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RESEARCH ARTICLE

Determinants of agricultural emissions: panel data evidence from a global sample

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Abstract
Using the panel data of 89 economies from 1995–2012, this study examines the major drivers of agricultural emissions while considering affluence, energy intensity, agriculture value added and economic integration. We find long-run cointegration among the variables. Furthermore, our empirical results based on a dynamic fixed effects autoregressive distributed lag model show that the increases in income and economic integration – proxied by trade and foreign direct investment (FDI) – are the major contributors to higher greenhouse gas (GHG) emissions from agriculture in the short run. Additionally, the increases in income, agriculture value added and energy consumption are the major drivers of agricultural emissions in the long run. Notably, trade openness and FDI inflows have significantly negative effects on GHG emissions from agriculture in the long run. These results apply to methane and nitrous oxide emissions. The empirical findings vary across three subsamples of countries at different development stages.

Keywords: agriculture; emissions; global sample; pollution

JEL classifications: Q56; O13; O17; Q53

1. Introduction

Despite a declining share in total greenhouse gas (GHG) emissions from 13.44 per cent in 1991 to 11.3 per cent in 2012, the total emissions from agriculture increased from 4,561 to more than 5,381 Mt in carbon dioxide (CO_2) equivalent during the same period (WRI, 2015). One of the reasons for this relatively small share of agricultural emissions in total GHG emissions is that, compared to other sectors, the agricultural sector generally consumes less energy, for example, electricity and heat, industry, and transportation (Krey *et al.*, 2012). From a historical perspective, agricultural production was formerly household-based or undertaken in areas using little or no energy, and transportation was often within short distances, which entailed little or no fuel use (Amate and De Molina, 2013). However, the evolution of agriculture to large-scale production in the last ten years might have changed this. Agricultural activities were one of the important sources of global GHG emissions (e.g., see Calvin *et al.*, 2016). Furthermore, there are two other critical emissions from agriculture, namely, nitrous oxide (N_2O) emissions (Audet *et al.*, 2017) and methane (CH_4) emissions (Caro *et al.*, 2019), which have been neglected in the literature (Perlman *et al.*, 2013).

A few studies have examined the determinants of CO_2 emissions from agriculture (see, for instance, Robaina-Alves and Moutinho, 2014; Luo *et al.*, 2017; Castesana *et al.*, 2018), but most have focused on the measurements of emissions or had no theoretical framework for empirical investigation. For instance, Audet *et al.* (2017) examined the case of Sweden from 2014–2015 and documented that agricultural streams added a significant source of N_2O emissions to the environment. Luo *et al.* (2017) used the Tapio decoupling method for the case of 30 Chinese provinces from 1997–2014 and concluded that fertilizer and cattle were the main drivers of CO_2 emissions in agriculture. Recently, Castesana *et al.* (2018) noted that mineral fertilizers, manure in pasture, manure management and agricultural waste burning were the main sources of NH_3 emissions in agriculture for Argentina from 2000–2012. Furthermore, in the context of globalization, trade openness and foreign direct investment (FDI) inflows should also be considered (Kastratović, 2019) because they might be critical sources of emissions for host countries (Naranpanawa, 2011; Pao and Tsai, 2011; Ren *et al.*, 2014; Le *et al.*, 2016).

This study attempts to provide new insights into the determinants of agricultural emissions by analyzing the impacts of income level, agriculture value added, energy consumption, trade (export and import) and FDI inflows on the emissions from agriculture. To achieve this objective, we employ one of the most important theoretical frameworks in environmental economics – namely, the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model – to examine the effects of income level, agricultural development, energy intensity, energy structure and economic integration on emissions from agriculture in a sample of 89 countries from 1995–2012. In addition, we might reasonably expect differences in the determinants of agricultural emissions across countries at different income levels. As such, we investigate the drivers of total GHG emissions from agriculture for three types of countries: low and lower-middle-income countries (LMEs), upper-middle-income countries (UMEs) and high-income countries (HIEs). In addition, the determinants of agricultural emissions are identified in both the short run and the long run to provide more insights for policy formulation in different time horizons.

Specifically, this study attempts to address three research questions:

(1) Do income per capita, agriculture value added, energy consumption per capita, trade, export, import and FDI significantly affect agricultural GHG emissions?
(2) Do the major drivers of GHG emissions from agriculture differ between the short run and the long run?
(3) Do the major drivers of GHG emissions from agriculture vary across types of GHG emissions and subsamples of countries at different development stages?

Methodologically, this study employs an extended version of the STIRPAT model of Dietz and Rosa (1997) by including economic integration, namely, trade openness (Ertugrul *et al.*, 2016) and FDI (Ren *et al.*, 2014; Zhu *et al.*, 2016; Rafindadi *et al.*, 2018), as augmented factors. The data are collected from the World Bank's World Development Indicators and WRI (2015). Subject to data availability, the total GHG emissions are extracted from 1995–2012, and N_2O and CH_4 emissions are obtained from 1995–2008.

The remainder of this study is organized as follows. Section 2 reviews the related literature to derive the knowledge gaps that our study endeavors to fill. The model, data and methodology are presented in section 3. Section 4 reports and discusses the empirical results in three regards: (i) total GHG emissions from agriculture with different model specifications, (ii) comparison of the estimation results among different types of GHG emissions from agriculture, and (iii) comparison of the estimation results among three subsamples of countries at different economic development stages. Section 5 concludes the study.

2. Literature review

Although the agricultural sector plays a vital role in the economy with regard to food security and nutrition, along with other economic, environmental and social impacts (Li *et al*., 2016), this sector is also often presented as one of the major sources of CO_2 emissions contributing to global warming and climate change (Oenema *et al*., 2001; Tubiello *et al*., 2013; Calvin *et al*., 2016; Agovino *et al*., 2019). Cole *et al*. (1997) acknowledged that technological advancement could help mitigate CO_2, CH_4 and N_2O emissions from the agriculture sector.

Beyond the measures related to land use, soil fertility and decisions on crop production and forests (De Pinto *et al*., 2016), Franks and Hadingham (2012) have suggested that policies attempting to reduce the emissions from agriculture should focus on the demand-side rather than the supply-side factors. This suggestion explains why many scholars have attempted to empirically investigate the determinants of agricultural emissions from the demand-side economic factors (Sebri and Abid, 2012; Chen *et al*., 2017; Paul *et al*., 2018; Waheed *et al*., 2018). For instance, Ben Jebli and Ben Youssef (2017) investigated a panel of five North African countries from 1980–2011 and found bidirectional causality between CO_2 emissions and agriculture in the short run and the long run.

