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Demand-Driven Structural Change in Applied General Equilibrium Models

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1 Introduction

Structural change refers to the variations in the patterns of industrial output, consumption and trade flows inside an economic system. In the short run, this change is mainly determined by income and relative prices, but in the medium and long run other forces shape the economic structure in a more persistent way. Technological progress, modifications of production processes, shifts in aggregate consumption, possibly driven by demographic evolution, all contribute to long lasting structural change.

Understanding structural change, and its determinants, is clearly an interesting and relevant scientific topic in itself, with direct policy implications. It is also practically important when applied, multi-sector general equilibrium models are used for the assessment of policies and effects having impacts in the long run, like in the case of climate change. Indeed, whereas these models are usually characterized by a detailed account of the economic structure, which is often essential when dealing with impacts affecting specific sectors, they are also normally calibrated on the basis of some past data (e.g., input-output or SAM tables), meaning that they mirror an economic structure quite different from the one we could possibly observe in the distant future.

Some of the factors affecting the long run structural change are clearly unpredictable. Most of the technological breakthroughs of the past, affecting various industries, appear to have occurred in a seemingly random fashion. Harberger (1998) points out that the whole dynamics of economic progress actually resembles the growth process of “mushrooms”, rather than the steady rise of “yeast” (as neoclassical models of economic growth posit).

Some other factors, however, are quite predictable, in the sense that some of the forces which will affect the economic structure tomorrow are already active and observable today. Technology adoption and diffusion is under way. Catching up by fast growing developing economies is occurring. Demographic transitions are taking place, as well as mass migrations.

Broadly speaking, there are two classes of effects at work. There are supply side effects, affecting industrial productivity, either directly or indirectly, and

there are demand side effects, involving variations in the structure of final demand. In this paper, we focus on the issue of modeling and numerical estimating changes in the pattern of aggregate household consumption, driven by varying (growing) levels of per capita income. Therefore, income levels are taken here as given, although in a full-fledged numerical model they could be determined endogenously, or obtained from an hypothetical scenario.

Modeling a time-varying and income-dependent structure of household consumption implies introducing a sufficiently sophisticated demand system, capable of capturing what Matsuyama (2016) terms “Generalized Engel Law”: the fact that budget shares in consumption expenditure (and, more generally, industrial shares in terms of employment, value added or output) do not vary monotonically over time at progressively higher income levels. Therefore, in the next section, we briefly review what functional forms have been employed in the recent economics literature for this purpose. We focus, in particular, on the AIDADS (An Implicitly, Directly Additive Demand System; Rimmer and Powell 1992), presenting in Section 3 an exercise of parameters’ estimation for this demand system, based on the recently published Report of the 2011 International Comparison Program (ICP, 2015). Section 4 illustrates how results obtainable from a dynamic, computable general equilibrium model may change when the AIDADS specification, instead of a simpler, conventional form is employed to model consumption demand. A final section draws some concluding remarks.

2 Long-run changes in consumption patterns

Several demand systems, utility and expenditure functions, all with differentiated income elasticity, have been proposed. Desirable properties for their utilization in applied economic models are: (1) relative simplicity and analytical tractability; (2) generation of well behaved demand curves; (3) easiness of parameters’ estimation. Of course, the choice should also depend on the characteristics of the underlying model and on its purpose, for instance:

- the model could focus either on relatively small variations in income or expenditure levels (e.g., a single country CGE for short run policy assessment), or on more substantial variations (long run scenarios or intercountry comparison);
- the model could primarily focus on changes in income, rather than changes in relative prices.

Assessing long run changes in the structure of consumption demand means considering significant changes in income, with variations in relative prices entering only as a second order effect. Therefore, the selection of a demand system should be restricted to functional forms that, at higher income levels but constant relative prices, simulate structural changes consistent with historical “stylized facts”.

