, 1997) is that domestic and import shares are not differentiated between the Armington agents. All other features of G-RDEM are used in this exercise, namely: (1) differentiated sectoral productivity growth, (2) debt accumulation generated by trade imbalances, (3) variable saving rates influenced by population and income dynamics, (4) time-varying and income dependent industrial input-output parameters, and, as usual in recursive-dynamic CGEs, (5) capital accumulation.

What is new here compared to Britz and Roson (2019) is that the budget shares for investment and government demand are income dependent, on the basis of a cross-sectional analysis undertaken with GTAP data. However, given that household consumption makes up for the largest share of final demand and that investment and government tend to be focused on a few commodity groups, we find that this new feature has limited consequences on the model results.

More important are changes introduced to the GTAP-AEZ setting[7], where land-supply elasticities are now calibrated to match crop land expansion under a business-as-usual scenario (FAO, 2018). This implies stronger increases in land rents as well as somewhat higher prices for agri-food commodities.

We simulated three variations of G-RDEM with LES, CDE and an AIDADS without sub-nests and compared the results to the default version, i.e. an AIDADS with CES sub-nests. The parameters of the CDE are taken from the GTAP data base and the LES income elasticities are calibrated from the CDE parameters. In these alternative cases we calibrated the TFP parameters so that they all reach the same global GDP. Table 5 below reports differences in output quantities and prices at the global level compared to the default G-RDEM configuration.

As could be expected, the differences for the LES functional form are the largest ones. The LES also generates a considerably higher demand for agri-food products and lower demand for certain types of services, especially recreational

[7] Details can be found in Britz and Escobar (2020).

activities and dwellings. Prices of services are generally lower, reflecting the larger change in endogenous TFP growth that is needed to match the GDP projections from SSP2. Land prices bid up dramatically (+235%) in the LES case such that, in relative terms, labor (-8%) and capital (-25%) become cheaper.

In the CDE, differences are quite pronounced for the agri-food sectors. It is interesting to see that CDE leads to a somewhat higher global demand for primary agriculture compared to the LES. When we compare a flat AIDADS with the default system of sub-nests for energy and agri-food, some sectors are quite different (last column). Without these nests, demand for the sector "Petroleum, coal products" is about 12% higher while electricity is reduced by 15%.

These comparisons show the big role played by the choice of consumption functions in determining relative prices, including factor prices, the output structure and factor allocation of the simulated economy. We have only simulated the baseline path here, modelers have to consider the separate differences of policy impacts.

Table 5: Relative differences in global sectoral output in 2050 under SSP2 for different functional form for final demand, no sub-nest, compared to AIDADS with sub-nests

	LES		CDE		AIDADS	
	Quant	Price	Quantity	Price	Quantity	Price
ALL sectors	8%	-5%	11%	-10%	0%	0%
Paddy rice	8%	236%	20%	383%	-1%	-8%
Wheat	5%	185%	11%	264%	0%	-4%
Cereal grains nec	11%	204%	14%	305%	0%	-4%
Vegetables, fruit, nuts	9%	206%	5%	214%	0%	-5%
Oil seeds	9%	181%	10%	253%	0%	-5%
Sugar cane, sugar beet	15%	167%	26%	291%	0%	-3%
Plant-based fibers	11%	167%	3%	161%	0%	-4%
Crops nec	2%	156%	14%	290%	0%	-4%
Cattle,sheep,goats,horses	102%	41%	64%	28%	-8%	-2%
Animal products nec	97%	48%	37%	34%	-21%	-4%
Raw milk	121%	54%	88%	32%	0%	-1%
Wool, silk-worm cocoons	99%	14%	57%	13%	-1%	-1%