Table A1 in the online appendix summarizes some studies on agricultural emissions. Overall, the current literature on agricultural emissions has mostly focused on the measurement or estimation of emissions (see Castesana *et al*., 2018; Rehman *et al*., 2019). Only a few studies have examined the determinants of agricultural emissions. For instance, Kastratović (2019) investigated the impacts of FDI on agricultural emissions but only considered CO_2 emissions and did not conduct a robustness check or short-run and long-run estimations. In another study, emissions from the agricultural sector were decomposed into factors such as economic growth, energy intensity, energy structure, human capital accumulation, emissions factors and labor productivity (Robaina-Alves and Moutinho, 2014). Ben Jebli and Ben Youssef (2019) studied the case of Brazil from 1980–2013 and documented that per capita combustible renewables and waste consumption and agriculture value added seemed to have negative impacts on total CO_2 emissions in the long run. Thus, insights can be gleaned from understanding the short-run and long-run determinants of agricultural emissions, especially at a global level, rather than the country level (see Ben Jebli and Ben Youssef, 2019) or a short time horizon. Understanding the dynamics of the determinants of agricultural emissions is also crucial for policy formulation in this field.

Overall, according to our review of the literature, a solid theoretical framework that can guide the effective determination of agricultural emissions is not in the literature. Although GHG emissions per unit of agricultural product have been reduced at the global level (Bennetzen *et al*., 2016), the rapid growth of economic integration and technology in recent decades continue to induce higher emissions from agriculture (WRI, 2015). The differences in emissions were also noted across economies (Dace and Blumberga, 2016). In addition, the short-run and long-run effects of the drivers of agricultural emissions should be investigated (Li *et al.*, 2016).

The subject matter of this study is so important that it must be urgently addressed because reducing agricultural emissions provides significant economic and social benefits. For example, Giannadaki *et al.* (2018) showed that agricultural ammonia emissions strongly contribute to fine particulate matter (PM2.5) air pollution and have significantly adverse impacts on human health, leading to increased mortality rate. They indicated that a 50 per cent reduction in agricultural emissions could prevent more than 200 thousand deaths per year in the 59 countries included in their study, notably in Europe, Russia, Turkey, the United States, Canada and China, accompanied by economic benefits of billions of US dollars (US$). In the European Union (EU), the mortality rate could be reduced by 18 per cent with an annual economic benefit of US$89 billion. Within the EU, 140 thousand deaths could be prevented per year with an associated economic benefit of approximately US$407 billion. A cost-benefit assessment of ammonia emissions abatement options for the EU indicates that the reduction of agricultural emissions generates net financial and social benefits. Therefore, an investigation of the drivers of total emissions in the agricultural sector across different income levels is worthwhile.

3. Model, data, and methodology

3.1 Model

In the current literature on the emissions from agriculture, there are four common approaches: the index decomposition method, the bottom-up method, the system optimization, and the econometric approaches (see Xu and Lin (2017) for further details). In this study, we apply the econometric methods to the extended STIRPAT model to investigate the agricultural emissions' determinants. The STIRPAT model is based on the IPAT model by Ehrlich and Holdren (1971), which relates the impacts of human aspects and activities including population (P), affluence (A), and technology (T) on the environment (I). The IPAT model (Ehrlich and Holdren, 1971) is a mathematical notation of the impacts of human activities on the environment, which can be expressed as:

$$I = P \times A \times T. \tag{1}$$

In this model, the environment (I) must be broadly considered with the inclusion of the physical environment of urban ghettos, the human behavioral environment and the epidemiological environment (Ehrlich and Holdren, 1971). That is, population growth, population size, population density, resource utilization and depletion, and environmental deterioration must be considered jointly. In the model, I represents the environmental impacts of human activities, which is modeled as a multiplication function of three terms: population (P), affluence (A) (i.e., income level), and technology (T) (i.e., the efficiency of resource utilization). The proposed proxies for the variables in this model are as follows. I could be measured using ecological footprint analysis. Additionally, P represents the population of an area, such as the world, and is expressed in human numbers. A represents the average consumption of each person in the population, which is commonly proxied by gross domestic product (GDP) per capita. As an efficiency factor, the environmental effects of T can vary in many ways. Hence, the unit for T is reliant on the situation to which $I = PAT$ is being applied.

The IPAT model is a heuristic model and cannot be used for estimation. As such, the stochastic version of IPAT was developed by Dietz and Rosa (1997), namely, the STIRPAT model, for empirical testing. The STIRPAT model can be summarized as follows:

$$I_{it} = \alpha_{it} P_{it}^{\beta_1} A_{it}^{\beta_2} T_{it}^{\beta_3} \varepsilon_{it}, \tag{2}$$

where I, P, A, and T have the same implications as in the IPAT framework for country i at time t. α represents the country-specific effect. β_1, β_2, and β_3 are the elasticities of the environmental impacts with respect to P, A and T, respectively. The logarithmic form of model (2) for testing takes the following form:

$$lnI_{it} = \alpha_{it} + \beta_1 lnP_{it} + \beta_2 lnA_{it} + \beta_3 lnT_{it} + ln\varepsilon_{it} \; . \tag{3}$$

Because the purpose of our study is to examine the determinants of emissions in the agricultural sector (across countries), equation (3) can be reformulated by integrating the appropriate factors. The equation therefore becomes:

$$lnAE_{it} = \alpha_{it} + \beta_1 lnPOP_{it} + \beta_2 lnLnGDP_{it} + \beta_3 lnEI_{it} + \varepsilon_{it}, \tag{4}$$

in which *AE* is GHG emissions from agriculture; *POP* is population; *GDP* is GDP, a proxy for affluence (economic development); and *EI* is energy consumption, a proxy for the technological progress in emissions reduction (Rafiq *et al.*, 2016; Lin and Zhu, 2017). ε is the residual term.

Furthermore, the nature of the agricultural sector implies that there are other potential determinants of agricultural emissions such as trade openness (Ertugrul *et al.*, 2016) and FDI inflows (Ren *et al.*, 2014; Zhu *et al.*, 2016; Rafindadi *et al.*, 2018). Specifically, trade, exporting and importing may facilitate extra economic activities that affect agricultural emissions. By contrast, the FDI inflows may have implications for the technological advancement in the production function, which help improve the efficiency in energy consumption, reducing emissions from the agricultural sector. This supports the pollution halo hypothesis. Nevertheless, the FDI inflows may also have unfavorable effects on the emissions because multinational firms could take advantage of the weak environmental regulations in the host countries (especially developing countries). This is in line with the pollution-haven hypothesis.