One interesting option is the Hierarchical Demand System (Matsuyama, 2002; Buera et al., 2013). The idea behind the HDS is deceptively simple:

goods and services are ranked from lowest to highest priority in terms of needs. All consumers spend their income in a sequential way, starting from basic needs and stepping up to the the highest level they can afford with their income. Once a need is satisfied, the corresponding good or service provides no more marginal utility. This is broadly consistent with the observation that goods could be initially regarded as a luxury (e.g., air conditioning), and when they can be obtained they become a necessity. When associated with a given income distribution, HDS can produce some interesting dynamics, with goods / industries “taking off” at various stages of economic development, possibly generating “hump shaped” trajectories as well.

Generally, HDS works well for theoretical models (possibly to be validated econometrically), but its implementation in applied macro-economic models like the CGEs would require information about the distribution of income and how it could evolve over time. This may be quite problematic, especially when a large set of countries are considered, including data-poor developing countries.

Gohin (2005) illustrates how to implement any regular configuration of price and income effects through “latent separability”. Latent separability can be seen within an intermediate production process, where goods are first used to produce commodities, which are the true arguments of the utility function and not the goods. Even if each intermediate utility function is homothetic, there is a wide spectrum of possible income and substitution effects for purchased goods generated from the combination of different groups to which each good belongs. The problem with this method here is that it assumes knowledge of income and substitution elasticities from the outset. Indeed, this information is used to infer a consistent latent separability structure, which is not observable.

A number of authors have recently work with some variants of CES functions, with industry-specific but time-constant income elasticities. In Fieler (2011) a single parameter plays the double role of substitution and income elasticity. Caron and Markusen (2014) set relative income elasticities equal to relative substitution elasticities, whereas Comin et al. (2015) use separate and independent parameters for the two good-specific elasticities.

In all cases, income elasticities are constant. This implies that the demand pattern does not stabilize over time and, actually, the good with the highest income elasticity would asymptotically cover 100% of the budget. Clearly, this is not an appealing property for a realistic assessment of long run changes in demand patterns.

A demand system for structural change simulation should be “sufficiently flexible” or, technically speaking, “full rank”. Rank one demands, the most restrictive demand systems, are independent of income; rank two demand systems are less restrictive, allowing linear Engel curves not necessarily through the origin; while rank three (i.e., full rank) demand systems are least restrictive, allowing for non-linear Engel responses (Cranfield et al., 2003).

Among the many full-rank demand systems which have been proposed, AIDADS (An Implicitly, Directly Additive Demand System; Rimmer and Powell 1992) appears to be especially suited for implementation in multi-sector, applied general equilibrium models. Indeed, it was introduced by CGE modelers and

it has already been applied in a number of CGE models (Yu et al., 2000, 2004; Golub and Hertel, 2008).

The AIDADS can be seen as a generalization of the Linear Expenditure System (LES). The demand for good i is expressed as:

$$q_i = \gamma_i + \phi_i \frac{y - \sum_j p_j \gamma_j}{p_i} \quad (1)$$

where y is total income or expenditure, γ_i is a parameter and ϕ_i (which in a LES would itself be a fixed parameter) is given by:

$$\phi_i = \frac{\alpha_i + \beta_i e^u}{1 + e^u} \quad (2)$$

with α_i, β_i parameters and u being the *implicitly* defined, *cardinal* utility function. To understand how AIDADS behaves, notice that:

$$\lim_{u \rightarrow -\infty} \phi_i = \alpha_i \quad (3)$$

$$\lim_{u \rightarrow \infty} \phi_i = \beta_i \quad (4)$$

$$\alpha_i < \phi_i < \beta_i \quad (5)$$

$$\lim_{y \rightarrow \infty} \frac{p_i q_i}{y} = \phi_i = \beta_i \quad (6)$$

Expenditure shares therefore stabilize at the level ϕ_i in the long run, although at different “speeds”. It is not possible to get a closed form solution for the utility level u , which must then be estimated numerically, alongside the parameters α_i, β_i and γ_i . A number of constraints must also be taken into account, to ensure regularity conditions for the system (Powell et al., 2002). Cranfield (1999) shows how to use maximum likelihood methods to this purpose, employing also bootstrapping techniques to get parameters statistics (e.g., confidence intervals) and maximum entropy for multiple demands, disaggregated in terms of per-capita income.

