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The impact of environmental attitudes of farmers on efficiency in the agricultural sector in the European Union

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Abstract: The aim of this paper is to investigate whether the more pro-environmental attitudes of farmers influence the technical efficiency of agricultural sectors in EU regions (NUTS-2). To answer this, I employed data envelopment analysis (DEA) for efficiency analysis combined with the double bootstrapped truncated regression to investigate the relationship between environmental attitudes and technical efficiency. I found that this relationship is positive, i.e. pro-environmental attitudes were related to greater efficiency. An increase in the environmental attitude variable by one standard deviation led to an improvement in efficiency of 2.8–6 p.p. The higher share of farmers with formal training also proved to be a positive and significant determinant of efficiency. The share of arable land on which conventional tillage was used, and soil erosion proved to be significant but negative determinants of efficiency. Policymakers should present to farmers the environmental benefits of agricultural policy but should also highlight that greater environmental awareness translates into a more efficient operation.

Keywords: agricultural policy; data envelopment analysis; farmers' identity; sustainable development; truncated regression

The new Common Agricultural Policy 2023–2027 and the announcement of the European Green Deal in 2020 have led to a tightening of the environmental requirements associated with farming. Receiving payments at levels similar to those in previous budget perspectives will require farmers to implement so-called eco-schemes, i.e. pro-environmental farming practices that go beyond the minimum set out in the Good Agricultural and Environmental Condition (GAEC) standards. At the same time, the instability of weather, climate and geopolitical conditions (e.g. the war in Ukraine) make it an important challenge for European agriculture to maintain high levels of efficiency and productivity with limited environmental impact. Achieving such objectives requires setting top-down standards, but it also requires the involvement of farmers themselves and their positive pro-environmental attitudes towards current challenges. Failure to account for behavioural factors in the design of agri-environmental policies may lead to inadequately designed measures (Brown et al. 2021). The question is whether greater concern for the environment must conflict with economic management

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objectives, such as improving efficiency, or whether there may be synergies between these objectives.

Numerous studies have analysed the impact of farmers' environmental attitudes on their decisions, including the adoption of pro-environmental farming practices. These practices could be implemented in the form of formalised contracts (agri-environmental schemes; e.g. Ma et al. 2012; Calvet et al. 2019; Thomas et al. 2019; Cullen et al. 2020) and practices implemented in an informal way (e.g. Laeple and Kelley 2015; McCan et al. 2015; Mase et al. 2017; Ulrich-Schad et al. 2017).

Recent systematic literature reviews have shown that a pro-environmental orientation does not always influence farmers' decisions. Schaub et al. (2023) studied factors influencing participation or willingness to participate in voluntary agri-environmental programmes in Europe, Australia and North America. In more than half of the studies (52%), attitudes towards the environment were not a significant determinant of participation. Nevertheless, in the remaining studies (where statistical significance was noted), the influence was always positive. The authors indicated that other factors (e.g. financial motivations) may wash out the importance of attitudes towards the environment. Similar conclusions were reached by Wang et al. (2023), who showed that although there are cultural differences in environmental attitudes among German- and French-speaking farmers in Switzerland, increased financial incentives to undertake pro-environmental practices reduced the influence of cultural factors.

In addition, the specificity of the questions is important for obtaining the significance of the impact of environmental attitudes – the more general the questions, the greater the likelihood of statistical insignificance (Schaub et al. 2023). However, more important than the general environmental approach was farmers' attitudes towards a specific programme – its validity, sensibility and cost-effectiveness. Similar conclusions were reached by Thompson et al. (2023), who also analysed the determinants of participation in agri-environmental practices, although they focused on informal but actually implemented practices (studies using discrete choice experiments for hypothetical scenarios were not considered). The general approach to the environment was significant in 40% of the models analysed, and the approach to a particular practice was significant in about 73%. The attitude towards the environment may play a greater role when adopting multiple practices is investigated. On the other hand, a literature review on farmers' decision-making by Bartkowski and Bartke (2018) indicated that environmental preferences influenced farmers' actions. Recently, Drescher et al. (2024) added to this discussion by analysing the impact of social psychological factors on adoption of environmental best management practices. They found that beliefs of a personal obligation for adoption and the perception of the capacity for adoption impact US farmers' decisions more than perceived benefits from introducing these practices. In turn, Doran et al. (2020) found that perceived behavioural control had the strongest effect on nutrient best management practices. However, perceived social norms and farmer attitudes toward these practices were each also significant.

Corresponding with the above analyses are studies that assessed the impact of the dominant objectives of a farm on taking pro-environmental action. Howley (2015) found that farmers with a productivist approach were less likely to convert their land to forests. Zemo and Termansen (2022) found that farmers with a more pro-environmental stance tended to need less financial incentive to implement pro-environmental investments than other farmers. In contrast, Tosakana et al. (2010) demonstrated that more profit-oriented farmers were paradoxically more willing to engage in pro-environmental measures.

