# Comparing CGE and PE Supply-Side Specifications in Models of the Global Food System


Lead Authors:

Sherman Robinson
*International Food Policy Research Institute*
Hans van Meijl
*LEI, Wageningen University and Research Center*
Hugo Valin
*International Institute for Applied Systems Analysis*
Dirk Willenbockel
*Institute of Development Studies at the University of Sussex*

Co-Authors:
Shinichiro Fujimori, Toshihiko Masui
*National Institute of Environmental Studies*
Ron Sands
*Economic Research Service, US Department of Agriculture*
Marshall Wise, Katherine Calvin
*Pacific Northwest National Laboratory*
Petr Havlik
*International Institute for Applied Systems Analysis*
Daniel Mason d'Croz
*International Food Policy Research Institute*
Andrzej Tabeau, Aikaterini Kavallari
*LEI, Wageningen University and Research Center*
Christoph Schmitz, Jan Dietrich
*Potsdam Institute for Climate Impact Research*
Martin von Lampe
*Organisation for Economic Co-operation and Development*

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## Abstract

This paper compares the theoretical and functional specification of production in partial equilibrium (PE) and computable general equilibrium (CGE) models of the global agricultural and food system included in the AgMIP model comparison study. The two model families differ in their scope—partial versus economywide—and in how they represent technology and the behavior of supply and demand in markets. The CGE models are "deep" structural models in that they explicitly solve the maximization problem of consumers and producers, assuming utility maximization and profit maximization with production/cost functions that include all factor inputs. The PE models divide into two groups on the supply side: (1) "shallow" structural models, which essentially specify supply curves with no explicit maximization behavior, and (2) "deep" structural models that provide a detailed specification of technology and optimizing behavior by producers, but do not include all factor inputs in production. While the models vary in their specifications of technology, both within and between the PE and CGE families, we consider two stylized theoretical models to compare the behavior of crop yields and supply functions in CGE models with their behavior in shallow structural PE models. We find that the theoretical responsiveness of supply to changes in prices can be similar, depending on parameter choices that define the behavior of implicit supply functions over the domain of applicability defined by the common scenarios used in the AgMIP comparisons. In practice, however, the applied models are more complex and differ in their empirical sensitivity to variations in specification—comparability of results given parameter choices is an empirical question. To illustrate the issues, sensitivity analysis is done with one global CGE model, MAGNET, to indicate how the results vary with different specification of technical change, and how they compare with the results from PE models.


## 1. Introduction

This paper compares the theoretical supply-side specification of various models of the global agricultural and food system that have been used for the analysis of long run impacts of climate change. There are two types of multi-country models in common use for such analysis: computable general equilibrium (CGE) models and partial equilibrium (PE) multi-market models that focus only on agricultural sectors. These two types of models differ in: (1) the extent of coverage of economic activity, (2) the specification of price determination in markets, (3) the specification of production technology and supply behavior of producers, (4) the treatment of technical change, (5) the specification of commodity demand, and (6) the treatment of foreign trade. The first is fundamental. CGE models cover all economic activity and their specification is based on general equilibrium theory, while PE models cover only part of the economy and their specification need not be concerned with indirect links to the rest of the economy or various adding up and homogeneity conditions arising from general equilibrium theory.

We compare the specifications of these two types of models in the first four areas, focusing on production technology, supply behavior and productivity growth, while other articles in this issue focus on their treatment of demand (Valin et al., 2013) and foreign trade (Ahammad et al, 2013). Some of the differences in treatment arise from differences in coverage and underlying theory, while others concern sectoral focus and issues of aggregation. On the supply side, the models vary in terms of geographical coverage, commodity detail, and treatment of biophysical processes in agriculture. Our goal is to understand to what extent differences in certain key characteristics of their specification of technology and supply behavior might lead to different empirical results when using consistent data to analyze comparable scenarios. While there are major theoretical differences in their specification of technology and supply behavior, our conclusion is that these differences need not lead to major differences in their empirical results. The models must be compared given a specified "domain of applicability" that is defined by the common scenarios that all the models were asked to analyze.

The CGE models specify general neoclassical production/cost functions for all sectors, while the PE models focus on a more detailed specification of technology in agriculture, focusing on inputs that affect land use and crop yields. To be consistent with general equilibrium theory, production/cost functions in CGE models must be complete, including all factor inputs, and satisfy various homogeneity and adding-up conditions. The specification of production in PE models need not be complete, and generally is not. As we note below, there are tradeoffs in the different approaches to production and supply in the two kinds of models. In comparing them, we start by demonstrating that the theoretical specification of agricultural supply in the PE models can provide a reasonable empirical approximation of that in the CGE models, and should give similar empirical results for the common scenarios if the parameters of the relevant functions are specified to be consistent. We demonstrate the consistency analytically for PE models where one can derive explicit supply functions and discuss the nature of the implicit supply functions for PE models with a more complex specification of agricultural technology.

Given the feasibility of reconciling their theoretical specifications for a given domain of application, the question then is the extent to which empirical implementation in the CGE and PE models are consistent. We compare the empirical specification of various important parameters across the models and discuss how sensitive are the empirical results to differences in parameter values. For the CGE models, differences in empirical implementation involve differences in choice of nesting structure in their constant elasticity of substitution (CES) functions, as well as in parameter values. We use one CGE model, MAGNET, to explore the sensitivity of results from some scenarios to differences in important parameters.

The paper is organized as follows. Section 2 provides a brief discussion of the main theoretical and conceptual differences between the two broad classes of models included in the AgMIP study: PE and CGE models. Section 3 focuses on theoretical differences in the specification of supply and technical change in the two model classes. We compare and contrast the use of production functions in CGE models with the specification of explicit or implicit supply functions in PE models. In particular, we consider the determinants of the effective price elasticities of supply in CGE models and multi-market PE model from a theoretical perspective using a stylized two-factor production function that focuses on land and crop yields. While this stylized theoretical perspective provides important insights, it is a simplification. Some of the applied PE models specify agricultural technology in terms of activity analysis, generating output by solving an explicit optimization problem, so supply functions are implicit and must be simulated, while participating CGE models employ different nested multi-factor CES production functions that are only approximated in the simple theoretical analysis. We provide a brief model-by-model description of supply-side features and technology specification in the models. Section 4 discusses conceptual issues arising from the need to calibrate the paths for sectoral productivity parameters in CGE models residually in order to replicate the assumed GDP growth path in the base scenario used by all the models, and illustrates that different ways to do this can affect results. We focus on the treatment of labor productivity as this is a key driver of global agricultural prices. Section 5 addresses two questions. To what extent is it possible to map differences in the scenario results across models to supply side features? Are CGE model projections systematically different from those of PE models? Section 6 concludes and suggests areas for further research.

## 2. Specification of market interactions

CGE and PE models differ in the way that they specify the operation of markets, and the extent of economic activity that they include (see e.g. van Tongeren *et al.* 2001). While both solve for equilibrium prices that "clear" or equilibrate markets, they differ in the way that they model supply and demand in the markets they include.

### *2.1. Computable general equilibrium (CGE) models*

CGE models simulate the behavior of market economies, specifying the behavior of all relevant "agents" (e.g., producers, households, government) as they interact across markets. They are "complete" models in that they take account of all economic activity in the specified economy (e.g., a single country or, as in the AgMIP models, many countries in the world economy). The accounting framework on which these models are based is also complete, taking account of all real and monetized flows in the economy and specifying "balance" in the economic accounts of every agent in the model. Every agent must exactly balance receipts and expenditures, and all markets must "clear", with supply exactly equaling demand for all factors and commodities.

In CGE models, producers sell output and purchase factor inputs, with total sales exactly equaling total payments (e.g., payments to factors of production, including value-added and intermediate-input costs). Producers are assumed to maximize profits subject to technology (production functions) and prices of inputs. The first-order conditions for profit maximization essentially define the factor demands and output supply behavior of producers. The production functions and dual cost functions must be complete, including all factor inputs and all costs.

Households receive income and purchase commodities. Their income from all sources must exactly equal their expenditures. Commodity demand is determined by assuming that consumers maximize utility subject to their income constraints and commodity prices. The utility functions are specified explicitly and the first-order conditions for utility maximization define the system of expenditure functions. These expenditure functions are theoretically consistent in that they satisfy standard assumptions about economic utility functions: (1) total expenditure exactly equals the value of the demand for all commodities, (2) commodity demand is homogeneous of degree zero in all prices and aggregate expenditure (increasing all prices and nominal expenditure by the same factor will leave all commodity demands unchanged), and (3) there are aggregation constraints on expenditure and price elasticities that the expenditure functions must satisfy. [1]

CGE models operate by generating the “circular flow” of income and expenditure, tracing all income flows by source and destination: sales revenue to factor payments from producers to households across factor markets; household expenditures from income for commodities across commodity markets; and hence sales revenue back to producers. They solve for simultaneous equilibrium in all commodity and factor markets, yielding equilibrium commodity and factor prices that “clear” these markets. The system of equations to be solved is highly nonlinear, but their solution has now become routine.

