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Testing for Environmental Kuznets Curve in the EU Agricultural Sector through an Eco-(in)Efficiency Index

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Abstract: Studies on agricultural production practices advance within international literature and new methods are proposed in order to assess the agricultural sustainability, either at farm or macro level. The present paper builds on these advancements and develops a synthetic Eco-(in)efficiency index by employing a directional distance function—data envelopment analysis (DEA) model. This index is used in order to assess the sustainability of the EU agricultural sector for the period 1999–2012 on a country level. Furthermore, Eco-(in)efficiency, together with the energy use and greenhouse gas (GHG) emissions are regressed on the gross domestic product (GDP) of EU countries, in order to check for any environmental Kuznets curve relationship existence. Results signify that efficiency improvements are possible, both towards output development and GHG emissions reduction. In addition, the potential of each country in adopting more sustainable production practices is not totally connected with its economic development, as Eco-(in)efficiency and GDP levels of EU countries seem to be linked with an N-Shaped curve.

Keywords: Kuznets curve; sustainability; agriculture; data envelopment analysis; energy; emissions

1. Introduction

Uncontrolled economic growth imposes severe risks for the environment as natural resources used for economic activities are not infinite [1]. Ice melting and the increase of temperature are considered as tangible examples of environmental degradation due to human activities [2]. After a long period of uncontrolled economic growth, policy makers, mostly representing matured economies, started to realize the risk imposed because of environmental degradation and initiated global actions in order to set the basis for sustainable development. Undoubtedly, the benchmark point towards sustainability has been the United Nations (UN) World Conference on the Environment which was held in Stockholm in 1972. Although the debate did not succeed in a strong commitment towards more environmental-friendly economic growth, its 26 common-agreed principles regarding environment and development could be regarded as the first common achievement towards global sustainability [3,4].

In the following years, a heated debate around the limits between environmental protection and economic growth evolved across academics, policy makers and practitioners. A common belief is that environmental degradation increases during the early stages of economic development. After a certain point of growth the trend is reversed, in a sense that development becomes more sustainable [5]. The rationale behind this trend is that in early stages of development, pollution-generating economic sectors are developed without concrete control, since economic targets surpass the respective environmental ones, and environmental degradation is an accepted byproduct of the desired economic outcomes. In addition, as income rises most people start to put a larger weight on their quality of life and thus environmental issues are addressed by legislation in a more systematic context [1].

This kind of functional relationship between environmental degradation and economic growth is graphically expressed by an inverted U-shape slope called the environmental Kuznets curve (EKC) [6]. Many scholars have tried to empirically verify the existence of EKC for different environmental dimensions (i.e., CO_2 emissions, particulate matter, energy use) and in various geographical and time contexts. The papers of [7,8] provide two comprehensive and detailed reviews of the relevant past empirical studies.

As far as the agricultural sector is concerned, production comes up with several environmental damages that mainly have to do with land–take, habitat loss, soil erosion and degradation, water contamination and climate change [9]. Nevertheless, research on the relationship between negative environmental impacts and economic growth is still limited. More precisely, the majority of studies focus their interest on developing countries seeking empirical evidence on the relationship between economic development and agricultural land expansion, particularly against forests [10,11]. Besides these studies, to the best of our knowledge, there is only one study examining environmental risks of agriculture in advanced economies. More precisely, ref. [12] analyzed the longitudinal fluctuations of environmental risks arising from pesticides used in agriculture within US states against real gross state product, abatement efforts and an environmental productivity index. Managi [12] argued that although environmental risks and economic growth seem to validate the EKC relationship, the risk of observing an N relationship still exists due to scale effects. Thus, even for advanced economies, such as USA, EKC in agriculture could not be taken for granted.

The existing literature testify that, for agriculture, there is a lack of studies regarding advanced economies' dynamics, such as those of EU countries, and other environmental impacts such as GHG emissions remain rather unexplored. The importance of examining the atmospheric impacts of agriculture is extracted from the fact that global agriculture accounts for about 24% of the total GHG emissions. In addition, the Organisation for Economic Co-operation and Development (OECD) countries account for more than one third of global emissions [13]. In a European context, the share of agriculture in total GHG emissions is exceeding 10%, with a total production of 470.6 million tons of CO_2 in 2012. Nevertheless, the contributions vary significantly across countries. To illustrate, Irish, Latvian and Lithuanian agricultural sectors account for more than 20% of the total national emissions, whereas the share of agricultural GHG emissions in countries such as Malta, Luxemburg and the Czech Republic do not exceed 7% [14]. In addition, focusing on agricultural nutrients, EU countries have managed to reduce their nitrogen and phosphorus balances during the period 2000–2012. Nitrogen Balance for EU-28 has been reduced from 63 to 51 and phosphorus from six to two. Nevertheless, efficiency in nutrient utilization, as this is expressed by the ratio of total nutrient outputs to total nutrient inputs, also varies profoundly across countries. For the period 2009–2014, the most efficient countries in nitrogen efficiency was Romania, Ireland and Bulgaria and the least efficient ones were Cyprus, Luxemburg, Greece, Malta and Croatia [15].

