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Assessing the impact of agri-environmental schemes on input use in Hungary's wine sector: Implications for sustainability and policy design

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ABSTRACT

Agri-Environmental Schemes (AES) are a key policy tool within the European Union's Common Agricultural Policy (CAP) aimed at promoting sustainable farming practices and mitigating environmental externalities. However, their effectiveness in reducing input use in high-value, resource-intensive sectors such as viticulture remains uncertain. This study evaluates the impact of AES participation on input expenditures in Hungary's wine sector, focusing on fertilizer use, crop protection costs, and energy consumption. Using a robust econometric approach - Propensity Score Matching (PSM), Entropy Balancing (EB), and Inverse Probability Weighting (IPW) - the analysis addresses selection bias and estimates the causal effects of AES participation. Findings indicate that AES participation significantly reduces crop protection costs, suggesting a shift towards more sustainable pest management practices. However, no significant effects are observed on fertilizer or energy expenditures, highlighting potential gaps in AES design concerning these critical inputs. Additionally, results suggest that AES participants manage larger, resource-abundant farms, raising concerns about the inclusivity of the scheme. These findings underscore the need for targeted policy refinements to enhance the effectiveness of AES in viticulture, particularly by improving accessibility for smaller farms and strengthening incentives for input reduction. The study contributes to the broader discourse on agri-environmental policy by providing empirical evidence to inform the design of more effective and inclusive sustainability interventions in the European wine sector.

1. Introduction

Agri-Environmental Schemes (AES) are a core instrument of the European Union's Common Agricultural Policy (CAP), designed to mitigate agriculture's environmental externalities while supporting a transition toward more sustainable farming systems. By offering financial incentives for voluntary adoption of environmentally friendly practices, AES aim to address biodiversity loss, soil degradation, water pollution, and climate change mitigation (Batáry et al., 2015; Hasler et al., 2022). Their relevance has increased under the European Green Deal and the Farm to Fork Strategy, which explicitly target reductions in agrochemical use, improved resource

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efficiency, and enhanced environmental performance of agriculture (European Commission, 2020) (see Fig. 1 sould be indicated after the first sentence of the paragraph right above the figure: "To further visualize the distribution of input use across AES and non-AES farms, a boxplot was constructed for fertiliser use, crop protection costs, and energy use.(Fig. 1)).

Despite their widespread implementation, empirical evidence on AES effectiveness remains mixed. A large evaluation literature documents substantial heterogeneity in outcomes, with impacts strongly dependent on scheme design, enforcement, and farm-level behavioural responses (Uthes and Matzdorf, 2013; Pacini et al., 2015; Röder et al., 2024). While some studies report improvements in biodiversity or eco-efficiency (Kleijn et al., 2006; Kleijn et al., 2006; Ait Sidhoum et al., 2023; Baráth et al., 2024), others highlight limited or non-additional effects, raising concerns about windfall payments and weak incentives for input reduction (Chabé-Ferret and Subervie, 2013; Hasler et al., 2022). These ambiguities continue to shape debates on the environmental effectiveness of voluntary agri-environmental instruments.

A key limitation of the existing literature is its strong focus on annual arable cropping systems, with considerably less attention devoted to specialised, high-value perennial sectors such as viticulture (Uthes and Matzdorf, 2013; Cullen et al., 2021). This gap is non-trivial. Viticulture is among the most input-intensive agricultural activities, characterised by high pesticide reliance, significant fertiliser use, and non-negligible energy demand (Kuhfuss and Subervie, 2018; Finger and Möhring, 2022). Crop protection practices are of particular concern, given their links to biodiversity loss, soil and water contamination, and human health risks (Deguine et al., 2023). At the same time, climate change has increased production risks, heightening the importance of environmentally resilient vineyard management systems (Béné et al., 2023).

From a policy perspective, viticulture also raises questions about the alignment between AES objectives and observable farm management outcomes. While some AES measures explicitly encourage reduced pesticide use or integrated pest management, many focus on biodiversity or landscape objectives with only indirect implications for input use (Röder et al., 2024). Recent evidence suggests that such design features may generate improvements in certain environmental dimensions without producing consistent reductions in fertiliser or energy use (Mennig and Sauer, 2020; Diop et al., 2024). Understanding these trade-offs is particularly important in sectors where quality requirements and biological constraints limit farmers' scope for adjustment.

Geographically, AES evaluations are disproportionately concentrated in Western Europe, where institutional settings, enforcement capacity, and farm structures differ markedly from those in Central and Eastern Europe (Arata and Sckokai, 2016; Michalek, 2022). In Hungary, viticulture plays a significant economic and cultural role, yet the sector faces persistent sustainability challenges related to pesticide dependence, soil degradation, and vulnerability to climate variability (Csizmady et al., 2021). Although Hungary has extensively implemented AES under the Rural Development Programme 2014–2020 (European Commission, 2025), systematic evidence on their effectiveness in reducing key production inputs in viticulture remains scarce.

