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Does organic farming mitigate agricultural emissions? A multi-dimensional panel analysis of cross-sectional moderation and dynamic causality in the EU-25

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Abstract: This study examines whether organic farming mitigates agricultural greenhouse gas (GHG) emissions in the European Union by distinguishing between structural associations and dynamic causal effects. Using an unbalanced panel of 25 EU countries from 2014 to 2024, it applies an integrated econometric framework combining two-way fixed effects, interaction models, Driscoll–Kraay standard errors, Difference GMM, quantile regression, and difference-in-differences approaches to address heterogeneity, endogeneity, and emissions persistence. The results show that organic farming moderates the impact of fertiliser use on emissions in cross-country comparisons, suggesting lower emissions sensitivity to input intensity in countries with higher organic adoption. However, this effect is not consistently observed within countries over time. Once dynamic processes and endogeneity are accounted for, the estimated mitigation effect becomes statistically insignificant, indicating that the observed relationship is driven mainly by structural differences across agricultural systems rather than by a robust causal effect. Additional analyses reveal that the moderation effect is concentrated in lower-emission agricultural systems and largely reflects between-country variation. Evaluation of the Common Agricultural Policy reform provides no consistent evidence that policy support for organic farming strengthened emissions mitigation. Overall, the findings suggest that organic farming may contribute to lower emissions pressure under specific conditions, particularly by reducing the environmental impact of fertiliser use, although the evidence does not support a consistent dynamic effect on aggregate agricultural GHG emissions during the study period. The results indicate that its climate-mitigation potential depends on broader structural conditions, production systems, and complementary policy measures.

Keywords: Organic farming; Greenhouse gas emissions; Panel data econometrics; Dynamic causality; Agricultural sustainability; European Union.

1. Introduction

Agriculture is a major source of greenhouse gas (GHG) emissions, particularly methane (CH₄), nitrous oxide (N₂O), and carbon dioxide (CO₂), generated through fertiliser application, livestock production, and intensive cultivation practices. The environmental pressure associated with agricultural production has intensified with the widespread use of synthetic nitrogen fertilisers. Consequently, agricultural systems are increasingly evaluated not only by their productivity, but also by their environmental performance.

Within this context, organic farming has emerged as an alternative to conventional agriculture. Tuomisto et al. (2012) reported that organic farming reduces energy use and N₂O emissions due to lower dependence on synthetic fertilisers. Similarly, Skinner et al. (2014) showed that reduced nitrogen application lowers N₂O emissions, although the magnitude of the effect varies according to the measurement scale. Organic farming may also mitigate climate impacts through lower fertiliser and pesticide use; however, lower productivity and yield-related trade-offs remain important limitations (Krause et al., 2024). Yield penalties of approximately 20–30% may offset part of the environmental gains, while environmental performance depends on whether impacts are assessed per hectare or per unit of output (Hashemi et al., 2024). These mixed findings raise questions about whether organic farming constitutes an effective climate mitigation strategy or mainly reflects structural differences across agricultural systems.

Micro-level evidence suggests that organic farming provides environmental benefits through lower synthetic input use, reduced nitrogen losses, and improved soil management (Tuomisto et al., 2012; Skinner et al., 2014). These studies report lower area-scaled emissions and better ecological performance under organic systems. However, the literature becomes more contradictory when broader system-wide effects and macro-level evidence are considered. Smith et al. (2019) argue that lower yields in organic farming may increase land demand elsewhere, potentially offsetting local emission reductions through indirect land-use effects. Similarly, Smith (2025) suggests that the environmental benefits of organic farming may weaken when rebound effects, lower yields, and broader land-use implications are incorporated into the analysis.

Macro-level studies often identify negative associations between organic farming and agricultural emissions, although limitations related to endogeneity and dynamic adjustment processes remain. Bocean (2025) reports that higher levels of organic farming are associated with lower emissions in the European Union, but the analysis does not fully address reverse causality. Squalli (2023) also finds a negative relationship between organic farming and GHG emissions; however, the estimates appear sensitive to structural heterogeneity and potential endogeneity. Wang et al. (2025a) show that environmental outcomes in the agricultural sector depend on technological and structural conditions across countries. Consequently, the literature does not clearly establish whether observed emission reductions result directly from organic farming or from underlying structural differences among countries.

A major gap in the literature on organic farming and GHG emissions is the limited distinction between cross-sectional (between-country) and dynamic (within-country) effects. Although many studies report negative relationships between organic farming and emissions, the evidence remains fragmented and largely based on static associational frameworks. As a result, structural associations are often conflated with causal effects, leading to ambiguous conclusions regarding the mitigation role of organic farming.

Another limitation concerns the limited use of moderating analysis, particularly whether organic farming mitigates the effects of fertiliser use and agricultural production intensity on emissions. The treatment of endogeneity also remains insufficient, since the adoption of organic farming is influenced by policy, environmental, and structural factors (Squalli, 2023). In addition, many studies overlook emissions persistence and delayed dynamic effects, despite the relevance of dynamic panel approaches such as Arellano & Bond (1991). Consequently, a more integrated empirical framework is needed to distinguish long-term structural relationships from dynamic causal effects.

This study addresses the following research question: Does organic farming mitigate agricultural greenhouse gas emissions in the European Union, and is this effect structural or causal? To answer this question, five objectives are pursued. First, the relationship between organic farming and agricultural emissions is examined using a fixed-effects panel model. Second, the study evaluates whether organic farming moderates the effects of fertiliser use and agricultural production intensity through interaction terms. Third, within-country and between-country variation is decomposed to distinguish structural relationships from dynamic effects. Fourth, endogeneity and emissions persistence are addressed using the Difference Generalized Method of Moments (GMM) estimator. Finally, the role of agricultural policy interventions is assessed through a difference-in-differences (DiD) model.

Building on the theoretical framework and the identified research gaps, this study develops two complementary hypotheses to distinguish structural associations from dynamic causal effects in the relationship between organic farming and agricultural GHG emissions:

Hypothesis H1 (Cross-sectional structural moderation): Countries with higher levels of organic farming adoption are expected to exhibit lower agricultural GHG emissions and weaker emission responses to fertiliser use and agricultural output. However, these relationships are expected to reflect structural heterogeneity, production systems, and scale-dependent measurement effects (e.g., emissions per hectare versus per unit of output), rather than a universally consistent mitigation effect across countries (e.g., Tuomisto et al., 2012; Skinner et al., 2014; Hashemi et al., 2024; Krause et al., 2024; Gerke, 2025; Bocean, 2025; and Wang et al., 2025b).

Hypothesis H2 (Limited dynamic causal effect): Increases in organic farming over time are not expected to generate a robust and generalisable causal reduction in agricultural GHG emissions once emissions persistence, unobserved heterogeneity, and endogeneity are adequately controlled for. Likewise, the moderating effects of organic farming on the relationships between fertiliser use, agricultural output, and emissions are expected to weaken in dynamic panel specifications (e.g., Squalli, 2023; Smith et al., 2019; Smith, 2025; Vejendla et al., 2025; and Wang et al., 2025).

The study contributes to the literature in three ways. First, it explicitly distinguishes structural cross-sectional associations from within-country dynamic effects, an issue rarely addressed in the organic farming literature. Second, it demonstrates that the apparent mitigation effect of organic farming is highly sensitive to the econometric framework employed. Third, it provides evidence that observed environmental advantages are driven predominantly by between-country heterogeneity rather than by short-run changes in organic adoption. Conceptually, it distinguishes between structural cross-sectional relationships and dynamic within-country

effects, clarifying whether organic farming acts as a causal mitigation mechanism or primarily reflects broader agricultural sector characteristics. Empirically, it introduces a moderation framework to evaluate how organic farming influences the relationship between fertiliser use, agricultural output, and GHG emissions through interaction effects. Methodologically, the study applies an integrated econometric framework combining fixed effects, Difference GMM, quantile regression, and difference-in-differences models to address heterogeneity, persistence, endogeneity, and distributional differences. This approach provides a more rigorous assessment of the environmental implications of organic farming in the European Union than single-method or purely associational analyses.

The remainder of the paper is organised as follows. **Section 2** reviews the literature and develops the theoretical framework and hypotheses. **Section 3** presents the data and methodology. **Section 4** reports the empirical results and robustness analyses. **Section 5** discusses the findings. **Section 6** concludes and presents the policy implications and directions for future research.

2. Literature Review

This section reviews the literature on the relationship between organic farming and greenhouse gas emissions and identifies the theoretical foundations and research gaps that motivate the study.

2.1 Empirical Evidence on Organic Farming and Greenhouse Gas Emissions

This subsection summarizes the main empirical findings on the association between organic farming and greenhouse gas emissions, highlighting key patterns, mechanisms, and sources of heterogeneity reported in the literature.

2.1.1 *Organic farming and emissions: a scale-dependent relationship*

The environmental effects of organic farming depend strongly on the unit of analysis. Organic systems generally improve environmental performance per hectare by increasing soil organic matter and reducing nutrient losses, including N₂O, ammonia emissions, and nitrogen leaching (Tuomisto et al., 2012). A meta-analysis found that organic farming reduces area-based GHG emissions by approximately 492 kg CO₂-eq ha⁻¹ yr⁻¹, largely due to the absence of synthetic nitrogen fertilizers (Skinner et al., 2014). However, lower yields often offset these benefits when emissions are measured per unit of output. Typical organic yield gaps of 20–30% increase land requirements and can weaken or eliminate environmental advantages at the product level (Skinner et al., 2014; Hashemi et al., 2024). Consequently, organic farming tends to perform better per hectare than per unit of production.

