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Catching up with history:
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Abstract

As a key adjunct to the process of policy formulation, market models are often called upon to quantify possible opportunities and threats. Significant improvements in computational power, database and modelling capacity contributed to a widespread usage of computable general equilibrium (CGE) frameworks in an array of policy fields. Curiously, however, in contrast to modelling efforts in, for example, the biophysical sciences, CGE model findings are seldom subjected to any systematic validation procedure. A cursory review of the literature reveals isolated single country CGE model validation exercises, although with a dearth of available data, there is a paucity of equivalent studies which implement such a procedure in a global CGE context.

This paper takes a first step in this direction by proposing a systematic methodological procedure for evaluating global CGE model performance, using a consistent macro and sectoral historical time series dataset and validation statistics taken from the biophysical literature. Focusing on sectoral output trends, the results show that model simulation performs better than extrapolation from past trends. Notwithstanding, simulation error remains high in some sectors, particularly in small economies which have undergone rapid growth. Further econometric tests reveal that simulation error is mainly caused by sector specific factors rather than country specific characteristics. The latter observation is consistent with previous research on productivity specifications in CGE models, which in concert with the validation techniques proposed in this paper, serves as a promising avenue of future research.

JEL codes

C52, D58, C68

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1 Introduction

The computable general equilibrium (CGE) approach has become a *de facto* tool of choice to quantitatively assess the economic ramifications of a (set of) policy shock(s) within a fully inclusive economic system. Indeed, demand for CGE work has been principally driven by policy orientated organisations and governments requiring detailed information on ‘how’ and ‘why’ changes in economic policy affect different sectors and actors within an economy. In response, CGE modelling as a whole has been greatly facilitated by significant advances in computing power, the adaptability and flexibility of both mainstream (i.e., GAMS, GAMS/MPSGE) and specialist (i.e., GEMPACK) software packages, open access to models and associated training (e.g., Global Trade Analysis Project - GTAP, GLOBE) and affordable availability of sophisticated databases (e.g., GTAP database). As the credibility of CGE models has steadily improved over the last two decades, this has resulted in an extensive body of CGE literature, much of which initially dealt with trade policy (e.g. Robinson et al., 1993) and market integration (Bach et al., 2000) scenarios, but has subsequently branched out into other areas of the academic literature to include (*inter alia*) tourism (e.g. Blake and Sinclair, 2003), renewable energy (e.g. Böhringer and Löschel, 2006), biofuels (e.g. Taheripour et al., 2011) and climate change (e.g. Böhringer and Rutherford, 2010).

Interestingly, Dixon and Jorgensen (2013) note that, "*Behind any policy-relevant CGE result is an enormous amount of background work on data, estimation and computation. Ideally, the result is also supported by model validation*" (pp.12). In the case of the former statement, it is beyond doubt that the level of sophistication of CGE modelling and data construction is at unprecedented levels. A cursory view of the literature, however, reveals that the issue of model validation has received relatively scant attention, whilst further reading shows that even the criterion upon which model validation should be conducted is not inherently clear. Earlier literature (McCarl, 1984; McCarl and Apland, 1986; McCarl and Spreen, 1997) draws a distinction between the validation of models by construct (i.e., theoretical rigour, model structure) and by predicted results. Unfortunately, even within these two broad definitions, McCarl (1984) observes that there remains a degree of ambiguity owing to the subjectivity of the chosen validation process; an issue which remains unresolved to this day (Bonsch et al., 2013). Thus, a model may perform well on some fronts, whilst in other areas it fails.

Consequently, McCarl (1984) takes the view that models cannot be validated *per se*, but rather 'invalidated' if they perform consistently poorly across a number of criteria.

With the widespread usage of multi-region multi-sector CGE models, there is a rapidly increasing need to provide a validation of the commonly employed 'baseline' or business as usual scenario, upon which subsequent policy analyses in areas as broad as (*inter alia*) climate change, food security and trade liberalisation, are based. This is important not only to gain greater appreciation of the need to generate better baseline forecasts, but also to enhance the credibility of commissioned quantitative economic policy evaluations as part of an integrated assessment study. This paper seeks to (ex post) validate a global CGE model, its model parameters and behavioural structure, by comparing the baseline outcomes from a global CGE simulation model with sector level historical data.

The rest of the paper is structured as follows. Section two discusses the relevant validation literature and proposes a validation method for the current study. Section three describes the CGE methodology, the measurement metrics and validation methodology. Section four presents and discusses the results. Section five concludes and provides directions for future research.

2 Background

Two approaches to validate CGE models have been used in the literature. First, what we term the 'partial' approach, which focuses on how well the model is able to deal with price shocks. In this approach, the price fluctuations of a single commodity projected by the model are compared with real world patterns. Typically, commodities are selected that exhibit high price volatility due to supply and demand shocks, such as agricultural products. As a first step, time series analysis is used to estimate the distribution of production shocks that are caused by random events for each region in the model. Subsequently, the observed pattern is mimicked by the model by introducing productivity shocks using stochastic simulation. Finally, the real world variance in commodity prices is compared with the variance in prices that result from the model. Employing the GTAP model, both Valenzuela et al. (2007) and Beckman et al. (2011) employ this technique to examine volatility in wheat and petroleum markets, respectively. Interestingly, both papers report that the model understates real world impacts. The authors argue that this can be (partially) remedied by modelling real world institutional arrangements (in case of wheat) or improving the parameterisation within the production nests (in case of petroleum).

The second approach is referred to as the ‘historical’ approach (Dixon and Rimmer, 2010, 2013). This approach relies on historical simulations to validate single-country CGE models with a view to improving the credibility of the model baseline. Firstly, a historical simulation is run where the model is calibrated using secondary data sources of actual movements in prices and quantities for consumption, exports, imports, government spending disaggregated by commodity, changes in employment, investment and capital stocks disaggregated by industry. By treating this information as exogenous, changes in consumer preferences and technologies (i.e. factor augmenting technical change) become endogenous and can be quantified. Secondly, it is assumed that calibrated changes in preferences and technologies from past time periods accurately reflect future developments, which are therefore used as exogenous variables in a forecast simulation. Together with projections for a number of aggregate macro-level variables such as total consumption and GDP, forecasts are made at the detailed industry level (e.g. production, capital, labour, imports and exports) as well as consumption and government spending. Finally, the model results are compared with actual data for the forecast simulation period. By successively introducing the ‘real’ pattern of exogenous variables (e.g. macro variables, trade and tariffs, technology and preferences) the impact of different exogenous factors on the forecast can be measured.

