Payments for agri-environmental schemes and green productivity in Germany: An impact assessment analysis

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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 environmental and economic impact of these schemes 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 Europe's agri-environmental schemes 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.

Keywords:

Agri-environment schemes, Policy evaluation, Green Productivity, Data envelopment analysis,

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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 & 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 (increasing productivity, especially through technical progress, fair standard of living for farmers, stable markets, guaranteeing the availability of supplies, reasonable food prices), several provisions and amendments of the TFEU lay down additional goals and have gradually become CAP goals without being mentioned in Article 39. 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). They are co-financed by the EU and its Member States. In most Member States, the biggest parts of the second pillar budget have so far been spent on three measures: investment support (23% of total second pillar expenditures), agri-environmental schemes (17%) and payments for areas subject to natural constraints or other specific constraints (16%) (Salhofer & Feichtinger, 2020). Especially the role of agri-environment schemes (AES), which became compulsory elements of the CAP following the 1992 MacSharry Reform, has become more important and popular over the years as a result of 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). Although agri-environment measures have evolved since their introduction, the core guiding principles have not changed considerably. Scheme participation is voluntary; i.e., each farmer can decide whether to participate or not. Contracts are typically multi-annual and usually cover a period of five years.[2] In general, an AES consists of a set of (environmentally friendly) measures or actions that farmers are expected to perform, with associated payments. However, in recent years, new contract designs such as result-based or cooperative measures have gained some popularity. Despite implementation differences on the national level, all AES share a number of over-arching goals. These relate to the reduction of the damage agricultural activities have on the environment and to the increase or stabilization of positive effects of agriculture (e.g., the provision of cultural landscapes or culturally significant agricultural practices) (Science for Environment Policy, 2017). Both goals shall be reached with AES design that is compliant 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). Furthermore, "the amount of payment shall be limited to the extra costs or loss of income involved in complying with the government programme" (WTO, 1995, p. 63). 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 & Sauer, 2020; Salhofer & Streicher, 2005). However, these authors do not use comprehensive indicators to measure production effects. They focus on marketable farm output and in this way identify windfall effects and production impacts related to AES. 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 might even have an enhancing effect, making them an important instrument in increasing agricultural production while, at the same time, reducing the burden agriculture puts on the environment and possibly being in line with WTO requirements.

Firms‘ performance measurement that integrates, in addition to the marketable output, environmental externalities, especially pollution (undesirable output), 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

[2] 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.

is to provide a measure of productivity change that integrate environmental aspects of production processes. In fact, the contributions to the technical literature on the adequate modeling of negative externalities differ in how the corresponding technology is defined. In particular, there has been considerable debate about whether pollution (undesirable outputs) should be modeled as a typical output or rather as an input. Another question has been related to whether pollution should be treated as a weakly or strongly disposable output. Finally, a recent path-breaking approach proposes to model polluting technologies as an intersection of several production sets, some of which govern the production of desirable outputs, while others involve by-products generating technologies (Murty et al., 2012). Dakpo et al. (2016) provide a good overview of the different approaches to modeling pollution-generating technologies.

As we are interested in measuring production-related effects of AES, especially in examining the 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, 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.

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 describes 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 & 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, given the substantial budget of the AES payments, 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 the desirable and undesirables outputs such that more of one cannot be produced without less of the other

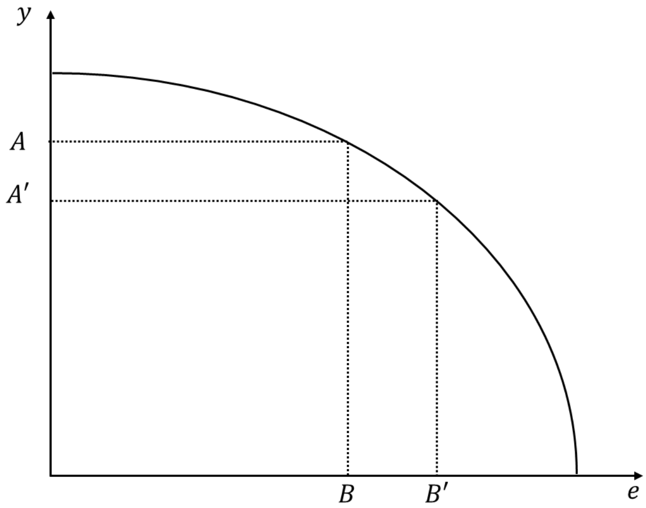

Figure 1. Trade-off between one desirable output and one environmental benefit under the influence of an environmental policy