2.1.2 *Environmental benefits, productivity trade-offs, and contextual heterogeneity*

Evidence from the long-term DOK experiment shows that organic farming reduces synthetic input use, lowers environmental impacts, and improves biodiversity and soil health, but yields remain approximately 15% lower than in conventional systems (Krause et al., 2024). Similarly, higher productivity in conventional systems is often associated with greater emissions, highlighting a trade-off between environmental sustainability and production efficiency (Gerke, 2025).

The magnitude of environmental benefits also varies across contexts. Organic farming increases species richness by about 30%, although effects differ by crop type, taxonomy, and farming conditions (Tuck et al., 2014). Diversification and organic soil amendments can simultaneously improve productivity and reduce emissions, but outcomes depend heavily on local soil, climatic, and management conditions (Wang et al., 2025). Therefore, results cannot be generalized across regions or production systems.

2.1.3 *Evidence from macro-level studies*

Macro-level studies generally report a negative association between organic farming and agricultural emissions. Cross-country evidence suggests that greater organic land use is associated with lower GHG emissions in the European Union (Bocean, 2025). However, most studies rely on associational evidence and often do not adequately address endogeneity, limiting causal interpretation.

2.2 Mechanisms Linking Organic Farming and Emissions

Organic farming reduces emissions primarily through lower input intensity and greater reliance on ecological processes. Reduced use of synthetic fertilizers lowers N₂O emissions and nitrogen losses, contributing to lower environmental impacts per hectare (Tuomisto et al., 2012; Skinner et al., 2014). Nevertheless, system-wide effects are more complex. Large-scale adoption may create yield gaps that require additional land use or food imports, potentially offsetting local emission reductions through indirect land-use change (Smith et al., 2019). Furthermore, emission responses differ across gases, agricultural practices, and environmental conditions, resulting in substantial heterogeneity across studies (Wang et al., 2025; Vejendla et al., 2025). Consequently, organic farming does not guarantee uniform emission reductions across all contexts.

2.3 Why the Literature Remains Inconclusive

Several methodological limitations contribute to the mixed evidence. First, endogeneity and selection bias complicate causal identification. Regions adopting organic farming often already possess favorable environmental conditions, stronger institutions, or supportive policies, making it difficult to isolate the independent effect of organic practices (Squalli, 2018; Ganda, 2023). Second, many studies employ static models that fail to capture the persistence of emissions over time. Dynamic approaches, such as GMM estimators, are better suited to account for path dependence and long-run environmental dynamics (Arellano & Bond, 1991; Coderoni & Esposti, 2014). Third, measurement choices strongly influence conclusions. Organic farming frequently reduces impacts per hectare but not necessarily per unit of output because of lower yields and higher land requirements (Hashemi et al., 2024). Finally, a disconnect exists between micro- and macro-level evidence. Experimental and farm-level studies often report local environmental benefits, whereas large-scale assessments indicate that yield reductions may generate indirect emissions through land expansion and increased imports (e.g., Smith et al., 2019; Hashemi et al., 2024; and Vejendla et al., 2025). Thus, differences in analytical scale and methodology contribute substantially to the divergent findings reported in the literature.

2.4 Research Gap

Despite extensive research, important gaps remain. Existing studies rarely distinguish between cross-sectional associations and dynamic relationships over time, while limited attention has been given to moderation effects and the role of regional heterogeneity. Moreover, few studies simultaneously address endogeneity, temporal dynamics, and contextual differences. To address these limitations, this study distinguishes structural from dynamic relationships between organic farming and emissions. It examines how organic farming adoption interacts with regional production conditions and employs a multi-method framework combining fixed effects GMM, quantile regression, and DiD approaches to account for endogeneity and heterogeneity.

2.5 Theoretical Framework

The relationship between organic farming and GHG emissions is rooted in the input-intensity and agroecological transition framework. By reducing synthetic fertilizer use and enhancing biological nutrient cycling, organic farming can lower nitrogen-related emissions, particularly N₂O (Tuomisto et al., 2012; Skinner et al., 2014). However, yield penalties of 15–30% create a trade-off between environmental performance per hectare and per unit of output (e.g., Krause et al., 2024; Hashemi et al., 2024; and Smith et al., 2019).

From a macro perspective, the STIRPAT framework views organic farming as part of broader structural and technological change. Its environmental effects vary according to agro-climatic conditions, production systems, and policy environments (Squalli, 2023; Gerke, 2025). Evidence consistently shows stronger environmental benefits per hectare than per unit of production and highlights substantial contextual heterogeneity (e.g., Skinner et al., 2014; Tuomisto et al., 2012; and Wang et al., 2025).

The dynamic relationship remains less certain because emissions exhibit persistence, organic adoption is endogenous to institutional and policy factors, and transition effects may emerge only after substantial time lags (e.g., Arellano & Bond, 1991; Wooldridge, 2010; and Smith, 2025). Rebound effects and non-linear responses further complicate causal identification (Smith et al., 2019; Vejendla et al., 2025).

A persistent gap therefore remains between micro-level biophysical evidence and macro-level structural analyses (Hashemi et al., 2024). By distinguishing cross-sectional (H1) and dynamic (H2) relationships, this study

seeks to integrate both perspectives within a unified empirical framework. **Fig. 1** presents the theoretical framework underpinning the analysis.

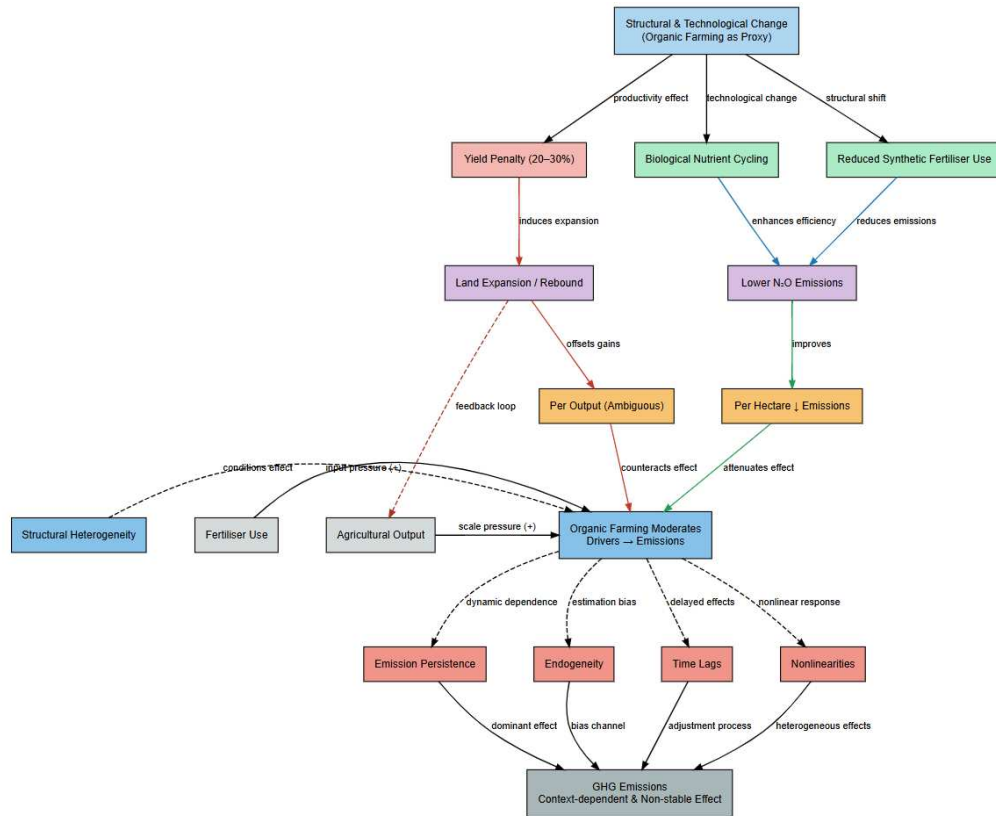


Figure 1. Theoretical framework of organic farming and greenhouse gas emissions: scale dependence, structural heterogeneity, and dynamic effects. This figure was created by the authors.

2.6. Link hypotheses

The literature distinguishes between cross-sectional associations and dynamic causal effects in the relationship between organic farming and GHG emissions. Meta-analyses indicate that organic farming is generally associated with lower emissions per hectare due to reduced synthetic input use, particularly nitrogen-related emissions such as N₂O (Tuomisto et al., 2012; Skinner et al., 2014). However, these benefits often weaken or disappear when measured per unit of output because of yield penalties and scale dependence (Hashemi et al., 2024; Krause et al., 2024). In addition, the environmental performance of organic systems depends on structural conditions and production system characteristics rather than reflecting a universal mitigation effect (Gerke, 2025). These findings support H1, suggesting that organic farming moderates the impact of key emission drivers across countries through structural heterogeneity.

By contrast, evidence on dynamic effects remains inconclusive. Yield gaps may induce land expansion and offset emission reductions (Smith et al., 2019; Smith, 2025), while meta-analyses report substantial heterogeneity in emission responses (Vejendla et al., 2025; Wang et al., 2025b). Furthermore, endogeneity and emissions persistence complicate causal identification in panel settings (Squalli, 2023). Accordingly, H2 posits that the expansion of organic farming does not generate a robust and stable causal reduction in emissions over time once these factors are accounted for.

3. Data and Methods

This section presents the data and econometric methods used in the empirical analysis. Due to space limitations, **Tables A1–A7** are provided in the Appendix, while **Tables S1–S9** are included in the Supplementary Material.

3.1. Data

This study uses an unbalanced panel of 25 European Union countries observed annually from 2014 to 2024. Luxembourg and Malta are excluded due to missing data on key variables, ensuring consistency and avoiding imputation bias. The unbalanced structure maximises data availability while preserving cross-country and within-country variation (Wooldridge, 2010; Baltagi, 2021). Variables (see **Table A1**) are selected based on their relevance to agricultural environmental pressure.