This study thus contributes to the scarce literature on agricultural emissions by providing a comprehensive analysis that explicitly considers all potential contributors of agricultural emissions in the baseline model. The drivers of agricultural emission are examined in an augmented version of the STIRPAT model, as in equation (4), by adding a set of additional explanatory variables. Specifically, our study is conducted with an annual panel dataset of 89 countries (table A2a, online appendix)[1] and three subsamples – 31 HIEs, 26 UMEs, and 321 LMEs[2] – from 1995 to 2012. The classification of three subsamples into groups based on country and income level is the same as that of the World Bank's country classification.[3]

[1]We excluded 68 countries from our global sample because the data required for empirical analysis was missing, namely, the data of agricultural value added, energy use and FDI net inflows. Please refer to table A2b in the online appendix for further details.

[2]See table A3 in the online appendix for data descriptions of the three subsamples.

[3]According to the World Bank, for the 2020 fiscal year, low-income economies are defined as those with a gross national income (GNI) per capita, calculated by using the World Bank Atlas method, of

For the model in equation (4), this study conducts data analysis in per capita terms by dividing both sides of the equation by the total population.[4] The extended STIRPAT model used in this study then takes the following form:

$$\begin{aligned} AE_{it} = \alpha_0 + \alpha_{1t} AE_{it-1} + \beta_1 Income_{it} + \beta_2 Agri_{it} + \beta_3 Energy_{it} \\ + \beta_4 Trade_{it} + \beta_5 FDI_{it} + \varepsilon_{it}, \end{aligned} \tag{5}$$

in which *i, t* denote country *i* at year *t*. *AE* is the total GHG emissions from agriculture, expressed in per capita terms. *Income* represents affluence, proxied by GDP per capita. *Agri* is agricultural value added per capita. *Energy* is proxied by energy use (kg of oil equivalent) per capita. *Trade* represents trade openness, proxied by total trade value per capita. All these variables are taken as natural logarithms. With this transformation, the estimated coefficients refer to the elasticities of agricultural emissions to the corresponding factors in the model (Sadorsky, 2013). *FDI* is the ratio of net FDI inflow to GDP to proxy for the capital flow. α and β are the constant and coefficients. ε is the residual term. In addition, export and import values per capita are used to compare the effects of trade openness on agricultural emissions through export and import channels. Finally, two other types of agricultural emissions – CH_4 and N_2O emissions – are employed for comparison purposes.

3.2 Data analysis

All the detailed descriptions of the variables are presented in the online appendix (table A3). Data descriptions of the full sample are presented in table A4, while table A5 refers to the data description of each income–country group. Meanwhile, table A6 reports their correlation matrix.

The dynamic of agricultural activities and emissions of the income groups in the past decades has provided some notable results. The ratio of agricultural-value-added-to-GDP is stable in the case of HIEs, while it decreased for both middle-income groups. In the case of low-income economies, the contribution of agriculture to GDP decreased in the period before 2003; afterward, it fluctuated with a slight increase in the following period (figure A1, online appendix). At the global level, the total emissions from agriculture are stable for the period before 2003 and increase in the period afterward (figure A2, online appendix).

Across the income–country groups, the total emissions increased for the case of upper-middle-income countries, and their total emissions exceeded the emissions from the high-income-country group in 2005 (figure A3, online appendix). The emissions from lower-middle-income and low-income economies presented the same pattern. We can therefore divide the countries into three groups: LMEs, UMEs and HIEs.

In 1995, the five largest emitters in agriculture were China, India, the United States, Brazil and Russia (figure A4, online appendix). Most of these countries, except for Russia, remained the world's largest emitters in 2012 (figure A5, online appendix). Specifically, the total emissions in China and India increased substantially, and the emissions in the United States and Brazil did not fluctuate much.

US$1,025 or less in 2018; lower middle-income economies are those with a GNI per capita between US$1,026 and US$3,995; upper middle-income economies are those with a GNI per capita between US$3,996 and US$12,375; and high-income economies are those with a GNI per capita of US$12,376 or more. See https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[4] We would like to thank an anonymous reviewer for this helpful suggestion.

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As shown in online appendix table A4, trade, import and export have strong positive correlations, approximately 0.99. As such, including these three variables altogether in the same equation will probably cause the problem of collinearity in the estimation. Therefore, we estimated the models using trade, export and import separately, one by one, for each equation.[5]

The study sample of this research has a relatively large number of cross-sections ($N = 89$ countries) and a reasonably long time dimension (1995–2012, namely, $T = 18$ years). To examine the existence of cross-sectional dependence in our study sample, Pesaran's CD test (Pesaran, 2020) is applied to the lagged variables. The results in table A7 (online appendix) show the existence of cross-sectional dependence in the variables. We therefore conducted the Pesaran (2007) CIPS ($Z(t$-bar)) unit root tests for the variables in levels and first differences.

Except for the total emissions and agriculture value-added variables, which are stationary at the 1 per cent level, and trade openness and export, which are stationary at the 10 per cent level, the remaining variables are nonstationary at the levels. The CIPS unit root tests for the variables in the first differences show that all the variables are stationary at the 1 per cent level. In this case, we recruit different panel cointegration tests: the Kao cointegration test (Kao, 1999), the Pedroni cointegration test (Pedroni, 1999), and the Westerlund cointegration test (Westerlund, 2005). The results (see table A8, online appendix) indicate strong empirical evidence of long-run cointegration relationships between the variables.

3.3 Estimation method

Because the variables are a mixture of $I(0)$ and $I(1)$ stationarities, in addition to the existence of cointegration, the autoregressive distributed lag model (ARDL model) for panel data is probably the most suitable estimator (Odhiambo, 2009; Bildirici, 2014; Abdullahi *et al.*, 2015).

Dynamic panel data estimation is often conducted by using difference or system GMM estimators to manage endogeneity. However, with the existence of cointegration, these estimators are no longer appropriate methods. Furthermore, in our empirical study, we have cointegration among the variables in combination with the mixture of the $I(0)$ and I(1) variables. In this case, the ARDL is regarded as the most appropriate estimator (Odhiambo, 2009; Bildirici, 2014; Abdullahi *et al.*, 2015). Moreover, the ARDL model allows us to identify short-term and long-term effects by including lags of dependent and independent variables, whether the regressors are endogenous or exogenous (Pesaran and Smith, 1995; Pesaran and Shin, 1998). This model can thus solve the problem of endogeneity in dynamic panel data. With the potential existence of country fixed effects and time fixed effects, the dynamic fixed effects estimator (DFE) is used for the ARDL model (Asteriou and Monastiriotis, 2004). The DFE-ARDL model first detects the short-run and long-run influences of the regressors, and then deals with fixed effects. Moreover, the bias of this estimator is reduced to zero when the time dimension of data is becoming larger, which is suitable for our case with relatively long time dimensions – that is, 1995–2012 (18 years) and 1995–2008 (14 years).

