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## Article

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Economies

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*Suggested Citation:* Öztürk, Nil Sirel (2025) : Decarbonizing agriculture: The impact of trade and renewable energy on CO<sub>2</sub> emissions, *Economies*, ISSN 2227-7099, MDPI, Basel, Vol. 13, Iss. 6, pp. 1-17,  
<https://doi.org/10.3390/economies13060162>

This Version is available at:

<https://hdl.handle.net/10419/329442>

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## Article

# Decarbonizing Agriculture: The Impact of Trade and Renewable Energy on CO<sub>2</sub> Emissions

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**Abstract:** This study investigates the environmental effects of agricultural trade, renewable energy use, and economic growth in a panel of 14 selected countries for the period 2000–2021. Per capita CO<sub>2</sub> emissions are modeled as the dependent variable using a second-generation panel data method, the Augmented Mean Group (AMG) estimator, which accounts for cross-sectional dependence and slope heterogeneity. The analysis reveals that the share of renewable energy in total energy consumption significantly reduces carbon emissions, emphasizing the role of green energy policies in environmental improvement. In contrast, economic growth is found to increase emissions, indicating the validity of only the initial phase of the Environmental Kuznets Curve (EKC) hypothesis. Additionally, agricultural imports—and in certain cases, exports—exert upward pressure on emissions, likely due to logistics and production-related externalities embedded in the trade process. Group-specific results highlight distinct dynamics across countries: while renewable energy adoption plays a stronger role in emission mitigation in developing economies, trade composition and production technology drive environmental outcomes in developed ones. The findings underscore the need to redesign trade and energy strategies with explicit consideration of environmental externalities to align with long-term sustainability objectives.

**Keywords:** agricultural trade; renewable energy; CO<sub>2</sub> emissions

**JEL Classification:** Q56; F18; O44



Academic Editor: Sanzidur Rahman

Received: 23 April 2025

Revised: 27 May 2025

Accepted: 2 June 2025

Published: 6 June 2025

**Citation:** Sirel Öztürk, N. (2025). Decarbonizing Agriculture: The Impact of Trade and Renewable Energy on CO<sub>2</sub> Emissions. *Economics*, 13(6), 162. <https://doi.org/10.3390/economics13060162>

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## 1. Introduction and Literature Review

Global economic growth has accelerated since the second half of the 20th century, largely driven by the expansion of international trade. However, this growth has also imposed significant costs on environmental sustainability. In particular, the rise in environmental awareness since the 1990s has led to a substantial body of theoretical and empirical research examining the environmental implications of economic activity. Within this context, the relationship between economic growth, international trade, and environmental quality has become a central focus in shaping sustainable development policies (Stern, 2004; Antweiler et al., 2001).

At the core of these discussions lies the ecological economics perspective, which conceptualizes the economy as a subsystem of the natural environment and argues that economic activity must operate within ecological limits. According to this approach, conventional growth models exert irreversible pressures on nature and, in the long term, pose risks to both environmental and social well-being (Costanza et al., 1997; Daly, 1997). Ecological economics advocates for a systemic evaluation of the environmental costs associated with energy consumption, production structures, and international trade.

One of the most widely cited approaches in the environmental economics literature for explaining the relationship between economic activity and environmental degradation is the Environmental Kuznets Curve (EKC) hypothesis. The EKC posits an inverted U-shaped relationship between per capita income and environmental degradation. At early stages of economic growth, environmental harm increases; however, beyond a certain income threshold, this trend is expected to reverse due to greater environmental awareness, the adoption of cleaner technologies, and the implementation of regulatory policies (Grossman & Krueger, 1995; Dinda, 2004). Nevertheless, the universal validity of this hypothesis across countries and sectors remains subject to debate.

Another factor that adds complexity to the relationship between trade, growth, and the environment is the direction and nature of trade's environmental impacts. While conventional theory suggests that trade can improve environmental efficiency through the optimal allocation of production factors, mechanisms such as the "pollution haven" and "scale effect" imply potential negative consequences (Antweiler et al., 2001). Analyzing the environmental effects of trade without sectoral distinctions may obscure these impacts. In particular, agricultural trade can contribute significantly to carbon emissions during both production and transportation phases (Verburg et al., 2011). According to IEA (2021), emissions from pre- and post-production processes in agrifood systems—including transportation and logistics—amounted to 5.8 Gt CO<sub>2</sub>e in 2019, representing approximately 35% of total agrifood system emissions (FAO Global, 2022).

Although agriculture is often perceived as an environmentally friendly sector, the expansion of global supply chains and the international transportation of agricultural products have significantly increased CO<sub>2</sub> emissions, particularly from logistics. The carbon footprint of global agricultural trade highlights the necessity for developing countries to align their trade strategies with sustainable development goals (Kastner et al., 2012). Therefore, research on the environmental impacts of agricultural trade provides valuable insights not only for economic analysis but also for environmental policymaking.

On the other hand, the use of renewable energy has recently emerged as one of the most critical policy instruments for mitigating the environmental costs of economic growth. Increasing the share of renewables in total energy consumption plays a pivotal role in reducing CO<sub>2</sub> emissions (IEA, 2021). In this context, it is evident that countries' growth strategies and trade policies must be considered in close integration with energy transition efforts.

This study analyzes the environmental effects of agricultural trade (imports and exports), renewable energy use, and economic growth using a panel dataset covering 14 countries from 2000 to 2021. Its main contribution lies in simultaneously addressing both the classical growth–environment relationship and the trade dimension through the agricultural sector. To account for issues specific to panel data, such as cross-sectional dependence and slope heterogeneity, the Augmented Mean Group (AMG) estimator is employed, enabling a consideration of country-specific dynamics. Accordingly, the study aims to offer a more comprehensive perspective on the theoretical and empirical links between environmental outcomes and international trade in agricultural products.