A CGE model is a “deep” structural model in the sense that it specifies: (1) the actors (producers, households), (2) their motivation (profit maximization, utility maximization), (3) technological constraints

[1] These are known as Engel aggregation for income elasticities and Cournot aggregation for price elasticities.

(production functions), (4) the signals they respond to (input and output prices), and (5) the institutional structure in which they operate (competitive markets), and finally (6) "system constraints" that include supply-demand balance across all product and factor markets. The deep structural characteristics of CGE models, their grounding in general equilibrium theory, and their consistent and complete data base provide a framework that captures direct and indirect market interactions, incorporates general equilibrium welfare analysis, and supports exploration of scenarios that include changes in policy, behavior and technology at the level of micro agents.

### *2.2. Partial equilibrium models*

Like CGE models, partial equilibrium models also simulate the operation of commodity markets. However, they only include agricultural commodities (hence, they are "partial") and do not specify the operation of factor markets. The fact that the models are partial, and hence incomplete, implies that they need not, and do not, account for all economic activity and do not track the complete circular flow of income. Since the PE models do not include all commodities and the endogenous generation of all income, they specify demand curves that are not derived from explicit utility functions. Early PE models used linear demand curves, which simplified solution of the models, while more recent models use exponential demand functions with constant price and income elasticities of demand, which complicates the solution problem somewhat, but is well within the capability of modern solution algorithms. The PE models in the AgMIP project either specify simple exponential demand curves (e.g. IMPACT, GLOBIOM) or assume fixed exogenous demands for commodities (e.g., MAgPIE). On the demand side, these are "shallow" structural models—they specify demand as a function of prices and income, but do not link it to maximizing behavior of agents subject to constraints.

On the supply side, the PE models can be divided into two groups depending on how they treat supply: (1) those which specify the demand for land and crop yields as simple functions of some prices, without describing the technology in detail or specifying maximizing behavior by agents (e.g., IMPACT, GCAM), and (2) those which specify production technology in detail, with choices to be made by farmers, and generate supply by solving the optimization problem of farmers (e.g., GLOBIOM, MAgPIE). The first are shallow structural models—these area and yield functions can be seen as reduced-form relationships that reflect production technology and optimizing behavior by farmers, but without completely specifying the technology and optimality conditions (e.g., profit maximization).[2] The second are deep structural models, with explicit specification of maximizing behavior by producers subject to technology constraints and costs of other inputs.

As we will demonstrate below, in the PE models with explicit area demand and yield functions, it is straightforward to derive the supply of crops as explicit functions of prices. Agricultural supply in GCAM and IMPACT is represented by such area-yield relationships. In GCAM, land is allocated among competing land use types according to a nested logistic function. Within any sub-regional agro-ecological zone, land may be converted from other land use types to cropland on the basis of changes in relative profit rates. In IMPACT, there are explicit land demand and yield functions that depend on prices of output and inputs. In the deep structural PE models, however, where supply is solved as a programming problem, there is no simple representation of an explicit supply function. In these models, however, one can describe some properties of the implicit supply function that is generated by the optimization procedures.

[2] While shallow, the specification of supply shocks can be detailed. For example, IMPACT includes specification of the impact of water shortages on yields, linking the economic model with detailed global hydrology and water basin management models.

GLOBIOM features a detailed spatial resolution of the supply side with over 200,000 simulation units. Production functions are calibrated by means of bio-physical process based models. The expansion of agricultural land into other land types in response to demand pressures is explicitly modeled. Therefore, the long-run supply behavior of the model is co-determined by the specification of land-use change as further detailed in Schmitz et al. (2013).

GLOBIOM specifies the supply side as a programming problem, choosing among different "technologies" for each crop and allocation of land across crops to maximize the value of output depending on the relative profitability of the individual activities. While GLOBIOM is solved by maximizing the sum of consumer and producer surplus (and hence simulating a market equilibrium), the model has implicit supply functions, with changes in prices yielding different cropping patterns across land types and different technology choices within each crop, including use of other inputs, hence solving for both yields and areas. It may be possible to prove, and can certainly be demonstrated empirically, that the implicit supply functions in GLOBIOM are upward sloping, monotonic functions of output prices in a partial-equilibrium environment. The properties of these implicit supply functions (e.g., partial equilibrium price elasticities of supply) could be explored empirically by doing controlled experiments.

MAgPIE is a nonlinear recursive dynamic optimization model that links regional economic information with grid-based biophysical constraints. In MAgPIE, agricultural production for all commodities and spatial cells at each time step is determined simultaneously as the optimal solution to a global cost minimization problem. The endogenous choice variables are crop areas, yield growth rates, and livestock production quantities. Global costs including production costs, land conversion costs and the costs of obtaining yield growth are minimized subject to land constraints, water constraints, crop rotation constraints, trade constraints and global demand constraints. Data on factor cost per unit of output and biophysical constraints as well as food demand enter the cost-minimization problem as exogenous parameters along with a range of other extraneous data - see Dietrich et al. (2012), for a complete technical description. Thus, agricultural output prices in MAgPIE are the shadow prices associated with the cost minimisation problem—they are determined by costs from the supply side, rather than through simulating market equilibria.

Supply in MAgPIE will behave in a manner similar to GLOBIOM, but operating on the input-cost side. The allocation of resources is done to minimize the cost of producing a given output mix (with the "mix" being determined by the exogenous demands). There is an implicit supply function in the cost minimization problem, which produces costs and hence output prices by crop, with the areas and yields determined endogenously. One can relate prices and outputs empirically, implicitly solving for the inverse of the supply function: start with output and generate the price. Again, there should be a monotonic relationship between outputs and costs/prices, whose properties could be explored empirically by doing controlled experiments with the model.[3]

Like CGE models, PE models have been used widely in scenario analysis. The range of changes in policies and exogenous shocks that PE models can incorporate in scenarios is more limited than in CGE models. On the other hand, PE models provide a good framework for focusing on detailed specification of the agricultural sector, describing agricultural technology in terms of land and yields that facilitates links to agronomy.

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[3] Based on theorems from parametric programming, we conjecture that one can prove that the implicit supply functions in both GLOBIOM and MAgPIE are continuous, as well as monotonic. To sketch a proof, drop the demand curves in GLOBIOM and fix prices in the objective function in order to focus on supply of one commodity. Now parametrically change the price of one commodity continuously. One can prove that the objective function, and hence outputs, will also change continuously, even though there will be discrete changes in technology choices.

The issue of when it is more appropriate to use a CGE or PE model is essentially an empirical question. If the agricultural sectors included in the PE model represent a "large" share of total economic activity, the feedback effects from agricultural production, sales, and income generation to demand for commodities will be empirically significant, and ignoring these indirect links will lead to inaccurate results from scenarios that involve significant changes in total agricultural production.[4] On the other hand, scenario analysis that focuses on changes in agricultural technology at a very micro level where the changes are small enough so that ignoring indirect effects through changes in income is acceptable will benefit from the focus of PE models on detailed specification of agricultural technology—the "bottom up" approach of deep structural models such as GLOBIOM and MAgPIE.

# 3. Specifications of production and technical change

### *3.1. Production and the elasticity of supply in PE and CGE models: a stylized look*

In CGE models, production technology in all sectors is specified by neoclassical production or cost functions, which include all factor inputs, including intermediate inputs (e.g., fertilizer, chemicals) and primary inputs (e.g., land, labor, capital). The production technology is specified by a nested structure, with a mixture of fixed-coefficient and CES (constant elasticity of substitution) functions.[5]

As discussed above, the supply side in some shallow structural PE models involves areas and yields specified by functional relationships with respect to output and input prices. In the IMPACT model, for ex-

[4] It is feasible to incorporate some indirect effects in PE multi-market models, but it is an ad hoc procedure that is not well grounded in general equilibrium theory, and is not pursued in any of the AgMIP PE models. For an example of such an "economy-wide multi-market" model, see Nin-Pratt et al., 2011, Chapter 3. It is also feasible to incorporate an activity-analysis programming approach to model supply in CGE models, but this has not been done in any of the AgMIP CGE models. See, for example, Robinson et al., 2008.

