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A Stochastic Frontier Model to Assess Agricultural Eco-efficiency of European Countries in 1990–2019

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Abstract

This paper aims at assessing agricultural eco-efficiency of 40 European countries, including non-European Union and ex-USSR ones, in the period 1990–2019 (30 years). A stochastic frontier model with a panel translog specification is employed to allow technology to change in time and across countries, and both output elasticities and returns to scale to vary with input levels and time. Our study is original compared to existing ones in the literature because it considers the almost totality of European countries and focuses on a long and recent period. As such, it is able to draw an exhaustive and updated picture of agricultural eco-efficiency in Europe that fills both temporal and spatial information gaps left by existing studies. In our results, countries with a definitely increasing eco-efficiency in the period 1990–2019 are Albania, Croatia, Iceland, Lithuania, North Macedonia, Portugal and Ukraine, while countries with a definitely decreasing eco-efficiency are Cyprus, Czechia, France, Greece, Hungary, Malta, Romania and Slovakia. All other countries have an approximately constant eco-efficiency in the period 1990–2019, ranging, in average, between 0.93 and 0.95, with the exception of two groups of countries: (i) Denmark, Italy, Serbia-Montenegro, Slovenia and Switzerland, which show a decline of eco-efficiency in recent years; (ii) Ireland and Latvia, which exhibit an upward inversion of the trend in the penultimate decade. These two groups of countries should be monitored in the near future to better establish whether the decline or the increase in eco-efficiency is temporary or permanent. Our study also provides, for the first time, evidence on agricultural eco-efficiency in non-European Union transition economies, specifically it emphasizes the promising performance of Albania, North Macedonia and Ukraine.

Keywords: country level, European agriculture, stochastic production frontier, sustainability, technical efficiency

1. Introduction

Agriculture plays a key role in satisfying food demand of the rapidly increasing world population, thus it constitutes one of the most important sectors for the economic development of countries. On the other hand, agriculture also gives rise to negative externalities on the environment in terms of soil degradation, groundwater depletion, biodiversity loss and nutrient pollution (Pretty, 2008; Foley et al., 2011). This is particularly true in recent years, because intensive farming practices have been largely put into practice to meet the increasing demand for fresh goods by developed countries (Oenema and Oenema, 2021; Domingues et al., 2020; Fabiani et al., 2020; García de Jalón et al., 2018). For this reason, one of the major objectives of the Common Agricultural Policy (CAP) of the European Union (EU) is to promote a balance between the economic and the environmental performance of agricultural production (Commission of the European Communities, 2000). However, this task is pretty challenging, as it requires a quantitative understanding of the relationship between agricultural production and the ecosystem. Therefore, there is an increasing need by international decision makers for methodologies allowing an integrated assessment of both environmental and economic performance of agriculture, so that appropriate policies can be designed to favour an efficient use of natural resources in agricultural production.

In this context, the term 'eco-efficiency' was proposed by Schaltegger and Sturm (1990) to denote a "business link to sustainable development", and subsequently adopted by the World Business Council to indicate a management practice linking "the desired goals of business and environmental excellence to achieve measurable commercial and social benefits" (Stigson, 1996). Later, eco-efficiency was defined by the Organization for Economic Co-operation and Development (OECD) as "the efficiency with which ecological resources are used to meet human needs" (OECD, 1998), thus extending the concept not only to enterprises, but also to entire economic sectors, regions and countries. According to Huppes and Ishikawa (2005), eco-efficiency is the ratio of economic value created per one unit of environmental impact. As such, it increases when the economic value of production is maintained or raised while reducing the impact on ecosystem services. Therefore, eco-efficiency represents an important index for assessing agricultural sustainability in terms of resource use and environmental pressure (UNESCAP, 2009). In particular, eco-efficiency of agriculture is increasingly attracting the interest of national and European institutions for what concerns policy development finalized to the achievement of 2030 Sustainable Development Goals (see, for example, Caiado et al., 2017; Quiroga et al., 2017; Toma et al., 2017; Czyzewski et al., 2021).

Table 1. Characteristics of studies assessing eco-efficiency of agriculture in European countries through Data Envelopment Analysis (DEA). All the studies employ yearly measurements and the output variables are valued in constant US dollars or euros. 'EU': European Union. 'LW': Labour force (annual working units); 'LN': Labour force (number of economically active persons); 'A': total agricultural area (hectares); 'LS': livestock (cattle or sheep equivalent units); 'K': value of capital stock (constant US dollars); 'T': total number of tractors; 'F': total amount of fertilizers (tonnes)

Authors (year)	Analysed countries	Units of obs.	Period	Output variables	Input variables
Tonini and Jongeneel (2006)	10 eastern EU countries	Countries	1993–2002	Net agricultural production.	LN; A; LS; total number of machineries; F.
Latruffe et al. (2012)	France and Hungary.	Farms	2001–2007	Milk production; cereal, oilseed and protein crops production; other output.	LW; A; K; intermediate consumption.
Bojnec et al. (2014)	10 eastern EU countries.	Countries	2001–2006	Gross value added of agriculture.	LW; A; LS; T; F.
Kocisova (2015)	27 EU countries	Countries	2007–2011	Gross output of crops and crop products; gross output livestock and livestock products.	LW; A; K.
Toma et al. (2017)	26 EU countries	Countries	1993–2013	Gross agricultural production.	LN; crop area; irrigation area; K; F.
Rybaczewska-Blazejowska and Gierulski (2018)	28 EU countries	Countries	2015	Gross domestic product of agriculture.	Energy; water; F; pesticides; waste; greenhouse gas emissions.
Moutinho et al. (2018a)	27 EU countries	Countries	2005–2012	Net value added of agriculture.	LW; A; energy.
Moutinho et al. (2018b)	22 EU countries	Countries	2005, 2010	Gross value added of agriculture to greenhouse gas emissions.	LW; A; K; F; lubricants.
Coluccia et al. (2020)	Italy	Regions	2004–2017	Gross agricultural production.	LN; crop area; irrigation area; K; F.
Exposito and Velasco (2020)	21 EU countries	Countries	2001–2012	Gross agricultural production; fertilizer intensity (F/value of production).	LN; A; K.
Czyzewski et al. (2021)	25 EU countries	Farms	2004–2017	Gross agricultural production.	A; stock density (K/A); energy; F; pesticides.

This paper focuses on the assessment of agricultural eco-efficiency in Europe, which is a quite relevant topic from the view of international policy makers, due to heterogeneity in the level of development and to the existence of gaps in technical efficiency among the various countries. Tables 1 and 2 summarize the characteristics of existing studies assessing eco-efficiency of agriculture in European countries. It can be noted that these studies are restricted to EU countries and to a period typically no longer than twenty years and no later than 2013, with few exceptions focused on more recent years but

Table 2. Characteristics of studies assessing eco-efficiency of agriculture in European countries through stochastic frontier models. All the studies employ yearly measurements and the output variables are valued in constant US dollars or euros. ‘EU’: European Union. ‘LW’: Labour force (annual working units); ‘LN’: Labour force (number of economically active persons); ‘A’: total agricultural area (hectares); ‘LS’: livestock (cattle or sheep equivalent units); ‘K’: value of capital stock (constant US dollars); ‘T’: total number of tractors; ‘F’: total amount of fertilizers (tonnes)

Authors (year)	Analysed countries	Units of obs.	Period	Output variables	Input variables
Tonini and Jongeneel (2006)	10 eastern EU countries	Countries	1993–2002	Net agricultural production.	LN; A; LS; total number of machineries; F.
Tonini and Pede (2011)	27 EU countries plus North Macedonia and Turkey	Countries	1993–2006	Net agricultural production.	LN; A; LS; T; F.
Tonini (2012)	28 EU countries plus North Macedonia and Turkey	Countries	1993–2006	Net agricultural production.	LN; A; LS; T; F.
Cechura et al. (2017)	24 EU countries	Farms	2004–2011	Milk production	LW; A; LS; K; feed.
Hidalgo González and Rodríguez Fernández (2017)	5 southern EU countries	Regions	2004–2012	Gross agricultural production.	LW; LS; K.
Quiroga et al. (2017)	10 EU countries	Farms	1996–2009	Gross output of crops and crop products.	LW; A; technology index derived from the amount of seeds, plants, machineries, fertilizer and energy in use.
Moutinho et al. (2018b)	22 EU countries	Countries	2005, 2010	Gross value added of agriculture to greenhouse gas emissions.	LW; A; K; F; lubricants.
Auci and Vignani (2020)	Italy	Regions	2000–2009	Crop yields.	LW; irrigation area; citrus area; fruit area; vegetable area; seeds; F.
Auci et al. (2020)	8 EU countries	Farms	2007–2017	Operating revenues.	A; K; cost of employment; intermediate consumption.
Bakucs et al. (2020)	Hungary	Regions	2002–2013	Total incomes and capitalized own performance.	LW; A; K; intermediate consumption.

limitedly to a single country (Coluccia et al., 2020; Auci and Vignani, 2020) or to a farm level analysis (Czyzewski et al., 2021). The prevalent methodologies adopted by these studies are Data Envelopment Analysis (DEA, Charnes et al., 1978) and stochastic frontier models (Aigner et al., 1977; Battese and Corra, 1977; Meeusen and van den Broeck, 1977). Both the two methods are adequate to assess eco-efficiency because they measure the distance between the observed and the maximum possible output (economic value) given the inputs currently employed in the production process (environmental pressure). However, the two methods have different characteristics: DEA exploits linear programming to construct a non-parametric piecewise linear production frontier, while a stochastic frontier model assumes a parametric formulation for the production frontier. It is important to note that DEA, although more flexible and completely free from assumptions, has the limitation to attribute all the deviations from the production frontier to technical inefficiency (i.e., perfectible eco-efficiency), while stochastic frontier models are able to account for shocks beyond the control of producers. See Hjalmarsson et al. (1996) for a detailed comparison of the two methods.