Undoubtedly, the variations among EU countries reflect, in a straightforward context, the composite nature of agricultural production sustainability issue. Countries such as Malta and Luxemburg present positive figures regarding GHG emissions whilst being inefficient in nutrient utilization. The opposite stands for countries such as Ireland. Such variations have been also identified by the recent study of [16] who employed the generalized Divisia Index to evaluate the effect of energy use and agricultural growth in energy-related GHG emissions of 17 EU countries from 1995 to 2012. These variations portray, that in order to extract a comprehensive picture regarding the sustainability levels of national agricultural practices, the analysis should focus on all aspects of agricultural production. That is to say, not only the amount of inputs or the produced outputs could define sustainability, but the level of efficiency of how inputs are utilized in order to produce certain outputs that lead to a comprehensive evaluation index of agricultural sustainability [16].

The link between sustainability and efficiency is reflected in the recent reforms of the common agricultural policy (CAP) which precisely focus on increasing the efficiency of use of agricultural inputs, and on reducing the production of undesirable outputs, such as GHG emissions [17]. Nevertheless, this goal requires the development of various technologies on both the production and application of agricultural inputs, like fertilizers, agrochemicals, water and fuels [18]. Additionally, efficiency of inputs use is an integral part of sustainability where economic and environmental parameters merge, in order for production cost reduction and mitigation of contamination to occur [19]. It is obvious that the economic and the environmental performance of agricultural production are controversial parameters, being at the core of a continuous debate between farmers and various stakeholder groups, with the latter requiring from the former to adjust the production process towards an environmentally friendly approach [20]. The experience of other economic sectors has shown that the costly environmental-friendly amendments to production are more easily applied in advanced economies [21,22]. By extension, and regarding the agriculture sector, mature economies are expected to present more sustainable agricultural production practices, such as those having resolved basic dietary issues, are usually characterized by increased environmental awareness and their demand focus on safe and clean, in environmental terms, agricultural products.

The justification of this debate necessitates the need for empirical evidence. As the relationship between agricultural sustainability and economic development is still rather unexplored by international literature, the present paper seeks to fill this gap by exploring the potential existence of an EKC for the European agricultural sector. In order to account for all dimensions of agricultural sustainability, a synthetic Eco-(in)efficiency indicator is developed and applied to the 28 EU countries in order to evaluate sustainability variations for the period 1999–2012. At a later stage, the countries' figures are regressed against GDP p.c. in order to test for an EKC relationship. The remainder of the paper is as follows. Section 2 describes the composition of the eco-efficiency indicator and the regression details for testing for the EKC function. In Section 3, the variables employed by the present study are explained and the results of the analysis are presented and discussed. The paper ends up with the main conclusions and some policy implications towards more sustainable agricultural practices on the European level.

2. Materials and Methods

2.1. Defining the Eco-(In)Efficiency Index

2.1.1. Considerations Regarding DEA Eco-Efficiency Indicators Development

The challenge of conceptualizing and measuring sustainability has captured the interest of scholars across various disciplines in developing synthetic quantitative indices which could be used as the basis of sustainability evaluation [23]. Towards this direction, eco-efficiency could be regarded as an effective approximation of sustainability since it measures the efficiency of a production unit in maximizing its desirable outputs whilst keeping the production of its undesirable outputs and the use of natural resources at the lowest possible levels [24,25]. That is, eco-efficiency could produce integrated assessments of various dimensions of production efficiency such as technical, economic, ecological, energy and environmental [26].

A large part of literature is based on production frontier theory, firstly introduced by [27], in order to develop eco-efficiency indices. The main methodologies based on the frontier theory are data envelopment analysis (DEA) and stochastic frontier analysis (SFA) [25,28]. The two methods are based on different assumptions concerning their application. DEA is a non-parametric method which involves the solution of a series of linear programming problems in order to extract the relative efficiency of each Decision Making Unit (DMU). In addition, SFA is based on the specification of a production function and efficiency estimates are extracted with the use of statistical regression models [29]. Between the two methods, DEA could be regarded as more easily applicable and thus has been rendered rather popular towards eco-efficiency estimations [30].

Among the various specifications of eco-efficiency DEA models there are some basic issues that should be taken into account before its empirical application. The first refers to the reference set and the type of desirable and undesirable output relationship that would be chosen for the formulation of the model. On the one hand, there are studies that assume weak disposability among outputs meaning that reductions of undesirable outputs result in desirable production losses [31,32]. On the other, when strong disposability is assumed, then reductions of undesirable outputs could be achieved without any reduction in the desirable outputs [33]. In addition, another issue that should be defined is whether the models are based on simple distance functions or directional distance functions. In the first case of studies, the adjustments of desirable and undesirable outputs are headed to the same direction after all undesirable outputs have been transformed mainly by using their reciprocals [34–36], whilst in the second case these could be realized to opposite directions [37–39]. In addition, before the formulation of a DEA model, one should also consider if the adjustments of inputs or outputs would be proportional or non-proportional. In the first case, radial DEA models are used [40,41] and in the latter, non-radial measures are employed [42,43]. The papers of [44,45] deal extensively with the aforementioned issues providing comprehensive reviews regarding the application of the DEA method in sustainability assessments taking into account the energy and environmental dimensions of production.

