A Bayesian stochastic frontier: an application to agricultural productivity growth in European countries

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Abstract This paper measures and compares total factor productivity (TFP) growth in agriculture for the European Union (EU) countries and candidate countries (CC), in order to distinguish and investigate cross-country differences in agricultural productivity growth rates from 1993 to 2006. A stochastic production frontier model is estimated using a Bayesian approach capturing country-specific time-invariant heterogeneity and country-specific time-varying inefficiency. Agricultural productivity growth is found to be mostly driven by technological change. The TFP growth rates of the EU-12 countries and CC are about twice the EU-15 growth rate. Catch-up in productivity levels is observed between EU-15 and EU-12 as well as between EU-15 and CC. The results are compared for a situation in which country-specific time-invariant heterogeneity is not taken into account.

Keywords Bayesian inference · Stochastic production frontier · Time-varying technical inefficiency · Total factor productivity growth · European agriculture

JEL Classification C15 · D24 · O47

1 Introduction

The empirical literature on cross-country (economic) growth can be classified along two main lines (Koop et al. 1999:457). The first, so-called *growth accounting*, usually specifies a Cobb-Douglas production function where real gross domestic

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product (GDP) linearly depends on capital and labour. Total factor productivity (TFP) is calculated as the residual from the specified production function. In order to explain growth, a two-stage method is used. It entails first calculating TFP and then regressing it on several explanatory variables. Production function parameters are calculated through factor shares without econometrics; in so doing, every country is characterized by its own production technology. The second line, so-called *cross-country growth regression*, also starts from a Cobb–Douglas specification but relies on econometric techniques. Parameter homogeneity is usually assumed, implying that all countries are characterized by a similar production technology with disembodied technological change.

This paper attempts to estimate and compare TFP growth in agriculture for the European Union (EU) countries and for candidate countries (CC). The objective is to estimate and investigate cross-country differences in agricultural productivity growth rates. These differences should explain any discrepancy between agricultural productivity in the new member states (EU-12) and CC and agricultural productivity in the former EU-15 countries. The paper addresses the following main questions: Is agricultural productivity growth driven by increases in efficiency bringing countries closer to the frontier? Or is it driven by movements of the frontier or along the frontier itself? Is there any evidence of country catch-up?

The data used are drawn from the FAOSTAT (2010) database of the Statistics Division of the Food and Agriculture Organization (FAO). This database, which has been used in similar analyses (Coelli and Prasada Rao 2005; Fulginiti and Perrin 1997; Suhariyanto and Thirtle 2001), comprises data on the former EU-15 countries, the EU-12 and three CC (Croatia, the Former Yugoslav Republic of Macedonia, and Turkey). The data used are for the period from 1993 to 2006, in order to allow for the inclusion of new independent states.

A parametric stochastic frontier approach is used in this paper for three reasons. First, the formal treatment of technical efficiency¹ in stochastic frontier models allows the issue of output growth to be disentangled to provide an interpretation of the unexplained residual that in the *growth accounting* is labelled as technical change. Second, the approach explicitly takes into account measurement error and the potential effect of unfavourable weather and disease—factors that frequently affect agriculture. Finally, the approach used here deviates from the classical *cross-country growth regression* literature, since the interest is in estimating productivity growth rather than explaining it. The focus is therefore on analyzing the properties of the distribution of agricultural output that is conditional on key agricultural inputs, and is empirically based on production theory. For a comprehensive overview on frontier techniques, see Murillo-Zamorano (2004).

The standard assumption of a common production technology is initially relaxed by estimating a model capturing country-specific time-invariant heterogeneity. This

¹ Technical efficiency is a particularly useful and neutral concept for assessing the performance of former socialist countries, because it focuses solely on the maximum attainable output level for a given set of inputs. As Brada et al. (1997:107) argues technical efficiency is a necessary, though not in itself sufficient, condition for profit maximization; it is also a precondition for fulfilling output plans, as they existed in former collective and state-owned farms.

is done by extending the ‘true’ fixed effects (TFEs) stochastic frontier model developed by Greene (2004, 2005). Latent class models have also been used to identify different technologies for analyzing different classes (Alvarez and Corral 2010). The reason it is important to capture potential country-specific time-invariant heterogeneity is that countries vary in their stage of development, and physical factors such as soil quality, drainage, relief and climate. Kumbhakar and Hjalmarsson (1993) highlighted that in the past literature inefficiency estimates were contaminated by producer heterogeneity unrelated to efficiency.

A Bayesian estimation is used because it allows us to: (1) derive precise small-sample results, which is especially relevant when the data set is small²; (2) derive the full posterior distribution of any individual efficiency; (3) consider parameter uncertainty by providing a probability distribution for each estimated parameter; (4) impose regularity conditions on the parameters that will be estimated consistently through the specification of the prior. For a more in-depth discussion on the advantages of using Bayesian estimation in a stochastic frontier framework, see Koop et al. (1999).

In order to estimate the changes in technical efficiency, the time-varying inefficiency model of Cuesta (2000) is introduced in a Bayesian framework, thereby allowing country-specific temporal variation in technical efficiency to be captured. This relaxes the standard assumption of imposing a common temporal pattern of technical inefficiencies on all countries as in Battese and Coelli (1992). Using an approach similar to that described in Terrell (1996), theoretical restrictions are enforced during the estimation in order to fulfil the economic requirements of a well-behaved production frontier). By so doing, technical efficiency scores complying with microeconomic theory³ can be derived.

The paper is structured as follows. Section 2 contains the model of TFP growth. Section 3 describes the Bayesian stochastic frontier estimation. Section 4 introduces the data used. Section 5 provides and discusses the results. Finally, Section 6 concludes.

2 Modelling TFP growth

In this paper, a stochastic production frontier is estimated in order to measure TFP. A TFP index measures the change in total output relative to changes in the use of all inputs. As such, it is usually preferred above simpler partial productivity measures, which may yield inappropriate results, particularly when countries experience asymmetric changes in inputs (Liefert and Swinnen 2002:23–24). TFP is measured using the so-called Malmquist index (MI) (Caves et al. 1982:1394). The MI has several advantages over the widely used Tornqvist/Fischer index, as discussed in Coelli et al. (1998:246). It can be defined by using either an input or an output

² In Bayesian econometrics there is no need to draw upon the concept of the performance of the estimator in hypothetical repeated samples (Kennedy 2003).

³ Estimating efficiency scores without enforcing the required theoretical restrictions may yield spurious estimates. By definition, the region of negative marginal products represents an inefficient stage of production because the extra unit of input leads to a decline in output.

orientation. The proper choice for country-level analysis is an output orientation (Coelli et al. 1998). An output orientation looks for the maximal proportional expansion of an output vector, given an input or resource vector.⁴ The MI used in this study is based on a single output production technology that is equivalent to an output distance function with a single output from which a MI can be defined (Fare and Primont 1995:7–40).