Given the reorientation of agricultural policy from rewarding actions (action-based approach) to rewarding concrete effects (effect-based approach), studies that address the relationship between pro-environmental attitudes and concrete results should be increasingly important. However, this strand of research is currently underrepresented. An important exception is the analysis of Wuepper (2020), who showed at the sectoral level that in European regions where farmers are characterised by a more pro-environmental culture, the mitigation of soil erosion is more effective.

To our knowledge, only Torres et al. (2019) have attempted to assess the relationship between technical efficiency in agriculture and environmental attitudes. Using the New Ecological Paradigm on farmers in Northwest Mexico, they found that more technically efficient farmers had an anthropocentric approach, while less efficient farmers tended to exhibit an ecocentric approach. However, their analysis was not causal (ANOVA and principal component analysis were used), and it was limited to a relatively small geographical area.

This article attempts to fill a gap in the literature by assessing the impact of the pro-environmental attitudes of farmers in the regions of the European Union on the level of technical efficiency using double

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bootstrapped truncated regression analysis. The hypothesis is that a more pro-environmental orientation of farmers not only does not translate into lower farming efficiency but rather into higher efficiency. In other words, a win-win situation is possible (Daxini et al. 2018). Farmers in regions with higher environmental sensitivity adapt more dynamically to current changes in agricultural policy (e.g. reducing the use of fertiliser and plant protection products). As part of these adjustments, they try to optimise their operations to achieve similar levels of production with fewer inputs. The level of input-oriented technical efficiency should, therefore, be higher in regions where farmers pay more attention to climate and environmental problems. Using the notions of the theory of planned behaviour (TPB) (Ajzen 1991), we can say that farmers' input-minimising behaviour results from the intention which is built on farmers' attitudes, subjective norms, and perceived behavioural control. The variable that reflects the pro-environmental orientation of the farmers used in this article contains all three main elements of TPB.

The aim of this article is therefore to assess the impact of farmers' attitudes towards environmental problems on the level of technical efficiency at the level of EU regions (NUTS-2). Input-oriented technical efficiency is calculated using a data envelopment analysis (DEA) model, and the impact of environmental attitude on efficiency is assessed using a procedure proposed by Simar and Wilson (2007) called double bootstrapped truncated regression. The information needed to construct a latent measure of environmental attitude was taken from a European Values Study (EVS) database (EVS 2022). The EVS survey was conducted using a standardised methodology on a representative sample of respondents in European countries. The present work may also complement another strand of research (e.g. Grzelak and Kryszak 2023), which examined the interrelationship between the technical efficiency of farms and various understandings of eco-efficiency. However, this work examined the relationship between the effects of farmers' actions, as expressed by technical efficiency coefficients, and the sensitivity that farmers displayed towards current environmental challenges. This study, like that of Wuepper (2020), also fits into an analysis of the effects of actions already taken rather than adopting actions.

MATERIAL AND METHODS

Data. All calculations were made for all of the EU regions on NUTS 2 level for which all necessary data were available [*cf.* Table S1 in Electronics Supplementary Material (ESM) for the detailed list]. Data for calculating technical efficiency indicators and control variables were taken from Eurostat (Eurostat 2023; specific codes are provided in the text below). Technical efficiency was calculated using the Economic Accounts for Agriculture data at the NUTS 2 level. The exception was Germany, where the regions in this study were identified as individual states (Länder; NUTS1 level). The NUTS2 level for some of the larger states (e.g. Bavaria) were the districts. However, EVS data were available only at the Länder level and not at the district level, so it was necessary to reconcile the availability of data from the two databases. On the output side, the value of agricultural production in millions of EUR (at current prices) in the region was included (Eurostat code: agr_r_accts). Inputs, on the other hand, included the labour factor (number of persons employed in agriculture in thousands – Agriculture, forestry and fisheries division, Eurostat code: lfst_r_lfe2en2), land (area of land used for agriculture in km^2 – Eurostat code: lan_use_ovw) and capital inputs understood through intermediate consumption in millions of EUR at current prices (Eurostat code: agr_r_accts). Fixed capital was not included for two reasons: data at the regional level were not available for some countries (e.g. Poland), and cross-country comparability of data on the value of fixed capital consumption was limited and was usually an approximation of fixed capital formation. Due to the stochastic nature of agricultural production (resulting, among other things, from weather and price factors), the average value of production, the average value of intermediate consumption and the average value of labour factor input (for 2017–2018) were used to calculate efficiency. Only the data on the land factor were from 2018, but the regional stock of this factor is changing at a relatively slow pace. Calculating efficiency indicators for a single period based on fluctuating financial values could lead to biased results in terms of actual efficiency. For this reason, financial variables were averaged.

