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Nonlinear relationships between Foreign Direct Investment decisions and environmental degradation in high- and middle-income countries

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Abstract
Globalization, although beneficial in spreading knowledge and improving green technologies worldwide, is also considered one of the main drivers of global warming. Recent world events, such as the pandemic, with all its economic and social consequences, have exposed the external dependence of many countries, particularly the reliance of many developing countries on foreign investment. Although it contributes to economic growth, Foreign Direct Investment may also be harmful to the environment. Hence, this study analyses the impact of Foreign Direct Investment on emissions of Greenhouse Gases, Carbon Dioxide, Nitrous Oxide and Particulate Matter 2.5. A Panel Autoregressive Distributed Lag model was conducted for a group of 25 high-income and 10 middle-income countries from 1995 to 2019, allowing the analysis of short- and long-run impacts. Given the likelihood of nonlinear impacts, a Nonlinear Panel Autoregressive Distributed Lag model was also conducted to provide a more detailed understanding of the effects of expansion or contraction on the variables, and also to analyse short- and long-run impacts. The main findings suggest that electrification and energy transition away from fossil fuels to renewable energy may be crucial to limiting the polluting effect of Gross Fixed Capital Formation, Trade Openness and Foreign Direct Investment. However, it would be a mistake to simply reduce these three factors as the results reveal that it also contributes to increase pollution. Foreign Direct Investment and Trade Openness reduce environmental degradation in high-income countries and increase it in middle-income countries, except for Nitrous Oxide emissions.

Keywords Asymmetric impact · Environmental pollution · Foreign Direct Investment · Nonlinear ARDL · Pollution Haven Hypothesis

JEL Classification F10 · F64 · Q53 · Q56

Extended author information available on the last page of the article

Abbreviations

ARDL	Autoregressive Distributed Lag
CFCs	Chlorofluorocarbons
CH_4	Methane
CIPS	Cross-Sectionally Augmented IPS
CO_2	Carbon Dioxide
DK	Driscoll and Kraay
EC	Energy Consumption
ECM	Error correction model
FDI	Foreign Direct Investment
GFCF	Gross Fixed Capital Formation
GHG	Greenhouse Gases
GVC	Global Value Chains
HFCs	Hydrofluorocarbons
IEA	International Energy Agency
NF_3	Nitrogen trifluoride
N_2O	Nitrous Oxide
NPARDL	Nonlinear Panel Autoregressive Distributed Lag
PARDL	Panel Autoregressive Distributed Lag
PAT	Number of patent applications
PFCs	Perfluorocarbons
PHH	Pollution Haven Hypothesis
PHIH	Pollution Halo Hypothesis
$PM_{2.5}$	Fine Particulate Matter with a diameter < 2.5 μm
REG	Environmental regulation
RES	Renewable Energy Sources
R&D	Research and Development
SF_6	Sulphur hexafluoride
TO	Trade openness
UNCTAD	United Nations Conference on Trade and Development
USD	United States Dollar
VIF	Variance Inflation Factor

1 Introduction

Economic activity increases the amount of Greenhouse Gases (GHG) a country emits, and is commonly considered by economists to cause greater environmental degradation. During lockdowns introduced to counter the COVID-19 pandemic, economic activity dwindled, and a decline in anthropogenic air pollution was observed. This period was also marked by a sharp decline in flows of Foreign Direct Investment (FDI). According to the United Nations Conference on Trade and Development (UNCTAD) (2021), globally, the fall in FDI was even more severe than the slowdown in Gross Domestic Product (GDP). Notwithstanding the consecutive waves of COVID-19, disruption to supply chains was one of the main reasons for this contraction, according to the UNCTAD (2021).

Although FDI to developing countries fell only 8% (mainly due to resilient flows to Asia), the COVID-19 pandemic prompted a rethinking of policies on trade liberalisation and foreign investment (UNCTAD, 2021). Economic globalization, and particularly FDI, can still be a major contributor to economic growth (Muhammad & Khan, 2019; Weimin et al., 2021), but it is also important to understand its environmental impact. The environmental effects of FDI are commonly disaggregated into three types: scale, structure, and technique. Environmental degradation tends to increase when economic output from domestic production is scaled up, mainly as an indirect effect of increased peak energy demands being met by non-renewable Energy Consumption (Wang et al., 2018a, b). Structure effects are determined by the structural composition of a country's industrial sector. If its industrial structure is based on highly-polluting industries, greater FDI inflows will increase pollution, while if it is based on cleaner industries and processes, more FDI will reduce pollution, as Hao et al. (2020) have argued. Lastly, the technique effect occurs when there is easy access to advanced technologies in the host country (Hao et al., 2020). The technique effect occurs when FDI introduces new production technologies than can increase the host country's efficiency, and reduce its Energy Consumption (Xie & Sun, 2020).

Besides these three effects, literature on the FDI-environment nexus largely focusses on two main hypotheses: the Pollution Halo Hypothesis (PHlH) and the Pollution Haven Hypothesis (PHH). The PHlH posits that FDI primarily reduces pollution through the transfer of green friendly technologies that save energy (see Nepal et al., 2021; Yin et al., 2021). This effect can be amplified if host countries adopt these innovative technologies in their industrial structure, to improve their environmental performance. Knowledge transfer also plays an important role in the environmental performance of countries, as is noted by Shahbaz et al. (2015), because it can accelerate innovation and efficiency. Conversely, the premise of the PHH is the harmful effect of FDI on the environment. There has been a tendency among firms to evade environmental restrictions in certain countries by transferring their polluting industries to countries with less demanding environmental laws. By making such investments, the firms lower their environmental compliance costs and maximize their profits although, according to Dou and Han (2019), this transference only occurs when industries are highly mobile.

The fragmentation of production is part of the creation of what literature terms Global Value Chains (GVCs), in which different stages of the production process are located in different regions/countries (Wang et al., 2018a, b). The authors consider it imperative to take into account the increased spatial fragmentation of production when analysing the environmental effects of different trade patterns, because this fragmentation usually involves the transfer of polluting industrial activity. Countries shift dirty production to countries with more relaxed environmental regulations (potentially through FDI) and then import the goods to complete the production process or for final sale; a process that reduces locally-produced emissions by increasing them elsewhere.

In addition to hitting the global economy, the COVID-19 pandemic also exposed the external dependency of certain countries, due in part to the fragmentation of production encouraged by FDI. Although it has raised levels of production and income in developing countries, this fragmentation has also increased their dependency on developed countries. As a result, the social and economic consequences of the pandemic have been harsher for developing countries. In its aftermath, renewed demand for economic growth, and the prospect of even tougher social and economic consequences will tempt some developing countries to further relax environmental restrictions to attract foreign investment, despite the risk of environmental damage. Given the urgent need to better understand these interlinked phenomena, this study analysed a group of 25 high-income countries and 10 middle-income countries over a period from 1995 to 2019.

Table 7 in the Appendix lists some of more relevant studies on the FDI-Environment nexus and reveals that they tend to focus solely on Carbon Dioxide (CO_2) emissions (identifying a gap in the literature) (see, e.g., Bildirici & Gokmenoglu, 2020; Nepal et al., 2021; Xie et al., 2020; Yin et al., 2021). However, CO_2 emissions are only one segment of anthropogenic GHG (Haug & Ucal, 2019), as Nitrous oxide (N_2O) and Methane (CH_4) emissions should also be considered to better understand environmental degradation (Hassan & Nosheen, 2019), and Rehman et al. (2021a) also note the important role played by CO_2 and N_2O emissions in triggering global warming. Furthermore, Fine Particulate Matter with a diameter < 2.5 μm ($PM_{2.5}$) emissions are a key cause of smog and have become a serious concern in both developed and developing countries, due to their association with increased death rates, reduced atmospheric visibility, and changes in ecosystems and climate (Zhou et al., 2018). As Xie and Sun (2020) report, these particles can easily entering the lungs and blood, and are considered a threat to human health (Zhou et al., 2018). In countries with high emission levels, economic growth can be a driver of $PM_{2.5}$ concentrations, as noted by Wang et al., (2018a, b), and Xie and Sun (2020) referred that such emissions may also be related to trade activity. In fact, greater trade liberalisation and economic activity may indirectly influence the environment by increasing the use of energy from non-renewable sources (the scale effect) (Wang et al., 2018a, b).

This study goes further by making a more granular assessment of the consequences of FDI on climate change, and even on certain aspects of human health. Thus, while looking at the impact of FDI on CO_2 emissions, this study also analyses its impact on total GHG, N_2O, and $PM_{2.5}$ emissions. N_2O and $PM_{2.5}$ emissions are considered local pollutants, while CO_2 emissions are considered global pollutants (Hassan & Nosheen, 2019). Therefore, it is crucial to appreciate that, in the same way that the environmental impact of FDI may vary between economic sectors with differing pollution intensities (Balsalobre et al., 2015), its impact may also differ depending on the type of pollution under analysis. Therefore, it is important to determine which types of pollution are most affected by FDI and to shed light on which types of environmental regulation are likely to be most effective.

The Appendix Table 7 also shows that most studies on this topic are based on linear relationships, and that the ascendant and descendant dynamics of some features are not empirically assessed in a panel analysis. Some of this has been broached in the literature, for instance, showing that the higher a country's level of innovation, the more likely it is to attract technology-seeking (and clean) FDI, due to lower adjustment costs (Adom et al., 2019). However, more detailed analysis is required to better understand the issue. Furthermore, the analysis of short and long-run impacts and adjustments are considered fundamental in economic analysis as referred by Bridel and Dal Pont Legrand (2017), and appears also pertinent in the analysis of the FDI-Environment Nexus. For instance, as found by Rasheed et al. (2023), climate finance have a vital role in mitigating climate change in the long-run, but appears to be non-statistically significant in the short-run. If only the short-run or only the long-run was analysed, this highly relevant finding would not have been even debated; this is an accurate guide for policymakers, where it shows that more action is required to mitigate pollution in developing countries in the short-run. Hence, while FDI can be considered a long-run phenomenon, climate action is required in the short-term before the damage becomes potentially irreversible.