2.1.2. DEA Applications on Agricultural Sector

As far as agricultural studies are concerned, the latest relevant literature has shown a remarkable progress in developing synthetic methods towards sustainability assessment, lying far from a simple measurement of output production or input use [12,13,16]. More precisely, until recently, most of the attention was given to the technical efficiency of agricultural sectors. In a cross-country context, ref. [46] assessed the technical efficiency of 93 countries for the 1980–2000 period based on DEA, ref. [47] analyzed the impact of CAP subsidies on the technical efficiency of crop farms in Germany, the Netherlands and Sweden and [29] assessed the longitudinal technical efficiency of EU countries by comparing the results of DEA and SFA methods. Martinho [48] employed DEA to assess the efficiency and total factor productivity in the European agricultural sector at both farm and regional level. Finally, ref. [49] extracted technical efficiency scores for EU countries and used a bootstrap method in order to extract their statistical properties.

In recent years, the notion of efficiency estimation through frontier deviations has been extended to account for environmental and energy dimensions of agricultural production. The flexibility of DEA provided a fertile ground for such modifications. In this second category of agricultural studies, it was [50] who firstly decomposed agricultural efficiency in its technical, economic and environmental dimensions. In addition, ref. [26] assessed the sustainability of Dutch sugar beet growers by taking into account indices of technical efficiency, environmental efficiency and a composite index of sustainable efficiency. Managi [12] modified the total factor productivity Malmquist–Luenberger index, in order to account for environmental factors. Later, ref. [51] developed a composite sustainability indicator consisting of the dimensions of technical efficiency and cumulative exergy allocative efficiency and evaluated the sustainability of the agricultural sector of OECD countries. Picazo-Tadeo et al. [24] extended the basic DEA model and used a directional distance function (DDF) in order to extract different estimates of the efficiency of olive-growing farms in Spain. Since both undesirable inputs and outputs were considered, authors regarded these estimations as representing the eco-efficiency of the DMUs' sample. Vlontzos et al. [30] employed a non-radial DEA model in order to extract different estimations of the environmental and energy efficiency of EU countries. Moreover, Tian et al. [52] used a slacks-based DEA model in order to incorporate undesirable agricultural emissions in the efficiency evaluation of rice farmers of China. The slacks of energy inputs have been also assessed by [53] within the technical efficiency measurement of French farms. Finally, Vlontzos et al. [35] used Window DEA to assess the longitudinal technical efficiency of EU countries taking into consideration their GHG emissions. GHG emissions factor was entered into estimations with two ways. The first involved its consideration as input and the second as output after being rescaled.

The preceding studies provide useful insights into the efficiency of the agricultural sector. Since the aim of this paper is to test for an EKC relationship between agricultural sector and economic growth, estimations of pure technical efficiency could not be used as the basis of the comparisons, as these do not encompass the environmental dimension of production. Thus, the present paper will mostly focus on the models of the second category of studies which can provide a more holistic assessment of agricultural sustainability. These kinds of models have been extensively used for testifying an EKC curve in other disciplines [33,54,55] but have never been adjusted for the agricultural sector. Keeping in mind, that for an EU cross-country evaluation context both non-radial [23] and radial [35] models have been used to quantify environmental efficiency, the present paper follows the rationale of [12,32] in order to enrich the methodological portfolio regarding environmental efficiency in EU countries. It should be noted that the difference between the present study and the study of [12] lies in the scope of efficiency estimation. On this, efficiency in the present paper is estimated in order to be used as a dependent variable in EKC testing, whereas within the context of [12], this was used as an independent variable capturing the environmental technology differences across US states. Taking into account the preceding remarks, the contribution of the present paper is twofold. Initially, it extends the previous sustainability assessments in the agricultural sector with a novel composite DEA indicator based on the DDF rationale. Secondly, it uses this indicator to test, for the first time, for an EKC relationship of agriculture sector in a group of advanced economies such as that of EU members. By doing so, the paper enriches the agricultural literature but also contributes to the global debate around the relationship between environmental degradation and economic growth.

2.1.3. Developing the DEA Eco-(In)Efficiency Indicator for EU Agricultural Sector Sustainability Assessment

In contrast to the basic DEA formulations which seek to maximize outputs or minimize inputs, DDF allows for simultaneous adjustments on both inputs and outputs. This rationale has been also incorporated in order to provide estimations of productive (in)efficiency when both desirable and undesirable outputs are taken into consideration [32].

Given the presence of x inputs, g desirable outputs and b undesirable outputs, the technology set is defined as:

$$[(x, g, b; ecoEff): x \text{ can produce } (g, b)]$$

In addition, all the feasible output vectors sets for a given input vector are the following:

$$P(x) = [(g, b): (x, g, b) \in T]$$

Then, the directional distance function has the following form:

$$\vec{D}_T(x, g, b; ecoEff) = \sup\delta: \left(g + \delta ecoEff^g, b - \delta eff^b\right) \in P(x + \delta eff^x)$$

Moreover, we suppose that we have n national agriculture sectors expressed as NAS_j $(j = 1, 2, \ldots, n)$, and $x_{ij} > 0$ is the amount of input i used in total by National Agricultural Sector (NAS) NAS_j, $g_{rj} > 0$ is the amount of desirable output r of NAS_j and $b_{cj} > 0$ the amount of undesirable output c of NAS_j. Then, the inefficiency score for the NAS_i is extracted by solving the following model [56]:

$$
\begin{aligned}
&\max_{Eff,\lambda} ecoEff \\
&\text{s.t.} \quad \sum_{j=1}^{n} x_{ij}\lambda_j + ecoEff f_{io}^{x} \leq x_{io} && i = 1,2,\ldots,m \\
&\sum_{j=1}^{n} b_{cj}\lambda_j + ecoEff d_{co}^{b} = b_{co} && c = 1,2,\ldots,k \\
&\sum_{j=1}^{n} g_{rj}\lambda_j - ecoEff d_{ro}^{g} \geq y_{ro} && r = 1,2,\ldots,d \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0 j \ = \ 1,2,\ldots,n \\
&\mathrm{d} = (0, \mathrm{g}, -\mathrm{b})
\end{aligned}
\tag{1}
$$