Approaches using stochastic-frontier production functions have been independently proposed by Aigner et al. (1977), Battese and Corra (1977), and Meeusen and van den Broeck (1977). Schmidt and Sickles (1984) extended the production frontier model to panel data. The agricultural production of country i ($i = 1, \dots, N$) at time t ($t = 1, \dots, T$), Y_{it} , is assumed to be produced using the input array, $\mathbf{X}_{it}$ constituted by land (X_{1it}), machinery (X_{2it}), labour (X_{3it}), fertilizer (X_{4it}) and livestock (X_{5it}).

A transcendental logarithmic (i.e. translog) production frontier is selected for its flexibility in measuring TFP growth. The translog functional form is the most frequently used flexible functional form in stochastic frontier analysis. It provides a second-order differential approximation that is linear in parameters. Although, a Cobb–Douglas functional form is parsimonious in terms of parameters to be estimated, a translog production frontier is preferable because it allows production elasticities to vary at each data point and non-neutral Hicksian technological change. The empirical model is specified following the TFEs model of Greene (2004, 2005). A fixed effects model is more adequate than a random effects model, given that our units are countries that can be seen as ‘one of a kind’ and not extracted as a random draw from some underlying population (Verbeek 2004). The empirical model is specified as follows:

$$y_{it} = \alpha_i + \sum_{n=1}^N \beta_n x_{in} + \beta_t t + \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \beta_{nm} x_{in} x_{im} + \frac{1}{2} \beta_{tt} t^2 + \sum_{n=1}^N \beta_{nt} x_{in} t - z_i + \varepsilon_{it} \quad (1)$$

where lower case letter (y, x) indicate natural logs of upper case letters (Y, X), α_i are country-specific effects capturing time-invariant heterogeneity, $\beta = (\beta_0, \beta_1, \dots, \beta_k)$ are the unknown parameters to be estimated, t is a time trend in order to account for technological change.⁵ The inefficiency $z_i = -\ln(\tau_i)$ is assigned a non-negative random variable and the random error $\varepsilon_{it} = \ln(\xi_{it})$ has a symmetric distribution, with mean zero. The results of the TFEs model⁶ are then compared to the standard (ST) model where time-invariant country-specific heterogeneity is not accounted for ($\alpha_i = \beta$). Regularity conditions are a priori imposed during the estimation, to ensure that input elasticities are nonnegative at all observed output levels (Terrell 1996) through the following inequality restrictions:

⁴ Neither an output nor an input orientation affects estimates when constant return to scale is imposed.

⁵ Technological change in the current translog stochastic frontier specification is specified in order to allow technological change to increase or decrease over time through parameter β_{tt} and to account for changes in the marginal rates of technological substitution through the parameters β_{nt} .

⁶ The question of whether the TFEs model captures time-invariant heterogeneity or time-invariant inefficiency heterogeneity remains unresolved (Carroll et al. 2011).

$$E_{x_{it,n}} \equiv \frac{\partial y_{it}}{\partial x_{it,n}} = \zeta_{it,n} \geq 0, \quad \text{for } n = 1, \dots, 5. \quad (2)$$

Several time-varying inefficiency models have been suggested in the literature; for a recent overview, see Greene (2009). Two specifications that have proved useful in applications are Kumbhakar's (1990) model,

$$z_{it} = z_i / [1 + \exp(\gamma_1 t + \gamma_2 t^2)] \quad (3)$$

and Battese and Coelli's (1992) specification,

$$z_{it} = z_i \exp[\eta(t - T)] \quad (4)$$

where γ_1 , γ_2 and η are parameters to be estimated. The Kumbhakar's (1990) functional form lies in the unit interval and can be non-increasing, non-decreasing, concave or convex. The Battese and Coelli's (1992) function is less flexible but parsimonious in terms of parameters to be estimated. It can be non-increasing or non-decreasing but it is always convex. A drawback of both specifications is that they do not allow for a change in the rank ordering of the unit under analysis over time because the change in technical efficiency is constant and equal across all units. Both specifications can be estimated, assuming that z_i has a truncated normal distribution. In this paper, a generalization of Battese and Coelli's (1992) function proposed by Cuesta (2000) is implemented in a Bayesian framework accounting for time-invariant heterogeneity. The Cuesta's (2000) function is specified as

$$z_{it} = z_i \times \exp[\eta_i(t - T)] \quad (5)$$

where the temporal pattern of inefficiency effects (i.e. η_i) is now a country-specific parameter responsive to different temporal variations among countries.⁷ The technical efficiency of each country in each year is obtained through the conditional expectation of $\exp(-z_{it})$ given the value of $\varepsilon_{it} - z_i$.

In order to measure the MI of TFP growth, the efficiency, technological change and scale components need to be calculated. The *efficiency change* component is given by:

$$EC_{is} = \exp(z_{it} - z_{is}) = z_{is}/z_{it} \quad (6)$$

The *technological change* component requires the partial derivatives of the production frontier to be evaluated with respect to time, using the data on the i -th country in period's s and t . Then the technological change between the adjacent period's s and t can be derived through the geometric mean of the aforementioned partial derivatives. In the case of a translog specification, this is equivalent to the exponential of the arithmetic mean of the log derivatives as given by:

$$TC_{is} = \exp \left\{ \frac{1}{2} \left[\frac{\partial y_{is}}{\partial s} + \frac{\partial y_{it}}{\partial t} \right] \right\} \quad (7)$$

⁷ This specification, as in other models, assumes that inputs are independent of technical inefficiency. Therefore, if they are correlated, the parameter estimates could be biased.

To detect potential scale-change effects, scale change is introduced in computing TFP following Orea (2002), who uses Diewert's quadratic identity to derive an MI. The *scale change* component is given by:

$$SC_{is} = \exp \left\{ \frac{1}{2} \sum_{n=1}^N [\zeta_{isn} SF_{is} + \zeta_{itm} SF_{im}] (x_{isn}/x_{itm}) \right\} \quad (8)$$

where $SF_{is} = (\zeta_{is} - 1)/\zeta_{is}$, $\zeta_{is} = \sum_{n=1}^N \zeta_{isn}$ (return to scale) and $\zeta_{isn} = \frac{\partial y_{is}}{\partial x_{isn}}$ (input elasticities). Each single component is then summed, to recover the MI of TFP growth.