This study addresses these gaps by empirically assessing the impact of AES participation on fertiliser, crop protection, and energy expenditures among Hungarian wine producers. Focusing on input use provides a direct link between policy participation and environmental pressures, complementing studies that rely on aggregate or composite performance indicators (Finger et al., 2024; Pakeman et al., 2024). Methodologically, the analysis contributes to the AES evaluation literature by applying a triangulated causal inference strategy that combines Propensity Score Matching, Entropy Balancing, and Inverse Probability Weighting. This approach responds to growing concerns about bias and estimator sensitivity in observational policy evaluations.

Beyond estimating average treatment effects, the paper also examines structural differences between AES participants and non-participants. A growing body of evidence suggests that AES participation is systematically associated with farm size, economic capacity, and managerial characteristics, raising concerns about inclusivity and the distribution of environmental benefits (Unay-Gailhard and Bojnec, 2015; Cullen et al., 2021; Bartkowski et al., 2023). If participation remains skewed toward larger and more resource-abundant farms, the aggregate environmental effectiveness of AES may be constrained (Bojnec and Latruffe, 2013; Fertő and

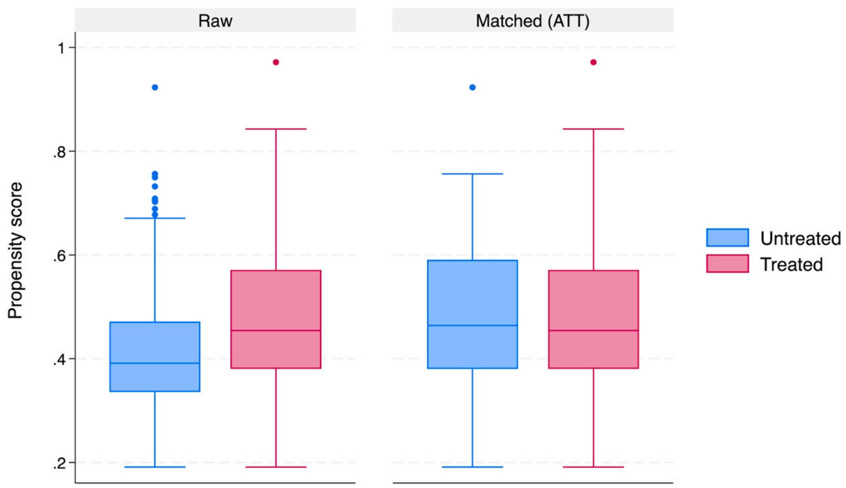

Fig. 1. Boxplots of propensity scores.

Bojnec, 2024).

By focusing on viticulture in an Eastern European context, this study contributes to ongoing debates on how agri-environmental policies perform in specialised, high-input agricultural systems. The findings provide policy-relevant insights into whether AES induce meaningful changes in input use and highlight areas where scheme design may require refinement to better align incentives with sustainability objectives under the evolving CAP framework.

The remainder of this paper is structured as follows. Section 2 provides an overview of Hungarian viticulture and its environmental challenges. Section 3 outlines the methodology and data used in this study. Section 4 presents the econometric results, followed by a discussion of key findings and policy implications in Section 5. Finally, Section 6 concludes with recommendations for future research and policy development.

2. Hungarian viticulture

Hungarian viticulture has a long-standing tradition, playing a crucial role in the national agricultural economy. The country's diverse wine regions, with unique climates and soil characteristics, contribute to the production of high-quality wines that are recognized both domestically and internationally. However, the Hungarian wine sector faces several sustainability challenges that affect its environmental footprint and economic viability.

One of the main issues confronting Hungarian viticulture is its reliance on high-input agricultural practices, particularly in the use of fertilizers and pesticides. These inputs are essential for maintaining grapevine health and ensuring high yields and quality, but they also pose significant environmental risks, including soil degradation, water contamination, and biodiversity loss (Muscas et al., 2017). Despite a growing awareness of the environmental impacts of conventional viticulture, the adoption of more sustainable practices, such as organic farming or integrated pest management, has been limited. The high costs of transitioning to these practices, combined with a lack of financial incentives and technical support, have been major barriers to their widespread adoption (Szamosközine Kispál, 2023).

Climate change has further compounded the challenges facing Hungarian viticulture. The sector is highly vulnerable to shifts in temperature and precipitation patterns, which can affect grapevine growth, yield stability, and the quality of the harvest (Csizmady et al., 2021). In response, farmers are increasingly seeking ways to mitigate these risks, such as by implementing water-saving technologies and adjusting planting schedules. However, these adaptive strategies often require significant investment and technical expertise, which may be beyond the reach of smaller producers.