Thus, this paper is innovative in four ways: (1) it considers the levels of innovation and environmental regulation of countries and their influence on the environmental impact of FDI; (2) it analyses the impact of FDI on total GHG, CO_2 emissions and N_2O emissions (the most important industrial pollutants) and also on $PM_{2.5}$ (a more local pollutant); (3) given the urgent need for climate action, this study examines both short- and long-run impacts; and (4) in addition to a linear analysis using the Panel Autoregressive Distributed Lag (PARDL) model, the likelihood (and evidence) of asymmetries in certain variables led to a nonlinear analysis using a Nonlinear PARDL (NPARDL) model to capture the dynamics of short- and long-run impacts within their asymmetries. The NPARDL model was also able to analyse the impacts of independent variables in their ascendant and descendant moments. During ascendant moments, an upward/increasing trend is observed in the independent variable whereas, in descendant moments, there is a downward trend in the independent variable.

The main findings suggest that the environmental impact of Energy Consumption may be indirectly influencing the environmental impact of Investment, Trade Openness and FDI. Indeed, all these phenomena can increase a country's level of production, thereby raising the demand for energy and, in turn, producing more pollution, a phenomenon known as the scale effect. However, this only occurs because these countries are largely reliant on fossil fuels to meet the increased demand for energy. Thus, electrification and transitioning from fossil fuel to renewables can play a crucial role in reducing environmental degradation (particularly concentrations of $PM_{2.5}$). However, innovation in developing countries currently appears more geared towards increasing economic growth than addressing climate concerns, at least in the short run. FDI seems to reduce environmental degradation in high-income countries while increasing it in middle-income countries. Thus, the polluting impact of increased trade openness can be a direct consequence of FDI, if this involves the transfer of polluting industries from developed to developing countries or if the increased energy demand generated by FDI in developing countries is predominantly met by fossil fuels.

The subsequent sections of this paper are as follows: Sect. 2 describes the data and methodology used. The results and their discussion are in Sect. 3, and Sect. 4 concludes.

Table 1 Variables' description and source

Variables	Definition	Sources
GHG	Total greenhouse gas emissions in kilotonnes of CO_2 equivalent	World Bank
CO_2	CO_2 emissions in million tonnes of CO_2 equivalent	Our world in data
N_2O	Nitrous oxide emissions in kilotonnes of CO_2 equivalent	World Bank
$PM_{2.5}$	Mean population exposure to particulate matter in micrograms per cubic metre	OECD stat
FDI	Inward FDI stock in constant 2015 USD prices	UNCTAD
GFCF	Gross fixed capital formation in constant 2015 USD prices	World Bank
TO	Trade as a share of Gross Domestic Product	World Bank
EC	Primary Energy Consumption in terawatt-hours (TWh)	Our world in data
PAT	Patent applications for residents	World Bank
REG	Environmentally related tax revenue as a share of Gross Domestic Product	OECD stat
POP	Total population	World Bank

2 Data and methodology

A balanced panel of 25 high-income and 10 middle-income countries was studied using data from 1995 to 2019. Countries were divided by income level according to the United Nations World Economic Situation and Prospects 2022.[1] The group of high-income countries were Australia, Austria, Chile, Croatia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Israel, Japan, Latvia, Lithuania, the Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, United Kingdom, and the United States. The group of middle-income countries consisted of Argentina, Brazil, Bulgaria, Colombia, Ecuador, Malaysia, Mexico, Peru, Romania, and South Africa. The limited availability of data on the variables used to measure environmental regulation (REG) and innovation (PAT) among lower-middle-income and upper-middle-income countries led to these two groups of countries being merged into a single group of middle-income countries. Data on the $PM_{2.5}$ concentrations variable was only available from 2010 to 2019, so this part of the analysis was limited to this period. Table 1 presents a description of the variables and their sources.

GHG emissions include not only CO_2, but others such as CH_4 and N_2O (Zhang et al., 2017). As understanding the transfer of polluting industries from developed to developing countries was a key part of this study, an analysis was made of the impacts of FDI on GHG, CO_2 and N_2O emissions, which are particularly linked to industrial activity. The rapid recent escalation of $PM_{2.5}$ concentrations has also caught the attention of scholars (see, e.g., Wang et al., 2018a, b; Xie & Sun, 2020; Xu et al., 2019; Yan et al., 2022; Zhou et al., 2018). This increase in $PM_{2.5}$ concentrations is related to both trade, as Wang et al., (2018a, b) have noted, and

[1] https://www.un.org/development/desa/dpad/publication/world-economic-situation-and-prospects-2022/.

to industrial activity, as mentioned by Yan et al. (2022). Therefore, this study also analyses the impact of FDI on $PM_{2.5}$ concentrations.

Gross Fixed Capital Formation (GFCF) was used as a proxy for a country's economic performance, while Trade Openness (TO), was used for trade activity, in line with other literature on the FDI-environment nexus (e.g., Essandoh et al., 2020; Sbia et al., 2014). Energy Consumption is often used in the analysis of environmental degradation (e.g., Essandoh et al., 2020) as it can reveal a country's energy mix. An FDI host country's level of innovation might be a valuable criterion for source countries seeking to disseminate their own innovative technologies. To reflect this, following Burhan et al. (2017), Patent Applications (PAT) were used as an indicator of a host country's level of innovation. Lastly, the strictness of environmental regulations in a host country is often considered a factor influencing the transfer of polluting industry, so environmental-related tax revenue was used to measure the degree of a country's environmental regulation, in line with Hashmi and Alam (2019).

According to Demena and Afesorgbor (2019), the potential endogeneity in the analysis of the FDI-Environment nexus is mainly due to: (1) bias from omitted variables, because environmental decisions may be influenced by other unobserved factors; or (2) potential reverse causality between FDI and the environment. The level of pollution in a country is also influenced by its history and other factors/variables outside the scope of this study. Demena and Afesorgbor (2019) noted that using country fixed effects can capture time invariant heterogeneity and control for bias arising from omitted variables, they also recommend using an approach that minimises potential endogeneity bias, to control for reverse causality. Thus, a PARDL model was used in this study, because it is robust in the presence of endogeneity (see Menegaki et al., 2017; Neves et al., 2020). According to Shin et al. (2014), NPARDL extends PARDL, to create a flexible dynamic parametric approach that is able to reveal both short- and long-run asymmetries and can correct for weak endogeneity, which is also supported by Uche et al. (2023). Following the example of Demena and Afesorgbor (2019), control variables were used in this study to minimise potential bias from omitted variables, specifically for Energy Consumption and Trade Openness.

Variables were converted into *per capita* values and then into natural logarithms, except for variables measured as percentages, which were directly converted into natural logarithms. Table 2 presents the descriptive statistics of the variables. Descriptive statistics of $PM_{2.5}$ concentrations are not included here because their period of analysis was different but are available upon request to the authors.

A series of preliminary tests were conducted to check for the presence of collinearity, multicollinearity, and cross-sectional dependence. Specifically, the correlation matrix, Variance Inflation Factor (VIF), and cross-sectional dependence tests (Pesaran, 2004) were carried out. The results presented in Appendix Tables 8, 9, 10, 11, 12 and 13 revealed that there were no concerns in this respect. Given the presence of cross-sectional dependence, both the first- and second-generation unit root tests were carried out, namely, respectively, the Maddala and Wu (1999) and the Cross-section Im-Pesaran-Shin (CIPS) proposed by Pesaran (2007). The results showed that all variables were stationary—I(0) or I(1), and none of the variables seemed to

Table 2 Descriptive statistics

	High-income					Middle-income				
	Obs	Mean	Std. Dev	Min	Max	Obs	Mean	Std. Dev	Min	Max
LCO_2	625	2.07	0.43	1.05	3.06	250	1.25	0.63	− 0.04	2.30
LN_2O	625	− 9.55	0.40	− 0.00	0.03	250	− 10.43	0.42	− 11.27	− 9.72
LGHG	625	− 4.62	0.43	− 5.55	− 3.44	250	− 5.19	0.40	− 6.14	− 4.54
LFDI	625	0.00	0.00	0.00	0.03	250	0.00	0.00	0.00	0.01
LGFCF	625	8.62	0.72	6.29	9.93	250	7.13	0.48	4.75	7.98
LTO	625	4.25	0.45	2.80	5.14	250	3.98	0.58	2.75	5.40
LEC	625	− 15.65	0.50	− 16.67	− 14.20	250	− 16.63	0.51	− 17.75	− 15.78
LPAT	625	7.37	2.31	2.48	12.87	250	5.81	1.70	0.69	8.61
LREG	625	1.48	0.19	0.96	2.00	250	1.15	0.31	− 0.76	1.69
$DLCO_2$	600	− 0.01	0.06	− 0.37	0.27	240	0.00	0.07	− 0.30	0.22
DLN_2O	600	0.00	0.04	− 0.18	0.21	240	0.01	0.05	− 0.15	0.20
DLGHG	600	− 0.01	0.05	− 0.34	0.21	240	0.00	0.04	− 0.17	0.10
DLFDI	600	0.00	0.00	− 0.03	0.01	240	0.00	0.00	− 0.01	0.01
DLY	600	0.03	0.09	− 0.65	0.37	240	0.03	0.15	− 1.12	0.92
DTO	600	0.02	0.06	− 0.34	0.23	240	0.01	0.10	− 0.30	0.65
DLTO	600	0.00	0.05	− 0.28	0.22	240	0.01	0.04	− 0.13	0.12
DLEC	600	0.00	0.16	− 1.14	0.62	240	0.02	0.30	− 1.03	1.87
DLPAT	600	0.00	0.04	− 0.31	0.27	240	0.00	0.16	− 1.35	1.57
DLREG	600	− 0.01	0.06	− 0.37	0.27	240	0.00	0.07	− 0.30	0.22

be I(2), suggesting that both the PARDL and NPARDL models were suitable (see Appendix Table 14).

2.1 Panel Autoregressive Distributed Lag model

The PARDL model was first introduced by Pesaran and Smith (1995) and has several advantages. It allows an analysis of the short- and long-run impacts of FDI on the environment, which is crucial given that immediate action is needed to address climate change, but long-term effects should also be considered in policy design. Besides handling variables with both I(0) and I(1), levels of integration, the PARDL model can also address endogeneity. Indeed, as first considered by Pesaran et al. (2001), long-run models provide unbiased estimates even in the presence of serial correlation, omitted variables and endogeneity. Therefore, PARDL models are among the most common approaches used in the literature to address endogeneity (see Asumadu-Sarkodie & Owusu, 2016; Chandra Voumik & Ridwan, 2023; Mirza & Kanwal, 2017; Salahuddin et al., 2018).