3 The Bayesian stochastic frontier model

This section describes the Bayesian stochastic frontier estimation used. Van den Broeck et al. (1994) introduced Bayesian stochastic frontier models. Bayesian methods appear to be suitable for stochastic frontier models because they provide precise small-sample inference on efficiencies, and they allow prior knowledge and regularities conditions to be incorporated during the estimation and more accurately represent parameter uncertainties through kernel densities. Stochastic frontier models require numeric integration methods because they are so complex; the most appropriate method is the Markov chain Monte Carlo (MCMC) introduced by Koop et al. (1995). In this paper, a MCMC Gibbs sampler following Griffin and Steel (2007) is used. The form of the likelihood function assumes that the inefficiency components z and ε are independent and that z is a vector of unknown parameters. For simplicity, (1) is rewritten without the t subscript as

$$y_i = \alpha_i + \sum_{n=1}^N \beta_n x_{in} + \beta_t t + \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \beta_{nm} x_{in} x_{im} + \frac{1}{2} \beta_{tt} t^2 + \sum_{n=1}^N \beta_{nt} x_{in} t - z_i + \varepsilon_i. \quad (9)$$

The standard corresponding likelihood function is

$$p(y|\alpha, \beta, \sigma_v^{-2}, z) = \prod_{i=1}^N \frac{(\sigma_v^{-2})^{\frac{t}{2}}}{(2\pi)^{\frac{t}{2}}} \left\{ \exp \left[-\frac{1}{2} \sigma_v^{-2} (\varepsilon_i)' (\varepsilon_i) \right] \right\} \quad (10)$$

where $\varepsilon_i = y_i - \alpha_i + \sum_{n=1}^N \beta_n x_{in} + \beta_t t + \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \beta_{nm} x_{in} x_{im} + \frac{1}{2} \beta_{tt} t^2 + \sum_{n=1}^N \beta_{nt} x_{in} t - z_i$.

The dependent variable is assumed to follow a normal distribution

$$y_i \sim N \left(\alpha_i + \sum_{n=1}^N \beta_n x_{in} + \beta_t t + \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \beta_{nm} x_{in} x_{im} + \frac{1}{2} \beta_{tt} t^2 + \sum_{n=1}^N \beta_{nt} x_{in} t - z_i, \sigma^2 \right) \quad (11)$$

where $N(\mu, \sigma^2)$ represents a normal distribution with mean μ and variance σ^2 . Priors are generally specified following Griffin and Steel (2007). The inefficiencies, z_i , capturing the difference between best practice and actual output, are assumed to have a truncated normal distribution as given by

$$z_i \sim N^+(\varsigma, \lambda^{-1}) \quad (12)$$

where λ has a gamma distribution

$$\lambda \sim Ga(\phi, \lambda_0) \quad (13)$$

with $\lambda_0 = \phi(\log(r^*))^2$ where r^* reflects the prior median efficiency.⁸ The temporal pattern of inefficiency effects [see (5)], η_i , follows a zero mean normal distribution ($\underline{\eta} = 0$) with variance $\underline{\Gamma} = 0.25$ characterizing the prior indifference between increasing and decreasing the country-specific temporal pattern of inefficiency effects

$$\eta_i \sim N(\underline{\eta}, \underline{\Gamma}). \quad (14)$$

The production frontier parameters α and β follow a multivariate normal distribution

$$\alpha \sim N(\underline{\alpha}, \underline{\Theta}), \quad (15)$$

$$\beta \sim N(\underline{\beta}, \underline{\Sigma}). \quad (16)$$

with prior mean $\underline{\alpha} = 0$ and $\underline{\beta} = 0$ and variance $\underline{\Theta} = 1.0^{-6}$ and $\underline{\Sigma} = 1.0^{-6}$.

The white noise precision, (σ_v^{-2}) , follows a gamma distribution as given by

$$\sigma_v^{-2} \sim Ga(\underline{a}_0, \underline{a}_1). \quad (17)$$

where the priors are set to 1.0^{-2} .

Regularity conditions are imposed on the value of the elasticity for the observed output. A non-standard likelihood function is used, in which each observation contributes a likelihood term (Spiegelhalter et al. 2003). The likelihood function is modified, assuming that the data is a set of ones originating from a Bernoulli distribution

$$p(y|\alpha, \beta, \sigma_v^{-2}, z) = \prod_{i=1}^N \Psi_i \frac{(\sigma_v^{-2})^{\frac{T}{2}}}{(2\pi)^{\frac{T}{2}}} \left\{ \exp \left[-\frac{1}{2} \sigma_v^{-2} (\varepsilon_i)' (\varepsilon_i) \right] \right\} = \frac{\Omega_i}{C} \quad (18)$$

where Ψ_i is a variable equal to zero for all cases when the regularity conditions in (3) are violated and is equal to one when the regularity conditions are fulfilled, Ω_i are the probabilities of the Bernoulli trials proportional to the likelihood values for which the regularity conditions are satisfied or violated, and C is a constant that ensures that $\Omega_i < 1$. The conditional distributions of the stochastic frontier model can be found in Koop (2003).

⁸ In this paper we follow Griffin and Steel (2007) by specifying the shape parameter $\phi = 5$ and the scale parameter $r^* = 0.8$. Appropriate prior values for the shape parameter ϕ and scale parameter r^* are documented in the literature (see for example Tsionas 2000; Griffin and Steel 2004).

4 The data

The data are drawn from the FAOSTAT database⁹ of the Statistics Division of FAO of the United Nations in Rome. The data include the former EU-15 countries as well as the new member states EU-12, notably: Austria, Belgium-Luxembourg, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, and United Kingdom, Bulgaria, Czech Republic, Cyprus, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia. In addition, three CC for EU accession are considered: Croatia, Former Yugoslav Republic of Macedonia (FYROM), and Turkey. The data consider the period 1993–2006. The sample comprises 29 countries for a period of 14 years, with 406 observations.¹⁰

The data consists of one agricultural aggregate output variable, defined as production net of amounts of various commodities used as feed and seed. The output series is based on 1999–2001 international commodity average prices¹¹ (1999–2001 I\$) and is expressed in a single currency unit. The international commodity prices are used in order to avoid using exchange rates to obtain continental and world aggregates, and also to improve and facilitate international comparative analysis of productivity at nation level. These international prices, expressed in so-called international dollars, are derived by FAO for the agricultural sector, using the Geary–Khamis method. This method assigns a single price to each commodity.¹² The commodities covered in the computation are all crops and livestock products that each country produces. Almost all products are covered, the main exception being fodder crops.

The data consists of five input variables: land, agricultural tractors, agricultural population, fertilizer and livestock. *Land* comprises land for arable land and permanent crops, as well as the area under permanent meadows and pastures. It is measured in 1,000 ha. Arable land is the land under temporary agricultural crops (multiple-cropped areas are counted only once), temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow (<5 years). The abandoned land resulting from shifting cultivation is not included in this category. Permanent crops cover land cultivated with long-term crops which do not have to be replanted for several years, land under trees and ornamental flowering shrubs (such as roses and jasmine), and nurseries. Permanent meadows and pastures cover land used permanently (5 years or more) to grow herbaceous forage crops, whether cultivated or wild (wild prairies or grazing land). *Agricultural tractors* refers to wheeled and crawler or track-laying tractors (excluding garden tractors) used in agriculture, without reference to the horsepower of tractors. It is measured in number

⁹ FAOSTAT is an on-line multilingual database currently containing over 1 million time-series records from over 210 countries and territories providing statistics on crops, livestock, irrigation, land use, fertilizer, pesticide consumption, and agricultural machinery. Pesticide consumption series are still sparsely available.