In recent years, there has been a growing movement toward more sustainable practices within Hungarian viticulture. While the adoption of organic farming is still limited, many winegrowers have begun to incorporate environmentally friendly practices, such as the use of cover crops to reduce soil erosion and increase biodiversity. Moreover, there is an increasing interest in precision agriculture technologies, which can help reduce the use of fertilizers and pesticides by targeting specific areas of the vineyard that require treatment (Szamosközine Kispál, 2023; Chapela-Oliva et al., 2022). These innovations align with the goals of the EU's Green Deal and Farm to Fork Strategy, which emphasize the importance of reducing the environmental impact of agriculture.

Despite this progress, there remain significant structural barriers to achieving widespread sustainability in Hungarian viticulture. The sector is characterized by a mix of small family-run farms and larger, commercial operations, with the former often facing greater financial constraints and limited access to new technologies (Kismarjai et al., 2024). Additionally, while the EU provides subsidies through Agri-Environmental Schemes (AES), participation remains uneven across regions and farm types, with larger farms more likely to engage with these programs due to their better financial and managerial resources (Montalvo-Falcón et al., 2023).

AES have the potential to play a pivotal role in addressing these challenges by incentivizing more sustainable farming practices. However, their design and implementation need to be tailored to the specific needs and capacities of Hungarian wine producers. For instance, smaller farms may require additional support in the form of technical assistance, simplified application processes, and targeted financial incentives to make participation in AES more accessible. By addressing these barriers, AES could foster greater environmental sustainability in Hungarian viticulture, helping to reduce the sector's reliance on high-input practices and enhancing its resilience to climate change.

Overall, Hungarian viticulture stands at a crossroads. While there is growing recognition of the need for more sustainable farming practices, the path to achieving these goals will require overcoming significant economic and structural challenges. Agri-Environmental Schemes offer a potential solution, but their effectiveness will depend on the ability of policymakers to design interventions that are inclusive, targeted, and responsive to the needs of both small and large-scale producers.

3. Methodology and data

This study applies a quasi-experimental evaluation framework to estimate the causal effects of participation in Agri-Environmental Schemes (AES) on input use - specifically fertiliser, crop protection, and energy expenditures - among Hungarian wine producers. As AES participation is voluntary, farmers self-select into the programme based on structural and socio-economic characteristics, creating the potential for selection bias. To address this, the analysis employs three complementary causal inference techniques commonly used in programme evaluation: Propensity Score Matching (PSM), Entropy Balancing (EB), and Inverse Probability Weighting (IPW). These approaches rest on the foundational work of Rosenbaum and Rubin (1983) on propensity scores and subsequent extensions by Imbens and Rubin (2015), Abadie and Imbens (2011), Hainmueller (2017), and Hirano and Imbens (2001). By combining these techniques, we strengthen identification and improve the robustness of the estimated treatment effects.

The empirical analysis draws upon a longitudinal dataset of 503 Hungarian wine producers covering the period 2014–2020. Data were obtained from the Hungarian Farm Accountancy Data Network (FADN), which follows harmonised reporting standards across the European Union and ensures consistency in the accounting, structural, and demographic information collected. Each annual observation corresponds to a complete farm-level survey verified by regional data offices. Although the panel experiences attrition, diagnostic checks indicate no systematic differences between farms exiting and those remaining, suggesting that attrition poses limited risk to inference. All statistical analyses were performed using Stata 17, including the psmatch2 routine (Caliendo and Kopeinig, 2008), the ebalance package for entropy balancing, and the teffects ipw module for inverse probability weighting. Replication files and anonymised datasets will be deposited in a public repository upon acceptance.

3.1. Rationale for combining PSM, EB, and IPW

The simultaneous use of PSM, EB, and IPW responds to a methodological concern highlighted in the causal inference literature: different balancing estimators impose different assumptions, and each may perform better under certain data conditions. While PSM remains the most widely used estimator in agricultural and environmental economics due to its intuitive appeal and interpretability (Austin, 2011), studies increasingly note its sensitivity to imperfect overlap and its potential for residual imbalance. Entropy Balancing, introduced by Hainmueller (2017), offers a deterministic reweighting strategy that enforces exact covariate balance, thereby addressing weaknesses sometimes found in matching algorithms. Meanwhile, IPW employs a reweighting procedure grounded in the theory of efficient treatment effect estimation (Hirano and Imbens, 2001) and has shown favourable finite-sample performance in comparative studies (Busso et al., 2014).

Although these methods have been applied individually in related agricultural policy evaluations, their combined use remains relatively rare. However, recent methodological work (Zhao and Percival, 2017) supports the use of triangulation across multiple estimators as a means of improving robustness. By analysing results across PSM, EB, and IPW, this study follows best practices in the evaluation of agri-environmental interventions, where issues such as heterogeneity in farm structures, variation in managerial capacity, and region-specific adoption constraints create challenges for single-method identification. Triangulation is particularly relevant in the context of viticulture, where structural factors such as farm size, labour intensity, and land tenure strongly influence both AES participation (Defrancesco et al., 2008; Podruzsik and Fertő, 2024) and input use patterns associated with sustainability outcomes.

