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Title: Assessing the impact of agri-environmental payments on green productivity in Germany

Year: 2024

Version: Published version

Please cite the original version:

Ait Sidhoum, A., Mennig, P., & Frick, F. (2024). Assessing the impact of agri-environmental payments on green productivity in Germany. Ecological Economics, 219, 108150. https://doi.org/10.1016/j.ecolecon.2024.108150

Ecological Economics 219 (2024) 108150

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Assessing the impact of agri-environmental payments on green productivity in Germany

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ARTICLE INFO

Keywords:
Agri-environment schemes
Policy evaluation
Green productivity
Data envelopment analysis

ABSTRACT

This study offers a novel empirical application for assessing the impact of agri-environment schemes (AES) on the performance of farms. The existing evidence about the impact of these schemes considering environmental and economic aspects equally is still limited. Therefore, our objective is to contribute to the literature on the impact evaluation of AES by considering three important aspects in our empirical analysis. First, the performance of farms is proxied by an indicator that incorporates environmental externalities into production activities. Second, our empirical analysis focuses on a sample of Bavarian dairy farms covering the period 2013–2018, thus, we can evaluate the effectiveness of agri-environmental schemes in one of Germany's leading agricultural and forestry regions during the latest programming period. Finally, in an effort to increase robustness, we employ an improved version of the Malmquist-Luenberger productivity index, which enables us to get around some of the shortcomings of the original index. The obtained results suggest that agri-environment payments have a limited effect on improving farm-level green productivity.

1. Introduction

One of the main challenges linked to providing enough food and fiber for a projected global population of over nine billion by 2050 under changing climatic conditions remains the need to increase production substantially while, at the same time, reducing agriculture's environmental footprint (Foley et al., 2011). A number of concepts have been developed to address this challenge. They range from *alternative agriculture* (NRC, 1989) to *green food systems* (DEFRA, 2012), *sustainable intensification* (Pretty, 1997) or *climate smart agriculture* (Lipper and Zilberman, 2018). All of these terms and concepts stress the necessity to increase the productivity of the agricultural sector and to simultaneously apply farming practices that are less harmful to the environment – a notion that has also found its way into the European Union's (EU) Common Agricultural Policy (CAP). While its initial goals, listed in Article 39, paragraph 1 of the Treaty on the Functioning of the European Union (TFEU), are centered around the interests of producers and consumers, several provisions and amendments of the TFEU lay down additional goals. Among these are environmental protection to promote sustainable development (Article 11) or animal welfare requirements (Article 13) (EU, 2021).

The latter goals shall mainly be achieved through the second pillar of today's CAP architecture, which comprises specific aid programmes for rural development and environmentally sound farming. Its schemes are "designed to support rural areas of the Union and meet the wide range of economic, environmental and societal challenges of the 21st century" (European Parliament, 2022). Among these programs, agri-environment schemes (AES), which became compulsory elements of the CAP in 1992, have become more important and popular over the years as a result of the consistently high environmental pressure of agricultural production (Pavlis et al., 2016). For the 2014–2020 CAP budgetary period, at least 30% of the Rural Development envelope were planned to be reserved for environmental/climate related action (being mainly covered by AES) (European Commission, 2021). AES contracts are typically multi-annual and usually cover a period of five years,[1] in which farmers can decide whether to participate or not in the implemention of environmentally friendly measures with related payments.

While AES designs may vary between member states, they share a number of over-arching goals. These relate to the reduction of the damage agricultural activities have on the environment and to the

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[1] This is a major difference compared to the eco-schemes that will be introduced as part of the CAP's first pillar in 2023. They can be signed up for on an annual basis.

https://doi.org/10.1016/j.ecolecon.2024.108150
Received 22 June 2023; Received in revised form 14 December 2023; Accepted 12 February 2024
Available online 16 February 2024

increase or stabilization of positive effects of agriculture (Science for Environment Policy, 2017). Importantly, AES designs must comply with domestic support rules of the World Trade Organization (WTO). According to these rules, agricultural subsidies may only be granted if they qualify for the so called "Green box", i.e., if they "have no, or at most minimal trade distorting effects or effects on production" (WTO, 1995, S. 59). From a production theoretical perspective, it is unclear whether AES programmed under the CAP do meet the WTO requirements. Some empirical evidence exists that casts doubt in this respect (Mennig and Sauer, 2020; Salhofer and Streicher, 2005). However, these authors do not use comprehensive indicators to measure production effects. If, though, production effects are defined in a broader sense covering marketable and non-marketable (environmental) goods, negative impacts of AES on yields, for example, might be offset by positive environmental effects. In terms of "green productivity", AES may even have an enhancing effect on production, while, at the same time, reducing the environmental impact of agriculture and possibly being in line with WTO requirements.

Firms'performance measurement that incorporates environmental externalities into efficiency and productivity modeling is an increasingly important area of recent economic research. In the technical literature, several approaches are available for modeling pollution in productive technologies when measuring firm performance. First, by relying on the flexibility of the directional distance function (DDF), Chung et al. (1997) introduce the Malmquist–Luenberger (ML) index as an alternative to the traditional Malmquist index. The idea behind the ML index is to provide a measure of productivity change that integrates environmental aspects of production processes. As we are interested in measuring production-related effects of AES, especially in examining productivity change, we could rely on the Malmquist–Luenberger (ML) index which is one of the most commonly used approaches to estimate productivity change when both good and bad outputs are produced. However, the ML index suffers from a number of weaknesses related to inconsistencies that might lead to erroneous interpretations (Aparicio et al., 2013; Aparicio et al., 2017). Therefore, in this paper, we rely on the recently introduced Global Malmquist–Luenberger (GML) index (Oh, 2010), which is based on defining a global frontier that envelopes all observations for all periods.

Among the few studies that have empirically examined the effect of different agri-environment measures on farm productivity are the studies by Baráth et al. (2020), Bokusheva et al. (2012), Mary (2013) and Mennig and Sauer (2020). Bokusheva et al. (2012) employed a production model formulation to analyzes the evolution of Swiss farm productivity during the implementation of environmental policy reforms. Mary (2013) used dynamic panel regression techniques to analyses the impact of Pillar 1 and 2 subsidies on productivity growth of French crop farms. Finally, Baráth et al. (2020) and Mennig and Sauer (2020) combined a difference-in-difference with a matching procedure to examine the effect of agri-environmental measures on farms' productivity in Slovenia and Bavaria, respectively. These papers, however, focus exclusively on economic productivity growth and do not consider environmental aspects.

Our research does so by taking into account nitrogen pollution as one of several externalities in agricultural production. Against the background of increased pressure to reduce nitrogen pollution and enhance the conditions of water bodies and groundwater quality in Bavaria, increasing the knowledge base with respect to this environmental category is crucial. Agri-environmental schemes play a vital role in these efforts. It is vital for these schemes to be effective in achieving their environmental objectives while ensuring that they do not negatively impact a farm's economic performance or hinder its development possibilities. Recent studies have started analyzing the effects of Bavarian agri-environment programmes on different aspects of farming (Ait Sidhoum et al., 2023; Stetter et al., 2022; Tzemi and Mennig, 2022). Stetter et al. (2022) combine economic theory with a machine learning method to identify the environmental effectiveness of AES at the farm level. Their results suggest that agri-environmental measures have limited effects on several environmental indicators. Tzemi and Mennig (2022) use a spatial econometric model to evaluate the impact of AES on groundwater nitrate concentrations. The results show a negative relationship between the allocation of grassland measures and nitrate concentrations. The other study, which is a companion paper, has estimated the effect of agri-environmental schemes on farm-level technical and environmental efficiency (Ait Sidhoum et al., 2023). In light of the foregoing, this paper aims to add to the small body of research by estimating the effect of agri-environmental measures using a farm-level productivity index that accounts for bad outputs, for the first time in the literature.