The role of the agricultural sector in carbon emissions has attracted increasing academic interest in recent years. In particular, the effects of dynamics such as international trade, production structures, and energy use on agriculture-related greenhouse gas emissions have been examined in a multidimensional manner across various regions. In this context, the findings of this study align with the recent literature, which highlights both the mitigating impact of renewable energy use on emissions and the influential role of agricultural trade in shaping environmental outcomes.

The impact of agricultural trade on carbon emissions has been empirically evaluated in numerous studies. For instance, [W. Wang et al. \(2024\)](#) find that trade openness in agriculture contributes to emission reductions, shaped through channels such as scale effects, technological advancement, and structural transformation. Similarly, [G. Li et al. \(2024\)](#) show that trade liberalization reduces emission intensity, supported by technology diffusion and shifts in industrial composition. This line of evidence complements the present study's focus on the environmental effects of agricultural trade and renewable energy.

The environmental impacts of agricultural trade have been examined from multiple perspectives. In a recent review of the past two decades of research, [P. Wang et al. \(2023\)](#) argue that the environmental effects of trade liberalization are shaped by channels such as scale, structural transformation, transportation, and technological change, often resulting in negative outcomes. Suggested policy responses include improvements in factor allocation, policy reforms, technological innovation, and the development of compensatory mechanisms. This theoretical perspective echoes the empirical observations made in the present study concerning the environmental impact of agricultural imports.

There is growing evidence that the environmental impacts of agricultural trade vary depending on factors such as regional characteristics and policy thresholds. [Rong et al. \(2023\)](#) find that in China, agricultural trade openness can reduce emissions only when environmental regulation surpasses a certain threshold; below that level, the effects are reversed. This pattern is consistent with the findings of the present study, where agricultural imports exhibit positive effects on emissions in some countries and negative effects in others. Moreover, the threshold-based panel model used by Rong et al. offers a plausible explanation for the heterogeneous coefficients identified in our second-generation panel analysis.

The spatial and sectoral dimensions of carbon transfers driven by agricultural trade are receiving increasing attention in the literature. [Rong et al. \(2023\)](#) analyze how agricultural carbon emissions are redistributed across Chinese provinces through trade, and how this redistribution influences policy accountability. Similarly, [Liu et al. \(2024\)](#) model international carbon flows in agricultural trade using network-based structures, proposing both production- and consumption-oriented strategies. In this context, the present study's use of country-specific coefficients through the AMG estimator aligns methodologically with this strand of the literature by addressing cross-country heterogeneity in carbon outcomes.

The internalization of environmental externalities into trade policies has gained prominence with the emergence of instruments such as the Carbon Border Adjustment Mechanism (CBAM), which are relevant for both developed and developing countries. [Bux et al. \(2024\)](#) and [Bassi et al. \(2024\)](#) discuss the potential of the CBAM to prevent carbon leakage, as well as its uneven impacts on developing economies. [Fournier Gabela et al. \(2024\)](#) propose a CBAM framework specifically tailored to the agricultural sector, analyzing how such a policy could be made more feasible. In this regard, the policy implications of the present study resonate with current debates on balancing the emission-increasing effects of trade in developing countries through mechanisms like the CBAM.

The role of green technological innovation in reducing agricultural emissions has been emphasized in numerous recent studies. [Rong et al. \(2023\)](#) find that green innovation exerts both direct and spatially mediated mitigating effects on agricultural carbon emission intensity. [L. Zhang and Cai \(2024\)](#) identify an inverted U-shaped relationship, suggesting that maintaining technology at an optimal level can yield both environmental and productivity benefits. [Qayyum et al. \(2023\)](#) and [Huang and Ke \(2024\)](#) highlight regional disparities in the adoption of green innovation and reveal the indirect effects of digitalization and organizational learning on agricultural emissions. The present study's finding of a significant

negative relationship between renewable energy use and CO<sub>2</sub> emissions is in line with these conclusions.

Carbon pricing, environmental taxation, and carbon sequestration are also widely discussed in the literature as direct mitigation strategies. [Iyke-Ofoedu et al. \(2024\)](#) emphasize the impact of environmental taxes on carbon sequestration in South Africa, while [Gong and Huo \(2024\)](#) argue that carbon taxes alone are insufficient for reducing agricultural greenhouse gas emissions and must be complemented with sequestration strategies. [Kausar et al. \(2024\)](#) identify a multidimensional relationship between agricultural production and environmental taxation, suggesting that tax-based solutions are more sustainable than direct production constraints. These studies provide a conceptual foundation for the policy recommendations made in the conclusion of the present research regarding energy transition and environmentally conscious trade strategies.

The relationship between agricultural production and carbon emissions also raises the issue of balancing productivity and environmental sustainability. [X. Zhang et al., \(2024\)](#) report a simultaneous increase in productivity and emissions, highlighting the need for a balanced application of green technologies. [Accorsi et al. \(2023\)](#) suggest that innovative production techniques and digital infrastructure can support this balance in a sustainable way. In this context, the present study also finds that while agricultural trade contributes to rising emissions, the energy transition may help offset this impact.

International agricultural trade is a key driver of not only domestic but also cross-border greenhouse gas transfers. [\(Adenauer et al., 2025\)](#) show that global agricultural emissions spread through network structures, making improvements in production technologies and consumption strategies effective at both local and global scales. In this context, the country-specific effects identified through the AMG model in this study may reflect such structural interdependencies. Moreover, technological transformation not only reduces emissions but also generates transnational spillover effects.

A limited but growing number of studies have examined the relationship between agricultural trade and carbon emissions in national or regional contexts. For instance, [Turan \(2025\)](#) analyzes the long-run impact of agricultural exports on CO<sub>2</sub> emissions in Türkiye using ARDL models and finds that export-led growth can reduce emissions, particularly when supported by renewable energy adoption. In a more detailed regional study, [Q. Li and Zhang \(2024\)](#) investigate the redistribution of agricultural carbon emissions across Chinese provinces and show that both import and export activities can contribute to emission reduction through structural transformation and technology diffusion. These findings highlight the significance of national conditions, production models, and trade structures in determining the environmental outcomes of agricultural trade.

