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Agri-environmental schemes reduce variable input costs: Evidence from Slovenian farms

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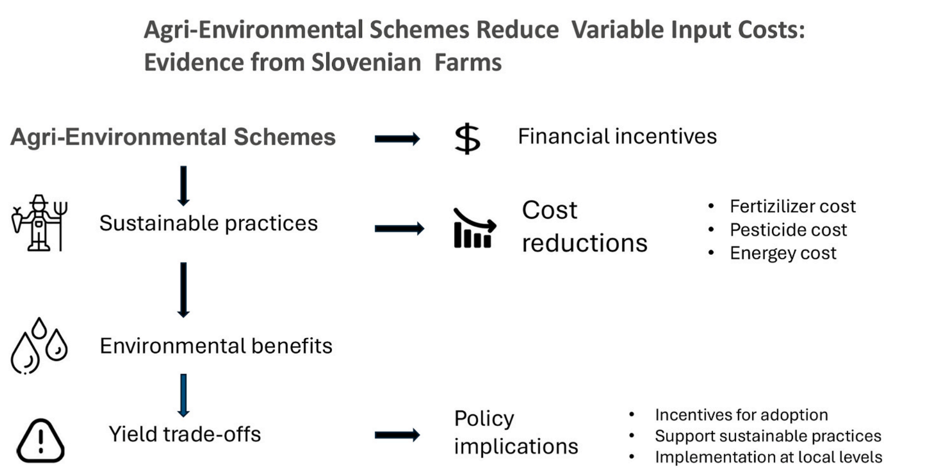
HIGHLIGHTS

- Agri-environmental schemes (AES) reduce energy and crop protection costs.
- Participation in AES shifts focus to less intensive tillage and sustainable farming.
- Yield trade-offs from AES may affect short-term farm profitability.
- AES help reduce variable chemical input use, boosting agricultural sustainability.
- Complementary policies needed to balance yields, economic and environmental goals.

GRAPHICAL ABSTRACT



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ABSTRACT

Agri-environmental schemes (AES) are central policy instruments designed to promote environmentally friendly agricultural practices by financially supporting the adoption of sustainable land management. While a substantial body of research examines how AES influence environmental outcomes and overall farm performance, far less is known about their direct effects on farm-level variable input costs, particularly in terms of energy, fertilizer, and crop protection expenditures. Existing studies typically analyse eco-efficiency or broad economic-environmental indicators, leaving a critical empirical gap regarding whether and how AES reshape the cost structure of farms during and after adoption. This study addresses this gap by estimating the causal impact of AES participation on key variable input costs using Slovenian Farm Accountancy Data Network data and a Differences-in-Differences (DID) design with staggered adoption, supported by robustness and sensitivity analyses. The findings indicate that AES participation leads to significant reductions in pesticide and energy costs, while fertilizer expenditures

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tend to increase in the short term before stabilizing or declining over time. These patterns suggest that AES trigger structural adjustments in production—such as reduced tillage intensity and transitions to organic or biological inputs—that can initially raise some input costs but contribute to longer-term sustainability. The study therefore offers new empirical evidence on the cost implications of AES, improving understanding of how environmental policy instruments affect farm-level economic decisions. These insights are essential for designing AES that support both environmental objectives and the economic viability of farmers, particularly in regions where sustainability transitions may involve short-term trade-offs.

1. Introduction

Balancing multiple foods, health, environmental and other sustainability commitments has attracted evidence-based policy research on trade-offs between higher productivity and lower environmental impacts for biodiversity-friendly farm-level farming practices and farming-oriented systems (Clark et al., 2019; Mondière et al., 2024). One investigated question is the cost-effectiveness of agri-environment policy measures (Pacini et al., 2015; Eory et al., 2018; Dueri and Mack, 2024). We focus on evaluating the effects of agri-environmental schemes (AES) on variable energy, fertilizer, and crop protection costs. AES have emerged as essential policy tools aimed at mitigating the environmental impacts of agricultural activities (Baráth et al., 2024). These schemes incentivize farmers to adopt sustainable practices, such as reducing chemical inputs, conserving biodiversity, and enhancing soil and water quality. The relationship between AES and key variable production costs—particularly energy, fertilizer, and crop protection expenses—has drawn significant interest in recent years, given the global emphasis on sustainable agricultural intensification and climate change mitigation (Clark and Tilman, 2017; Benedetti et al., 2019; Fukuyama et al., 2020; Lécuyer et al., 2022; Hasler et al., 2022; Mack et al., 2023; Cheng et al., 2025). The research specifically aims to fills gaps in the literature assessing the relationship between AES adoption and the costs of variable inputs for the European Union (EU) country in the context of Slovenian agriculture evaluating the success of AES in achieving associated economic and environmental policy objectives and impacts.

Agriculture is a resource-intensive sector that heavily relies on external inputs such as fertilizers, pesticides, and fossil fuels. While these inputs have been instrumental in boosting productivity over the past century, their extensive use has also resulted in adverse environmental consequences, including soil degradation, water contamination, greenhouse gas emissions, and biodiversity loss (Tilman et al., 2002; Foley et al., 2011; Benton and Bailey, 2019; Tudi et al., 2021; Lécuyer et al., 2022; Mondière et al., 2024; Efthimiou, 2025). Consequently, AES aim to reduce the dependence on these inputs by encouraging practices such as crop diversification, organic farming, integrated pest management (IPM) principles, and conservation tillage (Gaba et al., 2014; Batáry et al., 2015; Cullen et al., 2021; Hasler et al., 2022; Shen et al., 2022; Röder et al., 2024).

Energy use in agriculture is a critical component of overall production costs requiring improvements in energy efficiency in the agri-food chain (OECD, 2017; Paris et al., 2022; Rakshit et al., 2023). Conventional farming systems tend to be energy-intensive due to mechanization and high input reliance. In contrast, AES promote practices that can reduce energy use, such as minimal tillage, organic fertilization, and precision agriculture. Studies have shown that AES participants tend to have lower energy consumption intensity on agricultural land compared to conventional farms (Uthes and Matzdorf, 2013; Ait Sidhoum et al., 2023a) but can also lead to decline in productivity (Zhu et al., 2023). The energy consumption reduction is primarily attributed to the adoption of less intensive tillage practices and decreased use of synthetic chemical inputs. Conservation tillage, which minimizes soil disturbance, not only reduces fuel use but also enhances soil structure and carbon sequestration (Lal, 2004; Van Vuuren et al., 2017). Precision agriculture techniques on farm biodiversity management, often promoted under AES, further optimize energy use by ensuring efficient application of inputs (Higgins et al., 2019; Fukuyama et al., 2020; Klebl et al., 2024).

Fertilizer application is a major determinant of crop yields, but excessive use can lead to environmental problems such as nutrient runoff, eutrophication, and soil acidification (Pandey and Diwan, 2018; Hader et al., 2022). Recent policies aim to focus on pesticide-free agricultural production systems (Mack et al., 2023). By reducing reliance on synthetic fertilizers, AES can lower input costs and mitigate negative externalities associated with conventional farming. Different approaches have been applied to reduce chemical fertilizer and pesticide application in agriculture from economic taxation policy (Rougoor et al., 2001; Finger et al., 2017; Finger and Möhring, 2022; Schmidt et al., 2021; Nielsen et al., 2023), and contribution of behavioural sciences (Meunier et al., 2024), to mandatory agri-environmental regulation such as "Two Zero" policy in China (Cheng et al., 2025). Studies have documented significant reductions in fertilizer and pesticide use and crop protection costs among AES participants. Kleijn et al. (2006) found that farmers enrolled in AES reduced their nitrogen and phosphorus application rates without substantial yield reductions. Similarly, organic farming practices, which are frequently supported by AES, rely on compost, manure, and nitrogen-fixing crops to maintain soil fertility, thereby reducing the need for chemical fertilizers (Mäder et al., 2002; Styles et al., 2018). A meta-analysis by Pretty and Bharucha (2015) found that AES participants reduced pesticide expenditures while maintaining comparable yields. IPM, a cornerstone of many AES, emphasizes pest monitoring, biological control agents, and targeted pesticide application, thereby minimizing chemical input use.