3.2. Treatment variable and outcome measures

The treatment indicator takes the value one for farms that participate in an Agri-Environmental Scheme during the study period and zero otherwise. Three outcome variables are analysed, each measured in euros per hectare: fertiliser expenditure, crop protection expenditure, and energy expenditure. These variables capture core input categories that are directly relevant to the environmental outcomes targeted by AES and that represent major sources of chemical and energy use in viticulture (Batáry et al., 2015; Ait Sidhoum et al., 2023; Röder et al., 2024).

3.3. Covariates and measurement

To estimate the likelihood of AES participation and appropriately balance the sample, we incorporate variables commonly used in the AES adoption literature. Labour input is measured in Annual Work Units (AWU), defined by Eurostat as the equivalent of 1800 h of full-time labour per year. Unpaid labour is expressed using the same metric. Total utilised agricultural area and rented agricultural area are measured in hectares and reflect land constraints and business expansion strategies. Economic size, expressed in euros, follows the standard output classification used in FADN data. The manager's gender and age capture demographic influences on adoption behaviour, which have been shown to play meaningful roles in AES uptake (Wilson and Hart, 2002; Kismarjai et al., 2024). These covariates jointly reflect managerial style, resource endowments, labour availability, and financial constraints - factors repeatedly identified as drivers of AES participation (Defrancesco et al., 2008; Montalvo-Falcón et al., 2023).

3.4. Propensity score estimation and matching

PSM estimates the probability of AES participation based on observed covariates and matches treated and control farms with similar characteristics (Rosenbaum and Rubin, 1983). By balancing covariates such as farm size, economic scale, and labour input, PSM mimics a randomized experiment, reducing bias in treatment effect estimation.

To estimate the likelihood of AES participation, we employ a logit model where the conditional probability of treatment given covariates X_i is defined as follows:

$$p(X_i) = Pr(D_i = 1|X_i) = \frac{exp\left(\alpha + \beta^T X_i\right)}{1 + exp\left(\alpha + \beta^T X_i\right)}, \tag{1}$$

Here, D_i is a binary indicator that farm i participates in the Agri-Environmental Scheme, while X_i is the vector of observed covariates (farm size, labour input, economic size, gender, farm age, and land tenure). Maximum-likelihood estimates of α and β generate the fitted probabilities $\widehat{p}(X_i)$ that underpin every subsequent matching or re-weighting step.

The matching algorithm used in this study follows a nearest-neighbour approach with replacement, ensuring that treatment and control units share comparable baseline characteristics (Caliendo and Kopeinig, 2008).

The treatment effect is then calculated as the average difference in outcomes between treated farms and their matched controls, as shown below:

$$\widehat{ATTPSM} = \frac{1}{N_T}\sum i : D_i = 1\left(Y_i - \sum_{j:D_j=0} w_{ij}Y_j\right), w_{ij}\begin{cases}\frac{1}{m_i}, & if\ j \in N(i)\\ \text{[4pt]}0, & otherwise\end{cases} \tag{2}$$

where N_T is the number of treated units, Y_i denotes the outcome of interest, and $N(i)$ is the set of matched controls for treated unit i.

To assess the quality of the matching process, standardized mean differences before and after matching were examined. A reduction in bias across key covariates indicates that the treated and control groups are well-balanced (Austin, 2011).

3.5. Entropy balancing

While PSM relies on a probabilistic approach to achieve balance, EB directly reweights the control group to match the exact covariate distribution of the treated group (Hainmueller, 2017). This method is particularly useful when sample sizes are limited, as it prevents potential inefficiencies associated with matching algorithms (Zhao and Percival, 2017). By ensuring exact covariate balance, EB enhances the credibility of the estimated treatment effects, particularly when evaluating multiple treatment outcomes such as fertiliser use, crop protection expenditures, and energy consumption.

In contrast, entropy balancing constructs weights for the control group by solving the following constrained optimization problem:

$$\begin{gathered} min_{w_i} \sum_{i:D_i=0} w_i \, ln \, w_i \\ s.t. \sum_{i:D_i=0} w_i X_{ik} = \widehat{X_{Tk}}, k = 1, \ldots, K, \\ \sum_{i:D_i=0} w_i = 1, w_i > 0. \end{gathered} \tag{3}$$

This ensures that the reweighted control group matches the treated group exactly on the covariate means X_{Tk}.

3.6. Inverse probability weighting

IPW is grounded in causal inference theory and adjusts for differences in covariates by assigning weights inversely proportional to the probability of AES participation (Hirano and Imbens, 2001). This method is particularly effective in addressing selection bias by ensuring a balanced representation of treated and control units, even when observable characteristics differ substantially (Busso et al., 2014).