¹⁰ Belgium and Luxembourg are aggregated.

¹¹ The output series depends on the base 1999–2001. Changing the base to another reference year may potentially influence the results.

¹² For example, one metric ton of wheat has the same price regardless of which country it was produced in. The currency unit in which the prices are expressed has no influence on the indices published.

Table 1 Descriptive statistics, 1993–2006

Variables	Units	Avg	Min	Max	Std
Agr. output	$\times 10^3$ I\$	8,281,701.2	53,350.0	38,125,640.0	9,950,171.2
Land	$\times 10^3$ ha	8,335.2	9.0	41,223.0	10,174.4
Machinery	$\times 10^3$ tr	349.1	0.5	1,900.0	458.2
Labour	$\times 10^3$ pe	875.9	2.0	10,454.0	1,854.0
Fertilizer	$\times 10^3$ mt	740.6	0.9	5,064.0	1,019.5
Livestock	$\times 10^3$ su	42,007.8	236.8	191,956.0	50,067.3

I\$ international dollar price, ha hectare, tr number of tractors, pe number of persons, mt metric tons, su sheep equivalent units

Source: FAOSTAT (2010)

(no.) of tractors in use. *Agricultural population* is defined as all persons depending for their livelihood on agriculture, hunting, fishing and forestry. It comprises all persons economically active in agriculture as well as their non-working dependants. This population is not necessarily exclusively rural.¹³ It is measured in thousands (1,000). *Fertilizer* is an aggregate of Nitrogen (N), Potassium (P_2O_5) and Phosphate (K_2O) consumed in agriculture and expressed in tonnes of nutrients. *Livestock* is constructed by aggregating five categories of animals into sheep equivalents. The categories of animals considered are buffalo, cattle, pigs, sheep and goats. Numbers of these animals are converted into sheep equivalents using the same conversion factors as in Coelli and Prasada Rao (2005). Table 1 presents descriptive statistics for the data.

5 Results and discussion

This section presents some basic agricultural and economic indicators and discusses the estimates obtained. Agriculture represents a larger share of the GDP in EU-12 and CC than in EU-15 (see Table 2). It accounts for a large share of total employment, especially in Greece, Portugal, Latvia, Poland, Romania and Turkey. The percentage of agricultural area utilized is highest in Finland and Sweden and lowest in the United Kingdom. Compared to other countries, Poland and Turkey have a relatively high labour-to-land ratio, and at the same time have a very high unemployment rate. Inflation is particularly important in Bulgaria, Estonia, Latvia, Lithuania, Romania and Turkey.

Average annual agricultural output growth rates are highest in Spain and lowest in Belgium-Luxembourg (see Table 3). Within the EU-12 countries, the Baltic states, together with Slovakia, experienced the largest contractions in production, mainly due to the negative effect of the transition reform on capital-intensive agricultural production (i.e. the livestock sector), which is an important sector in these countries.¹⁴ The adjustment in input use varies greatly between countries.

¹³ It is likely that this variable overestimates the labour input used in agriculture.

¹⁴ In Estonia, animal production represented 58.6% of the average value of agricultural production between 1998 and 1999.

Table 2 Selected economic indicators in agriculture, 1994–2006

	Share of agriculture in GDP (%)	Share of agriculture in total employment (%)	Utilized agricultural area (% of total area)	Labour: land ratio (pers./ ha)	Unemployment (%)	Inflation rate (GDP deflator) (%)
EU-15						
Austria	1.8	4.9	39	0.06	5	2
Bel.-Lux.	1.1	1.4	45	0.06	8–5	2–6
Denmark	2.2	3.6	63	0.04	4	2
Finland	3.0	5.2	8	0.06	8	1
France	2.4	3.2	54	0.03	9	2
Germany	1.1	2.4	49	0.06	10	1
Greece	5.2	16.1	64	0.09	9	3
Ireland	2.8*	9.1	62	0.04	4	2
Italy	2.4	5.0	47	0.09	7	2
Netherlands	2.4	3.2	57	0.14	4	2
Portugal	3.5	12.3	38	0.18	8	3
Spain	3.4	6.9	57	0.05	9	4
Sweden	1.8	3.0	8	0.05	7	2
UK	0.9	1.7	73	0.03	5	3
EU-12						
Bulgaria	5.6	4.5	47	0.05	9	8
Czech Rep.	2.3	6.8	55	0.10	7	1
Cyprus	NA	6.1	17	0.22	5	3
Estonia	2.9	9.6	19	0.08	6	7
Hungary	4.0	8.3	65	0.08	7	4
Latvia	2.8	10.0	30	0.08	7	10
Lithuania	3.7	9.0	43	0.07	6	7
Malta	NA	1.2	29	0.24	7	3
Poland	4.5	18.3	53	0.22	14	2
Romania	12.8	10.7	59	0.12	7	11
Slovakia	2.6	7.6	40	0.11	13	3
Slovenia	1.8	0.9	25	0.04	6	2
CC						
Croatia	6.7	5.3	22	0.10	11	3
FYROM	9.8	8.8	42	0.09	36	4
Turkey	9.5	34.8	51	0.24	10	9

* Series only available up to 2005. Data on inflation refer to the year 2006

Source: FAOSTAT (2010)

On average, labour, livestock and land inputs contracted over time, but the use of fertilizers and machinery increased. The largest labour contraction is found in Slovenia, though in an exception to the rule, livestock did not decline appreciably

Table 3 Average annual output and input growths in agriculture, 1993–2006

	Agr. output	Land	Machinery	Labour	Fertilizer	Livestock
EU-15						
Austria	0.3	−0.4	−0.2	−2.9	−2.4	−1.5
Bel.-Lux.	−3.2	0.1	−0.7	−2.7	−0.6	−0.9
Denmark	0.3	−0.1	−2.3	−3.5	−3.2	−0.7
Finland	0.4	−0.2	−0.9	−3.4	6.3	−1.4
France	0.1	−0.2	−1.2	−3.8	−1.8	−0.3
Germany	0.3	−0.1	−2.2	−3.9	−0.9	−1.4
Greece	−0.4	−0.7	0.8	−1.8	−2.7	0.1
Ireland	0.1	−0.2	0.1	−0.5	−2.0	0.6
Italy	0.0	−0.8	1.9	−4.0	−2.2	−1.0
Netherlands	−0.7	−0.2	−1.2	−1.7	−2.7	−1.7
Portugal	1.0	−0.7	1.3	−2.0	−3.0	0.3
Spain	2.1	−0.3	1.8	−2.6	0.1	1.2
Sweden	−0.6	−0.4	−0.2	−2.5	−2.1	−1.0
UK	−0.4	0.1	0.0	−1.2	−1.9	−1.2
EU-12						
Bulgaria	−0.8	−1.2	−0.9	−6.5	1.6	−4.3
Czech Rep.	−1.4	0.0	0.4	−2.6	2.1	−4.0
Cyprus	−0.6	0.0	−2.1	−2.6	−2.6	1.3
Estonia	−2.0	−3.4	−2.1	−3.0	−3.7	−5.6
Hungary	1.2	−0.4	2.2	−3.3	4.6	−2.7
Latvia	−3.1	−1.8	0.1	−3.1	3.9	−6.4
Lithuania	−1.6	−1.1	3.0	−4.9	9.5	−4.5
Malta	1.7	−2.2	0.8	−2.4	2.1	−1.3
Poland	−1.3	−1.1	1.6	−2.4	3.3	−1.6
Romania	0.7	−0.4	0.7	−5.2	−2.6	−2.2
Slovakia	−2.3	−1.6	−2.3	−2.1	5.2	−5.3
Slovenia	0.6	−0.9	1.4	−7.9	1.7	−0.5
CC						
Croatia	0.4	−3.8	2.4	−6.3	6.3	−0.3
FYROM	1.9	−0.3	0.9	−4.1	−3.1	−2.1
Turkey	1.5	0.1	2.4	−0.5	0.5	−1.6

