Deriving CGE Baselines from Macro-economic Projections

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Abstract

Quantitative policy analysts are usually confronted with the problem to derive a base-line scenario that reflects the most likely state of an economy in a future year. The methods used in practice to derive such a base-line scenarios are heterogeneous and range from the usage of the last observable year to complete and consistent estimation procedures. In the case of general equilibrium (CGE) analyses, the Scenar2020 project (European Commission 2006a) is one example how projections of macro-economic indicators (exogenous drivers) are used to construct the base-line as a model scenario: Starting from a calibrated version, exogenous variables are modified until macro-economic projections are met. However, numerous projections refer to economic indicators which are endogenous variables within the CGE framework, such as gross domestic product (GDP), market prices, or produced quantities. To investigate methods that allow integrating projections for endogenous CGE variables is the main topic of this study. Our starting point is the work by Arndt et al (2002), where entropy-based (Golan et al 1996) techniques are employed for the estimation of behavioural parameters by fitting a CGE model to time series on endogenous variables. Following this concept, we investigate a method to fit a CGE´s parameters and endogenous variables to market- and macro-economic projections from major research institutes.

Keywords: general equilibrium model; baseline construction; parameter estimation; macro-economic projections

1. Background: Baseline Construction and CGE Parameter Estimation

Establishing baseline scenarios for the model-based analyses of anticipated or announced policy changes is a common exercise in the domain of applied partial equilibrium analysis. For instance in the context of agricultural sector models (CAPRI, ESIM, AgLink), projections for market prices and produced quantities are published by various organisations (European Commission - DG Agri, FAO,…), and are used to calibrate the respective simulation model for a future point in time. In contrast, there are few examples how projections for major macroeconomic variables and sector-specific indicators are used in the context of general equilibrium (CGE) models. The Scenar2020 project (European Commission 2006a) is one example for the use of forecasts on main macroeconomic drivers in a CGE framework. In this case, the change of some key variables was implemented as a cumulative scenario of a CGE model (LEITAP) calibrated on the GTAP v.6 database. This approach, although transparent and straightforward, does not take advantage of forecasts for variables which are endogenous to the model, such as prices or sectoral employment of factors. Furthermore, it keeps those parameters constant for which no projections are available. For instance, total-factor productivity coefficients may be changed in the CES-production functions (Constant Elasticity of Substitution), but share and shape parameters remain unchanged.

To derive baselines, some of the investigated models rely dominantly on expert knowledge, others on automatic processes. Two main examples of agricultural models relying on expert analyses for their baseline construction are AGLINK and FAPRI baselines. The AGLINK model of the OECD covers all OECD member states. The baseline is built on the base of questionnaires fulfilled by member state covering all the variables of the model. The questionnaires are filled following domestic agricultural models and/or national experts' insights. The model, in agreement with the market experts and with the member states, creates a baseline coherent with all the questionnaires received (OECD, 2007). The FAPRI model baseline represents a similar example. FAPRI baseline is agreed during a meeting of experts where different models and expertises are put together to reach a consensus on the baseline (FAPRI, 2010).

On the other hand, CAPRI (Common Agricultural Policy Regionalized Impact Analysis modelling system), relies on a more automatic approach and less on experts' judgements. The methodology utilized for the construction of the EU27 member states baseline is based on two main steps. In the first one, a trend for all variables of the CAPRI database is estimated, subject to some basic constraints as the closure of market balances. In the second phase, external projections, mainly provided by DG-AGRI, the main CAPRI client, enter the process. The CAPRI baseline is then forced to comply with DG-AGRI projections, through two main changes of the trend estimation. First of all, DG-AGRI results are used as support of the trend estimation. Secondly, deviations from DG-AGRI results are penalized 100 times higher as trend base supports. The process is based on a highest posterior density estimator which minimizes the distances between the endogenous variables of the baseline and the support points, while satisfying all the constraints.

In contrast, there are few examples how projections for major macroeconomic variables and sector-specific indicators are used in the context of general equilibrium (CGE) modelling. Usually static GCE models do not rely on baseline construction as they consider the starting Social Accounting Matrix (SAM) as the reference scenario. All the policy simulations are then compared to the SAM.

Dynamic CGE models usually calibrate their parameters in order to meet exogenous projections. In general, dynamic CGE models (see MIRAGE, MAMS…) take into account growth of Gross Domestic Product (GDP) and population as exogenous drivers. Total factor productivity (TFP) is firstly considered as an endogenous variable and once calculated put into the model as exogenous parameters (Decreux and Valin, 2007).

