Short- and long-run associations between environmental taxes and eco-efficiency in the agricultural sector

Evidence from six European countries, 1995-2023

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Short- and long-run associations between environmental taxes and eco-efficiency within the agricultural sector

Kort- och långsiktiga samband mellan miljöskatter och eko-effektivitet inom jordbrukssektorn

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Abstract

Environmental taxes are widely used policy instruments to incentivize sustainable production, yet their specific impacts on agricultural eco-efficiency remain highly complex. This study examines the short- and long-run associations between environmental taxes and eco-efficiency in the agricultural sector across six European countries (Austria, Denmark, Ireland, Luxembourg, Malta, and the Netherlands) from 1995 to 2023. Utilizing an Autoregressive Distributed Lag (ARDL) model, this thesis evaluates Mean Group (MG), Pooled Mean Group (PMG), and Dynamic Fixed Effects (DFE) estimators. The results indicate that changes in environmental taxes do not yield immediate impacts in the short run, aligning with the gradual nature of agricultural structural adjustments. In the long run, the Hausman test favors the MG model, revealing a positive but statistically insignificant energy tax revenue association alongside substantial country-specific heterogeneity. Additionally, livestock density is found to have a consistently negative impact on eco-efficiency across the models. The findings suggest that environmental taxation alone may be insufficient to enhance eco-efficiency uniformly, highlighting the need for country-specific fiscal designs and targeted, complementary agricultural policies.

Keywords: Agriculture, Eco-Efficiency, Environmental Taxation, ARDL, Panel Data

Sammanfattning

Miljöskatter är allmänt använda politiska styrmedel för att stimulera hållbar produktion, men deras specifika effekter på jordbrukets ekoeffektivitet är alltjämt mycket komplexa. Denna studie undersöker de kort- och långsiktiga sambanden mellan miljöskatter och ekoeffektivitet inom jordbrukssektorn i sex europeiska länder (Österrike, Danmark, Irland, Luxemburg, Malta och Nederländerna) under perioden 1995–2023. Genom att tillämpa en autoregressiv fördröjningsmodell (ARDL) utvärderar denna kandidatuppsats skattningsmetoderna Mean Group (MG), Pooled Mean Group (PMG) och Dynamic Fixed Effects (DFE). Resultaten visar att förändringar i miljöskatter inte ger några omedelbara effekter på kort sikt, vilket ligger i linje med jordbrukets gradvisa strukturella anpassningar. På lång sikt visar Hausman-testet att MG-modellen föredras, vilken påvisar en positiv men statistiskt icke-signifikant skatteeffekt tillsammans med en betydande landsspecifik heterogenitet. Därutöver visar resultaten att boskapstätheten har en genomgående negativ inverkan på ekoeffektiviteten i samtliga modeller. Slutsatserna tyder på att miljöbeskattning på egen hand kan vara otillräcklig för att enhetligt öka ekoeffektiviteten, vilket belyser behovet av landsspecifik skatteutformning och riktade, kompletterande jordbrukspolitiska åtgärder.

Nyckelord: Jordbruk, ekoeffektivitet, miljöskatter, ARDL, paneldata.

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Abbreviations

Abbreviation	Description
AI	Artificial intelligence, digital tools used for research and editorial assistance.
ARDL	Autoregressive Distributed Lag model, an econometric framework used to analyse short- and long-run relationships between variables
CADF	Cross-sectionally Augmented Dickey-Fuller test, a panel unit root test that accounts for cross-sectional dependence.
DFE	Dynamic Fixed Effects estimator, an econometric method that assumes both long-run and short-run coefficients are the same across groups while allowing group-specific intercepts.
ECT	Error Correction Term, which shows how quickly deviations from the long-run equilibrium are corrected.
GDP	Gross Domestic Product, a measure of the total economic output of a country.
GHG	Greenhouse gases, such as CO_2, CH_4, and N_2O that contribute to climate change.
LM	Lagrange Multiplier test, a diagnostic test used here to examine cross-sectional dependence.
MG	Mean Group estimator, an econometric method that estimates separate regressions for each group and then averages the coefficients across groups.
OLS	Ordinary Least Squares, a regression method used to estimate the relationship between dependent and independent variables.
PMG	Pooled Mean Group estimator, an econometric method that estimates long-run relationships as common across groups while allowing short-run dynamics and error variances to differ across groups.
SR	Short-run estimates, referring to the immediate effects in the ARDL model.
VIF	Variance Inflation Factor, a diagnostic measure used to detect multicollinearity among explanatory variables.

1. Introduction

1.1 Background

The agricultural sector is a significant contributor to greenhouse gas emissions, particularly through non-carbon dioxide gases such as methane and nitrous oxide (Food and Agriculture Organization, 2024). However, agriculture should also be understood within the wider agrifood system, where carbon dioxide equivalent emissions arise not only from production within the farm gate, but also from land-use change and activities before and after production. Globally, agrifood systems emitted approximately 16.2 billion tonnes of CO_2 equivalent in 2022, corresponding to almost 30% of total anthropogenic greenhouse gas emissions (Food and Agriculture Organization, 2024). These emissions originate from crop and livestock production, deforestation, peatland degradation, biomass burning, food processing, transport, retail, household consumption and food waste (Food and Agriculture Organization, 2024). This shows that agriculture-related emissions are not limited to farms themselves but are embedded in a broader system of production and consumption.

The continued release of greenhouse gases contributes to climate change by increasing the concentration of heat-trapping gases in the atmosphere (United States Environmental Protection Agency, 2025). This can lead to rising global temperatures, more frequent extreme weather events such as droughts and floods. For agriculture, these effects are particularly problematic, since the sector both contributes to climate change and is highly vulnerable to its consequences. Changes in temperature and rainfall can reduce crop yields and create greater uncertainty for food production systems (United Nations Development Programme, 2025). The largest sources of agricultural emissions are enteric fermentation in livestock, agricultural soils and manure management which together accounts for the vast majority of emissions in the sector. Despite existing policies, projections indicate that agricultural emissions will decrease only slowly, reaching around 10% below 2005 levels by 2030 under current measures (European Environment Agency, 2025). This highlights a broader political and societal challenge; agriculture must continue to provide food and economic value while simultaneously contributing to climate targets.

In this context, the concept of eco-efficiency provides an important analytical lens. Eco-efficiency describes the relationship between economic value and environmental impact, aiming to generate more value with lower environmental pressure (Čuček, Klemeš and Kravanja, 2015). In agrifood systems, greenhouse gas emissions intensity was estimated at 2.6 kg CO_2 equivalent per international dollar in 2022 representing a decline of about 39% since 2000. Emissions per unit of economic output have decreased over time. At the same time, total emissions from agrifood systems have increased by about 10 percent since 2000 and remain substantial (Food and Agriculture Organization, 2024). This indicates that reductions in emissions intensity can occur alongside stable or increasing total emissions. Eco-efficiency is therefore useful for distinguishing between changes in emissions intensity and overall emission levels. This is particularly relevant for agriculture, where productivity and environmental performance are closely linked. Rather than focusing solely on reducing emissions in absolute terms, eco-efficiency allows for assessing whether production becomes more sustainable relative to its environmental impact, for example by increasing output per unit of greenhouse gas emissions.