The dependent variable is agricultural greenhouse gas emissions (lnEM), which capture overall environmental pressure generated by the agricultural sector (e.g., De Silva et al., 2025; Ahmed et al., 2025; and Bărbulescu, 2025). While aggregate emissions constitute a widely used environmental indicator, they do not account for differences in agricultural output or land use efficiency. Consequently, the results should be interpreted as reflecting changes in total emissions rather than environmental efficiency. The main explanatory variables capture key emission drivers. Fertiliser use (lnFERT) reflects input intensity and is associated with higher emissions, particularly nitrous oxide from soils (Bărbulescu, 2025; Brown et al., 2026). Agricultural output (lnOUT) captures scale effects in production (Bărbulescu, 2025; Ma et al., 2024).

Organic farming (lnORG) reflects the adoption of sustainable practices and is modelled both as a direct determinant and as a moderating factor, potentially reducing emissions through improved land and input management (Bărbulescu, 2025; Topp et al., 2023). Livestock density (lnLIVE) proxies production intensity and is strongly linked to methane emissions (Bărbulescu, 2025; Hayek and Miller, 2021). GDP per capita (lnGDP) captures structural and technological development (Wang et al., 2025a; Haider et al., 2022), export intensity (lnEXP) reflects trade-related effects (Öztürk, 2025; Saghaian et al., 2022), and agricultural R&D expenditure (lnRD) represents innovation capacity (Fahad & Hossain, 2025; Fuglie et al., 2022).

All variables are expressed in natural logarithms to stabilise variance, reduce skewness, and allow coefficient interpretation as elasticities, including within interaction terms. The empirical specification focuses on lnFERT, lnOUT, and lnORG as core drivers, with lnORG also entering through interaction terms, while lnLIVE, lnGDP, lnEXP, and lnRD are included as controls.

3.1.1. Unbalanced Panel and Missing Data

Missingness is variable-specific and moderate, ranging from 2.16% (lnEXP) to 15.12% (lnEM), while lnOUT is fully observed. A mean comparison test shows no significant difference in emissions between observations with and without lnFERT ($p = 0.350$), though this does not establish Missing Completely at Random (MCAR) (Little & Rubin, 2019). A logit model indicates that missingness depends on observed variables, particularly livestock intensity and R&D ($p < 0.05$), supporting a Missing at Random (MAR) mechanism.

Under MAR, fixed-effects estimators remain consistent when missingness depends on observables (Wooldridge, 2010). Driscoll–Kraay standard errors ensure robustness to heteroskedasticity, serial correlation, and cross-sectional dependence (Driscoll & Kraay, 1998). Results from a balanced subsample are unchanged, confirming that missing data do not affect the estimates.

3.2. Methods

To examine whether organic farming mitigates environmental pressure in European agriculture, a multi-layer empirical strategy is employed, combining panel econometrics, interaction models, distributional analysis, and causal inference techniques. This approach identifies average effects, moderation mechanisms, heterogeneity, and dynamic adjustments, overcoming single-method limitations and strengthening inference. **Fig. 2** illustrates the methodological framework guiding this investigation.

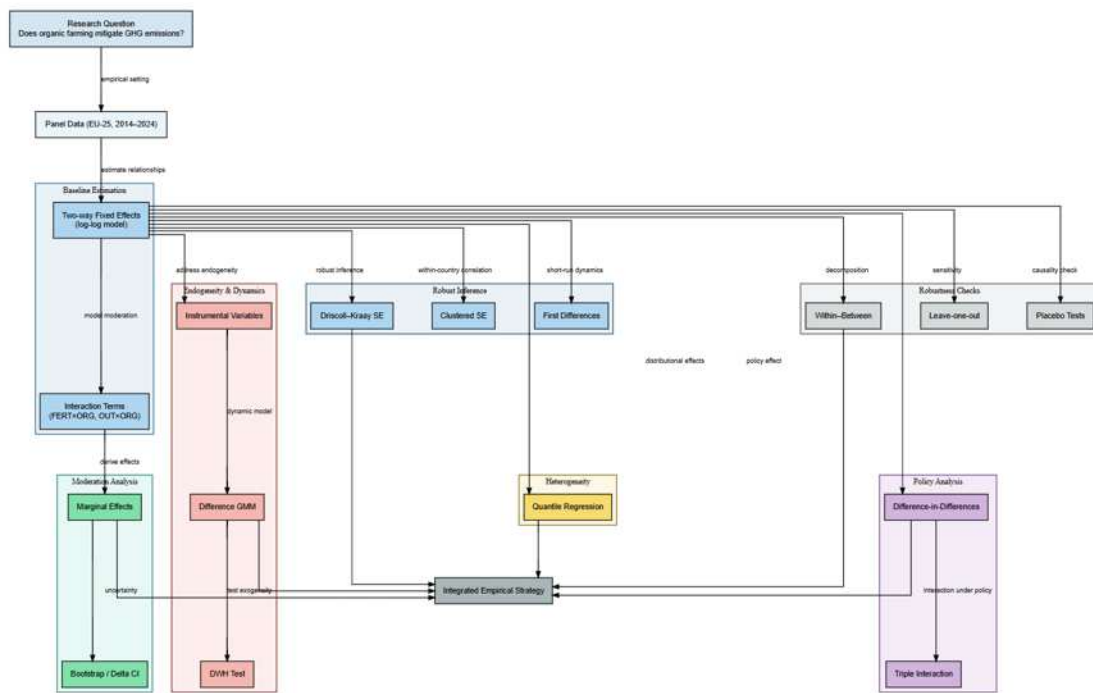


Figure 2. The methodological framework . This figure was created by the authors.

3.2.1. Baseline Econometric Specification

The empirical model is specified as a log-log two-way fixed effects panel regression, as shown in **Eq. 1** below.

$$\begin{aligned} \ln EM_{it} = & \beta_1 \ln FERT_{it} + \beta_2 \ln OUT_{it} + \beta_3 \ln ORG_{it} + \beta_4 (\ln FERT \times \ln ORG)_{it} \\ & + \beta_5 (\ln OUT \times \ln ORG)_{it} + \beta_6 \ln LIVE_{it} + \beta_7 \ln GDP_{it} + \beta_8 \ln EXP_{it} + \beta_9 \ln RD_{it} \\ & + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (\text{Eq. 1})$$

where i indexes countries and t denotes time; $\ln EM_{it}$ represents agricultural emissions, $\ln FERT_{it}$ fertiliser use, $\ln OUT_{it}$ agricultural output, $\ln ORG_{it}$ organic farming, $\ln LIVE_{it}$ livestock intensity, $\ln GDP_{it}$ economic development, $\ln EXP_{it}$ export intensity, and $\ln RD_{it}$ agricultural R&D; β_k are slope coefficients; μ_i captures unobserved country-specific effects; λ_t controls for time effects; and ε_{it} is the idiosyncratic error term. The fixed effects estimator is defined in **Eq. 2** below.

$$\hat{\beta}^{FE} = \arg \min_{\beta} \sum_{i=1}^N \sum_{t=1}^T (\tilde{y}_{it} - \tilde{X}_{it}\beta)^2 \quad (\text{Eq. 2})$$

where $\tilde{y}_{it} = y_{it} - \bar{y}_i$ and $\tilde{X}_{it} = X_{it} - \bar{X}_i$ denote within-transformed variables obtained by subtracting individual-specific means. This transformation eliminates μ_i , isolating within-country variation over time. This specification is appropriate given the likely correlation between regressors and unobserved heterogeneity, ensuring consistent estimation (Wooldridge, 2010; Baltagi, 2021).

3.2.2. Robust Inference and Model Diagnostics

Given violations of standard panel assumptions, inference is based on Driscoll–Kraay standard errors, as shown in **Eq. 3** below.

$$\widehat{Var}(\hat{\beta}) = (X'X)^{-1} \hat{\Omega}_{DK} (X'X)^{-1} \quad (\text{Eq. 3})$$

where X is the matrix of regressors and $\hat{\Omega}_{DK}$ is a consistent estimate of the covariance matrix allowing for heteroskedasticity, serial correlation, and cross-sectional dependence. This estimator ensures valid inference in panels with spatial and temporal dependence (Driscoll & Kraay, 1998). Robustness is further assessed using first-difference estimation, as shown in **Eq. 4** below.

$$\Delta \ln EM_{it} = \beta' \Delta X_{it} + \Delta \varepsilon_{it} \quad (\text{Eq. 4})$$

where $\Delta X_{it} = X_{it} - X_{it-1}$ denotes period-to-period changes in regressors and $\Delta \varepsilon_{it}$ is the differenced error term. This transformation removes time-invariant effects and captures short-run dynamics (Wooldridge, 2010). Cluster-robust standard errors are also computed, as shown in **Eq. 5** below.

$$\widehat{Var}(\hat{\beta}) = (X'X)^{-1} \left(\sum_{i=1}^N X_i' \hat{\varepsilon}_i \hat{\varepsilon}_i' X_i \right) (X'X)^{-1} \quad (\text{Eq. 5})$$

where X_i and $\hat{\varepsilon}_i$ denote the regressors and residuals for cluster i , allowing for arbitrary correlation within countries (Arellano, 1987). Consistency across estimators supports robustness.

