Modelling consumption and constructing long-term baselines in final demand

Ruth Delzeit, Mun Ho, Florian Leblanc, Franziska Schuenemann, Matthias Weitzel

January 25, 2019

Abstract

Modelling and projecting consumption, investment and government demand by detailed commodities in CGE models poses many data and methodological challenges. In this paper we review the state of knowledge of consumption models for commodities (price and income elasticities and demographics), and review the historical trends that we should be able to explain. We then discuss the current approaches taken in various global and national models to project the trends in demand at various levels of commodity disaggregation and identification of household/income groups. We discuss the pros and cons of the various approaches to adjust parameters over time or using functions of time, and discuss possible research to improve modelling and projection. We briefly discuss the allocation of total investment and government demand to individual commodities.

Written for Modelling Long-term Baselines volume, (eds.) Dellink and van der Mensburgghe.

1. Introduction

Personal Consumption Expenditures is by far the largest component of final demand in most countries. The commodity composition of Consumption is thus the dominant driver of the industry structure of most economies. Therefore, a model that can capture the key elements of Consumption is an essential component of models that are focused on industry structure, or on particular commodities such as energy or agricultural goods. Such models include CGE models and other disaggregated bottom-up models.

While different models are used for a range of purposes, each requiring some different "key elements," there are some common desirable features. Well-founded price and income elasticities are important elements of both static and dynamic models. The historical data indicate that income effects are non-monotonic; for example, certain types of food can be both normal goods and inferior goods at different levels of income. Gasoline is a luxury good in low levels of incomes but income inelastic in rich countries. Dynamic CGE models are a heterogenous lot, but all modelers would like to have a baseline path that incorporates these features as well as expected changes in demography, technology, preferences, income sources and distribution. Many studies are concerned with policies lasting decades, such as those related to climate change mitigation, and enormous changes in incomes are expected. A mere 4% annual growth would triple incomes in 30 years, in the four decades since 1978, per-capita income in China multiplied 23 times.

Demographic factors have been shown to have important implications for consumption decisions, which then drive the evolution of the industry structure of the economy. O'Neill et al, 2010, for example, show how demographic changes affect future carbon emissions. Unfortunately, as they discussed, much of the economics research has focused only on income and price effects on consumption given the difficulties in disentangling demographic change from income and separating the effects of demographic change that act through the labor supply side. Modelers take population size into account in making the baseline projection but only a few models consider changes in population characteristics.

Implementing these desirable features and establishing a base path have proven to be challenging. A conference organized by GTAP and OECD in January 2018 discussed some of these challenges. In this paper we first review the state of knowledge of consumption models that are used in a broad range of CGE models, summarizing their pros and cons, in part drawing on the discussions at that conference and from existing reviews. We highlight several approaches used in various models to establish the base case path over longer time horizons. We discuss the merits and deficiencies of these current approaches.

We cannot be exhaustive in this review and cover all types of CGE models. Our focus is on dynamic multi-country models, myopic or foresighted, although some of the issues we discuss about functional forms apply equally to static models. The level of industry disaggregation differs widely among models; those with a fine level of detail, such as agriculture-focused models, have more demanding data and parameter requirements that we discuss briefly.

The dynamic models in use typically feature a tiered approach with separability assumptions. In most foresighted model there would be a discounted stream of within-period utilities that is a function of aggregate consumption, ($U_t(C_t)$). For now, we note that it is often assumed that the goods aggregate exists for period t, $C_t = C(C_{1t}, C_{2t}, ...C_{nt})$, or a goods-leisure aggregate exists. The bulk of this paper is a discussion of modelling the allocation of total consumption to the individual commodities and projecting these demands. We briefly note the modelling of leisure demand, labor supply and savings.

Some models relax the assumption of an aggregate utility function and allow differences in household types. The utility function for households is typically assumed to be expressible as $U_{ht}(C_{1t}^h,...C_{1t}^h,L_t^h)$ for household *h*, i.e., assuming that only total household consumption matters and ignoring differences between husband and wife, for example[1]. We follow this approach and ignore these complexities. Some environmental models would include an index of environmental quality in the utility function and such extensions are also ignored here.

In section 2, we first discuss historical consumption behavior before reviewing modelling approaches used by CGE models. Each approach has pros and cons, including the different ability to capture historical consumption patterns. Section 3 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. Some countries in their rapid development stage have very high Investment shares of final demand, for example, China's share rose to 48% in 2011. We summarize the current approaches to modelling Investment functions and construction of their base paths in section 4. As in the consumption function, we focus on the commodity breakdown of total investment demand and not discuss the modelling of savings and total investment. Modelling the commodity composition of Government final demand is briefly discussed in Section 5. Exports are a major part of final demand for some economies and trade functions are discussed separately in this volume by Bekkers et al (this issue).

Section 6 then summarizes our recommendations on the best practices in making such projections and section 7 discuss a research agenda to fill in the gaps in knowledge of specifying and implementing consumption models.

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

2. Observed consumption behaviour and current models

We first establish what economists understand about past observed consumption behaviour. 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. There is a related literature on aggregate consumption that shows how it 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), e.g. Pollack and Wales (1981), Lahiri et al. (2000), and O'Neill et al. (2012). Most CGE models operate with representative agents which are only concerned withaggregate (or average) consumption and much of the variance between individuals or households is ignored. This aggregate approach is the focus of much of our discussion in this paper, for now we merely note a few disaggregated approaches.

A simple approach is used in some models to disaggregate total consumption to different household types, "household downscaling," such as Melnikov et al. 2017. Other papers have used household level data to disaggregate the simulated aggregate consumption results to different household types (by region or income groups), e.g. Rausch et al. 2011. Jorgenson et al. (2013) use an aggregate demand function that explicitly include variables for demographic composition and income distribution in each year of the projection.

Even if a model uses an aggregate consumption function that is a simple function of aggregate income and prices, modelers still wish to incorporate the effects of expected demographic changes and non-linear income effects indicated by the empirical estimates. This is especially important when projecting several decades into the future as profound changes in demography and income can be expected (O'Neill et al., 2012). Commodities that are normal goods at low incomes become inferior goods at higher incomes, or may change from income inelastic goods to elastic. It is thus important to examine the historical consumption patterns, considering both development over time within a region, and comparing across regions at a point in time.

Pollack and Wales (1981) have shown that demographic factors can have important implications for consumption decisions. These final demand patterns then drive the evolution of the industry structure of the economy. Changes to population size are considered by most models, and these act mainly through the supply side via changes in labor supply. Only a few consider changes in the demographic composition of the population which changes the demand side (e.g. iPETS, O'Neill et al., 2012, Jorgenson et al. 2013)

The impact of population characteristics and structural change on consumption behavior is especially visible in the case of food commodities. One of the reasons for the nutrition transition is the change in time allocation: as economies develop away from subsistence agriculture to wage employment in industry and services, people have less time to spend on food preparation (Popkin, 2012). This has led to a lower intake of fiber and increased demand for processed food and refined food (WTO, 2018), which is leading to higher consumption of sugar and vegetable oils mainly in emerging and developing economies (OECD-FAO, 2018).

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.

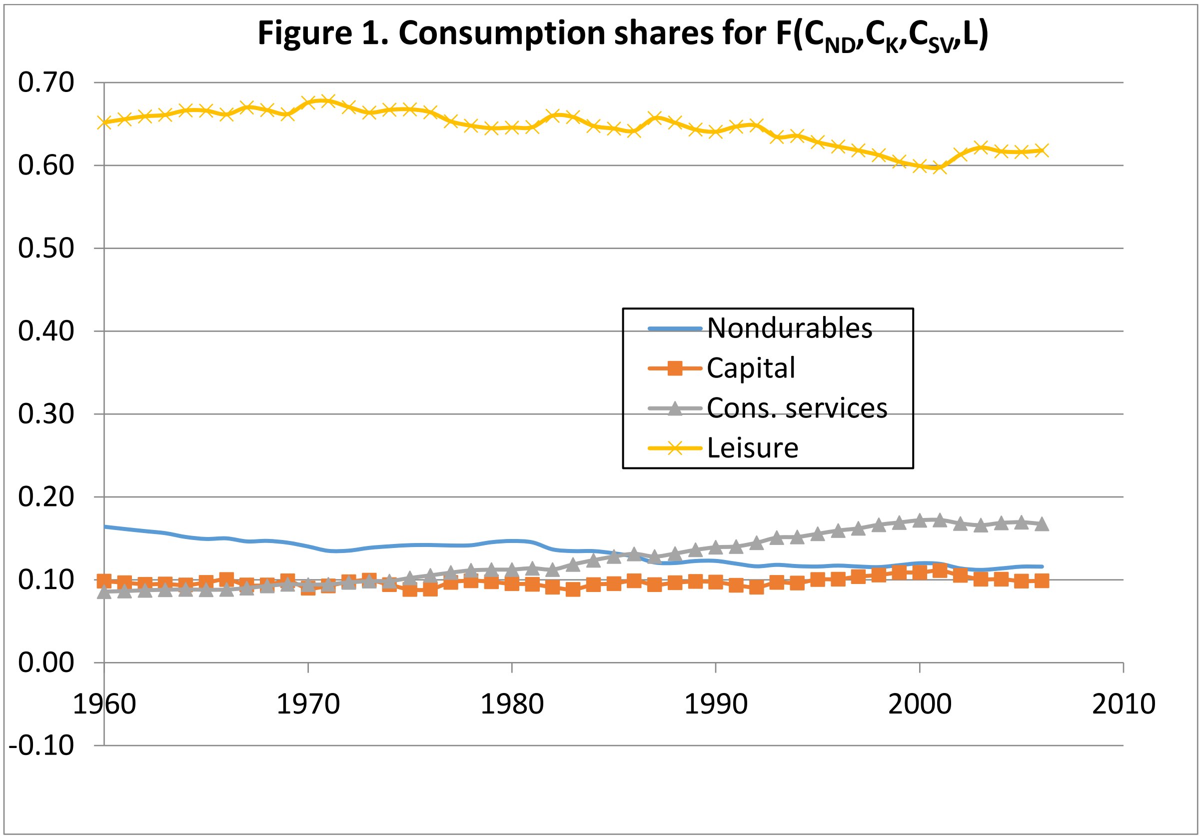
One major strand of empirical work is the estimation of the demand for specific commodities such as cereals, meat, tobacco, electricity, gasoline, transportation, etc. These are valuable for studies targeted towards those items, for example the analysis of changes in agriculture output due to income change or climate change. Other CGE models deal with the broader set of commodities and we also discuss the literature that deals with estimating complete demand systems in greater detail.

That is, we first discuss models that ignore complicated cross-price elasticities where demand for good *i* is a function only of price *i* and income, and possibly, demographic characteristics. This is the dominant approach in the global models that are the focus of this essay and includes forms such as the Linear Expenditure System, Constant Elasticity of Substitution and Constant Difference of Elasticities. There are other CGE models that employ a more flexible system in a tiered structure, for example, an utility function like U(food, energy, goods, services) at the top tier in an Almost Ideal Demand System (AIDS) or translog form with cross price elasticities and non-unit income elasticities that do not diminish over time. Empirical studies of such demand systems are discussed by Blundell (1988) and Barnett (2008). Deaton and Muellbauer (1980) is a standard reference for the major work prior to 1980 as well as describing the popular AIDS form.

We should note here how different accounting systems of private versus public expenditures could affect our view of consumption in different countries. Health and education services are provided by very different institutional structures in different countries, and these are major components of final demand. In the U.S., for example, education is mostly provided by local governments but there is a large private component, which is counted in Consumption Expenditures. Another country, at the same level of income as the U.S., with the same share of national resources devoted to Education, but with a much smaller private component would show a very different education demand in Consumption and in Government. We comment more on these differences in Section 5, this is to alert modelers making cross-country comparisons or transferring parameters from one country to another to be aware of these institutional and accounting differences.

2.1 Income and price elasticities and trends.

We first give a representative view of rich-country consumption by summarizing the results in Jorgenson et al. (2013). They model a full-consumption (F) function with 3 bundles of consumption commodities and leisure at the top tier – F(nondurables, capital services, services, leisure). The 3 bundles are disaggregated to 35 commodities in lower tiers. The first feature to note is that consumption expenditure shares change significantly over time, changes that do not correspond entirely to price movements. This is illustrated in Figure 1 giving the aggregate shares corresponding to the top tier of the F(.) function. The leisure share is large in their approach, but the downward trend after 1970 holds for other methods of defining time endowment, this is due to the rapid rise in the female labor force participation rate in the U.S. The falling share of nondurables (includes food) and the rising share for services is a common feature of rising incomes.



Food demand

The study of food demand is one of the earliest empirical economics work; Engel's Law was named in honor of his 1857 paper. Engel 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 1 shows food budget shares of countries grouped by income as reported in Muhammad et al. (2011). This 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").

Table 1: 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).

Table 2: 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).

Table 2, also from Muhammad et al. (2011), gives the budget shares for 9 major consumption bundles in 2005. Food continues to be a major portion (48%) of poor household budgets around the world today and it is no surprise that the huge empirical literature on food demand and food policy has continued to expand.

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). Global income elasticity estimates over time show a decrease of elasticities for all commodity groups as expected (Yu et al., 2004). However, as countries and households become richer, they reach a saturation point of food consumption where income elasticities cease to fall (Cirera and Masset, 2010b), or could even rise slightly again as shown by the income elasticity estimates of different food types in Table 3 for selected countries between 1996 and 2005.

Table 3: Income elasticities of different food types for selected countries and different years

Food type	Malawi*	Vietnam		Mexico		United States	
	2005	1996	2005	1996	2005	1996	2005
Cereals	0.65	0.59	0.54	0.40	0.18	0.05	-0.09
Meats	0.81	0.79	0.77	0.63	0.64	0.10	0.34
Fish	0.72	0.88	0.66	0.67	0.51	0.10	0.26
Dairy	0.84	0.83	0.80	0.65	0.66	0.10	0.35
Oils & Fats	0.66	0.55	0.55	0.32	0.24	0.03	0.00
Fruits & Vegetables	0.70	0.64	0.62	0.49	0.44	0.07	0.21
Other Food	0.98	0.79	1.34	0.63	0.85	0.10	0.44
Beverage & Tobacco	2.85	1.43	1.16	0.80	0.81	0.12	0.42

Source: Seale and Regmi (2006); Muhammad et al. (2011). *Note: No data available for Malawi for 1996.