The objective of the model is to maximize the desirable outputs and minimize the undesirable outputs whilst keeping the inputs stable. The value of $ecoEff$ portrays the Eco-(in)efficiency, meaning that for a fully efficient NAS, the value of $ecoEff$ will be 0. The constraints of the model portray that a weak disposable production process has been selected for the present dataset, which assumes that reductions in CO_2 emissions could not be realized without desirable output losses. This kind of model formulation seems more realistic than a strong disposable approach which allows for CO_2 emissions reductions without any loss in desirable outputs [51]. In addition, the model assumes variable returns of scale in the production process, thus eliminating the scale effects and resulting in more reliable targets for each NAS.

2.2. Defining the Model for EKC Testing

After extracting the $ecoEff$ scores for each country, a regression analysis will be conducted in order to check for an EKC relationship. For comparison reasons, three different models will be tested. The first will test for EKC between Eco-(in)efficiency and GDP. The second will focus on energy use and the third on total GHG emissions. The review of previous studies has shown that different modifications of regression models, such as time-series, cross-section and panel-data have been employed in order to check for EKC in other sectors [7]. Among them, panel-data is the most widely used method for acquiring cross-country empirical evidence [57]. The fundamental consideration regarding the adaptation of a panel-data regression on a study is the functional form of the relationship among dependent and independent variables. Three basic forms could be found in the literature. The first is the linear specification, the second is the log-log specification in which both dependent and independent variables are logged before being entered into the model and the third is the semi-log function in which only the dependent or the independent variables are logged. In the present paper, the linear form is preferred, as it leads to a direct approximation of the turning point of the curve.

The second consideration is the choice between fixed and random effects specification of the model. In fixed effects, the intercept is gathered as fixed whereas in random effects specification, it is assumed that it is extracted through the function $a_i = \overline{a} + \mu_i$, where $\overline{a}$ is an unknown parameter and μ_i are unknown *iid* variables. For the selection of the appropriate specification it is advisable to run a Hausman test before running the statistical model [55]. Finally, it should be noted that since DEA estimations portray the relative efficiency of each NAS, it is expected that a cross panel correlation will emerge in the respective panel data model which could result in biased estimations. To overcome this difficulty we employ a regression with panel-corrected standard errors (PCSE) which controls for heteroscedasticity and contemporary correlation of disturbances across panels [58]. The models specifications are given below:

$$
\begin{aligned}
&Y_{it} = a_i + \beta_{GDP} \cdot GDP_{it} + \beta_{GDP^2} \cdot GDP_{it}^2 + \beta_{GDP^3} \cdot GDP_{it}^3 + \varepsilon_{it} \\
&i = 1, 2, \ldots, N \text{ countries}, \; t = 1, 2, \ldots, T \text{ years} \\
&Y = ecoEff \text{ for model 2.1}, \\
&Y = ENERpc \text{ for model 2.2}, \\
&Y = GhGpc \text{ for model 2.3}
\end{aligned} \tag{2}
$$

3. Results and Discussion

3.1. Eco-(In)Effiiency Assessment Results

In order to depict the production process of EU agricultural sectors, respective inputs and outputs have been selected. The inputs used in this study are expressed as follows: land variable is expressed in total hectares, capital as the fixed capital consumption in monetary terms and labor as the employees' annual working units (AWU). In addition, total energy cost and the total cost of chemicals and fertilizers used in the production process have been also incorporated into the model as significant contributing factors to the agricultural output of each country. Moreover, output has been segmented to desirable output (total crop and animal output) and undesirable output (total GHG Emissions). The basic descriptive statistics of the input and output variables of model 1 are presented in Table 1.

Table 1. Descriptive statistics of DEA inputs and outputs.

Statistic	Land (1000 Ha)	Energy (mil. $)	Chemicals and Fertilizers (mil. $)	Fixed Capital Consumption (mil. $)	Labour (1000 AWU)	Output (mil. $)	GHG Emissions (1000 tonnesCO_2)
Mean	6642.64	786.57	880.12	1815.24	1210.88	11,720.45	17.69
St Dv	7901.59	933.03	1314.67	2730.81	1729.06	15,644.37	22.99
Max	35,177.80	4502.70	7599.10	12,377.39	7307.35	70,394.90	100.46
Min	9.70	5.44	1.73	3.76	3.59	115.18	0.08

Source: [59–61]; Own elaboration.