In this paper, we employ a stochastic frontier model to assess agricultural eco-efficiency of 40 European countries, including non EU and ex-USSR ones, in the period 1990–2019 (30 years). Our study is original compared to existing ones in the literature because it considers the almost totality of European countries and focuses on a long and recent period. As such, it is able to draw an exhaustive and updated picture of agricultural eco-efficiency in Europe that fills both temporal and spatial information gaps left by existing studies. We prefer the stochastic frontier approach to DEA for two main reasons: (i) it can disentangle pure technical inefficiency (i.e., perfectible eco-efficiency) from external shocks; (ii) it has a clear interpretability, allowing to assess differences in technology across countries, interactions among inputs and the trend of returns to scale. In particular, we criticize DEA because the weights assigned to the inputs are different across countries and may be equal to zero, thus being difficult or even impossible to interpret.

This paper is structured as follows. In Section 2, the data employed in our study are described. Section 3 includes technical details on the stochastic frontier model. In Section 4, the results are presented and discussed. Section 5 contains concluding remarks.

2. Data Description

The data employed in our study are sourced to Food and Agriculture Organization (FAO), International Labour Organization (ILO) and United States Department of Agriculture (USDA). They have annual frequency in the period 1990–2019 (30 years) and cover 40 European countries, including non-EU and ex-USSR ones. Table 3 shows the considered countries partitioned into geographical zones. Note that the eastern zone includes all and only the European transition economies. Due to lack of data, we excluded Andorra, Holy See, Liechtenstein, Monaco and San Marino. The output variable is the gross agricultural production, while the input variables consist of five measures: land use, labour force, livestock, machinery stock and fertilizer use. We basically consider the same output and input variables of existing studies at country level listed in Tables 1 and 2, but with an improved measure of land use and machinery stock consisting of a weighted aggregation based on rainfed cropland and 40 horsepower equivalent units, as detailed below.

Table 3. List of the considered countries partitioned into geographical zones

Zone	Countries
North	Denmark, Finland, Iceland, Norway, Sweden.
West	Austria, Belgium-Luxembourg, France, Germany, Ireland, Netherlands, Switzerland, United Kingdom.
South	Cyprus, Greece, Italy, Malta, Portugal, Spain.
East	Albania, Belarus, Bosnia-Herzegovina, Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Moldova, North Macedonia, Poland, Romania, Russian Federation, Serbia-Montenegro, Slovakia, Slovenia, Ukraine.

Gross agricultural production is the official measure by FAO made available in the database FAOSTAT. This is an aggregation of the production quantity for 157 crop and livestock commodities weighted by a fixed set of global average prices in US dollars from 2004 to 2006.

Land use is measured in hectares of rainfed cropland equivalents (Fuglie, 2012, 2015) and it is sourced to the ERS dataset, USDA. This is a quality-adjusted measure of land use relying on FAO data defined as the weighted sum of arable land (weight equal to 1), cropland (weight equal to 1), irrigated cropland (weight equal to 0.094), and permanent meadows and pastures (weight equal to 2.145). This measure is an improvement of the ones adopted by existing studies, where land use is either measured as the total agricultural area or distinguished into crop and irrigation area.

Labour force is measured as the number of economically active adults in agriculture, and consists of modeled estimates from ILO, April 2021 update. These estimates are based on periodic labour force surveys from individual countries, and are periodically revised and updated as more survey information becomes available.

Livestock is measured in cattle equivalent units, with stocks sourced to FAOSTAT and weights for each species borrowed from Hayami and Ruttan (1985, p. 450). Precisely, our measure of livestock is the weighted sum of the number of cattle and buffaloes (weight equal to 1), equidae (weight equal to 1), sheep and goats (weight equal to 0.1), pigs (weight equal to 0.2), and chicken (weight equal to 0.01).

Machinery stock is measured in 40 horsepower equivalent units (Fuglie, 2012, 2015) by aggregating the number of 2-wheel tractors (weight equal to 0.3), 4-wheel tractors (weight equal to 1), and combine-harvesters and threshers (weight equal to 0.5). Data on machinery stocks are sourced to the ERS dataset, USDA, and consist of FAO data for the period 1961–2009 and of modeled estimates after 2009. This measure is an improvement of the ones adopted by existing studies, where machinery stock is either measured in value or proxied by the number of tractors.

Fertilizer use is measured as the raw sum of FAOSTAT data on nitrogen, phosphate and potash fertilizer consumption in metric tonnes.

Table 4 shows mean level, standard deviation and average annual change of the output and each input by decade and zone, while Figure 1 shows the time series of the output and each input aggregated by geographical zone. We see that, in the period 1990–2019, agricultural output has a definitely increasing trend in northern, western and southern zones, while, in eastern Europe, the tendency begins to increase only in 2000 after an initial decrease. For what concerns agricultural inputs, we see that land use, labour force and livestock have a definitely decreasing trend across all zones, with the exception of western Europe, where the decline is preceded by an increase until 1998. Instead, the tendency of machinery stock is downward in northern and western zones, while, in southern Europe, the decrease begins only in 1997 after an initial increase, and, in Eastern Europe, the trend is initially decreasing and inverted upward in 2010. Fertilizer use shows a definitely declining tendency in northern and western Europe, while, after an initial decrease, southern and eastern zones show an upward inversion in 2007 and in 1994, respectively.

Table 4. Data summaries by decade and zone. Values are mean levels aggregated across all countries in each zone, with standard deviation and average annual percentage change within brackets

	1990–1999	2000–2009	2010–2019	1990–2019
Gross agricultural output (million 2004–2006 US dollars)				
North	18997.4 (591.3;−0.08)	19311.6 (233.8;+0.04)	19518.6 (447.6;+0.13)	19275.9 (484.9;+0.03)
West	177805.8 (4321.1;+0.04)	176185.2 (4297.1;−0.03)	182114.1 (4642.2;+0.16)	178701.7 (4968.8;+0.04)
South	100056.3 (4533.6;+0.23)	107688.9 (1757.6;−0.12)	106873.1 (4031.9;−0.02)	104872.8 (4949.4;+0.02)
East	214666.0 (28502.5;−1.42)	194284.5 (10946.7;+0.68)	230428.3 (18846.3;+0.86)	213126.3 (25020.0;−0.11)
Land use (hectares of rainfed cropland equivalents)				
North	10406.6 (85.5;−0.01)	10233.2 (44.4;−0.02)	9872.1 (256.4;−0.05)	10170.6 (273.1;−0.03)
West	53421.8 (758.4;+0.06)	54040.7 (225.0;−0.11)	53934.4 (291.6;+0.00)	53798.9 (544.2;−0.02)
South	59649.7 (1043.9;−0.11)	57439.8 (1430.9;−0.09)	54766.3 (508.3;+0.02)	57285.3 (2275.5;−0.05)
East	266021.3 (6991.5;−0.66)	247967.8 (3847.4;−0.39)	243132.5 (323.6;−0.07)	252373.8 (10962.0;−0.39)
Labour force (thousand persons)				
North	563.2 (55.2;−0.28)	409.6 (39.3;−0.48)	323.9 (14.6;−0.19)	432.2 (107.8;−0.30)
West	3816.8 (306.2;−0.28)	3019.5 (252.1;−0.48)	2402.8 (134.8;−0.44)	3079.7 (633.3;−0.40)
South	2883.6 (229.9;−0.16)	2276.7 (209.7;−0.20)	1777.9 (101.9;−0.35)	2312.7 (494.7;−0.24)
East	30491.7 (1979.0;−0.89)	23146.6 (3052.6;−1.99)	16392.5 (1654.1;−0.85)	23343.6 (6265.0;−1.32)
Livestock (thousand cattle equivalent units)				
North	7410.9 (140.7;−0.07)	6633.6 (247.3;−0.11)	6213.8 (141.4;−0.19)	6752.8 (534.6;−0.12)
West	78844.4 (2645.5;−0.17)	71780.1 (2303.4;−0.18)	67573.7 (2488.9;−0.32)	72732.7 (5302.1;−0.22)
South	23062.5 (541.3;−0.02)	22812.1 (525.8;−0.12)	21422.8 (727.7;−0.12)	22432.5 (937.6;−0.08)
East	112007.2 (26075.1;−3.05)	63289.7 (5544.9;−1.03)	52656.4 (2417.4;−0.79)	75984.4 (30216.7;−1.64)
Machinery stock (thousand 40 horsepower equivalent units)				
North	735.5 (32.5;−0.23)	621.2 (37.4;−0.17)	500.2 (32.0;−0.25)	619.0 (103.1;−0.21)
West	4136.1 (257.9;−0.26)	3479.9 (145.2;−0.22)	3053.0 (114.2;−0.22)	3556.3 (486.3;−0.23)
South	2599.3 (157.8;+0.26)	2568.4 (82.5;+0.17)	2375.6 (94.6;−0.05)	2514.4 (150.8;+0.11)
East	4527.9 (210.1;−0.22)	3925.0 (117.1;−0.28)	4117.4 (134.0;+0.17)	4190.1 (298.2;−0.10)
Fertilizer use (thousand tonnes of nutrients)				
North	1215.9 (96.8;−0.15)	1021.2 (93.6;−0.27)	924.6 (64.3;+0.14)	1053.9 (148.6;−0.13)
West	12010.4 (674.0;−0.48)	9238.3 (1074.3;−0.64)	8279.8 (213.8;−0.03)	9842.8 (1761.2;−0.37)
South	4693.2 (166.9;−0.18)	3829.9 (731.6;−0.83)	3128.4 (181.4;+0.70)	3883.8 (780.2;−0.13)
East	10461.3 (5988.5;−3.93)	7545.0 (1010.4;+0.60)	11351.9 (1457.8;+3.77)	9786.1 (3852.3;+0.02)

3. Model Formulation

Stochastic frontier models were proposed independently by Aigner et al. (1977), Battese and Corra (1977), and Meeusen and van den Broeck (1977), while Schmidt and Sickles (1984) addressed the extension to panel data. Let $i = 1, \dots, n$