Figure 1 depicts the production possibility frontier under the assumption of competitiveness when one desirable output y and one environmental outcome e are produced. Since AES adoption 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 $B' - B$.

Previous studies presented empirical evidence of trade-offs between environmental benefits and conventional output (Ruijs et al., 2013, 2017). However, recent literature has cast doubt on this 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 & 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 diagram for one environmental benefit e and one input x (Figure 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. This new investment will likely lead to better economic results (from savings effects) and will also result in environmental improvements (from B to B').

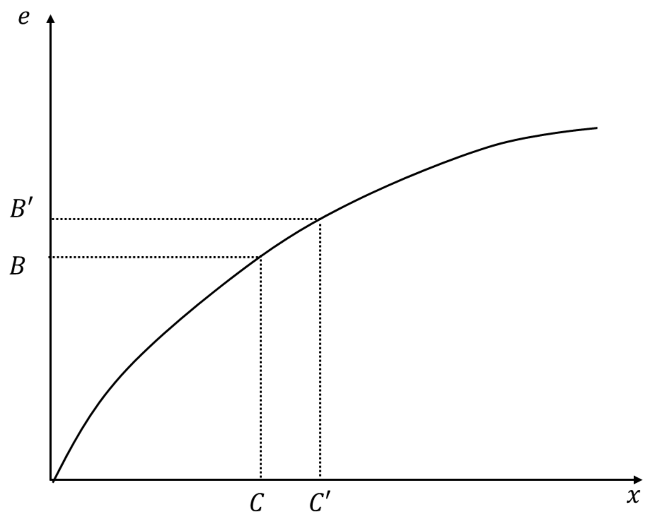

Figure 2. Trade-off between one input and one environmental benefit under the influence of an environmental policy

The assumptions discussed in the figures above are simple cases of one good output and one environmental benefit (Figure 1) and one input and one environmental benefit (Figure 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 of time. Productivity measurement requires a more complex modelling, 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 & 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 of some (ideally non-polluting) inputs (e.g., high-quality fertilizer spreader), but may reduce the need for other (polluting) inputs (e.g. pesticides). At this point, it is unclear whether AES tend to improve green productivity or not. Any possible 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

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. 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. However, rather than relying on a large number of observable characteristics, Rosenbaum & Rubin (1983) propose matching the participating observations 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 observations 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. (2013, 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[3]. 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 & Lovell's (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, 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 $P_t(x_t) = \{(y_t, b_t)|\ x_t\ can\ produce\ (y_t, b_t)\}$. 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:

[3] 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 $I(\cdot)$ is an index number. Additional information is available in Fried et al. (2008).

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

Moreover, the GML index can be decomposed into efficiency change ($GMLECH$) and technological change ($GMLTCH$) (Oh 2010):

$$GML = \frac{1 + \vec{D}_t^o(x_t, y_t, b_t; y_t, -b_t)}{1 + \vec{D}_{t+1}^o(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})}$$
$$\times \left[\frac{(1 + \vec{D}_G^o(x_t, y_t, b_t; y_t, -b_t))/(1 + \vec{D}_t^o(x_t, y_t, b_t; y_t, -b_t))}{(1 + \vec{D}_G^o(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1}))/(1 + \vec{D}_{t+1}^o(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1}))}\right] \tag{2}$$
$$= GMLECH \times GMLTCH$$