Source: FAOSTAT (2010)

there. Livestock declined particularly in the Baltic States and Slovakia, in line with the earlier-mentioned finding on the decline of livestock products.

Although, fertilizer use declined in all EU-15 countries except Finland and Spain, it increased in the majority of the EU-12 countries, especially in Lithuania, where poor-quality soils prevail. Machinery stocks rose significantly in Lithuania and Hungary. With the exception of Estonia, Malta and Croatia, land input did not vary much over time (see also Lerman et al. 2003:1012; Macours and Swinnen 2000: 174).

Poland and Slovakia had among the lowest annual rate of decline in labour within the EU-12 countries, which it may be attributed to the social buffer function of agriculture. In pre-transition industry, labour outflow was avoided by creating ‘over-full employment’ (Holzman 1955:455), facilitated by ‘soft budget constraints’ (Kornai 1986:3–30). However, hidden unemployment in agriculture had a different source, as farming represented the only way of obtaining a livelihood, especially in the case of small and privately owned farms. At the same time, farming’s role as a safety net constrained the outflow of labour from agriculture in many EU-12 countries, inhibiting agricultural labour productivity and the modernization of the sector.

The estimates of the empirical model are now presented and discussed. First, the TFEs model is discussed and then compared to the standard model. For simplicity and ease of interpretation, all variables are rescaled before estimation, in order to have unit means. This allows the estimated first-order coefficients of a translog production frontier to be interpreted in terms of production elasticities (when evaluated at the sample average). One of the main advantages of the Bayesian approach is that during estimation, regularity conditions can be imposed through inequality restrictions, to ensure that input elasticities are nonnegative (i.e. monotonicity in input elasticities) at all observed input levels and thus that the production frontier is well-behaved.¹⁵ This is done following Terrell (1996). The enforcement of regularity conditions also helps to mitigate potential multicollinearity problems during the estimation.

The Gibbs sampler was run for one chain, with burn-in of 5,000 iterations, 195,000 retained draws and a thinning to every 15th draw in order to decrease the autocorrelation of the chain. The accuracy of the estimation is checked by comparing the Monte Carlo (MC) error, which measures the variability of each estimate due to the simulation, with the corresponding posterior standard deviation. When the MC errors are lower than the standard deviation, convergence is normally achieved (Ntzoufras 2009:120).

At the sample average, the estimates of the production elasticities (see Table 4) are 0.34 for land, 0.05 for machinery, 0.08 for labour, 0.08 for fertilizer, and 0.47 for livestock. Unlike classical econometric approaches, the Bayesian approach allows the posterior kernel density to be recovered for all parameter estimates instead of for a single point estimate. This allows more information to be obtained on the underlying parameter uncertainty (see Fig. 1).

The parameter β_1 has a larger uncertainty than the other first order parameter estimates that have a wider kernel density. The first-order coefficients for land and livestock are relatively far from zero, indicating a notable contribution in explaining the response variable. All first-order coefficients have an unambiguous positive association with the response variable when the sign of the posterior summaries of central and relative location is considered; this implies that the production frontier is

¹⁵ Estimated translog functions often violate regularity conditions, including monotonicity. In most previous empirical applications, the required theoretical regularity conditions were not checked or tested, and conclusions were often drawn without critically assessing theoretical consistency. Computation of technical efficiency and measurement of productivity when units operate in the ‘third stage’ of a technology are inconsistent, because the third stage represents an economically inefficient region.

Table 4 Bayesian estimated parameters of the stochastic production frontier

Parameter	Avg	Std	MC err.	2.5%	Median	97.5%
β_1	0.3363	0.0623	0.0024	0.2191	0.3363	0.4609
β_2	0.0476	0.0166	0.0006	0.0204	0.0457	0.0848
β_3	0.0775	0.0224	0.0006	0.0397	0.0755	0.1274
β_4	0.0772	0.0180	0.0005	0.0445	0.0763	0.1149
β_5	0.4593	0.0440	0.0016	0.3733	0.4592	0.5453
β_t	0.0077	0.0040	0.0001	−0.0004	0.0078	0.0151
β_{11}	0.0777	0.0538	0.0024	−0.0216	0.0753	0.1813
β_{12}	−0.0190	0.0154	0.0006	−0.0499	−0.0184	0.0088
β_{13}	−0.0024	0.0272	0.0012	−0.0606	−0.0001	0.0483
β_{14}	−0.0132	0.0199	0.0008	−0.0545	−0.0123	0.0235
β_{15}	0.0031	0.0616	0.0029	−0.1144	0.0040	0.1148
β_{1t}	0.0021	0.0024	0.0001	−0.0026	0.0022	0.0066
β_{22}	−0.0009	0.0041	0.0001	−0.0093	−0.0008	0.0070
β_{23}	0.0022	0.0122	0.0004	−0.0223	0.0022	0.0261
β_{24}	−0.0150	0.0098	0.0003	−0.0365	−0.0143	0.0020
β_{25}	0.0394	0.0206	0.0008	0.0045	0.0378	0.0849
β_{2t}	0.0007	0.0010	0.0000	−0.0014	0.0006	0.0028
β_{33}	0.0095	0.0229	0.0008	−0.0359	0.0089	0.0561
β_{34}	0.0049	0.0133	0.0005	−0.0230	0.0054	0.0295
β_{35}	−0.0187	0.0281	0.0011	−0.0723	−0.0190	0.0378
β_{3t}	0.0017	0.0016	0.0000	−0.0014	0.0017	0.0049
β_{44}	0.0191	0.0166	0.0006	−0.0151	0.0199	0.0498
β_{45}	0.0070	0.0265	0.0011	−0.0401	0.0054	0.0614
β_{4t}	−0.0031	0.0020	0.0000	−0.0070	−0.0031	0.0009
β_{55}	0.0329	0.0783	0.0035	−0.1118	0.0306	0.1887
β_{5t}	−0.0007	0.0023	0.0001	−0.0053	−0.0008	0.0038
β_{tt}	−0.0021	0.0005	0.0000	−0.0030	−0.0021	−0.0012
λ	8.255	2.263	0.0341	4.465	8.040	13.280
$\sigma - 2$	247.6	19.25	0.2231	211.2	247.1	286.6

Subscripts on β_n coefficients indicate inputs: 1 = land, 2 = machinery, 3 = labour, 4 = fertilizer, 5 = livestock, 6 = trend

Source: own estimates

well behaved and increasing in inputs. The sum of these input elasticities is slightly below 1.00, indicating that the technology exhibits moderate declining return to scale at the sample mean. The hypothesis of constant return to scale in the agricultural literature is often accepted, as noted in Cuesta (2000:148).