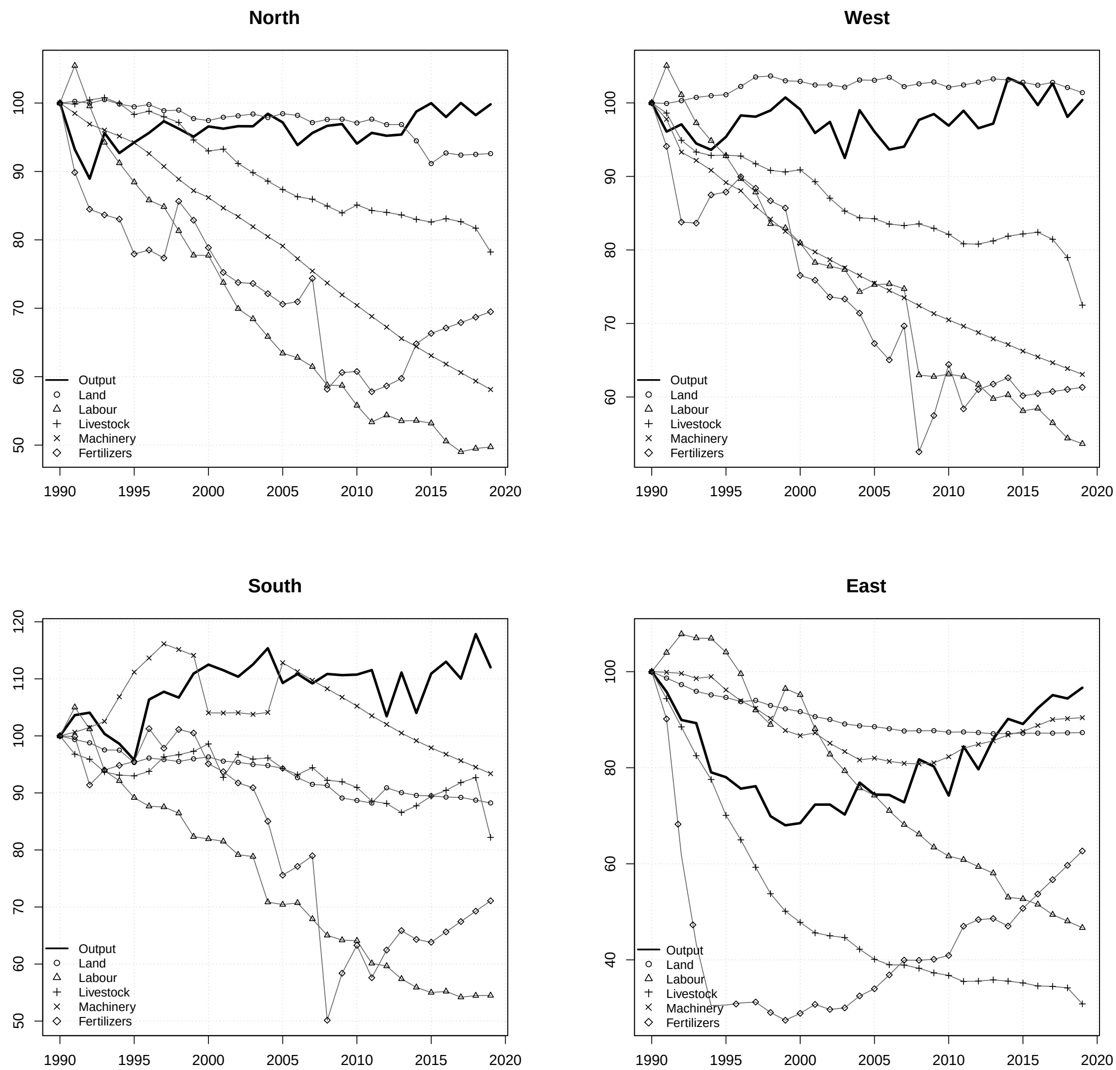

Figure 1. Time series of output (gross agricultural output) and inputs (land use, labour force, livestock, machinery stock, fertilizer use) by geographical zone, indices 1990=100

denote the production units (countries) and $t = 1, \dots, T$ the time points (years). Also, let $y_{i,t}$ be the output level produced by unit i at time t and $x_{i,j,t}$ the level of the j-th input ($j = 1, \dots, p$) employed by unit i at time t. The general stochastic frontier model has the following form:

$$y_{i,t} = f(\boldsymbol{x}_{i,t}; \Theta) \exp(v_{i,t} - u_{i,t}) \qquad i = 1, \dots, n; \ \ t = 1, \dots, T \tag{1}$$

where f is the production frontier, representing the maximum output level technically feasible based on a given combination of the inputs $\boldsymbol{x}_{i,t} = (x_{i,1,t}, \dots, x_{i,j,t}, \dots, x_{i,p,t})$ and a given technology Θ, while $v_{i,t} \in \mathbb{R}$ and $u_{i,t} \in \mathbb{R}^+$ are two random errors representing the deviation from the production frontier f due to shocks, respectively, independent of the producer and related to the production. As such, according to model (1), the maximum feasible output may differ from the maximum output level technically feasible due to the occurrence of either favourable or unfavourable events beyond the control of producers. Specifically, the maximum feasible output for unit i at time t is equal to $y^*_{i,t} = f(\boldsymbol{x}_{i,t}; \Theta) \exp(v_{i,t})$. As a consequence, technical efficiency of unit i at time t, that we denote as $\mathrm{TE}_{i,t}$, is equal to the ratio between the actual output level $y_{i,t}$ and the maximum feasible one $y^*_{i,t}$:

$$\mathrm{TE}_{i,t} = \frac{y_{i,t}}{y^*_{i,t}} = \frac{y_{i,t}}{f(\boldsymbol{x}_{i,t}; \Theta) \exp(v_{i,t})} = \exp(-u_{i,t}) \tag{2}$$

The production unit i achieves the maximum output level at time t if and only if $\mathrm{TE}_{i,t} = 1$, otherwise technical inefficiency occurs and $0 < \mathrm{TE}_{i,t} < 1$ measures the relative distance of the actual output level from the maximum feasible one. If the output is a measure of the production value and the inputs are resources with environmental impact, then $\mathrm{TE}_{i,t}$ is the eco-efficiency of unit i at time t.

A flexible and commonly adopted specification for the production frontier f is the translog function (see, for example, Greene, 2008):

$$f(\boldsymbol{x}_{i,t};\Theta) = \exp\left(\alpha_i + \delta\, t + \gamma\, t^2 + \sum_{j=1}^{p}\beta_j \log x_{i,j,t} + \sum_{j=1}^{p}\sum_{k=j}^{p}\beta_{j,k}\log x_{i,j,t}\log x_{i,k,t} + \sum_{j=1}^{p}\lambda_j\, t\log x_{i,j,t}\right) \tag{3}$$

where the technology Θ is characterized by the parameters appearing in the equation, specifically:

- for $i = 1,\ldots,n$, parameter α_i is the intercept for unit i;
- parameters δ and γ are, respectively, the linear and the quadratic component of the trend;
- for $j = 1,\ldots,p$, parameter β_j is the first order coefficient for the j-th input;
- for $j = 1,\ldots,p$ and $k = 1,\ldots,p$, parameter $\beta_{j,k} = \beta_{k,j}$ is the second order coefficient for the j-th input (if $j = k$) or the coefficient for the interaction between the j-th and the k-th input (if $j \neq k$);
- parameter λ_j is the coefficient for the interaction between the j-th input and time.

The Cobb-Douglas specification is obtained by setting $\beta_{j,k} = 0\ \forall j,k$ in equation (3). It can be shown that the translog functional form, compared to the Cobb-Douglas, allows output elasticities and returns to scale to vary with input levels and imposes no restrictions on substitution elasticities. For this reason, we prefer the translog specification, leading to the following stochastic frontier model:

$$\log y_{i,t} = \alpha_i + \delta\, t + \gamma\, t^2 + \sum_{j=1}^{p}\beta_j \log x_{i,j,t} + \sum_{j=1}^{p}\sum_{k=j}^{p}\beta_{j,k}\log x_{i,j,t}\log x_{i,k,t} + \sum_{j=1}^{p}\lambda_j\, t\log x_{i,j,t} + v_{i,t} - u_{i,t} \tag{4}$$

Model (4), also employed by Tonini and Pede (2011), Tonini (2012) and Cechura et al. (2017), is characterized by a high degree of flexibility, because: (i) the production units are allowed to have different technologies due to the intercepts $\alpha_1,\ldots,\alpha_n$; (ii) the technology can vary in time according to a second order polynomial trend on the logarithmic scale due to parameters δ and γ; (iii) the output elasticity of each input can vary in time according to a linear trend on the logarithmic scale due to parameters $\lambda_1,\ldots,\lambda_p$; (iv) the output elasticity of each input depends not only on its level, but also on its squared level and on the level of the other inputs due to parameters $\beta_{j,k}$, $j = 1,\ldots,p$ and $k = 1,\ldots,p$.

Although the flexibility of the translog production frontier is widely recognized, it has the disadvantage of requiring a high number of parameters, thus its estimation may be highly inefficient in short panel data. For this reason, most existing studies on agricultural eco-efficiency in European countries (precisely, all the ones listed in Table 2 excepting Tonini and Pede, 2011; Tonini, 2012; Cechura et al., 2017) have adopted the classic Cobb-Douglas specification, which neglects quadratic terms and first order interactions among inputs, i.e., $\beta_{j,k} = 0\ \forall j,k$, with the consequence of assuming unitary elasticities of substitution. In this paper, we consider a larger number of countries and a longer period of analysis compared to existing studies, thus the number of parameters required by the translog functional form results reasonably small compared to the sample size.