Information on the issues of farmers' environmental attitudes was taken from the EVS database. The EVS is a unique data source, allowing researchers to explore the research questions in the field of values. It has been conducted since 1981 in five waves, making the data available for waves rather than for every single year. The fifth wave of EVS was conducted between 2017 and 2020. The questionnaires for the regions analysed in this study were collected (depending on the region) mainly in 2017 and 2018, except for Portugal, where

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interviews were conducted in 2020. However, I assume that attitudes during the given wave were stable, and data for different regions from the same wave can be directly compared. For this reason, I calculated the efficiency score based on data from 2017 and 2018 and used the EVS data from the most recent wave. To derive the latent concept of farmers' environmental attitudes, answers for questions v199–v203 from card 56 were used. Respondents who identified as 10 (farm labour) or 11 (self-employed farmers) in question v246 were treated as farmers. For each of the five questions (v199–v203), the respondents were asked to indicate the extent to which they agreed with the statements given on a 5-point Likert scale (1 = strongly agree, 5 = strongly disagree). Statement v199 was worded in such a way that selecting 1 indicated the most pro-environmental attitude, while the other statements were worded in such a way that selecting 5 indicated the most pro-environmental attitude. Hence, the answers to question v199 were recoded so that 5 also meant the highest environmental sensitivity. Below are the statements to which the respondents surveyed referred:

– v199: I would give away part of my earnings if I could be sure that this money would be used to fight pollution.

– v200: For someone like me, it is simply too difficult to do something for the environment.

– v201: There are more important things in life than protecting the environment.

– v202: There is no point in me doing whatever I can for the environment unless others do the same.

– v203: Many claims about the environment are greatly exaggerated.

Although not explicitly, the statements above can be linked to the theory of planned behaviour (Ajzen 1991). The statement v200 is clearly linked to the concept of perceived behavioural control, i.e. how an individual perceives the ease or difficulty of performing behaviour. The statements v201 and v203 can be referred to as attitudes. It explains whether or not an individual has a positive orientation to pro-environmental behaviours. The statements v199 and v202 can be linked to subjective norms.

The explanatory variable expressing the attitude towards the environment included in the modelling was latent and constructed using factor analysis (with rotation), in which the creation of one factor was chosen based on five observable variables (v199–v203). Wuepper (2020) also used the EVS database to construct the 'environmental culture' of farmers, but he concentrated on time preferences, actual participation in environmental organisations and two more general variables regarding farmers' beliefs (whether humans' ingenuity can save the environment). In the present research, I constructed farmers' environmental attitudes based strictly on their beliefs regarding environmental issues. They explain whether a farmer feels that he or she should do something for the natural environment, but also, these statements approximate the level of trust in the rest of society and authorities.

Three further control variables as potential determinants of efficiency are included:

i) The share of farm managers with basic or full formal vocational training (other farmers have only practical experience, Eurostat code: ef_mp_training).

ii) The proportion of arable land with conventional tillage (Eurostat code: ef_mp_prac) – it has been hypothesised that in regions with a greater share of alternative tillage methods, environmental benefits are achieved, but high long-term yields can also be achieved with limited inputs (Ward et al. 2016).

iii) Estimated soil erosion in tonnes by water (Eurostat code: aei_pr_soiler) – it has been assumed that higher levels of erosion may adversely affect technical efficiency.

Data for the control variables were only collected for selected years since they concern farm structure that is not substantially changing in a short period of time. The last year before 2017–2018 for which all necessary data for control variables are available is 2016. Therefore, data for this year were used with the assumption that the values of control variables did not change much in 2017–2018 period. Due to the lack of available data, the average age of the farmers, which often appears as a standard determinant of farmers' efficiency, was not included as a control variable. The results from review studies indicate that, in practice, this variable is often not statistically significant (Thompson et al. 2023).

Empirical strategy. Technical efficiency in agriculture at the regional level was estimated using data envelopment analysis (DEA). Although stochastic frontier analysis (SFA) methods have the advantage of separating random error from pure (in)efficiency, they require the specification of the production function (Bogetoft and Otto 2011). In the case of studies on aggregated data, which include farms with different profiles, *a priori* adoption of a functional form is particularly difficult. Hence, the more flexible DEA models may find application in such studies. Since agriculture is typically a sector with high sensitivity to the scale of production, the assumption of variable returns to scale (VRS) was made. At the same time, due to the evolution of agricul-

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tural policy towards an emphasis on input reduction, an input-oriented model was chosen.

The linear programming for the input-oriented Banker-Charnes-Cooper (BCC) model (Banker et al. 1984) was established as follows:

$$
\begin{aligned}
&\min \theta \\
&\text{s.t. } \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ik} \\
&\textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \leq y_{rk} \\
&\textstyle\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda \geq 0 \\
&i = 1, 2, \ldots, m;\ r = 1, 2, \ldots, q;\ j = 1, 2, \ldots, n
\end{aligned}
\tag{1}
$$

where the decision making units (DMUs) are denoted by DMU_j (j = 1, 2, ...n), inputs are denoted by x_i (i = 1, 2, ...m) and outputs are denoted by y_r (r = 1, 2, ...q). For this article, there is one output and three inputs, as described in the data section.