Environmental taxes are used as policy instruments in the relationship between agriculture, emissions and sustainability. An environmental tax is defined as a tax whose base is a physical unit or a proxy of a physical unit of something that has a proven negative impact on the environment (Eurostat, 2024). The tax base can consist of a physical unit such as litres of fuel or a proxy measure and the tax is expressed in monetary terms. Environmental taxes are classified into four main categories: energy, transport, pollution and resource taxes (Eurostat, 2024). Energy taxation is relevant because it can influence production costs and create incentives to reduce fossil fuel use, improve energy efficiency or shift towards cleaner energy sources. The European Commission’s proposal to revise the Energy Taxation Directive aims to align energy taxation with EU climate policy by taxing fuels according to energy content and environmental performance rather than volume. Under this approach, fuels with higher environmental impacts are subject to higher minimum tax rates, while less polluting energy sources are taxed at lower rates (European Commission, 2021). In this way, energy taxes can support climate objectives by making environmental costs more visible in market prices.

Existing studies indicate that current environmental taxation may not fully reflect the environmental damage caused by different sectors. One study estimates that only 44% of the EU’s air pollution and greenhouse gas costs are internalised through taxation, charges or other market-based instruments. For agriculture, the internalisation rate is particularly low at around 6% of air pollution and greenhouse gas emission costs. (European commission, 2021). This indicates that a large share of the environmental costs generated by agricultural activity is still borne by society rather than directly by polluters. Environmental taxes, including energy taxes, are therefore relevant in discussions of eco-efficiency because they can affect both the economic value of production and the incentives to reduce emissions.

Previous research has examined both environmental taxation and eco-efficiency, but the link between the two remains insufficiently explored in the agricultural sector. Studies on environmental taxation show that environmental taxes can encourage firms to reduce environmental damage and adopt cleaner technologies, although the effects depend on tax design, implementation, firm characteristics, and production conditions (Jackson, 2000; Fu et al., 2023; Krass and Ovchinnikov, 2025). At the same time, research on agricultural eco-efficiency shows that farms can improve environmental performance without necessarily reducing output, but that technical efficiency and environmental efficiency are not always aligned (Minviel et al., 2024; Novaković et al., 2025). These studies suggest that policy instruments and farm-level characteristics both matter for environmental performance.

However, existing literature has paid less attention to the relationship between environmental taxation and agricultural eco-efficiency across countries. Previous studies have examined environmental taxation and eco-efficiency separately, but less attention has been given to how these areas are connected within the agricultural sector (Jackson, 2000; Minviel et al., 2024; Novaković et al., 2025). This leaves a gap in understanding whether environmental taxes are associated with agriculture's ability to generate economic value while reducing environmental pressure.

1.2 Research objective and hypothesis

Environmental taxes are intended to encourage more sustainable production by making environmental costs more visible in economic decision-making (Baumol, 1972). In agriculture, however, the response to such taxes is unlikely to be immediate. In the short run, producers often have limited flexibility to change input use, production methods, or technology. In the long run, they can adjust production practices, adopt cleaner technologies, improve resource efficiency, or reorganise production (Hochman and Zilberman, 2023). It is therefore important to study both short- and long-run associations, since focusing only on one time horizon may overlook either immediate adjustment constraints or gradual structural changes. This study therefore aims to examine the short- and long-run associations between environmental taxes and eco-efficiency in the agricultural sector across six selected European countries. To guide the empirical analysis, the following hypothesis is tested

1. Environmental taxes are positively associated with eco-efficiency in the agricultural sector in the short run and/or in the long run across the selected European countries.

1.3 Structure

The thesis is structured as follows. The first section presents the introduction, including the background to the study, the research problem, objective, and hypothesis. The second section reviews relevant literature on agricultural eco-efficiency, environmental taxation, and previous empirical findings related to environmental performance in agriculture. The third section presents the method and data used in the study. This includes the theoretical framework, data description, variable definitions, model specification, and econometric approach. The fourth section presents the descriptive and empirical results, including diagnostic tests, unit root tests, and the short- and long-run results from the PMG, MG, and DFE estimators.The fifth section discusses the results in relation to the theoretical framework and previous literature, while also considering policy implications and limitations of the study. Finally, the conclusion summarizes the main findings and provides suggestions for future research.

2. Literature review

This section reviews relevant literature and empirical evidence contributing to the understanding of eco-efficiency and its determinants, focusing on eco-efficiency and environmental taxation.

2.1 Definition of Eco-efficiency

Eco-efficiency refers to the relationship between economic performance and environmental impact. It describes the ability to produce goods or services while using fewer natural resources, generating less waste, and reducing pollution (Čuček, Klemeš and Kravanja, 2015). In agriculture, this is especially important because production depends on inputs such as land, labour, fertilisers, energy, and capital, which are transformed into agricultural outputs (Huang, 2026). However, agricultural production can also create environmental pressures, including greenhouse gas emissions, pollution, soil disturbance, deforestation, and biodiversity loss. Agricultural eco-efficiency therefore reflects how well the sector can maintain or increase agricultural output and economic value while reducing the environmental pressure connected to production. In this sense, eco-efficiency is not only about producing more efficiently, but about producing in a way that balances productivity with environmental sustainability (Huang, 2026).

2.2 Eco-efficiency in the agricultural sector

Previous research on agricultural eco-efficiency shows that technical efficiency and environmental efficiency are closely related, but not always aligned (Minviel et al., 2024). Evidence from French suckler sheep farms shows that eco-efficiency is influenced by the relationship between these two dimensions of performance. On average, farms show the potential to increase meat output by around 20% while reducing greenhouse gas emissions by approximately 24%, indicating substantial efficiency reserves. However, farms with high technical efficiency do not necessarily have high environmental efficiency. Only 32% of farms had both high technical and environmental efficiency, suggesting that productivity and environmental performance are not automatically achieved together (Minviel et al., 2024). Minviel et al. (2024) also identify several factors associated with efficiency. Decoupled direct payments are positively associated with environmental efficiency but negatively associated with technical efficiency, while green direct payments show no significant effect. Farm indebtedness is linked to higher technical efficiency but lower environmental efficiency, whereas farmer experience is positively associated with both types of efficiency. Overall, these findings suggest that improving eco-efficiency depends on both farm management and policy incentives (Minviel et al., 2024).