We complete the specification of model (4) by assuming the intercepts $\alpha_1,\ldots,\alpha_n$ to be fixed, and random errors $v_{i,t}$ and $u_{i,t}$ to be independent and identically distributed as, respectively, Normal and half Normal random variables:

$$v_{i,t} \sim_{i.i.d.} N(0,\sigma_V^2) \qquad u_{i,t} \sim_{i.i.d.} N^+(0,\sigma^2) \qquad i = 1,\ldots,n;\ t = 1,\ldots,T \tag{5}$$

Under this specification, the composed error $\varepsilon_{i,t} = v_{i,t} - u_{i,t}$ is often denoted as Normal-half Normal. Our preference towards fixed rather than random effects relies on the fact that the considered production units represent a fixed number of European countries which, in principle, cannot increase further. Instead, the choice of the half Normal distribution relies on its good balance between simplicity and flexibility compared to more complex distributions like the truncated Normal and the Gamma (Stevenson, 1980; Greene, 1980). Parameter estimation is performed by maximizing the likelihood (Aigner et al., 1977; Battese and Corra, 1977) and technical efficiencies are estimated as $\widehat{\mathrm{TE}}_{i,t} = \exp\left[-\mathbb{E}\left(u_{i,t} \mid \varepsilon_{i,t}\right)\right]$ (Jondrow et al., 1982).

A final remark on our model formulation regards the alternative specifications for random errors $u_{i,t}$. Although the use of the half Normal distribution has become prominent in empirical applications, several different specifications have been proposed to make technical efficiencies depend on time. For instance, Cornwell et al. (1990) proposed the specification $u_{i,t} = a + bt + ct^2 + \mathrm{u}_i$, where a, b and c are parameters to be estimated and $\mathrm{u}_i \sim N^+(0, \sigma^2)$; Battese and Coelli (1992) assumed $u_{i,t} = \mathrm{u}_i \exp[\eta(t - T)]$, where η is a parameter to be estimated and u_i follows the truncated Normal distribution $\mathrm{u}_i \sim N_{[0,\infty)}(\mu, \sigma^2)$; Lee and Schmidt (1993) proposed $u_{i,t} = \mathrm{u}_i b_t$, i.e., parameter b varies across time points; Battese and Coelli (1995) assumed a specification similar to the one of Cornwell et al. (1990), with the difference that only the linear component of the trend is considered and several determinants of technical efficiency are included; Cuesta (2000) allowed parameter η in the specification of Battese and Coelli (1992) to vary across production units, i.e., $u_{i,t} = \mathrm{u}_i \exp[\eta_i(t - T)]$. All these specifications for random errors $u_{i,t}$ have the common limitation of making production units share the same trend of technical efficiency, which is an unreliable assumption preventing production units to change their rank in time (parallel trends). The specification of different trends for the production units appears as the most reasonable option, but, although possible in principle (see, for example, Lee, 2006), it may easily lead to an overparameterized model in practice. For this reason, we adopt the unstructured specification $u_{i,t} \sim N^+(0, \sigma^2)$, which allows to investigate the country-specific trends of eco-efficiency without a priori constraints. Table 5 summarizes the specifications for the production frontier f and for random errors $u_{i,t}$ adopted by existing studies listed in Table 2.

Table 5. Model specification of studies assessing eco-efficiency of agriculture in European countries through stochastic frontier models. The specifications 'translog with fixed effects' and 'translog with random effects' are identical to model (4), with the difference that the intercepts are assumed fixed in the former case and random (Normal distribution with null expected value and constant variance) in the latter case. The Cobb-Douglas specification equates to model (4) with $\beta_{j,k} = 0\ \forall j, k$. Also, 'time-invariant elasticities' means that $\lambda_j = 0\ \forall j$, while 'unique intercept' means that $\alpha_i = \alpha\ \forall i$

Authors (year)	Production frontier f	Random errors $u_{i,t}$
Tonini and Jongeneel (2006)	Cobb-Douglas with unique intercept and time-invariant elasticities.	Battese and Coelli (1992).
Tonini and Pede (2011)	Translog with fixed effects.	Cuesta (2000).
Tonini (2012)	Translog with fixed effects.	Cuesta (2000) with spatial dependence.
Cechura et al. (2017)	Translog with random effects.	Unstructured without distributional assumptions.
Hidalgo González and Rodríguez Fernández (2017)	Cobb-Douglas with fixed effects and time-invariant elasticities.	Battese and Coelli (1992).
Quiroga et al. (2017)	Cobb-Douglas with unique intercept.	Battese and Coelli (1995).
Moutinho et al. (2018b)	Cross-sectional translog on separate years.	Unstructured without distributional assumptions.
Auci and Vignani (2020)	Cobb-Douglas with unique intercept, time-invariant elasticities, and dummies for the years in place of the trend.	Battese and Coelli (1995).
Auci et al. (2020)	Cobb-Douglas with fixed effects, time-invariant elasticities, and dummies for the years in place of the trend.	Unstructured: $u_{i,t} \sim N^+(0, \sigma^2)$.
Bakucs et al. (2020)	Cobb-Douglas with random effects and time-invariant elasticities.	Unstructured: $u_{i,t} \sim N^+(0, \sigma^2)$.

4. Results and Discussion

In this section, we present the results of parameter estimation for our stochastic frontier model (Subsection 4.1) and the estimated eco-efficiencies (Subsection 4.2), then we compare our results with those of existing studies (Subsection 4.3).

4.1 Parameter Estimation

Before estimating the parameters of model (4), the time variable is coded as the year minus 1990, thus $t = 0, 1, \ldots, 29$, and the input variables are divided by their respective sample mean. This allows first order coefficients $\beta_1, \ldots, \beta_p$ to be interpreted as the output elasticity of each input evaluated at the sample mean and at the first time point (year 1990), and makes the output elasticity of the j-th input evaluated at the sample mean and at year s equal to $\beta_j + \lambda_j(s - 1990)$. Maximum likelihood estimation of model (4) is obtained using the `R` (R Core Team, 2020) package `frontier` (Coelli and Henningsen, 2020) and the results are summarized in Table 6. Below, we discuss these results based on a 5% significance level.

Table 6. Maximum likelihood estimation of model (4). X_1: logarithm of land use; X_2: logarithm of labour force; X_3: logarithm of livestock; X_4: logarithm of machinery stock; X_5: logarithm of fertilizer use. The input variables are divided by their respective sample mean before applying the logarithmic transformation. The time variable is coded as the year minus 1990, thus $t = 0, 1, \ldots, 29$

Parameter	Estimate	Std. error	p-value
β_1	0.5200	0.0526	0.0000
β_2	0.0293	0.0235	0.2124
β_3	0.2155	0.0246	0.0000
β_4	0.1470	0.0237	0.0000
β_5	0.1567	0.0156	0.0000
$\beta_{1,1}$	0.0550	0.0172	0.0014
$\beta_{1,2}$	0.0927	0.0179	0.0000
$\beta_{1,3}$	−0.0600	0.0203	0.0032
$\beta_{1,4}$	0.0899	0.0208	0.0000
$\beta_{1,5}$	−0.0122	0.0118	0.3005
$\beta_{2,2}$	−0.0143	0.0070	0.0423
$\beta_{2,3}$	−0.0761	0.0177	0.0000
$\beta_{2,4}$	−0.0566	0.0153	0.0002
$\beta_{2,5}$	0.0129	0.0094	0.1674
$\beta_{3,3}$	0.0923	0.0165	0.0000
$\beta_{3,4}$	−0.1219	0.0249	0.0000
$\beta_{3,5}$	−0.0149	0.0127	0.2435
$\beta_{4,4}$	0.0427	0.0110	0.0001
$\beta_{4,5}$	−0.0119	0.0084	0.1563
$\beta_{5,5}$	0.0188	0.0047	0.0001
δ	0.0054	0.0016	0.0009
γ	0.0002	0.0000	0.0000
λ_1	0.0044	0.0006	0.0000
λ_2	0.0000	0.0005	0.9309
λ_3	0.0022	0.0007	0.0021
λ_4	−0.0059	0.0006	0.0000
λ_5	−0.0025	0.0007	0.0004
σ^2	0.0107	0.0011	0.0000
σ_V^2	0.0051	0.0019	0.0079
α_{Albania}	8.8119	0.1017	0.0000
α_{Austria}	9.7187	0.0625	0.0000
α_{Belarus}	9.2444	0.0412	0.0000
$\alpha_{\text{Belgium-Luxembourg}}$	9.9858	0.0895	0.0000
$\alpha_{\text{Bosnia-Herzegovina}}$	9.0314	0.0832	0.0000
α_{Bulgaria}	9.5571	0.0459	0.0000
α_{Croatia}	9.4437	0.0829	0.0000
α_{Cyprus}	9.4082	0.1378	0.0000
α_{Czechia}	9.6657	0.0521	0.0000
α_{Denmark}	10.0005	0.0575	0.0000
α_{Estonia}	8.7300	0.0939	0.0000
α_{Finland}	9.2503	0.0578	0.0000
α_{France}	9.6023	0.0906	0.0000
α_{Germany}	9.9885	0.0630	0.0000
α_{Greece}	9.6592	0.0243	0.0000
α_{Hungary}	9.9575	0.0380	0.0000
α_{Iceland}	8.1788	0.1449	0.0000
α_{Ireland}	9.1663	0.0962	0.0000
α_{Italy}	9.7955	0.0660	0.0000
α_{Latvia}	9.1369	0.0774	0.0000
$\alpha_{\text{Lithuania}}$	9.2639	0.0587	0.0000
α_{Malta}	8.4929	0.3629	0.0000
α_{Moldova}	9.3851	0.0627	0.0000
$\alpha_{\text{Netherlands}}$	10.3116	0.0670	0.0000
$\alpha_{\text{North Macedonia}}$	9.1295	0.0881	0.0000
α_{Norway}	9.0900	0.0788	0.0000
α_{Poland}	9.7324	0.0746	0.0000
α_{Portugal}	9.5400	0.0421	0.0000
α_{Romania}	9.1636	0.0705	0.0000
$\alpha_{\text{Russian Federation}}$	8.3631	0.2536	0.0000
$\alpha_{\text{Serbia-Montenegro}}$	9.6405	0.0468	0.0000
α_{Slovakia}	9.5508	0.0757	0.0000
α_{Slovenia}	8.9864	0.1128	0.0000
α_{Spain}	9.8113	0.1418	0.0000
α_{Sweden}	9.4179	0.0534	0.0000
$\alpha_{\text{Switzerland}}$	9.7008	0.0861	0.0000
α_{Ukraine}	9.1413	0.1268	0.0000
$\alpha_{\text{United Kingdom}}$	9.7097	0.0587	0.0000
Log likelihood: 1305.037 on 1073 degrees of freedom			