The remainder of this article is structured as follows: Section 2 describes the theoretical framework underlying the relationship between AES and farm performance. Section 3 presents the methodological approach. Section 4 gives a brief overview of the dataset, followed by a presentation and discussion of the main results in Section 5. Finally, Section 6 outlines the main conclusions.

2. Theoretical background

Agri-environment payments make a particularly interesting case for testing the impact of voluntary policy instruments on agricultural green productivity, because they ideally involve active changes in current farming practices. Further, decisions related to conservation and environmental management can significantly affect the productivity of the farm (Peerlings and Polman, 2004). The willingness of implementing these measures remains, though, typically related to a profit maximization condition. However, the assumed profit maximising behaviour has been contested in the literature. From this perspective, Mills et al. (2018) suggest that the adoption of environmental practices is motivated by extrinsic and intrinsic reasons. The former consists of agronomic and financial motivations. The latter is related to farmers` cultural and environmental concerns. These motivations, however, are not independent and interact with one another. In certain situations, these interactions may create trade-offs or synergetic relationships. Therefore and given the substantial budget share of AES payments in the second pillar of the CAP, testing the effectiveness of the schemes requires using appropriate indicators that integrate farmers' environmental and economic performance.

In the present article, we specifically investigate the impacts of AES on farm-level green productivity. From a theoretical point of view, the green productivity effects of agro-environmental schemes depend on the relationship between the production of outputs intended by farms and the resulting environmental impacts. For instance, a competitive relationship would occur when there is a trade-off between desirable and undesirable outputs such that more of one cannot be produced without less of the other.

Fig. 1 depicts the production possibility frontier under the assumption of competitiveness when one desirable output y and one environmental outcome e are produced. Since the adoption of action-based AES typically excludes or restricts the use of some polluting inputs that in non-windfall-profit cases have a strong influence on the desired output, a farm adopting an AES measure will see its output decrease from A to A'. This would lead to an increased environmental benefit from B to B'.

Previous studies presented empirical evidence of trade-offs between environmental benefits and conventional outputs (Ruijs et al., 2013; Ruijs et al., 2017). However, recent literature has cast doubt on this purely competitive relationship. Those studies claim that some environmental benefits are complementary to marketable production. This has been demonstrated for the quality of grassland and livestock production (Vatn, 2002), pollinator habitat and crop yields (Wossink and Swinton, 2007), as well as the whole ecosystem and total farm products (Hodge, 2000). Since farmers have enough control over their inputs, this relationship can be illustrated with a production possibility frontier

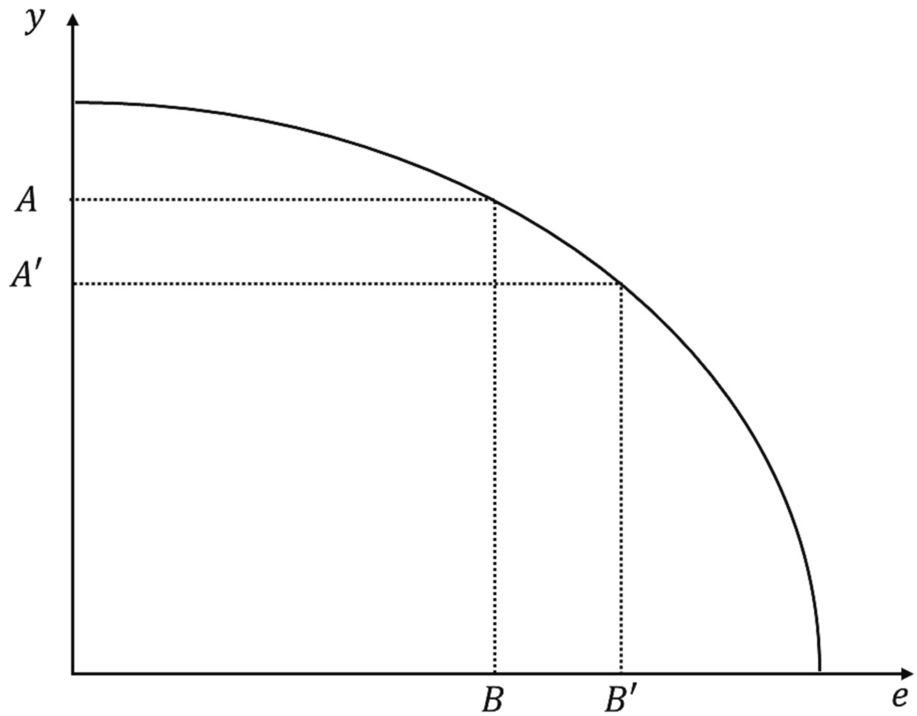

Fig. 1. Trade-off between one desirable output and one environmental benefit under the influence of an environmental policy.

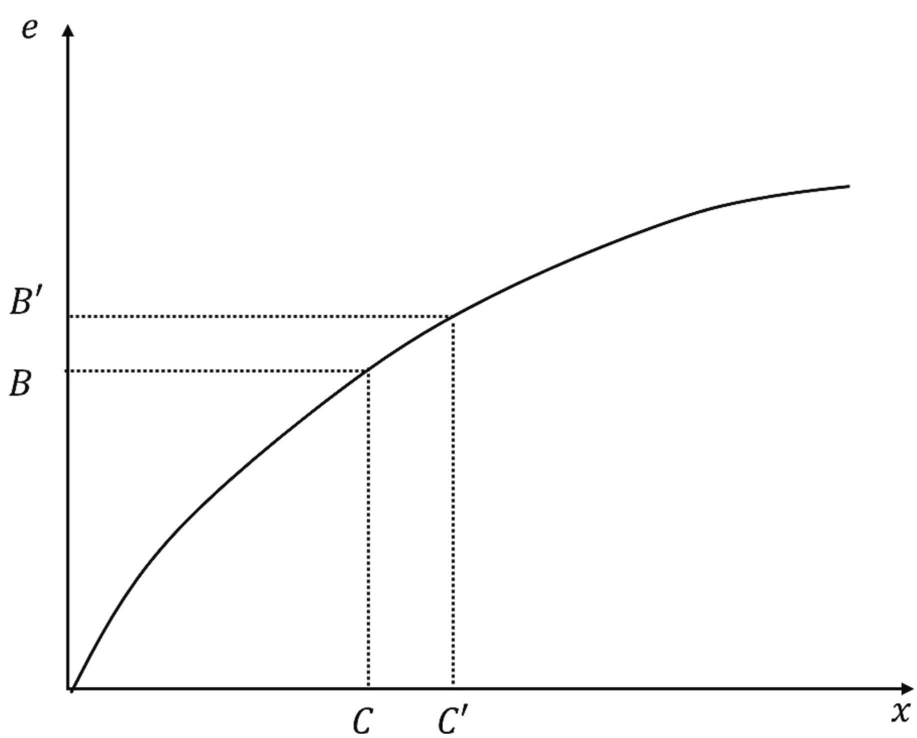

Fig. 2. Synergy between one input and one environmental benefit under the influence of an environmental policy.

diagram for one environmental benefit e and one input x (Fig. 2). A farmer who decides to join an AES might have to increase his capital from C to $C^{'}$ through the acquisition of new manure-spreading machinery for example. This new investment will likely lead to better economic results (from improved nutrient efficiency) and will also result in environmental improvements (from B to $B^{'}$) as less ammonia is emitted.