Previous research on crop production in the EU and Serbia also highlights the importance of internal farm-level factors for eco-efficiency (Novaković et al., 2025). In this context, eco-efficiency is assessed in relation to environmental pressures, particularly the use of fertilizers, plant protection products, and energy. The findings indicate that inefficiency is largely persistent rather than temporary, suggesting that long-term farm-level factors exert a stronger influence than short-term external shocks. Key determinants relate to internal farm characteristics, including management practices, organizational structures, and technology adoption. The results for Serbia suggest that improvements are possible through farm-level modernization and better knowledge transfer. Overall, eco-efficiency in crop production is shaped primarily by internal farm characteristics, while policy instruments can support improvements by encouraging sustainable input use and technological upgrading (Novaković et al., 2025).

These previous studies provide important evidence on agricultural eco-efficiency, however they mainly focus on farm-level determinants, technical efficiency, environmental efficiency, and input-use patterns. Less attention has been given to the role of environmental taxation as an external policy instrument influencing agricultural eco-efficiency. Existing studies also tend to focus either on specific farm types, individual countries, or particular environmental pressures, such as greenhouse gas emissions, fertiliser use, plant protection products, or energy use. Therefore, there remains a gap in understanding whether environmental taxation is associated with agricultural eco-efficiency across countries and whether this association differs between the short run and the long run.

2.3 Methods used in previous eco-effiency studies

Previous studies have measured agricultural eco-efficiency using frontier-based methods that combine production performance with environmental pressure. For example, Minviel et al. (2024) apply a multi-equation stochastic frontier approach to examine both technical and environmental efficiency in French suckler sheep farms. Similarly, Novaković et al. (2025) use a stochastic frontier analysis model to assess the eco-efficiency of crop production in the EU and Serbia, where agricultural output is compared with environmental pressures such as fertiliser, plant protection product, and energy use. These studies show that eco-efficiency is commonly analysed by comparing desirable agricultural output with the environmental burden generated in the production process. However, they mainly focus on measuring eco-efficiency and identifying farm-level or input-related determinants, rather than examining environmental taxation as a policy-related driver of eco-efficiency.

2.4 Environmental taxation

Previous research on carbon taxation shows that firm-level differences in emissions affect how firms respond to environmental taxes (Fu et al., 2023). Carbon-efficient firms may increase production and benefit from carbon taxation, while carbon-inefficient firms are more likely to reduce output or invest in green technology. The study also finds that carbon taxes do not automatically lead to green technology adoption, since firms' decisions depend on emission asymmetry, tax levels, and technology costs. In some cases, industry profit may even increase when carbon taxes are properly designed. This suggests that environmental taxation can support greener production, but its effects depend on firm-level emission differences and competitive conditions (Fu et al., 2023).

Environmental taxation research also emphasizes that firm-specific characteristics shape responses to policy instruments (Krass and Ovchinnikov, 2025). Krass and Ovchinnikov (2025) show that operational costs and emissions intensity play a central role in determining how firms respond to environmental taxes. Firms differ in both operational efficiency and environmental efficiency, and these differences strongly influence production decisions, market shares, and profitability under environmental taxation. As a result, the impact of taxation is not uniform across firms, but depends on their relative cost structures and technologies.

Earlier research also suggests that environmental taxation can improve environmental performance when taxes are carefully designed and implemented (Jackson, 2000). Environmental taxes may encourage firms to reduce environmental damage and adopt cost-effective cleaner alternatives. However, general employment and productivity gains from environmental taxes cannot be conclusively established, as outcomes depend on the design and implementation of the tax. Jackson (2000) emphasizes that environmental taxes are more effective when they target significant environmental externalities, are introduced gradually, and are combined with complementary policy measures. Revenue use is also important, as tax revenues can be recycled to reduce other taxes or fund environmental programmes. Overall, environmental taxation can contribute to improved environmental outcomes, but poorly designed taxes can create welfare costs that reduce their potential benefits (Jackson, 2000).

Recent cross-country evidence further shows that environmental performance is affected not only by policy instruments, but also by uncertainty and institutional conditions (Barra and Falcone, 2024). A study of 136 countries finds that economic policy uncertainty is associated with higher environmental inefficiency, suggesting that when future policy direction is unclear, countries tend to exhibit lower environmental performance. The study also finds that institutional quality plays an important role in this relationship. Stronger institutions reduce environmental inefficiency and weaken the negative effect of policy uncertainty. Political orientation is also relevant, as left-leaning governments moderate the relationship between uncertainty and environmental inefficiency. These findings indicate that environmental performance is shaped not only by economic uncertainty, but also by governance conditions and political context (Barra and Falcone, 2024).

2.5 Contributions

While previous research has examined environmental performance, emissions, and firm-level responses to environmental taxation, less attention has been given to how environmental taxation is associated with eco-efficiency in the agricultural sector**.** Existing studies often focus either on environmental taxation as a tool for reducing emissions or on eco-efficiency as a measure of agricultural performance, but the connection between these two areas remains underexplored. This creates a gap in understanding whether environmental taxes are linked to the ability of agriculture to produce economic value while reducing environmental pressure.

This study addresses this gap by examining the association between environmental taxation and agricultural eco-efficiency across six selected European countries. By using a cross-country panel, the study offers a comparative perspective that complements previous single-country or broader cross-sector studies. In addition, the literature provides limited evidence on whether the relationship between environmental taxation and agricultural eco-efficiency differs between the short run and the long run. This distinction is important because environmental taxes can create immediate cost and input-use adjustments, while longer-term responses can involve changes in technology, production practices, and resource efficiency.Methodologically, the study applies a panel ARDL approach with PMG, MG, and DFE estimators, allowing for the analysis of both heterogeneous short-run dynamics and long-run equilibrium relationships. Grounded in Pigouvian tax theory, the study therefore contributes to a more comprehensive understanding of how environmental taxation is associated with agricultural eco-efficiency across different time horizons.

3. Method and data

3.1 Theoretical framework

The study relies on Pigouvian tax theory, which originates from the idea that markets fail when production or consumption generates negative externalities that are not reflected in market prices (Kallbekken, 2013). In such cases, economic agents base their decisions only on private costs, ignoring the broader social costs imposed on others through environmental degradation (Tresch, 2015). This leads to an inefficient allocation of resources, where pollution intensive activities are overproduced relative to the social optimum. A Pigouvian tax corrects this distortion by imposing a tax equal to the marginal external cost thereby aligning private incentives with social welfare and restoring efficiency (Baumol, 1972). In environmental economics, Pigouvian taxation is an important tool for addressing greenhouse gas emissions and fossil fuel use. By raising the cost of carbon-intensive inputs, such taxes create incentives to reduce emissions and shift investment toward renewable energy and energy-efficient technologies. In this way, they support a transition to more sustainable patterns of production and resource use (Bollino and Polinori, 2011).

