Assessing Long Run Structural Change in Multi-Sector General Equilibrium Models
a research project

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1 Motivation

I have long worked with Computable General Equilibrium models, especially in the field of Environmental and Climate Economics. In that context, CGE models are often used to assess policies and environmental impacts occurring at some distant future. Whereas these models are characterized by a detailed account of the economic structure, which is often essential when dealing with impacts affecting specific sectors, they are also calibrated on the basis of some past input-output or SAM tables, meaning that they mirror an economic structure quite different from the one we could possibly observe in the future.

To partially circumvent this problem, I have sometimes used a simple methodology, which I termed "pseudo-calibration" (e.g., in Bosello et al., 2006). With this method, I have exogenously varied endowments and/or productivities of primary resources (according to some given forecasts or scenarios) *before* running any counterfactual numerical simulation exercise.

A similar kind of solution can be found in dynamic general equilibrium models, for instance in the ENVISAGE integrated assessment model (Roson and van der Mensbrugghe, 2012), where endogenous dynamics of capital accumulation coexist with exogenously imposed changes in labor productivity, set at a level making the model path consistent with aggregate GDP growth rates, obtained econometrically.

More recently, Shared Socio-Economic Pathways (SSP) have been proposed as standardized reference scenarios in the field of climate change assessment (O'Neill et al., 2014). Quantitative information for these benchmark scenarios is, at present, quite limited: a data repository is maintained at IIASA, where economic modelers can found estimates of GDP and population levels. Again, to get a more meaningful and detailed description of the future economy, a CGE model can be "forced" to reproduce given GDP trajectories, by making some productivity parameters endogenous. For instance, in Roson and Damania (2016) we swapped the normally endogenous CGE variable "Real GDP" with the normally exogenous parameter "Productivity of the Value Added Aggregate", in order to obtain an enriched (and internally consistent) baseline framework, including production levels, trade flows and demand patterns.

The common denominator of the three cases above is a procedure imposing aggregate macroeconomic constraints onto a disaggregated general equilibrium structure. Although this can be a reasonable way to proceed in some circumstances, it is also clear that changes in the economic structure could be generated by more complex adjustment mechanisms. Like in Comin et al. (2015) we can identify two main drivers of structural change. First, industrial total productivity may change at various speeds, or factor productivity could do so, thereby making industrial productivity growth rates divergent, because of different factor compositions. Second, consumption patterns may change, because of diverse income elasticities, possibly associated with varying income distributions.

In a general equilibrium setting, there is a fundamental difference between supply and demand driven structural change. Indeed, supply variables like primary resource endowments and productivity are naturally exogenous, meaning that it may suffice to modify them in a non uniform way. On the other hand, consumption levels and patterns are naturally endogenous, so the question becomes evaluating whether the demand system in the model correctly captures the variations induced by shifts in relative prices and income.

Earlier CGE models typically used nested utility functions of the CES type, therefore imposing homotheticity and unitary income elasticities. However, even the standard GTAP model (Hertel and Tsigas, 1997) adopts non-homothetic, non-additive Constant Differences in Elasticity (CDE) utility/expenditure functions. Simpler ways to introduce non unitary income elasticities are based on Stone-Geary or Linear Expenditure Systems. Yu et al. (2004) make an empirical comparison between various demand systems, noting that "the most serious problem with the CDE stems from the observation that it precludes the possibility of goods switching from luxuries to necessities as income rises" and that "the LES performs more poorly than the CDE for most developing regions, due to its rapid convergence on the HCD [Homothetic Cobb-Douglas]. The CDE does not differentiate itself from the LES for developed regions where income growth is rather slow". The conclusion is that, even if the CDE performs better than simpler functions, it may not be sufficient to simulate complex, long run adjustments in demand patterns.