Inverse probability weights are computed based on the estimated propensity scores, and the Average Treatment Effect on the Treated (ATT) is obtained as the difference between the weighted averages of the outcome for treated and control groups:

$$w_i^{IPW} = \frac{D_i}{\widehat{p}(X_i)} + \frac{1 - D_i}{1 - \widehat{p}(X_i)}, \widehat{ATT}_{IPW} = \frac{\sum_i w_i^{IPW} D_i Y_i}{\sum_i w_i^{IPW} D_i} - \frac{\sum_i w_i^{IPW}(1 - D_i)Y_i}{\sum_i w_i^{IPW}(1 - D_i)}. \tag{4}$$

This approach helps adjust for covariate imbalances by assigning more weight to underrepresented observations.

In this study, IPW provides a robustness check against PSM and EB, reinforcing the reliability of results. The overlap condition was tested to confirm that the estimated propensity scores for treated and control groups fell within a common support region, ensuring valid comparisons (Stuart, 2010).

3.7. Robustness and sensitivity checks

To evaluate the stability of the results, the study compares ATT estimates across PSM, EB, and IPW. Convergence in magnitude and sign across these estimators increases the credibility of the findings and reduces sensitivity to model-specific assumptions. We additionally inspect covariate balance diagnostics across all methods to ensure that observable differences between treated and control groups have been sufficiently mitigated. As an additional sensitivity test, Rosenbaum bounds (Rosenbaum, 2002) assess how strong an unobserved confounder would need to be to invalidate the estimated effects. Finally, supplementary analyses examine the influence of extreme values in expenditure data by re-estimating the models with outliers removed. These checks together provide a comprehensive assessment of the robustness of the estimated impact of AES participation on input use.

4. Results

4.1. Descriptive statistics

The descriptive statistics in Table 1 provide a descriptive overview of the baseline differences between AES participants and non-participants. These comparisons help illustrate the extent of observable heterogeneity prior to treatment and underline the necessity of applying matching and weighting techniques to address selection bias. The differences reported below refer to raw, unconditional comparisons and should not be interpreted as causal effects of AES participation.

Across input-use variables, fertiliser expenditure is slightly higher among participants, although this difference is only marginally significant. Crop protection expenditure is significantly lower for participants, indicating that the two groups differ in their baseline crop protection cost patterns. Energy expenditure does not differ significantly, suggesting that energy use intensity is broadly comparable between the groups.

Labour inputs also show notable contrasts. Participants report higher hired labour usage, and this difference is marginally significant. Unpaid labour inputs, by contrast, do not differ significantly between groups, indicating that family labour contributions are largely similar regardless of participation status.

Farm size variables exhibit several statistically significant differences. Participants manage significantly larger total utilised agricultural areas and rent significantly more agricultural land. They also display significantly greater economic size. These differences confirm that, in the raw sample, AES participants tend to be larger-scale and more commercially structured operations.

Demographic characteristics vary to a lesser extent. The gender composition does not differ significantly between the groups. Age, however, shows a statistically significant difference, with participants being younger on average.

Taken together, these descriptive differences - several of which are statistically significant -highlight the presence of systematic baseline heterogeneity between AES participants and non-participants. This reinforces the need for the matching and reweighting procedures applied in the following analysis to mitigate selection bias. The descriptive evidence presented here is therefore intended solely to contextualise the econometric strategy, not to draw substantive conclusions about the effects of AES participation.

4.2. Econometric estimations

The econometric analysis evaluates the causal impact of AES participation on input use, employing Propensity Score Matching (PSM), Entropy Balancing (EB), and Inverse Probability Weighting (IPW) methods to account for selection bias and improve the robustness of results. Table 2 summarizes the estimated treatment effects of AES participation on input use across the three econometric methods.

The analysis shows that AES participation has a positive but statistically insignificant effect on fertilizer expenditures. Specifically, the ATT estimates for fertilizer use are 12.29 (PSM), 9.69 (EB), and 11.73 (IPW). While these estimates suggest a slight increase in fertilizer expenditures among AES participants, none of these effects are statistically significant. This finding aligns with the conclusions of Ait Sidhoum et al. (2023), who found mixed effects on farm-level eco-efficiency from AES participation across EU countries. Their study suggests that while some AES measures lead to reductions in fertilizer use, others may inadvertently encourage compensatory practices, such as applying higher quantities of fertilizers, to meet yield targets.

Furthermore, the lack of significant changes in fertilizer use may reflect the nature of AES measures in Hungary, which often focus more on biodiversity, pest management, and soil conservation rather than explicitly targeting nutrient management. As observed by Röder et al. (2024), while AES can reduce certain input usages, the lack of targeted measures for key inputs like fertilizers may limit the overall environmental effectiveness of these programs. Thus, the absence of a clear impact on fertilizer use may indicate that AES design in Hungary could be refined to focus more explicitly on reducing fertilizer dependence, potentially through incentives for organic fertilizers or precision farming technologies.

In contrast, crop protection costs show more promising results, with a significant reduction in expenditures observed among AES participants. The ATT estimate for crop protection is negative across all three methods: −14.76 (PSM), −40.81 (EB), and −33.03

Table 1
Descriptive statistics of variables by AES participation.