The objective of this study is to investigate the relationship between AES and variable input costs for energy, fertilize, and crop protection in the Slovenian agriculture. Slovenia presents a unique case for examining these relationships due to its diverse agricultural landscape, small-scale farming structure, and strong policy emphasis on sustainability. With 61% of its territory covered by forests and a significant portion of agricultural land situated in less-favoured mountainous areas (LFAs) (SORS, 2025; European Commission, 2025d), Slovenian agriculture faces distinct challenges and opportunities. First, Slovenia plays proactive participation role in the European Union's (EU) Common Agricultural Policy (CAP), which has promoted AES measures since the country's accession in 2004 (Unay-Gailhard and Bojnec, 2015, 2016, 2019; Šumrada et al., 2022). Slovenia has developed a comprehensive national rural development program that prioritizes environmental sustainability, making it an ideal setting to study the impact of AES on energy, fertilizer, and crop protection costs. Second, the predominance of small and medium-sized mostly family farms in Slovenia, with an average farm size of around 7 ha of agricultural land (SORS, 2025). These smaller farms often operate under resource constraints, making them more sensitive to changes in input costs and more reliant on external support (Bojnec and Latruffe, 2013). AES can potentially play a critical role in enhancing their economic viability by reducing input dependency and promoting sustainable practices. Third, Slovenia's varied climatic conditions, ranging from Alpine to Mediterranean influences, result in diverse cropping systems and farming practices. This heterogeneity allows for a comprehensive analysis of how AES impact economic farm size (smaller vs. larger), different types of farms (crop vs. non-crops) and agri-ecological contexts (LFA vs. non-LFA) (Baráth et al., 2020). In Alpine regions, where livestock farming and grassland management are predominant, AES may focus on maintaining biodiversity and preventing overgrazing. In contrast, in lowland areas with arable farming, AES may target reduced chemical input use and soil conservation. Fourth, the country's commitment to sustainable development is evident in its high adoption rates of organic farming and IPM. According to Eurostat (2024), Slovenia in 2022 ranks among the top EU countries in terms of the share of organic farming, with more than 10% of its agricultural land managed organically. This widespread adoption of environmentally friendly practices provides a robust foundation for evaluating the effectiveness of AES in further reducing input costs. Finally, Slovenia's relatively small agricultural sector enables detailed farm-level data collection and monitoring, which are essential for rigorous impact assessments. The availability of farm-level data facilitates empirical analyses of AES outcomes.

Despite this rich context, we still know surprisingly little about how AES participation actually alters farms' variable input costs. Most studies evaluate AES through environmental indicators, adoption behaviour, or eco-efficiency, but far fewer examine the concrete cost adjustments farmers face when entering these schemes—even though these adjustments are central to both farmers' decisions and the economic sustainability of AES themselves. In particular, no study provides causal evidence on how AES participation affects energy, fertilizer, and crop protection expenditures over time, despite these inputs representing the core channels through which AES are intended to influence environmental and economic outcomes. Slovenia, with its diverse farming systems and detailed FADN microdata, offers an ideal setting to fill this gap. This paper therefore delivers the first causal assessment of the impact of AES on variable input costs in Slovenian agriculture, exploiting staggered adoption and a Differences-in-Differences (DID) design to estimate dynamic treatment effects. By focusing explicitly on the cost channel—rather than solely on environmental or behavioural outcomes—we provide new empirical evidence on whether AES meaningfully change farmers' spending on key inputs, and whether these changes emerge immediately or evolve gradually after adoption.

2. Literature review

The green revolution in agriculture with intensive use of resources and increasing yields in agriculture, which was driven particularly by industry for agricultural inputs such as fertilizers and pesticides requiring increasing direct and indirect use of energy. This have achieved in a stage of re-verification of productive use of natural resources and ecological modernization in agriculture as a challenge of food security of the increasing global population (Lal, 2004; Godfray et al., 2010; Horlings and Marsden, 2011; Horlings and Marsden, 2011, 2011; Feng et al., 2023; Yu et al., 2025). Moreover, during the last three decades several studies raised the question of agricultural sustainability, economic, environmental, and social impacts of intensive agricultural production systems versus sustainable agricultural systems, agricultural input efficiency, multiple health and food choices (Tilman et al., 2002; Petit et al., 2011; Pimentel and Burgess, 2014; Clark and Tilman, 2017; Clark et al., 2019; Ait Sidhoum et al., 2023a; O'Brien et al., 2023; Taoumi and Lahrech, 2023; Barnes et al., 2024).

In the EU member states, AES was introduced as part of the CAP reforms addressing the environmental consequences of intensive agriculture (European Commission, 2019b; Pe'er et al., 2019; 2020; Michalek, 2022; Bartkowski et al., 2023; Uehleke et al., 2024; Pakeman et al., 2024). AES has played central role to the EU strategy for promoting sustainable agricultural practices while addressing environmental and climate challenges. The AES measures incentivize farmers to adopt practices that enhance biodiversity, protect natural resources, and reduce the environmental impact of farming. AES have become an essential tool in achieving the EU's Green Deal (European Commission, 2019a, 2019b, 2022), and Farm to Fork strategy (European Commission, 2020a, 2020b, 2020c; Wesseler, 2022) goals, particularly in the context of climate change adaptation and mitigation (Munir et al., 2024; European Commission, 2025a). The 2013 CAP reform made these schemes mandatory for EU member states to offer, allowing farmers to voluntarily enrol in programs aligned with national and regional priorities. Under the post-2023 CAP, the emphasis has shifted towards more ambitious environmental and climate objectives, as articulated in the EU's Biodiversity Strategy (European Commission, 2021) and the Climate Action Pact (European Commission, 2019c, 2020d). The new CAP encourages member states to design AES tailored to local environmental needs through National Strategic Plans. These plans outline specific measures, such as protecting water resources, reducing pesticide use, promoting organic farming, and maintaining high-nature-value farming systems. Farmers who participate in AES receive financial compensation for income loss and additional costs incurred due to implementing environmentally friendly practices (Röder et al., 2024).

AES are important in Slovenian agricultural policy, aiming to harmonize farming practices with environmental conservation and climate action (Unay-Gailhard and Bojnec, 2015, 2016). Slovenian CAP Strategic Plan (MAFF, 2021) focuses on ensuring food security and promoting sustainable food production with interventions to enhance farm competitiveness and resilience while addressing environmental and climate challenges. In addition to farm competitiveness and food system resilience (Béné et al., 2023) a significant portion of the funding is dedicated to environmental protection and sustainable management of natural resources, with around one-third of the total funding allocated to these areas (European Commission, 2025d, 2025e).

AES in Slovenia are designed to encourage farmers to adopt practices that benefit the environment and contribute to climate change mitigation and adaptation. These measures include organic farming, soil conservation, water protection, and biodiversity enhancement. Promoting organic farming practices aims to reduce chemical inputs and enhance biodiversity. Soil conservation measure supports implementing crop rotation, cover cropping, and reduced tillage to prevent soil erosion and improve soil health. Water protection measure aims establishing buffer zones and sustainable water management practices to protect water resources from agricultural runoff. Biodiversity enhancement measure aims maintaining and creating habitats such as hedgerows and grasslands to support wildlife (European Commission, 2025d, 2025e). These measures are supported through various payments and incentives to encourage farmer participation. The implementation of AES is supported by both EU and national funds.

AES promote practices that can reduce energy use due to the adoption of low-intensity tillage, organic fertilization, and precision agriculture practices (Béné et al., 2023; Fukuyama et al., 2020). The adoption of less intensive tillage practices can reduce energy use and use of chemical agricultural inputs (Lal, 2004; Gordon et al., 2023; Garrido et al., 2023; Ait Sidhoum et al., 2023a).

Kelly et al. (2018), they summarize selected studies that use Farm Accountancy Data Network (FADN) data for assessment of farm-level sustainability. The results are mixed, and authors raised the question whether FADN is the answer regarding sustainability indicators for improved assessment of the effects of agricultural policy across the EU countries. Table 1 summarises most recent studies.

The previous studies confirm the viability of using the FADN to assess farm-level sustainability but also revealing environmental and social information gaps (Kelly et al., 2018; Stempfle et al., 2025). Different economic and environmental impacts at farm- and sector-level are measured using farm-level FADN type data in combination with some other datasets such as the relationship between agriculture and water quality (Schmidt et al., 2019; O'Donoghue et al., 2024; Bystricky et al., 2024), environment and economic performance (van der Ploeg et al., 2019; Thomas et al., 2020; Mondière et al., 2024), socio-economic and behaviour factors (Wang et al., 2023; Mouratiadou et al., 2024), and the soil testing that can lead to the use lower amounts of chemical fertilizers depending on landscape characteristics and farm intensity (Tscharntke et al., 2005; Micha et al., 2023) in the circular economy (De Pascale et al., 2023; Stempfle et al., 2024). The studies indicate the need for targeted management approaches to farm level management decision

Table 1
Some studies of farm-level sustainability.