The PARDL approach provides unbiased estimates and valid t-statistics, even in the presence of endogeneity (Menegaki, 2019). This is mainly because the PARDL model maintains the asymptotic distribution of long-run estimators and mitigates endogeneity bias through lagged variables (Shaohua et al., 2021). Briefly, PARDL models can address endogeneity by including lags in all variables (e.g., Asteriou et al., 2021; Neves et al., 2020), both dependent and independent (e.g., Isiksal & Assi, 2022; Sankaran et al., 2019), endogenous and exogeneous (e.g., Pesaran et al., 2001; Shaohua et al., 2021). As demonstrated by Harris and Sollis (2003), this transformation eliminates residual correlation (see Baharumshah et al., 2009; Boukhatem, 2022; Harris & Sollis, 2003; Isiksal & Assi, 2022; Malik et al., 2020; Marques et al., 2016; Menegaki, 2019; Nusair & Al-Khasawneh, 2022; Shin et al., 2014).

According to Pesaran and Shin (1995), the general PARDL(p,q) equation is specified as follow:

$$Y_{it} = \sum_{j=1}^{p} \varphi_{ij} Y_{it-j} + \sum_{j=0}^{q} \delta_{it} X_{it-j} + \mu_i + \varepsilon_{it}. \tag{1.1}$$

$$\Delta x_{it} = \beth_1 \Delta X_{it-1} + \beth_2 X_{it-2} + \cdots + \beth_s \Delta X_{it-s} + u_{it} \tag{1.2}$$

where i = 1,…,N is the number of countries under analysis, t = 1,…,T is the time and j is the number of lags. Y_{it} is the dependent variable and X_{it} denotes the independent variables that include both interest and control variables (the latter may also help control for omitted variables bias). μ_i and ε_{it} show the fixed effects and the error term, respectively. φ, δ, and $\beth$ are parameters to be estimated and $\beth$ captures the autoregressive process in ΔX_{it}. When Y_{it} is correlated with ε_{it}, the assumption of strict exogeneity is violated, and this can be overcome by including lags and interpreting the equation as a distributed lag (Wooldridge, 2002).

The Error Correction Term (ECT) is then added and specifies the dynamics of the variables in the short-run and how they is impacted by the deviation from equilibrium Teng et al. (2021). Hence, as stated by Menegaki (2019), short-run adjustments can be integrated with the long-run equilibrium through the Error Correction Mechanism (ECM). Based on the above Eqs. (1.1) and (1.2), the error correction equation is specified as follows:

$$\Delta Y_{it} = \emptyset_i \left(Y_{it-1} - \theta_i X_{it} \right) + \sum_{j=1}^{p-1} \varphi'_{ij} \Delta Y_{it-j} + \sum_{j=0}^{q-1} \delta'_{ij} \Delta X_{it-j} + \mu_i + \varepsilon_{it}. \tag{2}$$

where

$\emptyset_i = -(1 - \sum_{j=1}^{p} \varphi_{ij})$, $\theta_i = \sum_{j=0}^{q} \frac{\delta_{ij}}{(1 - \sum_k \varphi_{ik})}$, $\varphi'_{ij} = -\sum_{m=j+1}^{p} \varphi_{im} j = 1, 2, 3, \ldots, p-1$ and $\delta'_{ij} = -\sum_{m=j+1}^{q} \delta_{im} j = 1, 2, 3, \ldots, q-1$

$\emptyset_i$ indicates the speed of adjustment and measures the time it takes for the dependent variable to return to equilibrium after changes in the independent variables. The term θ_i indicates the long-run association among the independent and dependent variables. If this adjustment speed equals zero (i.e., $\emptyset_i = 0$), the ECT is expected to be negative and significant, based on the hypothesis that the variables return to a long-run equilibrium (Teng et al., 2021). To disentangle causality, the literature typically uses specific causality tests (Wen et al., 2022). The ECM of PARDL is known as the error correction version of Granger Causality, so, by using it, the PARDL model can address endogeneity, as confirmed by Menegaki et al. (2017).

The general equation of the PARDL model is re-parametrised to formulate Eqs. (3), (4), and (5) so as to reveal the dynamic relationship of the independent variables with GHG, CO_2 and N_2O emissions, respectively.

$$\begin{aligned}\Delta LGHG_{it} = {} & \alpha_{1i} + \gamma_{1i1}\Delta FDI_{it} + \gamma_{1i2}\Delta LGFCF_{it} + \gamma_{1i3}\Delta LEC_{it} \\ & + \gamma_{1i4}\Delta LTO_{it} + \gamma_{1i5}\Delta LPAT_{it} + \gamma_{1i6}\Delta LREG \\ & + \beta_{1i1}GHG_{it-1} + \beta_{1i2}FDI_{it-1} + \beta_{1i3}LGFCF_{it-1} \\ & + \beta_{1i4}LEC_{it-1} + \beta_{1i5}LTO_{it-1} + \beta_{1i6}LPAT_{it-1} + \beta_{1i7}LREG_{it-1} + \varepsilon_{1it}.\end{aligned} \tag{3}$$

$$\begin{aligned}\Delta LCO2_{it} = {} & \alpha_{2i} + \gamma_{2i1}\Delta FDI_{it} + \gamma_{2i2}\Delta LGFCF_{it} \\ & + \gamma_{2i3}\Delta LEC_{it} + \gamma_{2i4}\Delta LTO_{it} + \gamma_{2i5}\Delta LPAT_{it} \\ & + \gamma_{2i6}\Delta LREG_{it} + \beta_{2i1}LCO2_{it-1} + \beta_{2i2}FDI_{it-1} + \beta_{2i3}LGFCF_{it-1} \\ & + \beta_{2i4}LEC_{it-1} + \beta_{2i5}LTO_{it-1} + \beta_{2i6}LPAT_{it-1} + \beta_{2i7}LREG_{it-1} + \varepsilon_{2it}.\end{aligned} \tag{4}$$

$$\begin{aligned}\Delta LN2O_{it} = {} & \alpha_{3i} + \gamma_{3i1}\Delta FDI_{it} + \gamma_{3i2}\Delta LGFCF_{it} \\ & + \gamma_{3i3}\Delta LEC_{it} + \gamma_{3i4}\Delta LTO_{it} + \gamma_{3i5}\Delta LPAT_{it} + \gamma_{3i6}\Delta LREG_{it} \\ & + \beta_{3i1}LN2O_{it-1} + \beta_{3i2}FDI_{it-1} + \beta_{3i3}LGFCF_{it-1} + \beta_{3i4}LEC_{it-1} \\ & + \beta_{3i5}LTO_{it-1} + \beta_{3i6}LPAT_{it-1} + \beta_{3i7}LREG_{it-1} + \varepsilon_{3it}.\end{aligned} \tag{5}$$

where the prefix "L" stands for natural logarithm.

The short- and long-run impacts were analysed through the coefficients of semi-elasticities and long-run elasticities, respectively. The long-run elasticities were calculated using the following Eq. (6):

$$\pi_i = -\frac{\beta_{it-1}}{ECM} \tag{6}$$

where π_i denotes the computed long-run elasticity, β_{it-1} is the coefficient of the respective variable, and ECM is the coefficient of the dependent variable, both lagged once.

2.2 Nonlinear Panel Autoregressive Distributed Lag model

The NPARDL model was proposed by Shin et al. (2014). The main idiosyncrasy of this methodology is that it detects both short- and long-run asymmetries. Therefore, this methodology can overcome the main limitation of the PARDL model; its ineffectiveness in analysing the volatility (upward and downward moments) of the variables. It can, thus, provide further information about the impact on the dependent variable of ascending and descending moments of the independent variables (Marques et al., 2019). Ascending moments occur when the variable experiences upward momentum. For example, in the case of FDI, there is an upward trend in

FDI when there is an increase in FDI inflows into the host country. At descending moments, a downward trend in the variable can be observed.

The partial sums are defined as follow:

$$x_t^+ = \sum_{n=1}^{t} \Delta x_n^+ = \sum_{n=1}^{t} \max[\Delta x_n, 0]. \tag{7}$$

$$x_t^- = \sum_{n=1}^{t} \Delta x_n^- = \sum_{n=1}^{t} \min[\Delta x_n, 0]. \tag{8}$$

This methodology requires the same testing procedures as the PARDL model, and it is also crucial to consider whether the variables are stationary—I(0) or I(1)—or mutually cointegrated (Haug & Ucal, 2019). It should be mentioned that the NPARDL model, as an extended version of the PARDL model, can also address endogeneity (Shin et al., 2014; Uche et al., 2023).

Cointegration between the ascending and descending variables was identified by Granger and Yoon (2005), and "hidden cointegration" is generalized by Schorderet (2003) as follow:

$$z_t = \alpha_0^+ x_t^+ + \alpha_0^- x_t^- + \alpha_1^+ y_t^+ + a_1^- y_t^-. \tag{9}$$

If z_t is stationary, y_t is considered asymmetrically cointegrated, as assumed by Marques et al. (2019). The standard NPARDL equation is present in Eq. (10).

$$\Delta Y_{it} = \alpha_{1t} + \sum_{n=0}^{k} \beta_{1_{2it}} \Delta x_{it-n}^+ + \sum_{n=0}^{k} \beta_{1_{3it}} \Delta x_{it-n}^- + \delta_{1_{4it}} y_{it-1} + \delta_{1_{5it}} x_{it-1}^+ + \delta_{1_{6it}} x_{it-1}^- + \varepsilon_{1it}. \tag{10}$$

where α_{1t} denotes the constant. The operator "Δε indicates the first differences. β corresponds to the short-run coefficients and δ represents the long-run coefficients. The symbols "+" and "−" represent the positive and negative changes of the variables, respectively.

It is important to note that this methodology is mainly recommended for modelling large T-panels (Kouton, 2019), i.e., panels that consider many years. In this study, the number of years under analysis is moderate. Even so, this method has already been employed in the literature for small samples. Sarkodie and Adams (2020) used a NPARDL model for a time-horizon of 28 years (1990–2017), and Jareño et al. (2020) presented this methodology for a period ranging from 2010 to 2018.

3 Empirical results and discussion

This section, which is divided into three parts, describes the diagnostic tests performed to choose the most appropriate estimator. The first and second parts present and discuss the results regarding GHG, CO_2 and N_2O emissions of the PARDL and

NPARDL models, respectively. The third part focuses on the analysis of $PM_{2.5}$ concentrations, which is treated separately because its period of study differed from the others.