	LES		CDE		AIDADS	
	Quant	Price	Quantity	Price	Quantity	Price
Forestry	22%	-5%	28%	-30%	-1%	1%
Fishing	125%	58%	78%	20%	0%	0%
Coal	2%	-17%	-14%	-27%	-17%	-2%
Oil	-3%	-20%	-17%	-38%	11%	5%
Gas	1%	-17%	3%	-29%	-14%	-6%
Minerals nec	16%	-7%	17%	-17%	0%	1%
Meat: cattle,sheep,goats,horse	147%	9%	96%	-2%	-2%	0%
Meat products nec	166%	18%	88%	6%	-1%	-1%
Vegetable oils and fats	47%	98%	53%	96%	0%	-3%
Dairy products	125%	19%	72%	13%	0%	0%
Processed rice	32%	141%	51%	249%	-3%	-5%
Sugar	39%	105%	51%	170%	0%	-2%
Beverages and tobacco products	79%	41%	37%	55%	0%	-1%
Textiles	71%	12%	33%	8%	0%	0%
Other food processing, feed use[8]	194%	42%	84%	50%	-20%	-1%
Ohter food food processing, other	70%	52%	41%	63%	-1%	-1%
Wood products	15%	-11%	14%	-18%	0%	1%
Paper products, publishing	14%	-9%	12%	-14%	-1%	1%
Petroleum, coal products	-3%	-15%	-24%	-23%	12%	3%
Chemical,rubber,plastic prods	12%	-4%	10%	-8%	0%	0%
Mineral products nec	15%	-14%	15%	-19%	0%	1%
Ferrous metals	16%	-17%	21%	-25%	0%	1%
Metals nec	17%	-15%	26%	-29%	-1%	1%
Metal products	16%	-17%	18%	-25%	0%	1%
Motor vehicles and parts	12%	-16%	14%	-21%	0%	1%
Transport equipment nec	27%	-19%	28%	-29%	0%	1%
Electronic equipment	11%	-21%	18%	-30%	-1%	1%
Machinery and equipment nec	15%	-20%	19%	-30%	-1%	1%
Manufactures nec	14%	-12%	11%	-18%	0%	1%
Electricity	-1%	-15%	-11%	-19%	-15%	-1%
Gas manufacture, distribution	39%	-14%	32%	-23%	-5%	1%
Water	48%	-16%	37%	-20%	-1%	1%
Construction	9%	-14%	14%	-18%	0%	1%
Trade	-18%	-12%	14%	-15%	0%	1%
Transport nec	9%	-9%	10%	-12%	0%	1%
Sea transport	29%	-16%	27%	-20%	1%	1%
Air transport	17%	-14%	23%	-19%	-1%	1%
Communication	19%	-18%	20%	-26%	-1%	1%
Financial services nec	5%	-19%	27%	-30%	-1%	1%
Insurance	-8%	-19%	4%	-28%	-1%	1%
Business services nec	2%	-16%	13%	-26%	-1%	1%
Recreation and other services	-24%	-12%	-9%	-16%	0%	1%
PubAdmin/Defence/Health...	15%	-12%	1%	-21%	-1%	1%
Dwellings	-37%	-23%	1%	-23%	-1%	1%

Source: G-RDEM simulation

[8] The two Other Food Processing sectors split out intermediate use of “Other food processing” in animal production, i.e. the production of feed concentrates.

5. Investment and Government

Besides consumption of households, final demand includes investment and government purchases. In this section, we briefly discuss how models typically represent investment and government demand, in terms of aggregate as well as composition. Additional information can be found in the Appendix. The modeling of exports and imports is discussed by Bekkers et al. (this volume).

5.1 Commodity composition of investment demand

The investment component of final demand (the I in C+I+G+X-M) is typically very high during periods of rapid growth, such as the spurts of the East Asian tigers. Currently, the investment share of GDP in China exceeds 40%, and exceeds 30% in Indonesia and India. Modelling the commodity structure of investment demand is thus almost as important as modeling the commodity structure of consumption. The modelling and projection of savings and aggregate investment is discussed in Fouré et al. (this volume), here we focus on the commodity structure.

Unfortunately, the literature on structural patterns of investment is scarce compared to the huge one on aggregate investment and savings. In principle, any demand system discussed in section 3 could be employed. However, we do not detect in our sample of models any use of higher order demand systems for investment, so that Leontief and CES (including Cobb-Douglas) functions dominate (Figure 9). Some models project industry specific investment rather than aggregate investment for the entire economy (see Supplementary Appendix A2). In this case, instead of a vector allocating aggregate investment, there is a bridge matrix allocating each industry's investment to individual commodities. A change in the relative growth of sectors then changes the composition of aggregate investment, even if the matrix is fixed.