Non-food demand and levels of aggregation

A good estimate of demand parameters requires a large amount of data. Most current income and price elasticity estimations at the global level rely either on national aggregate data from the International Comparison Project (ICP) (as shown in Tables 3 and 4) or are estimated directly through GTAP national data. The ICP is led by the World Bank and, since 1968, collects price and expenditure data at the global level, which are then made comparable across countries using purchasing power parities (Seale and Regmi, 2006). The latest collection period in 2011 included data for 199 countries (World Bank, 2015). Recent demand elasticity estimates using this ICP data is made at different levels of aggregation for food commodities. Reimer and Hertel

(2004), for example, 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. 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 and 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).

Since demand elasticity estimates from ICP are only available at a relatively aggregated level (the 10 groups mentioned above), models with a more disaggregated set of demand and production commodities require either a separate elasticity calibration for the disaggregated commodity set or the use of transition matrices. The ENVISAGE model, for example, uses a transition matrix to convert a small number of commodity bundles into a larger number of commodities (van der Mensbrugghe, 2018). Such a matrix may be used to link consumption categories that modelers wish to focus on with the supply side that do not have the same level of detail. For example, transportation demand is to be allocated to fuels, vehicle maintenance, purchased transportation services – categories that are not identified on the supply side of the model. One may use an explicit nested function like in iPETS described in Section 2.3, or use a simpler bridge matrix.

Table 4: Income 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	0.82**	0.74	0.78**	0.59	0.65**	0.09	0.35**
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

Source: Seale and Regmi (2006); Muhammad et al. (2011). *Note: No data available for Malawi for 1996.

**Note: 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).

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 4 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 necessitiesare clothing and footwear and to some extent education. Still, at a range between 0.8 and 1.0, the income elasticities for these categoriesare much higher than for food.

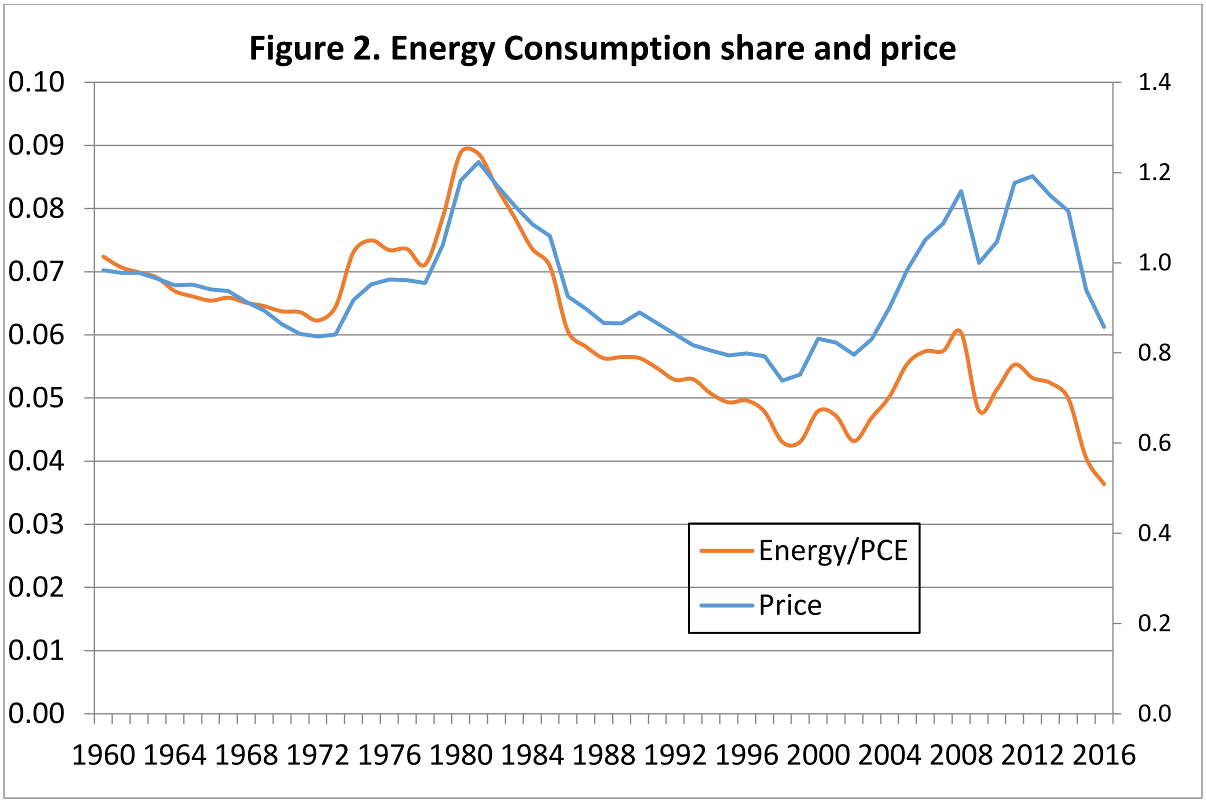
Goods with income elasticities greater than unity are often referred to as luxury goods. This is misleading, income elasticities greater than unity are observed for the majority of goods and services. The highest income elasticities can be observed for services and recreation (Kaus, 2013; Seale and Regmi 2006). As we just noted, even for food, the income elasticity can exceed one for some income ranges. 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.

The heterogeneity of goods within broad categories of consumption between different countries can make comparisons difficult and results hard to interpret. 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.

Demand for energy services

Figure 2, taken from Jorgenson et al. (2013), shows the energy consumption share which rose during the oil shocks of the 1970s, then falling rapidly in the 1980s and then rising in the mid-2000s. These changing energy shares are driven mostly by price effects, however, there are non-price effects too. In the literature on production functions, the bias of technical change refers to changes in input ratios that are not due to price effects; the best known being the increase in inputs of skilled workers at the same time that their relative wages are rising. Most models of consumption attribute changes that are not price related to income effects instead of a change in preferences that would be symmetrical with changes in production technology. In section 2.3 below we describe estimates that show complex income effects for energy consumption.

[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.



Price elasticities

Price elasticities have received less attention from the CGE modelling community compared to income elasticities. They may be used for calibration in the LES but are not absolutely needed, and are required to calibrate the CDE system used in the GTAP model (see section 2.2.). When econometric estimates of price elasticities are not available, they are derived from simple functions for such calibration exercises. Muhammad et al. (2011) give an overview over different ways to calculate either the uncompensated or compensated price elasticities from income elasticities and benchmark consumption expenditures.

Making use of the direct additivity of the LES, Frisch proposed a formula to calculate uncompensated own-price elasticities as shown in eq. 6b below (Zeitsch et al., 1991). This approach is used to calculate the GTAP parameters as described by Hertel and van der Mensbrugghe (2016).

There is no systematic disaggregated dataset of price elasticities available at the global level, just as it is for income elasticities. Muhammed et al. (2011) and Seale and Regmi (2006) estimated own-price elasticities together with the income elasticities using the ICP data as discussed above. Table 5 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 elasticity seems to 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 that indicate difficulty in access for poorer people.

Table 5: 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 particular products, or for complete systems, scattered in the literature. There is, for example, a big set of studies for electricity and gasoline (e.g. those reviewed in Cao et al. 2016). Unfortunately, there has been no systematic collection of these estimates and processing them for use in typical CGE models.

2.2 Review of current Consumption models in CGE models

Implementing a model that recognizes the full complexity of household consumption behaviour noted above 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. Most models employ the constant elasticity of substitution (CES) form, linear expenditure system (LES), or constant difference in elasticity (CDE) demand system as shown in Table 6. More flexible demand systems are complex to implement with few estimates from the empirical literature; the AIDADS, AIDS and translog forms (described below) are used in more limited settings or are in an experimental stage and have yet to become mainstream in large-scale multi-country CGE models. In this section 2.2 we summarize the various functional forms so that we can be explicit about which parameters are estimated or calibrated, and about which ones are being adjusted over time by modelers to construct baseline projections.

Table 6. Demand systems currently used in CGE models (results of our survey)

Model; institution/authors	Key features	Consumption function	Energy demand treatment	Cons. fn features	Income elasticity treatment
ADAGE; RTI	Global or US; myopic; 24 sectors + 10 biofuels	nested CES			
AIM CGE; Japan NIES	Global or national; myopic; 19 sectors + 19 energy	LES	LES or Logit	Food uses FAO projections	η^M adj. over time
DART; IfW Kiel	Global; myopic;	LES	Mixed Cobb Douglas & CES	η^M from GTAP; use Dellink (2005)	
Envisage; World Bank	Global; myopic; flexible no. of sectors (~30);	CDE and CES; options for LES, AIDADS		use FAO projections	
ENV-Linkages; OECD	Global; myopic; 22 sectors +7 elect.	ELES and CES		params from GTAP	LES params adj. over time
EPPA; MIT JPGC	Global; myopic; 9 sectors + 8 energy + 8 elect.	CES and CDE; LES in v6L	Detailed household transportation	CDE for food, converge to rich country shares; detailed household transportation	η^M from Reimer & Hertel (2004)
FARM; US ERS	Global; myopic; 24 sectors + 14 agriculture	LES and CES	Energy services	γ change over time	
G-cubed; McKibbin	Global; foresighted; 12 sectors	CES			
GDyn; GTAP	Global; myopic; flexible no. of sectors;	CDE and AIDADS	Nested CES in GDyn-E	params from GTAP	CDE parameters not adjusted
GEM-E3; EU JRC	Global; myopic; 31 ectors;	LES; explicit durable stock	Durables linked to energy use	Durables linked to energy use; φ based on	η^Madj. over time

				GDP/N (-3.5,-1.8)	
GLOBE; IDS, UK		LES		params from GTAP	
G-RDEM; IEFE, Bocconi		AIDADS			
ICES; FEEM		CDE		params from GTAP	
Imaclim-R; CIRED	Global; myopic; 12 sectors	LES	CES for transport services, travel time constraint		
iPETS; NCAR, Boulder	Global; forward-looking	nested CES		params from GTAP	parameters adjusted over time
Mirage; CEPII, Paris		LES; CES: non-subsistance cons.			
MIRAGRODEP; IFPRI					
MSMR; Env Canada	Global; myopic; 20 sectors	nested CES		η from GTAP and Okagawa and Ban (2008)	η^M not adjusted, but params adjusted to external proj.
PACE; ZEW, Mannheim		CES and CD		elasticities from GTAP CDE	
TEA; COPPE, Brazil		CES from EPPA			
USITC; US Intl Trade Comm.		CDE			
Wegener Ctr; U of Graz	Global; myopic; 14 sectors	nested CES	CES		η^M not adjusted
GTM WTO		CDE (GTAP)	CDE		parameters adjusted over time
1-country models					
DYNK; WIFO	Europe; 59 sectors	AIDS	Link to durables		

IGEM; Jorgenson	US; perfect foresight	Translog	Translog
MONASH, CoPS, Victoria University	Single-country models; 100s sectors		

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

Constant elasticity of substitution (CES):

The constant elasticity of substitution (CES) demand system is used in many CGE models (EPPAv6, ADAGE, PACE, etc.). It is relatively simple to implement and only requires an elasticity of substitution parameter (σ) to be chosen, and then share coefficients be calibrated. The utility (within a period t) from consuming commodities c_1, …, c_n is given by:

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

The α_{it} 's are parameters that may be calibrated on observed expenditure shares and are indexed by time t in models where they are changed exogenously over time. The t index is suppressed from here on unless needed for clarity. The budget constraint is expressed as the following for all utility functions discussed in this section:

(2) $$M = \sum_i p_i c_i$$

The demand for good i in the CES is a linear function of income, M:

(3) $$c_i = \frac{\alpha_i^\sigma M}{p_i^\sigma \sum \alpha_j^\sigma p_j^{1-\sigma}}$$

The income elasticities are simply, $\eta_i^M = 1$, for all periods and levels of incomes. The own-price elasticity given by:

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

In the case of unit elasticity ($\sigma = 1$), the CES system becomes the Cobb-Douglas (CD) form where demand is characterized by fixed expenditure shares independent of price or income. This is the easiest to implement, especially when combined with a constant propensity to save, or when a constant share of the consumer budget is used to finance government purchases. In these cases, a single demand system can be formulated to accommodate government, investment and consumption demand.

The CES demand system can be refined by introducing nested CES functions, thus allowing for different substitution relations for different classes of goods. Models use nested CES to reflect more detailed substitution possibilities between different types of goods within a broader category of goods (e.g. different types of energy or food goods) compared to substitution possibilities between broad categories. Due to the ease of implementation, (nested) CES utility functions for final household demand are common in models written in MPSGE (Rutherford 1999).

A severe limitation for CES and CD demand systems is the homotheticity of demand, i.e. income elasticities are constrained to be one. This restrictive assumption can be relaxed in LES or CDE demand systems that we describe next. The LES can be seen as an extension to a nested CES demand system, as the CES can be maintained as part of a LES.

Linear Expenditure System (LES) or Stone-Geary:

The Linear Expenditure System (LES, or ELES if it is extended to include savings) allows for non-homothetic demand and is thus one of the most common demand systems applied by both global and national CGE models, including AIM, ENVISAGE, FARM, DART and the IFPRI standard CGE model. The LES utility function is written as:

(5) $$u = \sum_i \alpha_i \ln(c_i - \gamma_i); \quad \sum_i \alpha_i = 1$$

where γ_i is the subsistence level of consumption of good *i*. The demand for good i, the own-price elasticity η_i ,income elasticity η_i^M , and number of parameters *np* are derived as:

(6) $$\begin{aligned} c_i &= \gamma_i + \frac{\alpha_i}{p_i}\left(M - \sum\nolimits_j p_j \gamma_j\right) \\ \eta_i &= -\frac{\alpha_i p_i \gamma_i + \alpha_i (M - \sum_j p_j \gamma_j)}{p_i \gamma_i + \alpha_i (M - \sum_j p_j \gamma_j)} = -1 + \frac{(1-\alpha_i) p_i \gamma_i}{p_i c_i} \\ \eta_i^M &= \frac{\alpha_i M}{p_i c_i} \to 1 \\ \phi &= -\frac{M}{M - \sum_j p_j \gamma_j} \\ np &= 2n - 1 \end{aligned}$$

The Frisch parameter ϕ is defined in the following way and it may be used to calibrate the subsistence parameter and price elasticity:

$$\phi = -\frac{M}{M - \sum_j p_j \gamma_j}$$

(6b) $$\gamma_i = c_i + \frac{\alpha_i M}{p_i \phi}$$

$$\eta_i = -w_i \eta_i^M (1 + \frac{\eta_i^M}{\phi}) + \frac{\eta_i^M}{\phi}$$

np denotes the number of parameters in a system with *n* goods. The subsistence demand γ_i is purchased regardless of prices (subject to the minimum income required). The remaining discretionary demand ($c_i - \gamma_i$) may then be modelled with a CES system or as in (5). The income elasticities η_i^M differ for different goods and the expansion paths are illustrated in Figure 3; (a) shows that if there is no subsistence element, e.g. a pure CES system, the expenditure shares remain unchanged and the expansion path is a straight line through the origin; (b) shows how the subsistence consumption in the LES shifts the origin of the expansion path, and hence changes its slope.