3.1 PARDL model outcomes

The Robust Hausman test ($\mathcal{Y}_{HAUSMAN}$) was used to check for individual effects. The results revealed that a fixed effects estimator was suitable. To detect first-order autocorrelation, cross-section correlation, and/or heteroskedasticity, the Wooldridge test ($\mathcal{X}_{AUT}$), the Breusch Pagan LM test ($\mathcal{X}_{CS}$), and the Modified Wald test ($\mathcal{X}_{HET}$) were carried out. These phenomena were found in all models for high-income countries, but no cross-sectional correlation or first-order autocorrelation was found in the GHG and CO_2 emissions models for middle-income countries, respectively. Consequently, the nonparametric estimator proposed by Driscoll and Kraay (1998) (DK) was chosen, as previously used by De Pascale et al. (2020) and Özokcu and Özdemir (2017). As Hoechle (2007) explains, in addition to allowing fixed effects, this estimator modifies the standard error of the fixed effects regression so that it can deal with cross-sectional dependence and be consistent in the presence of heteroskedasticity and autocorrelation (see also Hashmi & Alam, 2019) thus providing robust results.

To avoid misleading results and to check for potential structural breaks, the Zivot and Andrews (2012) (ZA) unit root test was also performed, as relying on conventional unit root tests can lead to ambiguous results in the event of a structural break, as noted by Caglar (2020). The results of the ZA test (shown in the Appendix Table 15), the residuals, and the socioeconomic context of each country were analysed, and any outlier events or structural breaks were identified.[2] Following this, these milestones were controlled by including impulse dummy variables in the PARDL model and their significance were tested, following the procedure outlined by Afonso et al. (2018). Only events that were statistically significant at a 1% level were kept in the model. Moreover, their overall significance was tested to confirm the importance of controlling the identified milestones (see Appendix Table 16). Table 3 presents the results of the PARDL model.

The results show that Energy Consumption is a driver of environmental degradation, except for N_2O emissions in high-income countries in the long run. This might suggest that high-income countries are aware of the massive damage caused to the ozone layer by N_2O emissions (Sinha & Sengupta, 2019), that they expending less resources (such as energy) in the agricultural sector, and/or that wastewater treatment plants have become more energy-efficient, as this has direct and indirect impacts on N_2O emissions, according to Gómez et al, (2018).

[2] According to the Greenhouse Gas Emissions in Estonia 1990–2020, National Inventory Report published by the Republic of Estonia, the shortfall on CO_2 emissions in Estonia (between 2007 and 2009) is related to the overall economic downfall. In 2019, Estonia also experienced a sharp decrease on and CO_2, but also on N_2O emissions. This might come from the reduction of about 8.7% (compared to 2018) of fuel consumption trend of the primary sector (agriculture, forestry, fisheries sector).

Table 3 PARDL outcomes

Dependent variable	DLGHG		$DLCO_2$		DLN_2O	
	High-income countries	Middle-income countries	High-income countries	Middle-income countries	High-income countries	Middle-income countries
Short-run semi-elasticities						
trend	− 0.003***		− 0.004***	− 0.002*	− 0.001***	
constant	− 0.432	0.591	1.874***	7.254***	− 1.581***	− 0.344
FDI	1.051	4.258	− 0.717	8.778**	− 1.329***	− 2.925
Investment	0.083***	0.016	0.090***	0.042	0.105***	0.086***
EnergyConsumption	0.442***	0.581***	0.521***	0.917***	0.296***	0.547***
TradeOpenness	0.077	0.019	0.097	− 0.042	0.036	− 0.017
Patents	0.003	0.005	− 0.003	0.006***	0.002	0.005
EnvironmentalRegulation	− 0.023	− 0.004	0.040	− 0.011*	0.026	− 0.001
Computed long-run elasticities						
ECM	0.442***	− 0.190***	− 0.204***	− 0.443***	− 0.124***	− 0.214***
FDI_{t-1}	− 4.324	9.803	− 1.136	8.968	− 20.330***	− 56.936***
$Investment_{t-1}$	0.243***	− 0.040	0.249***	0.030	0.459***	0.297***
$EnergyConsumption_{t-1}$	0.326**	0.485***	0.649***	0.919***	0.123	0.610***
$TradeOpenness_{t-1}$	0.278**	0.006	0.208**	0.003	0.3802***	− 0.218***
$Patents_{t-1}$	0.050	0.003	0.022	− 0.005	− 0.025	0.019
$EnvironmentalRegulation_{t-1}$	0.065	0.005	0.010	− 0.009	− 0.053	0.012
EST2009			− 0.090***			
EST2019			− 0.256***		− 0.090***	
Obs	600	240	600	240	600	240
F_{STAT}	F(16, 23) = 1096.63***	F(13, 23) = 153.55***	F(16, 23) = 1152.15***	F(14, 23) = 17.61***	F(15, 23) = 128.75***	F(13, 23) = 38.46***
R^2	0.391	0.527	0.452	0.419	0.289	0.459
$\mathcal{Y}_{HAUSMAN}$	31.44***	41.63***	52.76***	44.16***	52.62***	27.10**
$\mathcal{X}_{AUT}$	123.741***	58.99***	90.17***	0.27	30.94***	126.59***

Table 3 (continued)

Dependent variable	DLGHG		$DLCO_2$		DLN_2O	
	High-income countries	Middle-income countries	High-income countries	Middle-income countries	High-income countries	Middle-income countries
$\mathcal{X}_{CS}$	7.757***	1.187	9.64***	177.92***	3.53***	1.84*
$\mathcal{X}_{HET}$	1705.31***	240.21***	5765.30***	544.86***	1971.41***	207.19***

***, **, and *Denote significance at 1%, 5%, and 10% levels, respectively. The variables presented as short-run semi-elasticities are all in first differences

Gross Fixed Capital Formation, a long-run investment that, according to Södersten et al. (2018), generally increases a country's production capacity, was shown to worsen all air pollution variables in high-income countries in the short and long run, possibly due to the scale effect. In middle-income countries, these harmful environmental effects were limited to N_2O emissions. As noted by Van Tran (2020), agricultural activities and the burning of fossil fuels are major sources of N_2O emissions. This suggests that an increase in Investment (perhaps due to economic globalisation) results in greater land use and consequent environmental degradation (Yameogo et al., 2021). Countries most dependent on foreign investment, generally apply less of their wealth to climate action (Zaidi & Saidi, 2018). Given that Investment seems to harm the environment, should middle-income countries reduce investments to curb pollution, especially in agricultural activities? Evaluating this trade-off calls for an analysis of nonlinear relationships.

In high-income countries, Trade Openness increases GHG, CO_2 and N_2O emissions (Hassan & Nosheen, 2019; Van Tran, 2020). This impact is generally linked with increases in Energy Consumption (Sbia et al., 2014) often from the production of more energy-intensive goods for export (Murshed et al., 2021), and/or energy-based activities driven by trade liberalisation, such as transport and manufacturing (Van Tran, 2020). In contrast, Trade Openness unexpectedly reduces N_2O emissions in middle-income countries. A similar result was found with respect to FDI, thus, supporting the PHlH. Possibly due to the technological spill-overs that they engender, international trade and economic integration seem to be crucial for reducing N_2O emissions, (Nguyen et al., 2021). However, Sinha and Sengupta (2019) consider that Trade Openness and FDI have probably been directed towards industrialisation, thus decreasing agricultural land use and consequently N_2O emissions. This impact cannot be fully explained through an analysis of linear relationships.

Foreign investment appears to increase CO_2 emissions in middle-income countries, supporting the PHH. From this analysis of various air pollutants, one might conclude that the impact of FDI varies depending on which sector of the economy receives it. Therefore, policymakers should develop specific environmental regulations for each type of pollution and avoid "one size fits all" policies. Environmental regulation in middle-income countries seem capable of reducing pollution in the short run. With regard to patents, the greater the number of new applications in a country, the greater the increase in CO_2 emissions in the short run, suggesting that the ideas developed in these countries have focused on economic growth rather than carbon mitigation. Although carbon mitigation technologies are generally developed by high-income countries (Cheng et al., 2019), middle-income countries should also develop technologies to address climate change because, as mentioned by Cheng et al. (2019), it may be difficult to transfer such technologies from developed to developing countries.

3.2 NPARDL model outcomes

The suspicions raised by the results of the linear analysis, regarding the existence of nonlinear relationships, led to testing for short- and long-run asymmetries. This was

Table 4 Short- and long-run symmetries

	Dependent variable: DLGHG		Dependent variable: $DLCO_2$		Dependent variable: DLN_2O	
	High-income countries	Middle-income countries	High-income countries	Middle-income countries	High-income countries	Middle-income countries
SSR_{FDI}	6.75***	0.00	2.43	1.08	0.01	0.03
SSR_{GFCF}	0.34	0.04	0.02	0.62	0.00	0.74
SSR_{EC}	0.22	25.61***	0.67	2.15	1.00	9.04***
SSR_{TO}	0.11	5.02**	0.12	6.89***	1.27	0.00
SSR_{PAT}	0.07	7.96***	0.01	1.44	3.82**	1.56
SSR_{REG}	0.67	0.17	8.76***	0.00	4.92	0.07
SLR_{FDI}	7.24***	0.00	2.63	1.15	0.01	0.03
SLR_{GFCF}	0.39	0.04	0.02	0.57	0.00	0.67
SLR_{EC}	0.24	8.08***	0.72	2.13	1.11	11.28***
SLR_{TO}	0.12	5.63**	0.12	5.80**	1.07	0.00
SLR_{PAT}	0.07	9.62***	0.01	1.61	5.95**	1.53
SLR_{REG}	0.69	0.15	7.13***	0.00	4.67**	0.07

SSR and SLR means Short run and Long run symmetries, respectively

***, **, and * denote significance at 1%. 5%. and 10% levels, respectively

done by performing the standard Wald test, a common practise in the literature (see Haug & Ucal, 2019; Rehman et al., 2021a, b, c; Yirong, 2022). The short-run symmetry was tested, based on the null hypothesis: $\beta_{12it} = \beta_{13it}$. The null hypothesis of long-run symmetry is: $-\frac{\delta_{15it}}{\delta_{14it}} = -\frac{\delta_{16it}}{\delta_{14it}}$. Rejection of the null hypotheses means that asymmetries exist for the corresponding variables.