Dixon and Rimmer (2010) applied the method to a recursive dynamic 500-industry CGE model of the USA (USAGE). Using uniform weights for all commodities they found a mean absolute error of 19 per cent between the model forecast and the actual percentage change of output. Although the number seems high, the study revealed that the USAGE forecasts were still almost twice as good as a simple extrapolation of past trends. Using information on past trends to predict future development is the most basic approach to forecasting and helps put model results into perspective.

Other historical approaches to validate single country CGE models (Kehoe et al., 1995; Kehoe, 2003) do not include a calibration step, but rather focus exclusively on model performance. More recent single country studies (Hong et al., 2014) follow this same path, but take an additional step in seeking to remedy simulation error by refinements to the treatment of different sectors/activities over time.

The methodology to validate the multi-country multi-sector approach in this paper resembles the historical approach applied by Dixon and Rimmer (2010). However, in contrast to their approach and following Kehoe et al. (1995), Kehoe (2003) and Hong (2014) we also omit the calibration stage whilst focusing on comparing the outcomes of an existing model with historical data. The reason for this is that calibration of a multi-country, multi-sector model on historical data requires an enormous amount of internationally comparable and consistent data for all regions in the model, which are simply not available. It is precisely for this reason that CGE models with global coverage rely on econometric estimates and calibration procedures to set price elasticities, technology shifters and consumer preferences.

3 Data and Methodology

3.1 Economic simulation Model

In this study, a sophisticated variant of the Global Trade Analysis Project (GTAP) model (Hertel and Tsigas, 1997) is employed, known as the Modular Applied GeNeral Equilibrium Tool (MAGNET – Woltjer and Kuiper (2013)). MAGNET is a neo-classical recursive dynamic multi-sector, multi-region computable general equilibrium (CGE) model that has been widely used to simulate the impacts of agricultural, trade, land and biofuel policies on global economic development (Banse et al., 2011; Francois et al., 2005; Rutten et al., 2013, 2014). The model is calibrated upon an input-output structure that explicitly links industries in a value added chain from primary goods, over continuously higher stages of intermediate processing, to the final assembling of goods and services for consumption. In common with the standard GTAP model, economic behaviour is 'demand' driven, with behavioural equations characterised by multi-stage neo-classical optimisation to segregate factor, intermediate and final demands into 'nests'. Producers are perfectly competitive and exhibit constant returns to scale technology. Once an endogenous/exogenous variable split is determined (model closure), exogenous policy shocks catalyse an interaction between economic agents, subject to a series of accounting identities (i.e., zero normal profits, Keynesian macro conditions) and market clearing equations (i.e., supply equals demand), which ensures a new equilibrium ('counterfactual'). Medium to long run baselines are obtained by calibrating the model to exogenous macro assumptions of expected GDP and population growth (the latter serves as a proxy for employment growth). The main output of MAGNET is a set of economic indicators that describe the development of the global economy, including sectoral growth, employment, (food) consumption, prices and trade.

The simulation model is calibrated to an associated GTAP database replete with information on national economic accounts, gross bilateral trade flows, associated transport costs and trade protection data. For the validation exercise version six of the GTAP global database was employed, encompassing 87 regions, 57 commodities and benchmarked to 2001 (Dimaranan, 2006). This version was favoured because it covers a relative large number of countries and starts from a point in time (i.e. 2001) considered sufficient to carry out a validation based on historical observations. The database was aggregated to 38 regions – 30 of which correspond to the countries for which we have validation data (see below) and 8 aggregate regions (e.g. Latin America, Africa and Asia) for which there is no historical information. The sectors were aggregated to 22 sectors to match up with the historical data (see below).

3.2 Model validation statistics

In contrast to the economic literature, in the biophysical literature there are many validation studies of hydrological (Legates and McCabe, 1999), crop (Yang et al., 2014) and climate models (Reichler and Kim, 2008). A number of evaluation statistics have been developed that are commonly applied to evaluate and compare the 'goodness-of-fit' of such models. These can equally be applied to validate and compare the results of economic models with actual information on economic variables. Wilmott et al. (1981; 1985) provide overviews of the various statistics that are commonly used in the literature to measure simulation error (i.e. the difference between model simulation results and actual observations). Conventional measures such as the root mean squared error, Pierson's correlation coefficient and the coefficient of determination (R^2), are still regularly used for model validation. Nonetheless, it has been argued that they are poor measures of model performance because they are oversensitive to extreme values (outliers) and are insensitive to additive and proportional differences between simulated values and observations (Legates and McCabe, 1999; Willmott, 1982). For this reason a number of additional measures have been developed in the literature that are commonly used in model validation exercises.

The *mean absolute error (mae)* is the average absolute difference between the simulated (*S*) and observed (*O*) value for each observation (*i*) and can be written as:

$$mae = \frac{1}{N}\sum_{i=1}^{N}|S_i - O_i| \tag{1}$$

The mae is a dimensioned measure, which ranges from 0 to infinity, and therefore cannot easily be used to compare across different models and datasets. To accommodate this issue two dimensionless measures are proposed in the literature. First, the *modified index of agreement (md),* developed by Wilmott et al. (1985), which is defined as:

$$md = 1 - \frac{\sum_{i=1}^{N} |S_i - O_i|}{\sum_{i=1}^{N} \left(|S_i - \bar{O}| + |O_i - \bar{O}| \right)} \tag{2}$$

The denominator in the equation – the sum of the absolute distance from the simulated value to the observed mean value ($\bar{O}$) to the observed value – is a measure of the 'potential error', which represents the largest value that $|S_i - O_i|$ can reach for each model simulation-observation pair. For this reason, the *md* always lies between 0 and 1, with higher values indicating a better correspondence between model results and observations. Second, the *modified Nash-Sutcliffe efficiency (mNSE),* also sometimes referred to as the *coefficient of efficiency* or *modelling efficiency*, was developed by Legates and McCabe (1999) but based on earlier work by Nash and Sutcliffe (1970):