[5]For example, refer to the results in table 3 where trade is estimated first (column 1), then FDI is added into the estimation with trade (column 2). In column 3, trade is dropped, and export is estimated instead. FDI is then added in the estimation with export in column 4. Similarly, only import and FDI are estimated in columns 5 and 6. The same strategy is applied throughout the remaining estimations (tables 4 and 5).

Overall, the DFE-ARDL model can help manage the problems of endogeneity, heteroscedasticity and fixed effects (Pesaran and Shin, 1998), and estimate the short-run and long-run influences of the regressors.[6] Nevertheless, with this approach, we assume that there is only one cointegration relationship among the variables of interest.

4. Results and discussions

All the empirical results regarding the short-run and long-run effects of the potential determinants of agricultural emissions for the whole sample of 89 countries are summarized in table 1. Furthermore, the results from performing the same analysis for CH_4 emissions and N_2O emissions are reported in table 2, and those from conducting a similar analysis for the three subsamples are presented in tables 3–5.

4.1 Determinants of agricultural emissions: short-run and long-run effects

4.1.1 Baseline model

First, we examine the determinants of total agricultural emissions based on our main specification with the inclusion of income, agriculture value added, energy consumption, trade, and FDI inflows as the regressors (equation (5)).

Table 1 shows the estimation results for the whole sample of 89 economies from 1995 to 2012. According to the main model specification in column 2 of table 3, in the long run, income, agriculture value added and energy consumption per capita appear to contribute positively and significantly to the emissions from the agricultural sector. Specifically, the coefficient is 0.2183 for income, 0.1416 for agriculture value added, and 0.1371 for energy consumption. This finding is consistent with the literature of environmental economics, that is, economic development is one of the major causes of environmental degradation (Le *et al.*, 2019). The result of this study thus adds new evidence regarding economic development and its increasing impact on emissions from agriculture. The result is also in line with other studies (e.g., Waheed *et al.*, 2018); that is, increasing agricultural activities leads to higher CO_2 emissions. The findings provide global evidence on the long-run impacts of agricultural production on CO_2 emissions and add to the literature that has been mostly based on the country level (e.g., see Waheed *et al.* (2018) for Pakistan and Ben Jebli and Ben Youssef (2019) with evidence for Brazil).

The positive influence of economic development (proxied by the level of income per capita) on agricultural emissions is consistent with the literature and the STIRPAT theory, which claim that affluence is one of the major causes of emissions. This finding is also in line with findings from other studies (Zhangwei and Xungang, 2011; Tian *et al.*, 2014), according to which economic development increases income level, which generates demand for agricultural products and hence agricultural production. This situation induces higher capital-intensive production in agriculture and high energy intensity generating emissions. Additionally, the long-run positive impacts of agricultural value added and energy consumption on agricultural emissions are expected in theory.

Furthermore, trade and FDI seem to have significant and negative long-run impacts on agricultural emissions. This finding highlights the crucial roles of economic integration in reducing agricultural emissions in the long run, which is in line with the pollution halo hypothesis. The positive short-run impact of FDI inflows on agricultural emissions

[6]Technical details of the ARDL model for panel data analysis in this study are presented in online appendix B.

Table 1. Determinants of total emissions in agriculture: DFE ARDL

Dep. var: *AE*	(1)	(2)	(3)	(4)	(5)	(6)
Short-run effects						
EC term	−0.3935*** [0.0208]	−0.3992*** [0.0210]	−0.3832*** [0.0205]	−0.3920*** [0.0207]	−0.3927*** [0.0209]	−0.3963*** [0.0211]
D.Income	0.1894*** [0.0713]	0.2119*** [0.0721]	0.1752** [0.0705]	0.1966*** [0.0712]	0.2116*** [0.0701]	0.2327*** [0.0709]
D.Agri	−0.0237 [0.0170]	−0.0242 [0.0171]	−0.0245 [0.0165]	−0.0257 [0.0166]	−0.0219 [0.0170]	−0.0219 [0.0171]
D.Energy	−0.0026 [0.0429]	−0.0102 [0.0431]	0.0007 [0.0429]	−0.0094 [0.0431]	−0.0031 [0.0430]	−0.0088 [0.0433]
D.Trade	0.0303* [0.0182]	0.0264 [0.0185]				
D.FDI		0.0011** [0.0005]		0.0014*** [0.0005]		0.0010** [0.0005]
D.Export			0.0404** [0.0170]	0.0384** [0.0173]		
D.Import					0.0198 [0.0160]	0.0155 [0.0163]
Cons.	1.8552*** [0.1972]	1.8390*** [0.1987]	1.8186*** [0.2000]	1.7823*** [0.2015]	1.8880*** [0.1966]	1.8824*** [0.1982]
Long-run effects						
Income	0.2314*** [0.0614]	0.2183*** [0.0614]	0.2056*** [0.0627]	0.2036*** [0.0620]	0.1830*** [0.0579]	0.1665*** [0.0584]
Agri	0.1425*** [0.0283]	0.1416*** [0.0283]	0.1148*** [0.0277]	0.1158*** [0.0274]	0.1470*** [0.0289]	0.1450*** [0.0293]
Energy	0.1151** [0.0587]	0.1371** [0.0585]	0.1151* [0.0605]	0.1432** [0.0597]	0.1142* [0.0589]	0.1323** [0.0590]
Trade	−0.1835*** [0.0252]	−0.1766*** [0.0254]				
FDI		−0.0031** [0.0014]		−0.0041*** [0.0014]		−0.0024* [0.0014]
Export			−0.1550*** [0.0234]	−0.1530*** [0.0231]		
Import					−0.1697*** [0.0242]	−0.1611*** [0.0250]
N	1,506	1,498	1,506	1,498	1,506	1,498

Notes: *, **, and *** denote statistical significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively. Standard errors are in brackets.

is probably consistent with evidence found in Kastratović (2019), and the negative influence in the long run is consistent with Pazienza (2015). Additionally, according to our review of the literature, no study has investigated the impacts of trade activities on agricultural emissions. Our finding implies that trade openness and FDI inflows can result in technological spillovers to host countries' agricultural sector, shifting the techniques of