The results, shown in Table 4, revealed asymmetries in FDI, Energy Consumption, Trade Openness, Patents, and Environmental Regulation, both in the short and the long run, underlining the need for nonlinear analysis using a NPARDL model. The results of the diagnostic tests (see Table 5) indicated that a DK estimator was suitable. Potential structural breaks and outlier events[3] were also checked

[3] According to the National Environmental Research Institute, N_2O emissions have been falling in Denmark since 1999 as a result of the lower area available for cultivation. In 2000, a year with a mild winter, Norway implemented a petrol tax that reduced fuel consumption, according to the Norway's National Inventory Report 2003. Also in 2000, agricultural production grew in Estonia, consequently increasing fuel consumption and N_2O emissions, according to the report on Greenhouse Gas Emissions in Estonia 1990-2020. According to the Chile's Third Biennial Update Report, 2012, a peak in Chile's GHG emissions was mainly provoked by forest fires, forest land absorption and increases in natural gas use for energy production. Later in Spain, the National Reform Programme in 2013 led to significant changes in the electricity sector, as mentioned in the Assessment of climate change policies in the context of the European Semester report for Spain. In 2013 Lithuania experienced a peak in GHG emissions mainly because of increases in GDP and the closure of the Ignalia Nuclear Power Plant that year, according to the Lithuania's Fourth Biennial Report. In 2013, Malaysia spent about 2.2% of GDP on fossil fuel subsidies, according to Mohamed Yusoff and Bekhet (2016), which (along with that year's budget surplus) resulted in a spike in N_2O emissions.

Table 5 NPARDL outcomes

Dependent variable	DLGHG		$DLCO_2$		DLN_2O	
	High-income countries	Middle-income countries	High-income countries	Middle-income countries	High-income countries	Middle-income countries
Short-run semi-elasticities						
trend	− 0.005***		0.504***	− 0.008***	− 0.002***	
constant	− 1.096***	− 1.173***	− 0.006***	0.645***	− 1.289***	− 2.663***
FDI^+	− 2.546**	5.044*	− 2.164*	9.894***	− 1.515	− 9.998**
FDI^-	4.804**	5.991	0.877	25.415*	− 1.762	− 17.329
$Investment^+$	0.060	0.027	0.085*	0.114**	0.100**	0.080
$Investment^-$	0.127***	0.035	0.096***	0.064*	0.077***	0.032*
$EnergyConsumption^+$	0.585***	0.308***	0.703***	0.740***	0.343***	0.191
$EnergyConsumption^-$	0.294***	0.888***	0.471***	1.153***	0.198**	0.972***
$TradeOpenness^+$	0.068	0.069**	0.019	0.121**	− 0.047	− 0.001
$TradeOpenness^-$	0.059	− 0.029	0.108***	− 0.155**	0.115**	− 0.002
$Patents^+$	0.001	− 0.011	− 0.011	0.021	− 0.039	− 0.001
$Patents^-$	0.010	0.028***	− 0.008	− 0.026	0.020	0.017
$EnvironmentalRegulation^+$	− 0.039	0.011	− 0.141***	− 0.006	− 0.081	− 0.004
$EnvironmentalRegulation^-$	− 0.014	− 0.006	0.131*	− 0.007	0.111**	0.001
Computed long-run elasticities						
ECM	− 0.239***	− 0.227***	− 0.239***	− 0.585***	− 0.134***	− 0.257***
FDI^+_{t-1}	0.436	30.280	0.330	40.729**	− 22.292***	− 117.438*
FDI^-_{t-1}	2.967*	8.772	5.476*	26.919*	− 18.179***	− 58.845
$Investment^+_{t-1}$	0.051***	− 0.044	0.249***	0.089***	0.337***	0.317***
$Investment^-_{t-1}$	0.026	0.077	0.113	0.156***	0.406***	0.065
$EnergyConsumption^+_{t-1}$	0.149***	0.486***	0.890***	0.887***	0.475***	0.283
$EnergyConsumption^-_{t-1}$	0.179***	0.510***	0.864***	0.403***	0.077	0.921***

Table 5 (continued)

Dependent variable	DLGHG		$DLCO_2$		DLN_2O	
	High-income countries	Middle-income countries	High-income countries	Middle-income countries	High-income countries	Middle-income countries
$TradeOpenness^{+}_{t-1}$	0.061**	0.116*	0.270***	0.120*	0.395***	0.051
$TradeOpenness^{-}_{t-1}$	− 0.052	− 0.046	− 0.208	0.068	0.325	− 0.325***
$Patents^{+}_{t-1}$	− 0.004	− 0.015	− 0.029	− 0.026	− 0.077**	0.001
$Patents^{-}_{t-1}$	0.006	0.031	0.025	0.022	− 0.028	0.061*
$EnvironmentalRegulation^{+}_{t-1}$	− 0.027	− 0.004	− 0.341	− 0.059	− 0.242	− 0.045
$EnvironmentalRegulation^{-}_{t-1}$	0.005	0.018	− 0.051	− 0.002	− 0.335*	0.001
DNK1999					0.156***	
NOR2000	− 0.178***					
EST2010					0.175***	
LTU2010			0.197***			
CHL2012					0.164***	
ESP2013					− 0.151***	
MYS2013						0.146***
EST2019	− 0.374***		− 0.240***			
Obs	600	240	600	240	600	240
F_{STAT}	F(28, 23) = 10,339.41***	F(25, 23) = 4808.13***	F(28, 23) = 3276.41***	F(26, 23) = 8646.72***	F(30, 23) = 5291.70***	F(26, 23) = 2495.18***
R^2	0.455	0.592	0.503	0.519	0.402	0.540
$\mathcal{Y}_{HAUSMAN}$	86.27***	45.69***	160.75***	680.61***	82.40***	65.96***
$\mathcal{X}_{AUT}$	119.353***	36.517***	90.688***	220.035***	35.187***	62.031***
$\mathcal{X}_{CS}$	5.505***	0.910	7.161***	− 0.024	2.837***	1.570
$\mathcal{X}_{HET}$	1003.33***	83.68***	2021.67***	467.39***	1320.04***	170.62***

***, **, and *Denote significance at 1%, 5%, and 10% levels, respectively. The variables presented as short-run semi-elasticities are all in first differences

in nonlinear analyses, following steps similar to those taken for the PARDL models (see Appendix Tables 15, 16, 17).

Gross Fixed Capital Formation is a driver of environmental degradation, as an increase in capital may intensify Energy Consumption and consequently pollution (Sapkota & Bastola, 2017), depending on the goods produced and energy sources involved (Södersten et al., 2018). The nonlinear analysis adds by revealing that Investment$^+$ becomes non-statistically significant for GHG emissions in high-income countries in the short run. Södersten et al. (2018) found that investments tend to become less polluting as countries develop, perhaps as they are investing in cleaner assets and energy sources, or transfer polluting production to other countries, a phenomenon known as carbon leakage. In fact, in both the short and long run, Investment in middle-income countries appears to increase CO_2 emissions, being therefore considered the predominant air pollutant of their production processes. However, the nonlinear analysis also suggests that simply reducing GFCF is not an effective option for preserving the environment.

The positive and negative changes in Energy Consumption (Energy Consumption$^+$, Energy Consumption$^-$, respectively) appears to harm the environment, which could explain the pollutant impact of Investment in its ascendant (Investment$^+$) and descendant moments (Investment$^-$). These nonlinear outcomes suggest that the countries under analysis should improve their energy production structures, increase their use of Renewable Energy Sources (RES), and switch investments to cleaner and more energy-efficient assets. To make climate action affordable for middle-income countries, it is vital to remove the obstacles identified by Cheng et al. (2019) to the transfer of carbon mitigation technologies from developed to developing countries.

The nonlinear analysis allowed to capture that Trade Openness$^+$ worsens pollution in middle-income countries, while Trade Openness$^-$ increases pollution in high-income countries but reduces it in middle-income countries. This provides evidence that high-income countries may be outsourcing polluting production process to middle-income countries through GVC. As stated by López et al. (2013), without international trade or trade liberalisation, each country would have to domestically produce what it now imports. This may explain the harmful increase in pollution caused by Trade Openness$^-$ in high-income countries in the short-run, and demonstrate the potential negative effect of greater international economic participation for less developed countries if it results in them hosting polluting industries (Ma & Wang, 2021).

High-income countries seem to be developing patents aimed at reducing N_2O emissions. However, this is only statistically significant in the long run, because reducing pollution does not just require the development of patents, but also their adoption by industries, people, and countries in general. With respect to middle-income countries, a falling number of patent applications (PAT) tends to worsen environmental degradation in the short and long run. Therefore, these countries should reduce their dependence on external technology and invest in Research & Development (R&D) to develop their own patents to counter environmental degradation.

Increased Environmental Regulation (Environmental Regulation$^+$) appears to reduce CO_2 emissions in high-income countries. Environmental regulations may be divided into two types: market-based and non-market-based. Environmental taxes are a non-market-based form of regulation. This result (and the lack of statistical significance of environmental regulation for the other pollutants) might suggest that environmental regulation is more geared towards mitigating CO_2 emissions in high-income countries. In a deregulated market, economic agents tend not to adopt environmentally-friendly behaviour or investment decisions as this normally implies higher costs (Huang et al., 2021). This is further supported by the finding that ΔREG^- boosts pollution in high-income countries (known as highly polluting countries). It is worth noting that some economic agents may change their behaviour even without stricter environmental regulations due to their own beliefs, but this is better explained by behavioural economics, which is not the focus of this study.

Although relaxing Environmental Regulations (Environmental Regulation$^-$) appears to reduce N_2O emissions in the long run, this does not mean that high-income countries should relax their environmental standards. Where environmental taxes are perceived by firms as a sunk cost, they may tend to invest in cleaner production methods (such as increased use of RES), invest in another economic sector (such as agriculture) or, less desirably, resort to carbon leakage by switching industrial production from high- to middle-income countries. Nevertheless, more relaxed regulation, while increasing industrialisation and CO_2 emissions, may slow down other sectors such as agriculture and reduce their associated emissions, such as N_2O. Policymakers must therefore consider all GHG emissions when formulating environmental policies.