The first-order coefficient of the time trend variable provides information on the average annual rate of neutral technological change. The annual percentage change in output due to technological change is estimated to be 0.77%. In order to depict

Fig. 1 Kernel densities of the first order parameter estimates (input elasticities)

non-monotonic technological change, a time-squared variable is introduced in the model, and a time interacted with each input variable (the latter to allow for non-neutral technological change). The coefficient of time squared is negative, indicating that the increase in the rate of technological change is slowing down through time. The coefficient of time interacted with the land, machinery, labour, fertilizer and livestock input variables is positive for land, machinery and labour, and negative for fertilizer and livestock. This suggests that during the period considered, technological change has been land-, machinery- and labour-saving, but fertilizer- and livestock-using. The country-specific intercepts for the TFEs model and the standard model are reported in the Appendix.

The parameters capturing the temporal variation of technical inefficiency are presented in Table 5. The estimated parameters of the temporal variation by country show that technical efficiency declined over time in 18 countries but increased in the remaining 11 countries. Negative trends in the temporal variation of technical inefficiency are predominant in EU-12 and CC.

Average technical efficiency scores by country are reported in Table 6. Technical efficiency scores range from 0.2441 for Ireland to a maximum of 0.9074 for the Netherlands, with an unweighted country average of 0.4376. The average technical efficiency scores imply that on average the countries were producing about 43.8% of the outputs that could be produced using the observed input quantities. The unweighted average technical efficiency score was 0.4984 for the EU-15 countries,

Table 5 Bayesian estimated parameters of the temporal variation

Parameter	Avg	Std	MC err.	2.5%	Median	97.5%
η_1	−0.0045	0.0034	0.0001	−0.0107	−0.0047	0.0026
η_2	0.0000	0.4991	0.0011	−0.9800	0.0006	0.9793
η_3	0.0006	0.5007	0.0012	−0.9796	−0.0002	0.9810
η_4	−0.0012	0.5002	0.0011	−0.9785	−0.0020	0.9789
η_5	0.0018	0.4986	0.0011	−0.9751	0.0016	0.9826
η_6	0.0001	0.4995	0.0011	−0.9810	0.0000	0.9811
η_7	−0.0023	0.5000	0.0012	−0.9844	−0.0017	0.9761
η_8	−0.0016	0.5008	0.0012	−0.9852	−0.0023	0.9790
η_9	−0.0005	0.5006	0.0011	−0.9798	0.0002	0.9820
η_{10}	−0.0011	0.4988	0.0011	−0.9740	−0.0018	0.9786
η_{11}	0.0016	0.4990	0.0012	−0.9760	0.0012	0.9827
η_{12}	−0.0004	0.5009	0.0011	−0.9807	−0.0011	0.9790
η_{13}	0.0011	0.5017	0.0011	−0.9837	0.0024	0.9838
η_{14}	−0.0010	0.5000	0.0012	−0.9782	−0.0014	0.9807
η_{15}	−0.0002	0.5000	0.0012	−0.9792	0.0008	0.9776
η_{16}	−0.0007	0.5002	0.0011	−0.9780	−0.0004	0.9771
η_{17}	−0.0002	0.5003	0.0011	−0.9821	0.0002	0.9795
η_{18}	−0.0009	0.4999	0.0011	−0.9764	−0.0020	0.9782
η_{19}	−0.0006	0.4997	0.0011	−0.9847	0.0006	0.9820
η_{20}	−0.0016	0.5007	0.0011	−0.9843	−0.0019	0.9797
η_{21}	0.0001	0.5006	0.0011	−0.9823	0.0010	0.9776
η_{22}	0.0015	0.4998	0.0012	−0.9764	0.0005	0.9821
η_{23}	−0.0005	0.4999	0.0011	−0.9830	0.0001	0.9780
η_{24}	0.0016	0.4996	0.0012	−0.9745	0.0017	0.9791
η_{25}	0.0004	0.5000	0.0011	−0.9780	0.0009	0.9774
η_{26}	−0.0018	0.5003	0.0012	−0.9826	−0.0020	0.9823
η_{27}	−0.0006	0.5010	0.0012	−0.9836	−0.0010	0.9798
η_{28}	−0.0005	0.4988	0.0011	−0.9799	−0.0005	0.9734
η_{29}	0.0011	0.4993	0.0011	−0.9824	0.0009	0.9787

Subscript i indicates inputs: 1 = Austria, 2 = Bel.-Lux., 3 = Denmark, 4 = Finland, 5 = France, 6 = Germany, 7 = Greece, 8 = Ireland, 9 = Italy, 10 = Netherlands, 11 = Portugal, 12 = Spain, 13 = Sweden, 14 = UK, 15 = Bulgaria, 16 = Czech Rep., 17 = Cyprus, 18 = Estonia, 19 = Hungary, 20 = Latvia, 21 = Lithuania, 22 = Malta, 23 = Poland, 24 = Romania, 25 = Slovakia, 26 = Slovenia, 27 = Croatia, 28 = FYROM, 29 = Turkey

Source: own estimates

0.3990 for the EU-12 countries and 0.3084, for the CC. Swinnen and Vranken (2005) argue that technical efficiency scores in market economies are typically close to the best-practice frontier. The results obtained for the EU-12 indicate that the inevitable collapse in agricultural output after market liberalization was not immediately followed by efficient reallocations of agricultural assets. Brada and King (1993:47–54) and Carter and Zhang (1994:326) note that massive privatization of the farm sector does not necessarily imply greater technical efficiency. The