3.2.3. Endogeneity and Dynamic Specification

To address potential endogeneity, an instrumental variable approach is implemented. The first-stage specification is defined, as shown in **Eq. 6** below.

$$X_{it} = \pi_0 + \pi_1 X_{i,t-1} + \eta_i + \tau_t + u_{it} \quad (\text{Eq. 6})$$

where X_{it} denotes endogenous regressors (e.g., fertiliser use, output), $X_{i,t-1}$ are their lagged values used as instruments, η_i and τ_t are fixed effects, and u_{it} is the first-stage error term. Second stage, as shown in **Eq. 7** below.

$$\ln EM_{it} = \beta \hat{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (\text{Eq. 7})$$

where $\hat{X}_{it}$ are predicted values from the first stage. This approach exploits persistence in regressors, although the exclusion restriction may not fully hold (Angrist & Pischke, 2009; Wooldridge, 2010). To account for dynamic persistence, a Difference GMM model is estimated, as shown in **Eq. 8** below.

$$\ln EM_{it} = \gamma \ln EM_{i,t-1} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (\text{Eq. 8})$$

where $\ln EM_{i,t-1}$ captures persistence in emissions and γ measures dynamic adjustment. The model is estimated using internal instruments derived from lagged variables (Arellano & Bond, 1991; Roodman, 2009). Endogeneity is further assessed using the Durbin–Wu–Hausman test, which evaluates whether regressors are correlated with the error term (e.g., Durbin, 1954; Wu, 1973; and Hausman, 1978).

3.2.4. Moderation and Marginal Effects

Given interaction terms, marginal effects are defined, as shown in **Eq. 9** below.

$$\frac{\partial \ln EM_{it}}{\partial \ln FERT_{it}} = \beta_1 + \beta_4 \ln ORG_{it} \quad (\text{Eq. 9})$$

where β_1 captures the baseline effect of fertiliser use and β_4 reflects how this effect varies with organic farming, as shown in **Eq. 10** below.

$$\frac{\partial \ln EM_{it}}{\partial \ln OUT_{it}} = \beta_2 + \beta_5 \ln ORG_{it} \quad (\text{Eq. 10})$$

where β_2 is the baseline effect of output and β_5 captures the moderation effect. These marginal effects are evaluated across the distribution of $\ln ORG_{it}$, with uncertainty quantified using bootstrap confidence intervals and Delta method approximations (Brambor et al., 2006).

3.2.5. Distributional Heterogeneity: Quantile Regression

To capture heterogeneity, quantile regression is estimated, as shown in **Eq. 11** below.

$$Q_\tau(\ln EM_{it} | X_{it}) = X'_{it} \beta_\tau \quad (\text{Eq. 11})$$

where $Q_\tau(\cdot)$ denotes the conditional quantile at level τ , X_{it} is the vector of regressors, and β_τ are quantile-specific coefficients. The estimator solves, as shown in **Eq. 12** below.

$$\min_{\beta} \sum_{i,t} \rho_\tau(\ln EM_{it} - X'_{it} \beta) \quad (\text{Eq. 12})$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the check function and $I(\cdot)$ is an indicator function (Koenker & Bassett, 1978). This approach allows slope coefficients to vary across the distribution.

3.2.6. Policy Evaluation: Difference-in-Differences

Policy effects are assessed using a Difference-in-Differences specification, as shown in **Eq. 13** below.

$$\ln EM_{it} = \beta_0 + \beta_1(\ln ORG_{it} \times Post_t) + \mu_i + \lambda_t + \varepsilon_{it} \quad (\text{Eq. 13})$$

where $Post_t$ is a dummy variable equal to 1 in the post-reform period and 0 otherwise; β_1 captures the differential effect of organic farming after the policy intervention. A triple interaction specification is also estimated, as shown in **Eq. 14** below.

$$\ln EM_{it} = \beta_1(\ln OUT \times \ln ORG \times Post)_{it} + \dots \quad (\text{Eq. 14})$$

where the triple interaction captures whether the moderating effect of organic farming on output changes after the reform. Identification relies on the parallel trends assumption (Angrist & Pischke, 2009).

3.2.7. Robustness, Decomposition, and Sensitivity Analysis

Additional analyses include: (i) Within–between decomposition, separating within-country deviations from cross-country averages (Wooldridge, 2010); (ii) Leave-one-country-out estimation, testing sensitivity to influential observations; (iii) Placebo tests using lead variables, assessing reverse causality; and (iv) Alternative specifications, including non-linear transformations and subsamples. These procedures ensure that results are not driven by model specification or sample composition.

3.2.8. Integrated Framework and Limitations

The empirical strategy combines fixed effects, interaction models, dynamic panel methods (Difference GMM), quantile regression, and quasi-experimental approaches (difference-in-differences), providing complementary insights into the determinants of environmental pressure.

However, several limitations remain. The relatively short time span (2014–2024) and potential endogeneity inherent to observational data constrain causal inference, while identification relies on missing-at-random assumptions (Little & Rubin, 2019). Moreover, the transition to organic farming may involve substantial time lags (e.g., 3–5 years) before measurable effects on emissions materialise. Given the 11-year panel, long-term impacts may be only partially captured, and the absence of dynamic effects should be interpreted cautiously.

Accordingly, results are best viewed as robust associations with partial causal insights rather than definitive causal estimates. Additionally, the organic farming variable ($\ln ORG$) captures the share of certified organic area rather than the intensity of practices (e.g., crop rotations, compost use, reduced tillage). Cross-country heterogeneity in implementation may therefore attenuate estimated effects.

4. Empirical results

The empirical results are presented following a structured sequence consistent with the estimation strategy: descriptive statistics, diagnostic tests, baseline estimation, and robustness analyses. This ordering ensures coherence between the data properties and the econometric specifications.

4.1. Descriptive Statistics and Preliminary Diagnostics

Therefore, the analysis begins with the descriptive properties of the variable. **Table 1** below reports the summary statistics for all variables included in the model.

Table 1. Descriptive Statistics

Variables	N	Mean	SD	Min	Max
$\ln EM$	268	0.29	0.34	0.00	1.28
$\ln FERT$	282	11.97	1.23	6.28	14.61
$\ln OUT$	317	8.73	1.34	4.77	11.33
$\ln ORG$	282	4.26	0.82	1.50	5.46
$\ln LIVE$	290	0.95	0.61	0.19	2.36
$\ln GDP$	279	10.81	1.37	9.48	15.51

lnEXP	310	4.99	2.18	0.35	9.85
lnRD	294	3.60	1.57	0.38	7.00

Notes: All variables log-transformed. The sample is an unbalanced panel due to missing observations across variables.

Table 1 indicates that lnEM exhibits moderate dispersion, while lnFERT and lnOUT vary with agricultural intensity. lnORG and lnLIVE show lower variability, reflecting structural production characteristics. Greater dispersion in lnGDP, lnEXP, and lnRD captures economic and technological heterogeneity, supporting the use of panel methods (Baltagi, 2021; Wooldridge, 2010).

Pairwise correlations (see **Table A2**) show lnEM is positively associated with lnFERT and lnOUT. The negative bivariate correlation for lnORG contrasts with its positive regression coefficient, indicating omitted variable bias and conditional relationships (Tabachnick & Fidell, 2019; Field, 2018). High correlations between lnFERT–lnOUT (0.87) and lnOUT–lnRD (0.84) suggest potential multicollinearity. VIF results (see **Table A3**) indicate moderate values for lnFERT and lnOUT, with others within acceptable limits. While multicollinearity may reduce precision and inflate standard errors contributing to lnOUT instability it does not invalidate estimation.

Panel unit root tests (Levin et al., 2002; Im et al., 2003; see **Table A4**) indicate that lnEM, lnORG, lnGDP, lnEXP, and lnRD are stationary in levels ($p < 0.01$), while lnFERT, lnOUT, and lnLIVE yield mixed results. Given the short time dimension, these results should be interpreted cautiously.

4.2. Baseline Fixed Effects Results

Accordingly, two-way fixed effects with robust standard errors are employed (Baltagi, 2021; Wooldridge, 2010). **Table 2** reports estimates controlling for country and time heterogeneity.

Table 2. Two-Way Fixed Effects Model (Baseline Results)

Dependent variable: lnEM					
Independent variables	Coefficient	Std. Error	t-value	p-value	Significance
lnFERT	0.260	0.078	3.336	0.001	***
lnORG	1.127	0.152	7.433	0.000	***
lnOUT	0.265	0.105	2.534	0.012	**
lnLIVE	0.030	0.078	0.377	0.707	
lnGDP	-0.104	0.085	-1.228	0.221	
lnEXP	-0.0002	0.004	-0.054	0.957	
lnRD	0.022	0.009	2.565	0.011	**
lnFERT × lnORG	-0.049	0.016	-2.957	0.003	***
lnORG × lnOUT	-0.062	0.019	-3.260	0.001	***
Observations (N)	259				
Countries (n)	25				
Time periods (T)	6–11				
R-squared	0.326				
Adj. R-squared	0.191				
F-statistic	11.534				
Prob > F	0.000				

Notes: Two-way fixed effects model controlling for country and time effects. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Fertiliser use (lnFERT; $\beta = 0.260$, $p < 0.01$) is positively associated with emissions, conditional on lnORG = 0 due to the interaction term. Agricultural output (lnOUT; $\beta = 0.265$, $p < 0.05$) is similarly conditional. The coefficient on organic farming (lnORG; $\beta = 1.127$, $p < 0.01$) is not directly interpretable in isolation.

Interaction terms are negative and significant (lnFERT×lnORG: $\beta = -0.049$, $p < 0.01$; lnORG×lnOUT: $\beta = -0.062$, $p < 0.01$), indicating that organic farming attenuates the marginal effects of fertiliser use and, to a lesser extent, output. Evaluated at the sample mean of lnORG (4.26), the marginal effect of fertiliser is $\partial \ln EM / \partial \ln FERT = 0.260 - 0.049 \times 4.26 = 0.051$. Thus, a 1% increase in fertiliser use is associated with a 0.05% increase in emissions at average organic levels, substantially smaller than in countries with no organic adoption. This supports H1 (cross-sectional moderation), indicating that organic farming mitigates the impact of fertiliser use across countries.