Combining efficiency analysis with regression analysis, which seeks determinants affecting the level of efficiency examined, poses some important technical problems. In the past, authors have often used a two-step procedure in which efficiency was first estimated independently, and then regression analysis [ordinary least squares (OLS) or tobit due to the boundary problem in DEA analyses] was performed with potential covariates explaining efficiency. However, Simar and Wilson (2007) showed that this approach has serious weaknesses, and the results of estimating the regression model are questionable.

First, Simar and Wilson (2007) stressed that there is no clear theory of the underlying data-generation process that could justify a naïve two-stage approach. Further, technical efficiency (TE) scores (the dependent variable in regression) in DEA are not directly observable but are estimated from the common and finite sample of data and censored at 1. These DEA estimates are serially correlated, which is related to their relative nature. Any perturbations of observations on the frontier will change the efficiency levels estimated for other observations. To guarantee the accuracy of the analysis, Simar and Wilson (2007) recommended a parametric bootstrap of the truncated regression, which they called Algorithm 1 in their seminal paper.

The second issue is the high probability that DEA procedures overestimate true efficiencies (Salas-Velasco 2020). The estimated frontier is only the observed production frontier. There may be DMUs outside the sample that are truly efficient. If these DMUs were included in the analysis, the estimated production frontier would be different. Therefore, efficient DMUs would no longer be efficient in our case. Therefore, this may happen in this article because I did not analyse all EU regions. To overcome this issue, Simar and Wilson (2007) proposed double-bootstrapped truncated regression (Algorithm 2), in which not only is the truncated regression bootstrapped, but DEA scores in the first stage also are subjected to bootstrapping to control for bias. The regression equations can be described as follows:

$$\hat{\hat{\theta}}_i = z_i \beta + \varepsilon_i \tag{2}$$

where: $\hat{\hat{\theta}}_i$ – input-oriented bias-corrected technical efficiency scores from DEA; z_i – vector of variables that may affect technical efficiency variation (i.e. environmental attitude, share of farmers with basic or full agricultural training, share of conventional tillage and soil erosion in tonnes per ha); β – vector of parameters to be estimated; ε_i – statistical noise.

Bootstrapping is consistent with the assumed data-generating process and, thanks to this, the estimated standard errors are not biased. For the technical details of both algorithms, I refer to the original paper of Simar and Wilson (2007).

Robustness check. A procedure to test the robustness of the models was carried out to increase the reliability of estimates of the environmental approach's impact on the level of efficiency in agriculture at the regional level. For some regions in the sample, farmers were a very small proportion of the population, which was reflected in their low number in the EVS survey samples. An assessment of the attitudes towards the environment prevalent in a region's farmer population judged by the responses from the very small number of respondents (even if this farmer was running a farm that represented quite well the average farm in the region) may not be adequate (Wuepper 2020). In addition, it can be argued that the fact that one of the questions (v199) on environmental sensitivity was worded in the opposite way to the others may have confused the respondents and could have influenced the results. Thus, we present the modelling results excluding regions where only one farmer responded to the survey to check whether the results for the full and the limited sample vary substantially. I also show the models using the latent variable 'attitude towards the environment'

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constructed solely from the responses to questions v200–v203 (without question v199). Moreover, further models were estimated in which the variable 'environmental attitude' was constructed simply as the sum of the scores for the answers to each question. Therefore, it ranged from 5 (1 point for the answer showing the least concern for the environment in each of the five questions) to 25 (5 points for the most pro-environmental answer in each question).

RESULTS AND DISCUSSION

Table 1 summarises the descriptive statistics of the variables used in this study. It also covers the calculations of 'environmental attitude' variables constructed based on the methodology described in the Material and methods section.

Based on the data in Table 1, it can be said that, on average, farmers across the EU did not show a clear pro- or anti-environmental orientation. For all five questions (including recoded question v199), the average value was just over 3, where 3 means that the respondent neither agreed nor disagreed with the statement. While there were significant differences between regions, none of the extreme attitudes towards the environment were dominant. It is noteworthy, however, that the highest mean value for the pro-environmental attitude was recorded for question v201, which was worded in a very explicit but harsh way.

Farmers in the EU regions under study differed significantly in their levels of agricultural education. Similarly, there was a great deal of variation in the prevalence of conventional tillage methods and the intensity of the soil erosion process. For example, in some Italian, Polish and Romanian regions, conventional ploughing was used on almost the entire land area, while in the Alentejo region (Portugal), conservative or zero-tillage was used on about 80%. Such large differences can (to some extent) be justified by the different natural conditions for the introduction of conservation tillage in different regions. As noted by Busari et al. (2015), the benefits of minimum or no-tillage depend on the soil type. Conversely, soil erosion was marginal in the East Anglia region and some Dutch regions. In the Italian and Austrian regions, on the other hand, soil erosion was much more intense. The variables used for