The Scenar2020 project, which integrates a CGE model with the two partial equilibrium models CAPRI and ESIM (European SImulation Model), adopts a different process of baseline construction. The CGE adopted by this project is LEITAP, a global dynamic CGE model developed at LEI as a modified version of GTAP to treat explicitly agricultural policies. The baseline built by Scenar2020 takes into account both population ad GDP growths but in addition other external exogenous drivers. Among other, the most important demand driven drivers are the consumer preferences, i.e. more demand for value added and increasing absolute spending per capita while consumption of organic and regional food remain as observed in the past. Moreover, other exogenous drivers are more focused on the supply point of view, i.e. global slow down of yield growth of cereals, continuous trends in cost saving technical progress and environmental issues (yield increase effect caused by increased CO_2 concentrations, a temperature effect leading to a yield increase in most European regions and a water availability effect leading to a yield decrease in some European regions). On the world market, the study considers trends for agricultural markets, as reported in OECD and FAPRI outlooks.

Another approach has been followed with the USAGE model for USA (Dixon and Rimmer, 2009). A limited number of projections of endogenous CGE variables are available; mainly macro variables as GDP, aggregate consumption, investments imports and exports and energy variables as output, import and export of oil and gas. These projections have been used to endogenize some scalar propensities of the model as the average propensity to consume. At the same time typical exogenous variables as population, technical change and preference variables are shocked with data coming from available projections or derived from historical trends. The model, with a1998 base year, has bee used to forecast results for 2005, with projections available in 1998. The author showed that the CGE model significantly reduces the forecast error of a simple non-modelling extrapolation approach. Finally, introducing step by step the real data for the period 1998-2005, they conclude that the greatest pay-offs in reducing forecast errors is given by trade and tariffs data. This outcome is due also to the scarcity of accuracy of available projections in this area.

An approach to fit a CGE to time-series on key variables was presented by Arndt et al (2002), which has the particular appeal that it allows the consistent estimation of core CGE parameters. This approach employs a Maximum Entropy criterion (Golan et al 1996) to minimize the difference between historical values and model variables as well as the difference between model parameters to be estimated and their expected values.

In this paper, we follow the approach by applying an estimation procedure to projections on major macroeconomic aggregates as well as on exogenous model variables. A CGE serves as constraint for this estimation procedure. In contrast to the approach by Arndt et al (2002), we use a Highest Posterior Density measure as statistical criterion. Particular attention was devoted to the compilation of complete projected series for main macro-variables.

2. Used CGE Model and Social Accounting Matrices

Computable General Equilibrium (CGE) models allow to capture the economic, distributional and structural effects of external shocks, and to analyze in detail the effect of policies. As an economy-wide model, a CGE includes a complete description of the economy, and interlinks markets for commodities and factors of production. Compared to partial equilibrium models, CGEs allow evaluating the adjustments of agents on both the supply and the demand side, reactions in the labour market, and changes in resources allocation across activities. Moreover, CGEs capture the major budget constraints of an economy, particularly the balance of payment and the macroeconomic constraints; as well as the distributional impact on households in terms of both income and welfare.

This work presents an application of a modified version of the single-country static CGE model developed by IFPRI (Lofgren et al., 2002). This model follows standard specifications for production, allocation of output and consumption. In the top nest of the production function producers allocate value added and aggregate intermediate inputs according to a Leontief function. Capital and labour are allocated following a Constant Elasticity of Substitution (CES) function. Intermediate inputs follow a Leontief specification.

A Constant Elasticity of Transformation (CET) function allows producers to allocate domestic production between domestic and export use according to changes in relative prices. Export prices are exogenous world prices multiplied by the exchange rate, and adjusted for export taxes or subsidies and marketing costs. In the same vein, final domestic availability of outputs for final consumption and intermediate use is determined through an Armington (1969) specification, implying imperfect substitutability between domestic and imported goods.

A single representative household receives income from labour and capital and a single representative firm receives capital payments. The representative household and enterprise can receive government transfers and transfers from rest of the world. The household saves a quota of its earnings and consume the remaining income. Consumption is composed of composite goods (domestic and imported), evaluated at market price, including indirect taxes on commodities, import tariffs and trade margins. The household maximizes a Stone-Geary utility function, subject to a consumption expenditure constraint. The first order condition of the demand system is a Linear Expenditure System (LES) function, where spending on a single commodity is a linear function of the total consumption.