Among controls, lnLIVE, lnEXP, and lnGDP are not significant, while lnRD ($\beta = 0.022$, $p < 0.05$) is positive. The model is jointly significant, and interaction terms are jointly significant ($\chi^2 = 64.392$, $p < 0.01$; see **Table A5**) (Baltagi, 2021; Wooldridge, 2010). Diagnostics indicate serial correlation (Breusch, 1978; Wooldridge, 2002) and heteroskedasticity (Breusch & Pagan, 1979). Cross-sectional dependence is mixed: Pesaran CD is not significant, while the Breusch–Pagan LM test is significant (Pesaran, 2004; Breusch & Pagan, 1980) (see **Table A6**).

4.3. Robust Baseline: Driscoll–Kraay Estimates (Main Specification)

The results in **Table 3** represent the main specification, as they account for heteroskedasticity, serial correlation, and cross-sectional dependence using Driscoll–Kraay standard errors (Driscoll & Kraay, 1998). Given the diagnostic evidence particularly serial correlation, heteroskedasticity, and LM-based indications of cross-sectional dependence this estimator provides the most reliable inference within the fixed-effects framework.

Table 3. Two-Way Fixed Effects Model with Driscoll–Kraay Standard Errors (Main Results)

Dependent variable: lnEM					
Independent variables	Coefficient	Std. Error (DK)	t-value	p-value	Significance
lnFERT	0.260	0.081	3.225	0.001	***
lnORG	1.127	0.246	4.588	0.000	***
lnOUT	0.265	0.181	1.469	0.143	
lnLIVE	0.030	0.057	0.519	0.605	
lnGDP	-0.104	0.113	-0.917	0.360	
lnEXP	-0.0002	0.002	-0.117	0.907	
lnRD	0.022	0.007	3.118	0.002	***
lnFERT $\times$ lnORG	-0.049	0.012	-4.095	0.000	***
lnORG $\times$ lnOUT	-0.062	0.034	-1.854	0.065	*

Notes: Driscoll–Kraay standard errors are robust to heteroskedasticity, autocorrelation, and cross-sectional dependence. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Due to interaction terms, coefficients are conditional. Fertiliser use (lnFERT = 0.260, $p < 0.01$) is positive and significant, but applies only when lnORG = 0. Agricultural output (lnOUT = 0.265, $p = 0.143$) is not significant once cross-sectional dependence and serial correlation are accounted for, indicating no robust association with emissions in the absence of organic farming. The coefficient on organic farming (lnORG = 1.127, $p < 0.01$) is not directly interpretable in isolation. Among controls, lnLIVE, lnGDP, and lnEXP are not significant, while lnRD ($\beta = 0.022$, $p < 0.01$) is positive.

The interaction lnFERT $\times$ lnORG is negative and significant ($\beta = -0.049$, $p < 0.01$), indicating that organic farming attenuates the marginal effect of fertiliser use. The interaction lnORG $\times$ lnOUT is negative but only weakly significant ($\beta = -0.062$, $p < 0.10$), suggesting a less robust moderating effect on output. Evaluated at the sample mean of lnORG (4.26), the marginal effect of fertiliser is $\partial \ln EM / \partial \ln FERT = 0.260 - 0.049 \times 4.26 = 0.051$.

Thus, at average organic adoption, a 1% increase in fertiliser use is associated with a 0.05% increase in emissions, substantially smaller than in countries without organic farming. This supports H1 (cross-sectional moderation). The baseline model does not test H2 (dynamic causality), so results should be interpreted as associational. The loss of significance for lnOUT relative to **Table 2** underscores the importance of correcting for cross-sectional dependence.

4.4. Endogeneity and Dynamic Adjustment

Endogeneity is assessed using the Durbin–Wu–Hausman test (e.g., Durbin, 1954; Wu, 1973; Hausman, 1978; see **Table A7**). Exogeneity is not rejected ($F = 1.203$, $p = 0.326$), though with low power. Difference GMM (Arellano & Bond, 1991; Roodman, 2009) indicates that the estimated effects become statistically insignificant once persistence and potential endogeneity are incorporated. Although this finding weakens the causal interpretation of the baseline estimates, it should also be interpreted in light of the limited time dimension of the panel and the lower statistical power typically associated with dynamic panel estimators in small samples.

Table 4. Dynamic Effects and Endogeneity: Evidence from Fixed Effects (DK) and Difference GMM

Independent variables	Dependent variable: lnEM			
	FE (DK, with R&D lags)		Difference GMM	
	Coef.	Std. Error	Coef.	Std. Error
lnEM (t-1)	n.a	n.a	0.862***	(0.273)
lnFERT	0.258**	(0.102)	0.604	(0.427)
lnORG	1.733***	(0.083)	0.033	(0.263)
lnOUT	0.645***	(0.175)	-0.070	(0.529)
lnLIVE	-0.051**	(0.025)	-0.434	(1.265)
lnGDP	-0.309**	(0.129)	-0.133	(0.247)
lnEXP	-0.002	(0.002)	0.050	(0.036)
lnRD	0.004	(0.005)	0.054	(0.060)
lnRD (t-1)	0.033***	(0.006)	n.a	n.a
lnRD (t-2)	0.016***	(0.005)	n.a	n.a
lnFERT × lnORG	-0.040**	(0.020)	n.a	n.a
lnOUT × lnORG	-0.137***	(0.030)	n.a	n.a
Model diagnostics				
Statistic	FE Model		GMM Model	
Observations (N)	259		207	
Countries (n)	25		25	
R-squared	0.326		n.a	
AR(1) p-value	n.a		0.088	
AR(2) p-value	n.a		0.563	
Sargan p-value	n.a		0.520	

Notes: FE models include two-way fixed effects with Driscoll–Kraay standard errors. Difference GMM uses a two-step Arellano–Bond estimator with collapsed instruments; AR(1) is expected and AR(2) should not be significant. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. n.a. means not applicable.

Tables 2–3 report baseline and fixed-effects (main) estimates, while **Table 4** addresses endogeneity and dynamics. In the FE (DK) model with lagged R&D, past R&D is positive and significant, indicating persistence and potential reverse causality.

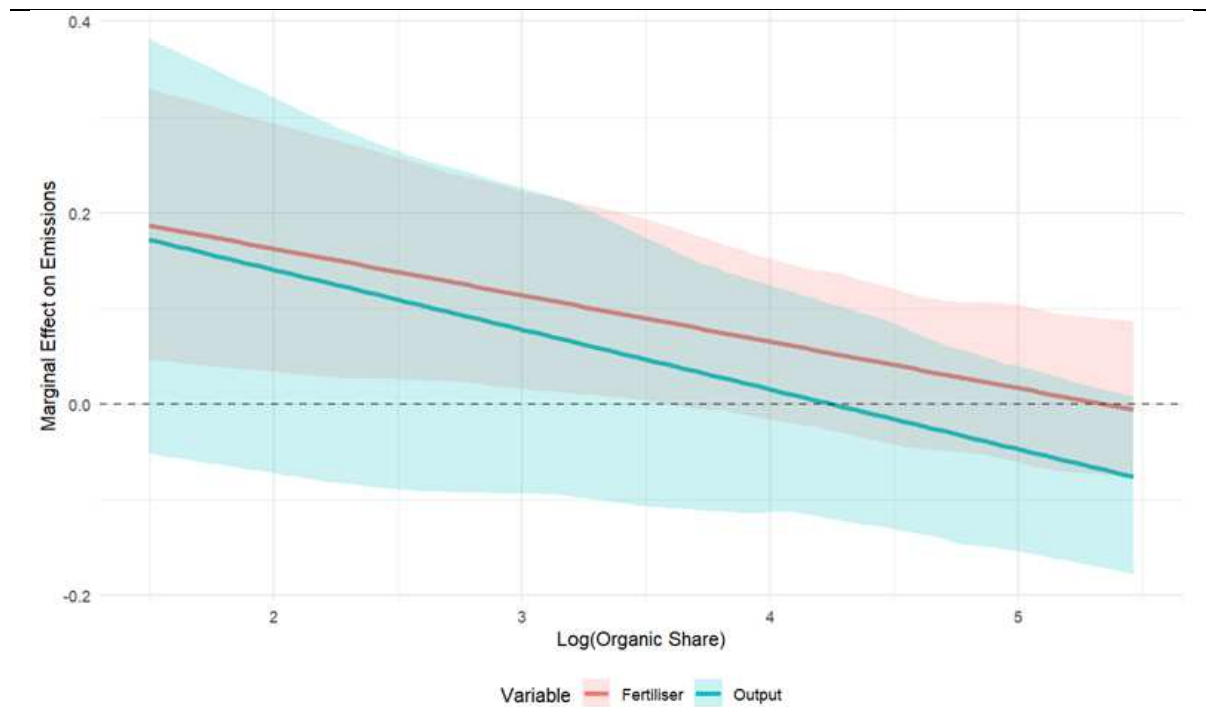
In the Difference GMM specification, most coefficients including fertiliser use, organic farming, and their interactions lose significance, while the lagged dependent variable remains positive and significant ($\beta = 0.862$, $p < 0.01$), indicating strong persistence in emissions. This supports H2, as no evidence is found that changes in organic farming causally reduce emissions or moderate input effects once endogeneity and dynamics are accounted for. Regarding H1, the cross-sectional moderating effect identified in fixed-effects models is not robust in the dynamic specification, suggesting it reflects between-country differences rather than within-country causal effects. Overall, the results indicate that baseline findings are primarily associational and sensitive to model specification.

4.5. Marginal Effects and Moderation Mechanism

Following this, marginal effects of fertiliser use and agricultural output across levels of organic farming are examined in **Table 5** using bootstrap confidence intervals.