Table 1. Descriptive statistics of the variables used in the study

Variable	Mean	SD	Min	Max
v199	3.04	0.79	1.00	5.00
v200	3.21	0.82	1.00	5.00
v201	3.27	0.72	1.50	5.00
v202	3.18	0.81	1.00	5.00
v203	3.24	0.81	1.00	5.00
Environmental attitude	0.00	0.87	–1.96	2.50
Environmental attitude*	0.00	0.86	–1.98	2.47
Environmental attitude**	15.94	2.84	9.67	24.00
Basic or full training (share)	0.49	0.28	0.03	1.00
Share of conventional tillage	0.75	0.19	0.20	0.99
Soil erosion in tonnes per ha	3.92	4.46	0.20	25.20
Output value in EUR million (2017)	2 168.91	2 231.74	115.41	14 045.29
Output value in EUR million (2018)	2 192.35	2 201.72	108.35	12 992.35
Intermediate consumption in EUR million (2017)	1 265.07	1 266.79	83.96	8 150.73
Intermediate consumption in EUR million (2018)	1 310.79	1 320.12	86.97	8 578.52
Agricultural land in km2 (2018)	8 713.47	7 431.71	523.00	46 912.00
Employment in 1000 of employees 2017	50.67	78.46	3.00	734.70
Employment in 1000 of employees 2018	49.01	77.27	2.20	736.30
Bias-corrected technical efficiency score	0.50	0.15	0.11	0.84

*Environmental attitude variable constructed from 4 instead of 5 survey questions; **variable constructed as the sum of points instead of using factor analysis; for more details, see the section on robustness check

Source: Author's own elaboration based on Eurostat (2023) and EVS (2022); specific Eurostat codes are provided in the text

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estimating performance indicators also showed a wide variation, but this was due, among other things, to differences in the size of the regions studied and the importance of agriculture in the region's economy.

Figure 1 shows that the average technical efficiency index in the EU regions (based on the baseline M1 model with one efficiency determinant) was most often in the range from just below 0.4 to 0.7. Very high (above 0.8) and very low efficiency indexes (below 0.2) were achieved relatively rarely. The values of the technical efficiency indicators for all study regions in all specifications analysed are provided in Table S1 in the ESM.

The ten regions with the highest efficiency rates are dominated by French regions such as Provence–Alpes–Cote d'Azur (1st), Alsace (2nd), Bourgogne (8th) and Nord-Pas-de-Calais (9th). The Danish regions of Southern Denmark (5th) and Midtjylland (7th) also were highly efficient. There was also one Austrian region in the top 10 (Burgenland, 3rd), one German region (Rhineland–Palatinate, 4th), one Spanish region (Balearic Islands, 6th) and one Italian region (Campania, 10th). In most of these regions, relatively good climatic conditions for agricultural production were accompanied by a high level of technical development as measured by the relatively high values of fixed assets to labour ratio and intermediate consumption to land ratio (Kryszak and Herzfeld 2021). Low efficiency was found in the Polish and Bulgarian regions, most of which were characterised by agrarian fragmentation. Besides the Polish and Bulgarian regions, Andalusia and South Holland were part of this group. This may be due to the orientation towards minimising inputs. In these two regions, high production values were achieved, but especially in the Netherlands, high production was accompanied by a high level of inputs. From the technical (efficiency) point of view, these results show that in these regions, there was a relatively potential to reduce inputs at a given production level. The large spatial variation in technical efficiency is shown in Figure 2. The main conclusion from the figure is that differences in efficiency between regions in the so-called old and new EU member states have persisted. The former had more regions with efficiency in the range of 0.6–0.8 and single regions with efficiency above 0.8. In Poland, Romania, Bulgaria and the Czech Republic, most regions are in the range 0.2–0.4, although some regions are classified in a higher group – these are regions such as Wielkopolska, Mazowsze and the border regions of Romania and Hungary, which traditionally have had higher levels of agricultural development. It can be also seen that countries where traditional tillage dominates (e.g. Poland and Romania) or where the problem of soil erosion is advanced exhibit rather low or medium levels of technical efficiency.

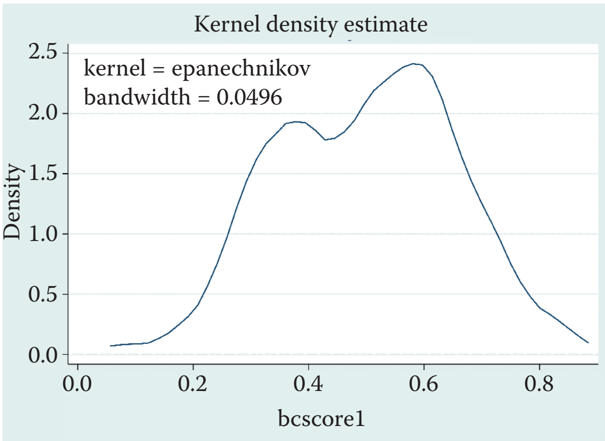

Figure 1. Distribution of bias-corrected technical efficiency scores from the baseline model

Source: Own elaboration based on Eurostat (2023) and EVS (2022); specific Eurostat codes are provided in the text

Tables 2–4 contain the results of model estimations. Models M1–M3 are baseline estimations on the full sample. Models M4–M6 present the results for the reduced sample (regions where only one farmer responded to the survey were excluded). Models M7–M9 were calculated using the environmental attitude variable constructed from 4 questions (differently phrased question v199 was excluded). Models M10–M12 use environmental attitude constructed as the sum of the scores for the answers to each attitudinal Likert-scale question.