[5] The nested structure for the various CGE models in the AgMIP comparisons is discussed below.

ample, area equations are functions of crop prices and yields are functions of both crop prices and some input prices (fertilizer and labor). In the deep structural PE models, there are implicit supply functions that should be well behaved (e.g., continuous, upward sloping). In the discussion below, we will start with an explicit supply function for the PE model and a simplified structure for the CGE production function in order to focus on the theoretical comparison of their supply behavior.

### *3.2. Production functions, yields, and supply curves*

To compare the specification of technology in PE and CGE models, it is convenient to start from the production approach used in CGE models. Consider a neoclassical production function for a crop that has two factor inputs, land in hectares (H) and a composite other factor denoted by Z:

$$X = F(H, Z) \tag{1}$$

In AgMIP CGE models, the composite factor Z is specified as a nested function of other factor inputs. For the moment, we can work with the composite. The function *F* is homogeneous of degree one in *H* and *Z*, which implies constant returns to scale. From Euler's equation for homogeneous functions, we can write:

$$X = \frac{\partial F}{\partial H} H + \frac{\partial F}{\partial Z} Z \tag{2}$$

The two partial derivatives represent the marginal products of land and the composite factor. Assuming that factors are paid the value of their marginal products, we have the "adding up" condition that total revenue will always equal the value of all payments to factors, where *P* is the output price and *W* is the "wage" of the factor input:

$$W_Z = P \frac{\partial F}{\partial Z} \text{ and } W_H = P \frac{\partial F}{\partial H} \tag{3}$$

Wages equal marginal product times output price and hence total value of output equals the payments to factors of production:

$$P\,X = W_Z\,Z + W_H\,H \tag{4}$$

Dividing output by land, we get an expression for output per unit of land, or yield (*y*):

$$y = \frac{X}{H} = \frac{\partial F}{\partial Z}\left(\frac{Z}{H}\right) + \frac{\partial F}{\partial H} \tag{5}$$

Partial equilibrium models typically work with the areas and yields, but only partly account for other factor inputs. In CGE models, the factor demand functions are derived from these relationships, assuming profit maximization. To explore the links between the two approaches, we specify a constant elasticity of substitution (CES) production function, which is commonly used in CGE models and can be written for the two-factor case as:

$$X = a\left[\delta Z^{-\rho} + (1-\delta)H^{-\rho}\right]^{-1/\rho} \tag{6}$$

Where *a,* δ, and ρ are parameters. The elasticity of substitution is:

$$\sigma = \frac{1}{1+\rho} \tag{7}$$

The marginal products of the factors are given by:

$$\begin{aligned} \frac{\partial X}{\partial Z} &= \frac{\delta}{a^{\rho}}\left(\frac{X}{Z}\right)^{1+\rho} \\ \frac{\partial X}{\partial H} &= \frac{(1-\delta)}{a^{\rho}}\left(\frac{X}{H}\right)^{1+\rho} \end{aligned} \tag{8}$$

The parameter $\delta$ is a "share" parameter, which has units in the CES function since it is multiplied by factor inputs measured in physical terms.[6]

PE models specify upward sloping supply curves for agricultural products, explicitly or implicitly. In the production-function approach, with all factors of production variable and all factor prices fixed, one can derive the cost function, which will depend on factor prices and the parameters of the production function. For homogeneous production functions, the marginal (and average) cost of production will be constant and not depend on the level of output, and hence the supply curve will be horizontal (with an infinite elasticity of supply). In CGE models, with all factors mobile, there are upward-sloping supply curves because, with increasing demand, factors become "scarce", with rising factor prices. This general-equilibrium supply relationship is not really comparable to the supply functions in PE models, which explicitly or implicitly specify that supply is an upward-sloping function of the output price, even with fixed input prices.

In CGE models, the general-equilibrium elasticity of supply for agricultural commodities relative to non-agricultural commodities depends on what happens to prices of factors which are used more intensively in agriculture and on the relative scarcity of factors used in agriculture compared to other sectors. In this comparison, land is especially important because it is not an input into production for non-agricultural sectors and we can then assume that it is a fixed factor for agriculture (as a whole sector). In this case, the supply elasticity for agriculture depends on the elasticity of substitution between land and other factors and on the importance of land in production compared to intersectorally mobile factors.

[6] It is mathematically convenient and does not affect the generality of the function to normalize the share parameters so that they sum to one, even though they might have different units.

In CGE models, with a fixed factor, the cost function derived from the production function assuming fixed prices of the non-fixed factors will be upward-sloping and will depend on the level of output. The marginal product of the fixed factor, and hence its "value" to the producer, will rise as output increases. Assuming that agriculture has sector-specific factors (e.g., land), we can derive the upward-sloping supply curve implicit in the CGE model, which can be compared to the specification of supply curves in PE models.

Solving for the variable cost function associated with the CES production function given that the factor *H* (land) is fixed , one can determine the elasticity of supply of output with respect to the price, ε (where the ˆ indicates percent change):

$$\varepsilon = \frac{\hat{X}}{\hat{P}} = \sigma\left[\frac{a^{\rho}}{1-\delta}\left(\frac{X}{H}\right)^{-\rho} - 1\right] = \sigma\left[\frac{\delta}{1-\delta}\left(\frac{H}{Z}\right)^{\rho}\right] = \sigma\left[\frac{\delta}{1-\delta}\left(\frac{H}{Z}\right)^{\frac{1-\sigma}{\sigma}}\right] \tag{9}$$

Note that if units are chosen so that *Z* = *H* = 1 in the base data, one can show that the parameters δ and (1 – δ) are the shares of the factors *Z* and *H* in the total value of output. In this case, the expression for the elasticity of supply simplifies to:

$$\varepsilon = \left(\frac{\delta}{1-\delta}\right)\sigma \tag{10}$$

In the case of a Cobb-Douglas production function, the elasticity of substitution equals one and the δ parameter is exactly equal to the value share of *Z* in total cost, which is fixed, and the supply elasticity is constant. In the CES case, as one moves away from the base data, the supply elasticity will vary with *H/Z*, which will generally fall over time as other factors grow relative to land. If the elasticity of substitution is less than one, then the supply elasticity will fall as *H/Z* falls, which is the usual assumption in CGE models. In this case, the supply elasticity should fall over time as the economy grows.[7] Assuming an elasticity of substitution of 0.5, the supply elasticity is a linear function of the *H/Z* ratio. With smaller substitution elasticities, the relationship becomes stronger—with a sigma of 2/3, the supply elasticity varies with the square root of the *H/Z* ratio.

In both the CES and Cobb-Douglas cases, the supply elasticity is sensitive to the share of the fixed factor in total factor returns, or value added. As the share of the fixed factor rises, δ is lower and the supply is more inelastic. In the CES case, the lower is the substitution elasticity, the more inelastic is supply.

TABLE 1 ABOUT HERE

Table 1 presents various values of the elasticity of supply for agriculture for different values of the elasticity of substitution and of the share of agriculture in GDP, assuming that land is a fixed factor. In the case of a unitary elasticity, the CES function goes to the Cobb-Douglas function in the limit. In the CGE models in the AgMIP project, the substitution elasticities for agricultural activities are generally low, well below one (Table 2). The implication is that supply elasticities for agricultural commodities are generally less than one (inelastic).

In PE models with explicit area and yield functions, the supply relationship is given by:

$$\begin{aligned} X &= y\,H \\ y &= \alpha \prod\nolimits_j P_j^{\eta_j} \\ H &= \beta \prod\nolimits_j P_j^{\mu_j} \end{aligned} \tag{11}$$

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[7] This conclusion is qualified if technical change in agriculture is land augmenting, which will be discussed below. There is a similar effect at work with PE models which assume fixed priced elasticities of demand. Price elasticities will not be constant with growth in demand systems arising from utility maximization.

where the prices include the output price of the commodity whose supply is being modeled and, for other *j*, input prices (e.g., fertilizer). The assumption is that yields will go up with the price of the output and down with respect to prices of inputs, while area demanded is a function of the output price (e.g., output price goes up, yield and demand for land also go up. Fertilizer price goes up, yield goes down).[8] In this specification, the overall supply elasticity with respect to the output price, holding all other prices fixed, is the sum of η and μ for that price. The assumption of a constant supply elasticity over time is inconsistent with the CES production function, where the supply elasticity depends on *H/Z*.[9]

In general, in the PE models with explicit supply functions, supply elasticities for agricultural commodities are less than one (inelastic), which is consistent with the implicit values of these elasticities in the CGE models. These PE models, however, tend to assume that the supply elasticities remain constant over the entire period, while these elasticities will tend to become smaller (more inelastic) over time in the CGE models as the share of agriculture in GDP falls and the share of land in total input costs fall. So, while the two modeling approaches can be reconciled empirically, it requires attention to the trends in supply elasticities in both approaches. The PE models with explicit supply functions can take this effect into account by changing the fixed supply elasticities over time.