Of all the models reviewed here, most models seem to fix the share parameters for the projection period. This is understandable, given that there is no available information comparable to that of income elasticities for consumption. Indeed, there is little discussion and no consensus about the form of an investment commodity allocation function. Since historical data about the composition of investment demand highlights that patterns are not stable over time, there is a strong argument for exogenously adjusting the composition shares. For example, intellectual property, including software, constitutes a rising share in total investment demand (see appendix A2). Of the global models surveyed in this article, C-GEM adjusts the share parameters for China to converge to investment patterns currently observed in other developed countries (Li et al., 2019), using an approach that mirrors the adjustment of share parameters on the consumption side. In the latest G-RDEM version (Britz and Roson 2019), the share parameters of the CD-demand system are shifted, depending on per capita income. Due to limited historical data on investment by commodity in many countries, another option is choosing ad-hoc adjustments based on expert judgement.

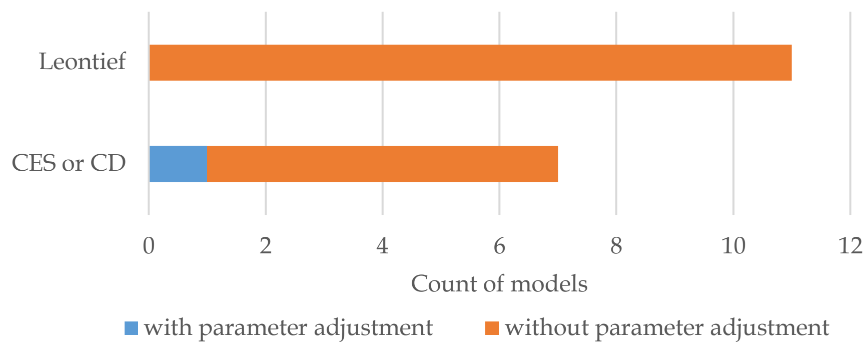

Figure 7. Demand systems for investment demand.

Source: Documentation and responses to survey of participants of the 2018 OECD/GTAP workshop.

5.2 Government demand

Aggregate government demand varies considerably between large economies, ranging from less than 10% to more than 20% of GDP (see Supplementary Appendix A3 for a more detailed analysis). Differences in government consumption levels are either driven by structural differences, that are unlikely to change substantially over time, or driven by different accounting principles. For example, health and education services are provided by very different institutional structures in different countries and affect our view of private versus public consumption. In the U.S., for example, education is mostly provided by local governments but there is a large private component, which is counted inside consumption expenditure.

There appears to be no systematic relationship between income and shares of government consumption. Countries experiencing bigger variations are those with radical changes in the political environment. An assumption of a constant total government purchases relative to GDP appears reasonable for long-run modelling, although a specific treatment might be needed for energy exporters, where the government share in GDP often fluctuates widely because of swings in international energy prices.

Several models allocate a constant share of GDP to government expenditure. For example, GDyn uses a Cobb-Douglas function that allocates fixed expenditure shares to private consumption and government consumption. Some other models do not identify an explicit government sector and combine it with personal consumption expenditures. The specification of the model of public spending and government deficit must be done in a unified manner as discussed by Fouré et al. (this volume). An alternative to allocating an exogenous share of GDP to government demand is to set the deficit exogenously and then the size of the government will be given by the endogenous tax revenues.

The composition of final demand for government is not modelled as elaborately as private consumption. Leontief, Cobb-Douglas or CES formulations are common choices and no model that we are aware of adjusts demand system parameters (Figure 10). In the GTAP dataset used by most global models, government purchases are predominantly from the "Public Administration, Defense, Education, Health" sector (Aguiar et al., 2016), which accounts for 94% of all government purchases in the GTAP 9 data for 2011. The commodity composition is thus driven by the production function of that sector. The latest available release of GTAP 10 (Aguiar et al., 2019) disaggregates this sector into three industries (Public administration; Education; Health and social work). This change from one to three sectors makes the allocation of total government demand more important, in particular if one wishes to incorporate the effect of aging on the demand for health and education.