The estimates of both linear and quadratic components of the trend (parameters δ and γ) are significantly different from 0, meaning that the technology of each country varies in time. In particular, the maximum technically feasible output given a unit of each input for country i at year s is estimated as: $\exp[\hat{\alpha}_i + 0.0058(s - 1990) + 0.0002(s - 1990)^2]$, where $\hat{\alpha}_i$ is the estimate of α_i (see Table 6). The countries with estimated value of α_i above the third quartile, and thus with the best technology, are: Netherlands, Denmark, Germany, Belgium-Luxembourg, Hungary, Spain, Italy, Poland, Austria and United Kingdom. Instead, the countries with estimated value of α_i below the first quartile, and thus with the worst technology, are: Latvia, North Macedonia, Norway, Bosnia-Herzegovina, Slovenia, Albania, Estonia, Malta, Russian Federation and Iceland.

The estimates of first order coefficients are all positive and significantly different from 0 excepting the one for labour force, indicating that output elasticities of land, livestock, machinery and fertilizers evaluated at the sample mean and at year 1990 are significantly greater than 0, while the one of labour force is not. Significance occurs also for the estimates of second order coefficients, meaning that the output elasticity of each input also depends on the squared input level. Furthermore, the estimated coefficients for the interaction among inputs are all significantly different from 0 with the exception of those involving fertilizer use, indicating that output elasticities of land, labour, livestock and machinery depend each on the level of the others. Note that the output elasticity of labour force, although not significantly different from 0 when evaluated at the sample mean, can be significantly different from 0 when evaluated at different input levels and/or time points, because the estimated second order coefficient, as well as the estimated coefficients for the interaction with the other inputs (excepting fertilizers) and with time, are significantly different from 0.

The estimated coefficients for the interaction between each input and time are all significantly different from 0, excepting the one for labour force, meaning that the output elasticity of each input besides labour force varies in time. In particular, output elasticities of land use and livestock increase in time (the estimates of λ_1 and λ_3 are positive), while those of machinery stock and fertilizer use decrease in time (the estimates of λ_4 and λ_5 are negative). Figure 2 shows the time series of estimated output elasticities at the sample mean, with the bottom-right panel displaying the overall elasticity, equal to the sum of all output elasticities by time point. The estimated overall elasticity at the sample mean ranges from 1.013 in 1990 to 1.068 in 2019 and is never significantly different from 1, indicating constant returns to scale.

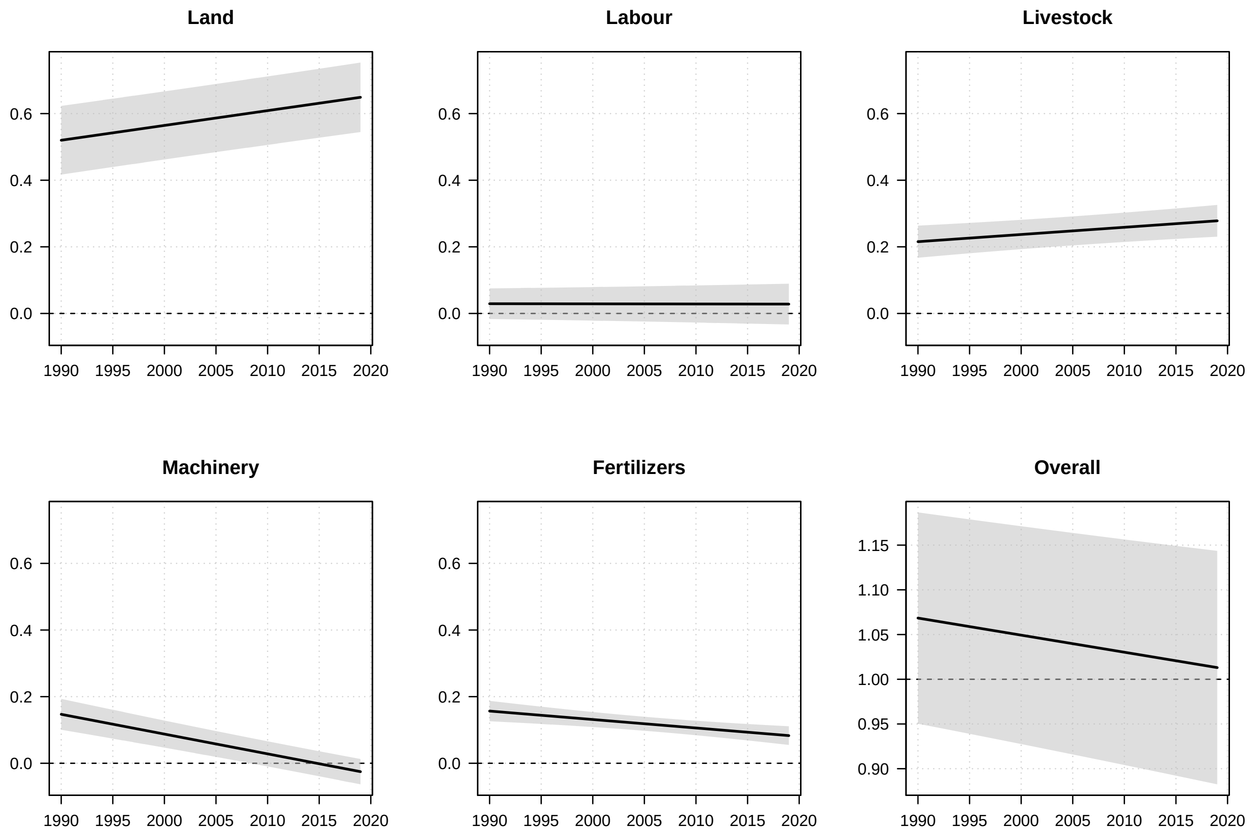

Figure 2. Time series of estimated output elasticities at the sample mean. The bottom-right panel displays the overall elasticity at the sample mean, equal to the sum of all output elasticities by time point. Shaded areas indicate 95% confidence intervals

The estimated variances of random errors $u_{i,t}$ and $v_{i,t}$ result 0.0107 (parameter σ^2) and 0.0051 (parameter σ^2_V), respectively, and are both significantly different from zero, confirming the existence of technical inefficiencies (i.e., perfectible eco-efficiencies) and external shocks which explain, respectively, 69% and 31% of the deviations from the production frontier.

4.2 Estimated Eco-efficiencies

The time series of estimated eco-efficiencies by country are summarized in Table 7 and displayed in Figure 3. The full estimates of eco-efficiencies are reported at the end of the paper in Tables 9 and 10.

Table 7. Summaries of estimated eco-efficiencies by period and country. Values are mean eco-efficiencies, with standard deviation and average annual percentage change shown within brackets