Increased FDI (ΔFDI^+) reduces GHG and CO_2 emissions in high-income countries, but increases them in middle-income countries, therefore supporting the PHlH for high-income countries and the PHH for middle-income countries. However, a slowdown in FDI (FDI$^-$) appears to boost GHG and CO_2 emissions in both groups of countries. To avoid the undesirable effects of FDI without losing its benefits, FDI should be channelled into cleaner investments. Tax incentives should be set up for foreign investors, and environmental regulations in both high- and middle-income countries should converge to avoid disparities between national environmental regulations (a major cause of carbon leakage). Moreover, to discourage corruption, regulators in both the source and host country should be involved in cross-country transactions to analyse the purpose of investments and check they are not being made to circumvent stricter environmental restrictions.

Focusing on the models for N_2O emissions, FDI$^+$ appears to reduce N_2O emissions in both high- and middle-income countries, corroborating the findings of Nguyen et al. (2021), and supporting the PHlH. As N_2O emissions mostly arise from agricultural activities and fossil fuel combustion (Van Tran, 2020), this effect might suggest that FDI reduces fossil fuel combustion. This may be due to the introduction into the agricultural sector of more energy-efficient processes and renewable energy technologies, such as solar-powered water pumping systems.

3.3 The impacts of foreign investment on $PM_{2.5}$

Given that high concentrations of $PM_{2.5}$ are a threat to human health and can be connected to trade-related events (Wang et al., 2018a, b) and industrial activities (Yan et al., 2022), one of this study's aims was to understand how the transfer of polluting industries from developed to developing countries would affect this pollutant and, thus, provide guidance to policymakers on affordable measures to reduce $PM_{2.5}$ concentrations. Because data on $PM_{2.5}$ emissions was not available for the entire period studied in this paper, an analysis of the impacts of FDI on $PM_{2.5}$ emissions was undertaken for a shorter period from 2010 to 2019. This implied recalculating the preliminary tests and the ZA tests[4] for all the variables under analysis for this period, and not just those for $PM_{2.5}$ emissions. Therefore, all the tests were redone and analysed but, to save space, it was decided not to present the tables with all these results, although they are available upon request to the authors. The results of the Robust Hausman and diagnostic tests are presented in Table 6, along with the results of PARDL and NPARDL models.

Industrial production still mostly relies on fossil fuels according to Xie and Sun (2020), and fossil fuel combustion increases $PM_{2.5}$ concentrations. The results expose that Investment and Energy Consumption drive $PM_{2.5}$ emissions, in accordance with Zhang et al. (2020). The nonlinear analysis confirms that Investment continues to be a driver of this type of pollution even when capital formation is slowing down (Investment^{-}). Thus, instead of reducing GFCF, countries should invest in cleaner assets, energy-efficient processes, and machines, and make greater use of RES. REG seem able to reduce $PM_{2.5}$ concentrations in high-income countries in the short term. Although lower levels of environmental regulations (REG^{-}) seem to reduce $PM_{2.5}$ emissions in high-income countries, it is worth comparing this outcome with the findings in this paper regarding the effect of REG^{-} reducing N_2O emissions. Briefly, stricter environmental regulations may cause high-income countries to deindustrialize, whereas relaxing environmental restrictions may encourage reindustrialization, boosting CO_2 emissions but diminishing $PM_{2.5}$ concentrations. Therefore, policymakers should consider these potential unintended consequences when designing policies for climate action.

The detrimental environmental impact of an increase in patent applications in middle-income countries remains for $PM_{2.5}$ concentrations, reinforcing the conclusion that R&D in these countries is focused on economic growth rather than environmental concerns. It is critical to change this focus not only to counter climate change, but also to avoid jeopardizing human health. Increased rates of mortality and cancer, and reduced atmospheric visibility are some of the major problems associated with high $PM_{2.5}$ concentrations referenced by Zhou et al. (2018). This paper's results show that slowdowns in the development of patents reduce $PM_{2.5}$ concentrations in high-income countries. This does not mean that patents should be discouraged, but rather, that they should take greater account of environmental factors. One way to develop new ideas beneficial to all parties would be to create clusters for joint climate action by both high- and middle-income countries.

[4] In 2011, a single terrorist attack (explosion and fires) increased Norway's $PM_{2.5}$ concentrations. The Tungurahua volcano erupted 6 times from 2006 to 2011, according to the WorldData.info. In 2011, $PM_{2.5}$ emissions experienced a sharp reduction. Jorquera (2021) notes that in 2012, Chile introduced stricter national emissions rules for coal-fired power plants that led to a reduction in $PM_{2.5}$ emissions.

Table 6 PARDL and NPARDL outcomes

Dependent variable	$DLPM_{2.5}$			
	PARDL		NPARDL	
	High-income countries	Middle-income countries	High-income countries	Middle-income countries
Short-run semi-elasticities				
trend	− 0.020***	− 0.020**	− 0.027***	
constant	− 8.694***	− 9.843***	− 10.233***	
FDI	4.577	5.164		
FDI^{+}			10.163*	413.488
FDI^{-}			0.186	-1.4×10^{2}
Investment	0.026	0.132		
$Investment^{+}$			− 0.084	0.276**
$Investment^{-}$			0.382**	0.002
EnergyConsumption	− 0.094	0.302*		
$EnergyConsumption^{+}$			− 0.313*	− 0.059
$EnergyConsumption^{-}$			0.236	0.536*
TradeOpenness	0.310**	− 0.152**		
$TradeOpenness^{+}$			0.799***	− 0.212
$TradeOpenness^{-}$			− 0.356	− 0.088
Patents	− 0.004	0.021**		
$Patents^{+}$			0.042	0.030***
$Patents^{-}$			− 0.037	0.035*
EnvironmentalRegulation	− 0.120**	− 0.001		
$EnvironmentalRegulation^{+}$			0.029	− 0.021
$EnvironmentalRegulation^{-}$			− 0.097*	− 0.029

Table 6 (continued)

Dependent variable	$DLPM_{2.5}$			
	PARDL		NPARDL	
	High-income countries	Middle-income countries	High-income countries	Middle-income countries
Computed long-run elasticities				
ECM	− 0.639***	− 0.847***	− 0.772***	− 0.826***
FDI_{t-1}	− 2.796	− 10.94		
FDI^{+}_{t-1}			− 6.080*	516.982**
FDI^{-}_{t-1}			− 8.38***	− 45.014
$Investment_{t-1}$	0.165***	0.002		
$Investment^{+}_{t-1}$			0.134**	− 0.026
$Investment^{-}_{t-1}$			0.198	− 0.1522
$EnergyConsumption_{t-1}$	0.264**	0.126		
$EnergyConsumption^{+}_{t-1}$			0.166	− 0.921**
$EnergyConsumption^{-}_{t-1}$			0.626***	0.876*
$TradeOpenness_{t-1}$	0.374***	− 0.223**		
$TradeOpenness^{+}_{t-1}$			0.698***	− 0.410**
$TradeOpenness^{-}_{t-1}$			0.031	0.129
$Patents_{t-1}$	0.002	− 0.015		
$Patents^{+}_{t-1}$			− 0.024	0.038*
$Patents^{-}_{t-1}$			− 0.025*	− 0.036
$EnvironmentalRegulation_{t-1}$	− 0.078	− 0.015		
$EnvironmentalRegulation^{+}_{t-1}$			− 0.090	− 0.060
$EnvironmentalRegulation^{-}_{t-1}$			− 0.122***	0.102
NOR2011			0.182***	
ECU2011				− 0.124***

Table 6 (continued)

Dependent variable	$DLPM_{2.5}$			
	PARDL		NPARDL	
	High-income countries	Middle-income countries	High-income countries	Middle-income countries
CHL2012			− 0.142***	
Obs	225	90	225	90
F_{STAT}	F(14, 8) = 132.85***	F(14, 8) = 5.94×10^9	F(28, 8) = 91.69***	F(27, 8) = 21.19***
R^2	0.461	0.583	0.615	0.717
$\mathcal{Y}_{HAUSMAN}$	141.17***	66.89***	484.99***	142.14***
$\mathcal{X}_{AUT}$	58.94***	23.20***	85.27***	38.58***
$\mathcal{X}_{CS}$	8.27***	1.17	6.57***	0.82
$\mathcal{X}_{HET}$	116.47***	61.65***	214.06***	27.57***

***, **, and *Denote significance at 1%, 5%, and 10% levels, respectively. The variables presented as short-run semi-elasticities are all in first differences

Trade Openness drives $PM_{2.5}$ emissions in high-income countries, as Wang et al., (2018a, b) found in a study of G20 countries. The authors consider that trade liberalisation is increasing the production of goods and services directly related to energy, thus increasing pollution through the scale effect (see, e.g., Hassan & Nosheen, 2019; Van Tran, 2020). Despite using innovation to chart a path to more renewable and efficient energy use, high-income countries continue to be highly polluting. Given the intermittent generation of renewable sources and occurrence of peak loads, renewable energy may not be sufficient to meet increased energy demands. With respect to middle-income countries, although Trade Openness has somewhat reduced fine particle pollution, perhaps due to technological spill-overs from the international market, as mentioned by Xie and Sun (2020), they are still heavily reliant on fossil fuels, so any increase in efficiency or RES use could significantly reduce $PM_{2.5}$ emissions.

The nonlinear analysis showed that, in high-income countries, FDI^{+} appears to increase $PM_{2.5}$ emissions in the short run but reduce them in the long run. Following the rationale of Wang et al., (2018a, b), $PM_{2.5}$ concentrations in countries with higher emissions (generally high-income/developed countries) depend on their level of GDP, mainly through the indirect effect of Energy Consumption. Indeed, FDI^{+} may increase $PM_{2.5}$ concentrations because of the positive effect FDI has on economic growth, at least in the short run. Conversely, a slowdown in FDI (FDI^{-}) may reduce $PM_{2.5}$ emissions in the long-run, due to an otherwise undesirable slowdown in economic growth. These contrasting impacts of FDI increasing $PM_{2.5}$ concentrations in middle-income countries but reducing them in high-income countries are, most likely, further evidence of the transfer of polluting production from developed to developing countries. This supports the findings of Wang et al., (2018a, b), that the trade in intermediate goods (produced by polluting industries relocated to countries with more relaxed environmental regulations) tends to increase $PM_{2.5}$ emissions in host countries.