### *3.3. Incorporating technical progress*

In the PE models, technical change is always assumed to be measured by changes in yields. In the production function used in CGE models, however, yields will change whenever factor inputs grow at differ-

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[8] Deep structural models such as GLOBIOM and MAgPIE, which include intermediate inputs and input prices in the optimization program, will generate similar qualitative effects.

[9] In the deep structural PE models, the supply elasticity may well not be constant. Its empirical properties can only be determined by simulation analysis.

ent rates. As other factors grow relative to land, yields will increase even without any changes in total factor productivity. Yield changes will also be sensitive to the nature of productivity growth. Extend the CES function to include the possibility of factor embodied technical change:

$$X = a\left[\delta\left(a_Z Z\right)^{-\rho} + \left(1-\delta\right)\left(a_H H\right)^{-\rho}\right]^{-1/\rho} \tag{13}$$

In this equation, "neutral" total factor productivity (TFP) growth involves increases in the parameter *a*, while changes in "factor embodied" technical change involve increase in the $a_Z$ and $a_H$ parameters. All types of productivity growth will increase yields, but they will have different effects on factor returns and on the relationship between growth and the elasticity of supply. For example, land-embodied technical change is equivalent to increasing the supply of "efficiency units" of land. In this case, even if the supply of land *H* grows less rapidly than other factors, *Z*, the ratio of effective units of land to other factors depends on the growth rate of land-embodied technical change relative to the growth rate of other factors. If they grow at the same rate, then the supply elasticity in equation (9) will not change over time, even though the number of hectares does not change.

Given that the specification of technical change affects the evolution of effective supply elasticities and hence equilibrium prices in CGE models, it is important to compare how the different AgMIP CGE models treat technical change. We compare the models in this respect section 4 below (Table 3) and also do sensitivity analysis with one model, MAGNET, to explore the empirical implications of alternative specifications.

Regarding the implementation of technical change within the AgMIP PE models, productivity growth in IMPACT and GCAM is exogenous and enters as a shift factor of the yield function. In contrast, in GLOBIOM technical progress in agriculture enters as an exogenous shift factor of the labor efficiency coefficients in agricultural production functions, and is hence labor embodied. Endogenous deviations from trend productivity growth occur due to endogenous change in management systems (subsistence, low input, high input, irrigated) and reallocation of crops within a region. In MAgPIE technical progress in the form of yield growth is part of the solution to the global cost minimization problem, and is thus completely endogenous.

These differences in the treatment of technical progress imply that even within the sub-group of PE models, the exogenous yield shift factors (YEXO) which are part of the harmonized scenario specification for the AgMIP exercise (see von Lampe et al. (2013) in this issue) cannot be implemented in a uniform manner; and in the case of MAgPIE they cannot be implemented at all.

### *3.4. From stylized to applied models*

The stylized analytical framework of section 3.2 deliberately abstracts from considerable heterogeneity within the two broad classes of models with respect to supply-side specifications. As noted, the applied AgMIP CGE models employ nested CES multi-level production functions of varying complexity, as detailed in Table 2. For example, in AIM agricultural commodity output is produced by combining non-energy intermediate inputs and a composite capital-labor-land-energy input (KLHE) in fixed proportions, i.e. the elasticity of substitution between this composite and intermediates is zero. The aggregate KLHE input is in turn composed of the primary factor composite KLH and energy inputs with an elasticity of substitution of 0.5, and the elasticity of substitution between capital, land and labor is 0.8.

TABLE 2 ABOUT HERE

The responsiveness of supply to demand growth in the CGE models also depends on the intersectoral mobility of factors. In all the CGE models, land is immobile out of agriculture, but they vary in their treatment of other factors. For example, GTEM assumes that both capital and labor are fully mobile across sectors. In contrast, in MAGNET, capital and labor markets are segmented between agriculture and non-agriculture. The two factors are assumed to be fully mobile within each of these two sectors, but imperfectly mobile across them, leading to differences in prices of capital and labor between agriculture and non-agriculture. This is implemented by using a dynamic constant-elasticity-of transformation (CET) function, where changes in capital and labor to supply in agricultural and non-agricultural sectors depend on relative agricultural to non-agricultural wage and total labor supply. The CGE models also typically impose limited "mobility" of land between agricultural sectors, using flat or nested CET specifications of varying complexity.

A further determinant for the effective general equilibrium long-run elasticities of agricultural supply is the specification of land supply over time. In all CGE models except GTEM, land supply is a function of returns to land. In ENVISAGE and MAGNET total land supply is modeled using a logistic or rational function with a maximum asymptote, while in AIM natural forest and pasture area can be transformed to anthropogenic land using a logistic function. In FARM, land is allocated among crops, pasture, and forest within six land classes for each world region using a CET formulation. The treatment of land use in all AgMIP models is described in further detail in Schmitz et al. (2013) in this issue.

While the differences in nesting structure will affect the supply behavior of agricultural commodities with respect to prices, the fact that some factors are immobile between the agricultural and non-agricultural sectors, and within the agricultural setors, will drive the nature of the upward-sloping supply functions for agricultural commodities, as discussed earlier with a simplified theoretical model. The point of comparison with the PE models is what happens to yields in the CGE models over time.

# 4. Macro and Sectoral Productivity Growth in the CGE Models: Conceptual Issues

*4.1 Implementation of Technical Progress in the CGE Models*

Technological change is one of the key determinants of economic growth, global prices, production and trade. The nature and causes of technical change, however, have long been studied, with no consensus on how the process works. Despite developments in the new trade and growth theories (e.g., Krugman, 1990 and Romer, 1990), the empirical evidence is still too weak and not persuasive enough to tell us how to endogenize technological change within CGE models. This section discusses conceptual issues arising from the need to calibrate the paths for sectoral "factor embodied" technical change in CGE models residually in order to replicate the given GDP growth path, and shows that different ways to do this can affect simulation results. In terms of section 3.1 we focus on the development of factor embodied technical change ($a_{ZI} and\ a_{HI}$) that might differ between the various production factors (Z and H) as identified in Section 3.2, but also between sectors (I). In section 1 to 3 the main focus was on yields but in this section we focus on labor productivity as a key driver of prices in CGE models.

Given the core AgMIP assumptions of exogenous GDP and population growth, total factor productivity (TFP) is calibrated within most of the CGE models residually so that the model achieves the targeted scenario GDP growth, given the growth generated by increases in production factors times their productivity. GDP growth in the CGE models can be attributed to growth in high and low skilled labor, capital, land and technical progress (TFP). The growth of land and capital is determined endogenously in most of the AgMIP CGE models, while the growth of labor follows from projections of population growth and sometimes participation rates, leaving TFP growth to be specified residually.

This mechanism operates at the macro level. In dynamic sectoral CGE models, however, such as AIM, ENVISAGE, GTEM, EPPA, FARM and MAGNET, an important question is how TFP growth is divided across sectors and production factors. With regard to factor-biased technical change, most models assume labor-augmenting or Harrod-neutral technical change, which yields the stylized fact of a long run constant capital-output ratio (Uzawa, 1961; Jones and Scrimgeour, 2008). How TFP growth rates differ among sectors is less conclusive. Is TFP growth equal for all sectors (balanced growth with unbiased technical change), or are there reasons to believe that TFP growth differs among the various sectors? Empirical results indicate that the assumption of uniform technical progress across sectors is generally not realistic. Studies indicate that TFP growth in developed countries is highest in agriculture, followed by manufacturing and services (Dollar and Wolff, 1993 and 1997; Kets and Lejour, 2003). Comparative empirical research is not conclusive concerning relative TFP growth for less developed countries.

All CGE models assume that land-embodied technical change ($a_{HI}$) is equal to the sectoral exogenous yield shift factors (YEXO). As this assumption is common across the CGE models, the focus in this section is on the treatment of labor-embodied technical change ($a_{ZI}$) and how this differs among sectors. AIM and FARM assume that labor-embodied technical change is identical across all sectors. ENVISAGE as specified for AgMIP assumes that the rate of labor-embodied technical change in agriculture is equal to that in services, while the rate in manufacturing is higher than for services and agriculture. GTEM assumes that economy-wide productivity growth is biased and uses a “technology matrix” to distribute technological change within the economy. The matrix applies a scaling factor for each input-industry combination to the economy-wide productivity change. In general, by the choice of the elements of the matrix, labor productivity growth is kept higher than productivity growth of other inputs. The technology matrix is also used to avoid generating productivity changes that reduce key inputs below technically feasible limits. Crude oil inputs into petroleum production represent a good example where such restrictions are necessary. MAGNET assumes different sectoral TFP developments which are based on estimates of CPB (Kets and Lejour, 2003). These estimates describe sectoral TFP developments in the OECD between 1970 and 1990. Based on the OECD International Sectoral Database, these estimates confirm the stylized fact that TFP growth is relatively high in agriculture and relatively low in services. Within manufacturing, TFP growth is higher for chemicals and capital goods and lower for food processing, paper and publishing and metals. TFP growth in services sectors (e.g. construction, financial services and other (government) services) is almost zero or even negative, while it is relatively high in transportation and communication. Table 3 summarizes how techical change is treated in the AgMIP CGE models.