The assumptions discussed in the figures above are simple cases of one good output and one environmental benefit (Fig. 1) and one input and one environmental benefit (Fig. 2). The empirical application of this paper is, however, related to productivity change, which is also related to the difference between efficiency levels achieved in different periods

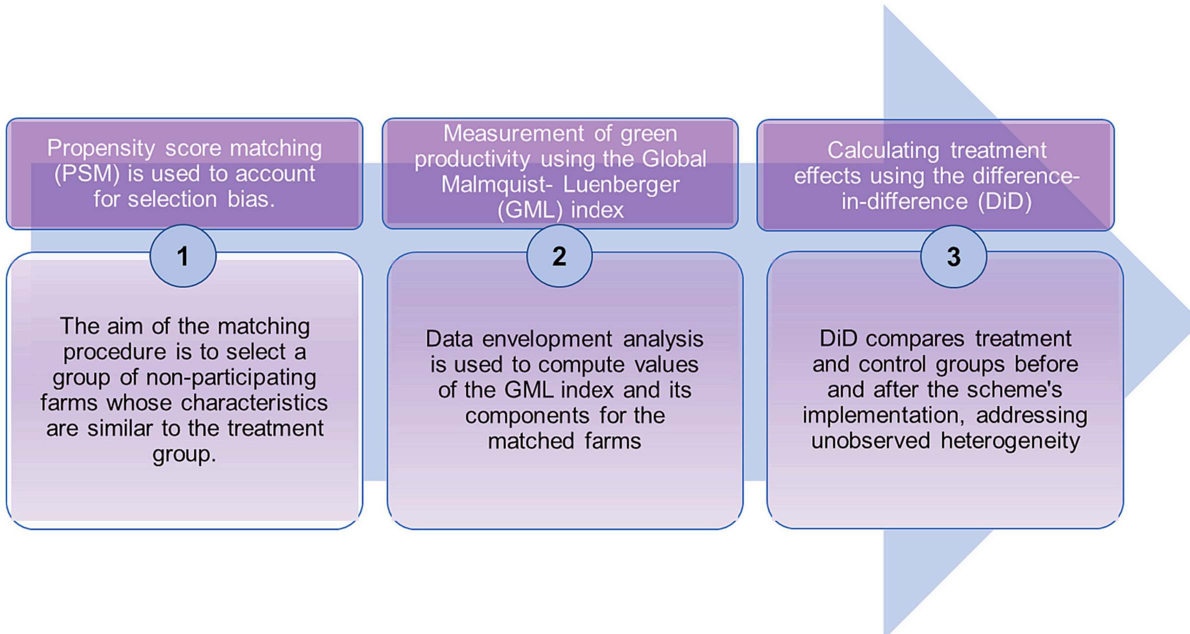

Fig. 3. Methodological framework.

of time. Productivity measurement requires a more complex modeling, such as the one in this article, where we take into consideration a variety of inputs and both desirable and undesirable outputs. Furthermore, productivity change can be decomposed into various components, which adds to the relevance of performing productivity measurement by strengthening its explanatory power. More specifically, we retain a specification that allows productivity change to be decomposed into efficiency, and technological change (Nishimizu and Page, 1982). Efficiency change refers to the distance of the evaluated firm to its production frontier between periods t_1 and t_2. On the other hand, technological change is identified as a measure of how the technology has progressed (upward shift) or deteriorated (downward shift) over time.

From an agri-environmental policy perspective, AES participating farms are ideally expected to introduce new farming practices that require more (ideally non-polluting) or less (ideally polluting) of some inputs (for the non-polluting case e.g., high-quality fertilizer spreader). At this point, it is unclear whether AES tend to improve green productivity or not. Any potential effect depends on the farm-level relationship between input use and marketable and non-marketable outputs produced. If the production relationship between agricultural outputs and environmental benefits is assumed to be complementary, it can be expected that AES participation will increase green productivity. If this relationship is assumed to be competitive, we would expect a differential effect on efficiency and technological change. Indeed, a positive (negative) association between AES and technical efficiency or technological change can be viewed as an indication of success (failure) in improving technical and economic (environmental) performance. One rational reason behind this assumption is that improvements in environmental benefits should be closely related to green technology implementation, which does not necessarily entail technical efficiency improvements, which are achieved by an optimal (non-wasteful) combination of inputs to obtain a maximum output level.

3. Methodology

This study investigates the impact of agri-environment schemes on green productivity, with the methodological framework outlined in Fig. 3.

3.1. The selection bias problem

Our empirical analysis aims at assessing whether adopting agri-environment schemes is associated with higher environmental and economic performance. As noted above, since the participation in AES is voluntary, the adoption of the programs may also be motivated by, for instance, a farm's structural preconditions favourable to its environmental performance, indicating that environmentally friendly farming practices may have been implemented, even partially, in the absence of the agri-environment program already. Due to this selection bias, a direct comparison of participating and non-participating farms will not accurately reflect the policy's causal effects. To address the selection bias problem, we employ the propensity score matching (PSM) approach.

The aim of the matching procedure is to select a group of non-participating farms whose characteristics are similar to the treatment group (i.e. participating farms). However, rather than matching farms directly on a large number of observable characteristics, Rosenbaum and Rubin (1983) propose matching the treated and control observations on their propensity scores, which are the probabilities of being assigned to a specific group conditional on observed characteristics and can be computed by estimating a simple probit or logit model. Once PSM has been performed and comparable participants and non-participants have been identified, the GML index can be applied to both groups to determine unbiased estimates of productivity, efficiency, and technical change.

3.2. Green productivity measurement

Nowadays, the method developed by Chung et al. (1997), which is based on the DDF and the Malmquist-Luenberger index, is the most widely used to evaluate productivity change over time when both desirable and undesirable outputs are produced. However, as it has been shown by Aparicio et al. (Aparicio et al., 2013; Aparicio et al., 2017), the Malmquist-Luenberger index suffers from a number of weaknesses that might lead to erroneous inferences, especially in relation to the technological change component. Another limitation of the method of Chung et al. (1997) is that it does not satisfy the circularity property.[2] Consequently, the direct comparison of two periods in contexts where it is important to compare the performance of more than two time periods is comparable to the indirect comparison of those two periods through a third period, regardless of the third period chosen for the assessment. Oh, 2010 overcomes the problem by introducing the Global Malmquist-Luenberger index. This index is based on Pastor and Lovell (2005) proposal to build a "virtual" reference technology by using all available data from all time periods.

Although both the GML index by Oh (2010) and the ML index are based on the estimation of the directional output distance function,[3] the estimation of the GML index requires the definition of two benchmark technologies: the classic contemporaneous technology and the global technology.