The data covers the period between 1999 and 2012. In order to extract the longitudinal Eco-(in)efficiency scores of each country, Model 1 is executed 14 times. The main results for each NAS are presented in Table 1, whereas the detailed annual Eco-(in)efficiency scores for each NAS are given in Table A1 of the Appendix A. Regarding Table 1, the mean Eco-(in)efficiency score for each NAS is given in the first column, the years for which each country presented zero (in)efficiency are presented in the second column, whereas the highest and lowest Eco-(in)efficiency score of each country through the whole 1999–2012 period are given in the third and fourth columns, respectively. As can be seen in Table 2, the average Eco-(in)efficiency score for the EU agricultural sector is 0.11. This finding implies that with the given inputs, EU agricultural could produce 11% more output and less GHG emissions. Nevertheless, variations exist among countries. More precisely, only Malta and the Netherlands kept a zero Eco-(in)efficiency for all the considered period, followed by Italy which was found to be rather inefficient only in one year (2005), and France, which was found to be inefficient in three years (1999, 2005, 2006). On the contrary, the least efficient group of countries consists of Lithuania, Slovakia and Finland, whose average Eco-(in)efficiency scores for the period 1999–2012 exceeded 0.3. A second group of inefficient countries is shaped by Latvia, Hungary, the United Kingdom, the Czech Republic and Slovenia with Eco-(in)efficiency scores ranging between 0.2 and 0.3.

Apart from the top-ranked countries, a number of other national sectors achieved remarkable figures in terms of times being evaluated as efficient during the recursive application of the DEA models. Poland, Spain, Luxemburg and Cyprus were found fully efficient for more than ten years and Belgium, Portugal, Germany, Bulgaria and Ireland for exactly ten years. In addition, Lithuania, Slovakia, Finland Hungary and Sweden have not acquired a zero Eco-(in)efficiency score in any of the annual estimations. Moreover, examining the last two columns, it is interesting to highlight the large variability of Latvia figures, as within the period under consideration its highest Eco-(in)efficiency score was 0.634 whilst the lowest 0. Rather high variability is found also for the United Kingdom, Estonia and the Czech Republic. As it is evident, the least efficient countries present a larger range of scores during the 1999–2012 period.

Table 2. Eco-(in)efficiency scores and longitudinal performance in EU agricultural sector (1999–2012).

Country	Average Eco-(In)Efficiency	Years Fully Efficient	Highest Eco-(In)Efficiency	Lowest Eco-(In)Efficiency
Netherlands	0.000	14	0.000	0.000
Malta	0.000	14	0.000	0.000
Italy	0.003	13	0.043	0.000
France	0.004	11	0.030	0.000
Spain	0.005	12	0.050	0.000
Austria	0.009	9	0.055	0.000
Belgium	0.010	10	0.068	0.000
Portugal	0.010	10	0.058	0.000
Poland	0.013	13	0.188	0.000
Germany	0.017	10	0.098	0.000
Greece	0.018	7	0.077	0.000
Bulgaria	0.021	10	0.133	0.000
Denmark	0.022	8	0.088	0.000
Luxembourg	0.025	11	0.136	0.000
Ireland	0.026	10	0.153	0.000
Cyprus	0.046	11	0.255	0.000
Romania	0.050	8	0.216	0.000
Croatia	0.075	8	0.241	0.000
Sweden	0.159	0	0.286	0.029
Estonia	0.175	6	0.479	0.000
Slovenia	0.199	1	0.312	0.000
Czech Republic	0.219	5	0.451	0.000
United Kingdom	0.220	6	0.492	0.000
Hungary	0.281	0	0.422	0.113
Latvia	0.282	3	0.634	0.000
Finland	0.311	0	0.375	0.239
Slovakia	0.351	0	0.513	0.167
Lithuania	0.402	0	0.551	0.213
Mean	**0.105**	-	-	-
St.Dv	**0.150**	-	-	-

Source: Own elaboration.

Having examined the individual records of the countries, Figure 1 presents the annual Eco-(in)efficiency estimations for three categories of countries against the respective scores of the whole sample. The first category of countries is composed of countries that joined the EU before 2004, the second of the countries that entered into the EU in 2004 and the third of the three countries that joined the EU after 2007. This division is critical in order to check the performance of countries with reference to the CAP policy guidelines. In general, average EU Eco-(in)efficiency presents variable trends through the considered period. The least efficient scores are observed over the years 1999 and 2005 whereas the most efficient scores are found in years 2007, 2011 and 2012. Among the group of countries, these that have accessed EU in 2004 are characterized with the highest average Eco-(in)efficiency scores during the whole period. It should be noted that average inefficiency of these countries exceeds the average EU inefficiency at all annual estimations. The other two groups of countries present lower inefficiency records, which is reflected in the fact that in any year their mean inefficiency exceeded the EU average. Finally, comparisons between the inefficiency trends of the two groups of countries, could lead to any safe conclusions, as these present high variability. The only remarkable observation is the significant better performance of late-joining countries during the period 2005–2007.