Table 5. Marginal Effects at Different Levels of Organic Farming (Bootstrap CI)

lnORG (quantile)	Fertiliser ME	95% CI	Output ME	95% CI
10%	0.104**	[0.012, 0.213]	0.066	[-0.095, 0.213]
25%	0.074	[-0.006, 0.167]	0.026	[-0.112, 0.138]
50%	0.046	[-0.035, 0.129]	-0.009	[-0.125, 0.094]
75%	0.022	[-0.052, 0.106]	-0.040	[-0.148, 0.050]
90%	0.007	[-0.071, 0.093]	-0.060	[-0.164, 0.024]



Notes: Marginal effects computed from two-way fixed effects model. 95% confidence intervals obtained via bootstrap (B = 200).

The marginal effect of fertiliser use declines with higher levels of organic farming, from 0.104 ($p < 0.05$) at the 10th percentile to 0.007 at the 90th percentile, becoming insignificant at higher quantiles, indicating a moderating effect. In contrast, the marginal effect of agricultural output declines but remains insignificant across all quantiles. Delta Method estimates (see Table S1) closely match **Table 5** and confirm that significance is concentrated at lower quantiles. These findings support H1, indicating cross-sectional moderation by organic farming, but provide no evidence of dynamic causal effects, consistent with H2.

4.6. Heterogeneity and Distributional Effects

Panel quantile regression (see Table S2) reveals heterogeneity: $\ln FERT$ and $\ln ORG$ are positive and significant at Q25–Q75 ($\beta = 0.277; 0.307; 0.229$), but not at Q90. The interaction $\ln FERT \times \ln ORG$ is negative and significant at Q25–Q75, but insignificant at Q90, while $\ln ORG \times \ln OUT$ is weak and only marginally significant at lower quantiles. Control variables are largely insignificant.

Robustness tests (see Table S3) confirm that $\ln FERT \times \ln ORG$ is generally negative, although it becomes insignificant in some subsamples, indicating heterogeneity. Leave-one-country-out estimates (see Table S4) remain stable. Placebo tests (see Table S5) show no significance for future $\ln FERT$ and $\ln OUT$, supporting temporal ordering. The first-difference model (see Table S6) yields insignificant interaction terms, indicating no within-country moderation. Effects are therefore driven by cross-country variation. Sensitivity analysis (see Table S7) shows that results are invariant to scaling.

Sectoral results (see Table S8) indicate that $\ln FERT$ and $\ln ORG$ remain positive and significant. The interaction $\ln FERT \times \ln ORG$ remains negative, though heterogeneous across sectors. Within-between decomposition (see Table S9) shows that effects are primarily driven by between-country variation, while within effects are largely insignificant. The evidence supports H1, indicating that organic farming moderates fertiliser-related emissions in cross-country comparisons. However, there is no consistent evidence of within-country or dynamic effects, in line with H2.

4.7. Policy Analysis: Difference-in-Differences

Policy heterogeneity is assessed using a Difference-in-Differences approach based on the CAP 2013–2020 reform (see **Table 6**, below). Due to data constraints, the post-treatment period is defined from 2015. The reform strengthened environmental conditionality and support for organic farming (European Commission, 2013). The interaction between organic farming and the post period tests whether the emissions relationship changed after the reform, following the DiD framework (Angrist & Pischke, 2009).

Table 6. Difference-in-Differences Estimates: CAP Reform Effects

Independent variables	Dependent variable: lnEM			
	(1) DiD Baseline	Std. Error	(2) Triple DiD (Main)	Std. Error
lnORG	-0.060	(0.042)	0.973***	(0.325)
lnFERT	0.072	(0.098)	0.224	(0.138)
lnOUT	0.076	(0.089)	0.238	(0.177)
lnLIVE	-0.073	(0.158)	0.013	(0.109)
lnGDP	0.077	(0.122)	-0.146	(0.112)
lnEXP	0.002	(0.003)	0.000	(0.005)
lnRD	0.029*	(0.014)	0.023	(0.014)
Policy and interaction terms				
lnORG × post	-0.003	(0.019)	0.353	(0.211)
lnFERT × lnORG	n.a.	n.a.	-0.035	(0.029)
lnOUT × lnORG	n.a.	n.a.	-0.061*	(0.035)
lnFERT × post	n.a.	n.a.	0.024	(0.076)
lnOUT × post	n.a.	n.a.	0.146***	(0.043)
lnFERT × lnORG × post	n.a.	n.a.	-0.011	(0.022)
lnOUT × lnORG × post	n.a.	n.a.	-0.026**	(0.012)
Model diagnostics				
Statistic	(1) Baseline		(2) Triple DiD	
Observations (N)	259		259	
Countries (n)	25		25	
Time periods (T)	11		11	
Fixed effects	Yes		Yes	
Within R ²	0.124		0.364	

Notes: All models include country and year fixed effects. Standard errors are clustered at the country level. Model (1) reports a continuous Difference-in-Differences specification where the interaction term (lnORG × post) captures the post-2015 effect of organic farming intensity. Model (2) extends the specification by incorporating triple interaction terms to assess whether moderating effects vary after the CAP reform. The variable post is omitted due to perfect collinearity with time fixed effects. Overall, the estimated coefficients indicate no robust policy effect, with only limited evidence of channel-specific dynamics through output interactions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. n.a. denotes not applicable.

Table 6 presents the Difference-in-Differences estimates. In the baseline model, organic farming (lnORG: $\beta = -0.060$, $p > 0.10$) is not significant. In the triple DiD specification, lnORG becomes positive and significant ($\beta = 0.973$, $p < 0.01$), while lnFERT, lnOUT, and control variables remain insignificant, including R&D ($\beta = 0.023$, $p > 0.10$). Among interactions, only lnORG × lnOUT is weakly significant ($\beta = -0.061$, $p < 0.10$), indicating limited moderation.

Policy effects are not supported, as lnORG × post is insignificant in both models ($\beta = -0.003$; $\beta = 0.353$). However, lnOUT × post is positive and significant ($\beta = 0.146$, $p < 0.01$), and the triple interaction lnORG × lnOUT × post is negative and significant ($\beta = -0.026$, $p < 0.05$), suggesting a conditional moderation of the output–emissions relationship. **Fig 3.** illustrates the dynamic effects of the CAP reform based on the event-study specification.

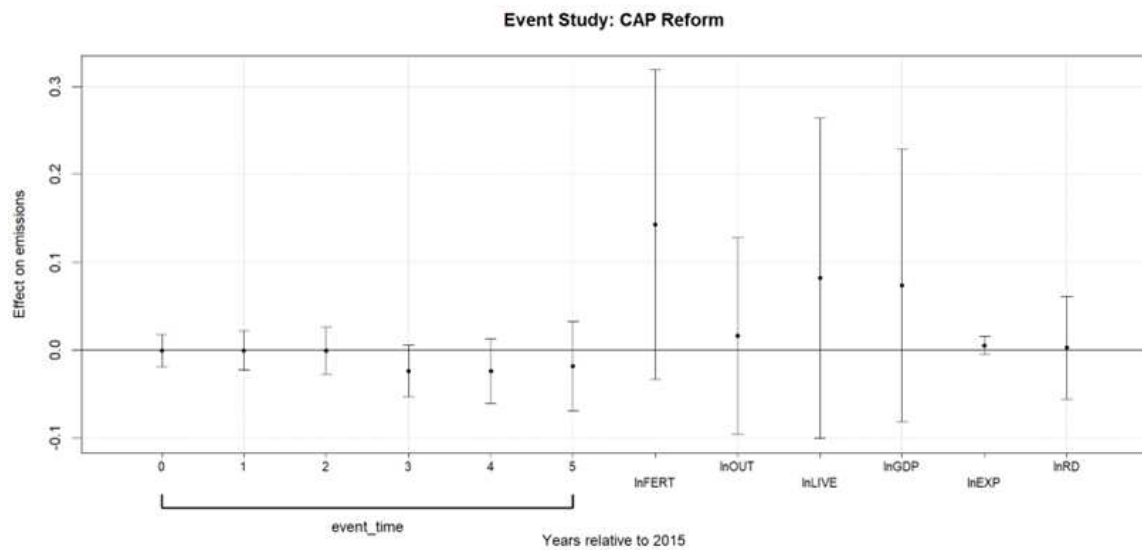


Figure 3. illustrates the dynamic effects of the CAP reform based on the event-study specification. This figure was created by the authors.

Given that only one pre-reform year (2014) is available, the test for pre-trends has very low power; the event study should be interpreted with caution. Within this limitation, the event study shows no clear pre-trends and no significant post-treatment effects. Results remain qualitatively unchanged when accounting for country-specific linear trends, confirming robustness.

The DiD results do not provide evidence that the CAP reform enhanced the moderating role of organic farming (which would be required to support a dynamic causal interpretation). This absence of a policy-induced causal effect is consistent with H2, while H1 remains supported only in the cross-sectional dimension (as shown in **Tables 2–3**, above). The DiD estimates are thus exploratory and should not be overinterpreted as definitive causal evidence.

As an additional robustness exercise, future research could examine whether the results remain consistent when environmental performance is measured using emissions intensity indicators, such as emissions per unit of agricultural output or carbon efficiency measures. This would allow a distinction between total environmental pressure and environmental performance relative to production levels.