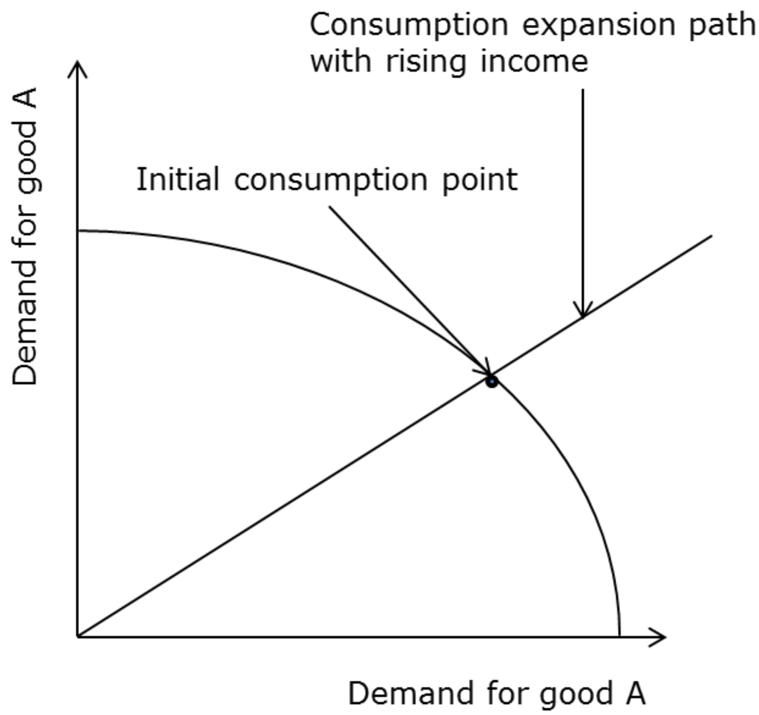
If income and price elasticities (η_i^M and η_i) were available, the equations in (6) may be used to calibrate the values of α_i and γ_i. In many cases the price elasticities are not available and some authors would choose a value for the Frisch parameter ϕ (the ratio of total to discretionary income), calibrate α_i using some income elasticity, and then calibrate the subsistence parameter (see Annabi et al. 2006 for details). Schuenemann and Delzeit (2019) test different ways of calibrating Frisch parameters and subsistence demand and their impact on consumption projections in a dynamic global CGE model. They show that simply using Frisch parameter values from the literature leads to unrealistically high subsistence demand shares. On the other hand, calculating subsistence demand based on a transformation proposed by Dellink (2005)[3] using only information on income elasticities is equivalent to calibrating the Frisch parameter and subsistence demand by solving the above system of equations.

As incomes rise, subsistence consumption become small relative to the discretionary consumption, and the LES converges to a Cobb-Douglas system. This also means that the LES will eventually contradict Engel's law, as the implicit income elasticities approach unity (from above or below). The adjustments to the parameters to deal with this are discussed in section 3.

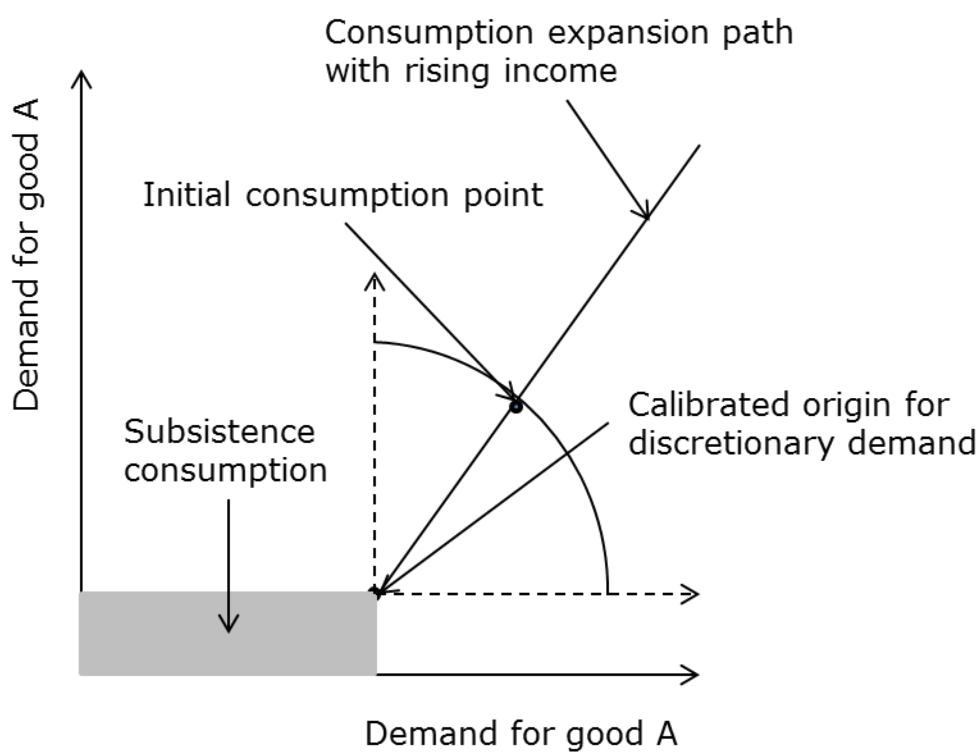
[3] $\gamma_i = \left(1 - \frac{\eta_i}{Max_j\{\eta_j\}}\right) \cdot c_i$

Figure 3. Consumption expansion paths. (a)under homothetic CES;(b) non-homothetic LES.

(a)



(b)



Constant differences of elasticities (CDE)

The Constant Differences of Elasticities (CDE) demand system is used in the standard GTAP model (Corong et al., 2017) and in other models using GTAP data (Envisage, EPPA, ICES, GTM), and represents a more general form of the CES system (van der Mensbrugghe, 2018)[4]. It was first introduced by Hanoch (1975) and can depict non-homothetic preferences as well as non-unitary price elasticities. The expenditure function, *E(p,U)*, underlying the CDE is an implicit indirectly additive function written as follows:

$$\text{(7)} \qquad \sum_i B_i U^{\beta_i \gamma_i} \left[\frac{p_i}{E(p,U)} \right]^{\beta_i} = 1$$

The income elasticities, η_i^M , uncompensated cross-price elasticities, ε_{ij} ,and number of parameters are given as:

$$\text{(8)} \qquad \begin{aligned} & w_i = \frac{Z_i}{\sum_k Z_k}; \quad Z_i = B_i \beta_i U^{\beta_i \gamma_i} (p_i / M)^{\beta_i} \\ & \alpha_i = 1 - \beta_i \\ & \eta_i^M = \frac{\sum_k w_k \gamma_k \alpha_k + \gamma_i (1 - \alpha_i)}{\sum_k w_k \gamma_k} + \alpha_i - \sum_k w_k \alpha_k \\ & \varepsilon_{ij} = w_j [\alpha_i + \sum_k w_k (1 - \alpha_k) - (1 - \alpha_i)] - \delta_{ij} \alpha_i \\ & np = 3n \end{aligned}$$

where w_i are expenditure shares and δ_{ij} is the Kronecker product that equals 1 when $i = j$ and 0 otherwise. γ_i is the expansion parameter and α_i is the substitution parameter.

There are 3n parameters to be estimated or calibrated in the CDE, and they cannot be directly calibrated to demand elasticities given the expressions in (8). The substitution parameters are calibrated to target own-price elasticities, while expansion parameters replicate target income elasticities (Hertel and van der Mensbrugghe, 2016). These substitution and expansion parameters are simultaneously calibrated using maximum entropy methods, but often do not match with the targeted income and own-price elasticities. Chen (2017) shows that a higher sectoral disaggregation of commodities, higher targeted income elasticities and lower targeted price elasticities lead to better matches, as long as target elasticities are valid with respect to Engel/Cournot aggregation and the matrix of Allen-Uzawa elasticities of substitution is negative semi-definite.

These calibration requirements make it difficult to calibrate CDE systems to the large set of empirical income and price elasticities that exist. The CDE system in the standard GTAP model, for example, is indeed calibrated to empirically 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) as described in section 2.1 (discussion of Table 5).

[4] Chen (2017) gives a detailed discussion of the CDE system from which we write eqs. 7 and 8.

A disadvantage of the CDE (like that of the CES and LES) is that it conserves the calibrated base year income elasticities for all years of the simulation; it does not allow for Engel flexibility such as luxury goods becoming necessities (Yu et al., 2004). Some models thus employ workarounds of recalibrating the parameters so that income elasticities may change over timeas described in section 3.

Flexible demand systems

Flexible demand systems refer to a whole range of more general functional forms. As discussed by Fisher, Fleissig and Serletis (2001), locally flexible forms include the (basic) translog and Almost Ideal Demand System (AIDS) while models with higher rank systems include the Laurent, QUAIDS, rank-3 translog and General Exponential Form models[5]. An even more general approach uses semi-non-parametric forms such as the Fourier and Asymptotically Ideal Model.

One system that allows for endogenous changes in income elasticities is the "An Implicitly Direct Additive Demand System" (AIDADS) that is a rank three system and a generalization of the LES (Preckel et al., 2010, Yu et al., 2000). It is written as an implicit directly additive utility function:

$$\sum_i u_i(c_i, u) = 1$$

(9) $$u_i = \frac{\alpha_i + \beta_i G(u)}{1 + G(u)} \ln\left[\frac{c_i - \gamma_i}{Ae^u}\right]$$

$$\sum_i \alpha_i = 1 = \sum_i \beta_i$$

γ denotes the subsistence consumption as in the LES, and $G(u)$ is a positive monotonic twice differentiable function. As discussed by Yu et al. (2000), when we choose $G(u) = e^u$, the demand function and income elasticities are given by:

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

(10) $$\phi_i = \frac{\alpha_i + \beta_i e^u}{1 + e^u}; \quad \gamma' p = \sum_i p_i \gamma_i$$

$$\eta_i^M = \frac{\psi_i(c_i, u)}{w_i}; \quad w_i = \frac{p_i c_i}{M}$$

$$np = 3n - 1$$

[5] The rank of a demand system is discussed in Lewbel (1991), and Bouet et al. (2014) explain it as the number of independent price indexes needed to specify the corresponding indirect utility function. Rank 1 systems correspond to homothetic functions with linear Engel curves (e.g. CES); rank 2 have linear Engel curves but do not need to pass through the origin (e.g. LES), rank 3 have non-linear Engel curves. Bouet et al. also summarize the conclusion of Lewbel (1991) as "for average incomes rank 2 functions are sufficient … but for very low or very high incomes, rank 3 are necessary." Gorman (1981) show that exactly aggregable systems must be rank 3 or less.

A, α_i and β_i are parameters to be estimated, w_i is the budget share and ψ_i is the marginal budget share. When $\alpha_i = \beta_i$, the system collapses to the standard LES. There are $(3n-1)$ parameters here compared to $(2n-1)$ for the LES. As the marginal budget shares ψ_i are flexible and individually estimated for low and high incomes, the income elasticities (η_i^M) may vary logistically (Chen, 2017).

The ENVISAGE model includes the option to use the AIDADS demand system and it is used to estimate income elasticities for the GTAP commodities (Hertel and van der Mensbrugghe, 2016; van der Mensbrugghe, 2018). However, calibration for a disaggregated 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 as the direct additivity limits substitution possibilities across a larger number of goods. In Table 6 the other models using AIDADS are G-RDEM and GDyn.

The AIDADS is not a second order flexible system like the basic translog or AIDS (which has $\frac{1}{2}n(n+3)-2$ parameters)[6]. In the translog system used in Jorgenson et al. (2013 Chap. 3) for a one-country model, the share demand vector for household of type k (w_k) is given as non-linear function of log prices, log income (M) and demographic 1-0 indicator variables (A_k):

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

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

This is derived from an indirect utility function $V(p, M_k)$, where p is the vector of prices. B is the matrix of price coefficients and the vector B_M gives the income effects. B_A is a matrix of coefficients that allow different household types to have different consumption shares even when they face the same prices and have the same incomes. The types of households in Jorgenson et al. include number of adults, number of children, location and race.

In flexible systems there is a full set of cross-price elasticities (in the translog case here represented by the B matrix) and the number of parameters is of order n^2. The aggregate share demand vector derived by summing over all household types is then a function of the demographic components of the whole population (ξ_t^d), the income distribution (ξ_t^M), aggregate income (M_t), in addition to the usual dependence on prices:

(12) $$\begin{aligned} w_t &= \frac{1}{D(p_t)}\left[\alpha + B\ln p_t - B_M \frac{\sum M_k \ln M_k}{\sum M_k} + B_A \frac{\sum M_k A_k}{M_k}\right] \\ &= \frac{1}{D(p_t)}\left[\alpha + B\ln p_t - B_M(\xi_t^M + \ln M_t) + B_A \xi_t^d\right] \end{aligned}$$

This translog approach with household type specific parameters thus allows for a full set of price substitutions and allow for a natural way to incorporate projections of demographic

[6] This is discussed by Bouët, Femenia and Laborde (2014).

changes into the aggregate demand function. The drawback to using such flexible functions is the large number of parameters to be estimated and the need to impose concavity on the B matrix. It also limits the number of commodity bundles, and the demand for commodities must be given by a nested structure with something like eq. (12) in the top nest. In Jorgenson et al. (2013) there are 4 bundles in this top tier, while Sommers and Kratena (2017) has 8 items in their AIDS function in DYNK. The complexity of estimating the cross-price elasticities has limited the use of these flexible forms to a few examples of one-region models.

Another limitation of using non-homothetic functions in the top nest is that the functions in the lower tiers must be homothetic for a well-defined price of the sub-aggregate. For example, if the top tier has total energy as a consumption bundle, then a second-tier function allocating energy to electricity, gas, and gasoline must be homothetic. In the system in Jorgenson et al. (2013) the trends observed in the historical data (beyond those captured by price effects) are captured with a state variable since they cannot be a function of income.