Author(s) (year)	Approach and data used	Findings
Stempfle et al. (2025)	Tool for Agroecology Performance Evaluation (TAPE) and Farm Accountancy Data Network (FADN) panel data	Agroecology transition has not been widely adopted by the Italian farms. The type of farming, farm management, farm economic and physical size, farm location, and farmer's socio-demographics play a significant role in explaining the variation in the transition intensity towards an agroecological production system.
Diop and Védrine (2025)	A difference-in-discontinuity design on a sample of French farms from Agricultural Census data in 2010 and FADN dataset	Farms around 10 ha experienced significant land reallocation and an increase in crop diversity. Farms around 30 ha increase their number of crops. The main effects were driven by farms that already met the diversification requirements. The crop diversity criterion did not result substantial additional change.
Grzelak and Staniszewski (2025)	FADN and a sample of farms from the Wielkopolska region in Poland applying the classification and regression trees method	The return on assets in farms is low. The return on net profit from assets is mainly sustained by subsidies. Relatively high productivity and scale of production in activities that are accompanied by greater environmental pressures.
Buttinelli et al. (2025)	A sample of Italian FADN arable farms and econometrically estimated translog production function	Reducing chemical inputs may lead to declines in agricultural production, income, and added value in the short to medium term, alongside reductions in variable costs, irrigation water, and labour. Maize grain production is particularly vulnerable,
Winter et al. (2024)	Interdisciplinary method and a data approach with combined several data sources and models.	Interdisciplinary method and a data approach with combined several data sources and models. a high level of direct payments and a 4-month calf fattening strategy has the highest GHG emission reduction potential in Swiss agriculture and a lower level of direct payments combined with a 4-month calf fattening strategy is more cost-effective with regard to GHG emission reduction. The other scenarios show lower GHG reduction potential and lower cost effectiveness.
Halytsia et al. (2024)	Water, energy, food and environment (WEFE) composite indicator values based on uploaded farm-level data for olive producers in Crete	Moderate performance from a WEFE Nexus perspective. Better perform farmers producing olives in an environmentally friendly manner and are concerned with the negative consequences of climate change.
Ait Sidhoum et al. (2023b)	A multi-equation representation the effects of AES on farm-level environmental and economic efficiency using a combination of propensity score matching and a difference-in-difference approach for a balanced sample of Bavarian dairy farms.	AES do not alter farms' economic efficiency. Environmental efficiency is less present by AES participation.
Wang et al. (2023)	Dutch dairy farmers' adoption behaviour of climate change mitigation measures using a Self-regulated Stage model of Behavioural Change using the FADN.	Negative emotion, personal norm, perceived goal feasibility, action planning, and coping planning vary significantly by stage. Personal norm, attitude, goal intention, behavioural intention, and implementation intention are found significantly positive influencing factors on adopting climate mitigation measures. Farmers younger than 45 years old with full agricultural education and farms with high livestock density are more likely to have taken steps in adopting mitigation measures.
Cortignani and Coderoni (2022)	Agro-economic supply model, based on mathematical programming and farm-level FADN data	Losses in added value, higher level of resource efficiency and synergies among different targets differently by sectors.
Cullen et al. (2021)	Ireland representative panel of data as part of FADN spanning 23 years to model the impact of AES on the type of participating farms.	Environmental issues surrounding intensive farms (such as the loss of nutrients and sediment to water and greenhouse gas emissions) are not being optimally addressed to reduce negative environmental impacts
Thomas et al. (2020)	Sample of farms in Ireland using import and export data collected by the Teagasc National Farm Survey (part of the FADN).	As agriculture intensifies, nutrient surpluses, use efficiencies and gross margins increase. Benchmark farms minimise surpluses to relatively low levels, thus are more sustainable due to, per ha, lower fertiliser and feed imports, greater exports of agricultural products, and for dairy, sheep and suckler cattle, relatively high stocking rates.

Source: Compiled by Authors.

making.

The extent to which AES can reduce energy costs depends on the specific design of the scheme and the baseline energy intensity of participating farms (Vlontzos et al., 2014). In some cases, energy savings may be offset by increased labour costs or the need for additional equipment to implement new practices (Pretty et al., 2000; Pacini et al., 2015; Unay-Gailhard and Bojnec, 2015; Bojnec and Fertő, 2022; Rakshit et al., 2023; Mondière et al., 2024). Based on the previous literature, we expect that participation in AES significantly reduces energy costs on farms.

AES often include measures that limit fertilizer use or encourage the adoption of organic fertilizers and cover crops to enhance soil fertility naturally (Hammad et al., 2020; Gazzarin and Jan 2024). By reducing reliance on chemical fertilizers, AES can lower fertilizer input costs and mitigate negative externalities associated with conventional farming, including greenhouse gas emissions, owing to the promotion of organic fertilization and cover cropping (Kleijn et al., 2006; Li et al., 2021; Wu et al., 2021; Micha et al., 2023). However, there can be also trade-offs from carbon and nitrogen footprints of intensive livestock farms, which cannot be neglected. Organic farming practices are frequently supported by AES, relying on compost, manure, and nitrogen-fixing crops to maintain soil fertility, thereby reducing the need for chemical fertilizers (Mäder et al., 2002; Zhang and Drury, 2024). Based on the previous literature, we expect that farmers enrolled in AES exhibit lower fertilizer costs compared to non-participants.

Crop protection costs, which involves costs for the use of herbicide and pesticides to control weeds, pests, and diseases, can represent significant cost for farmers. Intensive pesticide use has raised concerns about human health, environmental pollution, and the development of pest resistance with understanding different enablers and disablers of crop protection, its reduction and transformation for sustainable agriculture (Finger and Möhring, 2022; Young et al., 2022; Deguine et al., 2023; Nipers et al., 2024). It is important reducing over-pesticide use while preserving crop productivity and profitability on farms (Lechenet et al., 2017; Munir et al., 2024), and farming near-optimal use of pesticides in different cropping systems (Frisvold, 2019).

AES promote alternatives to conventional pest management, including IPM principles and techniques, biological control, and the use of pest-resistant crop varieties. AES can help to substantial reductions in herbicide and pesticide use and crop protection costs by adopting IPM and biological control strategies (Pretty and Bharucha, 2015; Kuhfuss and Subervie, 2018; Pergner and Lippert, 2023). AES emphasizes IPM and monitoring, biological control agents, and targeted pesticide application that can contribute to minimizing chemical input use. Based on the literature review, we expect that AES participation incurs reduction in crop protection costs.

Therefore, the overall reduction in variable input costs achieved through AES participation can enhance the long-term economic viability and sustainability of farms, despite potential short-term yield trade-offs. This might be a challenging issue in the decision-making context faced by Slovenian small- and medium-sized mostly family farms in adoption of AES practices. Similarly, to some other EU countries, farmers in Slovenia may apply for AES compensation following the AES adoption contract with extensification rotation and operations practices to diversify income (Czyżewski and Kryszak, 2023). Due to relatively high percentage of LFA areas in Slovenia, unlike to some other EU countries, for example the Netherlands, the influence of farming intensity on the willingness to engage in AES might less severe (Hasler et al., 2022). The mechanisms behind this effect in Slovenia between adopters and non-adopters is investigated in terms of economic farm size, type of farms (crop vs. non-crops), production intensity and technology adoption (LFA vs. non-LFA). The research question is whether voluntary participation in AES may differ according to these farm and location characteristics with pertained possible economic and production constraints.

Despite extensive research on AES adoption, environmental effects, and eco-efficiency, we still lack clear causal evidence on whether AES participation actually changes farms' variable input costs—energy, fertilizer, and crop protection. This gap matters: input costs shape farmers' incentives to enrol, determine the economic sustainability of AES, and represent the direct channel through which these schemes are intended to influence production practices. In addition, the cost effects of AES remain largely undocumented, especially using micro-level panel data and designs that account for staggered adoption. Thus, the key unresolved question is whether AES participation causally alters farmers' spending on major inputs, and how these effects evolve over time.

3. Material and methods

3.1. Methodological approach

This study employs a DiD estimator with staggered treatment timing (Callaway and Sant'Anna, 2021) to measure the causal impact of AES participation on variable input costs. Two primary considerations guided the choice of DiD. First, individual farms enrol in AES at different points in time, enabling a natural comparison between pre- and post-enrolment observations against a control group of non-participants (Goodman-Bacon, 2021). Second, DiD explicitly controls for farm-invariant heterogeneity and common time trends, which can provide a more rigorous assessment of policy effects than a standard fixed-effects model when the timing of policy uptake varies (Angrist and Pischke, 2009; Bertoni et al., 2020).

Although a fixed-effects approach could capture unobserved heterogeneity, it would be less effective in utilizing staggered adoption or mapping out the dynamic effects of AES participation. By contrast, the DiD framework leverages temporal and cross-sectional variation to isolate group- and period-specific impacts, thus disentangling AES-induced changes from broader sectoral trends.

To bolster internal validity, the DiD specification includes a wide array of *control variables* that capture socio-demographic and structural features: farmer age, gender, and agricultural training; unpaid family labour; farm economic size; land productivity; livestock density; and income composition (market vs. off-farm). By controlling for these factors, we help mitigate confounding biases that might otherwise obscure AES effects.

We further address the potential for self-selection into treatment by employing inverse probability weighting (IPW). Observations are reweighted according to their estimated probability of treatment, which reduces confounding from observable differences between AES participants and non-participants.

Finally, we implement *bootstrapped standard errors* to handle any heteroskedasticity and clustering at the farm level, enhancing the reliability of the inference drawn.

A key assumption of the DiD approach is that, in the absence of treatment, the outcomes for treated and untreated groups would follow parallel trajectories (Angrist and Pischke, 2009). To validate this *parallel trend* assumption, we conduct *placebo tests* by artificially assigning treatment status to periods before actual AES enrolment. If the placebo-treated group shows no significant difference compared to the control group in these pre-treatment periods, it suggests that the true DiD estimates are unlikely to be driven by underlying trends unrelated to AES. These placebo tests thus provide additional reassurance regarding the internal validity of our findings.

Given the diversity of farming contexts, it is plausible that AES effects vary according to farm characteristics or environmental settings. To explore potential *heterogeneity*, we perform interaction-based DiD analyses, testing whether AES impacts differ by:

Economic Farm Size – Using economic farm size area to categorize smaller versus larger farms. A median value was used as a criterion to distinguish between smaller versus larger farms. In addition, utilized agricultural area (UAA) farm size is used to calculate physical input use – energy, fertilizer, and crop protection – per hectare of UAA.