The contemporaneous frontier can be represented by $P_t(x_t) = \{(y_t, b_t) | \, x_t \textit{ can produce } (y_t, b_t)\}$. Where each observation i uses a set of inputs $(x \in \mathrm{R}_+^N)$ to produce a set of desirable $(y \in \mathrm{R}_+^M)$ and undesirable $(b \in \mathrm{R}_+^K)$ outputs. While the contemporaneous benchmark technology is only constructed at time t, the global benchmark technology is based on all observations for all periods and is represented as follows $P_G(x) = \bigcup_{t=1}^T P_t(x)$. Thus, the Global Malmquist–Luenberger index can be defined as:

$$GML = \frac{1 + \overrightarrow{D}^o_G(x_t, y_t, b_t; y_t, -b_t)}{1 + \overrightarrow{D}^o_G(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})} \tag{1}$$

Moreover, the GML index can be decomposed into efficiency change (*GML EFFCH*) and technological change (*GML TECH*) (Oh, 2010):

$$GML = \frac{1 + \overrightarrow{D}^o_t(x_t, y_t, b_t; y_t, -b_t)}{1 + \overrightarrow{D}^o_{t+1}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})} \times \left[\frac{\left(1 + \overrightarrow{D}^o_G(x_t, y_t, b_t; y_t, -b_t)\right) \Big/ \left(1 + \overrightarrow{D}^o_t(x_t, y_t, b_t; y_t, -b_t)\right)}{\left(1 + \overrightarrow{D}^o_G(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})\right) \Big/ \left(1 + \overrightarrow{D}^o_{t+1}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})\right)} \right] \tag{2}$$

$$= GML\ EFFCH \times GML\ TECH$$

In (1) and (2), the directional output distance function can be estimated by the following non-parametric approach for evaluating efficiency under the contemporaneous benchmark technology (3) and the global benchmark technology (4):

$$\overrightarrow{D}_o\left(x_n, y_m, b_k; g_y, g_b\right) = max\beta$$

s.t.

$$\sum_{j=1}^{J} \lambda_j x_{nj} \leq x_n, n = 1, \dots, N$$

$$\sum_{j=1}^{J} \lambda_j y_{mj} \geq y_m + \beta g_y, m = 1, \dots, M$$

$$\sum_{j=1}^{J} \lambda_j b_{kj} = b_k - \beta g_b, k = 1, \dots, K$$

$$\lambda_j \geq 0, j = 1, \dots, J \tag{3}$$

where the superscript j represents the number of farms and λ denotes a non-negative vector. The observation is located on the frontier of production if β equals zero. Given $g = \left(g_y, g_b\right) \in R_+$ which represents the directional vector, the objective function in (3) seeks to maximaze the production of desirable outputs while simultaneously reducing undesirable outputs.

Similarly, the directional distance function under the global benchmark technology set can be calculated through model (4):

$$\overrightarrow{D}^G_o\left(x_n, y_m, b_k; g_y, g_b\right) = max\beta$$

s.t.

$$\sum\nolimits_{t=1}^{T} \sum_{k=1}^{K} \lambda^t_j x^t_{nj} \leq x^t_n, n = 1, \dots, N$$

$$\sum\nolimits_{t=1}^{T} \sum_{k=1}^{K} \lambda^t_j y^t_{mj} \geq y^t_m + \beta g_y, m = 1, \dots, M$$

$$\sum\nolimits_{t=1}^{T} \sum_{k=1}^{K} \lambda^t_j b^t_{kj} = b^t_k - \beta g_b, n = 1, \dots, N$$

$$\lambda^t_j \geq 0, j = 1, \dots, J \tag{4}$$

Any value above one in productivity, efficiency, and technological change indicates progress when interpreting the values of the GML index in (1) and its components in (2). As opposed to this, scores equal to one denote stagnation, whereas values below one are linked to a performance decline.

3.3. Estimating the treatment effects

Although PSM helps to control for potential selection bias due to observed factors, it has been shown that farmers' decisions to take part in agri-environmental programs may also be influenced by unobserved factors, such as the farmers'environmental motivations, which can be assumed to be relatively stable over time (Wilson and Hart, 2000). Although we cannot account for factors like managerial ability or environmental motivations because they are not measured in our dataset, to some extent these unobservables should be correlated with observables like education and age that we do take into account. In order to further account for unobservables, we make the assumption that the impact of these unobservable factors on farming practices is constant throughout time. It is equivalent to assuming that the average treated

[2] The circularity property allows evaluation of the overall effects across time using results from sub-periods. For example, an intermediate period t_2 can be used to evaluate the productivity growth between t_1 and t_3. In other terms, the circularity condition can be expressed by $(t_1, t_3) = I(t_1, t_3) \times (t_2, t_3)$, where $I(\bullet)$ is an index number. Additional information is available in Fried et al. (2008).

[3] Chambers et al. (1996) introduced the Directional Distance Function (DDF) approach to estimate production technology involving multiple inputs and outputs. The DDF is highly regarded for its flexibility in measuring efficiency and productivity, as it enables the simultaneous enhancement of desirable outputs while reducing undesirable ones.

farmer and his average matched twin would have acted similarly in the absence of the AES to assume that selection bias on unobservables is constant over time. This assumption is reasonable, as supported by Chabé-Ferret and Subervie (2012) and our own experiences in agricultural sector analyses. Specifically, in farm contexts, unobserved factors that affect AES participation are more likely to be stable over time. For instance, a farmer's environmental motivation tends to be deeply ingrained and persistent (Mills et al., 2017; Reimer et al., 2012).

The use of difference-in-difference (DiD) regression methods allows us to control for time-invariant unobserved heterogeneity. It involves comparing participating farms (treatment group) and their matched counterparts (control group), before and after the scheme's implementation. The program impact (DiD) can be then estimated as follow:

$$DiD = E\left[Y_1^T - Y_0^T | T_1 = 1, \pi(X)\right] - E\left[Y_1^C - Y_0^C | T_1 = 0, \pi(X)\right] \quad (5)$$

Model (5) aims at estimating the average effect of AES participation on an outcome variable (Y) using the participation status of the farm (π) and farm characteristics (X) for participating (T) and non-participating (C) farms over two periods ($t = 0$ and $t = 1$) and then taking the difference between the two. To derive an estimate of the program impact (DiD), a simple t-test is used.

Rather than employing a t-test, it is possible to apply a DiD estimation through a regression approach. We use an OLS regression model with fixed effects structured as follows:

$$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 t_i + (DiD) T_i t_i + \beta_{3,j} D_{ij} + \eta_i + \varepsilon_{it} \quad (6)$$

Where Y_{it} is the outcome variable (e.g. GML index and its components) for the farm i at time t. The parameter α is the intercept of the regression model. T_i is a dummy variable representing AES participation, t_i serves as a time dummy, taking the value of 0 before the treatment period and 1 after the treatment period. The DiD estimator is represented by the coefficient (DiD) which gives the estimate for the impact of the AES on the outcome variable. D_{ij} represents a set of dummy variables representing four agri-environment categories. Finally, the term η_i is used to account for time-invariant unobserved heterogeneity[4] and ε_{it} is the unobserved time-varying error component.

4. Data

Our empirical analysis borrows from Ait Sidhoum et al. (2023) in that we make use of the same balanced panel of 1626 Bavarian dairy farms, which was obtained from the Farm Accountancy Data Network in Bavaria. This dataset has been enhanced with the official agricultural support data (IACS) that provide additional information on farm characteristics as well as on CAP payments received. In order to increase the accuracy of our matching, we also used publicly accessible data from the Bavarian Statistical Office that contained details about socio-economic factors (such as gross domestic product, unemployment, workforce and farmland rental price) at the municipality level.