Government income is made up of indirect taxes on commodities, import tariffs and direct taxes and possibly transfers from the rest of the world. Moreover, the government receives payments from capital. Government expenditure includes consumption, through the public administration, and transfers arising from industrial and welfare policies. The difference between Government income and expenditure represents public saving or dissaving. The sum of households, Government and foreign savings is collected by one single account, which finances investment spending and changes in stocks. Investment and stocks demand are modelled by multiplying the base-year amount of investments and stocks by an adjustment factor.

The database for the CGE is based on the AgroSAM project (Müller et al 2009), which combined detailed information on the agricultural sector with supply- and use-tables (SUT) from EuroStat. In principle, the procedure to derive this database comprised the following steps: first, a full set of macroeconomic indicators was collected and arranged in the format of macroeconomic accounting matrices or macroeconomic SAMs. Next, SUT and data on monetary flows between domestic and foreign institutions like taxes and income transfers were used to create a set of institutional SAMs following the ESA95 classifications, where SAMs were balanced with respect to the macroeconomic totals originating from the previous step. Finally, detailed data for the agricultural sector from the CAPRI model were mapped into a comparable SAM format and combined with the ESA95 based SAMs into an unbalanced a priori estimate for the final AgroSAMs. Again, these a priori SAMs were balanced with respect to the corresponding entries of the SAMs in ESA95 format. The AgroSAM database features 98 activity and 97 commodity accounts, which were aggregated to 22 sectors to facilitate the use in the underlying CGE model.

3. Fitting Procedure

The approach by Arndt et al (2002) to fit a CGE model to observed macro-economic indicators uses an entropy criterion (Golan et al 1996) to minimize the difference between historical observations and model variables as well as the difference between model parameters to be estimated and their expected values. This minimization is subject to the constraints imposed by the underlying CGE. In summary, the estimation procedure is implemented by Arndt et al (2002) as follows:

The CGE is expressed in its implicit form (F, see equation 1), with X representing the endogenous variables like domestic prices and produced quantities and Z representing the exogenous variables like total supply of labour or policy measures. Structural parameters like the substitution elasticities of CES production functions or their share and shift parameters are denoted B and δ, respectively. The index t denotes the time dimension, an index for the EU Member States for which the model was fitted is omitted here as each model can be solved independently.

$$1. \qquad F\left(X_t, Z_t, B, \delta\right) = 0 \quad \forall t \in T$$

During the calibration of a CGE, the choice of B in combination with the base-year data allows calculating the second set of parameters (δ), such that the CGE exactly replicates the base-year data. The derived model parameters are therefore expressed as a function P of exogenous model variables Z and behavioural parameters B.

$$2. \qquad \delta = P\left(Z_t, B\right)$$

The procedure developed by Arndt et al (2002) allows estimating the exogenous parameters B by fitting the CGE to an observed set of historical series (Y), where Y is expressed as a function G of endogenous and exogenous model variables (X, Z), and the structural parameters. A subset of the exogenous parameters is fixed (Zo), while another subset is allowed to vary (Zu). Deviations between observed series (Y) and the model results G(…) are expressed as an error term e, which is 0 for the year to which the model is calibrated.

$$3. \qquad Y_t = G\left(X_t, Z_t^o, Z_t^u, B, \delta\right) + e_t \quad \forall t \in T$$

In the context of Entropy estimations, the possible outcomes of the variables to be estimated are defined over a set of discrete support points (v, w), which are associated with probabilities for the respective outcome (p,r). The exogenous parameters are therefore defined as:

4. $$B_k = \sum_m p_{km} v_{km} \quad \forall k \in K$$

The error terms for the historical series are defined equivalently:

5. $$e_{tn} = \sum_j r_{tnj} w_{tnj} \quad \forall t \in T,\ n \in N$$

The probabilities have to be non-negative and add up to one:

6. $$\sum_m p_{km} = 1 \ \ \forall k \in K, \ \sum_j r_{tnj} = 1 \ \ \forall t \in T,\ n \in N$$

In principle, it is also possible to express the exogenous model variables to be estimated (Zu) in a similar manner, if prior information for Zu is available. In case of available prior information on the distribution of the parameters and error terms in question (q, s), the objective function of the estimation problem can be expressed as:

7. $$\min_{p,r,Z_t^u} \alpha_1 \sum_k \sum_m p_{km} \log\left(\frac{p_{km}}{q_{km}}\right) + \alpha_2 \sum_t \sum_n \sum_j r_{tnj} \log\left(\frac{r_{tnj}}{s_{tnj}}\right)$$