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Table 2. Determinants of GHG emissions in agriculture: comparisons of CH_4 and N_2O emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. var:	ME (CH_4 emissions)						NE (N_2O emissions)					
Short-run effects												
EC term	−0.2191***	−0.2208***	−0.2215***	−0.2231***	−0.2175***	−0.2191***	−0.3011***	−0.3025***	−0.3033***	−0.3046***	−0.2995***	−0.3008***
	[0.0256]	[0.0259]	[0.0255]	[0.0258]	[0.0256]	[0.0259]	[0.0267]	[0.0269]	[0.0267]	[0.0269]	[0.0267]	[0.0269]
D.Income	−0.0026	0.0041	−0.0318	−0.0322	0.0339	0.0429	0.0510	0.0567	0.0234	0.0233	0.0728	0.0796
	[0.1176]	[0.1194]	[0.1163]	[0.1184]	[0.1169]	[0.1185]	[0.1458]	[0.1480]	[0.1445]	[0.1471]	[0.1448]	[0.1468]
D.Agri	−0.0182	−0.0174	−0.0239	−0.0235	−0.0084	−0.0070	−0.0156	−0.0138	−0.0217	−0.0208	−0.0097	−0.0072
	[0.0275]	[0.0278]	[0.0268]	[0.0270]	[0.0275]	[0.0278]	[0.0342]	[0.0345]	[0.0333]	[0.0335]	[0.0341]	[0.0345]
D.Energy	−0.0354	−0.0407	−0.0396	−0.0473	−0.0269	−0.0304	−0.0165	−0.0214	−0.0216	−0.0292	−0.0100	−0.0133
	[0.0709]	[0.0716]	[0.0704]	[0.0711]	[0.0711]	[0.0718]	[0.0878]	[0.0887]	[0.0874]	[0.0883]	[0.0880]	[0.0889]
D.Trade	0.0706**	0.0683**					0.0475	0.0444				
	[0.0327]	[0.0332]					[0.0405]	[0.0411]				
D.FDI		0.0010		0.0012		0.0011		0.0011		0.0013		0.0011
		[0.0010]		[0.0010]		[0.0010]		[0.0012]		[0.0012]		[0.0012]
D.Export			0.1043***	0.1068***					0.0808**	0.0826**		
			[0.0303]	[0.0309]					[0.0377]	[0.0384]		
D.Import					0.0319	0.0275					0.0226	0.0177
					[0.0275]	[0.0280]					[0.0340]	[0.0347]
Cons.	1.1721***	1.1566***	0.9841***	0.9469***	1.2772***	1.2647***	1.6942***	1.6835***	1.5252***	1.4939***	1.8013***	1.7928***
	[0.3592]	[0.3626]	[0.3597]	[0.3651]	[0.3584]	[0.3610]	[0.4192]	[0.4238]	[0.4210]	[0.4289]	[0.4165]	[0.4200]

(continued)

Table 2. Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. var:	ME (CH_4 emissions)						NE (N_2O emissions)					
Long-run effects												
Income	0.1537 [0.1996]	0.1518 [0.2012]	0.2794 [0.1959]	0.2976 [0.1987]	0.0287 [0.1889]	0.0207 [0.1909]	0.1526 [0.1790]	0.1554 [0.1807]	0.2364 [0.1751]	0.2496 [0.1775]	0.0590 [0.1695]	0.0597 [0.1718]
Agri	0.1718* [0.0885]	0.1709* [0.0892]	0.1933** [0.0843]	0.1930** [0.0846]	0.1430 [0.0900]	0.1398 [0.0912]	0.2582*** [0.0804]	0.2576*** [0.0812]	0.2646*** [0.0769]	0.2640*** [0.0775]	0.2425*** [0.0814]	0.2415*** [0.0827]
Energy	−0.0092 [0.2047]	0.0052 [0.2061]	0.0247 [0.2017]	0.0391 [0.2033]	−0.0341 [0.2064]	−0.0192 [0.2079]	−0.2418 [0.1856]	−0.2333 [0.1876]	−0.2197 [0.1836]	−0.2094 [0.1858]	−0.2599 [0.1867]	−0.2518 [0.1886]
Trade	−0.1803** [0.0861]	−0.1769** [0.0877]					−0.1666** [0.0773]	−0.1678** [0.0790]				
FDI		−0.0018 [0.0046]		−0.0025 [0.0045]		−0.0022 [0.0048]		−0.0004 [0.0042]		−0.0012 [0.0041]		−0.0003 [0.0043]
Export			−0.2471*** [0.0789]	−0.2510*** [0.0793]					−0.2075*** [0.0702]	−0.2117*** [0.0708]		
Import					−0.1027 [0.0813]	−0.0938 [0.0847]					−0.1156 [0.0731]	−0.1152 [0.0764]
N	1,153	1,147	1,153	1,147	1,153	1,147	1,153	1,147	1,153	1,147	1,153	1,147

Notes: *, **, and *** denote statistical significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively. Standard errors are in brackets.

Table 3. Determinants of total emissions in agriculture: LMEs

Dep. var: *AE*	(1)	(2)	(3)	(4)	(5)	(6)
Short-run effects						
EC term	−0.3695*** [0.0338]	−0.3854*** [0.0349]	−0.3672*** [0.0335]	−0.3865*** [0.0347]	−0.3586*** [0.0338]	−0.3709*** [0.0348]
D.Income	0.0672 [0.1082]	0.0995 [0.1103]	0.0541 [0.1083]	0.0915 [0.1107]	0.0718 [0.1077]	0.0986 [0.1098]
D.Agri	0.0303 [0.0271]	0.0254 [0.0276]	0.0335 [0.0262]	0.0294 [0.0264]	0.0293 [0.0274]	0.0250 [0.0279]
D.Energy	−0.0915 [0.0640]	−0.1094* [0.0650]	−0.0792 [0.0638]	−0.1000 [0.0647]	−0.0964 [0.0645]	−0.1114* [0.0656]
D.Trade	0.0429* [0.0239]	0.0422* [0.0250]				
D.FDI		0.0014 [0.0012]		0.0018 [0.0012]		0.0013 [0.0012]
D.Export			0.0441* [0.0230]	0.0409* [0.0239]		
D.Import					0.0364* [0.0210]	0.0355 [0.0220]
Cons.	1.4858*** [0.2771]	1.4595*** [0.2806]	1.4869*** [0.2763]	1.4449*** [0.2797]	1.4973*** [0.2806]	1.4804*** [0.2844]
Long-run effects						
Income	0.2478** [0.0973]	0.2167** [0.0964]	0.2345** [0.0958]	0.2078** [0.0939]	0.1919** [0.0977]	0.1600 [0.0983]
Agri	0.1083** [0.0491]	0.1308*** [0.0493]	0.0581 [0.0454]	0.0834* [0.0450]	0.1070** [0.0525]	0.1238** [0.0533]
Energy	0.3408*** [0.0991]	0.3793*** [0.0971]	0.3483*** [0.0998]	0.3923*** [0.0970]	0.3058*** [0.1017]	0.3379*** [0.1004]
Trade	−0.2285*** [0.0437]	−0.2273*** [0.0443]				
FDI		−0.0039 [0.0028]		−0.0050* [0.0028]		−0.0037 [0.0030]
Export			−0.1979*** [0.0375]	−0.1977*** [0.0369]		
Import					−0.1957*** [0.0439]	−0.1896*** [0.0454]
N	541	536	541	536	541	536

Notes: *, **, and *** denote statistical significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively. Standard errors are in brackets.

production toward less pollution. Overall, economic integration (proxied by trade openness and FDI inflows) shows long-run negative effects on agricultural emissions. This result is strong evidence against the recent trend of closing the economy in the United States and some other large economies such as the United Kingdom.