Because of the different treatment of labor-embodied technical change among the AgMIP models, we performed sensitivity analysis attempting to understand better how technical change assumptions affect the simulation results.

TABLE ABOUT 3 HERE

*4.2. Sensitivity analysis with regard to technical change assumptions in the reference scenario*

In this section we run two scenarios to identify the impact of different assumptions with regard to sectoral labor-embodied technical change. Both additional scenarios are related to the middle-of-the-road SSP2 socio-economic scenario of the IPCC, or S1 in our study, and all three scenarios were run with MAGNET.

In the first scenario ("S1- no sect dif TFP"), we assume the same labor-embodied technical change across all sectors (unbiased). By doing so, we resemble the sectoral treatment of TFP growth in the models AIM, FARM and to a lesser extent ENVISAGE (see Table 3). Comparing this scenario with S1 allows identification of how sensitive are the results when we assume labor-biased technical change. Note that MAGNET assumes in S1 that labor-embodied technical change in agriculture is higher than in manufactures and services, based on estimates of CPB (Kets and Lejour, 2003).

In principle, in the AgMIP PE models such as IMPACT and GCAM where production technology for crops is specified by explicit yield functions, technical change implicitly applies to all factors. In the deep structural PE models such as GLOBIOM, yields are endogenous, depending on other factor inputs. This could be also followed by CGE models by assuming only land-embodied technical change (YIELDEXO) for the agricultural sector and no substitution among land and other production factors. We implement such a technology in the second scenario ("S1 – YIELDEXO").

TABLE 4 ABOUT HERE

FIGURE 1 ABOUT HERE

Figure 1 shows that assumptions with regard to how to distribute technical change across sectors and production factors are crucial. In the "S1 SSP2" scenario in MAGNET, world market prices decline slightly in the 2010-2050 period, except for sugar prices which increase due to biofuel policies. In the second scenario, "S1-no sect dif TFP", where all sectors get the same labor embodied technological change, world market prices hardly change. In this scenario, instead of decreasing 20% (under S1), agricultural world market prices (sector AGRI_PRIM) decrease by nearly 2%. For most commodities the trend is the same; namely the decrease in prices is dwarfed or reversed. The assumption with regard to labor-embodied technical change in the agricultural sector is therefore a key determinant of the relative price results. Models assuming the same rate of labor-embodied technical change across all sectors in the economy achieve an increase in agricultural prices from 5-20 percent in S1.

There is little consensus about which assumption is more plausible. However, there is empirical evidence that agriculture gets a higher labor-embodied technical change in developed countries than services, whereas the latter is the most important sector of an economy.

The scenario "S1_YieldEXO" shows the impact when the technological change of land within the agricultural sectors is equal to the exogenous yield growth specified by the IMPACT model. Under this assumption all production prices increase rapidly and, instead of decreasing prices of primary agriculture by 20%, their prices increase by almost 60%. In this case there is no labor-embodied technical change and this is a crucial difference which is often not considered when speaking about long-term agricultural prices. Many PE models indicated strong increasing prices in the future in line with these results (e.g. Nelson, et al. 2010). The PE models (GCAM, MAgPIE, IMPACT and GLOBIOM) used in this study, however, have very moderate price increase in the range from 0 (GCAM) to 20% (MAgPIE), suggesting that a different mechanism is in place preventing prices to increase more.

FIGURE 2 ABOUT HERE

Figure 2 shows the impact of different sectoral technical change assumptions on production. In comparison with global agricultural prices in Figure 1, the impacts on production are much more limited. For primary agriculture, growth in production decreases from 54% in S1 to 50% in 'S1-no sect dif TFP' and 46% in 'S1_YIELDEXO' scenario. The impact on agricultural production is generally low because price and income elasticities are relatively low for primary agricultural products, and it is highest for those commodities where prices increase the most (See Figure 1) and with relatively higher price elasticities of demand (e.g. oilseeds, horticulture, milk).

*4.3. Alternative socio-economic assumptions (S1 versus S2)*

In this section we consider some important technical change assumptions with regard to the socio-economic scenarios. We compare the fragmentation scenario of IPCC (SSP3) with the middle-of-the-road scenario (SSP2). SSP3 assumes higher population growth globally (especially in developing countries) and lower economic growth (GDP) especially in developing countries compared to SSP2.

With regard to macro-economic assumptions, this scenario implies lower technical change because GDP growth is lower and population growth (which is mostly used as an indicator of the labor force) is higher. The implications of these different socio-economic assumptions on global agricultural prices are not straightforward: higher population growth induces higher demand for food, while lower GDP implies lower demand for food.

FIGURE 3 ABOUT HERE

Five models indicate lower agricultural prices in SSP3 relative to SSP2 (Figure 3) suggesting that lower demand due to lower GDP dominates the additional demand due to a higher productivity growth. However, four models project increasing prices. A possible reason could be that population effects dominate GDP effects, but this is not the case as consumption in these models goes down. In this section we study the impact of various technical change assumptions on the relative price results. As we have shown, labor-embodied technical change in agriculture is very dependent on GDP growth and on its sectoral dimension in all CGE models. Most CGE models assume that different GDP growth leads to a different labor-embodied technical change within the economy and also within the agricultural sector. As sectoral productivity ratios are quite different, the impact of lower GDP growth is different for all models. If all sectors follow the same productivity growth (AIM, ENVISAGE, FARM), the impact of lower GDP growth rate on labor embodied technical change would be less compared to the assumption that agriculture has a higher than the average productivity growth (for example MAGNET).

We again considered three sensitivity scenarios to study the impact different labor productivity assumptions in agriculture have on agricultural prices (see Table 4). The first scenario presents the difference between S2 and S1 with a higher labor-saving technical progress in agriculture than in the rest of the economy (as in MAGNET). The second scenario assumes that all sectors have identical labor-saving technical change (as implemented in AIM, FARM and to a certain extent ENVISAGE). In the third scenario, we assume only land-embodied technical change (YIELDEXO) for agricultural sector and no substitution among land and other production factors. We run the additional scenarios with MAGNET.

TABLE 5 ABOUT HERE

Figure 4 shows the results of the various sectoral technological change assumptions of S2 relative to S1.

FIGURE 4 ABOUT HERE

Figure 4 shows that in the case of higher labor-embodied technical change in agriculture ("sectoral differences scenario"), prices increase from S1 (SSP2) to S2 (SSP3). A lower rate of calibrated labor-embodied technical change implied by lower GDP growth rates in S2 versus S1 explains the higher prices in S2 relative to S1. For example, the prices of primary agriculture increase by 7% if one moves from S1 to S2. With sectoral unbiased labor-embodied technical change ("No Sectoral Differences Scenario") the impact is substantially lower on agricultural prices. Instead of increasing prices by 7% for primary agriculture, if one moves from SSP2 (S1) to SSP3 (S2) prices increase by 2%. The main driver behind these results is that the decrease in labor-embodied technical change is much lower with sectorally unbiased technical change. The results in Figure 4 are consistent with the developments in Figure 3. Prices do not increase or decrease in the no-sectoral-differences models (AIM, ENVISAGE and FARM) and increase in the sectoral difference (MAGNET) model. When only exogenous yield growth (land-embodied technical change) is in place and no labor-embodied technical change and factor substitution possibilities are present (YIELDEXO scenario), prices decrease by almost 30%. If one takes this technology specification as a proxy for how PE models operate, then the direction of price decreases is in line with IMPACT, GLOBIOM and CGAM. However, the price decrease is much higher in the YIELDEXO experiment than in the PE models (see Figure 3 and Figure 4). The different labor-embodied technical change assumptions explain a part of the differences between models and are in line with the main price directions. Most PE models and CGE models that assume equal labor productivity growth in the economy obtain declining agricultural prices if one moves from S1 to S2. Models in which GDP is an important driver of labor-embodied technical change and agriculture has a relatively high labor productivity growth predict price increases. The latter is very close to the endogenous technical change process in MAgPIE. The lower GDP growth in

MAgPIE leads to a lower incentive to invest in R&D and therefore lower cost-saving technical change and, as a result, higher prices.