Our research focuses on the Bavarian Cultural Landscape Programme (Bayerisches Kulturlandschaftsprogramm (KULAP), part of the Bavarian Rural Development Programme), which was established in 1988 and serves as the main funding source for Bavarian agri-environmental policy. There were 34 different KULAP measures that fall under the headings of field-specific measures for arable land, field-specific measures for grassland, field-specific measures for organic farming, and measures for special farming practices in the 2014–2020 funding period. Our analysis is based on a single variable that aggregates the 34 individual agri-environmental schemes based on the payments received per farm to examine the effect of AES on green productivity.

In our empirical analysis, we aim to estimate how AES will affect green productivity over the period 2014–2018. For this purpose, the 2013 data were used to identify comparable AES participating farms and non-participating farms based on observable variables. The year 2013 is regarded as the pre-treatment period[5] (the year before the 2014–2020 programming period). The control group consisted of all farms that did not participate in any agri-environment programmes in 2013 and all farms that did not receive AES payments between 2014 and 2018. While farms that did receive a payment between 2014 and 2018 were assigned to the treated group.

We begin by using PSM to identify comparable participant and non-participant farms with similar observable characteristics. Rubin and Thomas (1996) recommended that when performing PSM, all relevant covariates should be considered even if they are not statistically significant because the main requirement of PSM success remains the balance of the key covariates between the control and treatment groups and not the accurate estimation of the logit model. Definitions and summary statistics of the covariates are available in the Appendix, Table A1.

To measure the GML index, seven inputs were considered: livestock units measured in number of dairy cows ($x1$); total labour ($x2$ measured in man work units); utilized land ($x3$ in hectares); capital depreciation ($x4$ in Euros); pesticides application ($x5$ in Euros); expenses for feed ($x6$ in Euros) and quantities of nitrogen input ($x7$ in kilograms). Two outputs are used: the value of total dairy output (y) expressed in 2015 Euros is considered the good output, while nitrogen balance (Z in kilograms)[6] is regarded as the undesirable output. Table 1 provides descriptive statistics on input and output variables used in the GML model. The average dairy output value per farm for the period under consideration (2013–2018) is around 223,000 Euros. On average, the farms in our sample have 58 ha of land, 58 dairy cows, 1.75 man work units of labour annually, a capital depreciation value of just over 35,500 Euros, and annual feed and pesticide expenditures of about 32,200 and 13,000 Euros, respectively. In terms of nitrogen inputs and outputs, our sampled farms apply 8452 kg of nitrogen annually, resulting in a nitrogen balance of 6284 kg per year. When examining the the nitrogen balance of our sample farms over the period under study, it amounts to 107 kg/ha. In comparison, data from the OECD (2013) reveals that the annual average nitrogen balance for the 15 agricultural sectors in the EU between 2007 and 2009 was 65 kg/ha, with notable variations ranging from 204 kg/ha in the Netherlands to 25 kg/ha in Greece. Bavaria also has a wide range of nitrogen surplus values, from <20 kg/ha to >100 kg/ha, depending on soil characteristics, crop types, and management practices (Schuster et al., 2023).

5. Results

5.1. Estimating the propensity score

Propensity score matching was performed to balance farm characteristics between farms that participated and farms that did not participate in agri-environmental schemes. After having defined the treated and untreated farms and the potentially relevant covariates for the matching procedure, the propensity score[7] is calculated using a logit

[4] Because time invariant unobserved heterogeneity is also a source of endogeneity, the fixed-effects model allows dropping the unobserved factors (η_i) thanks to the panel data structure (Wooldridge, 2002).

[5] The year 2018 is regarded as the post-treatment period for our DiD analysis.

[6] We adopt Gamer and Bahrs (2010)'s methodology to estimate the nitrogen balance output. Wendland et al. (2018)'s coefficients are used to estimate the quantities of nitrogen present in milk and meat outputs as well as the nitrogen content in feed input, while the LFL (2013)'s coefficients are used to estimate the quantities of nitrogen fixed by legumes. For mineral fertilizers, the quantities of nitrogen can be calculated from the data provided in STATBA (2018).

[7] The propensity score represents the conditional probability of participation for farm i given a set $X = x_i$ of observed characteristics $p(X) = Pr(P = 1|X = x_i)$. The propensity score is estimated from a logit model in which the binary treatment variable (AES) serves as the dependent variable conditional upon the observed variables (covariates).

Table 1
Summary statistics (average and standard deviation - in parenthesis) for the main variables in the sample (828 farms).

Variable	Symbol	Dimension	2013	2014	2015	2016	2017	2018	Full period 2013–2018
Total sales	y	€	210,665.51 (104,027.02)	237,141.27 (116,735.25)	219,212.20 (108,614.00)	201,702.05 (100,998.89)	214,421.12 (112,800.45)	257,445.99 (142,765.69)	223,431.36 (112,602.11)
Livestock units	$_1$	Number	55.49 (26.39)	57.69 (28.25)	58.28 (29.06)	59.05 (30.02)	60.14 (32.06)	60.60 (33.57)	58.54 (29.50)
Labour	x_2	Man-work units	1.70 (0.54)	1.73 (0.57)	1.75 (0.58)	1.76 (0.55)	1.79 (0.58)	1.79 (0.58)	1.75 (0.54)
Land	x_3	hectares	57.26 (24.56)	57.88 (24.67)	58.03 (24.55)	59.18 (25.95)	59.68 (26.62)	60.31 (26.82)	58.72 (25.35)
Capital depreciation	x_4	€	35,737.05 (22,372.23)	36,383.51 (23,241.15)	36,261.95 (23,414.60)	34,497.50 (23,314.33)	34,543.50 (25,116.38)	36,028.37 (27,437.59)	35,575.31 (23,338.10)
Chemicals	x_5	€	13,764.52 (10,303.63)	14,334.55 (9619.82)	13,857.73 (10,208.55)	13,406.20 (10,525.50)	11,546.54 (8401.37)	11,112.76 (7792.39)	13,003.72 (9183.28)
Feed	x_6	€	31,994.36 (20,020.74)	33,225.19 (20,315.27)	31,012.28 (19,996.46)	32,042.08 (21,409.53)	31,710.19 (21,654.38)	33,238.65 (22,950.68)	32,203.79 (20,333.09)
Nitrogen input	q	kg	7657.81 (4795.30)	9121.79 (5221.79)	8470.47 (5271.83)	8849.60 (5844.01)	8584.21 (5713.23)	8029.11 (5051.09)	8452.16 (5155.12)
Nitrogen balance	z	kg	5285.20 (3956.37)	6460.38 (4148.09)	5960.46 (4353.46)	6188.52 (4829.82)	5941.28 (4681.52)	5230.56 (3907.13)	6284.89 (4288.59)

Note: Monetary variables are expressed in 2015 EUR.

regression as a measure of the probability that a farm will be classified as a program participant. Logit model results for the propensity score matching are presented in Table A2. The likelihood ratio test is statistically significant at the 1% level, indicating that all farm characteristics considered are jointly significant in explaining program participation. Propensity scores were calculated for each observation based on the parameter estimates of the logit model, which were then used to match participant and non-participant farms using nearest neighbour matching. The matching techniques applied in this study resulted in a balanced distribution of dairy farms between the control and treated groups. Before matching, the control group consisted of 124 farms while the treated group had 147 farms, out of a total of 271 farms. After matching, both groups had 69 farms each, while the total number of farms was reduced to 138 because the observations out of the area of common support have been dropped from the initial sample. Different matching algorithms[8] were tested prior to selecting the nearest neighbour estimator (1:1) without replacement. Before matching, significant differences have been found between the treated and control group and therefore, the resultant balance of the relevant covariates assesses the success of propensity score estimation. Covariates' mean values before and after matching among the two groups are shown in Table 2. These results suggest that no significant differences[9] between participating and non-participating farms remain after matching. We can therefore conclude that the applied matching algorithm worked well, as the existing observable differences have been controlled for. Once similar participants and non-participants have been identified, productivity, efficiency, and technical change can be computed based on the pooled data for all the units.