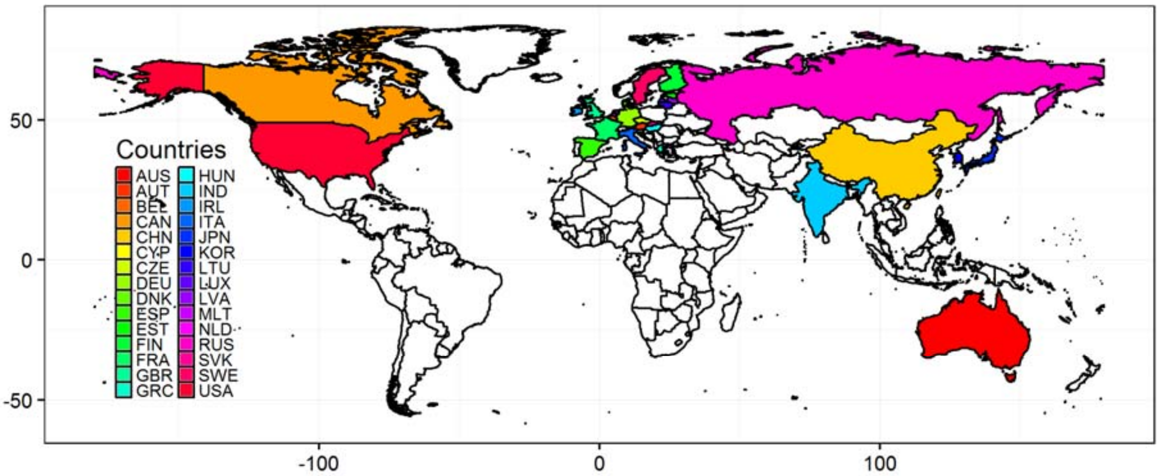
$$mNSE = 1 - \frac{\sum_{i=1}^{N} |S_i - O_i|}{\sum_{i=1}^{N} |O_i - \bar{O}|} \tag{3}$$

The mNSE ranges from minus infinity to 1, with higher values pointing at a better agreement between model results and observations. The mNSE is particularly advantageous since it compares if the simulated value is a better predictor than the observed mean value. If the mNSE becomes 0, the observed mean is as good a predictor as the model because the absolute distance between simulation-observation and observation-mean observation are the same. If the mNSE is negative the observed mean is a better predictor than the model.

3.3 Validation data and approach

To validate the model results, we constructed a database that contains historical observations for 30 countries marked in colour in Figure 1. For European countries (and several OECD countries), the EU KLEMS growth and productivity accounts database produced by the Groningen Growth and Development Centre (O'Mahony and Timmer, 2009) is employed. The EU KLEMS data includes indicators for economic growth, productivity, employment creation, capital formation and technological change at the detailed sector level for the period 1970-2007. Additional information for Canada, China, Japan, India and Russia is taken from the WORLD KLEMS database (www.worldklems.net), which provides comparable data. To generate a sectoral concordance between the GTAP and KLEMS datasets, we grouped the GTAP data into 22 activities (see Annex A). The database includes the largest economies in the world as well as the most important emerging economies (Russia, China and India). We are therefore able to validate the extent to which our model is able to simulate the world economy at large. Unfortunately, there is no detailed sectoral historical data available for neither the developing countries, nor for Africa and Latin America.

Figure 1: Country coverage



To keep the analysis tractable and similar to Dixon and Rimmer (2010), the validation exercise focuses on developments in sectoral output (in constant prices). This is a key indicator in CGE analysis when assessing the implications of policy shocks relating to trade, agricultural policy and biofuels.

To project the model towards 2007, we use historical information on GDP and population growth for the period 2001-2007. In order to ensure consistency at the macro-level, developments in GDP (total value added) and total labour growth are taken from our historical database for our 30 target countries. For all other regions in MAGNET, data for the macro-drivers is taken from the World Development Indicators (WDI) database (http://data.worldbank.org/data-catalog/world-development-indicators). Finally, we compare and analyse the differences in sectoral output growth from MAGNET and the historical observations using the validation statistics described above as well as a regression analysis.

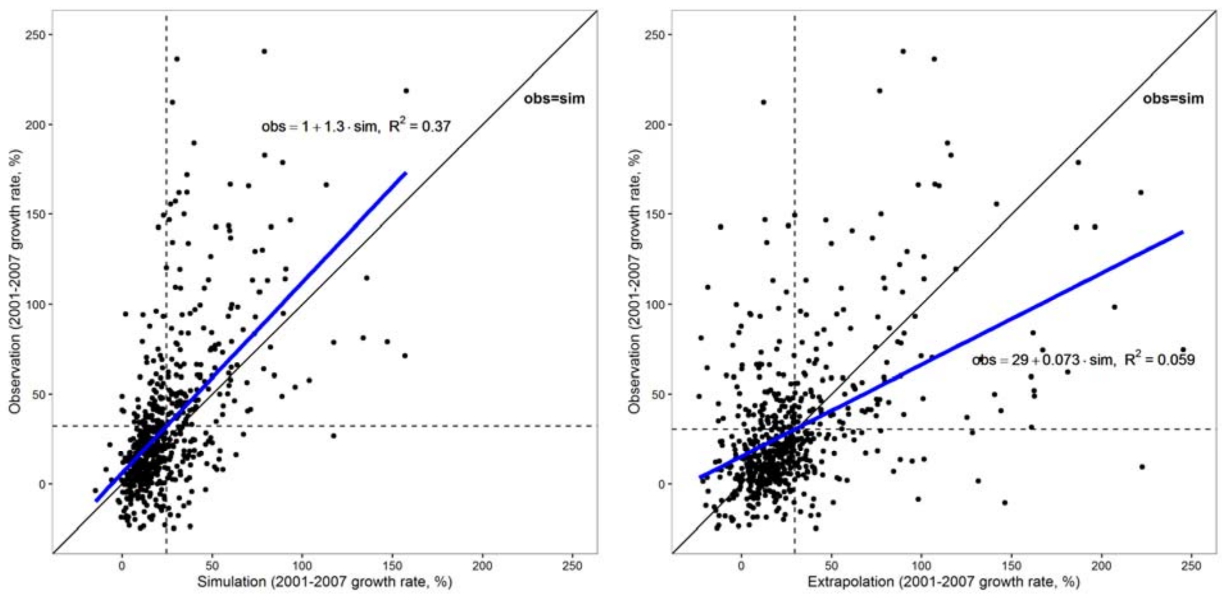
4 Results

4.1 Model validation statistics

Figure 2a compares the observed historical sectoral output growth rates with those of the model simulation. The figure also includes the 45 degree line which indicates a perfect fit and a simple linear regression between observed and simulated values. The figure shows that for growth rates between approximately 0% and 25%, model outcomes and observations are located around the 45 degree line, suggesting a reasonable fit. It seems that the model is not able to deal adequately with the extreme growth rates. For example, several sectors exhibited negative growth between 2001 and 2007, while the model projects (relative low) positive growth rates. In fact, only in 9 cases does the model produce a negative rate of growth. Similarly, a number of sectors exhibit considerable expansion over the studied period, sometimes reaching more than 200 percent, whereas the model only presents growth rates of over 100 per cent for a few sectors. The consistent bias between the simulated and observed growth rates is illustrated by the regression line which has a slope of more than one.