North	1990–1999	2000–2009	2010–2019	1990–2019
Denmark	0.904 (0.033; +1.02)	0.959 (0.006; +0.15)	0.950 (0.011; −0.39)	0.938 (0.032; +0.22)
Finland	0.928 (0.027; −0.65)	0.953 (0.008; +0.24)	0.944 (0.013; +0.37)	0.942 (0.020; +0.04)
Iceland	0.914 (0.015; −0.18)	0.949 (0.007; +0.08)	0.953 (0.017; +0.61)	0.939 (0.022; +0.20)
Norway	0.932 (0.013; −0.41)	0.940 (0.015; +0.37)	0.955 (0.009; −0.03)	0.942 (0.016; −0.01)
Sweden	0.945 (0.021; −0.27)	0.946 (0.012; −0.09)	0.938 (0.011; +0.27)	0.943 (0.015; −0.11)
West	1990–1999	2000–2009	2010–2019	1990–2019
Austria	0.920 (0.013; +0.28)	0.954 (0.010; +0.30)	0.950 (0.009; +0.19)	0.941 (0.019; +0.13)
Belgium-Luxembourg	0.929 (0.031; +1.05)	0.947 (0.010; −0.13)	0.950 (0.013; +0.25)	0.942 (0.022; +0.43)
France	0.953 (0.009; +0.15)	0.947 (0.013; −0.04)	0.928 (0.014; −0.09)	0.943 (0.016; −0.09)
Germany	0.926 (0.015; +0.09)	0.955 (0.011; +0.07)	0.946 (0.012; −0.06)	0.942 (0.018; +0.01)
Ireland	0.955 (0.012; −0.11)	0.921 (0.016; −0.34)	0.943 (0.022; +0.36)	0.940 (0.022; +0.01)
Netherlands	0.951 (0.011; +0.18)	0.945 (0.012; −0.32)	0.933 (0.013; +0.34)	0.943 (0.014; +0.04)
Switzerland	0.951 (0.009; +0.11)	0.948 (0.008; −0.16)	0.931 (0.015; −0.32)	0.944 (0.014; −0.12)
United Kingdom	0.949 (0.008; +0.08)	0.944 (0.008; −0.10)	0.940 (0.014; −0.11)	0.944 (0.011; +0.01)
South	1990–1999	2000–2009	2010–2019	1990–2019
Cyprus	0.964 (0.017; +0.02)	0.945 (0.041; −1.26)	0.806 (0.042; −1.15)	0.905 (0.079; −0.84)
Greece	0.958 (0.019; +0.59)	0.940 (0.019; −0.32)	0.912 (0.022; −0.58)	0.936 (0.027; −0.09)
Italy	0.935 (0.014; +0.65)	0.955 (0.013; +0.24)	0.932 (0.024; −0.72)	0.941 (0.020; +0.03)
Malta	0.946 (0.022; +0.49)	0.921 (0.022; −0.05)	0.939 (0.032; −1.12)	0.935 (0.027; −0.13)
Portugal	0.922 (0.024; +0.18)	0.942 (0.018; +0.71)	0.954 (0.014; +0.06)	0.939 (0.023; +0.14)
Spain	0.932 (0.039; −0.32)	0.936 (0.022; −0.20)	0.947 (0.024; +0.26)	0.938 (0.029; +0.02)
East	1990–1999	2000–2009	2010–2019	1990–2019
Albania	0.892 (0.048; +0.35)	0.926 (0.028; +0.63)	0.968 (0.006; −0.12)	0.929 (0.045; +0.30)
Belarus	0.925 (0.045; +0.19)	0.944 (0.021; +0.67)	0.942 (0.010; −0.03)	0.937 (0.030; +0.39)
Bosnia-Herzegovina	0.934 (0.037; −0.66)	0.926 (0.057; +1.93)	0.925 (0.038; −0.60)	0.928 (0.043; −0.26)
Bulgaria	0.939 (0.033; −0.01)	0.925 (0.046; −0.27)	0.941 (0.019; −0.27)	0.935 (0.034; −0.09)
Croatia	0.909 (0.036; +1.11)	0.919 (0.051; +1.45)	0.955 (0.020; −0.37)	0.928 (0.042; +0.22)
Czechia	0.965 (0.009; −0.05)	0.933 (0.026; −0.27)	0.901 (0.030; +0.54)	0.933 (0.035; −0.24)
Estonia	0.938 (0.022; −0.61)	0.946 (0.017; +0.34)	0.935 (0.034; +0.58)	0.940 (0.025; +0.10)
Hungary	0.957 (0.017; −0.39)	0.937 (0.036; +0.23)	0.890 (0.031; +0.04)	0.928 (0.040; −0.40)
Latvia	0.924 (0.039; −1.43)	0.914 (0.033; +0.66)	0.958 (0.019; +0.22)	0.932 (0.036; −0.04)
Lithuania	0.916 (0.033; −0.70)	0.925 (0.038; +0.57)	0.953 (0.032; +1.14)	0.931 (0.037; +0.23)
Moldova	0.930 (0.040; +0.38)	0.934 (0.034; +0.38)	0.926 (0.035; +0.07)	0.930 (0.035; +0.19)
North Macedonia	0.886 (0.052; +0.05)	0.930 (0.041; +0.47)	0.966 (0.010; −0.39)	0.927 (0.050; +0.03)
Poland	0.931 (0.033; −0.74)	0.920 (0.019; +0.44)	0.959 (0.007; +0.01)	0.937 (0.027; −0.09)
Romania	0.962 (0.017; +0.13)	0.927 (0.049; +0.19)	0.884 (0.045; +0.23)	0.925 (0.050; −0.23)
Russian Federation	0.945 (0.033; −0.82)	0.937 (0.012; +0.43)	0.935 (0.031; +1.16)	0.939 (0.026; −0.01)
Serbia-Montenegro	0.947 (0.020; +0.36)	0.938 (0.024; +0.71)	0.924 (0.042; −0.19)	0.937 (0.031; +0.10)
Slovakia	0.962 (0.009; −0.05)	0.942 (0.023; +0.48)	0.895 (0.035; +0.08)	0.933 (0.037; −0.31)
Slovenia	0.943 (0.028; +0.22)	0.955 (0.015; +0.31)	0.911 (0.023; −0.57)	0.936 (0.029; −0.08)
Ukraine	0.903 (0.037; −0.25)	0.929 (0.025; +0.65)	0.964 (0.013; +0.39)	0.932 (0.036; +0.39)

From Figure 3, we see that the countries with a definitely increasing eco-efficiency (average annual change in the period 1990–2019 reported within brackets) are Albania (+0.30%), Croatia (+0.22%), Iceland (+0.20%), Lithuania (+0.23%), North Macedonia (+0.03%), Portugal (+0.14%) and Ukraine (+0.39%). Instead, the countries with a definitely decreasing eco-efficiency are Cyprus (−0.84%), Czechia (−0.24%), France (−0.09%), Greece (−0.09%), Hungary (−0.40%), Malta (−0.13%), Romania (−0.23%) and Slovakia (−0.31%). All the other countries have an approximately constant eco-efficiency in the period 1990–2019, ranging, in average, between 0.93 and 0.95, with the exception of two groups of countries: (i) Denmark, Italy, Serbia-Montenegro, Slovenia and Switzerland, which show a decline of eco-efficiency begun in the last decade (average annual change in 2010–2019, respectively, equal to −0.39, −0.72, −0.19, −0.57 and −0.32%); (ii) Ireland and Latvia, which exhibit an upward inversion of the trend in 2006 and in 1999, respectively (average

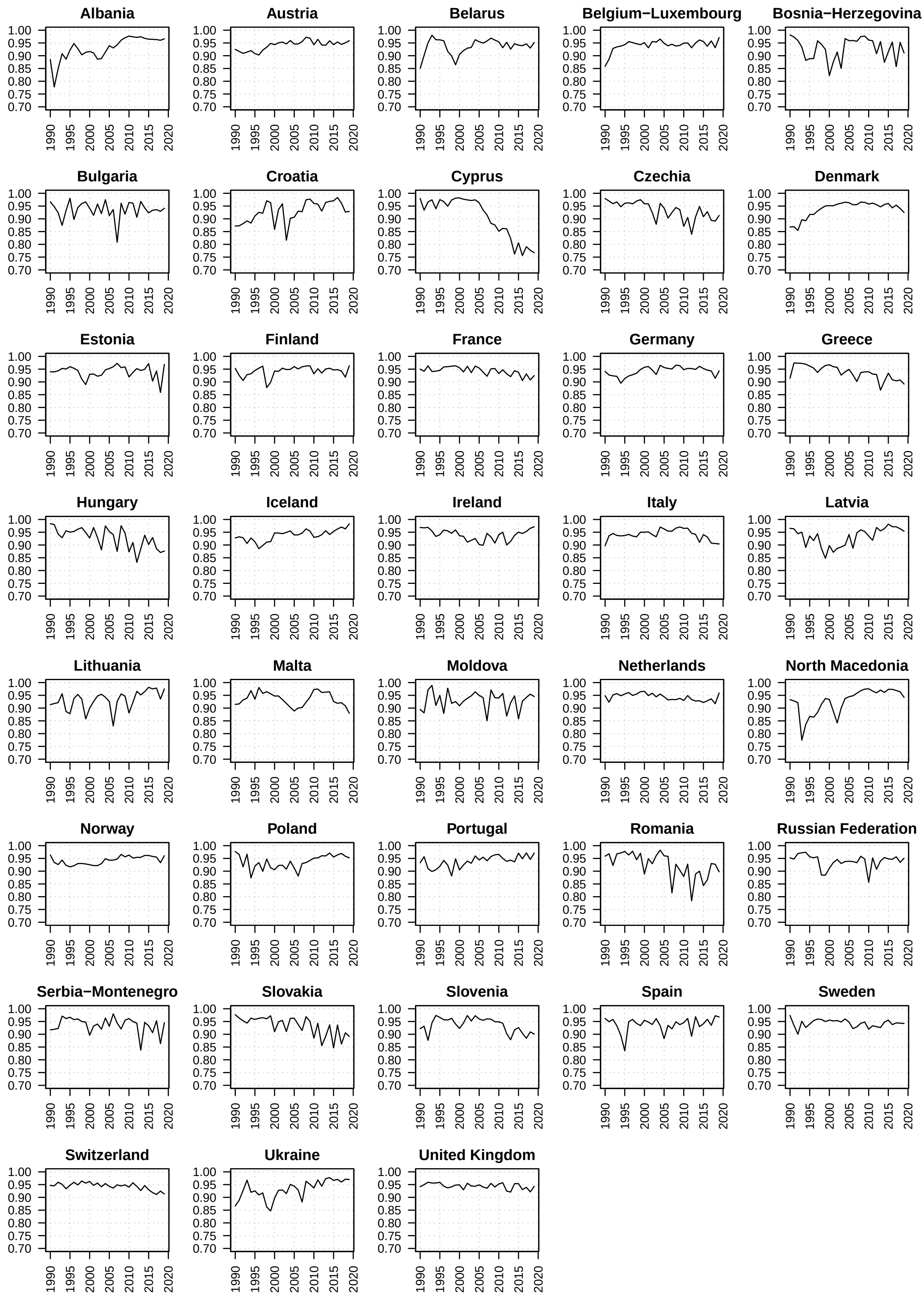

Figure 3. Time series of estimated eco-efficiencies by country

annual change in 2010–2019 equal to +0.36% for Ireland and +0.22% for Latvia). These two groups of countries should be monitored in the next years to better establish whether the decline or the increase in eco-efficiency is temporary or permanent. Note that our study, compared to existing ones, covers a longer and more recent period, thus it has the value of recognizing which countries should be kept under observation in the near future. On this point, we believe that eco-efficiency assessments should be performed not only on periods as long and recent as possible, but also with a reasonably high frequency, for example every three or at most five years: the lack of studies assessing eco-efficiency of European agriculture in the last decade (2010–2019), that can be noted from Tables 1 and 2, represents a severe information gap for international policy makers which is filled by our study.