2.3 Special features of food and energy demand in CGE models

Special features for Food demand

In Section 2.1 we noted how diets in developing countries are converging towards patterns in the rich countries – greater variety and more meat and dairy products. Modelling this convergence will be key for establishing the baseline paths for global food consumption. While the previously discussed desirable features of demand systems such as non-homotheticity apply to all types of commodities, modelling the dynamics of food demand requires an even higher flexibility in terms of reactions 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 inferior good, income elastic and inelastic, and thus need to be depicted with a rich set of income and price elasticities. In addition to flexible demand functions, long-term baselines of food should ideally include the impact of various interconnected macroeconomic demand and supply side drivers such as the introduction of supermarkets and refrigeration.

The first challenge of capturing detailed food demand dynamics in aggregate global 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. This means that aggregation of food demand is problematic when it comes to different food groups; food demand is not only a function of income but also of income distribution (Cirera and Masset, 2010). The typical regional household in global CGE models is an aggregation of all (richer and poorer) households within a region that 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 homothetic preferences and contradict the two major food demand laws in economics: Engel's law and Bennett's law.

Depicting saturation is a general problem in demand systems used in global CGE models. An important requirement of constrained utility maximization is the adding up condition where the marginal budget shares sum to unity (Deaton and Muellbauer, 1980). This condition however would be violated if all commodities reach saturation and approach zero income elasticities (Chai and Moneta, 2010b).

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

The common demand systems in CGE models reviewed above only partly consider the special features of food demand. The advantage of the LES is its flexibility in terms of number of commodities, which allows a rather disaggregated set of food commodities. The standard LES 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, since increasing income elasticities imply an increase in the marginal budget share of these goods. 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 accurate in regions where income is growing modestly. Similarly, the classical CDE system can neither reflect Engel's nor Bennett's law in food demand behavior as the income elasticities stay constant over time.

To avoid these problems, some model groups calibrate food demand 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 updating 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 projected food demand dynamics related to income changes, price induced changes in food demand along the baseline path are sometimes neglected, and should be considered simultaneously with income effects by iterating the baseline path (Lahiri et al., 2000)[7].

In a nested system, the substitution elasticities in the different nests simultaneously determine the implicit price elasticities of food demand (Valin et al., 2014), which can lead to implausible price behaviour. Some models combine the LES and CES approaches, for example, the Future Agricultural Resources Model (FARM) by the USDA has a top nest for aggregated food categories with a LES and CES functions for the lower nests within food categories. In addition, 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 as discussed above. So far, only the modified AIDADS (MAIDADS) is able to reflect saturation of food demand for regions with high income levels (Gouel and Guimbard, 2018), but has not been used in CGE models so far (Corong et al., 2017).

In the G-RDEM model, Britz and Roson (2018) first empirically estimate a ten-commodity AIDADS and then extend the system to include disaggregated food groups. The low-

[7] 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.

income and high-income marginal budget shares of the food commodities in the extended AIDADS are calibrated to estimates by Muhammad et al. (2011) using ICP data as discussed in section 2.1. Britz and Roson (2018) show that the less elastic reaction of staple crop consumption to income growth in their AIDADS compared to a CDE system (where income elasticities remain stable with income growth) leads to 14% lower consumption at the end of their forty-year simulation period. A more detailed discussion of modelling food and nutrition in CGE models is given in Sands et al. (this issue).

Special features of Energy Demand

Energy demand can be represented in the standard way symmetrically with other goods, which is the case of most models listed in Table 6). More than half of the models use nested CES, while other teams use other forms (LES, CDE or flexible functions) and some models use a combination of different functions (AIM and Imaclim-R discussed below).

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

Regardless of the chosen system (LES, CES, etc.), a nested approach makes it possible to specify energy services provided by the consumption of fuels and associated goods. In the following, we present a few examples of energy demand representation; a more exhaustive description of various attempts to model transportation and buildings can be found in Faehn et al (this issue).

We start with the SNoW-No model of Norway (Greaker and Rosnes, 2015) where the consumption structure is illustrated by equation 13. In the top tier, housing and transport services are nested within a CES along with other goods. In the second tier, housing services is a CES function of dwelling and energy, while transport services are a CES function of vehicles and fuel. In this representation, energy can be substituted for capital stocks (dwelling or vehicles) per unit of housing or transportation services consumed. Bye et al. (2015) used detailed bottom-up data and estimated the elasticity of substitution between dwellings and energy to be about 0.3 for Norway.

(13) $Private_{Cons} = CES(\ Housing, Transport, Other\ goods, \overline{\sigma_{PC}})$

$$Housing = CES(\ Dwelling, Energy, \overline{\sigma_H})$$

$$Transport = CES(\ Vehicles, Fuel, \overline{\sigma_T})$$

The EPPA model (Paltsev et al., 2005) has a nested series of CES functions as shown in equation (14). Aggregate consumption is a CES function of non-transportation consumption and transportation in the top tier. Non-transportation consumption is then an aggregateofenergy and a non-energy bundle. 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_OTHR) and operating costs (T_SERV, which includes vehicle maintenance, insurance, etc.). In this representation, transportation consumpton is further described by two additional 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.

(14) $Aggregate\_Cons \quad = CES(\ Consumption, Transport, \overline{s_9})$

$$Consumption = CES(\ Energy, Non - Energy, \overline{s_{10}})$$

$$Energy = CES(\ Oil, Gas, Coal, Electricity,\ \overline{s_{11}})$$

$$Transport = CES(\ Purchased, OWNTRN,\ \overline{s_{15}})$$

$$OWNTRN = CES(\ T\_ROIL,\ CES(\ T_{SERV}, T_{OTHER}, \overline{s_{17}}),\ \overline{s_{16}})$$

Cars sales (T_OTHER) are calibrated based on the GTAP motor vehicle sector (mvh), which is a part of anon-energy intensive manufacturing sector in EPPA. The shares of expenditures on own-transportation and vehicle fuels are calibrated using various national surveys. Vehicle operating costs is 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., (2005, tables 4 and 5) are: s9=0.5 between aggregate consumption and transport; s11=0.4 between the consumption of various energy goods; s16 = [0.3;0.7] between liquid fuels and other inputs; s17 = 0.5 between services and car sales for own-transport.

In the AIM model, household energy demand can be represented in two ways. In the first way, a generic LES differentiates the use of private cars from other sources of energy consumption, with fuels nested in a logit. 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 $b_{j,l}$:

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

Each technology is associated an energy content per unit of services it provides.

The Imaclim-R model (Waisman et al., 2013) also uses a LES function where one of the C_i consumption items is mobility services $S_{mobility}$, as shown in eq. 16 (*bn* denotes basic needs). Mobility services are a CES function of four modes – air transport, terrestrial public transport, private transportation by cars and non-motorized transports.

(16) $$U_c = \prod_i (C_i - bn_i)^{\varepsilon_i}\ (S_{mobility} - bn_{mobility})^{\varepsilon_{mobility}}$$

$$S_{mobility} = CES\big(pkm_{air}, pkm_{public}, pkm_{cars}, pkm_{non-mothorized}\big)$$

Besides the regular budget constraint for consumption expenditures, there is a time travel constraint which sets a ceiling on average daily travel time as found by empirical studies (Zahavi and Talvitie, 1980). Each transportation mode is then associated with a travel time efficiency parameter which drives the tradeoff 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. Congestion effects can then be represented, as well as transportation infrastructure policy that drives the congestion.

In the GEM-E3 model, private energy consumption for transportation and buildings is linked to a stock of durable goods (Capros et al. 2013). Private consumption is expressed in a LES form (see eq. 17), with a distinction between the consumption *HCFV* of nondurables (set nd), and a stock of durables *SHINV* (set dg). In equation 17, *chcfv* denotes the subsistence level.

(17) $$U_c = \prod_{nd} (HCFV_i - chcfv_i)^{\sigma_i}\ \ \prod_{dg} (SHINV_i - chcfv_i)^{\sigma_i}$$

$$dispcons_{nd,dg} = \alpha_{nd,dg}\ \left(\frac{PCI}{PHCFVDG_{nd,dg}}\right)^{\varepsilon_{nd,dg}}$$

The stocks of durables for transportation and heating are linked with non-durable goods to operate the stocks (mainly fuels and services for maintenance) in order to derive a service that benefits the agent. The variable *dispcons* represents the usage of the stock and is determined by the cost of operating the stock (PHCFVDG is an index of fuel, maintenance and other costs) relative to the consumer price index PCI in a relationship represented by two parameters ($\alpha_{nd,dg}$ and $\eta_{nd,dg}$). 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 durable good itself as well as the (expected) user costs.

Nesting durable goods with the energy requirement makes the substitution between capital and specific energy type explicit compared to a formulation that treats all energy types symmetrically. The representation of energy efficiency of durable goods, through specific rules or dedicated bottom-up models, allow for a decoupling of the services provided from the energy content. In the EPPA model, an increase of cars sales (T_OTHER) can substitute for energy for a given transport services level, i.e., an investment in more energy efficient vehicles. In the GEM-E3 model, households can invest in energy saving technologies to decrease the *dispcons* ratio linking durables to fuel consumption.

Whether or not energy consumption is represented through the services it provides, the parameters of the demand system can be adjusted through time in order to improve projections. For example, Schafer and Jacoby (2003) calibrated the elasticities of the EPPA model based on a detailed transport model representing vehicles as stocks. In the AIM model, 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. Similarly, in the Imaclim-R model, different choice of the income elasticities of the total stock of vehicles will influence the travel time efficiency of road transport.

3. Projection of consumption demand

We reviewed the commonly used consumption functions in section 2, all of which have terms for price and income effects, with some functions having terms for demographic and household composition effects. We now discuss how the parameters of these functions are set and possibly modified over time in the base path by various modelling groups.

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, it provides consistent effects for small and large shocks to income. The base case path of rapidly rising incomes over decades affects consumption demand along the same function as the small income changes 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 very much higher incomes. There are serious barriers to using complex 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.

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 alternative methods to adjust simpler consumption functions to create a dynamic baseline. This involves changing parameters of the consumption function and implies that expenditure shares (the α's in section 2.2) are calibrated independently of the sample period data that is used to determine the initial demand system. The share parameters in utility functions are adjusted by some modelers such that the consumption behaviour reflects what is judged to be reasonable expenditure shares for the level of income. In practical terms, this can be achieved by either iterating share parameters and preliminary income levels from a baseline or when calibrating to an exogenous GDP projection (e.g. iPETS, Ren et al, 2018 and GEM-E3, Rey Los Santos et al., 2018).

In the iPETS model (O'Neill et al., 2012), household surveys for representative countries are used to derive relationships between consumption and demographic characteristics (e.g. urbanization, household size) for the model regions. As we noted in Section 2.1, per capita income influences household consumption patterns. The share parameters α in the CES functions of iPETS (equation 1) are adjusted exogenously according to income projections. This is done by iterating on the baseline path; for a given guess path of per capita income, preference parameters are adjusted for each period and the model is solved, giving a different path of income. This approach captures income differences between periods. As the underlying within-period utility function is 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. It is less than ideal if the shocks result in big changes in income[8], but the procedure captures the income effects along the baseline path.

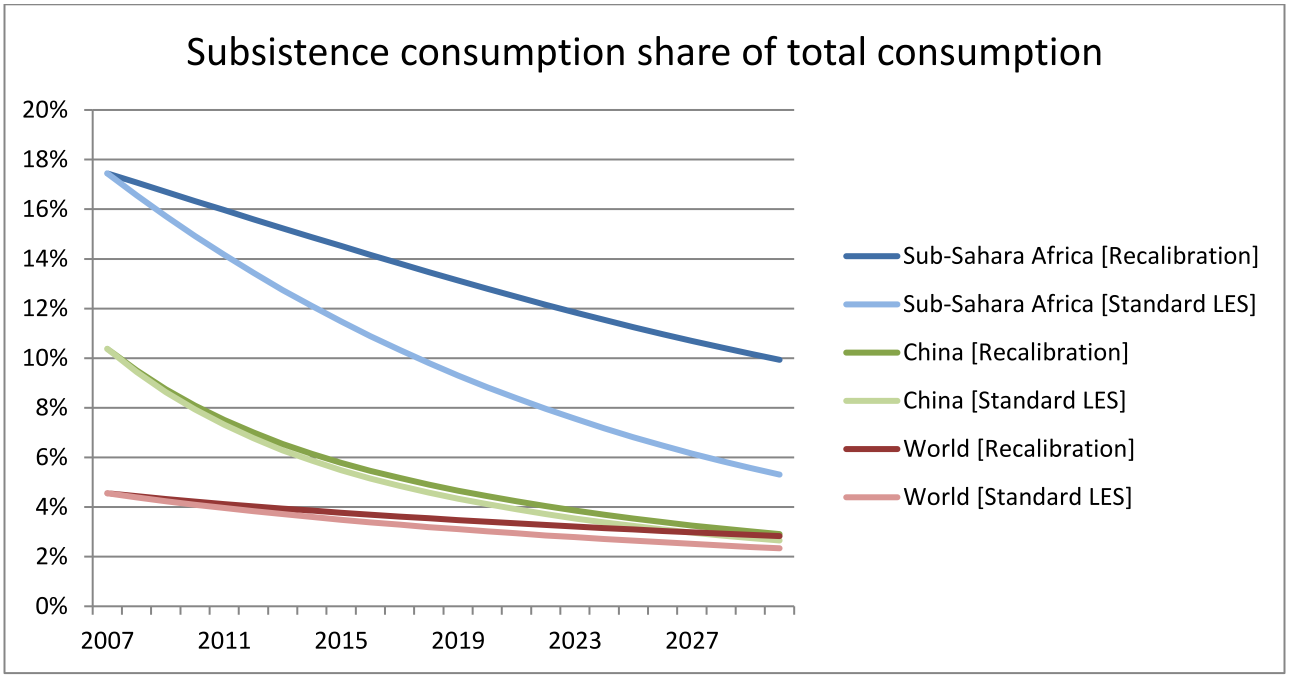
Chen et al. (2015) implement a recalibration of subsistence consumption shares in the LES demand of EPPA6-L[9]. After each time step in the recursive-dynamic model, the subsistence shares are recalculated so that the regional income elasticities match the observed values and not converge to 1 (see eq. 6). As the authors note, this procedure means that equivalent variation calculations can only be made within-period (present value calculations are not made).