The procedure described by Arndt et al (2002) allows the usage of available information on the distribution of parameters and exogenous variables in a very efficient manner. In the here presented applied case to fit number of single-country CGEs to projected time series, the need to introduce a set of probabilities for each variable and parameter to be estimated increased the computational demand tremendously. This problem has been addressed by Heckelei et al (2008) and Witzke and Britz (2005), who motivated a Highest Posterior Density (HPD) formulation as a less computationally demanding and more transparent alternative. If prior information is not already given in the form of support points and associated prior probabilities, it could be possible to specify expected means and standard deviations as a measure of uncertainty – for instance in the form of a Normal distribution as a prior density. For the estimation problem above, equation 3 could be translated into this framework by defining the observed (or projected) Y as expected values of a Normal probability distribution (PD) with a variance σ.

8. $$PD = \prod_t \frac{1}{\sigma_t \sqrt{2\pi}} \exp\left(-\frac{\left(G\left(X_t, Z_t^o, Z_t^u, B, \delta\right) - Y_t\right)^2}{2\sigma_t^{Y2}} \right)$$

Taking logs shows that the core of this objective function is a sum of squared deviations, scaled by variance of the respective observation or projection.

9. $$LPD = -\sum_t \left(\ln\left(\sigma_t\right) + 0.5\left(2\pi\right) + 0.5\left(\frac{\left(G\left(X_t, Z_t^o, Z_t^u, B, \delta\right) - Y_t\right)^2}{2\sigma_t^{Y2}} \right) \right)$$

As only the last term of Equation 9 is relevant for the maximization, the other parts are omitted in the following. Extending the problem also to elasticities B and exogenous variables Z^u, the final optimization problem can be formulated as:

10. $$\max_{B,Z_t^u} \sum_t -\left(\frac{\left(G\left(X_t, Z_t^o, Z_t^u, B, \delta\right) - Y_t\right)^2}{2\sigma_t^{Y2}} \right) - \left(\frac{\left(B - B^E\right)^2}{2\sigma^{B2}} \right) - \left(\frac{\left(Z_t^u - Z_t^{uE}\right)^2}{2\sigma_t^{Z2}} \right)$$

Where σ^Y, σ^B, σ^Z denote the standard deviations of target series, parameters, and exogenous model variables, and BE and ZE denote the expected values of B and Z, respectively. Objective function 10 is maximized subject to equation(s) 1, which imposes that the CGE has to be feasible for each period t, and subject to equation 2, which ensures that the derived model parameters are consistent with the initial calibration procedure. A prerequisite for the proposed estimation model is the derivation of the expected values and standard deviations for the variables to be estimated.

Another deviation from the model proposed by Arndt et al (2002) is the formulation of linear trends for derived model parameters which are assumed to change over time, like total factor productivity (TFP, the shift parameter of the CES production functions). In addition to adding a time-index to the defining functions for TFP (equation 2), a linear trend was imposed:

$$11. \qquad \delta_t = P\left(Z_t, B\right) = \lambda_1 + \lambda_2 t$$

Or more specifically in the case of the underlying CGE model:

$$12. \qquad ad_{A,t} = \frac{QA_{A,t}}{\left[\sum_F \delta_{A,F} QF_{A,F,t}{}^{-\rho_A}\right]^{-\frac{1}{\rho_A}}} = \lambda_1 + \lambda_2 t$$

Where ad is the shift parameter (TFP), QA is the level of activity A, QF the level of factor F demand by activity A, δ and ρ are share and shape parameters, and $\lambda 1$ and $\lambda 2$ are the linear trend parameters. Main purpose of this formulation is that it avoids that changes of GDP are mainly dumped in changes of TFP. In case projections or historical series on TFP and capital-stock growth become available for the countries included here, the trend equations will be associated with an error term.

4. Projection's Database

Projections for key variables like GDP, population growth, employment, or world-market prices are available from various organisations, often published periodically. Depending on the organisation, the projected time-frame and the considered variables usually differ. This is a particular challenge for the use of these projections for a country-wise CGE model as the economy-wide scope of such a CGE causes a need for equally comprehensive datasets. The European Commission's Directorate-General for Agriculture and Rural Development publishes medium-term projections for agricultural markets of the EU, which cover a wide range of agricultural commodities until 2015 (DG-AGRI 2009), but usually for country-aggregates like EU15, EU12, and EU2. The European Commission's Directorate-General for Economic and Financial Affairs provides detailed information on national macro-economic variables until 2011 (DG-ECFIN 2009). The most recent World Economic Outlook (WEO) by the International Monetary Fund (IMF 2009) includes projections for macro-indicators like population and GDP for 180 countries until 2014. Projections for a variety of commodity prices (agricultural and non-agricultural) until 2020 could be obtained from the Global Economic Prospects of the World Bank (2010).