Variable	AES = 0 (Non-participants)	AES = 1 (Participants)	Total Sample	Test (p-value)
N (%)	281 (55.8 %)	223 (44.2 %)	504 (100 %)	
Fertiliser use (€ per ha)	38.795 (63.147)	49.747 (77.412)	43.641 (69.959)	0.081
Crop protection (€ per ha)	309.397 244.455)	260.229 (197.253)	287.642 (225.910)	0.015
Energy (€ per ha)	158.855 (153.547)	144.218 (142.026)	152.379 (148.593)	0.272
Labour (AWU)	3.238 (6.732)	4.589 (8.972)	3.836 (7.823)	0.054
Unpaid labour (AWU)	0.795 (0.682)	0.817 (0.641)	0.804 (0.664)	0.708
Total Utilised Agricultural Area (ha)	16.549 (18.684)	22.184 (22.885)	19.042 (20.816)	0.002
Rented Utilised Agricultural Area (ha)	6.463 (16.875)	10.753 (22.970)	8.361 (19.898)	0.016
Economic Size (ESU)	28.484 (37.069)	42.491 (50.997)	34.682 (44.286)	<0.001
Gender (1 = Male, 0 = Female)	0.954 (0.211)	0.919 (0.273)	0.938 (0.241)	0.113
Age (years)	60.750 (12.152)	56.753 (11.968)	58.978 (12.221)	<0.001

Note: standard deviations are in brackets.

Table 2
Summary of estimation results.

Input	Method	ATT	Std. Error	t-Statistic	p-Value	95 % CI Lower	95 % CI Upper
Fertiliser	Propensity Score Matching	12.29	7.24	1.70	0.090	−1.93	26.51
	Entropy Balancing	9.69	6.81	1.42	0.155	−3.68	23.06
	Inverse Probability Weighting	11.73	6.94	1.69	0.092	−1.90	25.37
Crop Protection	Propensity Score Matching	−14.76	20.63	−0.72	0.475	−55.30	25.78
	Entropy Balancing	−40.81	19.95	−2.05	0.041	−80.00	−1.62
	Inverse Probability Weighting	−33.03	19.81	−1.67	0.096	−71.96	5.90
Energy	Propensity Score Matching	4.06	13.85	0.29	0.769	−23.14	31.27
	Entropy Balancing	−11.80	14.23	−0.83	0.407	−39.76	16.16
	Inverse Probability Weighting	−17.36	16.67	−1.04	0.298	−50.12	15.39

Notes: Average Treatment Effect on the Treated (ATT) is the estimated causal effect of participation in Agri-Environmental Schemes on fertiliser, crop protection and energy expenditures for participating Hungarian wine farms, measured as the mean difference in input use relative to observationally similar non-participating farms.

(IPW), with the EB result being statistically significant at the 5 % level. This suggests that AES participation leads to lower crop protection costs, which may be attributed to the adoption of more sustainable pest management practices. These findings are consistent with previous research, such as that of Meunier et al. (2024) and Vella et al. (2025), who highlighted the positive role of behavioural sciences in encouraging farmers to reduce pesticide use. Their study suggests that farmers' engagement in AES often leads to a shift towards integrated pest management practices, which can reduce the reliance on chemical pesticides.

For crop protection costs, all three methods yield negative ATT estimates (−14.76 for PSM, −40.81 for EB, and −33.03 for IPW). However, only the EB estimate is statistically significant at the 5 % level. Although the direction of effects is consistent across methods, the significance of the result under EB alone warrants a more cautious interpretation. Entropy Balancing enforces exact covariate balance (Hainmueller, 2017), which may produce more precise estimates in settings with substantial baseline heterogeneity. Nonetheless, because PSM and IPW do not produce significant effects, strong causal claims would be premature. The EB result may indicate that AES participation is associated with lower crop protection expenditures - potentially linked to more sustainable pest management - but the evidence is not robust across estimators. This partial pattern remains broadly consistent with Meunier et al. (2024) and Vella et al. (2025), who highlight how behavioural drivers can reduce pesticide use under well-designed agricultural schemes. Moreover, Schaub et al. (2023) emphasize that opportunity costs and behavioural factors influence adoption decisions, potentially explaining why some producers adjust their crop protection strategies more than others. Overall, while the EB estimate is encouraging, the mixed significance across methods suggests treating these findings as indicative rather than conclusive.

Energy expenditures, on the other hand, do not show significant reductions for AES participants. The ATT estimates for energy use range from 4.06 (PSM) to −17.36 (IPW), with none of the results reaching statistical significance. This suggests that AES has limited impact on energy consumption in Hungarian viticulture, possibly due to the lack of targeted energy-saving measures within the schemes. These findings echo those of Röder et al. (2024), who highlighted that, while the post-2022 CAP reform emphasizes environmental sustainability, energy efficiency measures within AES have been insufficiently integrated. As a result, many farms do not receive the necessary incentives or support to reduce energy use, which may explain why no significant reductions in energy expenditures were observed.