This framework is highly relevant to the agricultural sector. Agriculture plays a central role in food systems, but it is also a major source of environmental pressure, contributing significantly to greenhouse gas emissions and broader impacts on water, biodiversity, and ecosystems (European Environment Agency, 2026). At the same time, agricultural production depends heavily on natural resources and is vulnerable to environmental degradation and climate change. Policies and economic incentives can therefore play an important role in encouraging more sustainable practices, such as improved land and water management, adoption of efficient technologies, and climate-smart innovations. These changes can enhance productivity while reducing environmental impacts, although outcomes vary depending on local conditions, resource availability, and farming practice (Food and Agriculture Organization, 2020).

An important implication of Pigouvian taxation is that many of its effects are likely to unfold gradually rather than immediately, as firms and consumers adjust their behavior and investment decisions over time. By placing a price on negative externalities, such taxes can incentivize firms and consumers to reduce harmful activities over time, for example through energy conservation, investment in energy-efficient infrastructure, or a shift toward cleaner resources. (Bollino and Polinori, 2011). Because production decisions and investments are often irreversible and adjust slowly, the full impact of environmental taxation emerges dynamically as firms adapt their behavior and capital stock. This implies that responses may be limited in the short run but become more substantial in the long run as economic agents adjust more fully (Hochman et al., 2020).

This distinction between short-run constraints and long-run adjustment helps motivate the empirical strategy employed in this study. By analyzing both short-and long-run associations between energy taxes and eco-efficiency, the paper examines whether the gradual adjustment process associated with Pigouvian taxation is observed in practice. In particular, the existence of a stable long-run relationship between environmental taxation and eco-efficiency would be consistent with the theoretical expectation that Pigouvian taxes contribute to a more efficient allocation of resources over time.

3.2 Data description

The data used is a panel dataset collected from six countries (Austria, Denmark, Ireland, Luxembourg, Malta, Netherlands) in Europe over the period 1995–2023. This specific sample was selected to maximize the time dimension of the panel. While environmental taxation data for most European nations is only available from 2008 onward, these six countries provide consistent data back to 1995, thereby allowing for a more robust evaluation of long-term environmental policy trends.The dependent variable is agricultural eco-efficiency and the main independent variable is energy tax revenues in the agricultural sector. Control variables included in the model are temperature anomaly, share of agriculture in GDP, livestock density and fertilizer intensity. The data was collected from Eurostat, FAOSTAT and OurWorldInData.

Eco-efficiency is a proxy for agricultural eco-efficiency defined as the ratio of agricultural output to environmental pressure (Greenhouse gas emissions). Agricultural production value is measured as the gross production value of the agricultural sector, measured in current US$ (Our World in Data, 2026). Annual greenhouse gas emissions from the agricultural sector includes CO_2, CH_4, N_2O, and fluorinated gases expressed in CO_2 equivalents, reported in thousand tonnes (European Commission Eurostat, 2025).

Energy tax revenues measures annual tax revenues paid by the agriculture, forestry, and fishing sector, expressed in million euros (European Commission Eurostat, 2025).

Share of agriculture in GDP is the share of value added generated by the agriculture, forestry, and fishing sector in a country’s total GDP, expressed in U.S. dollars (Food and Agriculture Organization, 2026a).

Temperature anomaly measures annual land surface temperature change as a deviation from a historical baseline, expressed in degrees Celsius (°C). Positive values indicate that the year was warmer than the baseline, while negative values indicate cooler-than-baseline conditions (Food and Agriculture Organization, 2026b) (Food and Agriculture Organization, 2026b).

Livestock density is created with data for the annual stock of cattle and buffaloes across the selected countries, reported as the total number of animals divided by data for the total area of agricultural land, expressed in thousand hectares (1000 ha) (Food and Agriculture Organization, 2025a).

Fertilizer intensity is constructed by dividing data for total agricultural nitrogen use in tonnes by data for total area of agricultural land, thereby measuring fertilizer use tons per hectare of agricultural land (Food and Agriculture Organization, 2025b).

3.3 Model specification

This study applies the Autoregressive Distributed Lag (ARDL) framework in a panel-data setting to examine the short-run and long-run effects of energy taxes on agricultural eco-efficiency (Pesaran et al., 1995). An important implication of Pigouvian taxation is that its effects are dynamic rather than immediate. Because investment decisions, technological adaptation, and production structures adjust gradually over time, environmental taxes may have limited short-run effects but stronger long-run impacts as economic agents adapt their behavior (Hochman et al., 2020). This distinction between short-run adjustment and long-run equilibrium motivates the empirical strategy of the present study. The general ARDL error-correction specification is expressed as:

$$\Delta \ln EE_{it} = \phi_i \left(\ln EE_{i,t-1} - \theta_i' X_{i,t-1}\right) + \sum_{j=1}^{p-1} \lambda_{ij} \Delta \ln EE_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{1}$$

where

$$X_{it} = (\ln Tax_{it}, Temp_{it}, GDPshare_{it}, \ln LivestockDensity_{it}, \ln NitrogenIntensity_{it}) \tag{2}$$

where EE_{it} represents agricultural eco-efficiency for country i at time t, and X_{it} is a vector of explanatory variables consisting of energy taxes, temperature change, GDP share, livestock density, and nitrogen intensity. The parameter ϕ_i denotes the error-correction coefficient, while θ_i represents the long-run coefficients. The term μ_i captures country-specific fixed effects and ε_{it} is the disturbance term. A negative and statistically significant ϕ_i indicates convergence toward the long-run equilibrium following short-run deviations (Pesaran et al., 1995). Before estimating the ARDL model, several diagnostic tests were conducted to ensure the validity of the panel-data analysis. The dataset consists of a balanced panel with N cross-sectional groups observed over T time periods, where each country contains the same number of observations. Initially, a standard Ordinary Least Squares (OLS) regression was estimated to examine the general relationship between the variables. In addition, separate regressions were estimated for Malta and the Netherlands as robustness checks.

To ensure that the explanatory variables were not excessively correlated, multicollinearity tests were conducted using the Variance Inflation Factor (VIF). Multicollinearity can inflate standard errors and produce unstable coefficient estimates, reducing the reliability of the regression results (Shrestha, 2020). Values above 5-10 indicate problematic multicollinearity.

To test for cross-sectional dependence, the Breusch-Pagan Lagrange Multiplier (LM) test was conducted. The test examines whether the residuals are correlated across cross-sectional units, where the null hypothesis assumes cross-sectional independence (Breusch & Pagan, 1980). The Breusch-Pagan Lagrange Multiplier test was used to check for random effects in the panel data. A significant result indicates that random effects are present, while an insignificant result suggests that there is no strong evidence of random effects (Breusch & Pagan, 1980).The Wooldridge test for serial correlation in panel data was performed to examine whether the error terms were autocorrelated within countries over time. Detecting serial correlation is important in dynamic panel models because autocorrelation may lead to biased standard errors and unreliable statistical inference (Wooldridge, 2001).