This non-exhaustive outline of some available publications on economic forecasts shows that the compilation of a database of projected economic variables will have to rely on various sources.

An example for the combination of historical series and projections is given in Figure 1. Here, we combine the historical food price index by the IMF (2009) with the respective Worldbank forecasts (Worldbank 2010). In case forecasts are not available, we use trend estimates based on the historical data. A similar procedure was used for time-series on total employment. As the WEO datasets (IMF 2009) does not provide information on employment for several new Member States of the EU (e.g. Bulgaria, Rumania, or the Baltic States), we used the growth-rate of the total population to continue the series. The implicit assumption is that the share of employed population in total population is constant over time. Although this appears as a rather strong assumption, it was supported by the available time series: The coefficient of variation for the period between 1995 and 2010 ranged between 1 and 5 percentage points, with the notable exceptions of Spain, Ireland, and Cyprus, for which coefficients of variations of 9 percentage points were computed.

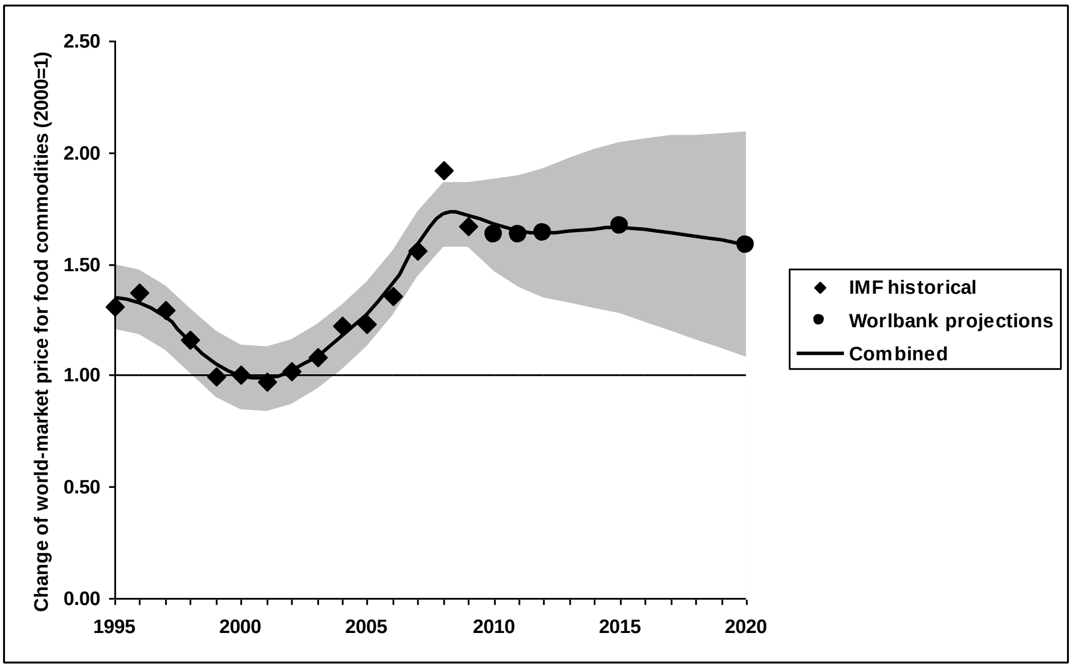
In some cases, the assumption of a trend-like behaviour of the future time series appeared as implausible, for instance in the case of foreign savings, which follow more a cyclical pattern. To avoid the creation of overly large positive or negative values in the case of "steep" trend estimates, we opted for using a five-year moving average to continue the projected series.

Historical and projected series are merged, gaps between the forecast are interpolated. To avoid strong breaks between the observed and projected series, we smooth them with a Hodrick-Prescott (HP) Filter (Hodrick and Prescott 1997), following the example of Britz (ed, 2005) for the database of the CAPRI model. The standard error (σ^{HP}) of the HP filter for the observed periods was used to determine the standard error of the target series Y in equation 10. Alternatively, the support points of the error term in equation 3 in the previous section could also be derived, e.g. by defining the outer support points as three times the standard error of the HP filter. For all periods before and including the last observation, we used σ^{HP}. For all years after the last observation, we adjust the standard deviation by the number of forecasted years (f) to permit larger deviations for years further ahead.

$$\sigma_t^Y = \begin{cases} \sigma^{HP} \quad \forall t \in T, t \leq t^{last} \\ \sigma^{HP}\sqrt{t^{last} + f} \quad \forall t \in T, t > t^{last} \end{cases}$$

The standard errors for exogenous model variables (σZ) were derived in a similar manner when projections were available. In the case of the structural parameters to be estimated, the expected value (B^E) was set to the initial value for which the models were calibrated in 2000. The standard error was derived by assuming a coefficient of variation of 10% around the expected values.