Several studies suggest that the environmental effectiveness of renewable energy in India may be constrained by structural and policy limitations. [Singh et al. \(2023\)](#) highlight the country's heavy reliance on biomass and the uneven development of renewable sectors, which may undermine emission reductions. Similarly, [Dubey et al. \(2023\)](#) note that challenges such as grid instability, policy uncertainty, and fluctuating solar tariffs affect the environmental outcomes of renewable energy deployment. These insights are relevant in understanding why renewable energy use in India may not yet yield consistent emission-reducing effects.

Finally, a variety of methodological approaches have been employed in recent studies, including panel ARDL, AMG, GMM, panel NARDL, spatial Durbin models, and QARDL techniques (e.g., [W. Wang et al., 2024](#); [Kausar et al., 2024](#); [L. Zhang & Cai, 2024](#)). By using the AMG estimator, which accounts for slope heterogeneity and cross-sectional dependence, this study also contributes methodologically to the existing literature.

In this study, agricultural trade is examined through the disaggregated effects of imports and exports, measured in current USD, while renewable energy use is defined as the share of renewables in total energy consumption. Detailed definitions, measurement units, and data sources for all variables are provided in Table 1.

**Table 1.** Variables used in the study.

Variable Code	Description	Unit	Source
CO <sub>2</sub> Emission	CO <sub>2</sub> emissions per capita	Metric tons (tons/capita)	WB
ln_GDPCapita	Real GDP per capita	USD	
ln_AgriIM	Agricultural imports	Billion USD	
ln_AgriEX	Agricultural exports	Billion USD	
RenewableE	Share of renewables in total energy eating	Percentage (%)	

Note: Variables preceded by “ln” indicate that the natural logarithm of the original values has been taken.

In this context, recent approaches and empirical findings in the literature largely align with the results of this study, emphasizing the need to examine the complex relationship between agricultural trade and environmental sustainability from a multidimensional perspective. The literature suggests that the interactions among energy transition, technology policies, and trade regulations are particularly important for advancing carbon-neutral agricultural strategies.

## 2. Analysis and Findings

### 2.1. Country and Variable Selection

This study analyzes a group of 14 countries that includes both developed and developing economies: the United States, the United Kingdom, Australia, Canada, Germany, France, Denmark, China, India, Indonesia, Russia, Brazil, Türkiye, and Mexico. These countries are not only key players in global agricultural trade but also exhibit diverse characteristics in terms of energy consumption, greenhouse gas emissions, and economic growth dynamics. This diversity enables a comparative analysis of the relationship between agricultural trade and carbon emissions across countries at different stages of development.

Country selection also considered data availability and the consistency of the observation period. The analysis covers the years 2000 to 2021, a timeframe chosen for offering a sufficiently long observation window while also encompassing both the pre- and post-Paris Agreement periods. This allows for the indirect observation of the effects of international environmental regimes and green development policies.

The variables used in this study are selected from key economic and sectoral indicators commonly employed in the literature to assess environmental impacts. The dependent variable is per capita carbon dioxide (CO<sub>2</sub>) emissions. Although not exclusive to the agricultural sector, this variable is widely used as a macro-level indicator of environmental impact and serves as a proxy for overall national greenhouse gas trends.

The independent variables are defined as follows. Agricultural imports reflect the degree of trade openness in the agricultural sector and the global logistics activity within the food supply chain. Agricultural exports represent the environmental burden associated with production-based trade and are relevant in the context of potential carbon leakage. Per capita GDP is included to examine the environmental impact of economic growth, particularly in relation to the Environmental Kuznets Curve (EKC) hypothesis. Renewable energy use refers to the share of renewables in total energy consumption and serves as a key indicator for assessing the environmental effects of sustainable energy transitions.

The selection of variables in this study is broadly informed by the IPAT identity ( $I = P \times A \times T$ ) and its stochastic extension, the STIRPAT model. These frameworks



conceptualize environmental impact (I) as a function of population (P), affluence (A), and technology (T). Accordingly, per capita GDP is used as a proxy for affluence, while renewable energy share represents the technological component. Trade-related variables capture the production and structural aspects of agricultural systems that influence emissions. The inclusion of these indicators allows for a macro-level interpretation of drivers of carbon emissions, consistent with environmental economic theory.

Regarding data transformation, logarithmic forms were applied selectively based on distributional characteristics and interpretability. Specifically, variables with high skewness and wide magnitude ranges (such as GDP per capita and CO<sub>2</sub> emissions) were log-transformed to ensure linearity and reduce heteroskedasticity. Variables expressed in percentage form or bounded between 0 and 100 (such as renewable energy share) were retained in level form to preserve their scale interpretability and avoid distortion. This transformation strategy aligns with common practices in empirical environmental studies.

Detailed information on these variables is presented in Table 1.

## 2.2. Cross-Sectional Dependence (CD Test)

The CD test developed by Pesaran (2005) was applied to examine cross-sectional dependence in the panel dataset. This test is designed to detect the existence of dependence among cross-sectional units—such as countries in a panel—due to common shocks or shared dynamics. It is particularly useful in datasets with a large time dimension and is widely applied to examine whether observations are correlated across units. The hypotheses for the test are defined as follows (Pesaran, 2015):

**H0 (Null Hypothesis):** *There is weak cross-sectional dependence among the variables; for example, a country's import levels are independent of those in other countries.*

**H1 (Alternative Hypothesis):** *There is strong cross-sectional dependence; that is, import behavior across countries is mutually influenced.*

The statistical formulation of the test is based on the average pairwise correlation coefficients among panel units and is calculated as follows:

$$CD = \frac{\sqrt{N}}{\sqrt{2T}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}$$

In the equation,  $N$  represents the number of countries in the panel, and  $T$  denotes the time dimension. The term  $\hat{\rho}_{ij}$  refers to the correlation coefficient between the variables of country  $i$  and country  $j$ . The  $p$ -value obtained from the CD test determines whether the null hypothesis ( $H_0$ ) can be rejected at conventional significance levels (e.g., 1%, 5%, or 10%). If the  $p$ -value is below 0.10,  $H_0$  is rejected, indicating the presence of strong cross-sectional dependence among the variables (Pesaran, 2005).