Similarly, in the dynamic recursive DART model, the subsistence minima of the LES are recalibrated after each time step with population growth. This method can lead to smaller or larger subsistence minima compared to the base year, for example, if some region's population is growing very fast as in the case of Sub-Saharan Africa. Then a significant change over the simulation period is needed, but generally the changes required are small. This is illustrated in Figure 4 (taken from Schuenemann and Delzeit, 2019) which compares the impact of this recalibration of the LES in the DART model for a period of 23 years and three selected regions. The lines show the decreasing subsistence minima shares in total consumption as incomes rise. While the differences are quite large for Sub-Sahara Africa and the recalibration prevents a fast convergence to homothetic preferences, in regions with fast income growth like China, and regions with low subsistence shares to begin with (such as the global average), the impact of the recalibration is relatively small.

[8]In principle, an adjustment of preference parameters can also be made in the counterfactual scenarios if the modelers 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.

[9] The regular version of EPPA (Paltsev et al. 2005) uses CES as listed in Table 6.

Figure 4: Impact of subsistence minima recalibration in the DART model, 2007 - 2030



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, an econometric model that resembles the flexible Exact Affine Stone Index (EASI) is estimated, providing income dependent income elasticities (in contrast to Chen et al. 2015, where constant income elasticities are used for the recalibration). The Engel curves 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 is achieved as in O'Neill et al. (2012). Caron et al. conclude that using homothetic preferences significantly overestimates energy demand and emissions in the baseline. This then has consequences for the economic impacts from emission reduction policies.

While the above adjustments 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. 7) are adjusted based on the growth of GDP per capita. To do this, the estimated expansion parameters provided in the GTAP database are first regressed on GDP per capita using a spline regression to account for non-linearities. The expansion parameters are then adjusted in the baseline such that they converge to their fitted values when the endogenous GDP is applied to the regression. 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).

We 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 a richer set of income elasticities. The MAIDADS has a flexible function for income effects that can capture saturation effects but has 3n parameters to be calibrated.

There seem to be no commonly accepted guidelines on how to generate expenditure shares that can be used for such exogenous adjustments of consumption parameters to capture income effects. Generally, an econometric estimation across countries is carried out to determine expenditure shares, assuming that poorer countries will follow consumption patterns in developed countries. More sophisticated methods could take into account deviations between observed and expected expenditure shares at current income levels and maintain all, or some, of the deviations when projecting income shares with rising income; these differences might reflect cultural differences that might persist with changes in incomes.

4. Investment models

The investment component of final demand (the I in C+I+G+X-M) is very high during periods of rapid growth such as the growth spurts of the East Asian tigers. Currently, the investment share of GDP in China exceeds 40%, and exceeds 30% in Indonesia and India. It is thus important to model the structure of investment commodity demand well in addition to carefully representing consumption. Unfortunately, while there is a huge literature on modelling total investment and savings, the literature on commodity structure is scarce and we will only review the methods used in current CGE models. This topic is, unfortunately, considered minor in the CGE literature and the documentation of many models reviewed do not even bother to describe how this total investment in allocated.

We first note that different models define Consumption and Investment differently. In the National Accounts there are often three components for Consumption – nondurables, durables and services. Most models label that total as consumption, however, some (e.g. IGEM) classifies consumer durables as Investment. Some countries do not clearly delineate private versus public investment and comparisons across countries or models should be made with care, especially when using parameters from one country for another. Other differences include the speed of adopting the U.N. System of National Accounts treatment of R&D and artistic creations as investment instead of expensing as intermediate purchases.

Total investment is the sum of fixed and inventory investment, but we ignore inventory modelling here since its transitory nature makes it unimportant for long range modelling. Figure 5 gives the composition of investment in the U.S. for 1960-2017; intellectual property (including software) investment rose from 5 to 25%, while information processing equipment (e.g. computers) rose steadily to 15% until the dot-com bust and then fell to 10% in 2017. Figure 6 gives the shares for Germany for 1995-2014, where there is a similar rise in intellectual property investment (11% to 17%), and a similar fall in IT equipment after 2000 (7.1% to 3.5%)[10]. Data for other countries compiled for the EUKLEMS show similar big changes in the composition of investment that cannot be wholly explained by price changes; in fact, for much of this period IT prices were falling, and IT investment shares were rising. There is a large literature of factor-biased technical change during the post-1995 period mostly focusing on a switch to skill-intensive technologies, but there is also a switch towards using IT-capital as shown in Figures 5 and 6 and described in Jorgenson et al. 2013 (Appendix B).

[10] The US data is taken from the National Income and Product Accounts Table 5.3.5 available at https://apps.bea.gov/iTable/index_UD.cfm. The German data is from the EUKLEMS database, at http://www.euklems.net/index_TCB_201701.shtml

Figure 5 Composition of Investment in the U.S., 1960-2017.

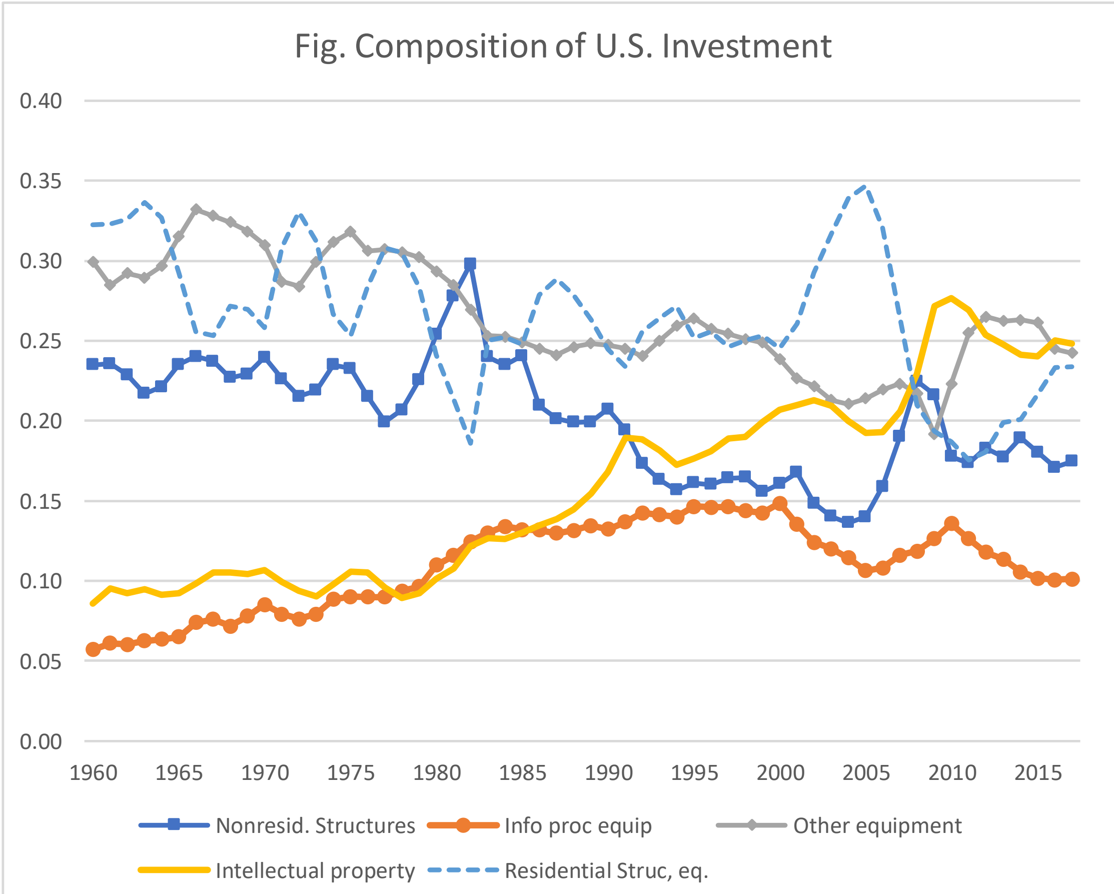
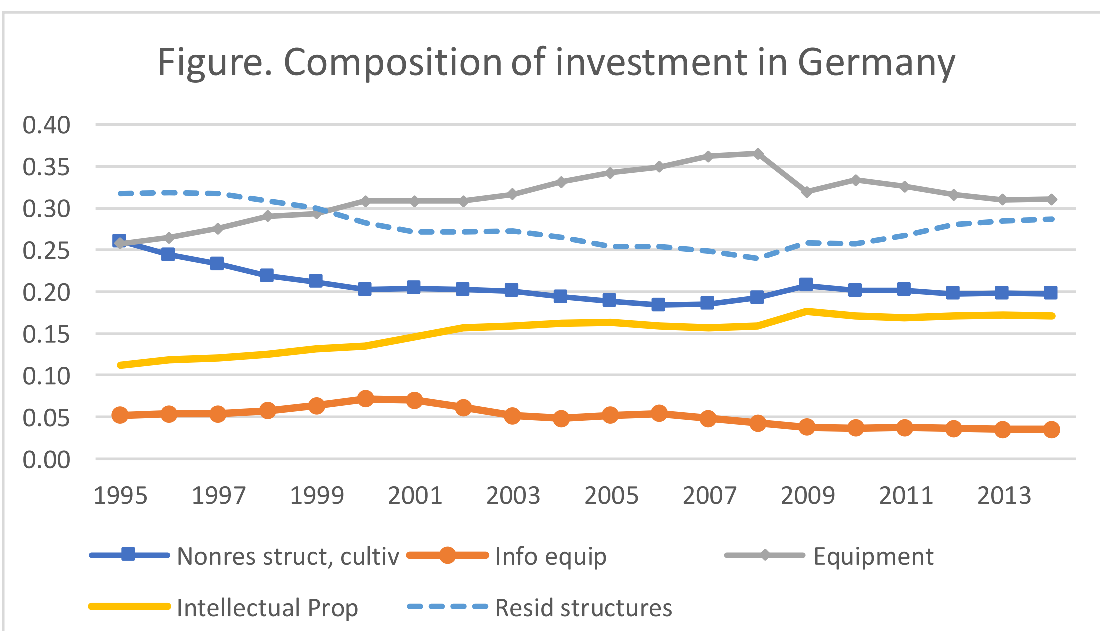


Figure 6. Composition of Investment in Germany, 1995-2014.



There is a large literature on the determinants of aggregate investment, especially in macroeconomics, and we do not focus on that here. In many myopic CGE models private savings is determined as a share of total income and investment would then include public and rest-of-the-world savings. Other simple approaches include exogenous investment and ad-hoc models that specify utility as a function of total current consumption and savings (e.g. EPPA):

$$U_t = U(C_t, S_t) \tag{18}$$

Intertemporal equilibrium models that are used in this area invariably take an Euler equation approach derived from utility functions that are assumed separable over time such as:

$$U = \sum_t^{\infty} \frac{F_t^{\gamma}}{(1+\rho)^t} \tag{19}$$

where full consumption, F_t, is an aggregate of goods, and possibly leisure, $F_t = F(C_t, L_t)$

We do not discuss any of the aspects related to the modelling of this stage of the utility function – how poorly the Euler equation performs, how to interpret the risk aversion parameter, how to implement the discounting, how the separability assumptions are violated, etc[11]. We merely note that explaining total savings and investment is a major unsolved challenge in macroeconomics and model builders must face the trade-off between model (and solution) complexity and being able to explain savings endogenously. In the remainder of this section we discuss the allocation of total investment to individual commodities.

We may divide investment allocation models into two broad categories, one that considers only the economy stock of capital and aggregate investment, and one that considers investment by each industry where there is an industry-specific price of the capital stock due to adjustment costs. The models with industry-specific investment includes foresighted models such as G-cubed, and myopic models such as GEM-E3 and Monash. The first approach derives the investment vector for aggregate investment, one can think of this as the Investment column in the Use table. The industry specific investment derives an investment matrix with a column for the capital stock of each industry. However, for our discussion here, the allocation issues for the two approaches are the same and we concentrate on projecting the aggregate Investment vector, $\{I_{it}\}$.

The simplest method is to set I_{it} exogenously, as done in the base version of Lofgren, Harris and Robinson (2002). In other closure settings of that model, this exogenous base investment may be multiplied by a common scale factor so that total investment hits an exogenous savings target. This approach may make sense in a short run model but is not realistic for long term projections as illustrated by the historical trends in Figures 5 and 6.

An easy way to allocate aggregate investment (I^{agg}) is using a Leontief function as in the GTAP model; in the percent change notation of Corong et al. (2017, eq. 42):

$$\widehat{I}_{it} = \widehat{I}_t^{agg} \tag{20}$$

[11] Those interested in empirical work on the Euler equation may start with Canzonieri, Cumby and Diba (2007).

This Leontief approach is also used in MONASH (Dixon and Rimmer 2002, Fig. 21.1) and GEM-E3 (Capros et al. 2013 Figure 9).

Other models use a more flexible approach than the exogenous or Leontief formulations. The ENVISAGE and G-cubed models use a CES function of all the component commodities, i.e. with a price elasticity that is common to all commodities. The demand for investment good *i* is thus a simple function of aggregate investment and its own price, PB_{it}^{I}:

$$I_{it} = \alpha_{it}^{I} \left(\frac{PI}{PB_{it}^{I}} \right)^{\sigma^I} I_t^{agg} \tag{21}$$

The *PB* notation denotes the "buyer's price," while *PI* is the price of the investment bundle (van der Mensburrghe 2008, D-13). This reduces to a simple Cobb-Douglas function when the elasticity parameter, $\sigma^I = 1$. The share parameters, α_{it}^{I}, would be calibrated to base year shares, but modelers have to decide on the projection beyond the base year. ENVISAGE (van der Mensburgghe 2009, p 8), for example, fixes the shares at the base year values.