An analysis by geographical zone emphasizes that northern and western countries have a non-decreasing trend and the highest level of eco-efficiency in the whole period 1990–2019, with only Denmark, France and Switzerland showing a declining tendency. For what concerns the southern zone, we note a heterogeneity in the trend of eco-efficiency across countries: Portugal shows a definitely increasing tendency and Spain has a high and almost stable level of eco-efficiency (mean equal to 0.938 in 1990–2019), but all the other countries exhibit a decreasing trend (Cyprus, Greece and Malta) or undergo a decline in the last decade (Italy). The trend of eco-efficiency is even more heterogeneous across eastern countries: Albania, Croatia, Lithuania, North Macedonia and Ukraine show a definitely increasing tendency, while the trend for Czechia, Hungary, Romania and Slovakia is definitely declining. These results clearly highlight that, among developed economies, northern and western countries have a better performance in terms of both level and growth of agricultural eco-efficiency than southern ones, and that several different patterns exist among transition economies, sometimes even more virtuous than those characterizing developed countries.

4.3 Comparison With Existing Studies

Our results are naturally comparable with those of Tonini and Pede (2011) and Tonini (2012), where a relevant number of countries (27 and 28, respectively) and time points (14 years from 1993 to 2006) is considered and the same model specification adopted in this work is exploited. The study in Cechura et al. (2017) adopts the same model specification and also covers a more recent period, but the comparison is not proper because the focus is on milk production. Our results can also be compared with those of existing studies employing DEA and considering a relevant number of countries and time points, like Kocisova (2015, 27 countries in 2007–2011), Toma et al. (2017, 26 countries in 1993–2013), Moutinho et al. (2018a, 27 countries in 2005–2012), Exposito and Velasco (2020, 21 countries in 2001–2012), and Czyzewski et al. (2021, 25 countries in 2004–2017). Unfortunately, Exposito and Velasco (2020) and Czyzewski et al. (2021) do not report the estimated technical efficiencies, thus we excluded these two studies from the comparison.

We compare our study and the selected ones based on the estimated average annual change of eco-efficiency by country. In order to make the comparison as proper as possible, we computed the average annual change by country from our estimated eco-efficiencies in three distinct periods: (i) 1993–2006 for the comparison with Tonini and Pede (2011) and with Tonini (2012), (ii) 2005–2012 for the comparison with Kocisova (2015) and Moutinho et al. (2018a), (iii) 1993–2012 for the comparison with Toma et al. (2017). Table 8 shows the ranks of countries according to the average annual change of eco-efficiency estimated by each study under comparison. We see that our ranks are quite in line with those of Tonini and Pede (2011), Moutinho et al. (2018a) and Toma et al. (2017), as confirmed by a Spearman correlation equal to 0.420, 0.452 and 0.528, respectively. Instead, the ranks of Tonini (2012) are in weak agreement with ours, as suggested by a Spearman correlation equal to 0.082, while a disagreement can be noted with the ranks of Kocisova (2015), as emphasized by a Spearman correlation equal to -0.265. The weak agreement with Tonini (2012) can be explained by the use of a Bayesian formulation of the stochastic frontier model, while the disagreement with Kocisova (2015) may be due to the use of DEA, even if the ranks of Toma et al. (2017), where DEA is employed as well, are in agreement with ours. In general, it is reasonable to think that the discrepancies between our results and those of existing studies are mainly due to differences in methodology, model formulation and period under analysis.

5. Concluding Remarks

In this paper, we have estimated agricultural eco-efficiency of 40 European countries, including non-EU and ex-USSR ones, in the period 1990–2019 (30 years). Our study considers the almost totality of European countries and focuses on a long and recent period, thus being able to draw an exhaustive and updated picture of agricultural eco-efficiency in Europe that fills both temporal and spatial information gaps left by existing studies. In particular, our study has identified two groups of countries with uncertain trend of eco-efficiency requiring to be monitored in the near future: (i) Denmark, Italy, Serbia-Montenegro, Slovenia and Switzerland, which show a decline in recent years, (ii) Ireland and Latvia, which exhibit an upward inversion in the penultimate decade. Furthermore, our study has provided, for the first time, evidence on agricultural eco-efficiency in non-EU transition economies, specifically it has emphasized the promising performance of Albania, North Macedonia and Ukraine.

A first limitation of our study is represented by quality and availability of data, an issue affecting all the longitudinal

Table 8. Ranks of countries according to the average annual change of eco-efficiency estimated by each study under comparison

Country	Tonini and Pede (2011)	Tonini (2012)	Our study 1993–2006	Kocisova (2015)	Moutinho et al. (2018a)	Our study 2005–2012	Toma et al. (2017)	Our study 1993–2013
Austria	12	28	5	4	13	11	6	6.5
Belgium-Luxembourg	28	10	13	18	19	17	10	10
Bulgaria	19	11	1	19	23	13	8	1
Croatia	13	18	4	–	–	5	25	2
Cyprus	16.5	12	21	25	4.5	24	10	28
Czechia	25	19	25	21	21	25	21	23
Denmark	3	6	2	12	12	14	2	3
Estonia	18	20	12	6	11	8	12.5	15
Finland	16.5	23	7	2	9	22	1	9
France	8	1	15	12	16	20	15	16
Germany	1	9	6	3	24	10	12.5	6.5
Greece	24	27	23	12	14	19	22	26
Hungary	9	17	9	12	22	27	20	21
Ireland	14	25	24	12	26	9	–	20
Italy	15	15	8	12	7	16	10	12
Latvia	22	24	26	22	15	4	–	11
Lithuania	20	8	28	20	1	3	7	13
Malta	7	4	22	12	4.5	1	17.5	8
Netherlands	6	22	19	12	4.5	15	15	18
Poland	23	14	27	26	2	2	15	14
Portugal	11	3	3	24	10	12	4.5	4
Romania	4	2	17	12	20	28	19	25
Serbia-Montenegro	2	16	11	–	–	6	–	27
Slovakia	26	7	16	12	25	26	23	22
Slovenia	10	26	10	1	18	23	24	24
Spain	5	13	14	23	4.5	7	4.5	5
Sweden	21	5	20	12	8	18	3	17
United Kingdom	27	21	18	5	17	21	17.5	19

assessments due to the practical difficulty of collecting reliable measurements on a large number of countries and time points. For this reason, we relied not only on official data, but also on modeled estimates and projections, like the measurements of labour force sourced to ILO and machinery stock sourced to USDA. On the other hand, differently from existing studies assessing agricultural eco-efficiency, we employed an improved measure of land use and machinery stock consisting of a weighted aggregation based on rainfed cropland and 40 horsepower equivalent units.

A second limitation of our study relies on model formulation. We have preferred stochastic frontier models to Data Envelopment Analysis (DEA) in order to maintain the economic interpretation as much as possible, but, although we have adopted the most flexible specification employed by existing studies assessing agricultural eco-efficiency, i.e., the translog functional form, several model assumptions are still restrictive. These include: (i) the trend of country-specific technologies, which is assumed to be deterministic (second order polynomial on the logarithmic scale) and equal across all countries (parallel trends); (ii) the trend of output elasticities, which is assumed to be deterministic (linear on the logarithmic scale); (iii) the unstructured trend of technical efficiencies.

Future work will be directed towards the refinement of our model formulation. In particular, we plan to explore the potentiality of random intercepts and slopes for countries and of stochastic (autoregressive) trends for input coefficients (first order, second order and interactions), that could allow non-deterministic trends for output elasticities. Also, a further refinement deserving attention is to let technical efficiencies depend on climatic (Skevas et al., 2018; Auci and Vignani, 2020; Bakucs et al., 2020) and technological (Auci et al., 2020) conditions, as well as to allow them to be autocorrelated (Skevas et al., 2018).

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Table 9. Estimated eco-efficiencies