When describing the estimation results in Tables 2–4, the focus is on the significance and direction of impact. The coefficients from the Simar and Wilson (2007) models in Tables 2–4 cannot be straightforwardly interpreted, but the marginal effects that are easy to interpret can be obtained through the margin function (Badunenko and Tauchmann 2019). These margins are derivatives of the response variable with respect to a given determinant (right-hand side variable). Table 5 shows the marginal effects for all estimated models. As the dependent variable (efficiency score) is within the unit interval, the marginal effects of unitary change in a determinant (explanatory variable) can be interpreted in percentage points. Since no interactions were introduced in the models, the marginal effects differed only slightly from the raw coefficients in Tables 2–4.

The results of estimation (*cf.* Tables 2–4) indicate that environmental attitude was consistently a signifi-

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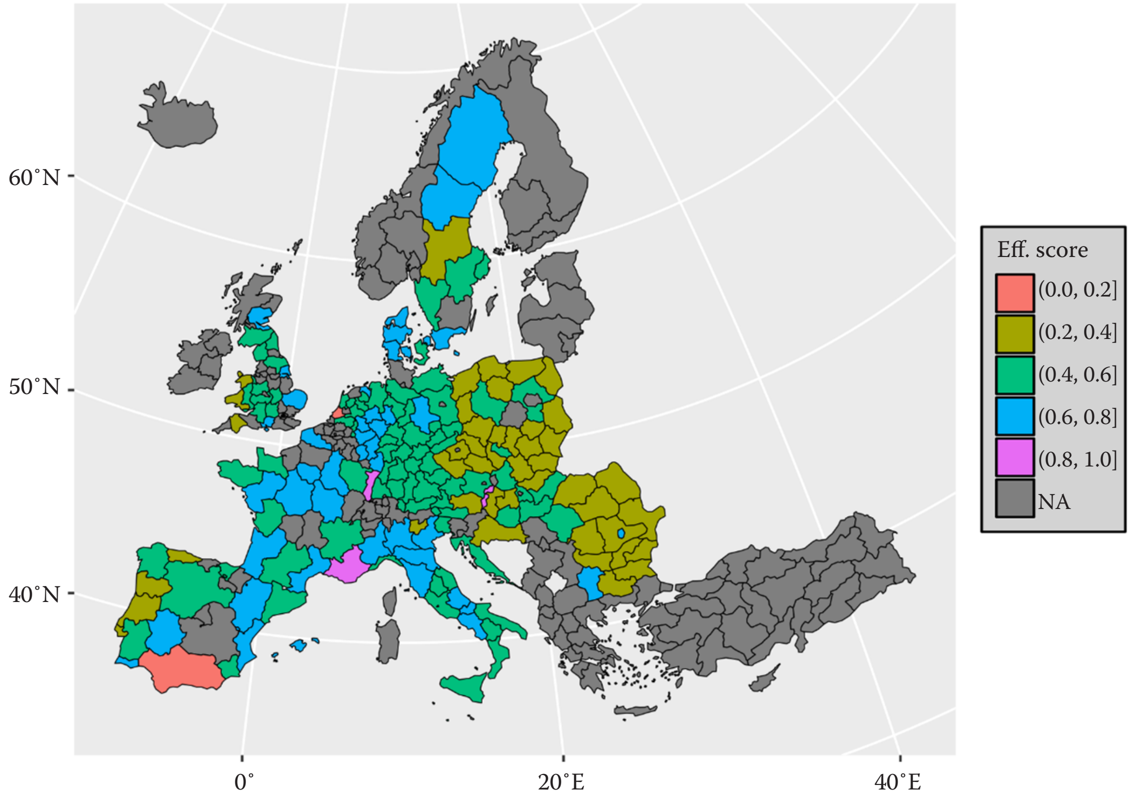

Figure 2. The values of bias-corrected efficiency scores in the NUTS-2 region of the EU (M1 model).

Efficiency scores for Germany were calculated on the NUTS-1 level; for the states that were further divided into *Regierungsbezirk*, the same efficiency value was assigned for all *Regierungsbezirks* for presentation purposes
Source: Own elaboration based on Eurostat (2023) and EVS (2022); specific Eurostat codes are provided in the text

cant and positive determinant of technical efficiency in agriculture at the regional level, even when controlling for education (basic or full vocational training), the share of conventional tillage and the level of soil erosion. Higher input-oriented efficiency means that inputs are used in a more optimal (more sparing) way. Therefore, the results show that a more favourable approach to environmental issues translated into more efficient input management.