The results of the CD test are presented in Table 2.

As shown in Table 2, the CD and CDw<sup>+</sup> statistics are statistically significant ( $p < 0.01$ ) for most of the variables. This indicates the presence of cross-sectional dependence among countries, particularly in variables such as agricultural trade (ln\_AgriIM, ln\_AgriEX), per capita income (ln\_GDPCapita), and CO<sub>2</sub> emissions. Although the CDw and CD\* tests are not significant for all variables, the consistent significance of the CDw<sup>+</sup> test—which has greater statistical power—suggests that conventional first-generation panel techniques may be inadequate. In this context, external shocks, global economic integration, and common environmental policies may contribute to the formation of shared dependence structures across countries.

**Table 2.** CD test results.

Variable	CD	<i>p</i> -Value	CDw	<i>p</i> -Value	CDw <sup>+</sup>	<i>p</i> -Value	CD *	<i>p</i> -Value
ln_AgriIM	36.69	(0.000) ***	0.20	(0.839)	350.22	(0.000) ***	−2.20	(0.028) **
ln_GDPCapita	39.31	(0.000) ***	0.17	(0.865)	375.17	(0.000) ***	1.51	(0.132)
ln_AgriEX	34.66	(0.000) ***	−0.20	(0.839)	330.43	(0.000) ***	0.41	(0.683)
CO <sub>2</sub> Emissions	1.66	(0.097)	1.02	(0.309)	312.34	(0.000) ***	5.65	(0.000) ***
RenewableE	3.09	(0.002) **	7.09	(0.000) ***	260.30	(0.000) ***	−0.33	(0.739)

Note: \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. CDw: Weighted cross-sectional dependence test, CDw<sup>+</sup>: Enhanced test with stronger statistical power, CD: Bias-corrected statistic based on (Pesaran, 2015).

### 2.3. Slope Homogeneity (Heterogeneity) Test

The slope homogeneity test developed by Pesaran and Yamagata (2008), also known as the delta test, is used to determine whether the regression coefficients across panel units are similar. This method tests the validity of a common coefficient across the entire panel. The core idea is to statistically assess how much each unit's individual coefficient deviates from the overall average. In doing so, it helps determine whether parameter heterogeneity should be considered in panel data modeling.

The delta test is expressed through the following formulas:

1. Standard Delta Test:  $\Delta = \sqrt{\frac{N}{2}} \left( \frac{1}{N} \sum_{i=1}^N \hat{\beta}_i - \beta \right)$
2. Augmented Delta Test (Delta Tilde):  $\tilde{\Delta} = \sqrt{N} \left( \frac{1}{N} \sum_{i=1}^N \frac{\hat{\beta}_i - \beta}{\sigma_i} \right)$

In these formulas,  $N$  represents the number of panel units,  $\hat{\beta}_i$  is the estimated slope coefficient for unit  $i$ ,  $\beta$  is the average slope coefficient across all units, and  $\sigma_i$  denotes the standard error of the estimated coefficient for unit  $i$ .

The results of the slope homogeneity test are presented in Table 3.

**Table 3.** Slope homogeneity test results.

Test Type	Statistic	<i>p</i> -Value
Delta Test	11.466	(0.000) ***
Adjusted Delta Test	13.445	(0.000) ***

Note: Under the null hypothesis of slope homogeneity, both the Delta and Adjusted Delta tests are asymptotically normally distributed. The *p*-values indicate significance at the 1% level (\*\*\*)  $p < 0.01$ .

The slope homogeneity test results presented in Table 3 (Pesaran & Yamagata, 2008) are highly significant based on both the Delta and Adjusted Delta statistics ( $p < 0.01$ ). This leads to the rejection of the null hypothesis, which assumes that slope coefficients are homogeneous across all countries.

The findings suggest that the impact of the independent variables in the model—such as agricultural imports, exports, per capita income, and the share of renewable energy—on the dependent variable (CO<sub>2</sub> emissions) differs across countries, indicating the presence of slope heterogeneity.

### 2.4. Unit Root Test

The Augmented Dickey–Fuller test developed by Pesaran (2007) offers a unit root testing approach that accounts for cross-sectional dependence in panel data settings. Known as the Cross-sectionally Augmented Dickey–Fuller (CADF) test, this method improves the reliability and realism of unit root testing by incorporating interdependencies among countries or panel unit factors often neglected in traditional panel unit root tests. As a result, it provides a more robust assessment of stationarity, particularly for time series influenced by common shocks or similar trends across countries.



The standard form of the Augmented Dickey–Fuller (ADF) test for panel data is expressed as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it} + \sum_{k=1}^{p_i} \gamma_{ik} \Delta y_{it-k} + \epsilon_{it}$$

In this formulation,  $y_{it}$ , represents the observation for unit  $i$  at time  $t$ ,  $\alpha_i$ , is the individual fixed effect,  $\beta_i$ , is the coefficient of the lagged level term (the speed of adjustment),  $\gamma_{ik}$ , are the coefficients of the lagged differences, and  $\epsilon_{it}$ , is the error term.

Pesaran’s CADF test incorporates cross-sectional dependence and is specified as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it} + \sum_{k=1}^{p_i} \gamma_{ik} \Delta y_{it-k} + \epsilon_{it} + \delta y_{t-1} + \epsilon_{it}$$

Here,  $y_{t-1}$ , denotes the cross-sectional mean at time  $t - 1$ , which captures common factors across units in the panel.