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):

$$\vec{D}_o\ (x_n, y_m, b_k; y_m, -b_k) = \max \beta$$
$$\text{s.t.}$$
$$\sum_{j=1}^{J} \lambda_j x_{nj} \leq x_{n0}, n = 1, \ldots, N$$
$$\sum_{j=1}^{J} \lambda_j y_{mj} \geq y_{m0} + \beta y_{m0}, m = 1, \ldots, M \tag{3}$$
$$\sum_{j=1}^{J} \lambda_j b_{kj} = b_{k0} - \beta b_{k0}, k = 1, \ldots, K$$
$$\lambda_j \geq 0,\ j = 1, \ldots, J$$

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

$$\vec{D}_o^G(x_n, y_m, b_k; y_m, -b_k) = \max \beta$$

$$\begin{gathered} \text{s.t.} \\ \sum_{t=1}^{T}\sum_{k=1}^{K}\lambda_j^t\, x_{nj}^t \leq x_{n0}^t,\ n = 1, \dots, N \\ \sum_{t=1}^{T}\sum_{k=1}^{K}\lambda_j^t\, y_{mj}^t \geq y_{m0}^t + \ \beta y_{m0}^t,\ m = 1, \dots, M \\ \sum_{t=1}^{T}\sum_{k=1}^{K}\lambda_j^t\, b_{kj}^t = b_{k0}^t - \beta b_{k0}^t,\ n = 1, \dots, N \\ \lambda_j^t \geq 0,\ j = 1, \dots, J \end{gathered} \tag{4}$$

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 & Hart, 2000). 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:

$$DiD = E[Y_1^T - Y_0^T | T_1 = 1, \pi(X)] - E[Y_1^C - Y_0^C | T_1 = 0, \pi(X)] \tag{5}$$

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.

4. Data

Our empirical analysis borrows from Ait Sidhoum et al. (2022) in that we make use of the same dataset. Thus, only a brief description will be given here. A balanced panel of 1626 Bavarian dairy farms, covering the period 2013–2018, is used. The year 2013 - which is the year before the begin of the 2014-2020 EU programming period - is defined as the pre-intervention period, while the year 2018 is considered to be the post-intervention period.

Rubin & 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.

The measurement of the GML index mainly selects livestock units ($x1$); labour force ($x2$); utilized land ($x3$); capital depreciation ($x4$); pesticides application ($x5$); expenses for feed ($x6$) and quantities of nitrogen input (x7). Total farm sales (Y) and nitrogen balance (Z)[4] are treated as output variables. Table 1 provides descriptive statistics on input and output variables used in the GML model. The data used in this study were a combination of two data sources: the Farm Accountancy Data Network in Bavaria and the official agricultural support data (InVeKoS) that contains further information on farm production characteristics as well as specific subsidy variables.

[4] We adopt Gamer & 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)'scoefficients 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).

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)	214421.12 (112800.45)	257,445.99 (142,765.69)	223,431.36 (112,602.11)
Livestock units	x_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 (9,619.82)	13,857.73 (10,208.55)	13,406.20 (10,525.50)	11,546.54 (8,401.37)	11,112.76 (7,792.39)	13,003.72 (9,183.28)
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	7,657.81 (4,795.30)	9,121.79 (5,221.79)	8,470.47 (5,271.83)	8,849.60 (5,844.01)	8,584.21 (5,713.23)	8,029.11 (5,051.09)	8,452.16 (5,155.12)
Nitrogen balance	z	kg	5,285.20 (3,956.37)	6,460.38 (4,148.09)	5,960.46 (4,353.46)	6,188.52 (4,829.82)	5,941.28 (4,681.52)	5,230.56 (3,907.13)	6,284.89 (4,288.59)

Note: Monetary variables are expressed in 2015 EUR.

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[5] is calculated using a logit 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. The total number of dairy farms decreased from 271 to 138 after the PSM because the observations out of the common support have been dropped from the initial sample. Different matching algorithms[6] 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 the Appendix, Table A3. These results suggest that no significant differences[7] 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] 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).

[6] 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.

[7] 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 standardized 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.