5.2. Green productivity growth

Table 3 reports the summary statistics of the global Malmquist-Luenberger index and its components. These findings indicate that, on average, farms experienced a green productivity increase of 4.3% from 2013 to 2018. This productivity growth is mostly due to the positive evolution of technical change (+ 4.95%), while efficiency change is close to unity, indicating stagnation. In Fig. 4, we report the estimated kernel density distributions of the GML and its components considering the performance of each farm through the whole period. The GML index was unimodal with a high concentration of units around the mean value. Specifically, with a calculated kurtosis of 3.1810, the GML index has a more leptokurtic distribution with a low variation in its values, while its components – technological change and efficiency change - are slightly more spread out. While summarizing these findings, it is worth mentioning that no previous literature on green productivity of Bavarian dairy farms has been found in our literature review, which does not permit us to make a proper comparison with other results in the literature.

The evolution of the green productivity changes and its components has experienced some variability over the period of study, especially since the abolition of the milk quotas in 2015. To highlight these fluctuations, we present in Table 3 the average annual change of the GML index and its components. Here we can notice an important drop between 2015 and 2016, which can be explained by the abolition of the milk quotas in 2015, which resulted in an increase in herd size with potentially poor dairy characteristics and therefore low economic growth (Osawe et al., 2021). When we explore the evolution of the technical component (GML TECH) and the efficiency change component (GML EFFCH) over the period of study, we notice a relatively similar trend over the years. An opposite trend is frequently observed in agricultural economics literature measuring classic productivity growth. Recent works have shown that it is possible to observe this opposite pattern between efficiency change and technological change when environmental indicators are considered as well (Dakpo et al., 2019; Pasiouras, 2013). This opposite trend could indicate a trade-off relationship between efficiency gains and investing in green technologies and environmentally sustainable practices. However, in our study, the finding that the components of the GML index follow a similar pattern can be interpreted as evidence of no trade-off between the environmental innovation effect and the catch-up effect. This leads us to the hypothesis that farms participating in AES might not engage in very innovative and differentiated production activities that could improve their farm-level green productivity. This hypothesis will be tested in the next sub-section using a difference-in-difference method and system generalized method of moment.

[8] We tested the most common matching algorithms: kernel matching, radius matching, and nearest neighbour matching without and with replacement from 1 to 10 neighbours. We compared the different matching algorithms and found that 1:1 nearest neighbour matching without replacement using a caliper width of 0.3 performed best.

[9] Rosenbaum and Rubin (1985) propose the additional use of standardised bias (SB) to compare treated unit means and untreated unit means before and after matching as a measure of covariate balance. As noted by Caliendo and Kopeinig (2008), a standardised bias below 5 after matching would be seen as sufficient. Our findings indicate that the overall SB was reduced from 38.5 to 3.2 by the matching procedure.

Table 2
Average and bias reduction of key covariates before and after matching for the pre-intervention period (2013).

Variables	Before matching		After matching		Standardised Bias	
	Control mean	Treated mean	Control mean	Treated mean	Before matching	After matching
Livestock units per ha	1.050***	0.840	0.949	0.947	−59.8	−0.7
Labour per ha	0.036**	0.028	0.032	0.032	−60.1	6
Capital depreciation per ha	628.810**	572.210	592.270	602.590	−16.5	3
Sales per ha	3913.70**	3275.60	3564.100	3574.100	−51.7	0.8
Fertilizers per ha	178.080**	158.750	163.830	166.070	−24.6	2.9
Pesticide per ha	62.950	63.460	60.068	59.446	1.3	2.6
Feed per ha	606.980***	501.440	564.640	553.360	−32.4	−3.5
Share of arable land	0.571	0.589	0.571	0.573	9	1.1
Share of grassland	0.427	0.411	0.425	0.426	−8.2	0.5
Yield index per ha	77.833***	49.025	56.518	58.738	−51.4	4
GDP	28,240.000***	27,454.000	28,031.000	28,033.000	−16.6	0.1
Number of farms	124	147	69	69		
Total number of farms	271		138			

*, **, *** Statistical significance at 5%, 1%, and 0.1%, respectively, of a t-test on the equality of mean differences between observations from the treated and the control group.

Table 3
Descriptive statistics of the Global Malmquist-Luenberger index and its components (2013–2018).

	Full Period 2013–2018	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018
GML						
Average	1.0430	1.0734	0.9639	0.9624	1.0675	1.1478
Sd	0.1583	0.1346	0.1153	0.1214	0.1693	0.1602
GML EFFCH						
Average	0.9985	1.0035	1.0002	0.9807	1.0356	0.9727
Sd	0.1220	0.0931	0.1261	0.1241	0.1362	0.1178
GML TECH						
Average	1.0495	1.0717	0.9692	0.9891	1.0363	1.1811
Sd	0.1385	0.1106	0.0989	0.1259	0.1404	0.1026

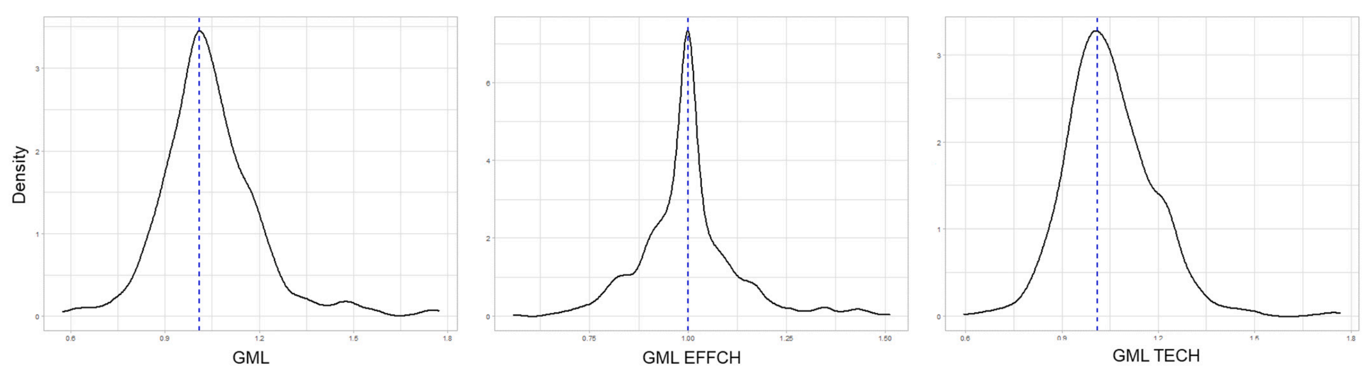

Fig. 4. Kernel density distributions of the GML index and its components.

Table 4
Impact of AES on GML index and its components (2013–2018).