Figure 2: Comparison between observed and simulated values

(a) Observation versus simulation (b) Observation versus extrapolation



Note: A small number of values larger than 250% are not depicted. The dotted lines represent the sample averages. The blue line represents an ordinary least squares (OLS) between simulated (model and trend extrapolation) and historically observed growth rates at the sector level.

Similar to Dixon and Rimmer (2010), Figure 2b provides a comparison between observed growth rates and the extrapolation of the historical trend on the basis of all available historical data up to and including the base year 2001, using a linear regression of output (in log) on time – the most simple approach for making projections when no more information is available.[1] The figure and regression clearly demonstrate that past growth rates are a very poor indicator of future growth, confirming the need to use models or other advanced approaches to make forward projections.

Table 1 presents the various model validation statistics that are explained above for both the comparison between observed and simulated values, and observed and extrapolated values. For reference, two conventional validation statistics are added (the root mean squared error (rmse) and the R^2). In line with Figure 1, all statistics reveal that the model results are superior to trend extrapolation when projecting actual observations. This is confirmed by a t-test, using bootstrapped standard errors, which shows that the validation statistics for model simulation are statistically different from those for the extrapolation. The mae for the model results is 24% while, with 44%, it is more than double for the trend extrapolation, which is very similar to the results of Dixon and Rimmer (2010). Similarly, the md and mNSE are much higher for the simulated values. Nonetheless, both indicators suggest that the model fit is far from perfect. The md is only 0.54, so only halfway between a very poor and a very good fit; whilst the nME is 0.26, which although far from a perfect score of 1, it is still better than the simple average (value of 0 or lower).

Table 1: Model validation statistics

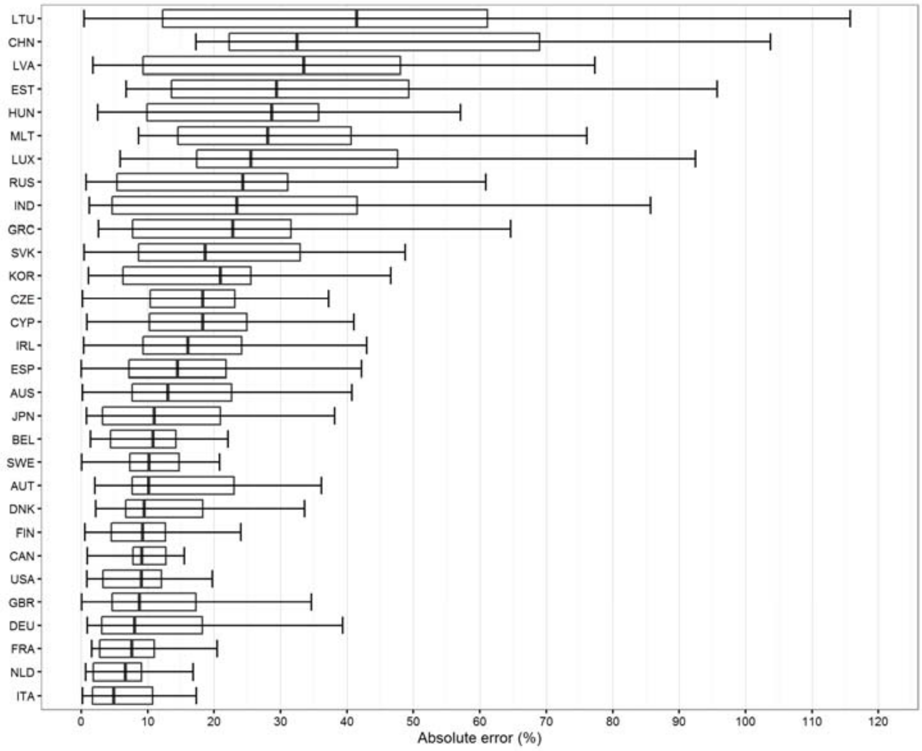
Name	Observed	Simulation	Extrapolation	t-test for (in)equality
Summary statistics				
Mean growth (%)	33	25	48	-
Standard deviation of growth	49	24	164	-
Validation statistics				
mae (%)	-	24***	44***	***
md	-	0.54***	0.42***	***
mNSE	-	0.26***	-0.38***	***
rmse	-	40***	157***	***
R^2	-	0.37***	0.06***	***

Note: Validation statistics are based on a comparison with the observed growth rates. All statistics are based on a bootstrap of 5000 replicates. *** indicates that the validation statistic is statistically different from zero or, in case of the t-test, that the means of the validation statistic for the simulation and extrapolation are not equal, both at the 1% level.

So far, we have only validated overall model performance, looking at observations for all sectors and countries simultaneously. However, CGE models are often used to assess the future growth of a selection of sectors or regions. It is therefore interesting to evaluate the model performance at a more disaggregated level. The boxplots in Figures 3 and 4 present the median absolute error and its distribution within countries and across sectors, respectively.

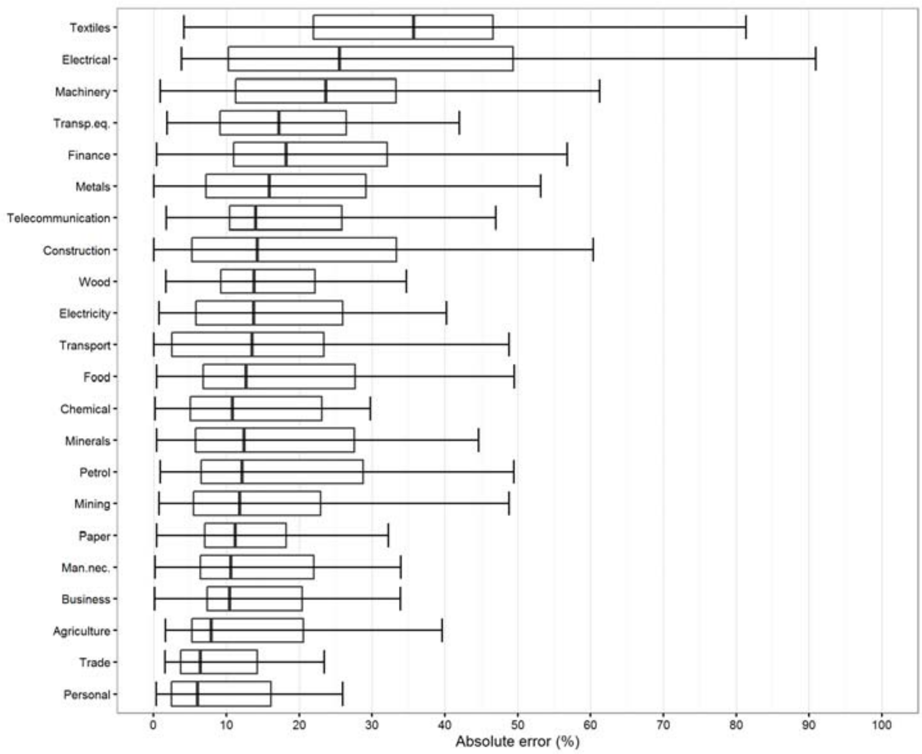
[1] Historical data availability differs per country. The first year data is available differs between 1970 and 1995. The trend extrapolation is based on all available data up to and including 2001.