The results of the unit root test are presented in Table 4.

**Table 4.** Pesaran CADF unit root test results.

Variable	Stationarity Level	t-Bar	Critical Value (5%)	Z[t-Bar]	p-Value	Conclusion
ln_AgriIM	Level [I(0)]	−2.309	−2.250	−2.079	0.019 **	Stationary
ln_GDPCapita	First Difference [I(1)]	−2.606	−2.250	−3.225	0.001 ***	Stationary
ln_AgriEX	First Difference [I(1)]	−2.972	−2.250	−4.635	0.000 ***	Stationary
CO <sub>2</sub> Emissions	First Difference [I(1)]	−2.474	−2.250	−2.715	0.003 ***	Stationary
Renewable Energy	First Difference [I(1)]	−3.250	−2.250	−5.709	0.000 **	Stationary

Note: \*\*\*, and \*\* denote statistical significance at the 1%, and 5% levels, respectively.

According to the results of the panel CADF test developed by Pesaran (2007), only the variable ln\_AgriIM is stationary at level [I(0)], while the remaining variables become stationary at their first differences [I(1)]. This indicates that the variables exhibit different orders of integration, which limits the applicability of conventional panel models assuming fixed coefficients.

Therefore, second-generation panel estimation methods—such as Panel ARDL structures, AMG, or CCE estimators—are more appropriate, as they allow for a combination of I(0) and I(1) variables.

## 2.5. Augmented Mean Group (AMG) Estimation Results

The Augmented Mean Group (AMG) estimator, developed by Eberhardt and Bond (2009) and Eberhardt and Teal (2010), is designed to estimate long-run relationships in heterogeneous panel datasets. This approach extends the conventional Mean Group (MG) estimator by incorporating a common dynamic process that accounts for cross-sectional dependence.

In a panel data model, where  $y_{it}$  denotes the dependent variable and  $x_{it}$  is a vector of explanatory variables, the general specification is given as follows:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it}$$

Here,  $i = 1, \dots, N$  denotes the countries, and  $t = 1, \dots, T$  represents the time periods.  $\alpha_i$  captures the country-specific fixed effects, while  $\beta_i$  is a  $k \times 1$  vector of coefficients for each country.  $u_{it}$  denotes the error term.

To account for cross-sectional dependence, the error term  $u_{it}$  is modeled as follows:

$$u_{it} = \lambda_i f_t + \epsilon_{it}$$

In this formulation,  $\lambda_i$  represents the country-specific factor loadings, while  $f_t$  denotes the unobserved common factors (common dynamic process), and  $\epsilon_{it}$  is the idiosyncratic error term.

The AMG estimator expands the error term  $u_{it}$  by incorporating a common dynamic process ( $R_c$ ) into the model to account for cross-sectional dependence:

$$y_{it} = \alpha_i + \beta_i' x_{it} + \gamma_i R_c + \epsilon_{it}$$

Here,  $R_c$  represents the common dynamic process, which is associated with the unobserved factors  $f_{tf}$ .

The AMG estimator is a method that simultaneously accounts for heterogeneity and cross-sectional dependence in panel data analysis. While the traditional Mean Group (MG) estimator considers cross-country heterogeneity, it overlooks cross-sectional dependence. The AMG approach addresses this limitation by incorporating a common dynamic process into the model, thereby capturing the dependence structure among units. The AMG estimation results are presented in Table 5.

**Table 5.** Augmented Mean Group (AMG) estimation results. Dependent variable: CO<sub>2</sub> emissions (per capita, metric tons).

Variable	Coefficient	Std. Error	z-Value	p-Value	95% Confidence Interval
Renewable Energy (%)	−26.133	6.137	−4.26	0.000 ***	[−38.161; −14.104]
ln(GDP per capita)	303.152	87.904	3.45	0.001 ***	[130.862; 475.441]
ln(Agricultural Imports)	206.742	69.972	2.95	0.003 ***	[69.600; 343.884]
ln(Agricultural Exports)	210.816	70.280	3.00	0.003 ***	[73.070; 348.563]
Country-specific trend	−30.677	3.449	−8.90	0.000 ***	[−37.436; −23.918]
Constant	−10,299.98	1122.36	−9.18	0.000 ***	[−12,499.76; −8100.20]

Note: Wald  $\chi^2(4) = 47.75$ ;  $p < 0.0000$  | RMSE: 55.35 | The trend is statistically significant at the 5% level for 12 countries. \*\*\* indicate statistical significance at the 1% level.

The mathematical representation of the model is as follows:

$$CO2it = \alpha_i + \beta_1 RenewableEit + \beta_2 \ln(GDPCapitait) + \beta_3 \ln(AgriIMit) + \beta_4 \ln(AgriEXit) + \gamma t + \epsilon_{it}$$

In this model,  $CO2it$  represents the per capita carbon dioxide (CO<sub>2</sub>) emissions of country  $i$  in year  $t$ , the variable  $RenewableEit$  denotes the share of renewable energy in total energy consumption (%), while  $\ln(GDPCapitait)$  refers to the natural logarithm of real GDP per capita. Similarly,  $\ln(AgriIMit)$  and  $\ln(AgriEXit)$  represent the natural logarithms of agricultural imports and exports (based on value), respectively. The term  $\gamma t$  captures time-specific effects that reflect the common dynamic process, as incorporated in the AMG framework. Finally,  $\alpha_i$  denotes the country-specific fixed effects, and  $\epsilon_{it}$  is the error term. All estimations were performed using Stata/SE 18.

The estimation results offer important insights into the environmental impacts of trade, economic growth, and renewable energy use. Given the structural variation in factors influencing carbon emissions across countries, the inclusion of country-specific trends and a common dynamic process makes the model theoretically well-aligned with economic realities.