	GML		GML EFFCH		GML TECH	
	Treated mean	Control mean	Treated mean	Control mean	Treated mean	Control mean
Pre-treatment	1.0780	1.0660	1.0076	0.9968	1.0725	1.0703
Post-treatment	1.1764	1.1018	0.9963	0.9349	1.1829	1.1783
Change	0.0627		0.0505		0.0022	
t-value	1.5751		2.036		0.0752	
P > |t|	0.1183		0.0438		0.9402	
Number of observations	276		276		276	

Note: While we assume a shared frontier for both participants and non-participants, our estimation of technological change is relative to the observed data points (see Eq. (2)) and, hence, allows for a non-uniform rate of technological change between segments along this frontier.

5.3. Impact of AES on green productivity growth

The effects of different environmental policies on farm-level productivity have been the subject of a growing amount of research (Baráth et al., 2020; Bokusheva et al., 2012; Bullock et al., 2007; Davis et al., 2012; Mennig and Sauer, 2020; Setchfield et al., 2012). However, the literature is less rich when it comes to the impact of agri-environmental regulations on productivity indices that account for both technical and environmental issues. Our conceptual approach clearly brings some new insights into the relationship between environmentally friendly farming practices and sustainable farm performance. In Table 4 we summarize the results of the DiD method on the impact of AES on green productivity change and its components. A positive (negative) change indicates an increase (decrease) in the average GML values of the participants that is larger than the increase (decrease) of their matched non-participants.

While agri-environmental policies were initially implemented to mitigate the detrimental effects of intensive agriculture systems on the environment, a number of studies have shown the potential of these agri-environment measures to strengthen the economic viability of agricultural holdings (Harkness et al., 2021). Given that economic considerations are important drivers of farm-level production decisions, evaluating the effectiveness and impact of environmental support programs cannot be done without examining the economic dimension. Our GML index that aimed at specifying green productivity indices is therefore based on this approach that accounts for both environmental and economic performances. As we explained in the second section of this paper, it is reasonable to expect that AES will have a positive impact on green productivity, and at least should not prevent its improvement. The reasons for this belief are related to the fact that AES would stimulate input productivity (Bokusheva et al., 2012), and relying on the Porter hypothesis theory, AES are expected to stimulate environmental innovation and thus improve green productivity (Porter and der Linde, 1995). The corresponding DiD parameter (based on a *t*-test) that represents the impact of AES on the GML index is positive (0.06) but not statistically significant, suggesting that the average change in green productivity from 2013 to 2018 does not significantly differ between the participating and the non-participating farms. Although this finding is not statistically significant, there is some evidence of a positive green productivity effect of AES adoption. In summary, by the absence of a clearly positive effect, our results point to an ineffective implementation of the existing schemes in terms of improving green productivity.[10]

Turning to the potential impact of AES on the components of the GML index, the technical efficiency change (GML EFFCH), and the technological change (GML TECH), there are some interesting results. First, in the sample period, the AES payments seem to have a significant and positive effect on efficiency change with an average growth of 5.05%. The efficiency change component accounts for catching up effects that could include learning by doing, improved production practices, and diffusion of new technological solutions, among others. Thus, efficiency growth can be reasonably interpreted as the result of a more optimal combination of inputs to produce a given quantity of outputs. Given this background, our findings may reflect technical and economic improvement induced by the agri-environmental programs. This effect is not expected as the schemes were implemented to improve environmental outcomes, but might reflect windfall gains (Chabé-Ferret and Subervie, 2013; Hynes and Garvey, 2009a). Second, AES participation has been found to have no significant effect on technological change values. This shows that a positive shift in the production frontier cannot be purely induced by implementing agri-environmental measures. Technological progress, also known as the change in the best practice frontier can mainly be attributed to an effective long-term planning and timely capital investment. For the dairy farm sector, market developments and policy reforms to promote environmental sustainability represent the driving force behind the adoption of cutting-edge technologies to foster technological change, which in turn can be considered as a measure to evaluate the deployment of new production technologies and practices (e.g. fertilization process, pest management, precision agriculture, etc.). In contrast to the possible effect on efficiency change, the level of technological progress should be higher for the participating farms. According to some scholars, this is related to one of the key features of environmental programs which is the promotion of investment in environmental technologies to improve environmental performance and competitiveness[11] (Jaffe and Palmer, 1997; Matzdorf and Lorenz, 2010). In our case, we do not observe any significant differences in terms of increased labour or capital investment for the post-treatment period between participating and non-participating farms. Therefore, this confirms that the participation in Bavarian agri-environment schemes seems to be not an important factor affecting environmental technologies implementation. This finding is consistent with the argument that most of the existing agri-environmental contracts do not require a significant shift in farming practices (Burton and Schwarz, 2013; Wilson and Hart, 2001). Indeed, it is important to note that our research focuses on action-based schemes, which are the most common type of agri-environment policies since they are simple to implement and don't need a major change in agricultural practices. Additionally, several studies indicated that farms are more likely to take part in programs that involve little change to their current practices (Defrancesco et al., 2008; Hynes and Garvey, 2009b; Murphy et al., 2014).

In summary, our findings indicate that there is no robust association between agri-environmental policies and dairy farmers' green productivity. It's important to note that our analysis relies on a single AES variable, and the potential effects of individual schemes might overlap, potentially offsetting one another, which could explain the absence of a significant impact. To address this issue, we categorized the different individual schemes into four agri-environment categories aligned with the primary program goals established by the Bavarian State Ministry of Food, Agriculture, and Forestry, namely climate protection, soil and water conservation, biodiversity conservation, and cultural landscape preservation. These categories were then included as dummy variables in our fixed-effects regression models (Eq. (6)). Notably, our findings remain consistent when examining the impact of AES on green productivity and its components, efficiency change, and technological change (refer to the Appendix, Tables A3-A5).

6. Concluding remarks

This study analyses green productivity change related to AES participation using panel data covering a sample of Bavarian dairy farms observed between 2013 and 2018, through the use of the Global Malmquist-Luenberger index. Given that the high levels of nitrogen pollution resulting from dairy production affect water quality in Bavaria, our farm-level total factor productivity index incorporates an undesirable output in the form of the nitrogen balance. We then investigate the effects of agri-environmental scheme payments on farm performance using the combined difference-in-difference propensity score matching estimator. First, we find that the average green TFP in our Bavarian sample dairy farms increased by 4.3%, which is equivalent to an average annual increase of 0.86%, in line with commonly reported productivity estimates for German dairy farms (e.g., (Frick and Sauer, 2018; Sauer and Latacz-Lohmann, 2015). These studies, however, focus exclusively on measuring classic TFP changes and do not consider the presence of

[10] It is crucial to contextualize this finding. Increasing green productivity is not usually the primary goal of the AES. However, this should not compromise the main contribution of this work, which is the development of a framework to assess the environmental economic impact of the schemes.

[11] On the other hand, non-participation in AES does not keep farmers from investing into new technology (e.g., using other investment subsidies), keeping pace with AES participants.

undesirable outputs.

Second, we find that AES payments have a limited effect on improving farm-level green productivity, as suggested by some literature (Baráth et al., 2020; Mary, 2013; Mennig and Sauer, 2020). Although the mean effect was estimated to be approximately 6%, the estimate was not statistically significant. Moreover, in contrast with previous works, we are able to show that AES participation has differential effects on the green productivity components. More specifically, we find that the AES subsidies have positive impacts on technical efficiency change which can be interpreted as evidence of farmers' success in optimally allocating resources over time. AES participation is found to have no significant impact on technological change. Policy-makers should create and enforce linkages between agri-environment policies and investment policies that sustain economic growth and allow farmers to adopt new environmental technologies.