Less Favoured Areas (LFA) status – Assessing whether farms located in LFA with natural or biophysical handicaps exhibit distinct treatment responses.

Farm Type – Splitting the sample into crop farms and non-crop farms to identify differential treatment effects based on production orientation. According to the TF8 FADN classification crop farms consist from: (1) field-crops, (2) horticulture, (3) wine, and (4) other permanent crops type of farms. Non-crop farms consist from: (5) milk, (6) other grazing livestock, (7) granivores, and (8) mixed type of farms.

These subgroup analyses facilitate a deeper understanding of which farms experience the largest or smallest cost shifts, offering insight for more targeted policy interventions. If, for example, effects are concentrated in one subgroup, policymakers can tailor incentives or advisory support accordingly.

In summary, the integrated DiD framework, augmented by a thorough set of controls, IPW, placebo tests, and heterogeneity analyses, enables a robust evaluation of how AES participation reshapes farm-level input usage. This approach reflects the study's objective to provide robust empirical evidence for cleaner production transitions in agriculture, with practical relevance for policy design and implementation.

3.2. Data

The balanced panel datasets provided by the FADN range from 2014 to 2021. The use of balanced panel data from FADN ensures consistency and comparability across years and farms. The FADN serves as an informative source of microeconomic data for assessing the effects of CAP measures and monitoring the financial performance and operational activities of farms within EU Member States (European Commission, 2025b), which since 2025 is replaced by the Farm Sustainability Data Network (FSDN) (European Commission, 2025c) to include additional sustainability indicators for improved assessment of the CAP effects (Kelly et al., 2018). The FADN provides farm-level data for agricultural holdings exceeding the size threshold that may be considered commercial, based on national surveys. The farm-level data are presented according to the following criteria: regional farm location (LFA vs. non-LFA), economic size, and farming type (crop vs. non-crop). For this analysis, we used a balanced panel data comprising 263 farms per year, resulting in a total of 2014 observations. The sample includes both AES participants and non-participants, enabling comparative analysis. Farms enrol in AES at different times, which enables natural comparison between pre- and post-enrolment periods.

Table 2 indicates that the sample consists of 68% of non-AES farms and 32% of AES farms. There are notable differences in input costs between farms participating in AES and those not enrolled. Although AES farms display lower fertilizer (1196.024 euro vs. 1625.795 euro) and crop protection (615.312 euro vs. 855.586 euro) costs, these differences are only significant when considered in total monetary terms ($p < 0.05$). Per-hectare values for fertilizer and crop protection do not differ significantly. In contrast, energy costs per hectare are significantly higher for AES farms ($p < 0.001$), suggesting that reduced reliance on chemical inputs may be partly offset by increased energy inputs, highlighting complex resource-use trade-offs.

Table 3 further underscores demographic and operational distinctions. AES farms register a lower proportion of women farmers (mean = 0.236, $p = 0.035$) and a slightly older average age (50.071 years, $p = 0.048$). Education, captured on a three-point scale, is lower in AES farms (1.515 vs. 1.667; $p < 0.001$), possibly reflecting different education and training paths or engagement with sustainable practices. AES farms exhibit significantly higher livestock density (1.205 vs. 0.939, $p < 0.001$), which may require additional land resources but could offer opportunities for diversification. In addition, AES farms vis-a-vis non-AES farms exhibit significantly ($p < 0.001$) higher land productivity, share of market income, and non-crop farms, as well as LFA location ($p < 0.02$), but significantly ($p < 0.001$) lower share of off-farm income as well as smaller economic farm size ($p < 0.09$).

Collectively, these insights underscore how policy-driven sustainability initiatives affect not only cost structures but also farm demographics, informing the development and refinement of AES strategies under the evolving CAP framework.

Table 2
Mean and standard deviation of the outcome variables by participating in AES.

	Non-AES farm	AES farm	Total	Kruskal-Wallis test
N	1430	674	2104	
fertilizer cost (euro)	1625.795 (4821.706)	1196.024 (2069.290)	1488.121 (4148.284)	0.027
crop protection cost (euro)	855.586 (2407.282)	615.312 (1446.429)	778.616 (2149.382)	0.017
energy cost (euro)	4270.544 (5049.977)	3419.485 (3058.111)	3997.914 (4525.432)	<0.001
fertilizer cost/ha	79.380 (122.790)	87.418 (140.478)	81.955 (128.742)	0.182
crop protection cost/ha	59.850 (160.379)	54.784 (125.778)	58.227 (150.154)	0.470
energy cost/ha	252.317 (157.721)	290.001 (178.478)	264.389 (165.550)	<0.001

Note: standard deviation in brackets.
Source: Authors' calculations

Table 3
Mean and standard deviation of the independent variables by participating in AES.

	Non-AES farm	AES farm	Total	Kruskal-Wallis test
Gender (men = 0, women = 1)	0.196 (0.397)	0.236 (0.425)	0.209 (0.406)	0.035
Age (year)	48.871 (13.345)	50.071 (12.279)	49.255 (13.022)	0.048
Education (1-3)	1.667 (0.697)	1.515 (0.645)	1.618 (0.684)	<0.001
Share of unpaid labour (%)	97.1 (11.0)	98.2 (8.1)	97.4 (10.2)	0.014
Land productivity (euro/ha)	2589.556 (2777.588)	2923.417 (2870.534)	2696.506 (2811.335)	0.011
Livestock density (livestock unit/ha)	0.939 (1.006)	1.205 (1.063)	1.024 (1.032)	<0.001
Share of market income (%)	0.414 (0.946)	0.690 (0.287)	0.502 (0.807)	<0.001
Share of off-farm income (%)	0.204 (0.257)	0.158 (0.208)	0.189 (0.243)	<0.001
Economic farm size (1000 euro)	39.343 (81.581)	33.618 (38.332)	37.509 (70.709)	0.083
LFA (LFA = 1, non LFA = 0)	0.799 (0.401)	0.841 (0.366)	0.812 (0.391)	0.019
Crop farm (Crop farm = 1, non-crop farm = 0)	0.252 (0.435)	0.188 (0.391)	0.232 (0.422)	0.001

Note: standard deviation in brackets.
Source: Authors' calculations

4. Results

This section provides detailed empirical findings on the impacts of participation in AES on variable input costs—energy, fertilizer, and crop protection—within Slovenian FADN farms. Utilizing a DiD estimation with staggered adoption methodology (Callaway and Sant'Anna, 2021), we examine both absolute input expenditures and relative input expenditures normalized per hectare. Our findings are illustrated in Tables 4–6 and are complemented visually by event study plots (Figs. 1–3).

4.1. Effect on energy costs

Our analysis indicates that AES participation substantially reduces both absolute and relative (per-hectare) energy costs on Slovenian farms. Specifically, as illustrated in Table 3, farms enrolled in AES experienced an average annual reduction in relative energy expenditures of 186.97 euro per hectare, which was statistically significant ($p = 0.012$). Absolute energy expenditures also decreased, albeit the reduction of 690.45 euro did not achieve conventional statistical significance ($p = 0.164$), likely due to greater variability in economic farm size and farming practices.

The event study plot (Fig. 1) clearly illustrates the temporal dynamics of these savings, demonstrating a distinct downward trajectory in energy expenditures immediately following AES enrolment. This consistent reduction likely reflects a systematic transition towards less energy-intensive agricultural practices, such as conservation tillage methods, precision agriculture technologies, and organic fertilization practices. These approaches inherently require less mechanical input and synthetic energy-intensive inputs, thereby significantly reducing the

Table 4
Difference-in-Differences estimates for energy costs
(Outcome: Annual farm energy expenditures; N = 160 farms).

Coefficient/Statistic	energy expenditures			energy expenditures/ha		
	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value
Pretrend Test	Chi^2: 1.338		0.247	Chi^2: 1.936		0.164
ATT	−690.45	496.60	0.164	−186.97	74.12	0.012
95% Confidence Interval	[-1663.78, – 282.87]			[−332.24, −41.70]		
ATT by Group						
G2016	−1155.61	412.31	0.005	−249.30	54.44	0.000
G2017	2274.91	2338.25	0.331	210.35	402.79	0.602
ATT by Calendar Period						
T2018	−2965.38	1325.03	0.025	−624.57	226.01	0.006
T2020	−1588.45	1031.14	0.123	−253.75	184.93	0.170
Event Study (Post-avg)	−735.673	371.25	0.048	−196.04	64.69	0.002

Notes: ATT = Average Treatment Effect on the Treated. The "Pretrend Test (p-value)" refers to the joint test that all pre-treatment coefficients are zero.
Source: Authors' calculations.

Table 5
Difference-in-Differences estimates for fertilizer costs
(Outcome: Annual farm fertilizer expenditures; N = 160 farms).