Figure 3: Distribution of absolute error by country



Note: Countries ranked by median absolute error.

Figure 4: Distribution of absolute error by sector



Note: Sectors ranked by median absolute error.

Both figures clearly show considerable differences in the absolute error across countries and sectors. For about 10 countries the model fit is relatively good with a median absolute error of around 10% and quartiles between 0% and 20%, while for the rest of the countries the dispersion around the median is much higher. In particular the results for Estonia, Lithuania and China are very poor. A similar pattern is observed at the sectoral level although the differences between sectors are somewhat smaller while the spread around the median is larger. For the personal and trade sector, the model projections are relatively good as indicated by a low median absolute error and quartile range between 0% and 20%, while the electrical and textiles sectors exhibit large median absolute error and variance.

4.2 Towards explaining the simulation error

4.2.1 Potential causes

An examination of the results shows a degree of error between the model simulation and the historical trends. A number of causes might be responsible for the deviation between model results and actual data.

Firstly, it is clear that mathematical market models are not equipped to predict unforeseen economic shocks (i.e. oil price hikes, financial crisis, conflict zones and trade embargoes) at the national and sector level or indeed anticipate the variance of sectoral performance indicators (e.g., output) in regions which surpass (e.g., China), or fall short, of forecasted expectations.[2] Moreover, it is well-known that developing countries exhibit more volatile growth patterns than advanced countries because of domestic social conflict and weak institutions (Pritchett, 2000; Rand and Tarp, 2002; Hausmann et al., 2005) or, in the case of small countries, due to volatility in their terms of trade (Easterly and Kraay, 2000; Guillaumont, 2010). We therefore expect to find a positive correlation between the simulation error and income per capita and a negative relationship with the size of the economy.

Secondly, in the search for greater credibility, great lengths have been taken within the CGE literature to more adequately capture the 'real world' functioning of market interventions and rigidities in the areas of (*inter alia*) agricultural policy (Boulanger and Philippidis, 2015), climate change (Antimiani et al., 2015), bioenergy markets (Banse et al., 2011), and firm heterogeneity (Waschik, 2015). On the other hand, the computational cost and additional data

[2] Note that we calibrate the model using observed historical macro data. Simulation error in our exercise is therefore not caused by poor macro-level projections. Nonetheless, CGE models are built on input-output tables that represent the structure of the economy and assume perfect market conditions. If economic shocks cause structural change or market distortions, this will result in simulation error even if the model is calibrated on observed macro projections.

demands often required to support state-of the-art modelling is high. As a consequence, simulation error will always exist within global CGE models owing to untreated policy interventions (Baldos and Hertel, 2013), or indeed, a failure to explicitly treat complex collusive (i.e. oil cartels) or geo-political (i.e., import bans) strategic behaviour which characterises real world markets.

Thirdly, whilst the ‘nesting’ complexity of technical constraints in CGE models in response to price changes has improved significantly, sectoral technological change is still typically reliant on a top-down *ad hoc* assignment of growth rates (either uniform or weighted). This approach, although flexible, makes the strong assumption that ‘relative’ technological progress across industries remains fixed, and therefore does not allow for rapid start-ups (i.e., silicon valley) and boom and bust cycles that characterise capital intensive sectors such as the paper (Dijk van, 2003) and steel industry (Gallet, 1997). In addition, in our specific modelling exercise Hicks-neutrality has been assumed, adding another structural bias in that there is no margin for input or factor saving technological changes. For example, the increased capitalisation in manufacturing (e.g., car construction) is not treated within the analysis.

A fourth factor is the total absence of money markets, where speculative financial considerations and absolute price levels (i.e., inflation) can have marked impacts on decision making behaviour, economy-wide expectations and macroeconomic policy. This general observation gives rise to the treatment of investment expectations in global CGE (e.g. Lakatos and Walmsley, 2012). Whilst undoubtedly a step in the right direction from the ‘static’ approach, the recursive dynamic treatment typically found in global CGE characterisations assumes that investment decisions are solely based on past and current experience, whilst there is relatively little attention paid to future expectations or the perception of risk, which are central to real world agent behaviour.

A final area of bias is due to the underlying data sources employed. It is certainly true that the GTAP database is unprecedented in terms of its coverage of sectors and regions. Notwithstanding, to keep this dataset relevant requires relatively up to date national input-output (IO) tables, either from national statistical offices, or contributed by researchers within the GTAP network. The inevitable result is that the technical coefficients for some regions exhibit bias owing to different levels of rigour in terms of data construction, sectoral coverage and availability of benchmark years, which could be exacerbated when implementing medium to long run baselines. A related point is the parameterisation of CGE models, where the response of agents to price changes is conditioned by invariant elasticities of substitution which either reflect current ‘expert judgement’ or are estimated from a specific time series dataset. In either case, such behavioural parameters are deemed less representative as one projects further into the future. Apart from the GTAP database and model parameters, there also might be errors in the construction of the historical data, which, for some sectors and countries, also need a number of assumptions and interpolations (Timmer et al., 2007).