## 5. A brief look at AgMIP scenario results from a supply-side perspective

The preceding analysis does not suggest a clear-cut *a priori* mapping from conceptual differences in supply-side specifications across models to differences in the scenario results. However, the econometric meta-analysis of the AgMIP scenario results by von Lampe et al. (2013) in this issue points towards the presence of systematic differences in the simulation results between the subset of CGE models as a group and the other models:

For the reference scenario (S1) “there appears to be a systematic difference in price changes between PE models on the one hand, and CGE models on the other, in that CGE systems tend to simulate lower prices than PE models” (von Lampe et al., 2013). With respect to the AgMIP S2 scenario (higher population growth and lower per-capita GDP growth than in the baseline scenario), the results suggest a clear and statistically significant difference in the impact of the scenario on world average producer prices between the CGE and PE models. Simulated price reductions across commodities are about 3 percentage points smaller for CGE models when compared to the PE models on average (von Lampe et al., 2013, Table 3). Moreover, with respect to the climate change shock scenarios (S3 to S6: RCP 8.5 emission scenario, two climate models, two crop model suites), the meta-analysis suggests that CGE models predict smaller price increases than PE models—a result that is statistically highly significant across all four climate-change scenarios and for both 2030 and 2050 (von Lampe et al., 2013, Table 3).

Do these findings allow us to infer that the CGE models tend to have in effect a more elastic supply side than the PE models? The various AgMIP scenarios involve simultaneous exogenous shifts in both supply and demand, so it is impossible to identify supply elasticities from the results. Despite this identification problem, a look at Figure 5, which plots the global producer price and production indices for AGR (all agricultural commodities) and CRP (all crops) in 2050 under the reference scenario (S1) allows us to draw a number of inferences with respect to the interpretation of the meta-regression results for this scenario.

FIGURE 5 ABOUT HERE

While the three models with the lowest 2050 equilibrium producer prices for CRP on average (EPPA, FARM and MAGNET) are CGE models, the model with the highest price increases for these aggregates (AIM) is also a CGE model. In fact, only one of the four PE models, MAgPIE, generates above-average producer price increases in the reference scenario, while the other three PE models (GCAM, GLOBIOM, IMPACT) project below-average equilibrium prices for 2050 (Figure 5). This indicates that the meta-regression results for the reference scenario are strongly influenced by the MAgPIE results. Two peculiar features of MAgPIE contribute to the higher price projections compared to the other PE models: price elasticities of demand for agricultural commodities are zero and endogenous technological progress requires costly R&D investments that push up costs and prices.

Moreover, it is important to note that in Figure 5 all PE models are located to the North-East of the low-price CGE models: FARM and MAGNET. The higher price projections by the PE models compared to MAGNET and FARM cannot be explained by a less responsive supply side, but must be attributed to stronger expansionary demand shifts (i.e. higher effective income elasticities of demand for AGR and CRP irrespective of the long-run price elasticities of demand and supply) compared to these low-price CGE models.

With respect to the two “high-price” models, the fact that AIM projects higher price and lower production increases than MAgPIE for both aggregates of MAgPIE in Figure 5 indicates that the CGE model AIM has actually a less elastic supply side than MAgPIE.

FIGURE 6 ABOUT HERE

# 6. Conclusions

The preceding analysis explored the extent to which differences in the specification of technology and supply behavior between partial and general equilibrium models for global long-run food system analysis might lead to different empirical results when using consistent data to analyze comparable scenarios. While there are major theoretical differences in their specification of technology and supply behavior, our conclusion is that these differences need not lead to major differences in their empirical results. The supply functions in the PE models (explicit or implicit) are theoretically comparable to those in the CGE models, with specifications that assume cost-minimizing/profit-maximizing behavior by producers. In the CGE models and the deep structural PE models (which both include explicit specification of economic objective functions), the specification of cost-minimization/profit-maximization is explicit, while in the shallow structural PE models (which do not include explicit cost functions) they are implicit. There are theoretical tensions between the specification of supply in the CGE models, which are complete in that they include all factor inputs and input costs, and the PE models which are not complete, but empirically these differences may not be significant.

The PE and CGE models should give similar empirical results for the domain of applicability of the models in the AgMIP comparisons if the parameters of the relevant functions are specified to be consistent and economy-wide real income feedback effects associated with supply shocks are small. If indirect feedback effects from increased production in the sectors included in the model through income generation and demand are empirically significant, then there is a strong case for using CGE models since they incorporate such indirect links in a manner that is based on a large body of well-established economic theory. The advantage of the PE approach is that the models support a “bottom up” specification of technology and producer behavior, with detailed specification of agriculture that is difficult to incorporate in CGE models.

Both the CGE and PE models incorporate detailed representations of technology and supply. The CGE models include elaborately nested CES functions, while the PE models incorporate various crop technologies and price sensitive yield functions and demand functions for land. Our theoretical analysis with simplified models is revealing, but does not capture the complexity of the behavior of the empirical models. It would be worthwhile for modelers to use controlled simulation experiments to delineate the empirical properties of their implicit supply and demand curves. Such analysis would facilitate comparisons at the aggregate level across different models and is important for model validation. Some progress was made in this work program in the AgMIP project, but much more work is needed.

The specification of technical change varies widely across all the models. Assumptions about the degree of factor bias within agriculture and the degree of sectoral bias between agriculture and the rest of economy are especially important in determining the evolution of price over long time periods. Sensitivity analysis indicates that the differences in assumptions about technical change across all the models are especially important in determining differences in their results for prices. There is as yet little consensus in the economics profession about the nature and drivers of technical change, and the results from the AgMIP models indicates the need for more research in this area, and for more sensitivity analysis and validation exercises with the empirical models.

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Table 1. Supply elasticities from the CES function with fixed land as a function of the elasticity of substitution and the value share of returns to land (H) in value added

| Land share | CES substitution elasticity, σ: **0.1** | **0.2** | **0.5** | **1** | **1.5** | **2** |
|---|---|---|---|---|---|---|
| **0.1** | 0.90 | 1.80 | 4.50 | 9.00 | 13.50 | 18.00 |
| **0.2** | 0.40 | 0.80 | 2.00 | 4.00 | 6.00 | 8.00 |
| **0.5** | 0.10 | 0.20 | 0.50 | 1.00 | 1.50 | 2.00 |
| **0.8** | 0.03 | 0.05 | 0.13 | 0.25 | 0.38 | 0.50 |

Table 2. CGE production function nesting structures and substitution elasticities.

| Model | Level 0 | Level 1 | Level 2 | Level 3 and Below |
|---|---|---|---|---|
| **AIM** | X=f(KLHE,M) 0 | KLHE=f(KLH,E) 0.5 | KLH=f(K,L,H) 0.8 | |
| **ENVISAGE** | | | | |
| - Crops | X =f($KLHEM_c$, $M_2$) 0 | $KLHEM_c$=f($KLEM_c$,H) 0.5 | $KLEM_c$=f(KE,$LM_c$) 0.9 | KE=f(K,E) 0 to 0.8<br>$LM_c$=f(L,$M_c$) 0.9<br>L=f($L_s$,$L_u$) 0.12 to 1 |
| - Livestock | X =f($KLHEM_f$, $M_2$) 0 | $KLHEM_1$=f(KLE,$HM_f$) 0.5 | KLE=f(KE,L) 0.9<br>$HM_f$=f(H,M) 0.2 | L=f($L_s$,$L_u$) 0.12 to 1 |
| **FARM** | X=f(KLH,E,M) 0 | X=f(K,L, $H_1$,…,$H_6$) 0.3 to 0.8 | | |
| **GTEM** | X=f(KLHE,M) 0 | KLHE=f(KLH,E) | KLH=f(KL,H) 0.5 | KL=f(K,L) 1.2 |
| **MAGNET** | | | | |
| - Crops | X=f(KLHEN,$M_2$) 0 | KLHEN=f(KLEN, H) 0.05 | KLEN=f(KE,L,N) 0.2 to 0.7 | KE=f(K,E) 0.5 |
| - Livestock | X=fKLHEN$M_f$,$M_2$) 0 | KLHEN$M_f$=f(KLEN,$HM_f$) 0.1 | KLEN=f(KE,L,N) 0.2 to 0.7<br>$HM_f$=f(H,$M_f$) 3 | KE=f(K,E) 0.5 |

X: Output, K: Capital, L: Labor, H: Land, E: Energy, N: Natural Resources, M: Intermediate Inputs (Materials), $M_f$: Crop Intermediates, $M_f$: Feed Intermediates, $M_2$: Other Non-Energy Intermediates, $L_{s/u}$: Skilled / Unskilled Labor, Hi: Land Class i. Notation: ABC: Composite input over inputs A, B and C Numbers refer to elasticities of substitution between inputs in the corresponding nest.