Coefficient/ Statistic	fertilizer expenditures			fertilizer expenditures/ha		
	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value
Pretrend Test	Chi^2: 0.3148		0.5748	Chi^2: 0.2635		0.6078
ATT	1133.10	345.95	0.001	38.34	19.44	0.049
95% Confidence Interval	[455.0, 1811.1]			[0.23, 76.44]		
ATT by Group						
G2016	1182.58	391.15	0.003	41.12	21.78	0.059
G2017	817.67	482.62	0.090	20.62	31.46	0.512
ATT by Calendar Period						
T2017	3589.64	1084.92	0.001	164.42	59.96	0.006
T2020	−176.7	181.09	0.329	−33.74	11.73	0.004
Event Study (Tp1)	3613.32	1075.50	0.001	165.98	59.51	0.005

ATT = Average Treatment Effect on the Treated. The "Pretrend Test (p-value)" refers to the joint test that all pre-treatment coefficients are zero.
Source: Authors' calculations.

overall environmental footprint and energy consumption per hectare. Importantly, these savings provide substantial economic benefits, potentially improving the overall financial viability and sustainability of participating farms.

4.2. Effect on fertilizer costs

In contrast to energy expenditures, the relationship between AES participation and fertilizer costs is more complex, characterized by short-term increases followed by longer-term stabilization or potential reductions (Table 5). Immediately following AES adoption, our analysis reveals a significant rise in absolute fertilizer expenditures amounting to 1133.10 euro annually (p = 0.001). Concurrently, the per-hectare fertilizer costs also showed a moderate initial increase (38.34 euro, p = 0.049). These results reflect a transition phase where farms invest in enhanced soil amendments, organic fertilizers, or other sustainable inputs that may initially be more expensive compared to conventional synthetic fertilizers.

However, the event study plots (Fig. 2) demonstrate a clear pattern where the initial increases in fertilizer expenditures diminish over subsequent years, eventually converging with or falling below the control group of non-AES participants. This suggests that the higher initial expenditures represent a necessary investment in the transition toward more sustainable nutrient management strategies, eventually leading to improved soil fertility and reduced need for synthetic inputs in the longer run. These findings highlight an important transition cost phase that policymakers should consider when designing and implementing AES programs. Proper financial and advisory support during the initial years can significantly alleviate these upfront costs and encourage wider adoption among farmers.

4.3. Effect on crop protection costs

AES participation consistently and significantly reduced both absolute and relative crop protection expenditures. Table 6 presents clear

Table 6
Difference-in-Differences estimates for crop protection costs
(Outcome: Annual farm crop protection expenditures; N = 160 farms).

Coefficient/Statistic	crop protection expenditures			crop protection expenditures/ha		
	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value
Pretrend Test (p-value)	Chi^2: 0.9022		0.3422	Chi^2: 1.4472		0.2290
ATT	−376.72	114.90	0.001	−36.94	10.28	0.000
95% Confidence Interval	[-601.93, – −151.51]			[−57.09, −16.79]		
ATT by Group						
G2016	−350.62	105.71	0.001	−34.06	7.17	0.000
G2017	−543.08	525.09	0.301	−55.31	62.67	0.377
ATT by Calendar Period						
T2016	−120.38	54.66	0.028	−18.63	7.99	0.020
T2017	−646.77	193.51	0.001	−61.52	15.19	0.000
T2020	62.17	74.20	0.402	13.99	10.26	0.173
Event Study (Tp1)	−655.42	189.06	0.001	−62.97	14.31	0.000

Notes: ATT = Average Treatment Effect on the Treated. The "Pretrend Test (p-value)" refers to the joint test that all pre-treatment coefficients are zero.
Source: Authors' calculations.

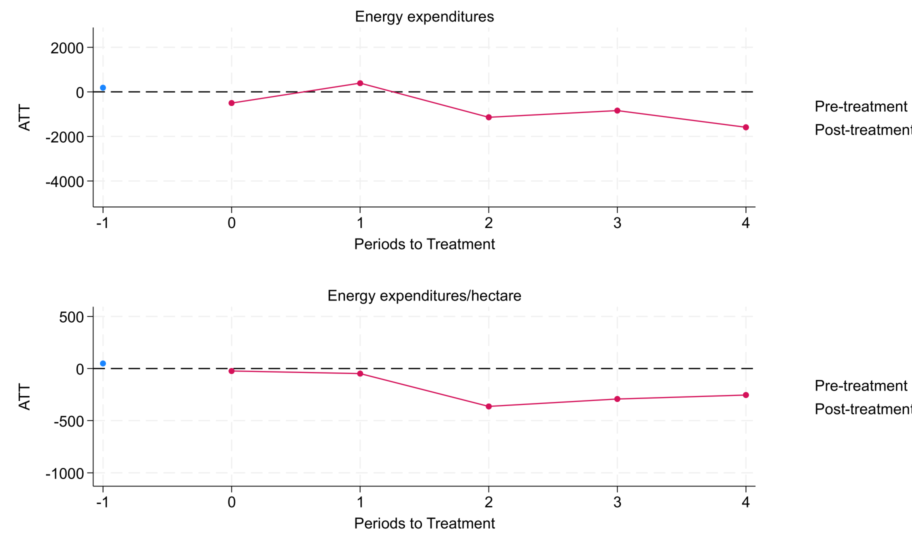

Fig. 1. Event study plots for energy expenditures.
Source: Authors' calculations.

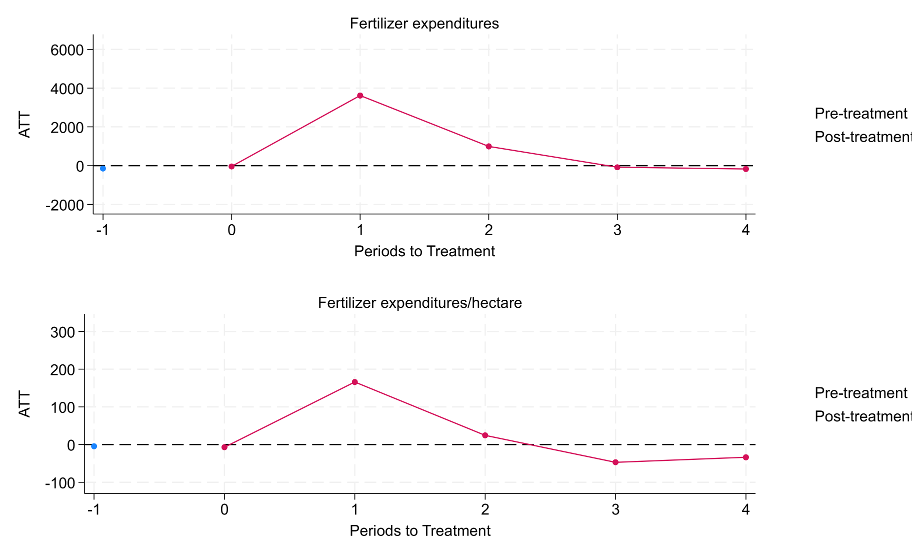

Fig. 2. Event study plots for fertilizer costs.
Source: Authors' calculations.

evidence of this, revealing that absolute expenditures on crop protection measures, including pesticides and herbicides, dropped significantly by 376.72 euro per year ($p = 0.001$). When normalized by farm UAA size, per-hectare crop protection expenditures also declined markedly by 36.94 euro annually ($p < 0.001$), reinforcing the robust impact of AES in reducing chemical inputs.

The event study analysis (Fig. 3) further clarifies this impact, showing an immediate and sustained decrease in crop protection costs post-enrolment. This persistent reduction underscores the long-term adoption of IPM practices and biological control strategies promoted through AES. Farmers shifting towards IPM typically apply fewer synthetic chemical interventions due to enhanced pest monitoring, biological pest control measures, and careful selection of pest-resistant crop varieties. Consequently, these practices not only lower input costs but also reduce environmental social costs as negative externalities such as soil and water contamination, pesticide resistance, and negative impacts on biodiversity.

4.4. *Validation of the parallel trend assumption*

The credibility of the DiD estimates relies heavily on the parallel trend assumption. To validate this, we conducted rigorous pre-treatment tests across all input categories—energy, fertilizer, and crop protection. Our results (Tables 4–6) consistently indicated no statistically significant divergence between treated and untreated groups in the pre-treatment period, with p-values exceeding standard significance levels. This confirms that both groups exhibited similar cost trajectories before AES adoption, strengthening our confidence in the causal interpretation of AES participation effects.

4.5. *Comprehensive synthesis of findings*

Collectively, our empirical results demonstrate that AES participation can lead to substantial reductions in farm input expenditures for energy and crop protection while temporarily increasing fertilizer costs during the early transition phase. The nuanced pattern of fertilizer cost dynamics provides important insights for policymakers: upfront costs in sustainable practices may represent necessary initial investments that

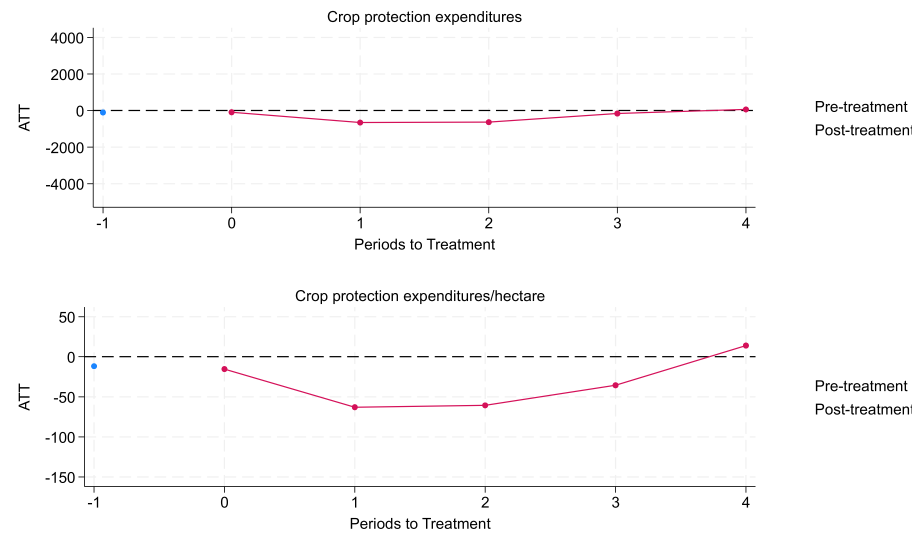

Fig. 3. Event study plots for crop protection costs.
Source: Authors' calculations.

ultimately yield environmental and economic benefits.