Matsuyama (2016) points out that, as a matter of fact, the evolution over time of industrial shares, in terms of employment, value added or expenditure, can well be non monotonic, and calls this phenomenon "Generalized Engel's Law". For instance, the share of manufacturing is typically hump shaped, increasing at earlier stages of economic development, then decreasing. To replicate this characteristic into a model, a sufficiently sophisticated demand system must therefore be adopted.

I wish to initiate a new research program, possibly in collaboration with other researchers, about establishing a correct methodology to obtain long run estimates of structural change, considering both supply and demand drivers and delivering relevant results for applied economic models, not only CGEs. I am not interested in forecasts; there are so many unpredictable factors which could ultimately affect the economic structure in the long run. Rather, I would like to focus on the unfolding trend of structural change.

I have started looking at some relevant literature, picking up some ideas about how to practically tackle the issue. They are briefly discussed in the following.

2 Demand side: generalized Engel's law

Several demand systems, utility and expenditure functions, all with differentiated income elasticity, have been proposed. Additional requirements 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. In addition, the choice should depend on the characteristics of the underlying model and on its purpose. In this respect, I see two key factors:

- 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 *primary* interest could be changes in income, rather than changes in relative prices.

On the basis of the considerations illustrated in the previous section, I would say that the problem I am interested in has the feature of significant changes in income, with variations in relative prices entering only as a second order effect. Therefore, I would start by trying to understand how the composition of demand would change at higher income levels but constant relative prices, comparing that simulated structural change 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. When a need is satisfied, the corresponding good or service provides no more marginal utility. This is seemingly 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.

In my opinion, 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. I also have the feeling that most of the characteristics of the HDS, at the aggregate level, could be satisfactorily captured by a sufficiently flexible demand system, like the AIDADS (see below).

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 is 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 the application I have in mind.

A demand system for the simulation of long run structural change should rather 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) seems to be especially suited for the issue at hand, also because it was introduced by CGE modelers and it has been applied to 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:

$$q_i = \gamma_i + \phi_i \frac{Y - \sum\limits_j p_j \gamma_j}{p_i} \tag{1}$$

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:

$$\phi_i = \frac{\alpha_i + \beta_i e^u}{1 + e^u} \tag{2}$$

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

$$\lim_{u \to -\infty} \phi_i = \alpha_i \tag{3}$$

$$\lim_{u \to \infty} \phi_i = \beta_i \tag{4}$$

$$\alpha_i < \phi_i < \beta_i \tag{5}$$

$$\lim_{Y \to \infty} \frac{p_i q_i}{Y} = \phi_i = \beta_i \tag{6}$$

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 bootstrapping to get parameters statistics (e.g., confidence intervals) and maximum entropy for multiple demands, disaggregated in terms of per-capita income.

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 Supply side: differentiated productivity growth

Changes in sectoral shares are not only driven by varying patterns of consumption, as industries may grow over time at different "speeds", that is, at different productivity growth rates. Of course, the two aspects are linked through changes in relative prices (Comin et al., 2015).

Therefore, when projecting the economic structure into the future, one would want to consider changing productivities alongside changing demand patterns.

To this end, it is important to consider that a model may have, in principle, not one but several industrial productivity parameters. For instance, production functions that are typically adopted in CGE models have a nested structure, with several layers of substitution (e.g., between intermediate factors and value added, between labor and capital, between different types of labor, or capital, etc.). At *each* node of the production tree there is an associated productivity parameter; the topmost accounts for multifactor productivity, then we can have value added productivity, labor productivity, skilled labor productivity, and so on. It is sufficient to have non-uniform productivity growth in the factors to get differentiated growth at the industrial level (Herrendorf et al., 2015).