Table 6 Average technical efficiency scores by country, 1993–2006

	Avg	Std	MC err.	2.5%	Median	97.5%
EU-15						
Netherlands	0.9074	0.0842	0.0022	0.6854	0.9323	0.9975
Belg.-Lux.	0.6848	0.0718	0.0021	0.5123	0.6969	0.7959
Denmark	0.6664	0.0910	0.0034	0.4691	0.6716	0.8286
Italy	0.6585	0.1219	0.0044	0.4288	0.6550	0.9066
Greece	0.5454	0.1004	0.0038	0.3511	0.5433	0.7423
Germany	0.4758	0.0785	0.0025	0.3250	0.4741	0.6354
Austria	0.4533	0.0703	0.0027	0.3093	0.4548	0.5854
Sweden	0.4250	0.0690	0.0027	0.2852	0.4256	0.5558
Portugal	0.4101	0.0668	0.0025	0.2732	0.4107	0.5365
Spain	0.4068	0.0885	0.0032	0.2482	0.4016	0.5914
France	0.4022	0.0807	0.0026	0.2578	0.3970	0.5736
Finland	0.3917	0.0642	0.0024	0.2618	0.3922	0.5144
UK	0.3055	0.0509	0.0016	0.2075	0.3049	0.4062
Ireland	0.2441	0.0283	0.0009	0.1797	0.2473	0.2912
EU-12						
Hungary	0.6518	0.1166	0.0044	0.4249	0.6497	0.8788
Czech Rep.	0.4805	0.0803	0.0031	0.3181	0.4808	0.6329
Bulgaria	0.4478	0.0802	0.0030	0.2930	0.4459	0.6052
Cyprus	0.4381	0.0852	0.0029	0.2778	0.4346	0.6144
Slovakia	0.4110	0.0692	0.0026	0.2720	0.4109	0.5441
Poland	0.4033	0.0779	0.0028	0.2555	0.4008	0.5611
Slovenia	0.3865	0.0662	0.0023	0.2568	0.3860	0.5180
Romania	0.3735	0.0734	0.0027	0.2350	0.3712	0.5197
Malta	0.3387	0.1157	0.0034	0.1671	0.3201	0.6154
Lithuania	0.3327	0.0562	0.0021	0.2204	0.3325	0.4406
Latvia	0.2688	0.0444	0.0016	0.1801	0.2687	0.3551
Estonia	0.2557	0.0431	0.0015	0.1703	0.2553	0.3402
CC						
Croatia	0.3779	0.0623	0.0023	0.2524	0.3780	0.4979
Turkey	0.2833	0.0661	0.0022	0.1664	0.2783	0.4232
FYROM	0.2641	0.0443	0.0016	0.1759	0.2638	0.3505

Source: own estimates

ranking within the EU-12 countries is very similar to the one previously obtained by Tonini and Jongeneel (2006), which highlights that the Central and Eastern European Countries that were the most advanced in their reforms (i.e. Hungary and Czech Republic) are also the countries performing best in terms of technical efficiency. Bulgaria's relatively good performance can be attributed to the large contraction in several key agricultural inputs (particularly labour and land), although, the agricultural output level remained fairly stable. A similar result was also reported by Lissitsa et al. (2007), who also explained that unlike other transition

Fig. 2 Kernel densities of technical efficiency for Ireland and Italy

Fig. 3 Box plot of technological efficiencies by group of countries, 1993–2006. Numbers refer to countries: 1 = Austria, 2 = Bel.-Lux., 3 = Denmark, 4 = Finland, 5 = France, 6 = Germany, 7 = Greece, 8 = Ireland, 9 = Italy, 10 = Netherlands, 11 = Portugal, 12 = Spain, 13 = Sweden, 14 = UK, 15 = Bulgaria, 16 = Czech Rep., 17 = Cyprus, 18 = Estonia, 19 = Hungary, 20 = Latvia, 21 = Lithuania, 22 = Malta, 23 = Poland, 24 = Romania, 25 = Slovakia, 26 = Slovenia, 27 = Croatia, 28 = FYROM, 29 = Turkey

countries the Bulgarian agricultural sector was highly subsidized by the government because of the relatively high contribution of agriculture to GDP.

Figure 2 provides the kernel densities for Ireland and Italy, two countries characterized by very different kernel densities. Compared to Italy, Ireland displays little variance around its mean. A box plot of efficiency scores is presented in Fig. 3. The horizontal line indicates the median technical efficiency for each country. The box contains the first and third quartiles that are the upper and lower boundaries of the middle 50% of the technical efficiency. The vertical lines, so-called whiskers,

Table 7 Decomposition of TFP growth by country

	Efficiency change	Technological change	Scale change	TFP change
EU-15	−0.0700	0.5404	−0.0388	0.4416
Portugal	0.1449	0.9575	0.0004	1.1027
Spain	−0.0405	0.8085	0.0805	0.8484
Greece	−0.2147	0.9277	−0.0534	0.7261
Sweden	0.1029	0.6116	0.0075	0.7219
Finland	−0.1094	0.6297	0.0468	0.5671
Italy	−0.0472	0.7890	−0.1989	0.5429
France	0.1632	0.5080	−0.1434	0.5278
Denmark	0.0584	0.3947	−0.0180	0.4351
Austria	−0.4200	0.7673	−0.0180	0.4351
Germany	0.0051	0.5613	−0.2414	0.3251
Bel.-Lux.	0.0037	0.2696	−0.0015	0.2718
UK	−0.0962	0.5112	−0.1531	0.2619
Netherlands	−0.0993	0.3965	−0.0518	0.2455
Ireland	−0.1519	0.3596	0.0029	0.2105
EU-12	−0.0278	0.7974	0.0683	0.8378
Estonia	−0.0870	0.8936	0.8449	1.6516
Malta	0.1431	0.3247	0.8887	1.3565
Latvia	−0.1503	0.9970	0.4846	1.3313
Romania	0.1484	1.1828	−0.2148	1.1164
Slovakia	0.0368	0.8079	0.2360	1.0807
Lithuania	0.0081	0.8545	0.1167	0.9793
Bulgaria	−0.0190	0.9082	0.0653	0.9544
Poland	−0.0457	0.9975	−0.1888	0.7631
Hungary	−0.0511	0.7858	−0.0016	0.7330
Czech Rep.	−0.0664	0.7372	−0.0082	0.6626
Cyprus	−0.0217	0.5524	0.1112	0.6418
Slovenia	−0.1631	0.3929	0.1885	0.4183
CC	0.0916	1.1633	−0.1542	1.1001
Turkey	0.0979	1.1940	−0.1727	1.1192
FYROM	−0.0490	1.0004	0.1175	1.0689
Croatia	−0.0516	0.5250	0.1284	0.6018

Average annual changes in %, 1993–2006

Growth rates for EU-15, EU-12 and CC are computed as weighted averages, where the weights are represented by the shares in agricultural production value for the year 2006

Source: own estimates

display either the maximum value or the location of twice the standard deviation, whichever is the smaller. The figure shows that the standard deviation around the point estimates is relatively large for Greece, Italy, Hungary and Malta.