Table 3. Macroeconomic growth mechanism: the treatment of technological change across sectors and production factors.

| Model | Key assumptions | Sectoral differences | "Endogenous" labor productivity between S1 and S2 |
|---|---|---|---|
| **AIM** | 1) Labor productivity growth is one third of the GDP growth. This growth rate is multiplied only to labor input; 2) in a next step and by using the expected total labor force and capital stock, TFP is dynamically calibrated. The calibrated TFP is then multiplied on the labor and capital aggregates. | The same procedure to calibrate TFP is used for all sectors . | Yes |
| **ENVISAGE** | 1) Population and labor force growth are exogenous; 2) Capital dynamics relies on the standard motion equation that equates the current capital stock to the sum of the previous period's depreciated stock of capital and volume of investment; and 3) There is an economy-wide (labor) productivity factor that is calibrated in the reference run to meet the overall target for GDP growth. Furthermore, exogenous productivity factors are applied to yields in agriculture, energy use in all sectors and final demand, and international trade and transport margins. The food related input-output coefficients linked to household consumption are also adjusted over time to target FAO's food consumption trends—coupled with changes to the LES parameters described above. | For the AgMIP exercise—agriculture and services have the same labor productivity which is lower than in manufacturing. | Yes |
| **FARM** | 1)The technological change factors for labor inputs are adjusted by region and time step until the endogenous GDP approximates the desired GDP path in each region; 2) Technological change factors for capital remain unchanged for all production functions in all regions for all time steps; 3) Exogenous yield shifters for AgMIP (variable YEXO) are applied as multiplicative factors to the land input for each crop type. For a particular crop type, identical yield shifters are applied to each of the six land types; 4) Technological change for intermediate inputs is handled separately: Technological change parameters for energy inputs are adjusted to get reasonable time paths of energy consumption and carbon dioxide emissions. | No sectoral differences. The rate of technical change for labor is the same across production sectors. | |
| **GTEM** | 1) Labor force growth equals population growth; 2) In the reference scenarios, S1 and S2, GDP is exogenous and the economy-wide productivity is endogenous. However, economy-wide productivity is biased using a 'technology matrix'. The matrix applies a scaling factor for each input-industry combination to economy-wide productivity change. By choice of the matrix elements, labor productivity growth is kept higher than productivity growth of other inputs. The technology matrix is also used to avoid productivity changes reducing key inputs below technically feasible limits; 3) For all AgMIP scenarios we have set the scaling factor of productivity for land in all agriculture sectors equal to zero and shocked land productivity by the AgMIP supplied values (yields). Therefore, land productivity in GTEM is sourced from AgMIP and productivity of other factors is derived from the economy-wide estimate; 4) For the climate change scenarios, S3 to S6, land productivity shocks are the scenario specific estimates supplied by AgMIP. At the economy-wide level the closure is changed and the economy-wide productivity and associated technology matrix are taken from the reference case, S1, and GDP is made endogenous. Therefore, climate change induces changes in land productivity but the productivity of other factors remains unchanged from S1. | TFP scaled to sectors via technology matrix;<br>Scaling factor for land in all agricultural sectors set to zero; Land productivity shocked based on AgMIP yield projections | |
| **MAGNET** | 1) Labor force growth is equal to exogenous population growth; 2) Capital dynamics rely on the standard motion equation which sets the current capital stock equal to the sum of the previous period's depreciated stock of capital and volume of investment; 3) There is an economy-wide (labor) productivity factor calibrated in the reference run so as to meet the overall target for GDP growth; 4) Exogenous productivity factors are applied to yields in agriculture. Assumption on crop yields are taken from AgMIP and for livestock are taken from IMAGE. | TFP (agriculture)>= TFP(manufacturing) >> TFP (services). Ratios taken from Kets and Lejour (2003). | Yes |

Table 4. Sensitivity scenarios with regard to different sectoral  technical change assumptions

| **Scenario name** | **Description** |
|---|---|
| Reference scenario: Sensitivity scenarios with regard to different technical change assumptions | |
| **S1** | AgMIP S1 scenario with sector-biased labor-augmenting technological change |
| **S1- no sect dif TFP** | AgMIP S1 scenario with uniform labor-augmenting technological change across all sectors |
| **S1_YieldEXO** | AgMIP S1 scenario with exogenous yield shifts only. No labor-augmenting technical change in agricultural sectors |
| Different socio-economic scenarios: Sensitivity scenarios with regard to different technical change assumptions | |
| **Sectoral differences** | AgMIP S2 scenario with sector-biased technological  change |
| **No sectoral differences** | AgMIP S2 scenario with uniform technological change across all sectors |
| **YIELDEXO** | AgMIP S2 scenario with exogenous yield shifts only. No labor-augmenting technical change in agricultural sectors |

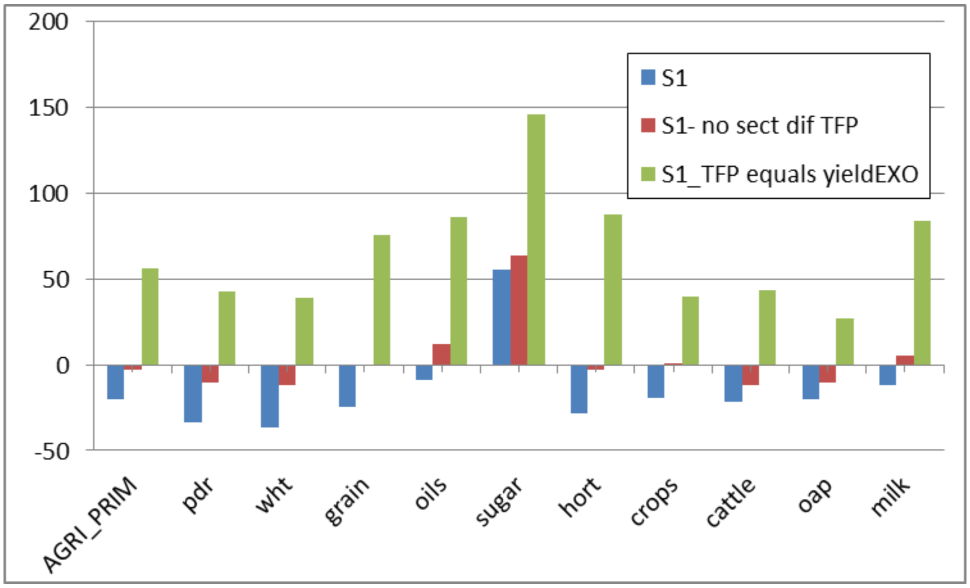


Figure 1. World market prices under different sectoral labor embodied technical change assumptions, 2010-2050 growth rates (%)

Notes: AGRI_PRIM (primary agriculture) includes the following sectors: paddy and milled rice (pdr), wheat (wht), coarse grains (grain), oilseeds (oils), sugar (sugar), fruit and vegetable (hort), other crops (crops), cattle, sheep, goat and horse animals and meat (cattle), other animals (oap), milk (milk).

Source: MAGNET calculations

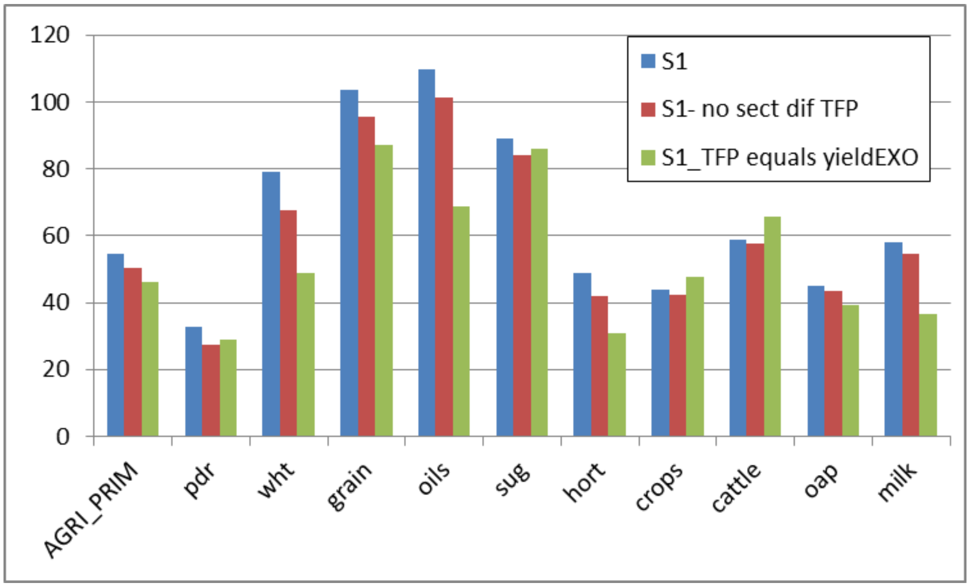


Figure 2. World production with different sectoral TFP assumptions, 2010-2050 growth rates
Notes: The sectors are denoted as in Figure 1.
Source: MAGNET calculations