There is little information in the models' documentation about the allocation of government expenditure. G-RDEM (Britz and Roson 2019) shifts share parameters of government demand depending on per capita income, like for their investment function.

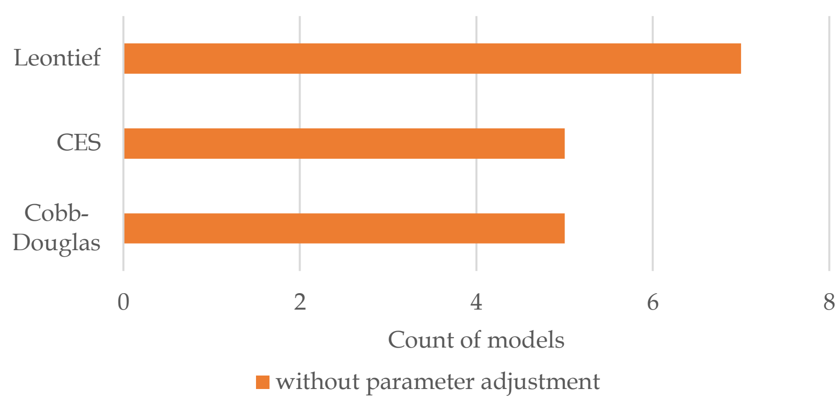

Figure 8. Demand systems for government demand.

Source: Documentation and responses to survey of participants of the 2018 OECD/GTAP workshop.

6. Observations and Recommendations

6.1 Conclusions from current state-of-the-art practices

We summarize here the main lessons we can draw from reviewing the literature and a large number of CGE models. Let us first note that this has been a challenging task due to the large differences in availability and detail in model documentation. In particular, the benchmarking process or the dynamic parameter adjustments are often not well documented. We believe that it would help other modelers to understand the results better and to learn other methods if the authors describe their adjustments in greater detail.

Given data and expertise needed, only a few modelling teams have opted to embody flexible demand systems in their long-run simulation exercises (cf. Jorgenson et al., 2013 for a single country CGE estimated using cross section household data; Roson and Van der Mensbrugghe (2018) and Britz and Roson (2019) for global models using country panel data). The majority continues to stick to simpler demand systems such as the CES or LES that were originally conceived for comparative static models. While CES nests under a LES or CES top level system offer flexibility to better depict cross-price effects, the homothetic character of the CES and the linear Engel curves of a LES cannot address the observed non-linearity of income effects.

Therefore, most of the models using CES, LES or CDE functions change parameters exogenously to yield plausible Engel curves. Caron et al. (2017), Chen et al. (2015), O'Neill et al. (2012), and Schuenemann and Delzeit (2019) provide good examples. This avoids implausible quantity and price changes from using constant calibrated parameters, as emphasized by Yu et al. (2000; 2004).

In Table 5, we compare projections using different demand systems in an otherwise unchanged model, supplementing the comparisons of Yu et al. (2004), Savard (2010), Bouët et al. (2014), Britz and Roson (2019). We believe that further testing of other functional forms would be very useful for the modeling community. We recognize, however, the high cost of doing so and suggest a collaborative effort to reduce learning costs.

While simple demand systems have fewer data requirements and therefore are easier to calibrate, they typically cannot capture relevant income and cross-prices effects. Several models considered here implement a simple solution by using a hierarchical approach with CES sub-nests e.g. for food commodity groups or energy demand to introduce more flexibility with regard to cross-price effects. The alternative to this are second-order flexible demand systems such as AIDS used in Sommers and Kratena (2017) and Savard (2010) or the translog function in Jorgenson et al. (2013). These demand systems require an n^2-order number of parameters and therefore are typically, at least in the context of CGE modeling, estimated only for a limited number of consumption bundles at the top tier. For consistent aggregation, sub-tiers must be of the homothetic type. A major obstacle to using these flexible systems is the lack of household and price data to estimate them for many countries.