Since panel ARDL estimation requires variables to be integrated of order zero, I(0), or order one, I(1), panel unit root tests were performed prior to estimation (Pesaran et al., 1999). The Pesaran Cross-sectionally Augmented Dickey-Fuller (CADF) test was employed to account for cross-sectional dependence among panel units (Pesaran, 2007). The CADF regression augments the standard ADF specification with cross-sectional averages:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it} \tag{3}$$

Following the panel unit root tests, a panel cointegration test was conducted to examine whether a stable long-run equilibrium relationship exists among agricultural eco-efficiency and the explanatory variables. This step is important because the ARDL error-correction framework is designed to distinguish between short-run dynamics and long-run equilibrium adjustment. In the presence of cointegration, the error-correction term can be interpreted as the speed at which deviations from the long-run equilibrium are corrected over time. The Kao residual cointegration test was applied, where the null hypothesis assumes no cointegration and rejection of the null indicates evidence of a long-run relationship among the variables(Kao, 1999).

After the diagnostics tests, three ARDL estimators were employed: the Mean Group (MG), the Pooled Mean Group (PMG), and the Dynamic Fixed Effects (DFE) estimator. These estimators differ in the degree of homogeneity imposed across countries. The Mean Group (MG) estimator, introduced by Pesaran and Smith (1995), estimates separate regressions for each cross-sectional unit and computes the arithmetic average of the coefficients across groups. The MG estimator allows all coefficients, both short-run and long-run, to differ across countries, thereby accounting for full heterogeneity. The MG estimator is expressed as:

$$\hat{\beta}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\beta}_i \tag{4}$$

The Pooled Mean Group (PMG) estimator imposes homogeneity on the long-run coefficients while allowing short-run coefficients, adjustment speeds, and error variances to vary across groups. The PMG estimator is appropriate when countries are expected to share a common long-run equilibrium relationship but differ in their short-run adjustment processes. A negative and statistically significant error-correction coefficient indicates cointegration and convergence toward long-run equilibrium (Pesaran et al., 1999). The long-run homogeneity restriction can be written as:

$$\theta_i = \theta \quad \forall_i \tag{5}$$

Finally,the Dynamic Fixed Effects (DFE) estimator imposes stronger restrictions by assuming that both short-run and long-run coefficients are identical across countries, while only the intercepts differ (Pesaran et al., 1999). The DFE specification is given by:

$$\Delta \ln EE_{it} = \phi(\ln EE_{i,t-1} - \theta X_{i,t-1}) + \sum_{j=1}^{p-1} \lambda_j \Delta \ln EE_{i,t-j} + \sum_{j=0}^{q-1} \delta_j \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{6}$$

where

$$X_{it} = (\ln Tax_{it}, Temp_{it}, GDPshare_{it}, \ln LivestockDensity_{it}, \ln NitrogenIntensity_{it}) \tag{7}$$

To determine the appropriate lag length, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were applied. These criteria evaluate the balance between model fit and parsimony, where lower values indicate the preferred specification (Salkind, 2007).

To determine the most appropriate estimator, Hausman tests were conducted to compare the different estimators. The Hausman test evaluates whether the homogeneity restrictions imposed by PMG are valid. Failure to reject the null hypothesis indicates that PMG is efficient and consistent, while rejection suggests that the more flexible MG estimator is preferable (Pesaran et al., 1999).

3.4 Limitations

This study is subject to several limitations that should be considered when interpreting the results. First, the analysis is based on a relatively small sample consisting of six European countries, which may limit the generalizability of the findings and reduce the efficiency of the estimators. Although the time dimension is relatively long, the small cross-sectional dimension makes model selection and estimation more challenging. Furthermore, the use of country-level data may conceal important regional and farm-level differences within countries.

Secondly, a limitation concerns the measurement of eco-efficiency. In this study, eco-efficiency is measured as the ratio between agricultural production value and greenhouse gas emissions. While this captures the relationship between economic output and emissions intensity, it does not account for other environmental impacts such as biodiversity loss, water pollution, or soil degradation. A primary limitation of this study is the use of current US dollars to measure agricultural production value within the eco-efficiency ratio. Because this relies on nominal rather than real values, the eco-effiency measure is susceptible to inflation, commodity price volatility, and exchange rate fluctuations. Consequently, an observed increase in eco-efficiency could merely reflect rising market prices which could theoretically be driven by the cost pass-through of energy taxes themselves rather than genuine, physical improvements in environmental performance.

There is also a potential risk of endogeneity and omitted variable bias. Environmental taxes may influence eco-efficiency, while environmental performance may also affect policy decisions regarding taxation and environmental regulation. In addition, there may be feedback between greenhouse gas emissions and climate-related variables. Since eco-efficiency is partly measured using agricultural greenhouse gas emissions, and temperature anomaly is included as a control variable, the relationship between emissions, climate conditions, and agricultural performance may involve reverse causality or simultaneous adjustment over time. Moreover, unobserved factors such as technological innovation, agricultural subsidies, or country-specific institutional differences may influence both environmental taxation and eco-efficiency. Finally, the study period includes external shocks such as energy price fluctuations, climate-related events, and changes in EU environmental policy, which may affect agricultural eco-efficiency independently of environmental taxation. Consequently, the results should be interpreted with caution.

4. Results

This chapter presents the descriptive and empirical results of the study. It begins with an overview of the balanced panel dataset, including the number of groups, time periods, and annual observations. The chapter then presents the results from the OLS regressions, including separate estimations for Malta and the Netherlands. This is followed by diagnostic tests and the Pesaran CADF unit root test, which are used to assess the properties of the data and the suitability of the empirical approach. Finally, the chapter reports the Panel ARDL estimations using the Mean Group, Pooled Mean Group, and Dynamic Fixed Effects estimators, followed by the Hausman test to determine the preferred model specification.

4.1 Descriptive results

Table 1 presents the descriptive statistics and variable definitions for the analysis. Structurally, the dataset covers 6 unique country groups over 29 annual time periods, yielding 29 potential observations per group. However, due to missing values across specific series, the final sample operates as an unbalanced panel data set. This variable-level missingness is reflected in the varying number of observations N, which ranges from a maximum of 174 observations for energy tax revenue and GDP share to a minimum of 167 observations for fertilizer intensity.