Country	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Albania	0.885	0.778	0.850	0.908	0.886	0.922	0.948	0.928	0.903	0.913	0.917	0.911	0.886	0.889	0.914
Austria	0.925	0.917	0.909	0.914	0.920	0.908	0.903	0.922	0.934	0.948	0.943	0.950	0.953	0.946	0.959
Belarus	0.850	0.901	0.951	0.980	0.963	0.962	0.959	0.917	0.899	0.865	0.905	0.920	0.930	0.933	0.963
Belgium-Luxembourg	0.858	0.886	0.928	0.935	0.938	0.943	0.955	0.951	0.947	0.943	0.952	0.931	0.956	0.953	0.965
Bosnia-Herzegovina	0.981	0.973	0.960	0.934	0.882	0.888	0.889	0.958	0.944	0.925	0.822	0.876	0.915	0.851	0.967
Bulgaria	0.967	0.948	0.924	0.874	0.933	0.980	0.898	0.944	0.960	0.966	0.941	0.914	0.958	0.920	0.975
Croatia	0.872	0.873	0.881	0.892	0.883	0.911	0.926	0.922	0.971	0.963	0.859	0.936	0.959	0.816	0.902
Cyprus	0.979	0.934	0.966	0.974	0.940	0.975	0.967	0.949	0.974	0.981	0.982	0.977	0.974	0.972	0.974
Czechia	0.979	0.970	0.959	0.966	0.947	0.961	0.963	0.958	0.969	0.975	0.959	0.959	0.924	0.879	0.960
Denmark	0.868	0.869	0.854	0.897	0.892	0.917	0.917	0.930	0.941	0.950	0.952	0.951	0.957	0.961	0.965
Estonia	0.940	0.939	0.943	0.953	0.950	0.960	0.953	0.945	0.911	0.890	0.930	0.931	0.922	0.926	0.947
Finland	0.953	0.925	0.905	0.928	0.932	0.945	0.954	0.962	0.878	0.899	0.943	0.941	0.954	0.948	0.949
France	0.950	0.942	0.963	0.941	0.942	0.945	0.959	0.960	0.962	0.963	0.955	0.939	0.961	0.936	0.962
Germany	0.941	0.927	0.924	0.922	0.895	0.914	0.923	0.928	0.934	0.949	0.957	0.960	0.946	0.929	0.965
Greece	0.915	0.974	0.974	0.972	0.970	0.962	0.954	0.937	0.953	0.964	0.967	0.960	0.957	0.927	0.939
Hungary	0.983	0.980	0.943	0.928	0.956	0.950	0.953	0.962	0.968	0.949	0.927	0.969	0.929	0.881	0.975
Iceland	0.928	0.932	0.928	0.906	0.927	0.913	0.886	0.898	0.911	0.913	0.947	0.947	0.944	0.949	0.955
Ireland	0.969	0.967	0.969	0.955	0.933	0.940	0.958	0.955	0.946	0.959	0.936	0.934	0.911	0.919	0.925
Italy	0.897	0.936	0.945	0.937	0.936	0.937	0.942	0.935	0.932	0.950	0.950	0.951	0.941	0.932	0.970
Latvia	0.965	0.963	0.944	0.950	0.890	0.936	0.917	0.945	0.886	0.848	0.898	0.871	0.887	0.892	0.899
Lithuania	0.914	0.918	0.922	0.956	0.887	0.878	0.937	0.954	0.935	0.858	0.899	0.926	0.947	0.954	0.943
Malta	0.915	0.916	0.932	0.939	0.969	0.935	0.981	0.958	0.964	0.956	0.947	0.947	0.933	0.919	0.903
Moldova	0.895	0.881	0.972	0.989	0.910	0.950	0.879	0.978	0.918	0.925	0.909	0.927	0.938	0.948	0.964
Netherlands	0.948	0.923	0.952	0.957	0.948	0.955	0.961	0.950	0.955	0.964	0.966	0.949	0.958	0.944	0.955
North Macedonia	0.933	0.928	0.922	0.774	0.836	0.867	0.864	0.883	0.915	0.937	0.934	0.888	0.842	0.900	0.938
Norway	0.964	0.934	0.926	0.944	0.923	0.917	0.921	0.930	0.930	0.928	0.925	0.922	0.922	0.929	0.949
Poland	0.976	0.966	0.917	0.967	0.874	0.920	0.934	0.899	0.948	0.913	0.906	0.922	0.923	0.908	0.939
Portugal	0.933	0.957	0.910	0.899	0.906	0.919	0.942	0.924	0.882	0.948	0.905	0.924	0.940	0.931	0.960
Romania	0.959	0.968	0.922	0.968	0.971	0.977	0.963	0.978	0.945	0.970	0.889	0.949	0.929	0.961	0.982
Russian Federation	0.952	0.948	0.969	0.972	0.974	0.956	0.953	0.956	0.885	0.885	0.911	0.934	0.946	0.930	0.938
Serbia-Montenegro	0.917	0.919	0.923	0.971	0.961	0.967	0.957	0.960	0.950	0.948	0.896	0.932	0.940	0.920	0.964
Slovakia	0.976	0.964	0.953	0.944	0.963	0.958	0.962	0.965	0.961	0.972	0.910	0.949	0.954	0.911	0.962
Slovenia	0.922	0.932	0.876	0.945	0.974	0.966	0.957	0.956	0.962	0.940	0.923	0.944	0.973	0.952	0.973
Spain	0.962	0.949	0.958	0.933	0.896	0.835	0.949	0.958	0.943	0.934	0.955	0.948	0.938	0.961	0.934
Sweden	0.974	0.935	0.900	0.951	0.927	0.940	0.954	0.960	0.958	0.950	0.955	0.952	0.954	0.948	0.960
Switzerland	0.947	0.945	0.959	0.951	0.934	0.947	0.959	0.949	0.964	0.956	0.962	0.947	0.956	0.941	0.954
Ukraine	0.866	0.889	0.927	0.967	0.920	0.925	0.910	0.917	0.862	0.847	0.897	0.928	0.929	0.915	0.951
United Kingdom	0.942	0.950	0.959	0.956	0.956	0.959	0.944	0.937	0.941	0.948	0.949	0.929	0.955	0.944	0.943

Table 10. Estimated eco-efficiencies (continued)

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Albania	0.939	0.931	0.943	0.961	0.970	0.977	0.974	0.972	0.974	0.968	0.965	0.964	0.963	0.961	0.966
Austria	0.946	0.946	0.955	0.972	0.969	0.943	0.964	0.942	0.941	0.959	0.943	0.954	0.944	0.951	0.959
Belarus	0.955	0.950	0.958	0.969	0.961	0.954	0.931	0.953	0.926	0.947	0.941	0.939	0.947	0.930	0.952
Belgium-Luxembourg	0.949	0.939	0.945	0.938	0.941	0.949	0.950	0.931	0.950	0.962	0.956	0.937	0.958	0.931	0.971
Bosnia-Herzegovina	0.959	0.960	0.957	0.975	0.977	0.961	0.959	0.908	0.955	0.874	0.916	0.954	0.857	0.952	0.911
Bulgaria	0.912	0.937	0.808	0.961	0.918	0.964	0.961	0.906	0.968	0.943	0.923	0.934	0.936	0.929	0.941
Croatia	0.906	0.930	0.928	0.974	0.977	0.960	0.958	0.930	0.964	0.968	0.971	0.983	0.962	0.927	0.929
Cyprus	0.963	0.935	0.915	0.882	0.876	0.851	0.863	0.861	0.823	0.762	0.806	0.756	0.791	0.777	0.767
Czechia	0.942	0.903	0.925	0.944	0.936	0.870	0.906	0.840	0.907	0.948	0.908	0.928	0.894	0.891	0.913
Denmark	0.963	0.955	0.956	0.966	0.964	0.958	0.961	0.955	0.947	0.956	0.960	0.943	0.954	0.941	0.925
Estonia	0.953	0.959	0.973	0.956	0.958	0.919	0.937	0.952	0.945	0.950	0.972	0.903	0.943	0.859	0.968
Finland	0.960	0.951	0.959	0.962	0.963	0.932	0.951	0.935	0.951	0.954	0.947	0.948	0.942	0.919	0.963
France	0.954	0.938	0.922	0.951	0.952	0.933	0.947	0.932	0.921	0.944	0.938	0.905	0.931	0.908	0.925
Germany	0.956	0.953	0.951	0.966	0.964	0.948	0.953	0.952	0.949	0.961	0.952	0.946	0.943	0.914	0.943
Greece	0.949	0.927	0.902	0.937	0.939	0.940	0.931	0.929	0.868	0.903	0.934	0.909	0.904	0.908	0.892
Hungary	0.952	0.941	0.875	0.975	0.946	0.873	0.910	0.832	0.885	0.938	0.902	0.929	0.885	0.871	0.876
Iceland	0.939	0.940	0.947	0.963	0.954	0.930	0.933	0.940	0.956	0.941	0.953	0.963	0.970	0.963	0.983
Ireland	0.902	0.899	0.945	0.932	0.907	0.940	0.950	0.900	0.914	0.938	0.951	0.945	0.953	0.966	0.971
Italy	0.963	0.954	0.954	0.966	0.971	0.965	0.966	0.946	0.942	0.910	0.941	0.931	0.907	0.906	0.904
Latvia	0.941	0.887	0.948	0.959	0.953	0.935	0.919	0.969	0.955	0.964	0.982	0.972	0.971	0.964	0.954
Lithuania	0.925	0.830	0.926	0.955	0.947	0.881	0.923	0.966	0.952	0.964	0.981	0.975	0.978	0.936	0.975
Malta	0.889	0.900	0.902	0.923	0.943	0.973	0.975	0.961	0.962	0.964	0.926	0.919	0.921	0.909	0.880
Moldova	0.950	0.941	0.850	0.971	0.941	0.939	0.958	0.869	0.921	0.948	0.858	0.927	0.942	0.955	0.945
Netherlands	0.944	0.932	0.934	0.933	0.938	0.930	0.949	0.934	0.928	0.929	0.922	0.929	0.936	0.917	0.959
North Macedonia	0.944	0.948	0.958	0.968	0.974	0.975	0.967	0.960	0.971	0.961	0.973	0.973	0.969	0.964	0.942
Norway	0.943	0.943	0.947	0.966	0.956	0.963	0.952	0.954	0.954	0.962	0.961	0.958	0.955	0.933	0.961
Poland	0.912	0.881	0.930	0.934	0.942	0.951	0.952	0.960	0.960	0.971	0.955	0.964	0.970	0.958	0.952
Portugal	0.944	0.955	0.941	0.957	0.964	0.966	0.950	0.939	0.943	0.937	0.971	0.949	0.972	0.946	0.971
Romania	0.960	0.958	0.815	0.927	0.904	0.879	0.928	0.784	0.889	0.900	0.844	0.866	0.930	0.927	0.898
Russian Federation	0.939	0.938	0.933	0.958	0.947	0.857	0.952	0.907	0.940	0.953	0.948	0.946	0.956	0.935	0.951
Serbia-Montenegro	0.931	0.980	0.944	0.921	0.955	0.961	0.950	0.943	0.838	0.947	0.933	0.906	0.953	0.863	0.945
Slovakia	0.963	0.938	0.915	0.969	0.950	0.885	0.943	0.855	0.892	0.937	0.847	0.936	0.862	0.906	0.891
Slovenia	0.960	0.955	0.960	0.959	0.949	0.949	0.943	0.902	0.879	0.917	0.926	0.904	0.884	0.909	0.901
Spain	0.883	0.935	0.921	0.949	0.938	0.946	0.962	0.892	0.969	0.930	0.941	0.959	0.935	0.973	0.968
Sweden	0.948	0.922	0.929	0.943	0.948	0.920	0.933	0.930	0.926	0.947	0.956	0.938	0.944	0.944	0.942
Switzerland	0.943	0.937	0.949	0.945	0.949	0.940	0.957	0.943	0.927	0.946	0.930	0.919	0.911	0.924	0.913
Ukraine	0.944	0.929	0.882	0.963	0.951	0.937	0.969	0.944	0.973	0.977	0.966	0.970	0.960	0.971	0.970
United Kingdom	0.949	0.941	0.936	0.955	0.941	0.953	0.957	0.925	0.921	0.954	0.954	0.931	0.939	0.921	0.943