In other words, when farmers were more environmentally oriented, there was less room to reduce inputs while maintaining the current production level in a given region. These results contradict the findings of Torres et al. (2019) that farms where managers use a more ecocentric approach tend to be less efficient.

The higher share of farmers with formal training (basic or full) also proved to be a positive and significant determinant of efficiency. Higher levels of expertise translated into more adequate input management. The share of arable land on which conventional tillage was used, on the other hand, proved to be a significant but negative determinant of efficiency. Therefore, it appears that a higher level of efficiency was achieved in those regions where farmers were more likely to opt for alternative tillage methods (i.e. conservational tillage or no-tillage). This shows that conservational practices are not only beneficial for the environment but also contribute to improved soil quality, resulting in better long-term yields with limited inputs (Ward et al. 2016). The estimated soil erosion in tonnes due to water was also found to be a significant and negative determinant of efficiency (despite the M6 model). As expected, lower levels of efficiency were achieved in regions with higher levels of this phenomenon, as more inputs are required under conditions of erosion to achieve satisfactory levels of production.

Regarding the effect of environmental attitudes, it can be concluded that a marginal increase in the value of this variable by 1 translated into an efficiency improvement of 3.5–4.8 percentage points (p.p.)

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Table 2. Baseline estimations

Variables	M1	M2	M3
Environmental attitude	0.048*** (0.014)	0.036*** (0.013)	0.042*** (0.013)
Basic or full training	–	0.272*** (0.041)	0.311*** (0.043)
Share of conventional tillage	–	–	–0.180*** (0.062)
Soil erosion in tonnes per ha	–	–	–0.006** (0.003)
Sigma	0.145*** (0.009)	0.136*** (0.008)	0.135*** (0.008)
Constant	0.499*** (0.012)	0.389*** (0.022)	0.523*** (0.049)
Observations	154	151	151

*, **, *** $P < 0.1$; $P < 0.05$; $P < 0.01$; bootstrapped standard errors in parentheses; M – model

Source: Own calculations based on Eurostat (2023) and EVS (2022); specific Eurostat codes are provided in the text.

Table 3. Robustness check estimates (34 NUTS-2 excluded)

Variables	M4	M5	M6
Environmental attitude	0.061*** (0.016)	0.042*** (0.014)	0.044*** (0.014)
Basic or full training	–	0.302*** (0.047)	0.322*** (0.048)
Share of conventional tillage	–	–	–0.200*** (0.073)
Soil erosion in tonnes per ha	–	–	–0.004 (0.003)
Sigma	0.149*** (0.010)	0.134*** (0.009)	0.131*** (0.009)
Constant	0.481*** (0.014)	0.364*** (0.025)	0.512*** (0.059)
Observations	119	117	117

*, **, *** $P < 0.1$; $P < 0.05$; $P < 0.01$; bootstrapped standard errors in parentheses; M – model

Source: Own calculations based on Eurostat (2023) and EVS data (2022); specific Eurostat codes are provided in the text

Table 4. Robustness check estimates (environmental attitude variable changed)

Variables	M7	M8	M9	M10	M11	M12
Environmental attitude[a]	0.049*** (0.014)	0.037*** (0.013)	0.042*** (0.013)	–	–	–
Environmental attitude (2)[b]	–	–	–	0.014*** (0.004)	0.010** (0.004)	0.012*** (0.004)
Basic or full training	–	0.270*** (0.040)	0.309*** (0.043)	–	0.275*** (0.039)	0.309*** (0.043)
Share of conventional tillage	–	–	–0.176*** (0.061)	–	–	–0.189*** (0.062)
Soil erosion in tonnes per ha	–	–	–0.007** (0.003)	–	–	–0.006** (0.003)
Sigma	0.143*** (0.008)	0.136*** (0.008)	0.135*** (0.008)	0.146*** (0.008)	0.135*** (0.008)	0.134*** (0.008)
Constant	0.501*** (0.012)	0.390*** (0.022)	0.520*** (0.049)	0.282*** (0.067)	0.231*** (0.066)	0.338*** (0.082)
Observations	154	151	151	154	151	151

*, **, *** $P < 0.1$; $P < 0.05$; $P < 0.01$; [a]environmental attitude variable constructed from 4 instead of 5 survey questions, [b]environmental attitude variable constructed as the sum of points instead of using factor analysis; bootstrapped standard errors in parentheses

Source: Own calculations based on Eurostat (2023) and EVS data (2022) specific Eurostat codes are provided in the text

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Table 5. Mean marginal effects on unitary change of explanatory variable on estimated efficiency scores

Variable	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Environmental attitude	0.048	0.035	0.041	0.060	0.042	0.043	–	–	–	–	–	–
Environmental attitude[a]	–	–	–	–	–	–	0.049	0.036	0.041	–	–	–
Environmental attitude[b]	–	–	–	–	–	–	–	–	–	0.013	0.010	0.012
Basic or full training	–	0.269	0.306	–	0.298	0.317	–	0.267	0.304	–	0.272	0.304
Share of conventional tillage	–	–	–0.177	–	–	–0.197	–	–	–0.173	–	–	–0.186
Soil erosion in tonnes per ha	–	–	–0.006	–	–	–0.004	–	–	–0.006	–	–	–0.006

[a]environmental attitude variable constructed from 4 instead of 5 survey questions; [b]environmental attitude variable constructed as the sum of points instead of using factor analysis

Source: Own calculation based on Eurostat (2023) and EVS (2022); specific Eurostat codes are provided in the text

in the model for all observations and 4.2–6 p.p. in the reduced-sample models (M4–M6).