This CES formulation is popular and used in Phoenix (Wing et al. 2011), ADAGE (Ross 2008), EPPA, MIRAGE and TEA. The documentations of these models do not discuss if these share parameters are projected on a path different from base year values. Some models use a nested structure for determining the commodity allocation instead of the flat and symmetrical structure of the Leontief and CES examples above. G-cubed (McKibbin and Wilcoxen, 1999) uses CES functions with a top tier of capital, labor, energy and non-energy bundles. IGEM has a 5-layer nest of translog functions to allocate aggregate investment to 36 commodities.[12]

Of the models reviewed here, all except IGEM seem to fix the share parameters for the projection period. This is understandable given that there is no parallel literature to that estimating income elasticities for consumption – there is little discussion and no consensus about the form of an investment allocation function. To give an idea of a possible approach that uses historical trends to project investment, we summarize the state-space function used in IGEM. At the top node, total fixed investment is an aggregate of long-lived and short-lived assets. The short-lived bundle is made up of Equipment-IT and Transportation-Trade-Services; the Equipment-IT bundle is allocated to Machinery, Information Technology and Transportation equipment, $I^{EIT} = I^{EIT}(I^{MACH}, I^{IT}, I^{TRNSP})$; and so on. At each node *m*, a translog price dual function is specified in Kalman filter form:

$$\ln PII_t^m = \alpha^{Im} \ln P_t^{Im} + \tfrac{1}{2} \ln P_t^{Im}{}' B^{Im} \ln P_t^{Im} + \ln P_t^{Im}{}' f_t^{Im} \tag{22}$$

For example, for *m=short-lived assets*, $PII^{m=short}$ denotes the price of the short-lived asset bundle, $P_t^{I,short} = (PII_t^{Equip-IT}, PII_t^{T-T-Services})'$ is the vector of input prices, and $f_t^{I,short}$ is latent vector representing the change in technology (or investor preferences). These price functions are estimated over historical data and in the econometric model the unobserved factor is assumed to follow a first-order VAR:

$$f_t^{Im} = F^{Im} f_{t-1}^{Im} + v_t^{Im}$$

[12] Jorgenson el al. (2013 p 403) describes an earlier version of IGEM based on the SIC. The current version is based on the NAICS and is described in Jorgenson et al. (2017, section A3).

The share demand equation derived from the price function (22) is then a linear function of (log) prices and the latent variable:

$$SI^{m=short} = \begin{bmatrix} PII_t^{Machinery} I^f_{Machinery,t} / PII^{short} I^{short} \\ \dots \\ PII_t^{Services} I^f_{Services,t} / PII^{short} I^{short} \end{bmatrix} = \alpha^{Im} + B^{Im} \ln P^{Im} + f_t^{Im} t \qquad (23)$$

In the projection period beyond the base year the forecasted series for the latent variable is used. The estimated series of the latent variables for the components of the Information Technology (IT) node are represented in Figure 7, together with the projected values out to 2030. The components are IT-equipment, Publishing & Telecom, and Software & IT-services, and the shares must add to 1. We plot the actual shares in the sample period and the fitted values for two of the 3 components. The fitted values consist of the price and latent terms and together fit the data quite well. In the projection period we plot the matched trend of the latent component of the share function. In the model, the shares are given by (23) with the endogenous price component in addition to this exogenous trend.

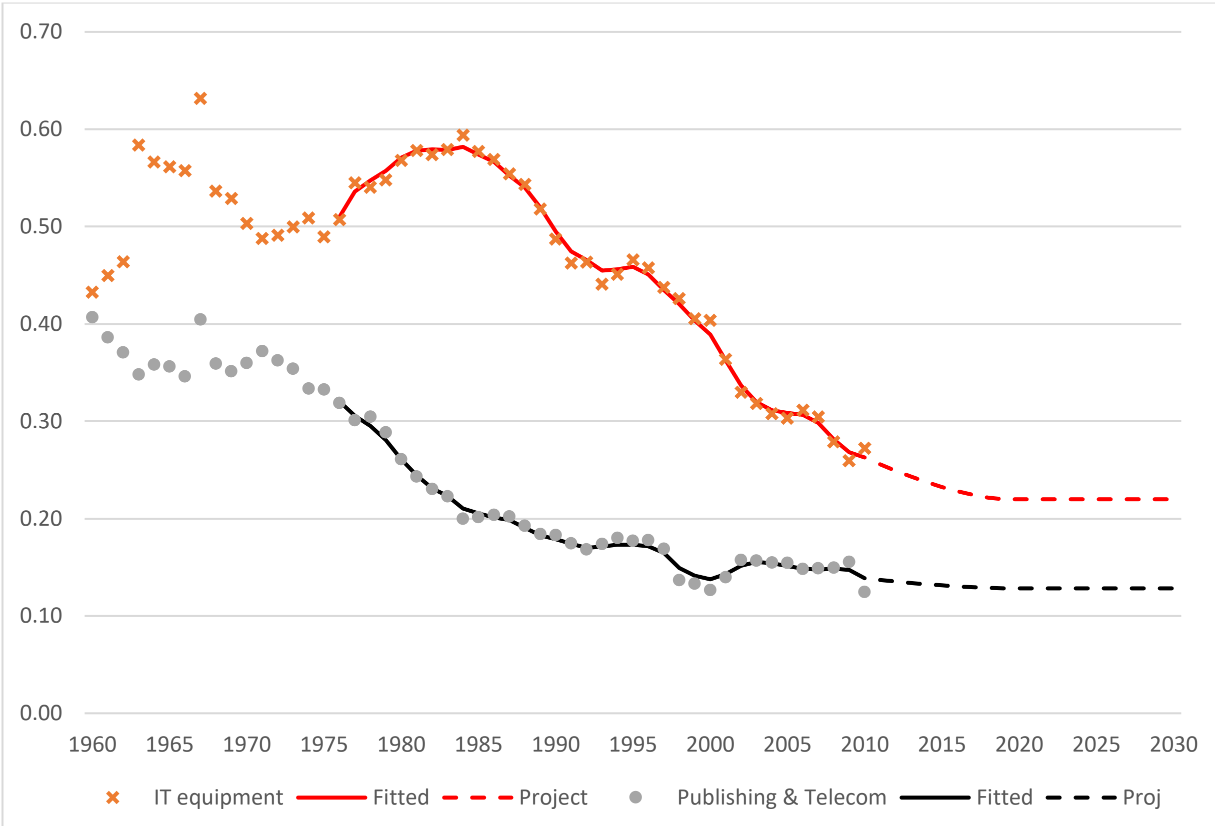
In this example we see a trend for falling share allocated to IT-equipment and a rising share to Software & IT-services. This is due to both changes in relative prices and changes in technology. The econometric model projects a continuing fall in the IT-equipment share due to changes in technology and that is included in the base case projection in IGEM.

The above is just one way of including changes in technology that modelers believe will likely happen. As with consumption modelling, one may prefer a simpler ad-hoc adjustment; in the case of eq. (23) we can exogenously change the α^{Im} parameter instead of having the f_t^{Im} term. Changes in the share parameters could be based on historical trends or expert judgements. There are, unfortunately, only limited historical data on investment by commodity for many countries. They may not be in the National Accounts, and modelers have to resort to input-output tables from different years which may not be compiled in a consistent fashion. The data source for Europe used in Figure 6 above for Germany may be the most convenient source of information on investment by commodity. Another source is the World Input-Output Database[13].

[13] This WIOD data is prepared by the University of Groningen and partners and is available at www.wiod.org, see Timmer et al. (2015).

Figure 7. Actual and fitted shares of US investment demand; projected latent term.

Node: IT = f(IT equipment, Publishing & Telecom, Software & IT-Services)



5. Government demand

Aggregate government final demand is specified in various ways in CGE models, but often is not modelled as elaborately as private consumption. Some models do not identify an explicit government sector and combines it with personal consumption expenditures (e.g. PACE, AIM). A simple approach is to allocate a constant share of GDP to government purchases (USITC, GLOBE, ICES). Some models use a Cobb-Douglas function that allocates fixed expenditure shares to private consumption and government consumption (e.g. Wegener Center, Bednar-Friedl et al., 2012). One may emphasize budget constraints (e.g. IGEM) and specify government purchases (G) as a residual in the budget equation with endogenous revenues and exogenous deficits, transfers and interest payments:

$$Deficit = TaxRevenue - G - transfers - interest \quad (24)$$

Before we describe the data and modelling approaches for government purchases let us first note the differences in public institutions and accounting conventions in different countries. In Section 2 we noted how some countries have a large private Education industry and a corresponding large demand for Education in the Consumption column of the input-output accounts. Other countries may have Government as the dominant source of final demand for

Education. Some IO accounts have two distinct industries for private and public education (e.g. the US), while others have one unified column in the Use matrix.

A similar situation holds for Health Services; some countries have a large private health industry while others are dominated by state hospitals. Thus, even if two countries devote a similar share of GDP to the Health sector, the share of Consumption allocated to Health may be very different. In the U.S. accounts we note that even if the hospital bills are paid by the government (through the Medicare program) the expenditure is recorded in the Consumption column, and the payments are recorded as transfers from government to the household. Countries with direct government provision of hospitals would record Health expenditures in the Government column. The level and composition of Government final demand is thus different among countries even if the underlying supply share of GDP is similar.

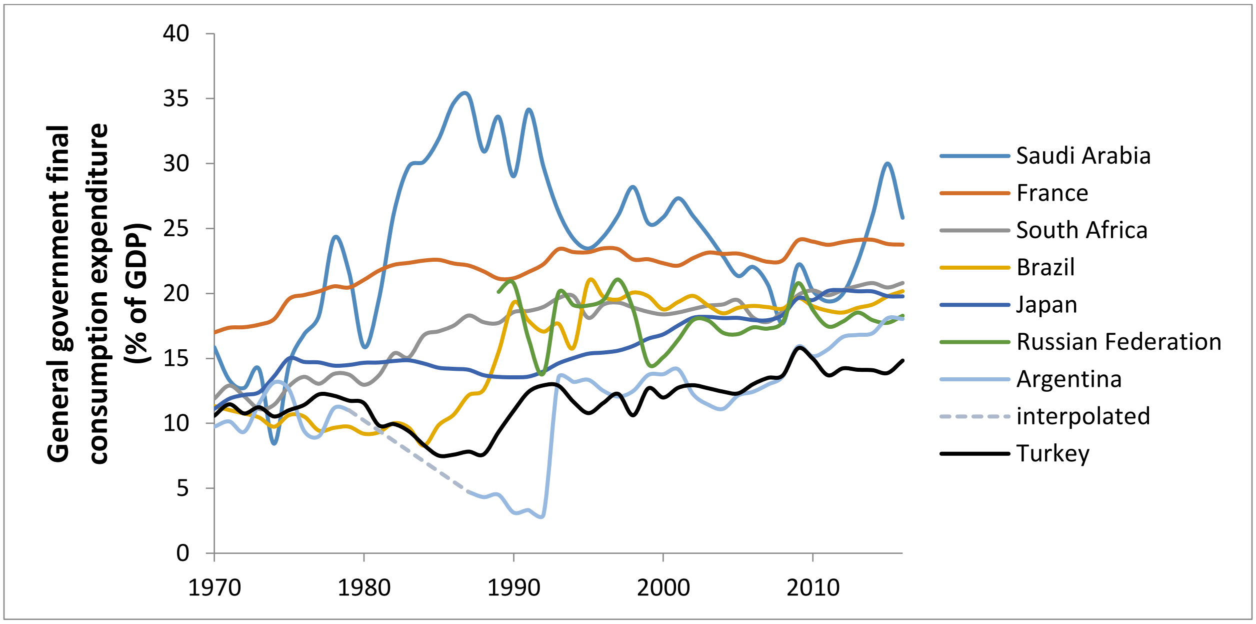
Other accounting differences come from different speeds of adopting the latest U.N. System of National Accounts (SNA). Many countries now include the depreciation of public capital in GDP and government demand, but others have not; some have included public R&D as (public) investment while other keep the old treatment of R&D expenses as intermediate purchases. One should keep all these differences in mind when reading this section.

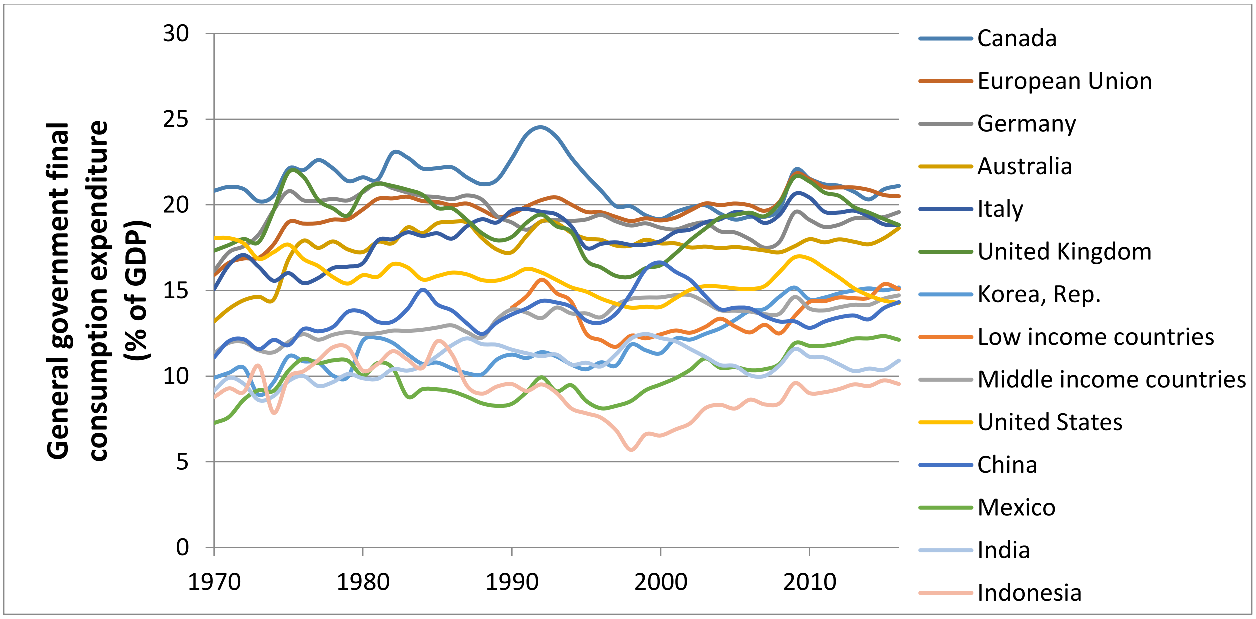
Figure 8 plots the share of government consumption in GDP over the past decades for G20 members. The top chart shows countries with an annual change exceeding 3 percentage points or a range of decadal average change exceeding 5 percentage points, i.e. countries where the government contribution fluctuates or have pronounced changes. The bottom chart shows countries and country groups without such changes. Most of the countries in the bottom graph have higher per capita incomes, and we add the low- and middle-income aggregates for comparison.

We draw two conclusions from this figure. First, there is considerable variation between countries for aggregate government consumption, ranging from less than 10% to more than 20% of GDP. Differences in government consumption levels are either driven by structural differences that are unlikely to change substantially over time (Shelton 2007), or driven by different accounting principles. Secondly, there appears to be no relationship between income and the share of government consumption. While India and Indonesia are the poorest G20 members and also characterized with the lowest government consumption share in GDP, this does not hold on a broader level. Figure 8 also plots data for the low and middle-income country aggregates. For recent years, both groups have shares similar to those of the United States.