Unexpectedly, increased Energy Consumption (Energy Consumption^{+}) appears to reduce $PM_{2.5}$ concentrations in both high- and middle-income countries. Given that this study analyses a period from 2010 to 2019, and that electricity consumption is included in overall Energy Consumption, this effect might be related to the growing electrification and use of RES by these countries. Conversely, a slowdown in Energy Consumption (Energy Consumption^{-}) appears to increase fine pollution in both high- and middle-income countries. These periods of lower Energy Consumption (which were only revealed by the nonlinear analysis) may also be associated with periods of reduced renewable energy production, and increased use of fossil fuels, such as coal, as a baseload to meet energy demand. Once more, the nonlinear analysis in this study was crucial for revealing that electrification, particularly in middle-income countries, is crucial for reducing $PM_{2.5}$ emissions and their consequent threat to human health.

4 Conclusion

Foreign Direct Investment has been used by some countries to circumvent international agreements on climate action by transferring their polluting industries to countries with lower environmental standards. This transfer is mainly analysed through linear relationships and primarily focused on CO_2 emissions. This study adds new understanding to this field by examining both the linear and nonlinear impacts of FDI on a range of emissions responsible for climate change, namely total GHG, CO_2, and N_2O. Furthermore, it extends this study to another cause of environmental degradation, which is considered a threat to human health, and analyses whether FDI is also increasing $PM_{2.5}$ concentrations. The main findings of this study reveal that the detrimental environmental impacts of increased Energy Consumption drive the harmful impacts of Investment, Trade Openness, and FDI due to the scale effect. Therefore, increasing the share of RES in the energy mix is crucial to reduce the polluting effect that may come through the scale effect.

Although the linear analysis exposed that Investment has been a driver of environmental degradation in the countries studied, the nonlinear analysis revealed that reducing Investment is not a solution, as it keeps increasing pollution. Instead, countries should shift Investment towards cleaner and more efficient assets and increase their use of RES, which would reduce the harmful environmental impact of Investment found in the empirical analysis. This process could be done by imposing regulations that encourage firms to switch to more efficient machinery (taking into account its depreciation rate).

Private investment (domestic and foreign) should be sought for renewable energy infrastructure, particularly in middle-income countries. Developing countries should take advantage of their unexploited characteristics to develop a new comparative advantage by exploiting the available land space and/or the roofs of buildings and houses to increase the installed generation capacity of renewable energy, given that this can benefit both high-income and middle-income countries. This development could be ensured by collaborative international clusters through which middle-income countries could increase the share of RES in their energy mix, and high-income countries could employ capital, earn profits, and import the resulting clean energy. Another key strategy for reducing pollution is electrification. Matching renewable energy production to consumption is one of the biggest challenges of energy transition. As mentioned above, investing in the creation of international clusters could also address this by facilitating the importing and exporting of renewable energy and thereby avoiding energy losses. Another recommendation is to provide subsidies/tax benefits for firms that use renewable energy to encourage them to become more self-sufficient so as to reduce the demand on national energy systems.

Middle-income countries seem to be developing new patents aimed at economic growth rather than addressing environmental concerns, as the empirical results show that such patents increase environmental degradation. Therefore, governments of middle-income countries should invest in R&D and education to develop environmentally-friendly technologies (especially in the agricultural sector) and reduce the cost of adjusting to incoming technologies. Environmental regulations are crucial to reducing CO_2 emissions in middle-income countries, but it has not proven to have the desired effect of reducing other types of pollution, namely GHG and N_2O emissions. Therefore, strengthening policies on GHG and N_2O emissions is also recommended.

The nonlinear impacts of Trade Openness and FDI provide evidence of polluting production transfer from developed to developing countries, but the results also suggest that trade liberalisation can facilitate technological spill-overs and reduce N_2O emissions since Trade Openness and FDI have been proven to be effective in reducing this type of emissions. Nonetheless, greater use of RES is vital to prevent increasing pollution via the scale effect (as the empirical results show that FDI and Trade Openness increase $PM_{2.5}$ and CO_2 emissions). Therefore, countries should incorporate fiscal benefits for firms with a higher share of RES use so they will attract clean FDI. Moreover, countries should increase the attractiveness of the primary sector for FDI (particularly agricultural activities), as the empirical results proved that FDI is a promising way of reducing N_2O emissions, possibly through the transfer of technology such as solar-powered water systems. Increasing the efficiency of electricity generation through improved power plants' wastewater and biomass burning is also vital to reduce N_2O emissions.

Since the 21st United Nations (UN) Climate Change Conference of the Parties (COP21), when the Paris Agreement was reached, there has been much debate on the vital role of developed countries in financing climate action in developing countries to contain climate change (mitigation) and to cope with its effects (adaptation). Coase's theorem postulates that a developed country will only pay to reduce pollution in another country if the outcome also benefits the developed country. This theorem might explain why climate finance targets were not met and were subsequently amended, especially at COP26. However, climate agreements are too important to depend on purely selfish interests. Self-interest will always override climate urgency if the benefits do not outweigh the costs leading to climate chaos. Thus, solutions that benefit all parties are needed.

Developed countries should be encouraged to increase the share of renewables in developing countries through green financing, perhaps through investment in renewable energy infrastructure. In fact, the results demonstrate that FDI might be increasing pollution via the scale effect, which suggests that increasing renewable energy could soften the polluting impact of FDI. The potential polluting impact of FDI can also be mitigated if it is used to transfer green technologies to developing countries. Developing countries that receive these technologies would benefit both economically and environmentally. In turn, developed countries making this type of investment in developing countries could benefit from cheaper labour and lower production costs without contributing to environmental degradation, potentially reducing overall pollution; a genuine win–win outcome.

The pollution level of a country is widely thought to be directly influenced by its income level, usually measured through GDP. In this study, domestic investment capacity was used to indicate a country's macroeconomic status, but income levels may still significantly influence estimations of causal effects. However, given the current climate and energy crises, Green GDP may be a more appropriate indicator for future studies. It reflects economic growth that does not deplete the environment or compromise the availability of resources for future generations. The conclusions of this study suggest that other promising areas for subsequent study include more detailed analyses of countries undergoing energy transition and the role of climate/green finance in reducing the environmental impact of FDI and Trade Openness.

Appendix

See Tables 7, 8, 9, 10, 11, 12, 13, 14, 15, 16 and 17.

Table 7 Literature review framework

Author(s)	Period	Study area	Method	Conclusions
Pao and Tsai (2011)	1980–2007 and 1992–2007 (Russia)	BRIC (Brazil, Russian Federation, India, and China)	Panel cointegration technique; Multivariate Granger causality	Strong bidirectional causality between emissions and FDI
Omri et al. (2014)	1990–2011	3 regional sub-panels: Europe and Central Asia, Latin America and the Caribbean; the Middle East and North Africa; and sub-Saharan Africa	Dynamic simultaneous-equation model	Bidirectional causality between FDI inflows and CO_2 emissions in all panels, excluding Europe and North Asia
Ren et al. (2014)	2000–2010	China's industrial sectors	IOA; Two-step GMM	FDI inflows aggravate China's CO_2 emissions
Sbia et al. (2014)	1975Q1-2011Q4	United Arab Emirates (UAE)	ARDL bounds testing approach; VECM Granger causality	FDI saves energy; FDI Granger promotes green energy
Seker et al. (2015)	1974–2010	Turkey	ARDL; VECM based Granger causality	FDI Granger causes CO_2 emissions in the long run; FDI increases pollution, but its impact is small
Shahbaz et al. (2015)	1975–2012	99 economies worldwide (high-, middle-, and low-income)	FMOLS	Inverted-U shaped relationship between FDI and CO_2 emissions in the global and middle-income panels; FDI reduces CO_2 emissions in high-income countries; FDI increases environmental degradation, confirming the PHH, in low-income countries
Zhu et al. (2016)	1981–2011	Association of South East Asian Nations (ASEAN-5): Indonesia, Malaysia, the Philippines, Singapore, and Thailand	Panel quantile regression	FDI decreases CO_2 emissions in middle- and high-income countries, supporting the PHIH
Sapkota and Bastola (2017)	1980–2010	14 Latin American countries (high and low-income countries)	Panel fixed and random effects models	FDI increases CO_2 emissions, validating the PHH, for both high- and low-income countries

Table 7 (continued)

Author(s)	Period	Study area	Method	Conclusions
Shahbaz et al. (2018)	1955–2016	France	Bootstrapping ARDL bounds test	FDI degrades the environment
Rafindadi et al. (2018)	1990–2014	GCC (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates)	Panel ARDL estimation: PMG; MG; and Dynamic fixed effects	Although the energy consumption associated with the FDI inflows can lead to pollution, FDI inflows generally reduce environmental degradation whereas energy consumption increases it
Zhou et al. (2018)	24-h average $PM_{2.5}$ concentrations levels in 2014	190 cities throughout the southeast coastal, central, and north-eastern regions of China	Spatial regression; geographical detector technique	FDI has no influence on $PM_{2.5}$ concentrations
Adom et al. (2019)	2000–2014	27 African countries	GM	Concave effect of FDI on energy consumption: dichotomous paths in terms of realizing the energy-savings benefits of FDI.; The benefits of FDI are felt sooner by countries with a higher capacity to absorb technology
Albulescu et al. (2019)	1980–2010	14 Latin American countries	Panel Quantile regression analysis	FDI has no clear impact on pollution

Table 7 (continued)

Author(s)	Period	Study area	Method	Conclusions
Demena and Afesorgbor (2019)	Not applicable	65 primary studies	Meta-analysis	There is an inverse relationship between FDI and emissions: an increase in FDI reduces pollution, supporting the PHIH for developed countries; There is a clear difference between developed and developing countries in the effect FDI has in reducing emissions; The FDI inflow to developing countries is less effective than the FDI that goes to developed countries, supporting thePHH
Dong et al. (2019)	2002–2015	China regions	FGLS	FDI conserves energy in high-income regions, but there is no evidence to suggest that FDI inflows increase energy consumption in low- and middle-income regions
Dou and Han (2019)	2000–2015	30 provinces, municipalities, and autonomous regions (except Tibet) of China	Dividing industries into strongly and weakly mobile; Mediation model	Highly mobile polluting industries tend to be transferred to areas with looser regulations, thereby supporting the PHH
Haug and Ucal (2019)	1974–2014	Turkey	ARDL; NARDL	FDI increases CO_2 emissions in the long run
Shahbaz et al. (2019)	1990–2015	The Middle East and North African (MENA)	GMM	N-shaped association is validated between FDI and carbon emissions