FIGURE 1: Usage of Historical Data and Projections for Commodity Prices



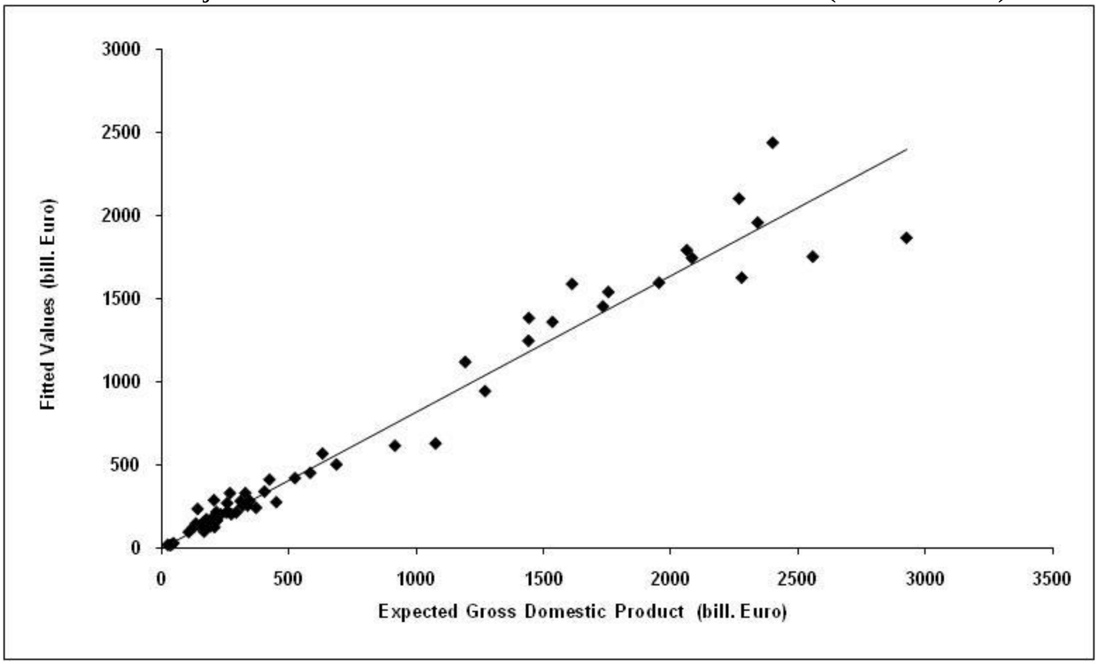
Note: The grey shaded area indicates the $\pm 3\sigma_t^Z$ range around the combined series

5. Projected and Fitted Indicators

The fitting procedure described in section 3 was applied for 15 Member States of the EU. The general idea was to approximate series of projected economic variables by changing structural parameters and exogenous variables of a CGE model (here: the IFPRI Standard Model as described in Lofgren et al 2002). In general, it is possible to permit for all structural parameters of the model to be changed, as done by Arndt et al (2002). In the presented case, we restricted the adjustable parameters to the substitution elasticity of the CES production functions, their share parameters, and the respective total factor productivities ("shift parameters"). This restriction was motivated by the need to test the behaviour of the fitting procedure and to keep the internal adjustments to the model tractable. Initially, the CGE was calibrated to a set of Social Accounting Matrices for the base-year 2000 and then fitted country-wise to projections on macro-economic indicators and prices for 2005, 2010, and 2015. Projections for GDP, total employment, and foreign savings were taken from the IMF's World Economic Outlook (WEO, IMF 2009) and projections for world market prices derived from the World Bank's Global Economic Prospects (GEP, World Bank 2010).

In the current version of the model, the approximation of the projected GDP growth rates is satisfying as the deviations between expected and fitted values are comparatively small in most cases (Figure 2). This goodness of fit is mainly due to the fact that no restrictions were imposed on most of the endogenous model variables. For instance, endowments of physical capital were assumed to grow at the same rate as GDP, but were associated with a larger variance, as no projections on this particular variable could be obtained for the full set of EU Member States for the targeted time horizon.