Second, for most countries, there is surprisingly little variation over time and many countries more or less maintained the expenditure shares and clear trends can be observed for most countries (bottom part of the figure). Countries with larger fluctuations between years (top part of the figure) are mainly countries exposed to international resource prices (Saudi Arabia, Russia). Countries that had bigger changes between decadal average values are those with big changes in the political environment (e.g. Brazil between 1985 and 1990, Argentina in the early 1990s). An assumption of a constant government purchases to GDP ratio may be reasonable for long-run modelling if an endogenous response to policy changes is not required.

Figure 8. Share of government final consumption as share of GDP (Source: World Bank national accounts data, https://data.worldbank.org/indicator/NE.CON.GOVT.ZS). The top chart shows countries with an annual change exceeding 3 percentage points or a range of decadal averages exceeding 5 percentage points. The bottom chart shows countries and country groups without such changes.





The commodity composition of aggregate government purchases is given in different ways in different Input-Output conventions. Some IO tables have a government column in the final demand sector symmetrically with Consumption, other IO tables have a Government Industry that is symmetrical with other industries and a simple Government final demand column that purchase from that Government Industry. The latest US IO system is a mixture of the two with both Government Industries and a final demand column. A model which treats the Government industry symmetrically with Services would be explaining the commodity composition with its chosen production function. A model that has an explicit government final demand column would have to specify the allocation; in the GDyn, ICES, and IGEM models this is done with a Cobb-Douglas function. In other models the allocation is with a Leontief system (GEM-E3, Globe, AIM, USITC) or a CES (Envisage, EPPA, TEA).

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). Globally, purchases from this sector account for 94% of all government purchases in the GTAP 9 data for 2011. That is, the main mechanism for allocating public purchases in GTAP models is the production function for this large sector; the specification of the final demand function for government is less important since it is dominated by just one sector.

There is little description of the projection of government commodity allocation, only EPPA contains a mention of incorporating an expected rise in the shares for health and education.

6. Observations and Recommendations

We have discussed the complexities of modelling final demand over a long horizon, especially for rapidly developing economies; the description of the rich set of modelling approaches show a vigorous attempt by many authors to deal with the challenges of implementing a tractable system that is consistent with observed consumption behaviour. We summarize here some of the lessons we have learnt.

If simpler demand systems with few parameters such as homothetic functions are used for long-term projections with considerable increases in per capita incomes, then modelers should consider exogenous adjustments of the parameters over time that will re-calibrate demand and expenditure shares to values that are projected by specialized studies or expert consensus. A fixed set of share parameters, in the CES, for example, could result in large differences with the expert projections within the simulation horizon. There are studies that relate consumption patterns to a cross section of countries at a point in time, and studies over a long period for particular economies that provide useful guideposts for projecting future demands of developing countries. We noted how, Caron et al. (2017), Chen et al. (2015), O'Neill et al. (2012), Schuenemann and Delzeit (2019) provide good examples for making such adjustments.

Such demand systems have fewer data (parameter) requirements and are therefore easier to calibrate. They might be more amenable to calibrating to projections from specialized models[14]. A more complicated demand system with more parameters might be harder to adjust to external requirements. The CDE system can reflect both non-homothetic income and own-and cross-price effects, but nevertheless only allow for limited Engel flexibility as it conserves the base year income elasticities. This might thus also require a recalibration of the system's parameters especially for fast-growing economies.

[14] Delzeit et al. (this issue) discuss linking CGE models to other models; while these are mostly focused on the production side, the lessons would apply to linking the consumption functions too.

Those who wish to experiment with more flexible systems may consult Yu et al. (2000) and Britz and Roson (2018) for the AIDADS approach which allow endogenous changes in income elasticities but do not require cross-price elasticities.

Those who wish to see how cross-price elasticities could affect their results might consider the AIDS approach in Sommers and Kratena (2017) and Savard (2010) or the translog function in Jorgenson et al. (2013). One further advantage of the translog is that an aggregate demand function may be derived by consistently adding over household demands, allowing household characteristics to enter explicitly into the aggregate demand function in a simple fashion. It thus allows a discussion of welfare at the household level, i.e. distinguishing the effects of policies on different household types (by size, age or region for example). These demand systems require a n^2-order number of parameters, and thus allow only a very limited number of consumption bundles in the top tier. For consistent aggregation, they also require that sub-tiers be of the homothetic form. A major obstacle to using these flexible systems for global models is the lack of estimates for many countries; estimating them requires household level data including prices.

We noted how some models use a transition matrix to link the commodities in the consumption function with the commodities specified in the supply side of the model. One reason for doing this is that the number of commodities identified in the supply side is greater than the consumption commodities, for example, allocating total food demand to the different crops (see discussion of ENVISAGE in van der Mensbrugghe 2018). A bridge matrix is used in Jorgenson et al. 2013 (section 2.3.6) to link consumption categories based on household survey data (and National Accounts) in purchaser's price to the categories on the supply side based on input-output accounts in factory gate prices. For example, household expenditure on "Clothing" is allocated to Apparel manufacturing, Trade, Transportation and Personal Services at factory gate prices. The big difference is that the gasoline value to the refiners versus the households is traced through such a bridge matrix.

We believe that testing different functional forms for a given model's choice of commodity classification and policy shocks could be a revealing exercise, showing what is gained and lost by alternative systems. We recognize the high cost of doing so and suggest a collaborative effort. A workshop where those who have implemented less typical systems describe their implementation and software may be a place to start by reducing the learning costs. The comparison of alternative demand systems in Yu et al. (2004), Savard (2010), Bouet et al. (2014) and Britz and Roson (2018) are good examples.

In this context of learning from other modelers, let us note that we found a wide range of user-friendliness in model documentation. There are instances where the documentation does not describe the parameter adjustments very clearly even while the other features of the models are well described. It would help readers to understand simulation results better, and for other modelers to learn, if authors would describe their adjustments in some detail.

Models which specialize in energy issues offer some insights that other modelers might find useful. In modelling the demand for energy services, the representation of substitution possibilities between the stock of equipment and the energy requirement improves the projection of energy consumption through embodied technical change; i.e. an explicit representation of changes in energy efficiency. This is particularly important when assessing energy or climate policies. However, even this more complex form is not sufficient if one wants to represent saturation effects in the demand for energy services (Fouquet, 2014). We noted one method to add additional constraints to the choice set, like a travel time constraint for transport (as in the Imaclim-R model), or constraining heating requirements by to total residential area. We briefly noted the modelling for leisure demand in describing Figure 1 and the concept of full consumption. The other side of leisure demand is labor supply which is a key factor driving economic growth in the baseline. Many of the models listed in Table 6 specify labor supply as an exogenous function of the population, a few models include leisure in the utility function (e.g. ADAGE, EPPA-HE, IGEM). Modelers wishing to include leisure into the consumption function may consider the discussion of labor supply elasticities and demographic change in papers using more aggregated growth models such as the one used by the U.S. Congressional Budget Office (Montes 2018) and the survey by Boeters and Savard (2013). The more sophisticated models would distinguish between the extensive margin (retirement and participation decisions) and the intensive margin (how many hours to work), and recognize that different demographic groups have different elasticities. Some approaches to labor force participation modelling are given in the references in Jorgenson et al. (2019).

There is a much smaller literature examining the modelling of the composition of investment and government final demand and there are few firm conclusions we can draw. The composition of investment has changed (beyond the changes that can be explained by sensible price effects) and since we do not think it is reasonable to attribute it to an income effect, we are left with exogenous technology models or other ad-hoc methods. These methods express the commodity share as some simple function of time or calibrate to an exogenous path.

For government purchases, models using the GTAP industry classification may use a simple treatment (e.g. constant share of GDP) since it is dominated by just one commodity. The projection of the Public Administration sector is still an issue to be addressed, but within the framework of projecting production function parameters. For models without such a government industry, or those that have a full set of commodities for government final demand, there is no systematic compilation of trends for the countries of the world that one might conveniently use for projections of the baseline. We have noted how total public expenditures could be volatile for many of the low-income countries and so one might conclude that there are no useful trends to consider. There are certainly many official projections of government spending, including those affected by expected demographic transitions (e.g. fewer young people requiring education and more elderly requiring health care). Such projections differ by country and a more collaborative effort would be needed for a comprehensive inventory of estimates.

7. A research agenda for improving consumption modelling

We have noted five distinct challenges to modelling final demand in multi-sector multi-region dynamic models – data; estimates of elasticities at the desired commodity detail; collecting expert baselines or specialized bottom-up model projections; making exogenous adjustments to parameters to these external projections; choosing a level of aggregation or choice of nested structure to balance a rich set of cross-price elasticities with tractability.

Data on consumption, especially household level data, is the foundation for other improvements in consumption modelling; one needs a variety of data to identify income and price elasticities, and identify variation of behaviour across household types. Identifying heterogenous behaviour allow us to project the baseline more accurately by incorporating projections of age distribution, urbanization, and migration. While household surveys are often the responsibility of official statistical agencies, the resources are more limited in the low-income countries and the collection of more consumption data would be useful to many institutions and researchers. The CGE modelling community cannot be the primary organization for the expensive task of collecting primary data but it would be good to begin to have an inventory of the data that is available for different countries, to share information on what is available. For example, there are specialized surveys of energy use that are not widely known.

The second task is the estimation of consumption functions for more commodities, more regions and household types. We described the work of Seale and Regmi (2006) and Muhammad et al. (2011) using the World Bank's ICP data that are widely used as sources of income and price elasticities. These are major contributions, but as we discussed, they are limited to about 10 consumption bundles. A survey of existing estimates of demand elasticities and demographic effects that catalogues those that are particularly suitable for typical multi-sector CGE models would be a good first step. This would identify the main gaps that are missing.

The development of CGE models have followed the requirements for policy analysis. There is a rich tradition of models for analysing trade, energy consumption, transportation and agriculture and food issues; this is reflected in the models listed in Table 6. We noted the special features of models for food and energy in section 2. There are specialized demand models for other commodities that are not often included in CGE models such as health and tourism. There is a growing literature on consumption of information technology that has not yet been incorporated in any economy-wide model that we know of. These commodities make up large shares of consumption; for example, the composition for the U.S. in 2016 is: health services (excluding medical goods) 16.9%, communications-video equipment-computers (including internet services) 4.9%, financial services and insurance 7.7%. As a comparison, the much-studied food (excluding restaurants) share is 7.1%[15]. Writing a guide to these specialized studies of major consumption categories should be useful for modelers wishing to extend their capacities.

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. Dixon et al. (2013, section 2.5.2.3), for example, describes how the MONASH model incorporates the work of specialist forecasting organizations. A catalogue of such work should be valuable to the CGE modelling community; i.e. a listing of the sources of such specialized projections for different commodities and regions.

We noted that the calibration of parameters in the consumption function to incorporate external projections of population and income effects are described for the CDE system in Woltjer et al. (2014) for MAGNET, for the LES in Schuenemann and Delzeit (2019) and for the CES in Chen et al. (2015). It would be extremely helpful if other model documentations also include such descriptions of these adjustments to model parameters. The discussion of the difficulty in calibrating both price and income elasticities simultaneously highlight an area that deserves more attention.

[15] U.S. National Income and Product Accounts Table 2.5.5. https://apps.bea.gov/iTable/index_nipa.cfm.

There is no systematic comparison between a demand system that makes use of the parameter adjustment path and a model with a rank-3 demand system. This would show how much of non-linear Engel curves are captured by a demand system of lower rank that is extended by parameter adjustments to mimic a rank-3 demand system (both for baseline building and policy scenario runs). Such comparisons would be very helpful for modelers to choose demand systems that are most suitable for their particular needs.

Concluding remark

The empirical consumption function literature is huge as is the variety of multi-sector global CGE models and one cannot discuss all the possibilities here. We have endeavored to summarize the key elements of selecting, specifying and implementing final demand functions that gives insightful endogenous responses to policy shocks. We noted how models need to use tractable functions that may not be able to give the full range of endogenous responses to income shocks or to population and income growth in the baseline path. We discussed how the parameters of consumption functions may be adjusted to incorporate external information about the evolution of commodity demands in the baseline if the model is not able to do so endogenously.

While there is an enormous amount work on consumption modelling in CGE models to date, as reflected in our references, there are still significant gaps in data and parameter estimates. We have cited a few papers that compare the performance of different consumption models, but there is a need for more comparisons to show more comprehensively what the trade-offs are. We suggested some avenues for future research, especially collaborative work that is a hallmark of the CGE community.

References

Aguiar, Angel, Badri Narayanan, & Robert McDougall.2016. "An Overview of the GTAP 9 Data Base." *Journal of Global Economic Analysis* 1(1), 181-208.

Annabi, Nabil, John Cockburn and Bernard Decaluwe. 2006. Functional Forms and Parametrization of CGE Models, Partnership for Economic Policy (PEP) Working Paper 2006-04, www.pep-net.org.

Barnett, William. 2008. Rotterdam model versus almost ideal demand system: will the best specification please stand up? *Journal of Applied Econometrics*. 23 (6), 795-824.

Bednar-Friedl, B., Schinko, T., & Steininger, K. W. (2012). The relevance of process emissions for carbon leakage: A comparison of unilateral climate policy options with and without border carbon adjustment. *Energy Economics*, 34, S168-S180.

Bekkers et al (this issue).

Bennett, M.K., 1941. Wheat in national diets. *Wheat Studies.* 18(2), 37–76.

Blundell, R., Stoker, T. M. 2005 Heterogeneity and aggregation. *Journal of Econonmic Literature* 43, 347–391.

Blundell, Richard. 1988. Consumer Behavior: Theory and Empirical Evidence – A Survey, *The Economic Journal*, 98(389), 16-65, March.

Bouët, Antoine, Fabienne Femenia and David Laborde. 2014. On the role of demand systems in CGE simulations of trade reforms. International Food Policy Research Institute (IFPRI) Paper, presented in GTAP Conference, Dakar, GTAP Resource 4460.

Boeters Stefan and Luc Savard. 2013. Labor Market Modeling in a CGE context, in Dixon and Jorgenson (eds.) *Handbook of Computable General Equilibrium Modeling*, Volume 1B, North Holland.

Britz, W., Roson, R., 2018.G-RDEM: A GTAP-based recursive dynamic CGE model for long-term baseline generation and analysis. Bocconi Working Paper N. 105.

Bye, B., T. Fæhn, O. Rosnes, (2015): Residential energy efficiency and European carbon policies: A CGE-analysis with bottom-up information on energy efficiency technologies, Discussion Papers No. 817, Statistics Norway.