The environmental attitude variable is a latent variable produced by the factor analysis with a minimum value of –1.96 and a maximum value equal to 2.5. These values can be ranked but they do not have a direct economic interpretation, and an increase in the value of this variable by one unit does not tell much. Therefore, the more objective measure of sample standard deviation as a measure of change is used further. It can be concluded that an increase of one standard deviation (SD) in the value of this environmental attitude variable (0.87) led to an improvement in the efficiency of 3.1–4.2 p.p. in the full-sample models (M1–M3) and 3.7–5.2 p.p. in the reduced-sample models (M4–M6). The marginal effects of environmental attitude were almost identical for models M7–M9 (environmental attitude variable constructed based on four rather than five attitudinal questions). In the case of environmental attitudes constructed as a simple sum of scores for the responses to the five sub-questions, an increase of 2.84 (one SD in the value of the variable thus created) translated into an increase in efficiency of 2.8–3 p.p.

Summarising the marginal effects estimated for all models, it can be concluded that an increase in environmental attitudes by one SD led to an improvement in efficiency of 2.8–6 p.p. This improvement in efficiency is therefore noticeable, although it may seem relatively small. Nevertheless, in model M1, an efficiency improvement of 4.2 p.p. would allow a region with an efficiency equal to the median to move up the efficiency ranking by 24 positions (out of 154 regions studied). In the M3 model, an improvement in efficiency of 3.6 p.p. would allow for a similar move up 16 positions.

In terms of marginal effects for the control variables, there was a particularly strong effect of formal vocational education. An increase of one SD in the percentage of farmers with a field education (28 p.p.) translated into an improvement in efficiency of 7.5–8.9 p.p. An increase of one SD in the percentage of land under conventional tillage (19 p.p.) translated into a decrease in efficiency of 3.3–3.7 p.p. A 14.46 t/ha (one SD) increase in soil erosion translated into a decrease in efficiency of 1.8–2.7 p.p., bearing in mind that statistical significance was not obtained for this variable in the M6 model.

These results can add to the discussion raised by Tosakana et al. (2010), who advocated that more profit-oriented farmers were more eager to implement sustainable practices and developed recently in reviews by Schaub et al. (2023) and Thompson et al. (2023), who claimed that pro-environmental orientation is either a positive or (quite often) an insignificant determinant of undertaking eco-friendly practices. In this paper, I did not analyse the implementation of specific practices but rather showed that a more favourable approach to the environment translates into more rational resource management, resulting in greater efficiency. In other words, it is possible that farmers can be both efficient and environment-oriented at the same time.

CONCLUSION

The aim of this paper was to investigate whether the more pro-environmental attitudes of farmers influenced the technical efficiency of agricultural sectors in EU regions (NUTS-2). To answer this, I employed DEA efficiency analysis combined with the approach of Simar and Wilson (2007) to find a causal relationship between environmental attitudes and technical efficiency. I found that this relationship was positive, i.e. pro-environmental attitudes were related to greater efficiency. The most important limitation of this paper is that the analysis was conducted on a sectoral level.

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Further investigation of samples of individual farmers in specific regions or countries could shed more light on the studied relations on the microeconomic level. It would also be helpful if Eurostat provided data for European agricultural regions that are easily comparable on the lower level, for example, the NUTS-3 level. It would make it easier to study both interregional and intraregional differences in efficiency and its relation with selected determinants. Another limitation is that the article is based on data from before the Green Deal was announced. The challenges and limitations of the strategy could have a significant impact on farmers' approaches to environmental problems in the future.

The most important message of this paper is that there need not be a contradiction between increased awareness of environmental challenges among farmers and the realisation of the economic goals of farming. Farmers are sometimes afraid that if they pay more attention to environmental issues, their operational efficiency may suffer. In fact, it can be the other way around.

This conclusion can be used by policymakers when designing campaigns to promote sustainable farming practices such as eco-schemes in new common agricultural policy or when promoting EU green policy in general (e.g. EU Green Deal). Not only should they present the environmental benefits of the policy, they should show that greater environmental awareness translates into better economic results. For example, less use of capital inputs decreases environmental pressure, but this can be done (at least in some cases) without deteriorating production levels. In other words, policymakers should promote a vision that being an eco-friendly farmer is not only good for the planet but also has economic benefits. The easiest way to promote this is to show examples of farmers who implemented some actions because of their beliefs and these actions have proved economically beneficial to their farms.

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