There is a tradition in economic growth analysis that focuses on the characteristics of the industrial structure as a determinant explaining (part of) the aggregate growth performance (Fagerberg, 2000; Chen et al., 2011). Other works have stressed the role of external shocks or policies affecting the industrial structure (international trade, skill-biased technological change, R&D), thereby indirectly influencing the aggregate growth (Griffith et al., 2004; Triplett and Bosworth, 2003; McMillan and Rodrik, 2011; Buera et al., 2015). Fewer papers have directly tackled the time evolution of industrial productivity in different countries (Griliches and Mairesse, 1991; Bernard and Jones, 1996; Sorensen, 2001).

In particular, Bernard and Jones (1996) examines the role of sectors in aggregate convergence for 14 OECD countries. They found that, while aggregate productivity was converging over the period, the sectors show disparate behavior. For all measures of productivity, the manufacturing sector shows no or little convergence, while other sectors, especially services, show strong evidence in favor of convergence. This finding for services, together with the declining share of manufacturing in all 14 countries, contributes to the convergence found at the aggregate level. Sorensen (2001) argues that the established evidence of nonconvergence in manufacturing depends heavily on the choice of base year. The simple equation used to estimate industrial growth rates for both labor and total factor productivity[1] (ρ) is a variant of the one previously adopted by Baumol (1986):

$$\dot{\rho}_r^i = a + b \ln \rho_{r,t0}^i$$

where a and b are estimated parameters, with $b < 1$ indicating convergence in productivity for industry i across the various regions r.

Parameters for the equation above can be estimated rather easily with a panel data base, but I see two main problems when region and industry specific (constant) growth rates are applied at a long time horizon. First, higher rates for lagging regions may ultimately cause not merely a catching-up effect, but rather a "leapfrogging" one, thereby bringing about a distorted ranking. Second, looking at historical data, one may argue that fast-growing industries may not stay in the leadership forever. This is the famous "mushrooms vs. yeast" vision of the technological progress underlined by Harberger (1998).

[1]Possibly expressed relative to the highest productivity level.

These two issues could be addressed quite naturally by introducing some way to progressively fade out productivity growth differences, first between regions within the same industry, then between industries. At present, however, I have no specific idea about how to reasonably implement such a mechanism, nor I have found relevant references in the literature.

4 Data, resources and modeling strategy

The latest release of the GTAP data base (9A) includes Social Accounting Matrices for the years 2004, 2007 and 2011. There is data on industrial cost structure, value added, consumption patterns for 57 industries in 140 regions, all expressed in current US$. This would be a quite natural starting point. However, estimation of the demand systems needs information on prices, and most of the studies I have examined rely on the International Comparison Program (ICP). The data covers 26 expenditures categories for goods and services, and several indicators including PPPs, expenditure shares of GDP, total and per capita expenditures in US$ both in exchange rate terms and PPP terms, and price level indices. The latest report of the ICP (2015) presents data for the year 2011.

For productivity, data is needed on real inputs. This is quite straightforward for labor, using work hours, but much less so for other factors, for instance capital. Therefore, I would focus on labor and I would relate work hours to the amount (by industry, region, year) of wages and labor compensation (from GTAP), expressed at constant 2004 US$ values (using GDP deflators).[2] Therefore, and contrary to other studies, I would focus on the labor contribution to the value added, rather than on the value added itself or the gross output, which would make labor productivity dependent on other complementary factors.

I am planning to mix exogenous growth rates for labor productivity with endogenous value added TFP, obtained by imposing exogenously given GDP levels. To illustrate the implications of a more sophisticated treatment of structural trends in a general equilibrium setting, I would show and compare two simulation results with the GTAP standard model. First, I would apply a reference GDP (and population) scenario, possibly the "middle of the road" SSP2, in the conventional way, namely by just swapping value added productivity with the real GDP. Second, I would do the same, but with the newly estimated AIDADS system and by using labor productivity growth rates in addition to the endogenous TFP. I expect that a comparison of results obtained with the two numerical experiments would shed some light on some relevant characteristics of long-run structural changes.

[2]PPPs are not useful in this context, as growth rates will be applied to a CGE model calibrated with the same GTAP data.

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