Table 1| *Variable description and descriptive statistics*

Variable	Mean	Std. Dev. (Overall)	Min	Max	Obs (N)	Groups (n)
Eco-efficiency	13.367	0.529	12.198	14.408	169	6
Energy tax revenue	2.994	2.722	-2.813	6.664	174	6
Fertilizer intensity	4.334	0.419	3.429	5.298	167	6
Livestock density	7.123	0.467	6.305	7.770	169	6
Temperature anomaly	1.339	0.671	-0.771	2.917	169	6
Share of agriculture in GDP	1.396	0.814	0.191	5.580	174	6

Source: Author's estimation.

Notes: Values are rounded to three decimals. The panel contains six country groups; N varies across variables because of missing observations.

4.2 Empirical results

4.2.1 OLS regression

Table 2 reports the pooled OLS regression results, which are used as an initial starting point for the analysis and as a benchmark for comparison with the subsequent dynamic panel estimations. The results show that tax, temperature change, fertilizer intensity, and livestock density are statistically significant, while share of GDP is statistically insignificant. However, the OLS model does not account for the dynamic structure of the data or distinguish between short-run and long-run associations. Therefore, the analysis proceeds with dynamic panel estimations to examine both short-run and long-run relationships.

Table 2| *OLS Regression Results*

Variable	Coefficient	Std. Error	t-statistic	P-value
Energy tax revenue	0.034*	0.017	1.93	0.054
Temperature anomaly	0.181***	0.057	3.16	0.002
Fertilizer intensity	-0.602***	0.106	-5.66	0.000
Livestock density	0.406***	0.089	4.56	0.000
Share of agriculture in GDP	-0.011	0.054	-0.20	0.841
_cons	12.322	0.636	20.03	0.000
R-squared	0.213			
Observations	167			

Source: Author's estimation.

*Note: Eco-efficiency, energy tax revenue, fertilizer intensity, and livestock density are expressed in natural logarithmic form. *** p<0.01, ** p<0.05, * p<0.10*

Table 3 and table 4 report the separate country regression results for Malta and the Netherlands. For Malta, fertiliser density and GDP share were both statistically significant and negatively associated with agricultural eco-efficiency, while the other variables were not statistically significant. For the Netherlands, fertiliser density is were also negative and statistically significant, while tax, temperature, livestock density, and GDP share were not statistically significant.

***Table 3**| OLS regression results for Malta*

Variable	Malta Coeff.	Std. Error	t-statistic	P-value
Energy tax revenue	0.002	0.078	0.02	0.983
Temperature anomaly	-0.098	0.085	-1.14	0.265
Fertilizer intensity	-0.321**	0.136	-2.36	0.027
Livestock density	-0.002	0.271	-0.01	0.993
Share of agriculture in GDP	-0.197**	0.090	-2.18	0.040
_cons	15.825***	1.957	8.09	0.000
R-squared	0.532			
Observations	29			

Source: Author's estimation.

*Note: Eco-efficiency, energy tax revenue, fertilizer intensity, and livestock density are expressed in natural logarithmic form. *** p<0.01, ** p<0.05, * p<0.10*

***Table 4**| OLS regression results for Netherlands*

Variable	Netherlands Coeff.	Std. Error	t-statistic	P-value
Energy tax revenue	0.097	0.088	1.10	0.282
Temperature anomaly	-0.041	0.043	-0.97	0.342
Fertilizer intensity	-1.095**	0.426	-2.57	0.017
Livestock density	-0.067	0.625	-0.11	0.916
Share of agriculture in GDP	0.149	0.178	0.84	0.410
_cons	18.685***	4.932	3.79	0.001
R-squared	0.753			
Observations	29			

Source: Author's estimation.

*Note: Eco-efficiency, energy tax revenue, fertilizer intensity, and livestock density are expressed in natural logarithmic form. *** p<0.01, ** p<0.05, * p<0.10*

4.2.2 Diagnostic tests

Table 5 presents the multicollinearity diagnostics using variance inflation factors (VIF). All VIF values were below the conventional threshold value of 10.

Table 5*| Multicollinearity diagnostics*

Variable	VIF
Livestock density	1.77
Fertilizer intensity	1.49
Energy tax revenue	1.48
Share of agriculture in GDP	1.45
Temperature anomaly	1.15
Mean VIF	1.47

Source: Author's estimation.

Note: Mean VIF below 10 indicates no serious multicollinearity.

Table 6 reports the Pesaran CADF panel unit root test results. The results show that most variables were nonstationary in levels but stationary after first differencing, while temp and GDP_share are stationary in levels.

Table 6*| Pesaran CADF Unit Root Tests*

Variable	Transformation	CADF Statistic	P-value	Integration Order
Eco-effiency	First Difference	-7.106	0.000	I(1)
Energy tax revenue	First Difference	-4.185	0.000	I(1)
Fertilizer intensity	First Difference	-7.529	0.000	I(1)
Livestock density	First Difference	-3.424	0.000	I(1)
Temperature anomaly	Level	-1.708	0.044	I(0)
GDP_share	Level	-2.439	0.000	I(0)

Source: Author's estimation. Source: Author's estimation.

Note: Eco-efficiency, energy tax revenue, fertilizer intensity, and livestock density are expressed in natural logarithmic form.

Table 7 show the Kao cointegration test results which provided evidence of a long-run relationship between the variables. Since most test statistics are statistically significant at the 5 percent level, the null hypothesis of no cointegration is rejected. This supports the use of the panel ARDL error-correction framework for analysing both short-run and long-run associations.

Table 7| *Kao cointegration test results*

Test	Statistic	P-value
Modified Dickey-Fuller t	-2.124	0.0168
Dickey-Fuller t	-2.411	0.0080
Augmented Dickey-Fuller t	-1.158	0.1234
Unadjusted modified Dickey-Fuller t	-4.393	0.0000
Unadjusted Dickey-Fuller t	-3.26	0.0006

Source: Author's estimation.
Note: H0: no cointegration. Ha: all panels are cointegrated.

Table 8 show that the Breusch-Pagan LM test rejects the null hypothesis of cross-sectional independence. The Breusch-Pagan LM test for random effects results show no evidence of random effects and the Wooldridge test indicate the presence of serial correlation.

Table 8| *Diagnostics test*

Test	Statistic	P-value
Breusch-Pagan LM test for cress sectional dependance	155.394	0.0000
Breusch-Pagan LM test for random effects	0.00	1.0000
Wooldridge Serial Correlation Test	65.020	0.0005

Source: Author's estimation.

4.2.3 Lag selection and Model fit

Table 9 show the lag selection criteria for the ARDL models. The AIC and BIC values suggest that the two-lag specifications provide a better statistical fit than the one-lag specifications, with the MG lag 2 model reporting the lowest values. However, the expanded PMG lag 2 model failed to converge, likely due to the limited panel dimensions and reduced degrees of freedom. Therefore, the one-lag specification was retained for the final ARDL analysis to ensure model stability and reliable inference.