For long-run analysis, we consider a top-level system with non-linear Engel curves combined with well-chosen and parameterized CES sub-nests as a robust, and relatively easy to implement, option. However, more empirical effort should be devoted to test such an approach on actual data. Currently, the parameters of the CDE demand system for up to 65 sectors shipped with the GTAP 10 data base are derived from the estimation of an AIDADS function with ten categories, drawing on demand prices constructed from the GTAP data base directly (Hertel and van der Mensbrugghe 2016). This data set could be used for comparing nested systems, for instance, an AIDADS combined with CES sub-nests with a nested or non-nested QUAIDS, or other functional forms which combine second-order and third-order flexibility, as well as demand systems that operate with parameter adjustments to induce expenditure shares evolving with income.

We noted how some models use a transition matrix to link the commodities in the consumption function with the commodities specified in the production side of the model. One reason for doing this is that the number of commodities identified in the production side is typically greater than the numbers of consumption commodities or services. On the other hand, products can enter multiple consumption items, which could be characterized by different income and price elasticities.

In particular, models specializing in energy issues must take into account that households are not simply consuming energy goods but actually complex energy services. These services may use different energy carriers as intermediates in combination with durables to produce energy services, e.g. cooking, heating, washing or transportation services. Just as in the formal production sector of the economy, home production should also allow for technological change, and thus, efficiency changes. This is particularly important when assessing energy or climate policies. However, even this more complex formulation is not sufficient if one wants to model saturation effects in the demand for energy services (Fouquet, 2014).

For the composition of final demand going to investment, most global models use relatively simple Leontief or CES demand functions. Without adjustments of parameters, these do not capture changing investment patterns over time, e.g. shifts towards a higher investment expenditures for software and licenses. Yet, currently only very few global model perform parameter adjustments.

For government purchases, most models employ simple assumptions like total expenditure expressed as a constant share of GDP. This is because the modeling of the public sector in CGE frameworks is uncharted territory. More work is needed to adequately reproduce with the models facts like the volatility of public expenditure in resource-based economic systems, or the dependence of consumption patterns from demographic (and political) characteristics of the countries.

6.2. A research agenda for improving final demand representation

We note four distinct challenges to improve the modelling of final demand in multi-sector models. First, data, in particular estimates of elasticities at the desired commodity detail. Second, the choice of a functional form, balancing the various trade-offs among desirable features of a demand system (non-homotheticity, flexibility, aggregability, conformability and parsimony). Third, the adaptation of empirical estimates to parameters of the model. Fourth, validation of the model.

Data on consumption, especially household level data, is the necessary condition for achieving improvements in consumption modelling. Data is needed to identify income and price elasticities, as well as behavioral differences across household types. Identifying heterogenous behavior would allow projecting the baseline more accurately by incorporating information like age distribution in the population, urbanization, and migration. Identifying differences across income groups would also allow an analysis of distributional impact of policies.

Better estimates of consumption functions could be realized by considering more commodities, more regions and household types, and by adopting functions that can adequately capture the complex, non-monotonic income relationships.

The task of choosing functional forms would be greatly aided by more comparative studies, such as discussed in section 6.1, possibly extended to compare the models' responses to common policy shocks.

For the challenge of calibrating parameters to incorporate external projections, it would be helpful to get a systematic comparison between models making use of parameter adjustments and models with complex demand system.

There are specialized demand models for other commodities that are not often included in CGE models such as health, tourism and information technology that are now major expenditures. A catalog of these should be very useful.

Modelling teams seem to be using their own sources of information for expert projections or linking with their own detailed (bottom-up or partial equilibrium) models[9]. Dixon et al. (2013), for example, describes how the MONASH model incorporates the work of specialist forecasting organizations. A catalogue of such

[9] Delzeit et al. (this volume) discuss the linking of top-down and bottom-up models on the production side. Many of the issues there would be relevant for demand side models too.

works should be valuable to the CGE modelling community, paving the way for sharing information, which makes model comparisons more meaningful.

Finally, let us raise the need to address the issue of social welfare measurement when there are different household types. This appears especially problematic when a model accounts for the (possibly endogenous) switching of people from one household category to another, as a result of policy shocks or economic development.

Acknowledgements

We thank survey respondents, journal reviewers, the editors, participants at the GTAP 2019 Conference, and the organizers of the Long-term baseline project for their comments and suggestions, which have improved this paper. Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the authors and should not be regarded as the official position of the European Commission. Ho is supported by a grant from the Harvard Global Institute.

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