Furthermore, Cranfield et al. (2003) assesses the ability of five structural demand systems to predict demands when estimated with cross sectional data spanning countries with widely varying per capita expenditure levels. Results indicate demand systems with less restrictive income responses are superior to demand systems with more restrictive income effects. Among the least restrictive demand systems considered, the AIDADS and the Quadratic Almost Ideal Demand System (QUAIDS) seem roughly tied for best, while the Quadratic Expenditure System (QES) is a close second. They notice that an important advantage of the QUAIDS model over AIDADS is its ease of estimation. Yet, and despite the fact that AIDADS is not exactly aggregable, the latter has fewer price related parameters to estimate and is designed so that budget shares lie

between zero and one at all expenditure levels. This property suggests a preference for AIDADS when expenditure (income) shows substantial variation (or when extrapolations would involve large changes in expenditure) but prices are anticipated to experience little change.

3 Estimation of an AIDADS demand system

ICP (2015) provides data on real and nominal consumption expenditure for 180 countries at the year 2011, in 14 categories, which are further aggregated here in 11 consumption classes:

- Food and nonalcoholic beverages (**FOOD**)
- Alcoholic beverages, tobacco, and narcotics (**BEVTOB**)
- Clothing and footwear (**CLOTHING**)
- Housing, water, electricity, gas and other fuels + Furnishings, household equipment and maintenance (**HOUSE**)
- Health + Education (**HEAEDU**)
- Transport (**TRANSP**)
- Communication (**COMMUN**)
- Recreation and culture (**RECREAT**)
- Restaurants and hotels + Miscellaneous goods and services (**OTHER**)
- Machinery and equipment (**MACHINE**)
- Construction (**CONSTR**)

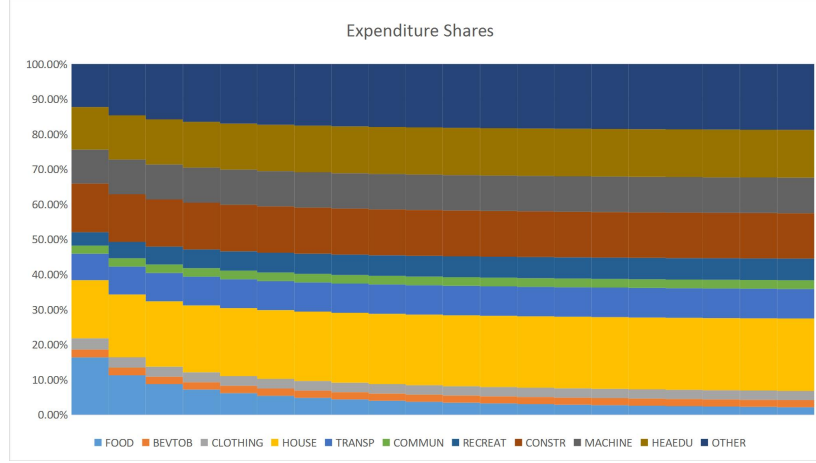
Ratios between real and nominal consumption readily give a set of country and sector specific price indexes. For the estimation of AIDADS parameters, we closely follow Cranfield (1999), by formulating the equations in terms of budget shares, and adding a stochastic error term:

$$w_{ir} = \frac{p_{ir}\gamma_i}{y_r} + \frac{\alpha_i + \beta_i \exp(u_r)}{1 + \exp(u_r)} \left(1 - \frac{\sum_i p_{ir}\gamma_i}{y_r} \right) + \epsilon_{ir} \quad (7)$$

where w_{ir} is the observed household budget for the item i in country r ; y_r stands for total *per capita* expenditure (income) in country r ; p_{ir} is the price index for the item i in country r ; ϵ_{ir} is a normal multivariate error term, distributed independently across observation, with zero mean and finite covariance matrix, where the sum over all items in each country is zero. All remaining symbols, including the cardinal utility u_r , are parameters to be estimated.