Table 9*| Lag-Length Selection Based on AIC and BIC*

Model	N	Log likelihood	df	AIC	BIC
PMG lag 1	161	162.812	10	-305.624	-274.809
MG lag 1	161	177.181	5	-344.362	-328.955
DFE lag 1	-	-	12	-	-
PMG lag 2	155	208.262	10	-396.524	-366.090
MG lag 2	155	293.946	5	-577.893	-562.675
DFE lag 2	-	-	18	-	-

Source: Author's estimation.

*Note: AIC = Akaike information criterion; BIC = Bayesian information criterion. BIC uses N = number of observations. Although AIC and BIC indicated better fit for the two-lag specification, the expanded PMG model failed to converge, likely due to the limited panel dimensions (*T ≈ *26,* N *= 6) and reduced degrees of freedom.*

The diagnostic, unit root, cointegration, lag selection, and country-specific OLS results provide the basis for the subsequent estimation method. The Pesaran CADF test shows that the variables are a mixture of I(0) and I(1), supporting the use of a Panel ARDL approach, provided that none are I(2). The Kao cointegration test further indicates a long-run equilibrium relationship between the variables, while the lag selection criteria suggest that the two-lag models provide a better statistical fit. However, since the expanded PMG model failed to converge, the more parsimonious one-lag specification was retained. In addition, the Breusch–Pagan LM test indicates cross-sectional dependence, while the Wooldridge test suggests serial correlation. The separate OLS regressions for Malta and the Netherlands also show country-specific heterogeneity in coefficient size, sign, and significance. Overall, these findings indicate that static OLS is insufficient for capturing the dynamic and heterogeneous nature of the data. Therefore, the analysis proceeds with the Panel ARDL model to estimate both long-run relationships and short-run adjustment dynamics.

4.2.4 Panel ARDL Long-Run Estimation and Error Correction Results

To ensure the robustness of the Panel ARDL analysis, this study utilizes three alternative estimators that span a spectrum of parameter heterogeneity: Mean Group (MG), Pooled Mean Group (PMG), and Dynamic Fixed Effects (DFE). Rather than being purely isolated methods, these models build upon one another by systematically varying the degree of pooling allowed across the sampled countries. These models compete methodologically and require a Hausman test to determine the statistically optimal balance between efficiency and consistency, however they also complement each other analytically by providing a comprehensive sensitivity analysis of the core variables.

Table 10 show the results for Mean group (MG) estimation results. The MG estimation model shows that livestock density were statistically significant and negatively associated with agricultural eco-efficiency in the long run, while the remaining long-run variables were not statistically significant. In the short run, none of the explanatory variables were significant, although the error correction term is negative and statistically significant. This indicates that deviations from the long-run equilibrium are corrected over time. This suggests that when agricultural eco-efficiency moves away from its long-run relationship with the explanatory variables, the system adjusts back toward equilibrium.

***Table 10**| MG estimation results for agricultural eco-efficiency*

Variables	Long-run estimates (ECT)	Short-run estimates (SR)
Energy tax revenue	0.105	-0.028
	(0.070)	(0.042)
Temperature anomaly	-0.077	0.003
	(0.079)	(0.009)
Fertilizer intensity	-0.389	0.035
	(0.354)	(0.067)
Livestock density	-2.409***	0.070
	(0.711)	(0.354)
Share of agriculture in GDP	-0.009	0.211
	(0.172)	(0.146)
ECT		-0.394***
		(0.095)
Observations	161	161
Countries	6	6

Source: Author's estimation.

*Note: Dependent variable: D.ln_Eco-effiency. Panel: Austria, Denmark, Ireland, Luxembourg, Malta, and Netherlands (1995-2023). Eco-efficiency, energy tax revenue, fertilizer intensity, and livestock density are expressed in natural logarithmic form. Standard errors are in parentheses. Significance is shown with stars: * p<0.10, ** p<0.05, *** p<0.01. Long-run estimates report the ECT section; short-run estimates report the SR section.*

Table 11 shows the results from the Pooled Mean group (PMG) and Dynamic Fixed effects (DFE) estimations of the ARDL model. For the PMG estimator the results in the long-run show significant coefficients for energy taxes, fertiliser intensity, and livestock density. In the short run, the error correction term is significant, while GDP share is significant only at the 10% level. The results for the DFE estimator show that fertiliser intensity were weakly significant and negatively associated with eco-efficiency in the long run, while the remaining long-run variables were not statistically significant. In the short run, GDP share were positively associated with eco-efficiency and statistically significant at the 1% level. The error correction term were also negative and statistically significant.

Table 11| *PMG and DFE estimation results for agricultural eco-efficiency*

Variable	PMG Model		DFE Model	
	Long-run estimates (ECT)	Short-run estimates (SR)	Long-run estimates (ECT)	Short-run estimates (SR)
Energy tax revenue	0.161**	-0.033	0.047	-0.042
	(0.063)	(0.048)	(0.110)	(0.038)
Temperature anomaly	-0.033	0.002	0.062	-0.001
	(0.048)	(0.011)	(0.083)	(0.016)
Fertilizer intensity	-0.514**	0.014	-0.579*	-0.052
	(0.203)	(0.063)	(0.347)	(0.071)
Livestock density	-1.974***	0.077	-0.442	0.016
	(0.554)	(0.233)	(0.568)	(0.224)
Share of agriculture in GDP	-0.057	0.217*	-0.076	0.144***
	(0.079)	(0.115)	(0.099)	(0.046)
ECT		-0.291**		-0.231***
		(0.117)		(0.049)
Observations	161	161	161	161
Country	6	6	6	6

Source: Author's estimation.

*Note: Dependent variable: D.ln_Eco-effiency. Panel: Austria, Denmark, Ireland, Luxembourg, Malta, and Netherlands (1995-2023). Eco-efficiency, energy tax revenue, fertilizer intensity, and livestock density are expressed in natural logarithmic form. Standard errors are in parentheses. Significance is shown with stars: * p<0.10, ** p<0.05, *** p<0.01. Long-run estimates report the ECT section; short-run estimates report the SR section*

4.2.5 Hausman test

Table 12 presents the Hausman test results for the PMG, MG, and DFE estimators. The Hausman test rejected the long-run slope homogeneity restriction required for the PMG estimator ($p < 0.05$). While the subsequent comparison with the highly restrictive DFE model yielded a non-significant result, this is a known artifact of inflated variance or small-sample bias in DFE estimation. Therefore, the consistent Mean Group (MG) estimator is adopted to avoid pooling bias.

Table 12| *Hausman test*

Comparison	Chi-square	P-value	Comment
MG vs PMG	86.95	0.0000	Reject H0; MG preferred (Biased and inconsistent PMG)
MG vs DFE	0.17	0.9994	Invalid H0; Statistical anomaly (MG preferred)

Test of H0: Difference in coefficients not systematic.