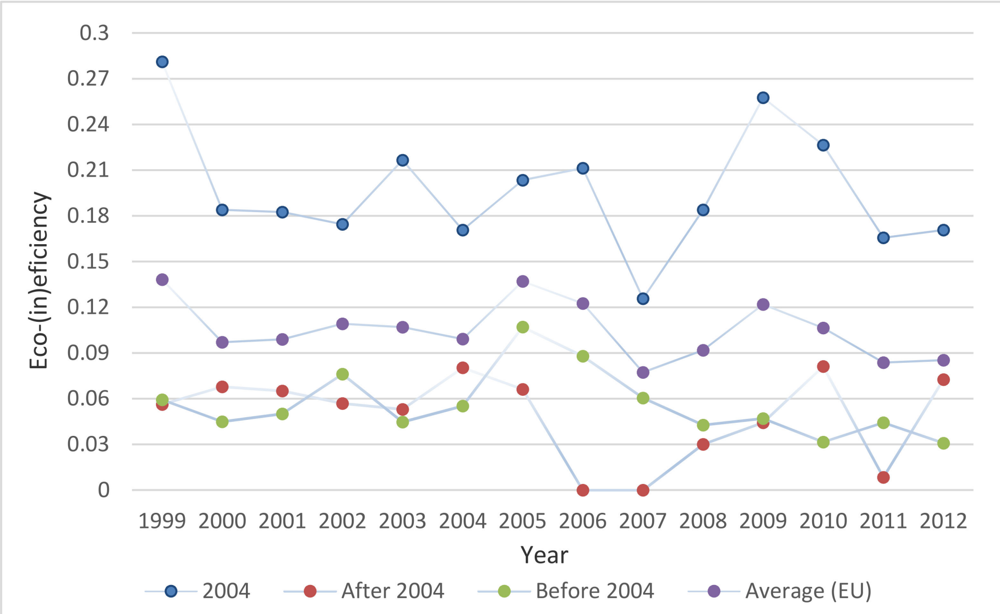


Figure 1. Average Eco-(in)efficiency of EU agricultural sector and average Eco-(in)efficiency by groups of countries according to their date of accession (1999–2012) (Source: Own elaboration).

3.2. EKC Testing Results

As it was stated in Section 2, the scores of Eco-(in)efficiency will be used as the basis for fitting an EKC curve on the relationship of agriculture environmental efficiency and economic growth in EU countries. In addition, the existence of an EKC will be also examined for p.c. energy use of agriculture and p.c. GHG emissions. The annual GDP p.c. of EU countries for the years 1999–2012 will be used as the variable to represent the economic growth of each country. In order to achieve an unbiased representation of the economic level of each country, the GDP will be expressed in purchasing power parity (PPP), as this measure allows for more accurate cross-country comparisons and has been employed in several empirical studies regarding EKC [5]. A cubic function has been selected in order to check for any N-shape relationships. The empirical recognition of an EKC or N-shaped pattern is based on the estimations of the regression parameters and, more precisely, on their signs and their statistical significance. In this sense, an EKC curve would be confirmed only under the following signs of estimated parameters $\beta_{GDP} > 0$, $\beta_{GDP^2} < 0$, $\beta_{GDP^3} = 0$. Finally, it should be mentioned that the final sample includes 27 EU countries. Luxemburg data was omitted from estimations because it presents GDP figures that are exceptionally higher than the respective figures of other countries, and thus could lead to biased estimations.

Table 3 presents the results for the three models. As far as the goodness-of-fit tests are concerned, the statistical significance of the Wald test result denotes that all three models are performing better than the respective models with zero parameters. In addition, for models 2.2 and 2.3, the results of the Hausman test indicate that for both models, a random effect specification could be used with the available data. For model 2.1, estimations present statistical significance for all parameters at the 0.01 level, except for the intercept. The estimations for the β_{GDP} and β_{GDP^3} are positive, whereas the estimation of β_{GDP^2} is negative. This finding signifies that eco(in)efficiency and economic growth are linked through an N-Shaped curve. More specifically, in early stages of development, agricultural production is rather inefficient with desirable output shortages and undesirable output excesses. As the national income increases, production becomes more efficient in input utilization but after a certain point of income, inefficiency presents increasing trends again. This fact could be attributed to the ability of wealthier countries to afford more undesirable inputs such as fertilizers and energy. Hints for this explanation are provided by the examination of the estimated coefficients of model 2.2. As for model 2.1, all estimations acquire statistical significance except for the constant term. The pattern of parameter sign change is exactly the same as that of model 2.1. This finding provides hints that Eco-(in)efficiency is strongly connected to energy use. Finally, model 2.3 estimations are all statistically significant with the exception of β_{GDP^3}. Thus, agricultural GHG emissions seem to be connected to economic growth through an EKC relationship.