From an economic perspective, reduced energy and crop protection expenditures contribute to enhanced farm profitability and financial resilience. Environmentally, the shift towards less intensive resource use aligns directly with broader sustainability objectives and EU policy frameworks, such as the European Green Deal and Farm to Fork Strategy. These changes directly support achieving EU-wide targets for sustainable agriculture by significantly lowering greenhouse gas emissions, reducing reliance on synthetic inputs, and enhancing biodiversity (Shen et al., 2022).

Policymakers should therefore consider both short-term transitional costs and long-term gains when designing and implementing AES. Effective AES should incorporate robust support mechanisms, including targeted subsidies, technical training, and knowledge transfer initiatives, enabling farmers to successfully navigate initial investments in sustainable practices.

In conclusion, our detailed empirical analysis underscores the critical role of AES in promoting sustainable agricultural practices that effectively balance environmental sustainability and economic viability. The clear reductions in energy and crop protection costs, combined with insights into fertilizer management strategies, highlight the need for well-designed AES to incentivize broader adoption and achieve long-term sustainability goals.

5. Robustness checks

5.1. Placebo tests

To rigorously assess the credibility of our DiD identification strategy, we implemented a set of placebo tests in which artificial AES treatment dates were assigned to periods preceding the actual adoption of the schemes. These tests serve two complementary purposes: (i) to verify that estimated AES effects are not driven by pre-existing trends or spurious correlations, and (ii) to provide evidence in support of the parallel trends' assumption. We examined both *relative (per-hectare)* and *absolute* cost measures across three major input categories: energy, crop protection, and fertilizer. The aggregated results are presented in Table 7.

For *absolute energy costs*, the placebo average treatment effect on the treated (ATT) was small and statistically insignificant (104.89 euros; p = 0.266). Likewise, dynamic placebo estimates around the artificial treatment date—including the contemporaneous effect (Tp0 = 49.01 euros; p = 0.164)—show no indication of meaningful pre-trends. This pattern provides strong reassurance that the main DiD estimates for energy expenditures are unlikely to be driven by confounding trends in total energy spending prior to AES adoption.

In contrast, the *per-hectare energy cost* estimate yielded a sizable and statistically significant placebo effect (1422.88 euros; p = 0.004). This anomalous result suggests that energy intensity (rather than total expenditures) may have been influenced by external shocks or unobserved factors in the artificially treated periods. While this does not undermine the overall validity of our identification strategy, it indicates the presence of input-specific dynamics that may warrant additional exploration—such as sensitivity checks focusing on model specification, adjustment for outlier farms, or alternative normalizations of energy expenditure.

Turning to *crop protection costs*, the placebo results are largely reassuring. The per-hectare placebo ATT is marginally significant at conventional levels (−32.88 euros; p = 0.076), but the effect is modest in magnitude and not accompanied by a consistent temporal pattern in the event-study analysis. The placebo estimate for absolute crop protection costs is clearly insignificant (−299.68 euros; p = 0.123). Taken together,

Table 7
Summary of Placebo test results for per hectare and absolute costs.

Input Type	Absolute costs			Per hectare costs			Key Interpretation
	Placebo ATT	Std. Error	p-value	Placebo ATT	Std. Error	p-value	
Energy	104.89	94.23	0.266	1422.88	496.36	0.004	Costs per hectare significant; Absolute costs insignificant—potential unobserved confounding
Crop Protection	−32.88	18.53	0.076	−299.68	194.27	0.123	Mostly insignificant effects; marginal cost per hectare result demands cautious interpretation
Fertilizer	−13.37	29.20	0.647	163.03	596.46	0.785	Both per hectare and absolute costs insignificant; strong support for parallel trends

Source: Authors' calculations.

these findings indicate the absence of systematic pre-treatment biases in crop protection spending, although the marginal per-hectare result suggests caution when interpreting the corresponding main estimates.

The placebo tests for *fertilizer costs* provide the strongest support for parallel trends. Both per-hectare and absolute placebo effects are unequivocally insignificant (163.03 euros, $p = 0.785$; −13.37 euros, $p = 0.647$), and the dynamic profiles show no discernible patterns suggestive of pre-existing trends. These results indicate that fertilizer expenditures evolve smoothly before actual adoption and are not subject to confounding time-varying factors.

Overall, the placebo analyses offer robust evidence in favour of the validity of our DiD approach. The predominance of insignificant estimates across input types and cost measures supports the parallel trends assumption and minimizes concerns about unobserved confounding. The notable exception—significant per-hectare energy costs—warrants additional investigation into potential idiosyncratic shocks or modelling issues specific to energy intensity. Nonetheless, the broader pattern of results reinforces the credibility of the estimated AES impacts reported in the main analysis.

5.2. Heterogeneity tests

5.2.1. Farm economic size

This section presents findings on the impacts of AES participation on input costs, including energy, fertilizer, and crop protection expenditures, and assesses whether these impacts vary by farm economic size (SE005). We used an interaction-based DiD approach to explicitly examine potential heterogeneity in treatment effects. However, the interaction analysis revealed no statistically significant differences in treatment effects by farm economic size. Consequently, the ATT remained consistent with those obtained without interaction terms. Results are summarized in Table 8.

AES participation was associated with a significant short-term increase in fertilizer expenditures, with an absolute ATT of 1133.10 euro. Expenditures per hectare increased moderately (38.34 euro). The event study analysis highlights a peak increase one year after AES enrolment (3613.33 euro), followed by stabilization or decline in subsequent years. Pre-treatment tests confirmed no significant differences between treated and untreated farms, validating the parallel trends assumption. Importantly, despite testing for farm economic size heterogeneity, the interaction term was insignificant, indicating the effect of AES on fertilizer costs is uniform across farm economic sizes. Thus, policy interventions to support transitional costs should be universally available rather than farm economic size specific.

Crop protection expenditures significantly decreased due to AES participation, with reductions in both absolute (376.72 euro) and per hectare (36.94 euro) terms. Event study results showed consistent post-treatment reductions, particularly pronounced two years after enrolment (−634.01 euro). Pre-treatment parallel trends tests were satisfied ($p = 0.229$). Interaction analysis indicated no significant moderation by farm economic size, suggesting uniform effectiveness of AES measures like IPM and biological control practices across different farm economic sizes. These results emphasize AES as broadly applicable measures for sustainable pest management without a need for differentiated incentives based on farm economic size.

AES participation significantly decreased energy costs per hectare (−186.97 euro), though the absolute expenditure reduction (−690.45 euro) was not statistically significant. Event study results confirmed significant absolute cost reductions notably two years post-enrolment (−2965.38 euro), and pre-treatment trends tests validated the causal interpretation ($p = 0.164$). Farm economic size interaction terms were again insignificant, reinforcing the conclusion that AES effects on energy expenditures do not depend significantly on farm economic size. Policies promoting energy-efficient practices can therefore be effectively designed without differentiation based on farm economic size.

The analyses confirm AES significantly affects fertilizer, crop protection, and energy expenditures, yet do not indicate significant farm economic size heterogeneity. Consequently, policymakers can efficiently design universal AES incentives and supports applicable across diverse farm economic sizes, facilitating broad adoption of environmentally sustainable agricultural practices.

5.2.2. Heterogeneity analysis by Less Favoured Areas (LFA)

This section explores the heterogeneity in AES impacts on input costs based on farm location within LFAs. Using an interaction-based DiD approach, we explicitly examine whether farms located in LFAs experience different AES effects compared to those in non-LFA regions. The results for fertilizer, crop protection, and energy costs, both in absolute and per hectare terms, are summarized in Table 9.

AES participation increased fertilizer expenditures by 31.56 euro per hectare with absolute costs rising significantly (981.72 euro). Although no significant pre-treatment differences were observed ($p = 0.945$), post-treatment dynamics varied significantly across individual years. Specifically, immediate post-enrolment fertilizer expenditures significantly rose (130.34 euro per hectare) but gradually returned towards baseline levels. These findings indicate an initial investment period in LFA farms, aligning with the broader AES goal of promoting sustainable fertilizer use. However, the statistically insignificant interaction term implies similar impacts irrespective of LFA status.