4.2.2 Country-sector case studies

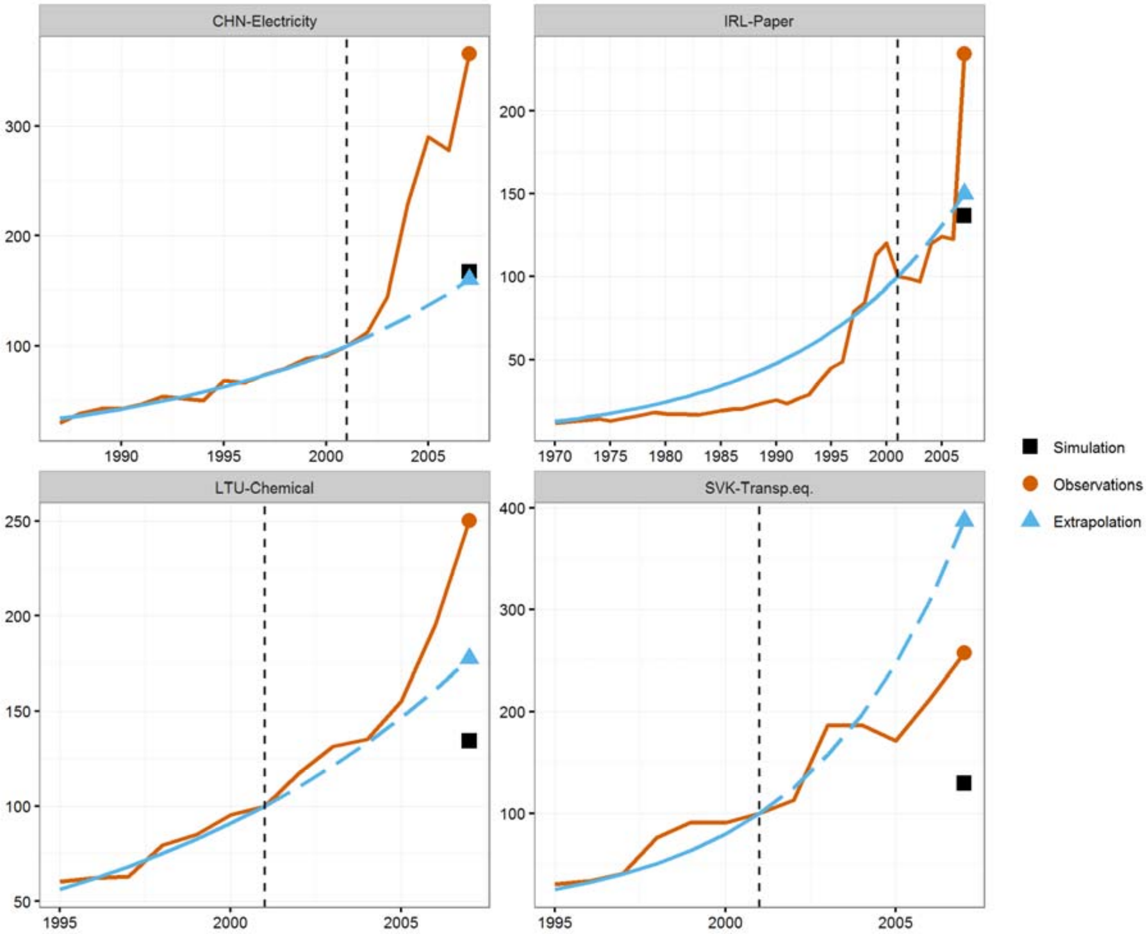
To better understand the bias between model simulation and historical data, we start by analysing the historical growth pattern and simulated growth rates of observations with the largest absolute error. We visually inspected all 30 sector-country combinations with an absolute error of more than two standard deviations from the mean and selected four cases that present distinct but typical examples of industrial growth. Figure 5 presents historical growth rate and simulated growth rate for the four country-sector case studies, expressed as an index number (2001=100). For comparison, we also included the same output-time trend extrapolation that is presented in Figure 2b and Table 1.

The Figure shows that the model is not able to anticipate the extreme growth of the Electricity sector in China (CHN-Electricity) that occurred after 2001. The growth acceleration was also much higher than the exponential trend growth predicted by the trend extrapolation line, which result in an equally poor fit. This pattern is typical for several Chinese sectors, explaining the large absolute error for China in Figure 3.

The paper sector in Ireland (IRL-paper) is an example of volatile industrial growth, characterised by a cyclical pattern of boom and bust. Both the model and the trend extrapolation are not able to capture the volatile industry dynamics.

The chemical sector in Lithuania (LTU-Chemical) and the transport equipment sector in Slovakia (SVN-Transport.eq.) are examples of industrial development in small Eastern European countries that experienced structural change following accession to the European Union (Crespo and Fontoura, 2007). It seems that for this group of countries (also including Estonia, Latvia and Hungary – Figure 3), our model is performing poorly. The chemical sector in Lithuania exhibits a growth explosion starting from 2005, which is not anticipated by the model and is higher than the projected exponential growth rate. The transport equipment sector in Slovenia shows a more or less linear growth pattern, which is underestimated by the model and overestimated by the trend extrapolation.

Figure 5: Case-studies



Note: Model base year is 2001. Extrapolation for the period 2001-2007 based on all available data before and including base year 2001. Data availability differs per country.

4.2.3 Multi-level analysis

In this section, we explore the potential causes of the simulation error described above by means of multi-level analysis. The multilevel regression model (also known as the random coefficient model, generalised linear mixed model (GLMM) and hierarchical model), is designed to analyse grouped and hierarchically structured (i.e. nested) data that are characterised by one single outcome variable, measured at the lowest level, and explanatory variables at all other levels (Hox, 2010; Snijders and Bosker, 2012). In contrast to OLS, it specifically accounts for the fact that observations which belong to the same group are more similar to each other (within group variance) than observations that belong to different groups (between group variance).

The multi-level model is particularly suited to analyse the simulation error (measured by the absolute error), which is determined by sector-level factors (e.g. technical change) as well as country-level factors (e.g. national policies) that are expected to have an impact on the growth of all sectors. Multilevel modelling is extensively used in ecology (Zuur et al., 2009) and social and behavioural science (Tashakkori and Teddlie, 2003) and has also recently become popular in environmental and agricultural research (e.g. Reidsma et al., 2007; Neumann et al., 2011).

We applied the following multilevel regression model, which distinguishes two levels; the country (group) level (subscript *c*) and the sector (individual) level (subscript *s*):

$$Y_{sc} = \beta_{0c} + \beta_{1c}X_{sc} + \beta_2 Z_c + U_{0c} + R_{sc} \tag{4}$$

The independent variable Y_{sc} is the absolute error. As the distribution of the absolute error is both truncated at zero and highly skewed towards lower values, we take the natural log to ensure a normal distribution. X_{sc} are the independent variables at the sector level and Z_c are independent variables at the country level. U_{0c} is the random error term at the country level and R_{sc} the random error term at the sector level. Both errors have a mean zero and are mutually independent. We estimate the regressions coefficients β_{0c}, β_{1c} and β_{2c} using restricted maximum likelihood (REML) (McCulloch et al., 2001; Snijders and Bosker, 2012).