Source: Author's estimation.

5. Discussion

The results provide some indication of a positive association between energy taxes and agricultural eco-efficiency, although this relationship is not uniform across the selected countries. In the preferred MG model, see Table 10, the tax coefficient is positive but not statistically significant, meaning that the results do not provide strong enough evidence of a systematic long-run assocciation across the full sample. Nevertheless, the positive sign is partly consistent with Pigouvian tax theory, which argues that environmental taxes can improve resource allocation by making environmental costs visible in production decisions (Pigou, 1920).This interpretation is in line with Jackson's (2000) argument that environmental taxes are most effective when they are carefully designed, gradually implemented, and supported by complementary measures. It also relates to Fu et al. (2023), who show that environmental taxation can encourage more environmentally efficient production when firms face incentives to reduce emissions intensity. More broadly, the findings suggest that the relationship between energy taxation and agricultural eco-efficiency depends not only on the existence of the tax, but also on production conditions, technological capacity, and the wider policy context.

The comparative estimators provide additional insight. The PMG model indicates a positive and statistically significant long-run association between energy taxes and eco-efficiency, while the DFE model also shows a positive but statistically insignificant relationship, see table 11. Taken together, the positive sign across MG, PMG, and DFE suggests that energy taxes may be associated with improved eco-efficiency over time. However, since the Hausman test rejects the PMG restrictions, the PMG result should be interpreted cautiously, as it represents an average long-run relationship that does not fully account for country-specific differences.

The absence of strong short-run associations is theoretically reasonable. Agricultural producers often face adjustment costs and limited flexibility in the short run, since investments in new technologies and changes in production practices require time and financial resources. Hochman et al. (2020) similarly emphasize that policy effects take time to materialize when production decisions and investments are partly irreversible. This supported the use of the ARDL framework, where short-run dynamics and long-run equilibrium relationships are treated separately.

The results further indicate that country-specific heterogeneity is important. The preferred MG estimator allows the long-run relationship to differ between countries, which is relevant because the selected countries vary in agricultural structure, economic size, environmental conditions, and policy context. This suggests that a common association between energy taxes and eco-efficiency should not be assumed across all countries. Instead, the observed relationship is likely to depend on national production systems and on the extent to which farmers are able to respond through technological adaptation or changes in input use.

Livestock density appears to be an important constraint on agricultural eco-efficiency. This finding is consistent with the literature highlighting livestock production as a major source of agricultural greenhouse gas emissions, particularly methane emissions from enteric fermentation and manure management (FAO, 2023). This suggests that livestock-intensive systems may generate environmental pressures that are not fully offset by the economic value of production. Therefore, improving eco-efficiency in livestock-intensive countries may require targeted measures beyond energy taxation, such as support for low-emission livestock systems, improved manure management, and climate-smart production practices.

Fertilizer intensity shows a negative association with eco-efficiency in the comparative PMG and DFE models. However, this relationship is not statistically significant in the preferred MG estimator, suggesting that the evidence should be interpreted cautiously. This relates to Novaković et al. (2025), who emphasize that agricultural eco-efficiency is closely connected to input-use intensity and environmental pressures from fertilizers, energy, and other production inputs. The findings therefore suggest that more efficient fertilizer use may support improved environmental performance, but that the strength of this relationship differs across countries depending on farming systems, soil conditions, and input management practices.

Temperature anomaly and the share of agriculture in GDP are not statistically significant in the preferred MG model. This suggests that these variables do not have a clear systematic long-run association with agricultural eco-efficiency across the selected countries. One possible explanation is that climate effects may operate indirectly through crop yields, production choices, or adaptation strategies rather than through a direct relationship captured by the model. Similarly, the insignificant GDP share result suggests that the relative economic importance of agriculture does not directly explain differences in eco-efficiency in this sample. Although the PMG and DFE models show some short-run significance for GDP share, this result is not consistent across all estimators and should therefore be interpreted carefully.

From a policy perspective, the findings suggest that environmental taxation alone may not be sufficient to improve agricultural eco-efficiency in all countries. Since the associations appear to vary across national contexts, energy taxes should be designed with attention to country-specific agricultural structures, production systems, and policy frameworks. Complementary measures, such as support for low-emission livestock systems, efficient fertilizer use, technological investment, and climate-smart agriculture, may strengthen the effectiveness of environmental taxation. This is consistent with Jackson's (2000) argument that environmental taxes are more effective when combined with complementary policy measures. Improving agricultural eco-efficiency is therefore likely to require a combination of market-based instruments and targeted agricultural policies.

Overall, the results should be interpreted with caution due to the small sample size. The study includes only six countries, meaning that the MG estimates, standard errors, and Hausman tests may be sensitive to individual countries. With a small cross-sectional dimension, the statistical power of tests comparing MG, PMG, and DFE is limited, and conclusions about common long-run coefficients may be fragile. This is particularly important because the Hausman test rejects the PMG restrictions, suggesting that country-specific heterogeneity matters. Therefore, the findings should be seen as indicative of potential relationships rather than definitive evidence of causal effects.

6. Conclusion

This study examined the association between energy taxes and agricultural eco-efficiency in six European countries between 1995 and 2023. The results provide some indication of a positive association between energy taxes and eco-efficiency, but the evidence is not strong enough to conclude that this association is systematic across all countries. While the PMG model suggests a significant positive long-run relationship, the preferred MG model does not find a statistically significant association. A more consistent result is the negative association between livestock density and eco-efficiency, highlighting the environmental pressures associated with livestock-intensive production systems. From a policy perspective, the results suggest that energy taxes alone may not be sufficient to improve agricultural eco-efficiency. Their effectiveness is likely to depend on country-specific conditions and complementary measures, including support for low-emission livestock systems, efficient fertilizer use, technological innovation, and climate-smart agricultural practices.

The findings should be interpreted in light of several limitations. The study is based on a small sample of six countries, which limits generalizability and makes the results sensitive to country-specific characteristics. In addition, the eco-efficiency measure is based on agricultural production value relative to greenhouse gas emissions and therefore does not capture other environmental pressures such as biodiversity loss, water pollution, or soil degradation. The use of current US dollars may also affect the measure through inflation, commodity price changes, and exchange rate fluctuations. Furthermore, the study identifies associations rather than causal effects, as potential endogeneity, omitted variables, and measurement limitations may influence the results. Future research could address these limitations by expanding the sample of countries, using regional or farm-level data, constructing eco-efficiency measures based on constant prices or physical output indicators, and including additional variables such as agricultural subsidies, energy prices, innovation, or policy design indicators. Applying methods that account for cross-sectional dependence, serial correlation, and heteroskedasticity, such as the Driscoll-Kray estimator, could also improve the robustness of future analyses.

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