5.2. Green productivity growth

Table 2 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 Figure 3, 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 2 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.

Table 2. 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

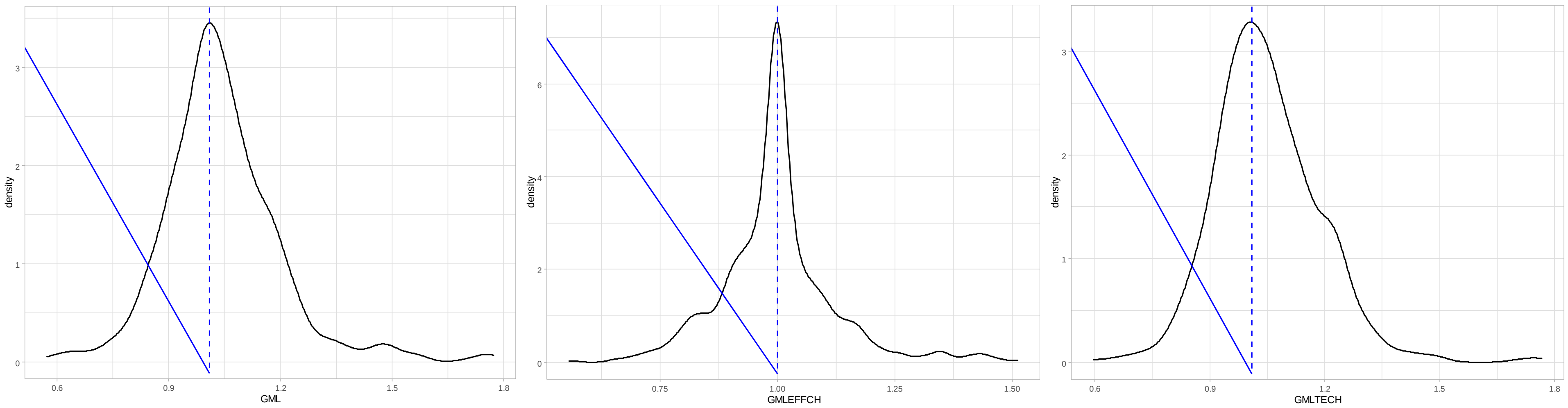

Figure 3. Kernel density distributions of Global ML index and its components.

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 & 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.

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	

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 sectuion 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 &

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.[8]

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 & Subervie, 2013; Hynes & Garvey, 2009). 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[9] (Jaffe & Palmer, 1997; Matzdorf

[8] 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.

[9] 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.

& 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 & Schwarz, 2013; Wilson & Hart, 2001).

5.4. The dynamic impact of AES

Using a difference-in-difference approach combined with matching to estimate the effect of agri-environmental programs on farm performance helps us to account for some econometric challenges such as unobserved farm heterogeneity and sample selection bias. However, other issues such as the dynamic nature of the productivity change and the need to adequately solve possible endogeneity problems require the use of dynamic panel regression techniques. The system GMM is employed as the most appropriate estimation approach that addresses the econometric challenges associated with the relationship between AES payments and green productivity. The approach can estimate a possible lagged effect of AES on green productivity, with the potential of taking into account time-varying unobserved heterogeneity through the use of instrumental variables (time lags of the endogenous variable). Results of the dynamic impact of AES on green productivity of a sample of Bavarian dairy farms from 2013 to 2018 are shown in Table 5.

Table 5. Dynamic impact of AES on GML (2013-2018)

	Model 1	Model 2
TFP (t-1)	0.732*** (0.079)	0.722*** (0.083)
AES per ha (t-1)	-1.0E-04 (1.5E-04)	-1.4E-04 (1.6E-04)
Farm size class (1=reference)		
2	0.013 (0.014)	0.019 (0.014)
3	0.021 (0.017)	0.028* (0.017)
Capital-labour ratio		-6.8E-07 (6.8E-07)
Share grassland		0.007 (0.043)
Insurance per ha		-3.3E-05 (8.6E-05)
Year (2013=reference)		
2014	0.318*** (0.088)	0.341*** (0.092)
2015	0.235*** (0.087)	0.257*** (0.091)
2016	0.218*** (0.084)	0.239*** (0.088)
2017	0.299*** (0.083)	0.321*** (0.086)
2018	0.416*** (0.084)	0.438*** (0.088)
Number of observations	690	690
Number of instruments	31	34
AR(2)	(0.109)	(0.117)
Sargan		(0.000)
Hansen stat,		(0.009)