The absolute value of the error correction (EC) term is estimated to be approximately −0.3935; this is statistically significant and implies a relatively speedy adjustment to

Table 4. Determinants of total emissions in agriculture: UMEs

Dep. var: *AE*	(1)	(2)	(3)	(4)	(5)	(6)
Short-run effects						
EC term	−0.4848*** [0.0410]	−0.4816*** [0.0409]	−0.4776*** [0.0408]	−0.4772*** [0.0407]	−0.4874*** [0.0411]	−0.4827*** [0.0410]
D.Income	0.4985*** [0.1804]	0.5791*** [0.1835]	0.4061** [0.1766]	0.4618*** [0.1783]	0.5295*** [0.1732]	0.6291*** [0.1774]
D.Agri	−0.0814** [0.0412]	−0.0797* [0.0411]	−0.0874** [0.0393]	−0.0943** [0.0393]	−0.0758* [0.0417]	−0.0660 [0.0418]
D.Energy	0.0961 [0.1043]	0.0710 [0.1047]	0.0780 [0.1040]	0.0477 [0.1045]	0.1091 [0.1048]	0.0887 [0.1048]
D.Trade	−0.0292 [0.0494]	−0.0472 [0.0499]				
D.FDI		0.0042** [0.0017]		0.0042** [0.0017]		0.0047*** [0.0018]
D.Export			0.0136 [0.0427]	0.0166 [0.0427]		
D.Import					−0.0458 [0.0423]	−0.0782* [0.0439]
Cons.	2.6514*** [0.4379]	2.6428*** [0.4368]	2.6288*** [0.4498]	2.5642*** [0.4491]	2.7377*** [0.4280]	2.7469*** [0.4280]
Long-run effects						
Income	0.2114* [0.1174]	0.2030* [0.1204]	0.2051* [0.1243]	0.2154* [0.1249]	0.1369 [0.0969]	0.1340 [0.1019]
Agri	0.1552*** [0.0588]	0.1343** [0.0601]	0.1300** [0.0551]	0.1194** [0.0551]	0.1581*** [0.0590]	0.1339** [0.0621]
Energy	−0.0747 [0.1058]	−0.0748 [0.1084]	−0.0886 [0.1073]	−0.0754 [0.1095]	−0.0568 [0.1065]	−0.0717 [0.1086]
Trade	−0.1242** [0.0600]	−0.1014 [0.0620]				
FDI		−0.0032 [0.0029]		−0.0043 [0.0029]		−0.0027 [0.0031]
Export			−0.0995* [0.0545]	−0.0932* [0.0546]		
Import					−0.1032* [0.0527]	−0.0760 [0.0577]
N	442	441	442	441	442	441

Notes: *, **, and *** denote statistical significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively. Standard errors are in brackets.

equilibrium after short-run shocks. In detail, approximately 39.35 per cent of disequilibrium caused by previous period shocks converges back to the long-run equilibrium. In other words, it takes approximately 2.54 years (1/0.3935 = 2.54 years) to correct disequilibrium in the case of total emissions. Thus, the correction is rapid.

In the short run, we are only able to find two statistically significant effects of the explanatory variables on agricultural emissions: the positive impacts of income and

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Table 5. Determinants of total emissions in agriculture: HIEs

Dep. Var: *AE*	(1)	(2)	(3)	(4)	(5)	(6)
Short-run effects						
EC term	−0.3211*** [0.0348]	−0.3193*** [0.0350]	−0.3028*** [0.0341]	−0.3013*** [0.0343]	−0.3348*** [0.0349]	−0.3325*** [0.0351]
D.Income	0.1100 [0.0983]	0.1080 [0.0986]	0.0797 [0.0928]	0.0756 [0.0931]	0.1737* [0.0999]	0.1727* [0.1002]
D.Agri	−0.0237 [0.0206]	−0.0218 [0.0207]	−0.0302 [0.0203]	−0.0285 [0.0205]	−0.0152 [0.0203]	−0.0130 [0.0205]
D.Energy	0.0324 [0.0552]	0.0333 [0.0554]	0.0313 [0.0553]	0.0317 [0.0555]	0.0397 [0.0549]	0.0409 [0.0551]
D.Trade	0.0372 [0.0280]	0.0353 [0.0282]				
D.FDI		0.0003 [0.0004]		0.0004 [0.0004]		0.0003 [0.0004]
D.Export			0.0608** [0.0262]	0.0597** [0.0263]		
D.Import					0.0064 [0.0265]	0.0043 [0.0267]
Cons.	1.8644*** [0.3622]	1.8182*** [0.3679]	1.8614*** [0.3654]	1.8098*** [0.3712]	1.8238*** [0.3604]	1.7807*** [0.3659]
Long-run effects						
Income	0.1534 [0.1155]	0.1599 [0.1170]	0.0738 [0.1192]	0.0826 [0.1209]	0.2016* [0.1110]	0.2064* [0.1124]
Agri	0.2022*** [0.0430]	0.2009*** [0.0439]	0.1994*** [0.0457]	0.1976*** [0.0465]	0.2024*** [0.0410]	0.2016*** [0.0419]
Energy	−0.0133 [0.0993]	−0.0040 [0.1014]	−0.0132 [0.1058]	−0.0018 [0.1078]	−0.0217 [0.0948]	−0.0138 [0.0970]
Trade	−0.1820*** [0.0374]	−0.1829*** [0.0378]				
FDI		−0.0007 [0.0018]		−0.0010 [0.0019]		−0.0005 [0.0017]
Export			−0.1547*** [0.0379]	−0.1561*** [0.0382]		
Import					−0.1962*** [0.0362]	−0.1969*** [0.0367]
N	523	521	523	521	523	521

Notes: *, **, and *** denote statistical significance at the 10 per cent, 5 per cent, and 1 per cent levels, respectively. Standard errors are in brackets.