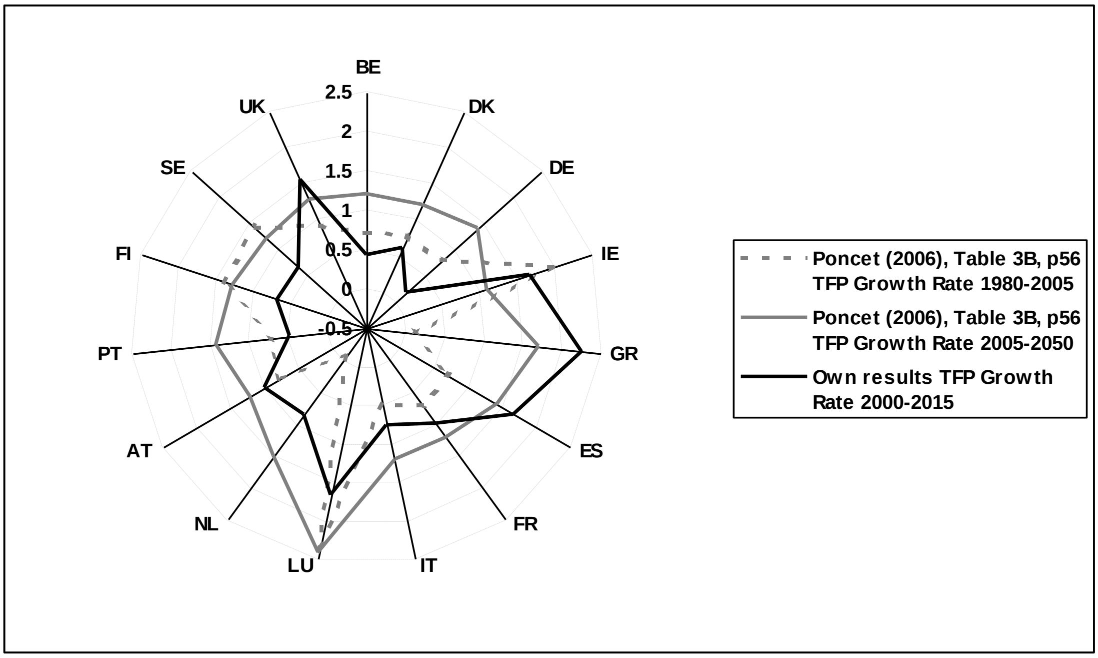
FIGURE 2: Projected and Fitted GDP for EU15 Member States (in bill.. Euro)



The small variances of the HP-filter for GDP growth, compared to the higher variances for foreign savings result in higher deviation between expected and fitted values.

To avoid that the projected GDP growth was translated into overly large and possibly fluctuating changes of the TFP parameters, a linear trend on TFP growth was imposed (see Equations 11 and 12). The resulting average annual growth rate between the base year 2000 and the target year 2015 is depicted in Figure 6 for the activity-set of the CGE used here. The EU15-average for TFP-growth in the model's agricultural activities (Cereals: A_CERE, Oilseeds: A_OILS, Other crops: A_OCRP, and Animal production: A_ANIM) range between 1% and 0.5% p.a. and are considerably lower than the estimates for TFP-growth in service-sectors like "Public administration" (A_PBAD) or "Education" (A_EDUC), which appears implausible as technical progress is public administration is not likely to be larger than in sectors of the economy dominated by private enterprises. It has to be noted that no prior information on sectoral TFP growth was used in the fitting procedure, the slope parameter of the trend functions was not constrained and deviations from an expected value were not penalized by the HPD objective function. Further screening of the relevant literature may permit to identify prior information on sectoral TFP growth rates, at least for some sectors. With regard to the economy-wide context, Poncet (2006) provides estimates for total TFP growth rates on a global scale, including historical values from 1980 to 2005 and projections from 2005 to 2050. A comparison between our results and the figures provided by Poncet (2006, Table B3, p56) is provided in Figure 3. The largest positive deviations between our results and the historical and projected values by Poncet (2006) can be observed in the cases of Greece and Spain, while our estimates for Belgium, Finland, Sweden, and Germany are clearly below the values by Poncet (2006).