An increase in the share of renewable energy in total energy consumption has a statistically significant and negative effect on CO<sub>2</sub> emissions ( $\beta = -26.13$ ;  $p < 0.01$ ). This finding suggests that sustainable energy policies can improve environmental quality and reduce carbon footprints. It supports the widely accepted view in the environmental economics literature that renewable energy serves as a “clean energy source” (Stern, 2004).

Per capita GDP is found to have a statistically significant positive effect on CO<sub>2</sub> emissions ( $\beta = 303.15$ ;  $p < 0.01$ ). This result aligns with the first phase of the Environmental Kuznets Curve (EKC) hypothesis, which suggests that environmental degradation tends to increase during the early and middle stages of economic growth (Grossman & Krueger, 1995). However, since the model does not include a squared GDP term (GDP<sup>2</sup>), it is not possible to empirically test whether the relationship follows the expected inverted U-shape.

Interestingly, both agricultural imports ( $\beta = 206.74$ ;  $p < 0.01$ ) and exports ( $\beta = 210.82$ ;  $p < 0.01$ ) are found to significantly increase CO<sub>2</sub> emissions. This finding suggests that although the agricultural sector may appear relatively eco-friendly at the production stage, trade-related components—such as transportation, cold chain logistics, and processing—impose substantial environmental costs. Moreover, the results align with broader debates on carbon leakage and embedded emissions, indicating that international trade in agricultural goods contributes to the global carbon footprint beyond national borders.

A significant proportion (85.7%) of the country-specific time trends is found to be statistically significant. This indicates that countries have followed distinct environmental policy paths, production structures, or energy transition strategies over time. As such, modeling heterogeneity rather than assuming homogeneous dynamics proves to be an appropriate and necessary approach in this analysis.

The model results reveal that agricultural trade and economic growth have direct environmental impacts in both developed and developing countries, while renewable energy use appears to be an effective tool for mitigating these adverse effects. Overall, the findings provide both theoretical and empirical support for the importance of sustainable development policies that prioritize the balance between environment, economy, and trade.

## 2.6. Variance Inflation Factor (VIF) Test

Prior to estimation, a multicollinearity diagnostic was conducted using Variance Inflation Factors (VIFs) to assess the linear dependency among independent variables. This test is essential in regression models to detect potential redundancy in explanatory variables that may distort coefficient estimates.

As shown in Table 6 all VIF values were well below the conventional threshold of 10, with a mean VIF of 1.46, indicating no significant multicollinearity problem.

**Table 6.** Variance Inflation Factor (VIF) results.

Variable	VIF	1/VIF
ln_GDPCapita	1.61	0.620
RenewableE	1.58	0.631
ln_AgriEX	1.34	0.745
ln_AgriIM	1.29	0.775
<b>Mean VIF</b>	<b>1.46</b>	

**Note:** No multicollinearity is detected as all VIF values are below the critical threshold of 10.

## 2.7. Robustness Check: CCEMG Estimation

As a robustness check, the model was re-estimated using the Common Correlated Effects Mean Group (CCEMG) estimator, which accounts for both cross-sectional dependence and slope heterogeneity. The results remained broadly consistent with those obtained from the AMG estimator. In particular, the positive and statistically significant relationship between agricultural imports and CO<sub>2</sub> emissions was confirmed, and the negative effect of renewable energy use persisted, albeit with marginal significance. These findings support

the stability and reliability of the core results. The detailed estimation results from the CCEMG model are presented in Appendix A, Table A1.

Table 7 presents the group-specific coefficients obtained from the model reveal that the determinants of CO<sub>2</sub> emissions vary significantly across countries. This result supports the validity of the slope heterogeneity assumption and theoretically confirms the appropriateness of using the AMG method.

The AMG estimation results by country group indicate that the impacts of agricultural trade, economic growth, and renewable energy use on CO<sub>2</sub> emissions differ substantially. In the case of the United States, agricultural imports are found to have a positive effect on carbon emissions, while agricultural exports appear to have a mitigating effect. Additionally, the significant negative impact of renewable energy use on emissions ( $\beta = -16.13$ ;  $p < 0.01$ ) confirms the contribution of energy transition to environmental sustainability.

Similarly, in major importing countries such as the United Kingdom and China, the increase in emissions associated with agricultural imports is both highly significant and substantial. This finding indicates that the consumption-oriented and import-dependent agricultural structures in these countries generate considerable environmental costs throughout the logistics and production chains.

In developing countries such as India and Indonesia, the positive relationship between per capita income (GDP) and CO<sub>2</sub> emissions is particularly noteworthy. The notably high coefficient observed in Indonesia ( $\beta \approx 1317$ ) suggests that economic growth in these countries may intensify environmental pressures.

The renewable energy variable generally shows a statistically significant negative effect on CO<sub>2</sub> emissions. This effect is clearly observed in the cases of Brazil and Türkiye (for example,  $\beta = -14.53$ ;  $p < 0.01$  for Türkiye). In these countries, the shift toward renewable energy sources appears to be effective in reducing the carbon footprint. On the other hand, in some countries such as India and Russia, this effect is not found to be statistically significant. This may be related to the effectiveness of energy transition policies or the limited role of renewable energy technologies within the overall energy system.

One of the notable findings of the study is the negative and statistically significant GDP coefficient observed for Russia ( $\beta = -220.48$ ;  $p = 0.010$ ). This result suggests that the country has managed to reduce carbon emissions alongside economic growth, possibly due to improvements in energy efficiency, green transformation, or sectoral shifts in its production structure.

Agricultural imports are found to significantly increase emissions in countries with high consumption intensity such as China, India, the United Kingdom, and Indonesia. In contrast, in developing countries like Türkiye, Mexico, and Brazil, the use of renewable energy appears to enhance environmental performance, indicating that these countries are achieving positive outcomes from their sustainable energy policies.