FDI inflows. Although the positive influence of income is consistent with that found in the long run, that of FDI inflows is different from the finding in the long run. The significantly positive impact of FDI inflows on agricultural emissions in the short run supports the pollution haven hypothesis, which refers to possible asymmetries between foreign capital and local environmental standards. Specifically, through foreign investment, multinational firms – especially those engaged in highly polluting activities – could

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take advantage of the weaker environmental standards in the host countries. In this regard, a higher level of FDI inflows could lead to higher emissions in the FDI recipient country.

Furthermore, the insignificant short-run impacts of agriculture value added and energy use, which are among the major long-run drivers of agricultural emissions, imply that the determinants of agricultural emissions vary across time horizons (see Sadorsky, 2013). For instance, in the case of FDI inflows, in the short term, countries may have incentives to attract large amounts of FDI inflows for promoting economic activities, which probably come at the cost of higher emissions. However, in the longer term, although economic growth may not be as important as sustainable development goals, countries may impose stringent environmental regulations on FDI inflows. Green FDI projects will become a higher priority, which facilitates the spillover of environment-friendly technologies and thus reduces emissions.

4.1.2 Robustness check: different model specifications

For a robustness check, we perform the same analysis on different specifications of the model. Specifically, we conduct the same empirical analysis for five other models, with some modification in the specification compared with the baseline model, as follows: (1) we drop FDI inflows from the main specification (column 1 in table 3); (2) we drop FDI inflows and replace trade with export (column 3 in table 3); (3) we keep FDI inflows and keep export (in lieu of trade) (column in table 3); (4) we drop FDI inflows and replace trade with import (column 5 in table 3); and (5) we keep FDI inflows and keep import (in lieu of trade) (column 6 in table 3).

Overall, we obtain findings similar to the baseline model. The results show that income (proxied by log of GDP per capita) has a significantly positive coefficient ranging from 0.1752 to 0.2327 in the short run and 0.1665 to 0.2314 in the long run. Agricultural development (proxied by agriculture value added) and energy consumption have significantly positive coefficients in the long run. The coefficients vary from 0.1148 to 0.1470 for agricultural development and from 0.1142 to 0.1371 for energy consumption. Additionally, the elasticities of emissions with respect to energy intensity and agriculture value added are insignificant in the short run. The results imply that affluence is a critical driver of agricultural emissions in both the short run and the long run. More specifically, the long-run impacts seem to be much larger than those in the short run. In addition, agricultural development and energy consumption are crucial contributors of GHG emissions from agriculture in the long run.

The results in table 1 also reveal that the elasticities of agricultural emissions to trade openness, export, import and FDI inflows have positive short-run coefficients, but they are only statistically significant for FDI inflows and export. Notably, all the elasticities of agricultural emissions to trade openness, export, import and FDI are negative and significant in the long run. The consistency in signs and statistical significance of the estimates confirm the robustness of our estimations.

Regarding the speed of adjustment to the long-run equilibrium, the estimate of the EC term is relatively similar among the six models, which ranges from −0.38 to −0.40, and statistically significant. This finding shows that all six models indicate a similar speed of adjustment toward the long-run equilibrium. Specifically, approximately 38–40 per cent of the disequilibrium caused by previous period shocks turns back to the long-run equilibrium. Approximately 2.5–2.63 years are necessary to correct the disequilibrium in these equations.

4.1.3 Comparison: different emissions

Next, for comparison purposes, we conduct the same empirical analysis to examine the determinants of CH_4 and N_2O emissions from agriculture (which are available until 2008) for the whole sample. The results reported in table 2 reaffirm the significantly positive impacts of income for both CH_4 and N_2O emissions in the long run. Notably, the results show significantly positive short-run impacts and significantly negative long-run impacts of economic integration, particularly for trade openness, export and import, on CH_4 emissions and N_2O emissions. Additionally, other factors, including income, agriculture value added and energy consumption, seem to have insignificant effects in the short run. The results suggest that although increased trade openness is a crucial source of CH_4 and N_2O emissions from agriculture in the short run and long run, increased economic integration could help mitigate agricultural emissions in the long run. By contrast, agricultural development significantly contributes to higher agricultural emissions in the long run.

The results re-emphasize the positive contribution of economic integration through trade openness and capital openness to the environment through reducing the types of agricultural emissions. This evidence is probably the first global evidence on the impacts of trade openness on agricultural different emissions, and it adds new evidence on the influences of FDI inflows. This finding enhances the contribution of our study to the literature because the findings concern both strands of economic integration (i.e., trade and FDI) in addition to decomposing the effects into short-run and long-run effects, which is meaningful for policy formation or interventions.

The EC term of the CH_4 emissions models is estimated at −0.22 on average (i.e., the speed of adjustment is 22 per cent per year), implying that the average time of adjustment to the long-run equilibrium is approximately 4.5 years. Additionally, the EC term of the N_2O emissions models is estimated to be −0.30 on average (i.e., the speed of adjustment is 30 per cent per year), meaning that the average time of full adjustment to the long-run equilibrium is approximately 3.3 years.

4.2 Determinants of agricultural emissions across different income groups

Tables 3, 4 and 5 report the results for conducting a similar empirical analysis for three subsamples of countries: LMEs, UMEs, and HIEs.

In the case of LMEs (table 3), the results indicate that trade openness, export and import have significantly positive influences on total agricultural emissions in the short run. All the other variables have insignificant coefficients. In the long run, the results show that income, agriculture value added and energy consumption have significantly positive impacts on agricultural emissions; and trade openness, FDI inflows, export and import have significantly negative effects. Because most of the LMEs in our study sample are developing countries, the negative effects of FDI inflows on agricultural emissions is opposite that of the findings of Kastratović (2019). This difference could be attributable to the different types of FDI inflows used in the empirical estimations. Kastratović (2019) used data on FDI inflows in agriculture, whereas we use the net inflows of aggregate FDI to the whole economy. Thus, the FDI net inflows to agriculture in LMEs may reduce emissions as expected in Kastratović (2019), but the aggregate FDI inflows as employed in our study do not.[7]

[7] The data for FDI inflows in agriculture are unavailable for a global study.

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The results imply that economic development in LMEs is not a significant source of their agricultural emissions in the short run because agricultural sectors in these LMEs are reliant on labor-intensive production. Additionally, in the long run, economic development, agricultural development and energy consumption appear to be important drivers of GHG emissions in agriculture in LMEs. Similar to the whole sample, the results reaffirm that enhanced economic integration causes higher agricultural emissions in the short run but reduces it in the long run.