The model specification considers four macro- and three sectoral independent variables. The macro determinants are *GDP per capita* as a proxy for the development level of the country; *GDP* (in log) as an indicator for the size of the economy; *GDP growth* over the period 2001-2007 to proxy for (exceptional) rapid growth or decline of the economy; and to capture data quality, *IO age*, the age of the input-output table in our model measured by the difference between the reference year of the table and the base year. The sectoral variables are the size of the sector in the economy (*(Sector size* in log) measured as the share in total output; Labour productivity growth (*LP growth*), measured as the average growth rate for the period 2001-07 as a proxy for technical change; and *Volatility* measured as the standard deviation of the output growth.[3] Finally, dummies are added to capture sector specific characteristics that might cause simulation errors. Annex B presents information on data sources and descriptive statistics.

Table 2 presents the results of the analysis. For comparison, we also applied a fixed effects model and OLS. Similar to the multi-level model, the fixed effects model controls for group

[3] This indicator is also frequently used to analyse macro-economic volatility (e.g. Malik and Temple, 2009).

effects but assuming they are non-random. A disadvantage of this approach is that all higher level determinants that are constant within groups are ‘dropped’ from the analysis, such as the macro-economic variables that are relevant for our analysis.

Table 2: Multi-level, fixed effects and OLS analysis

	Dependent variable: ln(ae)		
	Multi-level	**Fixed**	**OLS**
Constant	2.400***	-	2.600***
GDP per capita	-0.016*	-	-0.016*
ln(GDP)	-0.039	-	-0.039
GDP growth	0.008**	-	0.010**
IO age	0.020	-	0.020*
ln(Sector size)	-0.092**	-0.160**	-0.150**
LP growth	0.060***	0.049***	0.050***
Volatility	0.045***	0.037***	0.039***
Sector dummies	No	Yes	Yes
var($\boldsymbol{U_{0c}}$)	0.03 (2%)	-	-
var($\boldsymbol{R_{sc}}$)	1.24 (98%)	-	-
var($\boldsymbol{U_{0c}}$)+var($\boldsymbol{R_{sc}}$)	1.27 (100%)	-	-
Observations	611	611	611
R^2	-	0.18	0.32
Adjusted R^2	-	0.17	0.28
Log Likelihood	-960.000	-	-
AIC	1,941.000	-	-
BIC	1,985.000	-	-
F Statistic	-	5.300*** (df = 24; 559)	9.700*** (df = 28; 582)

Note: *p<0.1; **p<0.05; ***p<0.01; IO age is missing for two countries and for some sectors historical information is missing resulting in a lower number of observations.

The findings are largely in line with our expectations. At the macro-level, the absolute error is significantly higher for low income and rapidly growing countries. Although the sign of *ln(GDP)* and *IO age* are in the right direction, we do not find a significant relationship for the size of the economy and the age of the input-output tables with respect to the absolute error. At the sector-level, we find that the simulation error is larger for small sectors with rapid technological change and volatile growth patterns. The multi-level model shows that only 2% of the variance of the absolute error is due to country level factors, while the remainder is related to sector-specific determinants. This indicates that the differences in the absolute error between sectors within a country are much larger than (average) differences between countries. Thus, sector specific factors, rather than country characteristics are the main cause of the absolute error.

The results are robust to model specification as all three models provide very similar results. Nonetheless, the model diagnostics (large share of (adj.) R^2 of between 0.32 and 0.31) indicate that the models are only able to explain a relative small part of the simulation error. It is envisaged that model specific factors, as alluded to in section 4.2.1. (e.g., nest structures, behavioural parameters and market failures), and which are not treated explicitly in the statistical models, play a key role in explaining much of the remaining error.

5 Conclusions

The computable General Equilibrium (CGE) model has become a standard tool of choice for impact assessment and foresight studies for many policy and academic institutions. However, a clear validation procedure for these models is sorely lacking. In part, this is owed to a lack of clarity on the best systematic validation approach, whilst unlike single country CGE models which employ the historical approach when calibrating appropriate shocks for generating credible baselines (e.g., Dixon and Rimmer, 2010), the application of such an approach to global CGE models requires a level of data which is not available.

With this limitation in mind, the current approach does not attempt calibration, but rather focuses on developing a systematic methodological procedure for evaluating model performance using detailed macro and sectoral historical time series and a selection of recognised model validation statistics taken from the biophysical literature.

An appealing feature of this study is that the techniques employed could easily be generalised to compare different model frameworks, or different variants of a standard model representation (either resulting from different parametric choices, and/or different modelling assumptions). A limitation encountered, however, is that owing to scarcity of data, the analysis was restricted to developed countries and a selection of developing countries. Thus, to broaden the appeal of this approach, future resources would be required to provide a broader geographical panel of data to encompass lower income countries.

An underlying, and encouraging, result is that when comparing actual data observations of real sectoral output across 22 activities and 30 countries with simulation results, the simulation model is found to perform better than extrapolation from past trends due to its ability to capture the economic structure of the countries under consideration. This clearly vindicates the need to employ models for foresight studies.

There remain, however, significant differences between simulation outcomes and actual data. These differences can be attributed to a number of key factors. Firstly, CGE models do not capture the stochastics of unforeseen events (e.g., climatic, political etc.), the complexities of real markets and institutional arrangements and the nature of human behaviour under uncertainty. Moreover, bias inevitably arises because of imperfect data quality of input-output tables, large uncertainties about the right parametrization, the modelling of production structure and technological change, modelling of consumption dynamics and other uncertainties on the structure of the economy and parametrization.

Econometric tests examining sectoral and regional performance reveal a high degree of heterogeneity in simulation error. In particular, it is statistically observed that model predictions suffer in cases where economies have experienced rapid growth and the model subsequently fails to predict the disperse nature of the output trends. Another and even more important cause of the simulation error is the specificities inherent within individual sectors (i.e., size of the sector, rapid technical change and volatility) that are not captured adequately by the model. Unexplained errors are mainly related with sector specific factors in contrast with country characteristics.

In terms of future avenues of research, whilst there will always be data quality issues when servicing global modelling endeavours, the current paper presents statistical evidence on the need to keep this bias to a minimum. On the issue of sector specific simulation error, attempts to compensate, through a re-parameterisation of the model’s behavioural elasticities (i.e., Valenzuela et al., 2007; Beckman et al., 2011) has had some degree of success. Finally, an alternative, and promising strand of literature, seeks to minimise this simulation error through improved total factor productivity (TFP) shocks (Kehoe, 2005), whilst more recent attempts (Hong et al., 2014; Smeets Kristkova et al., 2016) further enhance the treatment of (factor augmenting) technological change through endogenous links to research and development. These studies reveal tangible improvements in model fits, which if combined with the validation methodology outlined in this paper, could be generalised within a global CGE framework to greatly reduce simulation error.