Note: Considering the possible serial correlation, we perform the Arellano-Bond test of second-order autocorrelation on the residual from the System GMM approach. The results indicate that the null of no serial correlation cannot be rejected in both models, suggesting serial correlation is not an obvious problem for our estimation.

Sargan and Hansen statistics give the test for for over-identifying restrictions. The null of exogenous instruments can be rejected with small levels of significance. Nevertheless, because appear to be weakened by a high instrument count, these tests should be interpreted with caution. Additionally, it is worth mentioning that we ran the model with a reduced instrumental variable set and the results remain unchanged no matter whether Sargan and Hansen statistics rejected or accepted the null hypothesis.

Significance levels are as follows: *** = 1%, ** = 5%, and * = 10%

Model 1 represents the results of the system GMM approach without considering control variables, while Model 2 gives the regression results when the control variables are included in the analysis.[10]. Turning to the estimation results, the first-order lag of GML index is found to be positive and significant in both dynamic models. This implies that previous farm performance indices matter and should be taken into account, and the result is consistent with previous literature that highlighted the role of production history (Zeng et al., 2017; Zhengfei & Lansink, 2006). For lagged effects of AES (model 1)[11], we find that increasing the amount of schemes payments has no effect on green productivity. This result in general points in the same direction as our previous findings. This can be taken as empirical evidence that Bavaria's current agri-environmental policy is insufficient to foster green economic growth.

In sum, our findings show that there is no powerful connection between agri-environmental policy and dairy farmers' green productivity. Our analysis is based on a single AES variable that includes measures related to grassland protection, arable land, and organic farming. While measures for arable land[12] have mainly focused on the implementation of diversified crop rotations, conservation tillage, and the use of cover crops, grassland measures mainly aimed at restricting the use of mineral fertilisers, as well as putting a limit on the number of animals per hectare (they have a lot in common with organic farming measures). While the latter are typically some schemes that should have a positive impact on green productivity when nitrogen pollution is considered, future research should separate the possible differential effects of grassland measures from arable measures on green productivity.

[10] Both models account for time and farm size effects.
[11] Although after adding some control variables, the lagged effects of AES variable still shows a non significant impact on green productivity in dynamic Model 2.

[12] These practices do not usually impose restrictions on the use of productive inputs (e.g. mineral fertilizers)

6. Concluding remarks

This study analyses the 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 the high levels of nitrogen pollution resulting from dairy production affect water quality in Bavaria, our farm-level total factor productivity index incorporates undesirable outputs 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 TFP change 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 & Sauer, 2018; Sauer & Latacz-Lohmann, 2015). These studies, however, focus exclusively on measuring classic TFP changes and do not consider the presence of 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 & 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 insurance policies that sustain economic growth and allow farmers to adopt new environmental technologies.

Finally, we also find that the impacts of lagged effects of AES payments are insignificant. At the same time, the first-order lag of green productivity is found to exert an influence on green productivity during the sample period. According to these results, agri-environment schemes have failed to deliver a long-term and cumulative impact on green productivity. Future research would be useful to test the robustness of our results using alternative datasets. The importance of long-term effects of environmental programs represents valuable information for policy-makers for understanding the role of environmentally friendly farming practices for sustained economic and ecological benefits (Sharpley et al., 2013).

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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	3,145.65
Total Sales	€/ha	3,567.60	1,256.20	1,390.59	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	1,091.56	602.35	-572.70	4,059.40
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	4,782.03	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	Coef.	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. 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	3,913.70**	3,275.60	3,564.100	3,574.100	-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 dairy 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.