AES significantly reduced crop protection expenditures per hectare (−41.62 euro) and absolute expenditures (−468.52 euro), reflecting consistent adoption of sustainable pest management practices. Pre-treatment trends showed marginal differences ($p = 0.075$), but the robust post-treatment reductions, notably in the immediate years post-enrolment (−63.25 euro per hectare), underscore AES efficacy. While the absolute crop protection costs reduction was consistently significant, the interaction analysis showed no substantial moderation by LFA location, suggesting uniform AES benefits in sustainable crop protection across farm types.

AES significantly reduced energy costs per hectare (−151.68 euro). Although absolute cost reductions (−282.76 euro) were statistically insignificant, notable annual reductions emerged two years post-enrolment (−452.35 euro). Pre-treatment trends validated the causal interpretation ($p = 0.312$). Despite considerable reductions in energy costs per hectare, no significant differences emerged based on LFA status, indicating comparable AES-driven energy savings across diverse farm location geographic contexts.

The interaction analysis generally found uniform AES effects across LFA and non-LFA farms for fertilizer, crop protection, and energy costs. These results indicate that AES policies provide consistent economic and

Table 8
Summary of AES effects.

Input Costs	Absolute ATT (euro)	p-value	Per hectare ATT (euro)	p-value
Fertilizer	1133.10	0.001	38.34	0.049
Crop protection	−376.72	0.001	−36.94	<0.001
Energy	−690.45	0.164	−186.97	0.012

Source: Authors' calculations.

Table 9
Summary of AES effects considering LFA status.

Input Costs	Absolute ATT (euro)	p-value	Per hectare ATT (euro)	p-value
Fertilizer	981.72	0.002	31.56	0.081
Crop protection	−468.52	0.001	−41.62	0.001
Energy	−282.76	0.599	−151.68	0.036

Source: Authors' calculations.

environmental benefits regardless of geographic disadvantages. Thus, policy frameworks can apply uniformly across LFA and non-LFA regions, simplifying AES implementation.

5.2.3. Heterogeneity analysis by farm type (crop versus non-crop farms)

This section investigates how AES impacts vary between crop farms and non-crop farms using an interaction-based DiD approach. Farms were classified based on their main production orientation into crop farms (coded as 1) and non-crop farms (coded as 0). Results of AES effects on fertilizer, crop protection, and energy costs, presented in both absolute and per hectare terms, are summarized in Table 10.

AES participation significantly increased fertilizer expenditures on a per-hectare basis (69.19 euro, $p = 0.007$) and in absolute terms (1687.34 euro, $p = 0.001$). Notably, substantial increases were observed in the first-year post-enrolment, with per-hectare expenditures rising sharply (187.49 euro, $p = 0.004$), and absolute expenditures escalating dramatically (4084.20 euro, $p = 0.001$). These short-term increases reflect an initial investment phase likely associated with transitioning to sustainable fertilizer management practices. No significant pre-treatment differences were detected ($p = 0.945$), affirming the robustness of the treatment effect. Importantly, these AES-driven increases were observed uniformly across both crop and non-crop farms, indicating a generalizable effect independent of farm production type.

AES adoption consistently led to significant reductions in crop protection expenditures per hectare (−48.19 euro) and in absolute terms (−486.78 euro). The largest relative decreases emerged one year after treatment (−71.95 euro per hectare), emphasizing the rapid adoption of IPM strategies promoted by AES schemes. Pre-treatment trends showed marginal significance, but robust post-treatment declines affirm AES effectiveness. These significant cost savings were consistent across both crop and non-crop farms, underscoring AES as a broadly applicable strategy to reduce reliance on chemical inputs.

Energy expenditures significantly declined following AES participation, both in per hectare (−261.89 euro) and absolute terms (−1142.67 euro). The largest absolute decrease occurred two years post-treatment (−3313.61 euro), potentially reflecting delayed effects from investments in energy-efficient technologies or practices. Pre-treatment tests supported the parallel trends assumption, strengthening causal interpretation. Again, the absence of significant interaction terms highlights that energy cost reductions due to AES participation were similar for crop and non-crop farms, suggesting universal potential for energy cost savings through AES participation regardless of farm specialization.

The analysis revealed no significant differences in AES impacts between crop and non-crop farms for fertilizer, crop protection, and energy costs. Thus, AES policies demonstrate broad-based applicability and can effectively be promoted across diverse farm types to achieve sustainability objectives.

6. Discussion and implications of findings

This study used a DiD estimator with staggered adoption to explore the effects of AES on three key farm input costs—energy, fertilizer, and crop protection—drawing on a balanced panel of Slovenian FADN farms. Sections 4 and 5 present detailed empirical evidence that AES can drive both short-term and persistent changes in production practices.

Table 10
Summary of AES effects by farm type.

Input Costs	Absolute ATT (euro)	p-value	Per hectare ATT (euro)	p-value
Fertilizer	1687.34	0.001	69.19	0.007
Crop protection	−486.78	<0.001	−48.19	<0.001
Energy	−1142.67	0.044	−261.89	0.001

Source: Authors' calculations.

The discussion below synthesizes these results, highlighting immediate cost shifts, longer-run patterns, and important robustness checks.

6.1. Energy expenditures

Section 4 shows that AES participation yields an *overall decrease in energy spending*, particularly on a per-hectare basis (−186.97 euro, $p = 0.012$). Although absolute energy expenditures (−690.45 euro) do not attain conventional statistical significance, the event-study plots confirm a clear downward trajectory in the years following enrolment. By fostering transitions toward less intensive tillage, organic fertilization, and adoption of precision agriculture, AES appear to reduce reliance on fossil fuel inputs (OECD, 2017; Fukuyama et al., 2020).

One positive implication is that farms can potentially reduce their carbon footprint without necessarily compromising output. Nonetheless, Section 5 raises a caveat via the *placebo tests:* although energy costs pe hectare show no significant pre-trend bias, absolute energy costs occasionally display large shifts that may reflect external shocks or outliers. Overall, the robustness checks support a genuine AES-induced reduction in energy intensity, albeit with some residual noise in year-to-year spending. Policymakers could enhance these gains through targeted training in energy efficiency and possible subsidies for low-carbon innovations and bioenergy (Gérard and Pierre-Alain Jayet, 2023).

6.2. Fertilizer costs

By contrast, *fertilizer expenditures increase significantly* in the short run. Section 4 reports an immediate jump of +1133.10 euro per farm ($p = 0.001$) and +38.34 euro per hectare ($p = 0.049$). These spikes likely originate from front-loaded investments in improved soil fertility management, including organic amendments, cover cropping, or more specialized nutrient applications (Mäder et al., 2002). Although costs moderate over time, the initial surge can pose financial barriers for certain farms, particularly if a short-term spikes in fertilizer cost increases are also driven by external shocks with fertilizer price increases.

Section 5's *robustness checks* bolster confidence in these findings. Placebo analyses fail to detect a pre-trend bias, indicating that the fertilizer cost jump is indeed tied to AES adoption rather than unobserved confounders. Furthermore, heterogeneity tests (Section 5) show that neither farm economic size nor location in LFA significantly alters the fertilizer spending pattern. Thus, the transition-phase increase appears to affect diverse farm types. From a policy perspective, the results imply that bridging measures—such as short-term grants or tax deductions—could help farmers overcome up-front fertilizer expenses and transition more smoothly to lower overall reliance on synthetic inputs later.

6.3. Crop protection costs

A more uniformly positive effect emerges in *crop protection costs*. Section 4 identifies a statistically significant drop in absolute pesticide expenditures (−376.72 euro, $p = 0.001$) and in per-hectare spending (−36.94 euro, $p < 0.001$). The event-study figures also indicate that this reduction appears quickly and persists, reflecting sustained adoption of IPM, biological control, or targeted pesticide applications.

Crucially, Section 5 reaffirms this result through placebo tests and checks for farm-type variation: neither artificially assigned treatment dates nor differences in production orientations (e.g., crop vs. non-crop farms) undermine the core finding. These consistent results across multiple specifications suggest that AES reliably encourages practices that cut pesticide use and associated costs (Pretty and Bharucha, 2015; Kuhfuss and Subervie, 2018). For policymakers, the decline in chemical inputs represents a major environmental gain—mitigating groundwater contamination, fostering biodiversity, and reducing health risks to farm workers. While the groundwater quality in different regions can depend on different factors, Slabe-Erker et al. (2017) argued the impacts of AES on groundwater quality in Slovenia. Pairing AES with technical advice in pest scouting and biological controls could scale the ecological benefits.

6.4. Robustness checks and parallel trends

Section 5 provides an important assessment of *parallel trends* and potential confounders. The DiD design crucially depends on the assumption that, in the absence of AES, treated and untreated farms would have followed similar cost trajectories. Across the three cost categories analysed, pre-treatment tests reveal no statistically significant differences, supporting the model's validity. Moreover, the *placebo analyses*—in which artificial treatment dates are assigned before actual AES participation—largely yield null results, indicating minimal evidence of spurious pre-existing trends.

Additionally, *heterogeneity analyses* show that neither farm economic size, LFA status, nor production orientation types (crop vs. non-crop) significantly modify the direction of estimated AES effects. While there may be minor variations in the magnitudes of cost changes, the broad pattern of *energy and pesticide reductions, short-term fertilizer increases* hold across these groups. This suggests that AES policies can be broadly effective, reducing the need for extreme tailoring to particular farm segments—though specialized measures could still benefit unique contexts (e.g., intensive horticulture vs. extensive grassland systems).