The following restrictions apply:

Figure 1: Expenditure shares by income levels



$$\begin{aligned}
 \sum_i \alpha_i &= 1 \\
 \sum_i \beta_i &= 1 \\
 0 \leq \alpha_i, \beta_i &\leq 1
 \end{aligned} \tag{8}$$

The estimation is performed using a non-linear maximum likelihood procedure¹, and gives the results shown in Table 1.

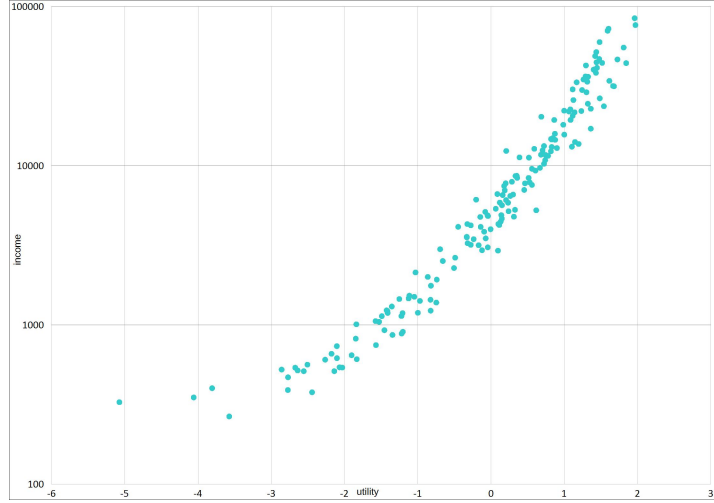
Table 1: Estimated parameter values

	<i>alpha</i>	<i>beta</i>	<i>gamma</i>
FOOD	0.40	0.00	116
BEVTOB	0.02	0.02	16
CLOTHING	0.04	0.03	29
HOUSE	0.08	0.21	136
TRANSP	0.07	0.09	6
COMMUN	0.02	0.02	1
RECREAT	0.00	0.07	10
CONSTR	0.16	0.13	40
MACHINE	0.10	0.10	16
HEAEDU	0.08	0.14	98
OTHER	0.02	0.20	38

Figure 1 graphically displays how the budget shares evolve at constant prices, when annual per capita income (total consumption expenditure) varies from a minimum level of 8691 USD up to 168788 USD.

¹Technical details about the specific algorithm and software are available on request.

Figure 2: Income vs. cardinal utility levels



To interpret the meaning of the estimated parameters, consider that gamma (γ) expresses the fixed and unavoidable consumption, therefore the higher the value for this parameter, the more essential a certain good or service is seen, in terms of basic needs. On the other hand, beta (β) is the asymptotic budget share, for income levels going to infinity. The higher this share is, the more important a consumption item becomes, as we get very rich.

To make the AIDADS system functional for a numerical simulation model, an additional step is necessary. Indeed, the procedure illustrated above allows to estimate country specific values for the cardinal utility u , but that variable is not available in the destination model, so a link must be established between utility and income levels. To this end, observe the plot contrasting income (vertical axis, logarithmic scale) with cardinal utility levels in Figure 2.