The effect of agricultural exports on emissions varies across countries. For example, while exports appear to reduce emissions in the United States, positive and statistically significant results are observed in countries like Russia and Brazil. This suggests that factors such as the mode of agricultural production, the emission intensity of exported products, and the carbon footprint of international trade may differ by country, highlighting that the structure of production and trade plays a critical role in shaping environmental impacts.

Table 7. Country-specific AMG coefficient estimates.

Country	Renewable Energy	ln(GDP per Capita)	ln(Agri Imports)	ln(Agri Exports)	Common Dynamics	Constant
USA	−16.13 (0.000) ***	40.52 (0.217)	45.49 (0.025) **	−81.21 (0.000) ***	−0.067 (0.522)	999.22 (0.206)
UK	−160.91 (0.011) **	725.63 (0.274)	427.71 (0.027) **	−550.50 (0.103)	−1.97 (0.039) **	1043.15 (0.860)
Australia	−11.37 (0.000) ***	48.03 (0.000) ***	−11.78 (0.493)	16.02 (0.113)	0.091 (0.003) ***	−135.24 (0.679)
Canada	−19.73 (0.059) *	138.50 (0.055) *	−125.26 (0.327)	77.47 (0.121)	0.022 (0.701)	468.89 (0.736)
Germany	−0.20 (0.980)	−122.77 (0.275)	102.95 (0.227)	−106.95 (0.377)	−0.28 (0.044) **	2169.29 (0.267)
France	−8.29 (0.017) **	−34.12 (0.187)	66.89 (0.155)	−47.11 (0.284)	−0.035 (0.553)	352.47 (0.612)
Denmark	−1.97 (0.000) ***	3.00 (0.503)	20.97 (0.001) ***	2.80 (0.464)	0.033 (0.001) ***	−453.07 (0.000) ***
China	−46.31 (0.189)	1213.94 (0.068) *	1203.03 (0.035) **	1070.82 (0.179)	3.83 (0.006) ***	−54,370.31 (0.000) ***
India	20.76 (0.045) **	734.11 (0.000) ***	456.79 (0.002) ***	−70.17 (0.223)	0.90 (0.000) ***	−13,383.27 (0.000) ***
Indonesia	−3.72 (0.766)	1316.93 (0.000) ***	870.72 (0.000) ***	102.71 (0.541)	1.69 (0.001) ***	−29,009.85 (0.000) ***
Russia	−75.37 (0.133)	−220.48 (0.010) **	98.88 (0.276)	380.36 (0.000) ***	0.22 (0.000) ***	−6759.62 (0.004) ***
Brazil	−14.73 (0.000) ***	42.79 (0.029) **	−29.49 (0.276)	111.06 (0.000) ***	0.03 (0.405)	−1163.80 (0.000) ***
Türkiye	−14.53 (0.000) ***	−13.62 (0.550)	63.84 (0.047) **	15.18 (0.480)	0.28 (0.000) ***	−1083.93 (0.002) ***
Mexico	−17.90 (0.000) ***	38.21 (0.426)	79.36 (0.005) ***	−1.86 (0.939)	0.05 (0.044) **	−1417.63 (0.001) ***

Note: *p*-values are reported in parentheses. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

### 2.8. Granger Causality Test

To test the direction of influence between key variables and CO<sub>2</sub> emissions, a panel Granger non-causality test was conducted using the [Dumitrescu and Hurlin \(2012\)](#) approach. This method accounts for heterogeneity across cross-sectional units and is appropriate for unbalanced panels. The test results indicate that agricultural imports and renewable energy consumption Granger-cause CO<sub>2</sub> emissions, while no such relationship was found for agricultural exports. These findings suggest that causality runs from agricultural imports and renewable energy to emissions, providing additional robustness to the main analysis.

The Granger causality test results presented in Table 8 provide important insights into the directionality of the relationships between the key explanatory variables and CO<sub>2</sub> emissions. The findings indicate that agricultural imports Granger-cause carbon emissions at the 5% significance level, suggesting that past values of import activity have predictive power over current emission levels. This supports the interpretation that agricultural imports are not merely correlated with emissions but may act as a leading factor in driving them—potentially through mechanisms such as increased transportation demand, global supply chain integration, and embedded emissions in imported food products.

**Table 8.** Dumitrescu–Hurlin panel Granger causality test results.

Null Hypothesis	Z-Bar	p-Value	Conclusion
ln_AgriIM does not Granger-cause CO <sub>2</sub> Emission	2.4119	0.0159 **	Reject H <sub>0</sub> → Causality exists
ln_AgriEX does not Granger-cause CO <sub>2</sub> Emission	0.8869	0.3751	Fail to reject H <sub>0</sub>
RenewableE does not Granger-cause CO <sub>2</sub> Emission	3.9834	0.0001 ***	Reject H <sub>0</sub> → Strong causality

Note: \*\*\*, and \*\* indicate statistical significance at the 1%, and 5% levels, respectively.

Furthermore, renewable energy consumption is found to Granger-cause CO<sub>2</sub> emissions at the 1% level. This result, while initially counterintuitive given the environmental role of renewables, aligns with earlier discussion in the manuscript regarding the transitional energy dynamics in certain countries. When renewable energy deployment remains insufficiently integrated or technologically limited—as in the case of biomass or poorly managed solar investments—its expansion may not immediately translate into emission reductions.

In contrast, the absence of Granger causality from agricultural exports to emissions suggests that export-driven production does not exert a consistent or direct effect on carbon outcomes across the sample. This could be due to heterogeneity in production technologies, regulatory practices, or emission intensity across exporting countries. These results reinforce the importance of distinguishing between trade types and their environmental implications, and they lend further robustness to the core findings of the study by clarifying the temporal precedence of key drivers.

## 3. Discussion and Conclusions

This study contributes to the growing literature on the relationship between trade openness, renewable energy use, and carbon emissions, particularly within the agricultural sector. The empirical results obtained using the Augmented Mean Group (AMG) estimator reveal both expected alignments and nuanced divergences across different country groups.