4.8. Limitations of the study

A number of limitations should be considered when interpreting the results. First, the observed moderating effect of organic farming is driven primarily by cross-country differences rather than within-country changes over time, limiting causal interpretation. Second, although the study employs dynamic panel methods and multiple robustness checks, the observational nature of the data prevents definitive causal inference. Third, the relatively short period covered (2014–2024) may not fully capture the long-term effects of organic transitions. Agronomic evidence suggests that changes in soil carbon stocks, nutrient cycling, biodiversity recovery, and ecosystem functioning may require more than a decade before measurable environmental effects become observable. Consequently, the estimated coefficients should be interpreted as medium-term rather than long-term effects. Fourth, organic farming is measured by the share of certified organic area rather than by specific management practices, potentially masking differences in implementation across countries. Moreover, the national-level analysis may conceal regional, sectoral, and farm-level heterogeneity that could influence the relationship between organic farming and agricultural greenhouse gas emissions. These limitations do not invalidate the findings but suggest that the results should be interpreted as evidence of structural associations rather than definitive causal effects. Finally, aggregate agricultural emissions may not fully capture environmental performance because organic farming can generate benefits through biodiversity conservation, soil quality improvements, nutrient management, and ecosystem services that are not directly reflected in national emissions

indicators. Future research should therefore complement aggregate emissions measures with indicators of emissions intensity, carbon efficiency, and broader ecological performance

5. Discussions

This study examined the structural and dynamic relationships between organic farming and agricultural GHG emissions across 25 EU countries. Two main conclusions emerge. First, the cross-sectional evidence supports H1: organic farming moderates the environmental impact of fertilizer use, reducing emissions across different agricultural systems. Second, the findings support H2 by revealing no stable dynamic causal effect. Within countries, increases in organic farming over time do not produce consistent reductions in emissions. Overall, organic farming appears to function both as a structural characteristic of agricultural systems and as a broader sustainability strategy whose climate-mitigation effects depend on production conditions, adjustment periods, and complementary policies. Nevertheless, the results do not imply that organic farming lacks environmental benefits. Instead, they suggest that such benefits depend on broader structural conditions, production systems, adjustment periods, and complementary agricultural policies.

Importantly, the absence of a robust causal effect on aggregate agricultural GHG emissions should not be interpreted as evidence that organic farming lacks environmental value. A substantial body of literature indicates that organic systems contribute to biodiversity conservation, improved soil quality, reduced pesticide dependence, enhanced nutrient management, lower nitrogen losses, and greater ecosystem resilience (e.g., Tuomisto et al., 2012; Tuck et al., 2014; Krause et al., 2024). The present study focuses specifically on aggregate agricultural greenhouse gas emissions at the national level and therefore captures only one dimension of environmental sustainability. Other documented benefits of organic farming, including biodiversity enhancement, soil health improvements, reduced pesticide dependence, and ecosystem resilience, remain outside the scope of the present analysis. Consequently, the findings suggest that while organic farming may not consistently reduce aggregate emissions in a causal sense over the study period, it may still generate important environmental benefits through multiple ecological pathways that are not directly captured by emissions indicators alone.

The discrepancy between cross-sectional and dynamic results reflects structural heterogeneity among countries. Nations with higher organic adoption generally have less intensive agricultural systems, different climatic and soil conditions, and distinct policy trajectories (e.g., Gerke, 2025; Tuomisto et al., 2012; and Wang et al., 2025). Thus, organic farming acts as a proxy for broader production regimes rather than an isolated practice (García-Velázquez et al., 2026). Countries with larger organic sectors tend to rely less on synthetic inputs, which reduces the marginal contribution of fertilizer use to emissions, consistent with evidence from Skinner et al. (2014). However, these associations are structural rather than universally causal, since less intensive countries are also more likely to adopt organic systems (Pawlewicz, 2026).

A key contribution of this study is demonstrating that the apparent mitigation effect weakens once persistence and endogeneity are considered. Fixed-effects estimations initially suggested that organic farming moderated fertilizer-related emissions, but these relationships lost robustness in Difference GMM, first-difference, and within-country models (Arellano & Bond, 1991). Agricultural emissions are highly persistent because production systems, fertilizer dependence, livestock structures, and land use evolve slowly (Smith et al., 2019). Moreover, organic adoption is likely endogenous, reflecting pre-existing institutional and structural conditions rather than an independent treatment effect (Squalli & Adamkiewicz, 2018).

Adjustment lags also complicate identification. Soil recovery, biodiversity restoration, and nutrient-cycle stabilization often require several years before measurable environmental gains emerge (Nurbekov et al., 2023). Consequently, once persistence and endogeneity are incorporated, the mitigation effect is no longer statistically robust, suggesting that organic farming exerts long-term and context-dependent influences rather than immediate effects (Smith, 2025; Vejendla et al., 2025).

The interaction terms indicate that organic farming functions mainly as a buffering mechanism rather than a direct emissions-reduction strategy. The Fertilizer $\times$ Organic interaction suggests that countries with larger organic sectors are less sensitive to fertilizer-induced emissions because they rely more on ecological nutrient management and lower input intensity. However, the Output $\times$ Organic interaction shows that these buffering effects are constrained by productivity levels. Organic farming performs better when emissions are measured per hectare rather than per unit of output, since lower yields may offset environmental gains (Krause et al., 2024; Tuomisto et al., 2012). Similarly, reductions in input intensity do not necessarily reduce aggregate emissions once land-use adjustments and production requirements are considered (Hashemi et al., 2024). Therefore, organic farming should be viewed as a partial mitigation buffer rather than a standalone scalable solution.

The quantile results further reveal substantial heterogeneity. Organic farming was more effective in low- and medium-emission systems, but its moderating effect weakened in high-emission contexts. This suggests that mitigation potential depends on pre-existing structural conditions. Lower-emission systems are generally less

input-intensive and more adaptable (Lee et al., 2015), whereas high-emission systems are characterized by fertilizer dependence, intensive livestock production, and structural rigidities (Conchedda et al., 2024; Stetter & Sauer, 2022). These features limit the capacity of organic farming to reduce emissions, implying that broader structural transformations are required in highly intensive agricultural systems.

The DiD analysis found no evidence that the 2013–2020 CAP reform strengthened the mitigating role of organic farming. The interaction between organic area and the post-reform period was statistically insignificant in most specifications, suggesting that policy support for organic adoption alone does not guarantee emission reductions (Rees et al., 2023; Rey Vicario et al., 2025). Policy incentives may increase organic adoption without substantially altering production intensity or reducing input dependence (Pata, 2021). Thus, structural conditions appear to dominate policy effects. These findings indicate that promoting organic farming alone is insufficient as a climate-mitigation strategy and must be accompanied by broader transformations in agricultural production systems (Bocean, 2025).

The results also help explain contradictory findings in previous studies. Micro-level analyses often identify environmental benefits because they focus on controlled biophysical processes, but they may overlook system-wide adjustments and therefore overestimate mitigation potential (Hashemi et al., 2024). Conversely, macro-level studies may conflate structural differences with causal effects, especially when relying on static frameworks that ignore dynamics and aggregation bias (Vejendla et al., 2025). Furthermore, local gains may be offset by broader trade-offs during scaling processes (Smith et al., 2019). By separating structural and dynamic effects, this study reconciles these perspectives and demonstrates that structural associations do not necessarily imply persistent causal mitigation.

The findings reinforce the theoretical framework presented in Section 2. Consistent with H1, organic farming should be interpreted as a context-dependent structural characteristic rather than a uniform environmental treatment (Rey Vicario et al., 2025). Future research should therefore distinguish between cross-country structural associations and within-country dynamic causal effects. From a policy perspective, rejecting H2 indicates that organic farming cannot operate as a standalone climate solution. Effective mitigation requires complementary strategies focused on technological innovation, precision agriculture, sustainable land management, and improvements in input efficiency (Wang et al., 2025c).

This study also has limitations. The relatively short panel period (2014–2024) restricts the analysis of long-term ecological adjustments associated with organic transition. In addition, measuring organic farming through certified areas rather than management practices may obscure differences in operational intensity and quality (Gerke, 2025). Long-term environmental effects may also emerge beyond the study period (Vejendla et al., 2025). Future research should therefore employ longer panels, integrate micro- and macro-level evidence, and adopt practice-based indicators capable of distinguishing different forms of organic management. Further work should also explore threshold effects, non-linearities, and advanced causal inference techniques to better identify the conditions under which organic farming contributes to long-term emission reductions.

6. Conclusions and policy implications

This study examined whether organic farming mitigates agricultural greenhouse gas emissions in the European Union and whether any observed relationship reflects structural differences across countries or dynamic causal effects over time. Using an unbalanced panel of 25 EU countries from 2014 to 2024, the analysis combined complementary econometric approaches to identify average associations, moderation mechanisms, dynamic adjustment processes, distributional heterogeneity, and policy-related effects. Rather than treating organic farming as a homogeneous intervention, the study assessed whether it moderates the emissions impact of fertiliser use and agricultural output and whether increases in organic farming are associated with reductions in agricultural emissions within countries over time.

The results provide support for both H1 and H2, albeit along different dimensions. H1 (cross-sectional structural moderation) is supported by the evidence that countries with higher levels of organic farming exhibit a weaker relationship between fertiliser use and agricultural greenhouse gas emissions. The negative and statistically significant interaction between organic farming and fertiliser use indicates that organic systems are associated with lower emissions sensitivity to input intensity. This finding suggests that organic farming is linked to broader production structures characterised by lower dependence on synthetic inputs and different environmental management practices.

H2 (limited dynamic causal effect) is also supported. Once emissions persistence, endogeneity, within-country variation, and dynamic adjustment processes are explicitly considered, the apparent mitigation effect of organic farming becomes statistically insignificant. Consequently, the results do not provide robust evidence that increases in organic farming within countries systematically reduce agricultural emissions over the period analysed. This finding suggests that the observed mitigation effects are primarily associated with structural

differences across agricultural systems rather than with short- to medium-term causal changes in emissions.

Overall, the findings indicate that organic farming contributes to lower emissions pressure under specific structural conditions, particularly through moderating the environmental impact of fertiliser use. However, the evidence does not support a consistent dynamic causal effect on aggregate agricultural greenhouse gas emissions. Organic farming therefore appears to operate as part of a broader agricultural transition process, with its contribution to climate mitigation depending on structural conditions, production systems, and complementary sustainability measures.