Finally, the time range that was chosen for our analysis is linked to the five-year commitment period, but it would be interesting to study long-term effects of environmental programs on farm performance (Sharpley et al., 2013). While it's important to note that our results are limited to the specific geographic context of Bavaria, it would be worthwhile to assess the reliability of our findings by comparing them with data from other sources or employing alternative methodologies.

CRediT authorship contribution statement

Amer Ait Sidhoum: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Philipp Mennig:** Conceptualization, Data curation, Methodology, Writing – original draft, Writing – review & editing. **Fabian Frick:** Formal analysis, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgments

This research is part of the EFFECT Project. The authors gratefully acknowledge financial support from the European Union Horizon 2020 Programme for Research, Technological Development, and Demonstration under grant agreement no. 817903.

Appendix A. Appendix

Table A1
Summary Statistics for the covariates used in the PSM in the pre-treatment year 2013.

	Dimension	Average	S.d.	Min	Max
AES	1 if yes, 0 if no	0.54	0.50	0	1.00
Livestock unit	number	57.11	27.43	8.00	162.00
Labour	Man-work units	1.79	0.62	0.40	5.00
Land	Hectares	66.48	35.55	12.75	290.05
Capital depreciation	€/ha	597.55	339.56	29.81	3145.65
Total Sales	€/ha	3567.60	1256.20	1390.59	10,294.10
Fertilizers	€/ha	167.49	78.84	0	487.14
Pesticides	€/ha	63.22	39.48	0	231.47
Feed	€/ha	6.13	0.64	2.69	7.73
Farmer's age	number	56.96	9.98	33.00	91.00
Share of arable land	%	0.58	0.19	0	0.97
Share of grassland	%	0.42	0.19	0.03	1.00
Share of rented land	%	0.61	0.36	0.02	2.89
Yield index	number/ha	62.07	56.58	5.31	317.65
Agricultural income	€/ha	1091.56	602.35	- 572.70	4059.40
Dummy variable 'Swabia'	1 if yes, 0 if no	0.15	0.36	0	1.00
Dummy variable 'Lower Franconia'	1 if yes, 0 if no	0.10	0.30	0	1.00
Dummy variable 'Middle Franconia'	1 if yes, 0 if no	0.23	0.42	0	1.00
Dummy variable 'Upper Franconia	1 if yes, 0 if no	0.20	0.40	0	1.00
Dummy variable 'Upper Palatinate'	1 if yes, 0 if no	0.17	0.38	0	1.00
Dummy variable 'Lower Bavaria'	1 if yes, 0 if no	0.03	0.17	0	1.00
Dummy variable 'Upper Bavaria'	1 if yes, 0 if no	0.12	0.33	0	1.00
Dummy variable 'no agric. Education'	1 if yes, 0 if no	0.04	0.21	0	1.00
Dummy variable 'skilled worker	1 if yes, 0 if no	0.54	0.50	0	1.00
Dummy variable 'University education'	1 if yes, 0 if no	0.41	0.49	0	1.00
Gross value added in agriculture, forestry, fishing	€ million	72.46	32.34	6.00	144.00
Gross domestic product per capita	€	27,818.60	4782.03	18,470.00	55,265.00
Unemployment rate	%	0.03	0.01	0.01	0.07
Workforce	number	36,464.44	12,961.64	21,672.00	76,017.00
Farmland rental price	€/ha	227.78	74.47	108.00	412.00
Number of observations	271				

Table A2
Estimation of the propensity score.

Logistic regression
LR chi2(27) = 101.26
Prob > chi2 = 0.0000
Log likelihood = −135.624
Pseudo R2 = 0.272
Number of observations = 271
Dependent variable: AES

Regressors	Coefficient	z-stat	*p*-value
Livestock per ha	−0.984	−1.13	0.260
Labour per ha	−2.441	−0.14	0.889
Land	0.040	3.88	0.000
Capital depreciation per ha	−0.040	−0.11	0.909
Total sales per ha	0.829	0.62	0.538
Fertilizers per ha	0.001	0.22	0.830
Pesticides per ha	−0.286	−1.36	0.174
Feed per ha	−0.326	−0.89	0.376
Ln farmers' Age	−0.917	−0.97	0.334
Share arable land	−7.580	−2.69	0.007
Share Grassland	−2.576	−2.5	0.013
Share rented land	0.155	0.62	0.537
Ln Yield index per ha	0.674	1.71	0.087
Agricultural income per ha	0.475	0.63	0.528
Dummy variable 'master's certificate or 'university degree	1.012	1.31	0.190
Dummy variable "in education or skilled worker"	0.621	0.81	0.418
Dummy variable 'Swabia'	−17.295	−0.01	0.993
Dummy variable 'Lower Franconia'	−16.946	−0.01	0.993
Dummy variable 'Middle Franconia'	−15.657	−0.01	0.993
Dummy variable 'Upper Franconia	−14.582	−0.01	0.994
Dummy variable 'Upper Palatinate'	−15.675	−0.01	0.993
Dummy variable 'Upper Bavaria'	−17.383	−0.01	0.993
Ln Gross domestic product per capita	1.752	1.51	0.132
Unemployment rate	0.446	0.42	0.674
Gross value added in agriculture, forestry, fishing	0.818	2.25	0.024
Intercept	−9.502	−0.01	0.996

Table A3
The difference-in-difference fixed-effects regression results for green productivity growth (GML index).

	GML (dependent variable)			
	Coef.	Std. Err	t	p-value
Time dummy	0.033	0.029	1.130	0.259
AES participation	–	–	–	–
DiD estimator	0.059	0.039	1.500	0.135
Climate AES	0.029	0.036	0.800	0.428
Soil and water AES	0.006	0.041	0.140	0.885
Biodiversity AES	−0.010	0.044	−0.220	0.823
Cultural landscape AES	−0.010	0.055	−0.190	0.849
Intercept	0.058	0.024	2.410	0.017
Number of observations	276			

Table A4
The difference-in-difference fixed-effects regression results for the AES impact on efficiency change (GML EFFCH).

	GML EFFCH (dependent variable)			
	Coef.	Std. Err	t	p-value
Time dummy	−0.065	0.021	−3.14	0.002
AES participation	–	–	–	–
DiD estimator	0.062	0.028	2.19	0.03
Climate AES	0.028	0.026	1.08	0.283
Soil and water AES	0.018	0.030	0.61	0.541
Biodiversity AES	−0.040	0.032	−1.26	0.209
Cultural landscape AES	−0.019	0.040	−0.48	0.634
Intercept	−0.002	0.017	−0.1	0.924
Number of observations	276			

Table A5
The difference-in-difference fixed-effects regression results for the AES impact on technical change (GML TECH).

	GML TECH (dependent variable)			
	Coef.	Std. Err	t	p-value
Time dummy	0.098	0.022	4.540	0.000
AES participation	–	–	–	–
DiD estimator	−0.003	0.029	−0.110	0.916
Climate AES	0.001	0.027	0.020	0.982
Soil and water AES	−0.012	0.031	−0.400	0.691
Biodiversity AES	0.031	0.033	0.920	0.360
Cultural landscape AES	0.008	0.041	0.210	0.838
Intercept	0.059	0.018	3.320	0.001
Number of observations	276			

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