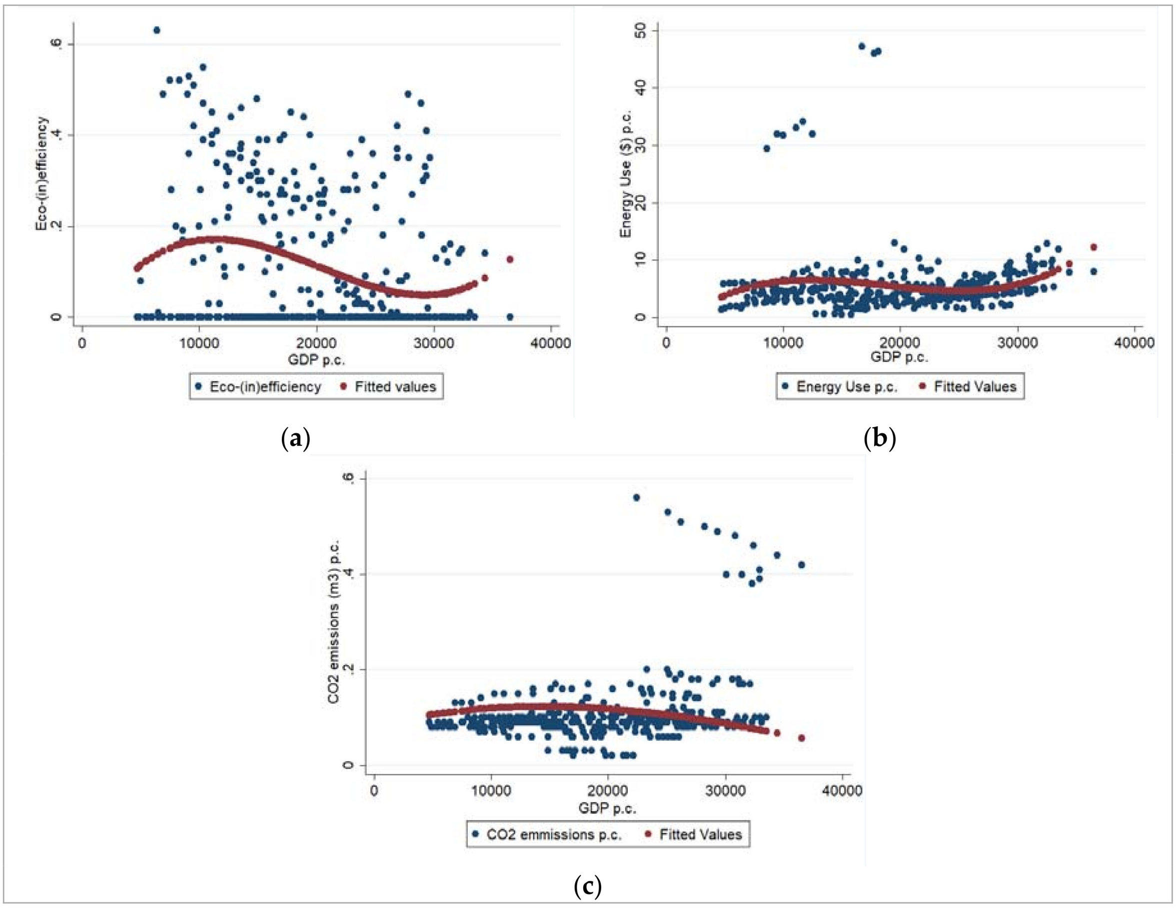
Table 3. Models 2.1, 2.2 and 2.3 estimation results.

	Models (Dependent Variable)					
	2.1 (*ecoEff*)		**2.2 (*ENERpc*)**		**2.3 (*GhGpc*)**	
Estimators	**Estimation**	**St.Error**	**Estimation**	**St.Error**	**Estimation**	**St.Error**
β_{GDP}	0.0428 ***	0.0145	1.759 **	0.7169	0.0060 ***	0.00195
β_{GDP^2}	-2.62×10^{-9} ***	7.75×10^{-10}	-1.06×10^{7} ***	3.92×10^{-8}	-2.43×10^{-10} **	1.09×10^{-10}
β_{GDP^3}	4.30×10^{-14} ***	1.27×10^{-14}	1.89×10^{-12} ***	6.55×10^{-13}	1.65×10^{-15}	1.82×10^{-15}
a	−0.0399	0.0820	−2.6329	4.0450	81.5590 ***	15.490
T			14			
N			27			
WaldTest chi2(1)	8.68		9.75		137.46	
Prob > chi2	0.003		0.021		0.001	
Hausman Test chi2(1)	-		0.01		3.84	
Prob > chi2	-		0.943		0.051	
TurningPoint 1 (000€)	11,326		12,428		12,325	
TurningPoint 2 (000€)	29,294		24,961		-	

Statistical significance: (***) at 0.01 level (**) at 0.05 level. Source: Own elaboration.

As far as the turning points are concerned, these are visualized with Figure 2 which presents the original and fitted values of the dependent variables extracted from the three different models, plotted together with the GDP variable. As can be seen from Figure 2a, Eco-(in)efficiency increases up to 11,326€ and starts decreasing until 29,294€. After this point, there are hints that countries return to more unsustainable practices. Nevertheless, inefficiency at this part of GDP levels is still lower than the respective of the lowest GDP levels. The same trends are observed over the energy use (Figure 2b), although with two remarkable differences. The first regards the turning points, which are closer than those of Eco-(in)efficiency (12,428€ and 24,961€) and the second on the fact that after the second turning point, energy use, in some cases, surpasses the respective use at the lowest GDP levels. Finally, GHG emissions and GDP level relationship seems to match with the characteristics of an EKC curve. Emissions are expanding until the point of 12,325€, and afterwards they present declining trends.

The aforementioned findings provide useful insights into the state and evolution of primary sectors in the EU. A typical analysis focusing only on the GHG emissions would provide hints that the CAP fulfills its targets, at least on the emissions side. As confirmed by the present paper, EKC relationship confirms the general impression that emissions is a matter of economic growth that could be solved together with the global target of EU regional and national economic convergence. Nevertheless, the results of Eco-(in)efficiency and energy use analyses which showed that inefficiency and energy use excesses are also observed in countries with higher income levels, add a question mark for whether EU convergence is only a necessary or/and sufficient conditionfor rendering the EU agricultural sectors more sustainable. The findings of the paper, extend the debate of previous papers [12,16] on the necessity of developing more advanced methods on agricultural sustainability assessments, especially in economies where technological, institutional and scale factors are rather complex.



(**a**) (**b**) (**c**)

Figure 2. The Turning Points of Models 2.1, 2.2. and 2.3 (**a**) The turning points of Eco-(in)efficiency curve (**b**) The turning points of the energy use curve (**c**) The turning point of the GHG curve (Source: Own elaboration).