The lack of effect may also reflect structural characteristics of the wine sector. Larger commercial operations - already more energy-efficient due to economies of scale - may have little room for further reductions, while smaller vineyards often lack the resources needed to invest in energy-efficient equipment (Kismarjai et al., 2024). Meunier et al. (2024) note that behavioural approaches could help promote energy-efficient practices, but targeted measures addressing financial and technical constraints remain necessary.

The descriptive statistics reveal important differences between AES participants and non-participants. AES participants tend to manage larger farms, both in terms of total utilised agricultural area and economic size. This aligns with findings from Podruzsik and Fertő (2024), who noted that farm size and economic capacity are key determinants of AES participation. Larger farms often have greater access to the financial and managerial resources required to comply with AES requirements, making them more likely to participate in these schemes. Smaller, resource-constrained farms may face significant barriers to participation, including financial constraints, lack of technical knowledge, and limited access to support services.

The skew in farm size raises concerns about the inclusivity of AES benefits. As noted by Montalvo-Falcón et al. (2023), targeting

Table 3
Covariate balance summary.

Covariate	Raw Treated Mean	Raw Untreated Mean	StdDif	Matched Treated Mean	Matched Untreated Mean	StdDif
Labour	4.589	3.246	0.169	4.589	5.224	−0.080
Unpaid Labour	0.817	0.797	0.029	0.817	1.007	−0.287
Total Utilised Agricultural Area	22.184	16.596	0.267	22.184	22.692	−0.024
Rented Utilised Agricultural Area	10.753	6.474	0.212	10.753	11.067	−0.016
Economic Size	42.491	28.555	0.312	42.491	45.266	−0.062
Gender	0.919	0.954	−0.141	0.919	0.887	0.131
Age of Farmer	56.753	60.750	−0.331	56.753	56.276	0.040

smaller farms with tailored financial incentives, simplified application processes, and technical assistance could enhance the accessibility and effectiveness of AES. By addressing these barriers, AES could become a more inclusive policy tool, ensuring that the environmental benefits of these schemes are more widely distributed across the sector.

Table 3 presents the balance of covariates before and after matching. The standardized mean differences for critical variables, such as economic size and land use, substantially improved after matching. For instance, the standardized difference for economic size decreased from 0.312 to −0.062, indicating effective balancing. This improved balance strengthens the reliability of the estimated treatment effects by reducing selection bias.

To further visualize the distribution of input use across AES and non-AES farms, a boxplot was constructed for fertiliser use, crop protection costs, and energy use. The boxplot reveals that AES participants exhibit lower median values and reduced variability in crop protection costs, supporting the econometric findings. In contrast, the distribution of fertiliser and energy use remains similar across groups, aligning with the non-significant econometric results. The boxplot also highlights the presence of outliers, suggesting that some AES participants still maintain high input use, possibly due to specific farm practices or scheme exemptions.

5. Discussion

This study examined the effects of AES participation on input use among Hungarian wine producers using three complementary quasi-experimental approaches - Propensity Score Matching, Entropy Balancing, and Inverse Probability Weighting. The findings indicate generally limited effects of AES on fertiliser and energy use, with more mixed evidence for crop protection expenditures. While these results contribute to a more nuanced understanding of how wine producers respond to agri-environmental policies, several methodological and data-related limitations should be acknowledged.

A first methodological challenge concerns the non-random selection of farms into AES, which introduces the risk of selection bias. Although the study applies three well-established balancing and matching techniques to mitigate this issue, these approaches rely on the assumption that all relevant confounders are observable. Unobserved characteristics - such as farmers' risk preferences, attitudes toward sustainability, or unmeasured differences in soil quality - may still influence both AES participation and input use. While the triangulation of PSM, EB, and IPW improves robustness, the reliance on observational data limits the ability to rule out hidden bias entirely. This limitation is inherent to quasi-experimental evaluations and is widely discussed in the literature (e.g., Imbens and Wooldridge, 2009). Future research combining matching with longitudinal fixed-effects modelling or instrumental variable strategies could offer additional safeguards against unobserved heterogeneity.

A second limitation relates to data availability. The study draws on a balanced panel of wine producers from 2014 to 2020. Although the dataset is relatively rich, attrition occurred over the study period as some producers exited the sample. Attrition may introduce bias if dropout differs systematically between AES participants and non-participants. While descriptive checks suggest no strong differential attrition, the possibility cannot be completely ruled out. Furthermore, data constraints limit the inclusion of variables such as detailed soil characteristics, parcel-level management practices, or specific technology adoption indicators, all of which could influence input use. The absence of such variables may partly explain some of the statistically insignificant findings, particularly for fertiliser and energy use.