Importantly, these findings should not be interpreted as evidence that organic farming lacks environmental benefits. A substantial body of research demonstrates that organic systems contribute to biodiversity conservation, improved soil quality, reduced pesticide dependence, enhanced nutrient management, lower nitrogen losses, and greater ecosystem resilience. The present study focuses exclusively on aggregate agricultural greenhouse gas emissions and therefore captures only one dimension of environmental sustainability. As a result, the absence of a robust causal effect on aggregate emissions does not preclude the existence of important environmental benefits operating through other ecological pathways.

The findings contribute to the theoretical framework by highlighting the importance of scale dependence and structural heterogeneity in evaluating the environmental performance of organic farming. The results suggest that the relationship between organic farming and emissions varies according to production systems, agricultural intensity, input use, and country-specific conditions. Consequently, organic farming should be understood not simply as an isolated agricultural practice but also as an indicator of broader structural characteristics of agricultural systems. This distinction helps reconcile the apparent contrast between micro-level studies reporting environmental benefits and macro-level analyses that often identify weak or inconsistent causal effects.

From a policy perspective, the results suggest that organic farming alone is unlikely to deliver substantial reductions in agricultural emissions. Although countries with larger organic sectors tend to exhibit weaker emissions responses to fertiliser use, expanding organic area does not automatically translate into measurable emissions reductions over time. The effectiveness of organic farming as a climate-mitigation strategy depends on complementary factors such as input efficiency, livestock management, technological innovation, research and development, and the overall structure of agricultural production systems.

The findings also have important implications for the Common Agricultural Policy (CAP). While CAP instruments may encourage the adoption of organic farming and promote more sustainable land-use practices, the empirical evidence does not indicate that the CAP reform strengthened the emissions-mitigating role of organic farming. Future policy frameworks may therefore benefit from linking support for organic farming more directly to measurable environmental outcomes, reductions in input intensity, and broader system-level transformations.

Several limitations should be acknowledged. First, the study covers the period 2014–2024, which may not fully capture the long-term ecological and structural adjustments associated with organic transitions. Second, organic farming is measured through certified organic area rather than specific management practices, potentially masking differences in implementation intensity across countries. Third, environmental improvements associated with organic farming may emerge only after extended periods of soil recovery, ecosystem adaptation, and management change. Consequently, the results should be interpreted as evidence of short- to medium-term relationships rather than definitive long-term effects.

Future research should employ longer time horizons to better capture delayed environmental responses and long-run agricultural transitions. Greater integration between micro-level biophysical evidence and macro-level panel analyses would help clarify how farm-level practices translate into national environmental outcomes. Future studies should also incorporate practice-based indicators of organic farming, explore threshold effects and non-linear relationships, and apply advanced causal inference techniques to identify more precisely the conditions under which organic farming contributes to long-term reductions in agricultural greenhouse gas emissions.

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Declarations

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Appendix

Table A1. Variable Definitions and Data Sources

Variables	Definition	Source
lnEM	Natural logarithm of agricultural greenhouse gas emissions, measured in million tonnes of CO ₂ equivalent (Mt CO ₂ eq).	European Environment Agency / Eurostat (env_air_gge)
lnFERT	Natural logarithm of fertiliser use intensity, measured as tonnes of fertilisers per hectare of utilised agricultural area (tonnes per ha of UAA).	Eurostat (aei_fm_usefert)
lnOUT	Natural logarithm of agricultural output, measured in million euros (€).	Eurostat (Economic Accounts for Agriculture – aact_eaa01)

lnORG	Natural logarithm of the share of organic farming, defined as the percentage of organic agricultural area over total utilised agricultural area (% of UAA).	Eurostat (org_cropar)
lnLIVE	Natural logarithm of livestock density, measured as total livestock (cattle, pigs, sheep, and goats) per hectare of utilised agricultural area (livestock units per ha of UAA).	Eurostat (livestock datasets: apro_mt_lscatl, apro_mt_lspig, apro_mt_lssheep, apro_mt_lsgoat)
lnGDP	Natural logarithm of GDP per capita in constant prices (local currency units per capita).	World Bank (World Development Indicators)
lnEXP	Natural logarithm of agricultural export intensity, defined as the ratio of agricultural exports to agricultural output (dimensionless).	Eurostat (international trade statistics)
lnRD	Natural logarithm of government expenditure on agricultural research and development, measured in million euros (€).	Eurostat (sdg_02_30)

Notes: All variables are expressed in natural logarithms. UAA denotes utilised agricultural area.

Table A2. Correlation Matrix

Variables	lnEM	lnFERT	lnOUT	lnORG	lnLIVE	lnGDP	lnEXP	lnRD
lnEM	1.00	0.78	0.65	-0.30	-0.08	-0.16	0.36	0.46
lnFERT	0.78	1.00	0.87	-0.26	0.06	0.22	0.50	0.73
lnOUT	0.65	0.87	1.00	-0.18	0.42	0.15	0.64	0.84
lnORG	-0.30	-0.26	-0.18	1.00	-0.30	0.01	0.26	-0.01
lnLIVE	-0.08	0.06	0.42	-0.30	1.00	0.06	0.26	0.42
lnGDP	-0.16	0.22	0.15	0.01	0.06	1.00	-0.04	0.17
lnEXP	0.36	0.50	0.64	0.26	0.26	-0.04	1.00	0.65
lnRD	0.46	0.73	0.84	-0.01	0.42	0.17	0.65	1.00

Notes: Values represent pairwise correlation coefficients. All variables are in natural logarithms. Correlations above 0.70 may indicate potential multicollinearity concerns.

Table A3. Variance Inflation Factors (VIF)

Test / Variable	Statistic	Result / Interpretation
lnFERT (GVIF adj.)	3.805	Moderate
lnORG (GVIF adj.)	1.352	Low
lnOUT (GVIF adj.)	4.428	Moderate–High
lnLIVE (VIF)	2.073	Acceptable
lnGDP (VIF)	1.113	Low
lnEXP (VIF)	1.605	Low
lnRD (VIF)	2.127	Acceptable

Notes: Variance Inflation Factors (VIF) are reported as adjusted GVIF for comparability across variables with different degrees of freedom.

Table A4. Panel Unit Root Tests (Levin–Lin–Chu and IPS)

Variables	LLC Statistic	LLC p-value	IPS Statistic	IPS p-value	Stationarity Conclusion
lnEM	-4.328	0.000	-7.900	0.000	Stationary
lnFERT	-1.364	0.086	-6.179	0.000	Weak / Mixed evidence
lnOUT	0.989	0.839	-1.907	0.028	Mixed evidence

lnORG	-4.518	0.000	-4.942	0.000	Stationary
lnLIVE	-0.790	0.215	-4.081	0.000	Mixed evidence
lnGDP	-7.273	0.000	-7.361	0.000	Stationary
lnEXP	-4.094	0.000	-5.768	0.000	Stationary
lnRD	-18.514	0.000	-16.135	0.000	Stationary*

Notes: The table reports Levin–Lin–Chu (LLC) and Im–Pesaran–Shin (IPS) panel unit root tests with individual intercepts and linear trends. The null hypothesis in both tests is a unit root; rejection implies stationarity. Lag length is set to 2. Given the short time dimension ($T = 6\text{--}11$), test power may be limited. Results for lnRD should be interpreted with caution due to the small cross-section ($N = 4$).

Table A5. Joint Significance of Interaction Terms

Test / Model Component	Chi-square	df	p-value	Significance	Decision
lnFERT×lnORG = 0; lnORG×lnOUT = 0 Restricted Model (Residual df)	64.392	2 217	0.000	***	Reject H_0

Notes: The null that both interaction terms are jointly zero is rejected ($p < 0.01$), indicating that the moderating effect of organic farming is statistically significant and should be retained in the specification.

Table A6. Post-Estimation Diagnostics

Test / Variable	Statistic	df	p-value	Result / Interpretation
Serial Correlation (BG/Wooldridge)	60.047	6	0.000	Present (reject H_0)
Heteroskedasticity (Breusch–Pagan)	74.277	9	0.000	Present (reject H_0)
Cross-Sectional Dependence (CD)	-0.428		0.669	Not detected
Cross-Sectional Dependence (LM)	691.470	300	0.000	Present (reject H_0)

Notes: Diagnostics indicate serial correlation and heteroskedasticity, with mixed evidence on cross-sectional dependence: the Pesaran CD test is insignificant, while the Breusch–Pagan LM test suggests dependence. Accordingly, Driscoll–Kraay standard errors are used to ensure robustness to heteroskedasticity, autocorrelation, and cross-sectional dependence.

Table A7. Endogeneity Test (Durbin–Wu–Hausman)

Component	Result
Model specification	Pooled OLS (augmented regression)
Dependent variable	lnEM
Regressors tested for endogeneity	lnFERT, lnOUT
Instruments	lag lnFERT, lag lnOUT
Control variables	lnORG, lnLIVE, lnGDP, lnEXP, lnRD
Test type	Durbin–Wu–Hausman (regression-based approach)
F-statistic	1.203
Degrees of freedom	(2, 16)
p-value	0.326
Variance estimator	Heteroskedasticity-robust (HC1)
Null hypothesis (H_0)	Regressors are exogenous
Decision	Fail to reject H_0
Conclusion	No evidence of endogeneity

Notes: The Durbin–Wu–Hausman test is implemented in a regression-augmented framework with heteroskedasticity-robust (HC1) standard errors. The null of exogeneity for lnFERT and lnOUT is not rejected. Due to identification constraints under the within transformation, the test is estimated in a pooled specification; results should therefore be interpreted with caution. The baseline model relies on fixed effects and extensive controls to mitigate potential endogeneity.

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