4. Conclusions

This analysis revealed that EU agriculture is quite far from being fully sustainable. The Eco-(in)efficiency index results signifies that the overall EU primary sector could produce 11% more output and less GHG emissions. Inefficiency seems to be higher for the group of countries that accessed the EU in 2004, as for countries such as Slovakia and Lithuania output shortages and GHG emissions excesses, surpass 30%. Moreover, the EKC analysis revealed that despite the fact that GHG emissions seem to be reduced as national incomes increase, a more advanced economic level does not ensure a more sustainable agricultural production, as a whole. This is reflected in the N-Shaped curve linking the Eco-(in)efficiency and energy use levels with the GDP of EU countries during the period of 1999–2012. Thus, a future success of the convergence process within the EU should not be regarded as a decisive factor of agricultural sustainability improvement.

The contradictory results among the three agricultural sustainability dimensions tested by the present paper highlight the challenge of measuring agricultural sustainability in a more holistic and systematic context. To this end, the models of the present paper could be enriched with additional control variables representing particular characteristics of EU countries, such as, their institutional framework, their technological advancement, their specialization in crop and livestock production etc. Moreover, new synthetic indicators for measuring agricultural sustainability could be added to the ones employed by the present paper. In addition, at the policy level, community initiatives such as the European innovation scoreboard should be capitalized and adapted to the specific challenges of the EU agricultural sector.

Finally, further improvement of efficiency scores for inefficient countries can be achieved through utilization of good practices being implemented in efficient ones. It is therefore necessary that advanced technology are reachable by farmers, hence more effectively and efficiently utilizing energy resources, while reducing GHG emissions. The continuous training of farmers is also necessary in order to increase their ability to adopt and implement new cultivation and production practices. It has been proven that continuous engagement with new knowledge leads farmers to more appropriate decision-making processes which have a positive impact on efficiency improvements [62]. The new CAP provides considerable degrees of freedom to farmers to organize their cultivation and production plans, and is an appropriate framework for efficiency change and efficiency improvement.

Author Contributions: All authors designed the structure of the paper and contributed to its writing; George Vlontzos prepared the data, conducted the literature review and estimated the Eco-(in)efficiency scores; Spyros Niavis and Panos Pardalos developed the framework for Eco-(in)efficiency estimation and tested the EKC curve.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Annual Eco-(in)efficiency scores of EU agricultural sector (1999–2012).

	Year													
Country	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Belgium	0.06	0.00	0.00	0.07	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bulgaria	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.03	0.03	0.11
Czech Republic	0.00	0.00	0.00	0.00	0.00	0.39	0.45	0.44	0.27	0.27	0.40	0.33	0.25	0.28
Denmark	0.03	0.00	0.00	0.05	0.02	0.08	0.09	0.00	0.00	0.05	0.00	0.00	0.00	0.00
Germany	0.00	0.00	0.00	0.06	0.03	0.00	0.10	0.00	0.00	0.00	0.05	0.00	0.00	0.00
Estonia	0.28	0.00	0.00	0.00	0.21	0.00	0.00	0.10	0.00	0.40	0.48	0.39	0.30	0.29
Ireland	0.07	0.00	0.00	0.00	0.00	0.00	0.15	0.14	0.00	0.00	0.00	0.00	0.00	0.00
Greece	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.08	0.05	0.05	0.02	0.00	0.05	0.00
Spain	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00
France	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00
Croatia	0.17	0.12	0.20	0.17	0.15	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Italy	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cyprus	0.00	0.15	0.23	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Latvia	0.63	0.00	0.00	0.00	0.36	0.28	0.38	0.36	0.28	0.34	0.44	0.35	0.30	0.22
Lithuania	0.49	0.52	0.52	0.53	0.55	0.40	0.33	0.38	0.21	0.32	0.46	0.39	0.27	0.26
Luxembourg	0.00	0.00	0.00	0.00	0.12	0.00	0.14	0.00	0.00	0.00	0.00	0.00	0.10	0.00
Hungary	0.42	0.39	0.34	0.32	0.36	0.30	0.31	0.32	0.22	0.13	0.30	0.25	0.11	0.16
Malta	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Netherlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Austria	0.03	0.00	0.00	0.00	0.01	0.00	0.05	0.00	0.00	0.00	0.02	0.00	0.00	0.01
Poland	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Portugal	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.06	0.00
Romania	0.00	0.08	0.00	0.00	0.01	0.00	0.20	0.00	0.00	0.09	0.00	0.22	0.00	0.11
Slovenia	0.31	0.27	0.27	0.18	0.27	0.06	0.18	0.16	0.00	0.21	0.22	0.25	0.18	0.23
Slovakia	0.49	0.51	0.47	0.45	0.41	0.29	0.37	0.36	0.27	0.17	0.28	0.32	0.24	0.26
Finland	0.30	0.28	0.28	0.28	0.31	0.24	0.31	0.37	0.33	0.35	0.35	0.35	0.30	0.31
Sweden	0.19	0.03	0.09	0.29	0.18	0.08	0.21	0.18	0.12	0.15	0.27	0.13	0.16	0.14
United Kingdom	0.17	0.36	0.39	0.36	0.00	0.42	0.49	0.47	0.41	0.00	0.00	0.00	0.00	0.00

Source: Own elaboration.

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