Firstly, the finding that agricultural trade has differentiated effects on CO<sub>2</sub> emissions across countries supports the idea that structural factors—such as trade composition and environmental regulation—play a critical role. In emerging economies, increased agricultural trade is associated with higher emissions, likely to reflect limited technological capacity and less stringent environmental oversight. In contrast, developed countries



appear to mitigate the environmental impacts of trade more effectively, suggesting that cleaner production processes and regulatory enforcement can shape outcomes.

Secondly, the negative relationship between renewable energy use and carbon emissions affirms the important role that renewable technologies can play in decarbonizing the agricultural sector. This result reflects the broader understanding that energy transition strategies have measurable benefits for emission reduction, particularly when renewables are efficiently deployed and integrated into national energy systems.

Thirdly, the positive association between per capita GDP and emissions aligns with the early stages of the Environmental Kuznets Curve (EKC) hypothesis, where economic growth often coincides with increased environmental degradation. The model does not include a squared GDP term, as the primary objective was to evaluate linear relationships. Nonetheless, the finding suggests that in emerging economies, modernization processes in agriculture may initially raise emissions before technological upgrades or policy improvements yield environmental benefits.

One possible direction for future research is the incorporation of interaction terms—such as  $\text{GDP} \times \text{Agricultural Imports}$ —to better capture how the effects of trade may vary depending on development level. Such terms could uncover threshold effects or nonlinear relationships that basic models do not reveal.

From a methodological standpoint, the use of second-generation panel econometric methods marks an improvement over earlier approaches. These methods explicitly account for cross-sectional dependence and heterogeneous slopes, thereby enhancing the robustness and validity of the findings.

A central contribution of this study is its sector-specific and comparative focus. By examining 14 countries and accounting for variation across development levels, the study moves beyond single-country analyses and offers a broader view of the interplay between agricultural trade, energy use, and emissions. The use of the AMG estimator further enables country-specific interpretations, which enriches the overall policy relevance of the findings.

That said, several limitations should be acknowledged. The study period spans years during which renewable energy transitions evolved at different speeds across countries. More granular data, especially on agricultural practices, inputs, and land-use changes, would enhance the understanding of causal mechanisms. Future research may also benefit from the use of dynamic panel models or sector-disaggregated renewable energy indicators.

The model results confirm that increasing the share of renewable energy in total energy consumption robustly reduces CO<sub>2</sub> emissions. This highlights energy transition as a strategic domain for climate mitigation, especially in developing countries.

In the case of India, however, renewable energy use is positively and significantly associated with emissions. This finding may reflect structural characteristics of the national energy system, where fossil fuels—particularly coal—continue to dominate despite growth in renewables. Challenges related to technological integration, system efficiency, and grid readiness may explain this pattern.

Per capita income remains positively and significantly related to emissions, underscoring the environmental costs of early-stage growth. In countries such as China, India, and Indonesia, this may be closely tied to production methods and fossil-based energy systems. As the model does not test the full EKC curve, this relationship should be interpreted cautiously.

Agricultural imports are found to increase emissions significantly, pointing to the environmental footprint of global trade—not in production alone but also in transport, storage, and cold chain logistics. This effect is especially pronounced in high-import countries such as China, India, and the United Kingdom, where embedded carbon flows are likely more substantial.

Agricultural exports, by contrast, do not have a significant effect in the overall model, but country-specific results offer useful insights. In Brazil and Russia, exports are associated with higher emissions, possibly due to large-scale, industrialized farming. The United States presents a contrasting case, where exports appear to reduce emissions, potentially due to advanced technologies and resource-efficient practices.

Country-level results suggest that the impact of growth, trade, and energy variables differs meaningfully across national contexts. For instance, in Russia, per capita income is negatively associated with emissions—hinting at the possibility of decoupling between economic growth and environmental harm. Likewise, countries such as Türkiye, Brazil, and Mexico exhibit statistically significant emission-reducing effects from renewable energy use, indicating the effectiveness of current energy policies.

These variations reinforce the conclusion that universal policy recommendations may not be effective. Instead, country-specific strategies that consider structural and sectoral dynamics are likely to yield better outcomes. The study emphasizes the value of disaggregated environmental analysis for both academic research and policy design.

The analysis also demonstrates that agricultural imports and renewable energy use have predictive power over emission levels, as confirmed by Granger causality tests. This adds robustness to the empirical findings and strengthens the policy relevance of the model.

Addressing the emission intensity of agricultural imports will require strategies such as carbon certification schemes, sustainable sourcing standards, and greener supply chains. In countries where renewable energy contributes to emission reduction, energy transition should be deepened through better infrastructure and efficiency gains. Where renewables are not yet delivering emission reductions, structural barriers must be addressed to unlock their potential.

In conclusion, this study integrates trade, energy, and growth into a comprehensive framework to explain cross-country variation in carbon emissions. The results confirm that sustainable development requires more than economic expansion—it necessitates a fundamental rethinking of how trade and energy systems interact with the environment. Future work may benefit from testing nonlinear growth effects, analyzing green product trade, and incorporating more detailed sectoral data.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data used in this study are publicly available from the World Bank Open Data platform: <https://data.worldbank.org>, accessed on 27 May 2025, as also stated in Table 1. No new data were created.

**Conflicts of Interest:** The author declares no conflict of interest.

## Appendix A

**Table A1.** Robustness check: CCEMG estimation results.

Variable	Coefficient	Std. Err.	p-Value
ln_GDPCapita	387.82	233.14	0.096 *
ln_AgriIM	227.65	94.89	0.016 **
ln_AgriEX	−20.02	55.44	0.718
RenewableE	−30.64	17.46	0.079 *

\*\*, and \* indicate statistical significance at the 5%, and 10% levels, respectively.

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