6.5. Policy and sustainability implications

Synthesizing the evidence from Sections 4 and 5, the net effect of AES is a *twofold shift* in farm-level resource use. On the one hand, *energy and pesticide reductions* emerge relatively quickly, aligning with policy goals to curb agriculture's carbon footprint and chemical intensity. On the other hand, *fertilizer costs* may temporarily rise, highlighting that some environmentally beneficial practices (e.g., organic soil amendments) can demand up-front investment.

Supporting *transition costs.* Considering these findings, policymakers should account for the potential strain of higher fertilizer bills, especially for smaller or more budget-constrained farms. Short-term financial support (grants, favourable credit) or specialized advisory services (precision fertilization training) could help participants reap long-term economic and environmental rewards. Such measures are essential to prevent early dropouts and ensure robust participation rates.

Co-benefits and long-run viability. In the medium to long term, the improved soil health arising from organic fertilizers and adjusted crop rotations may lower synthetic input use. Although our analysis did not directly measure yields or profitability, prior literature (Pacini et al., 2015; Wu et al., 2021) suggests that improved soil management can enhance farm resilience—an especially relevant outcome given climate change pressure. Reducing pesticide use similarly fosters biodiversity and may reduce the risk of pest resistance, ultimately benefiting productivity. Future evaluations could broaden the scope to include yield effects, soil carbon stocks, or farm incomes over a longer panel.

Linking to broader EU targets. The European Green Deal and Farm to Fork Strategy aim to cut pesticide usage, reduce greenhouse gas emissions, and promote soil health across member states (European Commission, 2019a, 2020a). This study's findings confirm that AES can serve these agendas on multiple fronts, provided schemes are designed with awareness of transitional fertilizer spikes and accompanied by robust advisory support. Integrating AES with farm diversity impacts and complementary instruments (e.g., eco-schemes, cross-compliance standards) on food production, income generation and environmental preservation may amplify synergy and encourage widespread adoption of sustainable practices (Pedolin et al., 2023).

Sustainability implications. Overall, the results in Sections 4 and 5 highlight the *effectiveness* of AES in lowering energy and crop protection costs while also revealing *short-term fertilizer cost increases* that moderate over time. Placebo tests, pretrend checks, and heterogeneity analyses corroborate these effects, suggesting they are neither driven by selection bias nor by specific farm types or LFAs. For farmers, the shift away from fossil fuels and pesticides can generate immediate cost savings and reduced environmental risk. Kaligarič et al. (2019) argued that Slovenia failed of AES implementation regarding promotion and conservation grassland biodiversity. Therefore, upfront investments in soil fertility and conservation of grassland biodiversity, which is particularly widespread in LFAs, may create transitional challenges but promise long-term gains.

The evidence underscores AES as valuable policy tools that balance environmental stewardship with farm-level economic outcomes. To optimize adoption, policymakers should account for the initial fertilizer cost burden and support or advice farmers accordingly (Baležentis et al., 2022). Strengthening technical advice and bridging finance can boost uptake, aiding the EU's broader objectives for a climate-friendly, resource-efficient agricultural sector (Wuepper et al., 2021). Over time, the synergy between reduced energy inputs, lower pesticide reliance, and refined soil management could lead to more resilient farming systems—benefiting not only individual producers but also consumers and society at large through cleaner and circular production principles.

6.6. Environmental outcomes

While our findings show that AES can promote substantial input cost reductions—particularly in energy use and crop protection—these economic indicators also have implications for environmental outcomes, which are a cornerstone of cleaner production. Although direct environmental data (for example, actual fertilizer application rates, soil carbon levels, or water quality measures) were unavailable in our dataset, the literature supports a link between these forms of cost savings and ecological benefits (Grzelak and Staniszewski, 2025; Buttinelli et al., 2025; Buttinelli and Zhu, 2025). Reduced pesticide expenditures, for instance, are often associated with fewer chemical residues in soil and water, thereby lowering pollution risks, slowing the development of pest resistance, and fostering greater biodiversity. Similarly, lower energy expenditures typically imply less reliance on fossil-fuel-intensive farm operations, translating to reduced greenhouse gas emissions. Meanwhile, the short-term increase in fertilizer costs we observe can reflect a strategic shift toward more sustainable nutrient management—such as organic fertilization or cover-cropping—that, after an initial investment phase, may enhance soil structure and fertility. These assumed mechanisms (i.e., cost savings underpinned by reduced input intensity leading to environmental benefits) should be more explicitly verified in future work by integrating direct indicators of soil health, air and water quality, or biodiversity. Doing so would more conclusively establish how AES-driven input cost changes translate into tangible improvements in environmental sustainability.

6.7. Comparative discussion of the findings to existing findings

Our findings contribute to a better understanding of how AES shape farm-level production decisions by documenting their direct effects on variable input costs, a dimension that has received less attention in existing work (Unay-Gailhard and Bojnec, 2021; Fertő and Bojnec, 2024, 2025). The result that AES participation reduces crop protection expenditures align with earlier evidence showing that IPM-oriented AES shift farmers away from synthetic pesticides (Pretty and Bharucha, 2015; Kuhfuss and Subervie, 2018; Pergner and Lippert, 2023). What our study adds is causal evidence that these behavioural changes also translate into lower monetary outlays, confirming that environmental compliance can reduce operating costs even in the short term.

The observed decline in energy costs is likewise consistent with studies demonstrating that AES promote less energy-intensive practices through reduced tillage or lower chemical input use (Lal, 2004; Ait Sidhoum et al., 2023a). While prior studies typically focus on energy intensity or eco-efficiency, our results show that these agronomic shifts also carry economic implications, suggesting a channel through which

AES can enhance both environmental and cost efficiency.

In contrast, the short-run increase in fertilizer costs appears to diverge from some studies reporting reduced synthetic fertilizer use among AES participants (Kleijn et al., 2006; Styles et al., 2018). However, this short-term rise aligns with recent findings that transitions toward organic amendments or improved soil fertility management can generate initial adjustment costs before longer-term stabilization (Micha et al., 2023; Buttinelli et al., 2025). Our dynamic estimates therefore help reconcile seemingly contradictory findings in the literature by showing that both reactions—initial cost increases and eventual reductions—can occur within the same adoption trajectory.

Finally, our results complement broader work on economic and environmental efficiency. Ait Sidhoum et al. (2023b) and Baráth et al. (2024) find that AES do not harm economic efficiency and may improve eco-efficiency. Our evidence suggests a mechanism consistent with these results: lower energy and pesticide costs may offset initial fertilizer investments, contributing to medium-term economic stability. By focusing explicitly on the cost channel, this study sheds light on an underexplored mechanism linking AES participation to farm-level economic outcomes.

7. Conclusion

This study provides new causal evidence on how AES reshape farm-level cost structures by exploiting staggered adoption among Slovenian farms. The results show that AES participation consistently reduces energy and crop protection expenditures, while fertilizer costs rise in the short term before stabilizing. These patterns suggest that AES affect farmers' decisions through a clear economic channel: they lower the cost of some inputs immediately while requiring transitional investment in others. That mechanism helps explain why AES can promote cleaner production without necessarily undermining economic performance.

These findings carry several implications. The decline in energy and pesticide expenditures indicates that AES can generate economic co-benefits alongside environmental ones, strengthening the case for continued public investment in such schemes. At the same time, the temporary increase in fertilizer costs highlights a predictable adjustment phase that policymakers should account for. Transitional support—-whether through advisory services, co-financing of organic fertilisers, or risk-sharing instruments—may be necessary to prevent early attrition and to ensure that resource-constrained farms can benefit from AES participation.

The analysis also has limitations. FADN data do not report direct environmental outcomes, meaning that we infer ecological mechanisms from cost changes rather than observing them directly. Unobserved time-varying factors may still influence both AES participation and input costs, despite the strengths of the DID framework. Moreover, the study covers a relatively short period, limiting our ability to capture longer-run effects, such as soil fertility gains or cumulative improvements in energy efficiency.

These limitations create opportunities for future work. Linking economic data with environmental monitoring indicators would allow researchers to measure the joint evolution of costs, practices, and ecological outcomes. Examining how AES interact with other CAP instruments may further clarify whether their effects are complementary or overlapping. A longer-term analysis of yields, profitability, and resilience would help determine whether initial fertilizer investments ultimately pay off. Finally, comparative work across EU member states would illuminate how institutional context shapes the cost dynamics we document here.

Taken together, the results suggest that AES operate through meaningful and measurable cost channels that help explain their environmental and economic effects. Understanding these channels more fully will be crucial for designing policies that nudge farms toward sustainability without imposing undue financial burdens, thereby contributing to a more resilient and climate-aligned agricultural sector.

CRediT authorship contribution statement

Štefan Bojnec: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Imre Fertő:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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.

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Data availability

The data that support this study's findings are available from the Ministry of Agriculture, Forestry, and Food of the Republic of Slovenia, but restrictions apply to their availability. These data were used under license for the current study and are not publicly available. The datasets used and/or analysed during the current study are available from the corresponding author upon reasonable request.

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