Table 8 Deviance information criterion for the estimated models

	TFEs	ST
DIC	5,689.79	5,690.07

Source: own estimates

The decomposition of TFP growth for each country is presented in Table 7. The estimated weighted average annual TFP growth is 0.44 for the EU-15, 0.84 for the EU-12 and 1.10% for the CC. This suggests that on average the EU-12 and CC have annual productivity growth rates that are about double that of the EU-15. This is also consistent with the results found by Lissitsa et al. (2007). Given the observed strong decline in agricultural output induced by transition in nearly all EU-12 countries (with Hungary, Malta, Romania and Slovenia as exceptions) and taking account of the known immobility of production factors in agriculture, it would not have been surprising to find a decline in TFP. In spite of this, however, we find that agricultural TFP rose at a higher rate in the EU-12 than in the EU-15 countries. This is in line with Brada (1989:443), who found that technical progress did not decline when the relation between outputs and inputs was adjusted for systematic changes in efficiency. TFP growth ranges from 0.21 for Ireland to 1.63 for Estonia, with an unweighted average of 0.75. All the countries analysed showed productivity growth. Efficiency change ranges from -0.42 for Austria to 0.16 for France, with an unweighted average of -0.03 and 18 countries showing negative efficiency changes. Technological change ranges from 0.27 for Belgium to 1.19 for Turkey, with an unweighted average of 0.71 and none of the countries show productivity regression. Scale change ranges from -0.24 for Germany to 0.89 for Malta, with an unweighted average of 0.06 and Portugal displaying very small changes in scale. The estimates suggest that productivity growth was mostly driven by technological change.

The results of the TFEs model are compared to the results of the standard model, which does not take account of country-specific time-invariant heterogeneity. The deviance information criterion (DIC) introduced by Spiegelhalter et al. (2002) was used to compare both models (Table 8). A low value for DIC indicates a better fit for the model.

From the DIC it appears that although, the TFEs model has a lower DIC than the standard model, the difference is less than the minimum value of below two and therefore both models can be considered to be equally good. However, we retain the results of the TFEs model, because they account for country-specific time-invariant heterogeneity. In Fig. 4, the cumulative changes are reported for both models. The main difference is in the cumulative TEC. The standard model shows a very moderate increase in TEC whereas the TFE displays negative TEC. For the other cumulative changes, both models present very similar trends. Carroll et al. (2011) reported similar findings.

6 Conclusions

This paper estimated and compared TFP growth in agriculture for the EU countries and CC over the period 1993–2006. The data used were drawn from the FAOSTAT

Fig. 4 Cumulative technical efficiency change (TEC), technological change (TC), scale efficiency change (SEC) and TFP change (TFPC) for the TFEs and ST models. Source own estimates

database of the Statistics Division of the FAO of the United Nations in Rome, which is the best available global database for cross-country comparisons in the agricultural sector. A Bayesian estimation framework was used, imposing global regularity conditions on the estimated production frontier and obtaining posterior kernel densities for each parameter estimate. Two types of nested models were estimated and compared: the extended TFEs model and the inefficiency model proposed by Cuesta (2000). Given the importance for country-level analysis of taking account of differences in the stage of development, market liberalization and physical conditions (soil quality, drainage, relief and climate), the TFEs model was preferred.

The main results illustrate important differences in the level and trends in agricultural productivity for European countries. On average, EU-15 countries used agricultural inputs more efficiently than the EU-12 countries and the CC. Agricultural productivity growth was mostly driven by advances in technology over time, through technological developments. Efficiency change contributed particularly to growth in agricultural productivity in EU-15 countries, whereas scale change contributed particularly to agricultural productivity in EU-12 countries and CC. Therefore, productivity gains were also due to moves toward the best practice frontier and to moves along the frontier. The EU-12 countries and CC displayed TFP growth rates that were about double the EU-15 growth rate. There was catch-up in productivity levels between EU-15 and EU-12 as well as between EU-15 and CC. Most of the countries that were well below the frontier at the beginning of the sample period had high TFP growth rates. This is especially the case for the Baltic States, Malta, Romania and Poland within the EU-12, and for Turkey and FYROM within the CC.

Care should be taken when interpreting the results, since they are conditional on the data and the assumptions underlying the estimation procedure used (for

example: functional form, error-generating process, etc.). In addition, the data used do not allow differences in input quality to be controlled for. Input quality may differ across the countries considered in the analysis and so the results should be interpreted with this in mind. However, we believe that our results have drawn attention to several important trends in agricultural productivity.

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Appendix

See Table 9.

Table 9 Intercepts of the ST and TFEs models

Parameter	Avg	Std	MC err.	2.5%	Median	97.5%
β_0	0.78	0.1794	0.01	0.4904	0.77	1.19100
α_1	0.82	0.1787	0.01	0.5131	0.81	1.19400
α_2	-2.79	998.80	2.27	-1,955.00	-1.86	1,958.00
α_3	-0.91	1,001.00	2.22	-1,970.00	-2.68	1,961.00
α_4	-1.94	1,001.00	2.12	-1,962.00	-0.73	1,956.00
α_5	3.61	1,002.00	2.38	-1,959.00	2.08	1,967.00
α_6	1.22	999.80	2.16	-1,958.00	2.61	1,951.00
α_7	1.34	1,003.00	2.20	-1,963.00	0.16	1,972.00
α_8	1.00	1,001.00	2.30	-1,965.00	-0.37	1,962.00
α_9	-3.78	999.40	2.19	-1,962.00	-3.43	1,958.00
α_{10}	-0.35	1,004.00	2.25	-1,961.00	-1.76	1,964.00
α_{11}	0.62	1,002.00	2.20	-1,955.00	1.54	1,954.00
α_{12}	0.46	1,002.00	2.26	-1,968.00	1.70	1,959.00
α_{13}	-2.13	999.90	2.32	-1,967.00	-3.35	1,962.00
α_{14}	-1.64	996.80	2.27	-1,964.00	-4.38	1,953.00
α_{15}	-1.83	1,002.00	2.51	-1,972.00	-3.02	1,955.00
α_{16}	1.38	1,002.00	2.30	-1,966.00	3.27	1,961.00
α_{17}	3.52	1,002.00	2.28	-1,954.00	3.02	1,967.00
α_{18}	2.99	998.80	2.28	-1,950.00	1.54	1,956.00
α_{19}	3.69	999.30	2.27	-1,954.00	3.66	1,966.00
α_{20}	2.95	998.90	2.33	-1,955.00	5.10	1,964.00
α_{21}	1.60	999.40	2.15	-1,959.00	2.12	1,965.00
α_{22}	-0.63	1,001.00	2.29	-1,966.00	0.11	1,951.00
α_{23}	-1.95	1,001.00	2.21	-1,965.00	-1.90	1,961.00

Table 9 continued

Parameter	Avg	Std	MC err.	2.5%	Median	97.5%
α_{24}	−0.02	1,001.00	2.38	−1,962.00	−1.51	1,970.00
α_{25}	−2.38	996.60	2.31	−1,949.00	0.42	1,943.00
α_{26}	−2.54	1,002.00	2.21	−1,973.00	−0.31	1,950.00
α_{27}	0.64	999.40	2.16	−1,959.00	0.20	1,956.00
α_{28}	−0.83	1,003.00	2.26	−1,972.00	−0.94	1,964.00
α_{29}	−0.75	1,002.00	2.39	−1,968.00	0.04	1,967.00

Source: own estimates

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