Table 4 shows the estimation results for the group of UMEs. The results show that increases in income level result in significantly positive impacts on agricultural emissions in both the short run and the long run. Additionally, agricultural development proxied by agriculture value added has significantly negative impacts in the short run but significantly positive impacts in the long run. Notably, FDI inflows appear to have significantly positive effects in the short run and negative (but insignificant) influences in the long run. Trade openness, export and import mostly have negative impacts in the short run (statistically insignificant) and in the long run (statistically significant). The results imply that economic development and FDI inflows are critical contributors to higher agricultural emissions in UMEs in the short run, and agricultural development is the long run. Additionally, trade openness seems to be a major mitigator of GHG emissions from agriculture in the long run.

Finally, the estimation results for the HIEs are reported in table 5. We observe that most of the examined factors have insignificantly positive influences on agricultural emissions in the short run. The only exception is export, which has significantly positive impacts, and income, which has significantly negative impacts on GHG emissions from agriculture. In the long run, the results demonstrate the significantly positive impacts of agricultural development and significantly negative impacts of economic integration factors including trade openness, export and import on agricultural emissions. The results imply that agricultural development is a crucial driver of higher agricultural emissions in HIEs in the long run, and economic integration – especially trade openness – is a major mitigator of agricultural emissions.

Our results are obtained from three income–country groups and are consistent with those of Fan *et al*. (2006) and Le *et al*. (2016, 2019); that is, the impacts of different factors on emissions vary across groups of countries at different levels of economic development. Overall, compared with poorer countries, richer countries tend to better manage environmental sustainability (Le *et al*., 2019).

For the speed of adjustment to the long-run equilibrium, table 3 shows that the EC term of the total emissions (AE) models for LMEs is estimated at −0.36 on average (i.e., the speed of adjustment is 36 per cent per year), indicating that the average time of adjustment to the long-run equilibrium is approximately 3 years. Table 4 shows that the EC term of the AE models for UMEs is estimated at −0.48 on average (i.e., the speed of adjustment is 48 per cent per year), suggesting the average time of adjustment to the long-run equilibrium is approximately 2 years. Table 5 shows that the EC term of the AE models for HIEs is estimated at −0.32 on average (i.e., the adjustment speed is 32 per cent per year), meaning the average time of adjustment to the long-run equilibrium is approximately 3 years.

5. Conclusion

Although agriculture plays a major role in the economy (Li *et al*., 2016), it also increases vulnerability in terms of global warming and climate change (Oenema *et al*., 2001;

Tubiello *et al.*, 2013; Calvin *et al.*, 2016; Agovino *et al.*, 2019). Because agricultural activities are one of the major sources of GHG emissions, further understanding of the determinants of agricultural emissions is required. This study uses a global sample of 89 economies from 1995–2012 to examine the short-run and long-run influences of economic factors on total emissions from agriculture. Using advanced estimation methods for long-run cointegration estimations, namely, a dynamic fixed effects ARDL model, both the short- and long-run effects are investigated.

The principal findings of our study are as follows. First, income level, agricultural development and energy consumption seem to be the major contributors to the increase in GHG emissions from agriculture. Specifically, income level appears to be a crucial driver of agricultural emissions in both the short run and the long run, and agricultural development and energy consumption are the major sources in the long run. Notably, economic integration, including trade openness, export, import and FDI net inflows, shows a significantly positive impact on agricultural emissions in the short run, but has significantly negative effects in the long run. This finding implies that there are long-run environmental benefits of economic integration, particularly in reducing GHG emissions from agriculture. Notably, the results for the two types of agricultural emissions, namely, CH_4 and N_2O emissions, show consistent findings regarding the unfavorable short-run and favorable long-run environmental effects of economic integration. Consistency is also found for the long-run impacts of income level and agricultural development on GHG emissions from agriculture. The speed of adjustment to the long-run equilibrium is also found to be similar across different model specifications of the same emission type.

Second, the dynamics of the determinants of agricultural emissions are mostly consistent with some heteroscedasticity across different income–country groups. In LMEs, income level, agricultural development and energy consumption appear to be the main drivers of agricultural emissions in the long run, and economic integration has positive short-run impacts and negative long-run impacts. In UMEs, income level is a crucial contributor to higher agricultural emissions in the short run, and income and agricultural development are the main long-run drivers. Notably, trade openness appears to have negative impacts in both the short and the long run, and FDI inflows induce higher agricultural emissions in the short run. In HIEs, agricultural development is the crucial source of agricultural emissions in the long run. Economic integration, especially export, is a driver of higher GHG emissions from agriculture in the short run, but trade openness, export and import appear to reduce agricultural emissions in the long run. These findings have meaningful implications for policymakers in mitigating GHG emissions from the agricultural sector.

Because the growth of food demand worldwide is likely to increase in the next few decades, substantial increases in GHG emissions by the agri-food sector are expected, unless improved management systems are adopted (Verge *et al.*, 2007). The findings of this study have several implications. First, the theoretical models to explain the aggregate emissions in environmental economics could be used to explain the dynamics of CO_2 emissions from a special sector, namely, the agriculture sector in our study. Our empirical results reveal that economic development, agricultural development and energy consumption are the main factors explaining agricultural emissions. Thus, a plan for a sustainable development strategy for agricultural production should consider these factors, for instance, using less energy.

Furthermore, policymakers should pay attention to agricultural activities, one of the major contributors to emissions from agriculture. Addressing climate change in agricultural development should involve adopting green technologies in food production and reducing food loss and waste, which help reduce emission intensity (Galford *et al*., 2020). For instance, in this regard, to reduce waste, individuals' food consumption behaviors must change. FAO (2019) estimates that one-third of the world's food is lost or wasted each year. Every effort to reduce food waste could help lower emissions and thereby support sustainable development. As such, we may have a win–win situation for international development (Galford *et al*., 2020).

In addition, the findings of the negative impacts of economic integration on agricultural emissions in the long run could generate meaningful implications for policymakers. Instead of being against economic openness, governments should support this process with an appropriate strategy, that is, suitable regulations and policies to attract green FDI should be prioritized. Additionally, fair trade with a policy to support agricultural product upgrading would, in return, benefit farmers such that they could practice sustainable agricultural production. This recommendation is also supported by Hodges *et al*. (2011), who documented that poor investment led to the majority of food loss and waste in the early stages of the value chain.

Overall, for all groups of countries, because we find that agricultural activities contribute to a higher level of emissions from this sector in the long run, there is room for improvement in ecosystem and natural resource management in countries of all income levels, including the HIEs. This implication is consistent with the findings of Le *et al*. (2019).

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