Canzoneri, Matthew, Robert Cumby and BehzahDiba. 2007. Euler equations and money market interest rate: A challenge for monetary policy models, *Journal of Monetary Economics*, 54(7), 1863-1881, October.

Cao, Jing, Mun Ho and Huifang Liang. 2016. Household Energy Demand in Urban China: Accounting for Regional Prices and Rapid Income Change" *Energy Journal* 37, SI1:87-110.

Capros, P., Van Regemorter, Paroussos, P., D., Karkatsoulis, P., Fragkiadakis, C., Tsani, S., Charalampidis, I., Revesz, T., Perry, M., Abrell, J., Ciscar, J.C., Pycroft, J., Saveyn, B. 2013. GEM-E3 Model Documentation. JRC Technical Report. https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/gem-e3-model-documentation

Caron, J., V.J. Karplus and G.A. Schwarz (2017): Modeling the Income Dependence of Household Energy Consumption and its Implications for Climate Policy in China. Joint Program Report Series Report 314, July, 40 p. (http://globalchange.mit.edu/publication/16737)

Chai, Andreas, and Alessio Moneta. "Retrospectives: Engel curves." *Journal of Economic Perspectives* 24, no. 1 (2010): 225-40.

Chai, A.; Moneta, A., 2010b.The evolution of Engel curves and its implications for structural change.Griffith Business School Discussion Papers Economics.No. 2010-09.

Chaudri, R.,Timmer, C., 1986. The Impacts of Changing Affluence on Diets and Demand Patterns for Agricultural Commodities.(English). Staff working paper No. SWP 785. Washington, D.C.:The World Bank.

Chen, Y.-H. Henry. 2017. The Calibration and Performance of a Non-homothetic CDE Demand System for CGE Models. *Journal of Global Economic Analysis*, 2(1), p. 166-214

Chen, Y. H., Paltsev, S., Reilly, J. M., Morris, J. F., &Babiker, M. H. (2015). The MIT EPPA6 model: Economic growth, energy use, and food consumption. MIT Joint Program on the Science and Policy of Global Change Report No 278.

Chiappori, Pierre-Andre and Maurizio Mazzacco. 2017. Static and Intertemporal Household Decision, *Journal of Economic Literature*, 55(3), 985-1045.

Cirera, X., Masset, E., 2010. Income distribution trends and future food demand Phil. Trans. R. Soc. B, 365, 2821-2834; DOI: 10.1098/rstb.2010.0164.

Corong, E., Hertel, T., McDougall, R., Tsigas, M., & van der Mensbrugghe, D. (2017). The Standard GTAP Model, Version 7. Journal of Global Economic Analysis, 2(1), 1-119.

Deaton, A., Muellbauer, J., 1980. *Economics and Consumer Behavior*. Cambridge University Press, Cambridge.

Dixon, Peter, Robert Koopman and Maureen Rimmer. 2013. The MONASH style of Computable General Equilibrium Modeling: A Framework for Practical Policy Analysis, in P Dixon and D. Jorgenson (editors) *Handbook of Computable General Equilibrium Modeling*, North-Holland.

Dellink, R., 2005. Modelling the Costs of Environmental Policy - A Dynamic Applied General Equilibrium Assessment. Edward Elgar, Cheltenham, Northampton, MA.

Faehn et al (this issue).

Fisher, Douglas, Adrian Fleissig and Apostolos Serletis, 2001.An Empirical Comparison of Flexible Demand System Functional Forms, *Journal of Applied Econometrics*, 16(1):59-80.

Fouquet, Roger; Long-Run Demand for Energy Services: Income and Price Elasticities over Two Hundred Years, *Review of Environmental Economics and Policy*, Volume 8, Issue 2, 1 July 2014, Pages 186–207, https://doi.org/10.1093/reep/reu002

Fujimori, Shinichiro, Toshihiko Masui and Yuzuru Matsuoka, 2014. Development of a global computable general equilibrium model coupled with detailed energy end-use technology, Applied Energy, Volume 128, Pages 296-306,https://doi.org/10.1016/j.apenergy.2014.04.074.

Gorman, William. (1981) Some Engel curves. In: Deaton A (ed) *Essays in the theory and measurement of consumer behaviour in honour of Sir Richard Stone*. Cambridge University Press, Cambridge, pp 7–30.

Gouel C. and Guimbard H., 2018. Nutrition Transition and the Structure of Global Food Demand. *American Journal of Agricultural Economics*, June 2018.

Greaker, M., O. Rosnes, 2015. Robuste norske klimamålsetninger, Samfunnsøkonome 1, 67-77.

Hanoch, G., 1975. Production and Demand Models with Direct or Indirect Implicit Additivity. *Econometrica* 43 (3), 395-419.

Hawkes, C., Harris, J., Gillespie, S., 2017. Changing diets: Urbanization and the nutrition transition. In: 2017 Global Food Policy Report. Chapter 4. Pp 34-41. Washington, DC: International Food Policy Research Institute (IFPRI).

Hertel, T., and van der Mensbrugghe, D., 2016. Chapter 14: Behavioral Parameters. GTAP 9 Data Base Documentation.The Center for Global Trade Analysis, Purdue University.

Jorgenson, Dale, Richard Goettle, Mun Ho and Peter Wilcoxen. 2013. *Double Dividend: Environmental Taxes and Fiscal Reform in the U.S.*, The MIT Press, Cambridge, MA.

Jorgenson, Dale, Richard Goettle, Mun Ho and Peter Wilcoxen. 2017. “IGEM, a Model of U.S. Growth and the Environment. Version 20. Appendix A”. Manuscript available at: http://www.igem.insightworks.com/docs/189.html

Jorgenson, Dale, Mun Ho and Jon Samuels. 2019. “Education Attainment and the Revival of U.S. Economic Growth,” in Hulten and Ramey (eds.) *Education, Skills and Technical Change*, University of Chicago Press.

Kaus, Wolfhard, 2013. Beyond Engel's law – A cross-country analysis. The Journal of Socio-Economics 47: 118-134.

Lanz, Bruno, and Thomas F. Rutherford. "Gtapingams: Multiregional and small open economy models." Journal of Global Economic Analysis 1, no. 2 (2016): 1-77.

Lahiri, S., M. Babiker and R.S. Eckaus, 2000.The Effects of Changing Consumption Patterns on the Costs of Emission Restrictions. MIT Joint Program on the Science and Policy of Global Change, Report 64, Cambridge, Massachusetts.

Lewbel, A. (1991). The rank of demand systems: theory and nonparametric estimation. Econometrica, 59(3): 711-730.

Lofgren, H., R.L. Harris, S. Robinson (2002). A standard computable general equilibrium (CGE) modelin GAMS. International Food Policy Research Institute, Washington, D.C.

McKibbin, Warwick and Peter Wilcoxen. 1999. The theoretical and empirical structure of the G-Cubed Model, *Economic Modelling*, 16:123-148.

Melnikov, Nikolai B., Brian C. O’Neill, Michael G. Dalton, and Bas J. van Ruijven."Downscaling heterogeneous household outcomes in dynamic CGE models for energy-economic analysis."*Energy Economics* 65 (2017): 87-97.

van der Mensbrugghe, D., 2018. The Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE) Model, Version 10.01. The Center for Global Trade Analysis, Purdue University.

Montes, Joshua. 2018. “CBO’s Projection of Labor Force Participation Rates,” Congressional Budget Office Working Paper 2018-04, March.

Muhammad, Andrew, James L. Seale, Jr., Birgit Meade,and Anita Regmi. International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data. TB-1929. U.S. Dept. of Agriculture, Econ. Res. Serv. March 2011. Revised February 2013

OECD-FAO, 2018, OECD-FAO Agricultural Outlook 2018-2027, OECD Publishing, Paris/Food and Agriculture Organization of the United Nations, Rome.

O'Neill, Brian C., Michael Dalton, Regina Fuchs, Leiwen Jiang, Shonali Pachauri, and Katarina Zigova."Global demographic trends and future carbon emissions."*Proceedings of the National Academy of Sciences* (2010): 201004581.

O'Neill, Brian C., Xiaolin Ren, Leiwen Jiang, and Michael Dalton."The effect of urbanization on energy use in India and China in the iPETSmodel."*Energy Economics* 34 (2012): S339-S345.

Paltsev S., J. Reilly, H. Jacoby, R. Eckaus, J. McFarland and M. Babiker, 2005. The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Version 4. MIT Joint Program on the Science and Policy of Global Change Report 125, Cambridge, MA.

Paltsev S.,Jacoby H.D., Reilly J.M., Viguier L., Babiker M. 2005. Transport and Climate Policy Modeling the Transport Sector: The Role of Existing Fuel Taxes in Climate Policy. In: Loulou R., Waaub JP., Zaccour G. (eds) Energy and Environment. Springer, Boston, MA. DOI: https://doi.org/10.1007/0-387-25352-1_9.

Pingali, P., 2006. Westernization of Asian diets and the transformation of food systems: Implications for research and policy. Food Policy 32, 281–298.

Pollak, Robert A., and Terence J. Wales."Demographic variables in demand analysis."*Econometrica: Journal of the Econometric Society* (1981): 1533-1551.

Popkin, B. M., Adair, L. S. and Ng, S. W. (2012), Global nutrition transition and the pandemic of obesity in developing countries. Nutrition Reviews, 70: 3-21. doi:10.1111/j.1753-4887.2011.00456.x

Preckel P.V., Cranfield J.A.L., and Hertel T.W.A Modified, Implicit, Directly Additive Demand System.Applied Economics, 42(2):143–155, January 2010.

Rausch, Sebastian, Gilbert Metcalf and JohnReilly. 2011. Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics*, 33:S20-S33.

Reimer, J.J., and T.W. Hertel. 2004. Estimation of International Demand Behavior for Use with Input-Output Based Data. *Economic Systems Research*, Vol. 16(4), pp. 347-66.

Ren, X., Weitzel, M., O’Neill, B.C., Lawrence, P., Meiyappan, P., Levis, S., Balistreri, E.J. and Dalton, M., 2018. Avoided economic impacts of climate change on agriculture:

integrating a land surface model (CLM) with a global economic model (iPETS). *Climatic Change*, 146(3-4), pp.517-531.

Rey Los Santos, L., Wojtowicz, K., Tamba, M., Vandyck, T., Weitzel, M., Saveyn, B., Temursho U. 2018. Global macroeconomic balances for mid-century climate analyses - Supplementary material to Global Energy and Climate Outlook 2018. JRC Technical Paper EUR 29490 EN, doi:10.2760/858469, JRC113981.

Ross, Martin. 2008. *Documentation of the Applied Dynamic Analysis of the Global Economy (ADAGE) Model*.Research Triangle Institute. Available at: https://www.rti.org/sites/default/files/resources/adage-model-doc_ross_sep08.pdf

Rutherford, Thomas. 1999. "Applied General Equilibrium Modeling with MPSGE as a GAMS Subsystem: An Overview of the Modeling Framework and Syntax." *Computational Economcis*, 14: 1 – 46.

Sands et al. (this issue).

Savard, Luc. 2010. Using an Almost Ideal Demand System in a Macro-Micro Modelling Context to Analyze Poverty and Inequalities, Working Paper, Groupe de Recherche en Economie et Developpement International, University of Sherbrooke.

Schafer, Andreas & D. Jacoby, Henry. (2005). Technology detail in a multisector CGE model: Transport under climate policy. Energy Economics. 27. 1-24. 10.1016/j.eneco.2004.10.005.

Schuenemann, F. and Delzeit, R. 2019. Higher Income and Higher Prices: The Role of Demand Specifications and Elasticities of Livestock Products for Global Land Use. Schriften der Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaues e.V., forthcoming.

Seale, James L., and Anita Regmi. 2006. Modeling International Consumption Patterns. *Review of Income and Wealth*, Vol. 52(4), pp. 603-24.

Shelton, C. A. (2007). The size and composition of government expenditure. *Journal of Public Economics*, *91*(11-12), 2230-2260.

Sommer, Mark and Kurt Kratena. 2017. "The Carbon Footprint of European Households and Income Distribution," *Ecological Economics*, 136:62-72.

Timmer, Marcel, Eric Dietzenbacher, Bart Los, Robert Stehrerand Gerard de Vries. 2015. "An Illustrated User Guide to the World Input-Output Database: the Case of Global Automotive Production," *Review of International Economics*, 23:575-605.

Valin, Hugo; Sands, Ronald D.; van der Mensbrugghe, Dominique; Nelson, Gerald C.; Ahammad, Helal; Blanc, Elodie et al., 2014. The future of food demand. Understanding differences in global economic models. *Agricultural Economics* 45 (1), 51–67.

Waisman, H., Guivarch, C., Grazi, F., and Hourcade, J. C. (2012a). The Imaclim-R model: infrastructures, technical inertia and the costs of low carbon futures under imperfect foresight. Climatic Change, pages1-20.

Wing, Ian Sue, Kathryn Daenzer, Karen Fisher-Vanden and Katherine Calvin. 2011. *Phoenix Model Documentation*. PNNL Joint Global Change Research Institute. Available at: http://www.globalchange.umd.edu/models/phoenix/

Woltjer, G.B.; Kuiper, M.; Kavallari, A.; Meijl, H. van; Powell, J.P.; Rutten, M.M.; Shutes, L.J.; Tabeau, A.A., 2014. The MAGNET model: Module description (No. 14-57). LEI Wageningen UR.

World Bank, 2015. Purchasing Power Parities and the Real Size of World Economies: A Comprehensive Report of the 2011 International Comparison Program. Washington, DC: World Bank.

World Trade Organization (WTO). 2018. *World Trade Report 2018*, WTO Secretariat, Geneva. https://www.wto.org/english/res_e/publications_e/wtr18_0_e.pdf

Yu, W., Hertel, T., Eales, J., Preckel, P., 2000. Integrating the AIDADS demand system into the GTAP model. Paper presented to Third Annual Conference on Global Economic Analysis, Melbourne, Australia, July 2000.

Yu, Wusheng, Hertel, Thomas W., Preckel, Paul V., Eales, James S., 2004. Projecting world food demand using alternative demand systems. *Economic Modelling* 21(1), 99–129.

Zahavi, Yacov and Antti Talvitie. (1980). Regularities in travel time and money expenditures. Transportation Research Record. 13-19.

Zeitsch, J., R. McDougall, P. Jomini, A. Welsh, J. Hambley, S. Brown, and J. Kelly. 1991. SALTER: A General Equilibrium Model of the World Economy. SALTER Working Paper N. 4. Canberra, Australia: Industry Commission.