The Figure suggests that the relationship is semi-logarithmic. Indeed, after trying several specifications of the functional form, the best regression results have been obtained with the following heteroskedasticity corrected OLS formulation, where u_r is regressed against $\ln(y_r)$:

```

Model 1: Heteroskedasticity-corrected, using observations 1-177
Dependent variable:  u
               coefficient std.error  t-ratio p-value
-----
const         -7.17788      0.160788   -44.64  1.45e-097 ***
lnm           0.839040     0.0183408    45.75  2.80e-099 ***
Statistics based on the weighted data:
Sum squared resid 656.4597 S.E. of regression 1.936801
R-squared 0.922833 Adjusted R-squared 0.922392
F(1, 175) 2092.804 P-value(F) 2.80e-99
Log-likelihood -367.1501 Akaike criterion 738.3002
Schwarz criterion 744.6525 Hannan-Quinn 740.8764
Statistics based on the original data:
Mean dependent var -0.047430 S.D. dependent var 1.348156
Sum squared resid 28.07932 S.E. of regression 0.400566

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When the estimated coefficients of the regression are plugged into the AIDADS demand (2), the latter becomes a function of income and prices only, as one would expect from a regular demand function:

$$q_i = \gamma_i + \left(\frac{\alpha_i + \beta_i K y^Z}{1 + K y^Z} \right) \cdot \frac{y - \sum_j p_j \gamma_j}{p_i} \quad (9)$$

where we have added the two constants $K = 0.000763284$ and $Z = 0.83904$.

4 Introducing a flexible demand system into a dynamic CGE model

5 Conclusion

References

- Buera, F. J., Kaboski, J. P., Zhao, M. Q., 2013. The Rise of Services: the Role of Skills, Scale, and Female Labor Supply. NBER Working Paper 19372.
- Caron, J., Markusen, J. R., 2014. International Trade Puzzles: a Solution Linking Production and Preferences. The Quarterly Journal of Economics, 1501–1552.
- Comin, D. A., Lashkari, D., Mestieri, M., 2015. Structural Change with Long-run Income and Price Effects. National Bureau of Economic Research Working Paper Series No. 21595.
- Cranfield, J. A. L., 1999. Aggregating non-linear consumer demands: A maximum entropy approach. Ph.D. thesis, Purdue University.

- Cranfield, J. A. L., Eales, J. S., Hertel, T. W., Preckel, P. V., 2003. Model selection when estimating and predicting consumer demands using international , cross section data. *Empirical Economics* 28, 353–364.
- Fieler, A. C., 2011. Nonhomotheticity and Bilateral Trade: Evidence and a Quantitative Explanation. *Econometrica* 79 (4), 1069–1101.
- Gohin, A., 2005. The specification of price and income elasticities in computable general equilibrium models: An application of latent separability. *Economic Modelling* 22 (5), 905–925.
- Golub, A., Hertel, T. W., 2008. Global Economic Integration and Land Use Change. *Journal of Economic Integration* 23 (3), 463–488.
- Harberger, A. C., 1998. A Vision of the Growth Process. *The American Economic Review* 88 (1), 1–32.
- ICP, 2015. Purchasing Power Parities and Real Expenditures of World Economics: A Comprehensive Report of the 2011 International Comparison Program. World Bank, Washington, D.C.
- Matsuyama, K., 2002. The Rise of Mass Consumption Societies. *Journal of Political Economy* 110 (5), 1035–1070.
- Matsuyama, K., 2016. The Generalized Engel’s Law : In Search for A New Framework. Public lecture, Canon Institute for Global Studies.
- Powell, A. A., McLaren, K. R., Pearson, K. R., Rimmer, M. T., 2002. Cobb-Douglas Utility - Eventually! CoPS Working Paper No. IP80.
- Rimmer, M. T., Powell, A. A., 1992. Demand Patterns across the Development Spectrum: Estimates for the AIDADS System. CoPS Working Paper No. OP75.
- Yu, W., Hertel, T., Preckel, P., Eales, J., 2004. Projecting world food demand using alternative demand systems. *Economic Modelling* 18 (21), 205–236.
- Yu, W., Hertel, T. W., Eales, J. S., Preckel, P. V., 2000. Integrating the AIDADS Demand System into the GTAP Model. Third Annual Conference on Global Economic Analysis.