Beyond methodological limitations, the representativeness and generalisability of the results require careful consideration. The sample consists exclusively of Hungarian wine producers, a specialised subsector with unique production systems, land-use patterns, and policy environments. This limits the extent to which findings can be directly extrapolated to other agricultural systems. However, certain structural characteristics - such as the predominance of small and medium-sized family farms and the voluntary nature of AES participation - are shared with other contexts in Central and Eastern Europe. Therefore, the mechanisms observed here (e.g., the stronger participation of larger farms with greater economic capacity) may provide relevant insights for countries facing similar challenges. Following the guidance of Johnston et al. (2017) on representativeness and generalisability, the results should be interpreted as context-specific yet informative for comparable agricultural settings, particularly those with similar institutional designs and adoption barriers.

Moreover, the heterogeneity of AES measures in Hungary complicates generalisation. As Röder et al. (2024) highlight, many Hungarian AES measures focus on biodiversity and landscape management rather than direct input reduction. This may partly explain the lack of significant effects on fertiliser and energy use. In contrast, the negative (though only partially significant) effects on crop protection expenditures align with studies demonstrating that behavioural and management-related components of AES can shift pesticide application practices (Meunier et al., 2024; Vella et al., 2025; Schaub et al., 2023). These findings underscore the importance of carefully aligning AES measures with targeted environmental objectives, as also suggested by Ait Sidhoum et al. (2023).

Finally, while the matching procedures successfully improved covariate balance - as shown in Table 3 - effect estimates remain sensitive to the choice of estimator, particularly for crop protection. The significant effect detected under Entropy Balancing but not under PSM or IPW highlights the importance of triangulation and cautious interpretation. This reinforces the broader literature's emphasis on using multiple estimators to assess the robustness of policy impacts.

Overall, while the study identifies some encouraging patterns-particularly in relation to crop protection - it also highlights structural and policy-related limitations within the Hungarian AES framework. At the same time, the methodological and data-related constraints discussed above suggest that further research is needed to validate and extend these findings, particularly in other agricultural contexts and with richer datasets.

6. Conclusions

This study analysed the effects of AES participation on fertiliser, crop protection, and energy use among Hungarian wine producers using three complementary quasi-experimental approaches - PSM, Entropy Balancing, and IPW. The results indicate limited impacts of AES on input use, with only the reduction in crop protection expenditures showing partial statistical significance under the EB estimator. These findings highlight both the potential and the limitations of current AES design in Hungary.

From a policy perspective, the results suggest several concrete recommendations. First, the design of Hungarian AES could be strengthened by introducing input-specific incentive structures, particularly for fertilisers and energy use, where no significant changes were observed. This may include financial rewards for adopting precision fertilisation, explicit requirements for nutrient management planning, or targeted support for renewable or energy-efficient technologies. Second, given the partial evidence of reduced crop protection costs, policy-makers could expand integrated pest management (IPM) components within AES, including mandatory training modules, advisory services, or behavioural nudges that help farmers transition away from chemical-intensive practices. Third, the clear difference in participation rates between smaller and larger farms indicates the need for tailored support for small-scale producers, such as simplified application procedures, higher per-hectare payments for small farms, or technical assistance aimed at lowering administrative barriers.

In addition, the findings underscore the importance of aligning AES measures more closely with environmental objectives. As the results show, general land-management obligations may be insufficient for delivering material reductions in key inputs. More targeted, measurable, and enforceable commitments - particularly for nutrient and energy efficiency - would likely enhance the environmental performance of AES.

The study also offers methodological insights for future research. The use of three distinct matching and weighting estimators provides a transparent assessment of robustness and highlights how treatment effects may vary depending on the balancing method employed. Future researchers evaluating AES or similar voluntary schemes may benefit from adopting a multi-estimator framework, as relying on a single quasi-experimental method could produce incomplete or misleading conclusions. In contexts with substantial baseline heterogeneity, Entropy Balancing may offer advantages due to its ability to achieve exact balance on covariate means, but it should be complemented with additional estimators - such as PSM, IPW, or doubly robust approaches - to ensure that findings are not artefacts of the chosen method.

At the same time, researchers should be aware that matching methods depend on the availability of high-quality covariates and may not fully correct for unobserved differences. Where possible, future studies could enhance causal identification by combining matching with panel fixed-effects models, instrumental variables, or natural experiments, particularly when richer datasets become available. Further work could also explore heterogeneous treatment effects across farm types, regions, or management systems to better understand which producers benefit most from AES participation.

Overall, this study provides empirical evidence on the limited but nuanced effects of AES on input use in Hungarian viticulture and identifies opportunities to refine both policy design and methodological approaches. Strengthening input-specific incentives, supporting smaller farms, and enhancing the alignment between scheme obligations and environmental goals are key areas for improvement. At the same time, continued methodological innovation and richer data will be essential to deepen understanding of the environmental outcomes of agri-environmental policies.

CRediT authorship contribution statement

Imre Fertő: Supervision, Formal analysis, Conceptualization. **Gergely Csurilla:** Validation, Formal analysis. **Szilárd Podruzsik:** Writing – original draft, Visualization, Investigation.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the grammar and clarity. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Data availability

Data will be made available on request.

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