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Annex A: GTAP-KLEMS sector mapping

Sector	GTAP code	GTAP description	KLEMS code	KLEMS description
Agriculture	pdr	Paddy rice	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	wht	Wheat	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	gro	Cereal grains nec	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	v_f	Vegetables, fruit, nuts	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	osd	Oil seeds	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	c_b	Sugar cane, sugar beet	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	pfb	Plant-based fibers	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	ocr	Crops nec	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	ctl	Bovine cattle, sheep and goats, horses	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	oap	Animal products nec	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	rmk	Raw milk	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	wol	Wool, silk-worm cocoons	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	frs	Forestry	AtB	Agriculture, Hunting, forestry and fishing
Agriculture	fsh	Fishing	AtB	Agriculture, Hunting, forestry and fishing
Mining	coa	Coal	C	Mining and quarrying
Mining	oil	Oil	C	Mining and quarrying
Mining	gas	Gas	C	Mining and quarrying
Mining	omn	Minerals nec	C	Mining and quarrying
Food	cmt	Bovine meat products	15t16	Food products, beverages and tobacco
Food	omt	Meat products nec	15t16	Food products, beverages and tobacco
Food	vol	Vegetable oils and fats	15t16	Food products, beverages and tobacco
Food	mil	Dairy products	15t16	Food products, beverages and tobacco
Food	pcr	Processed rice	15t16	Food products, beverages and tobacco
Food	sgr	Sugar	15t16	Food products, beverages and tobacco
Food	ofd	Food products nec	15t16	Food products, beverages and tobacco
Food	b_t	Beverages and tobacco products	15t16	Food products, beverages and tobacco
Textiles	tex	Textiles	17t19	Textiles, textile products, leather and footwear
Textiles	wap	Wearing apparel	17t19	Textiles, textile products, leather and footwear
Textiles	lea	Leather products	17t19	Textiles, textile products, leather and footwear
Wood	lum	Wood products	20	Wood and products of wood and cork
Paper	ppp	Paper products, publishing	21t22	Pulp, paper, paper products, printing and publishing
Petrol	p_c	Petroleum, coal products	23	Coke, refined petroleum products and nuclear fuel
Chemical	crp	Chemical, rubber, plastic products	23t25	Chemical, rubber, plastics and fuel products
Minerals	nmm	Mineral products nec	26	Other non-metallic mineral products
Metals	i_s	Ferrous metals	27t28	Basic metals and fabricated metal products
Metals	nfm	Metals nec	27t28	Basic metals and fabricated metal products
Metals	fmp	Metal products	27t28	Basic metals and fabricated metal products
Transp.eq	mvh	Motor vehicles and parts	34t35	Transport equipment
Transp.eq	otn	Transport equipment nec	34t35	Transport equipment
Electrical	ele	Electronic equipment	30t33	Electrical and optical equipment
Machinery	ome	Machinery and equipment nec	29	Machinery, nec
Man.nec	omf	Manufactures nec	36t37	Manufacturing nec, Recycling

Electricity	ely	Electricity	E	Electricity, gas and water supply
Electricity	gdt	Gas manufacture, distribution	E	Electricity, gas and water supply
Electricity	wtr	Water	E	Electricity, gas and water supply
Construction	cns	Construction	F	Construction
Trade	trd	Trade	G	Wholesale and retail trade
Transport	otp	Transport nec	60t63	Transport and storage
Transport	wtp	Water transport	60t63	Transport and storage
Transport	atp	Air transport	60t63	Transport and storage
Telecommunication	cmn	Communication	64	Post and telecommunications
Finance	ofi	Financial services nec	J	Financial intermediation
Finance	isr	Insurance	J	Financial intermediation
Business	obs	Business services nec	71t74	Real estate, renting and business activities
Personal	ros	Recreational and other services	LtQ	Community social and personal services
Personal	osg	Public Administration, Defense, Education, Health	LtQ	Community social and personal services
-	dwe	Dwellings	NA	NA

Source: Timmer et al. (2007) and GTAP database (https://www.gtap.agecon.purdue.edu).

Annex B: Summary statistics

Statistic	Description	N	Mean	St. Dev.	Min	Max
ae	Absolute value of the difference between simulation output growth and observed output growth over the period 2001-2007.	611	23.00	30.00	0.021	247.00
GDP	Gross Domestic Product in the 2001 on the basis of KLEMS data.	611	918,623	1,966,599	3,611	10,082
GDP per capita	Gross Domestic Product per capita in 2001 on the basis of KLEMS data.	611	16.00	11.00	0.46	36.00
GDP growth	Growth in GDP over the period 2001-2007 on the basis of KLEMS data..	611	29.00	21.00	6.30	89.00
Sector share	Output share of the sector in total economy output (%) in 2001 on the basis of GTAP data.	611	4.60	4.50	0.03	30.00
LP growth	Average labour productivity growth between 2001 and 2007, estimated by means of a log-linear growth regression using KLEMS data.	611	3.80	4.50	-26.00	21.00
Volatility	Standard deviation of annual growth rate between 2001 and 2007 on the basis of KLEMS data.	611	5.30	5.20	0.39	53.00
IO age	Number of years between the base year (2001) and the year the input-output table was constructed (Dimaranan, 2006) .	611	8.80	4.40	1	19

FOODSECURE
FOR POLICIES THAT MATTER

The FOODSECURE project in a nutshell

Title	FOODSECURE – Exploring the future of global food and nutrition security
Funding scheme	7th framework program, theme Socioeconomic sciences and the humanities
Type of project	Large-scale collaborative research project
Project Coordinator	Hans van Meijl (LEI Wageningen UR)
Scientific Coordinator	Joachim von Braun (ZEF, Center for Development Research, University of Bonn)
Duration	2012 - 2017 (60 months)
Short description	In the future, excessively high food prices may frequently reoccur, with severe impact on the poor and vulnerable. Given the long lead time of the social and technological solutions for a more stable food system, a long-term policy framework on global food and nutrition security is urgently needed. The general objective of the FOODSECURE project is to design effective and sustainable strategies for assessing and addressing the challenges of food and nutrition security. FOODSECURE provides a set of analytical instruments to experiment, analyse, and coordinate the effects of short and long term policies related to achieving food security. FOODSECURE impact lies in the knowledge base to support EU policy makers and other stakeholders in the design of consistent, coherent, long-term policy strategies for improving food and nutrition security.
EU Contribution	€ 8 million
Research team	19 partners from 13 countries

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