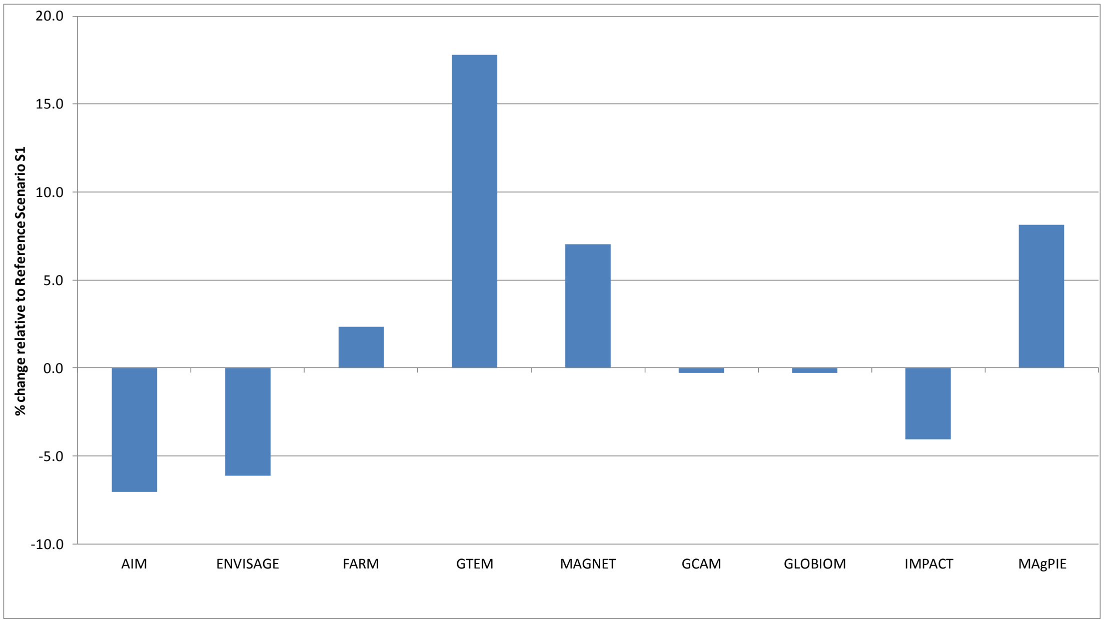


Figure 3: Changes in prices of agricultural products, SSP3 relative to SSP2, 2050

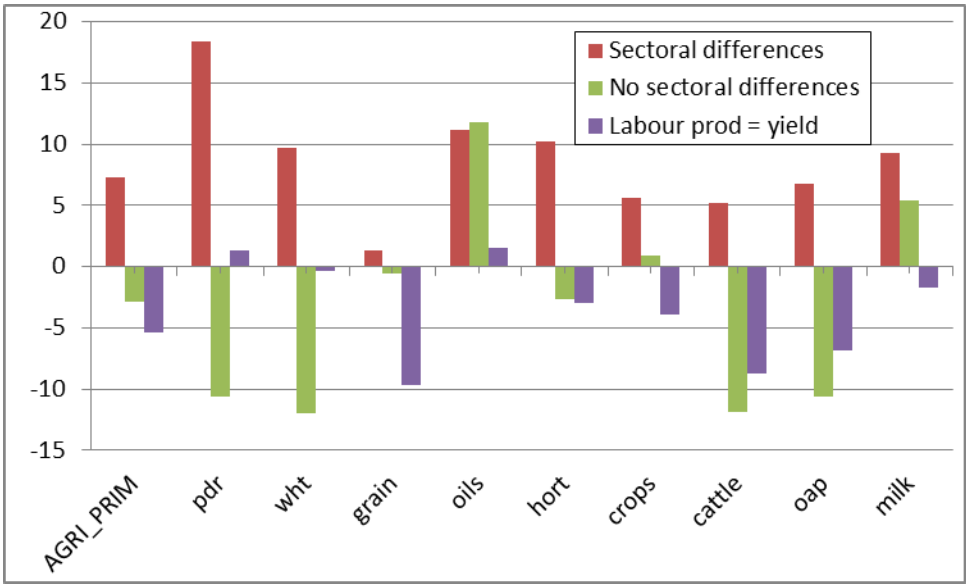


Figure 4. World market prices and difference of socio-economic scenarios (S2 relative to S1) under different labor productivity assumptions, 2010-2015 growth rates (%)

Source: MAGNET calculations

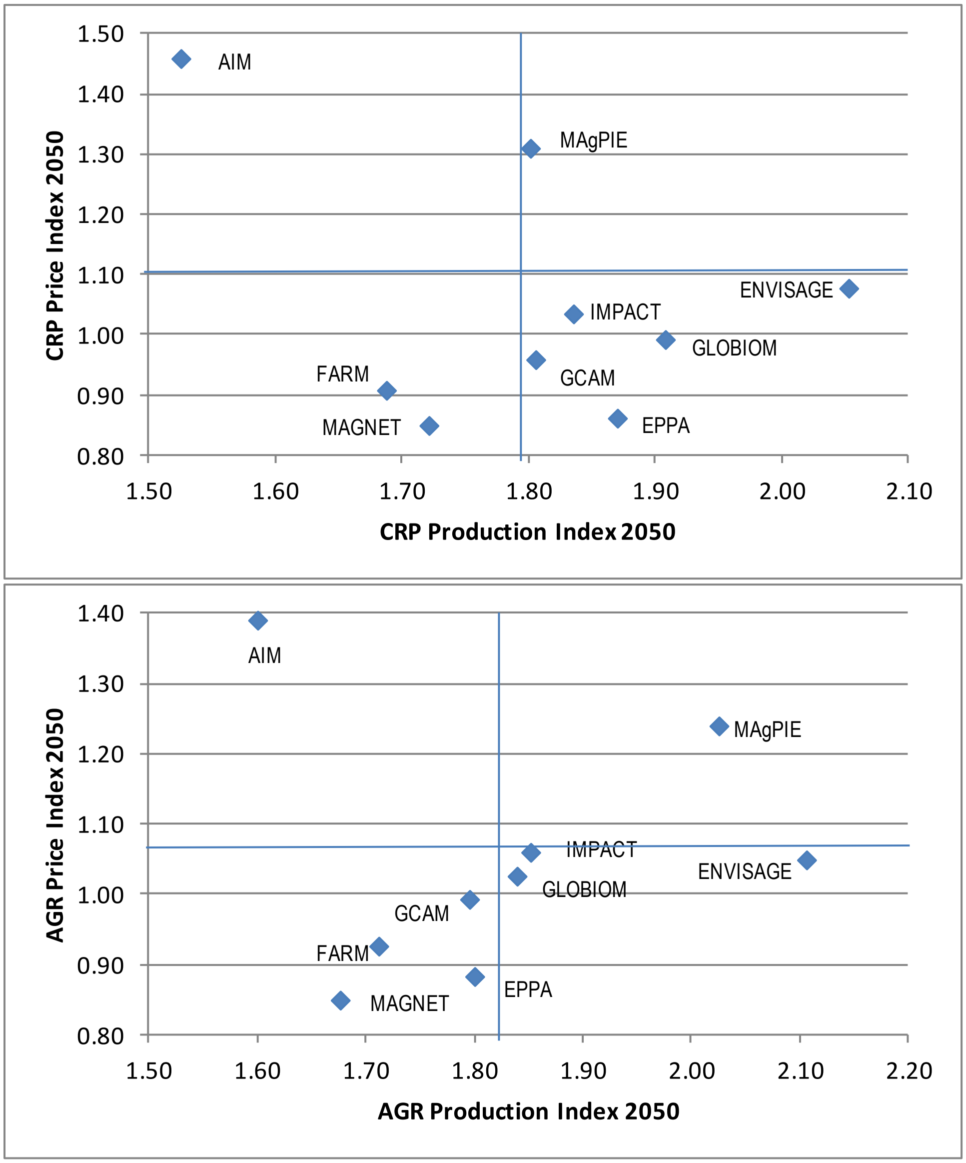


Figure 5. Global producer price and global production indices 2050 (2005 = 1) for all crops (CRP) and all agricultural commodities (AGR) for AgMIP reference scenario (S1).