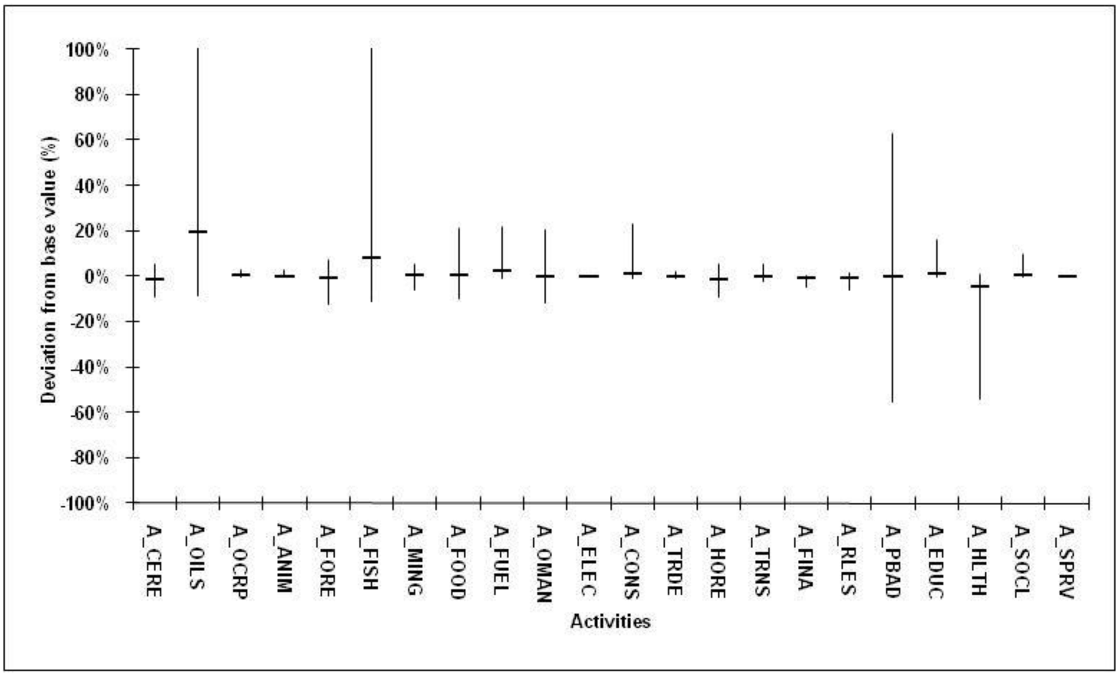
FIGURE 3: Comparison between Poncet (2006) and Own Results for Average Annual TFP Growth Rates (in %)



Note: Figures for Luxemburg refer to TFP growth 1990-2005 (Poncet, 2006, Table B2bis, p54)

An additional test for the performance of our fitting procedure is the comparison of base values for the shape parameter of the CES production functions (parameter ρ in Equation 12). Figure 4 illustrates how the proximity to indicators like GDP is compensated by larger deviations from base-values of structural parameters: although the average deviation across the included EU15 Member States lies in a narrow interval around 0% of their base values. The largest positive and negative deviations can be observed for "Production of oilseed" in DK (A_OILS, +282%) and for "Fisheries" in GR (A_FISH, +148%). In most cases, the imposed fit of model variables to the projected series on macro-indicators (Equation 3) did not translate into large adjustments of the sectoral shape parameters.

FIGURE 4: Relative Deviation of Fitted from Base Values for the Shape Parameters of CES Production Function for EU15 Member States



Note: Vertical lines indicate range between largest and smallest deviation between fitted and base values. Horizontal dashes indicate average deviations for EU15

6. Summary and Outlook

The fundamental challenge for the applied CGE baseline exercise described in this study was to obtain the needed projections in an appropriate format, for the targeted time horizon, and on national level. Projections on macro-economic variables, commodity prices, or growth rates of factor endowments and population are published by various organizations as briefly outlined in section 4. In contrast to partial equilibrium models, the economy-wide scope of CGE models creates a more extensive data demand. The compilation of an exhaustive database will be one of the next steps to develop a baseline procedure that includes all information available, including information on growth rates of TFP. Also, by now only projections on macro-economic variables have been included in the fitting procedure. Policy parameters like tax or tariff rates have been kept constant for the period from 2000 to 2015, which has to be amended. As the main objective is to analyse the effect of alternative policy scenarios and the sequence of their implementation over time, the projection database will have to be extended with information on planned or proposed policy changes.

Apart from the data-related challenges, a further step will have to be the introduction of feedbacks between investments in one period and the change of physical capital stock and the utilization of historical series on labour and capital use by economic branch. In general, the approach proposed by Arndt et al (2002) proved to be applicable for the presented case, and the change from Cross Entropy to Highest Posterior Density function could speed up the computational process, which is an important factor when fitting numerous single-country models with 22 activity and commodity accounts simultaneously to projected series.

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