Table 7 (continued)

Author(s)	Period	Study area	Method	Conclusions
Shen et al. (2019)	2001–2014	Guangdong's 21 administered cities: 9 cities in the Pearl River Delta (PRD), and 12 cities in the Peripheral Non-Pearl River Delta (NPRD) area	DEA; PMG/ARDL	Pollution is transferred by the migration of pollution-intensive industries from the PRD to the NPRD region, supporting the PHH
Xu et al. (2019)	2006–2016	China: east, central, and west regions	STIRPAT model	FDI reduces air pollutants
Bildirici and Gokmenoglu (2020)	1975–2017	9 countries: Afghanistan, Iraq, Nigeria, Pakistan, Philippines, Syria, Somalia, Thailand and Yemen	Panel cointegration tests; ANOVA tests, long run estimators, and panel trivariate Causality tests	FDI causes CO_2 emissions in the short run; In the long run, there is bidirectional causality between FDI and CO_2 emissions; FDI is concentrated on high-emissions industries
Essandoh et al. (2020)	1991–2014	52 countries	PMG-ARDL	FDI transfers high emission-intensive production units from developed to developing countries, decreasing pollution in the developed countries but increasing it in developing countries
Xie et al. (2020)	2005–2014	11 emerging countries (Argentina, Brazil, China, India, Russia, South Korea, Mexico, Turkey, Indonesia, South Africa, and Saudi Arabia)	Extended PSTR with nonlinear and dynamic features	FDI can increase CO_2 emissions concentrations; The economic growth triggered by the spill-over effect suggests that FDI can decrease CO_2 emissions. FDI has a "W + V-shaped" temporal effect on carbon emissions
Zhou et al. (2020)	2005–2015	47 cities in the Bohai Rim	OLS; GMM; Panel quantile regression	FDI has a positive influence on eco-efficiency (with carbon emissions as the undesired output)

Table 7 (continued)

Author(s)	Period	Study area	Method	Conclusions
Xie and Sun (2020)	2010–2016	11 selected emerging countries: China, India, Brazil, Russia, Indonesia, South Korea, Mexico, Argentina, Saudi Arabia, Turkey and South Africa	GPSTR; cross-sectional dependence, heterogeneity, nonlinear unit root, nonlinear cointegration tests and non-parametric kernel density estimation	FDI directly contributes to decreasing $PM_{2.5}$, but indirectly increases $PM_{2.5}$ emissions. Overall, the effect of FDI on $PM_{2.5}$ concentrations is negative@Evidence was found for both the PHH and the PHIH
Cai et al. (2021)	2005–2016	30 provinces in China	Nonlinear threshold regression model; carbon emissions expansion model	Supports both the PHH and PHIH, depending on the threshold value
Nepal et al. (2021)	1978–2016	India	ARDL; VECM; Granger causality tests	FDI reduces CO_2 emissions, supporting the PHIH
Nguyen et al. (2021)	1995–2012	89 economies (high-income, upper-middle-income, and lower-middle-income)	Dynamic fixed effects ARDL model	FDI increases GHG emissions from agriculture in the short-run (supporting the PHH) but reduces it in the long-run for the overall sample (supporting the PHIH)@ FDI reduces GHG emissions from agriculture in the long-run in lower-middle-income countries, therefore supporting the PHIH FDI increases GHG emissions from agriculture in the short run in upper-middle-income countries, thus supporting the PHH FDI is not statistically significant to high-income countries' GHG emissions from agriculture

Table 7 (continued)

Author(s)	Period	Study area	Method	Conclusions
Singhania and Saini (2021)	1990–2016	20 countries (developed and developing countries)	Pooled panel data regression; Fixed effects regression; Random effects regressions; 2SLS; Differenced and System GMM approach	FDI increases pollution in developing countries and decreases it in developed ones
Yin et al.(2021)	1990–2014	101 countries (high-income, upper-middle-income, lower-middle-income and low-income)	Simultaneous equations model estimated within Dynamic GMM framework	Dynamic-GMM-estimation results FDI increases CO_2 emissions in a global panel, in lower-middle-income countries and in high-income countries, supporting the PHH FDI reduces CO_2 emissions in low-income and upper-middle-income countries, supporting the PHIH

ARDL autoregressive distributed lag, *FGLS* feasible generalized least squares, *FMOLS* fully modified ordinary least squares, *GMM* generalized method of moments, *GPSTR* generalized panel smooth transition regression, *IOA* input–output analysis, *MG* mean group, *OLS* ordinary least squares, *PMG* pooled mean group, *PSTR* panel smooth transition regression, *STIRPAT* stochastic impacts by regression on population, affluence and technology, *VECM* vector error correction model, *2SLS* two-stage least squares

Table 8 Correlation matrices

	LGHG	*FDI*	*LGFCF*	*LTO*	*LEC*	*LPAT*	*LREG*		*DLGHG*	*DLFDI*	*DLGFCF*	*DLTO*	*DLEC*	*DLPAT*	*DLREG*
LGHG	1.00							*DLGHG*	1.00						
FDI	0.11	1.00						*DLFDI*	0.04	1.00					
LGFCF	0.52	0.23	1.00					*DLGFCF*	0.28	0.20	1.00				
LTO	− 0.38	0.08	− 0.29	1.00				*DLTO*	0.20	0.02	0.24	1.00			
LEC	0.61	0.27	0.78	− 0.21	1.00			*DLEC*	0.50	− 0.09	0.22	0.18	1.00		
LPAT	0.32	− 0.09	0.45	− 0.66	0.23	1.00		*DLPAT*	0.06	0.01	0.02	0.04	0.07	1.00	
LREG	− 0.20	0.11	− 0.04	0.51	− 0.09	− 0.35	1.00	*DLREG*	− 0.05	0.08	− 0.01	− 0.08	− 0.01	0.12	1.00
VIF		1.13	3.48	2.12	2.88	2.24	1.44			1.07	1.16	1.09	1.10	1.02	1.03
VIF_{MEAN}		2.21				1.08									
CD-test	32.71***	14.46***	43.22***	46.61***	15.80***	7.35***	9.60***		19.43***	7.95***	32.58***	42.81***	15.34***	4.89***	11.55***

VIF statistics and cross-sectional dependence test (high-income countries) – GHG emissions

***, **, and * state significance at 1%. 5%. and 10% level, respectively

Table 9 Correlation matrices

	LCO_2	FDI	$LGFCF$	LTO	LEC	$LPAT$	$LREG$		$DLCO_2$	$DLFDI$	$DLGFCF$	$DLTO$	$DLEC$	$DLPAT$	$DLREG$
LCO_2	1.00							$DLCO_2$	1.00						
FDI	0.13	1.00						$DLFDI$	− 0.04	1.00					
$LGFCF$	0.57	0.23	1.00					$DLGFCF$	0.26	0.20	1.00				
LTO	− 0.38	0.08	− 0.29	1.00				$DLTO$	0.21	0.02	0.24	1.00			
LEC	0.70	0.27	0.78	− 0.21	1.00			$DLEC$	0.56	− 0.09	0.22	0.18	1.00		
$LPAT$	0.39	− 0.09	0.45	− 0.66	0.23	1.00		$DLPAT$	0.05	0.01	0.02	0.04	0.07	1.00	
$LREG$	− 0.16	0.11	− 0.04	0.51	− 0.09	− 0.35	1.00	$DLREG$	− 0.05	0.08	− 0.01	− 0.08	− 0.01	0.12	1.00
VIF		1.13	3.48	2.12	2.88	2.24	1.44			1.07	1.16	1.09	1.10	1.02	1.03
VIF_{MEAN}		2.21				1.08									
CD-test	28.11***	14.46***	43.22***	46.61***	15.80***	7.35***	9.59***		23.39***	7.95***	32.58***	42.81***	15.34***	4.89***	11.55***

VIF statistics and cross-sectional dependence test (high-income countries) – CO_2 emissions

***, **, and * state significance at 1%. 5%. and 10% level, respectively

Table 10 Correlation matrices

	LN_2O	FDI	$LGFCF$	LTO	LEC	$LPAT$	$LREG$		DLN_2O	$DLFDI$	$DLGFCF$	$DLTO$	$DLEC$	$DLPAT$	$DLREG$
LN_2O	1.00							DLN_2O	1.00						
FDI	0.06	1.00						$DLFDI$	− 0.01	1.00					
$LGFCF$	0.63	0.23	1.00					$DLGFCF$	0.30	0.20	1.00				
LTO	− 0.30	0.08	− 0.29	1.00				$DLTO$	0.11	0.02	0.24	1.00			
LEC	0.59	0.27	0.78	− 0.21	1.00			$DLEC$	0.41	− 0.09	0.22	0.18	1.00		
$LPAT$	0.31	− 0.09	0.45	− 0.66	0.23	1.00		$DLPAT$	0.05	0.01	0.02	0.04	0.07	1.00	
$LREG$	− 0.19	0.11	− 0.04	0.51	− 0.09	− 0.35	1.00	$DLREG$	− 0.02	0.08	− 0.01	− 0.08	− 0.01	0.12	1.00
VIF		1.13	3.48	2.12	2.88	2.24	1.44			1.07	1.16	1.09	1.10	1.02	1.03
VIF_{MEAN}		2.21				1.08									
CD-test	5.35***	14.46***	43.22***	46.61***	15.80***	7.35***	9.59***		9.91***	7.95***	32.58***	42.81***	15.34***	4.89***	11.55***

VIF statistics and cross-sectional dependence test (high-income countries) – N_2O emissions

***, **, and *State significance at 1%. 5%. and 10% level, respectively

Table 11 Correlation matrices

	LGHG	*FDI*	*LGFCF*	*LTO*	*LEC*	*LPAT*	*LREG*		*DLGHG*	*DLFDI*	*DLGFCF*	*DLTO*	*DLEC*	*DLPAT*	*DLREG*
LGHG	1.00							*DLGHG*	1.00						
FDI	0.18	1.00						*DLFDI*	0.13	1.00					
LGFCF	0.26	0.13	1.00					*DLGFCF*	0.25	0.09	1.00				
LTO	0.37	− 0.17	0.23	1.00				*DLTO*	0.10	− 0.02	− 0.13	1.00			
LEC	0.94	0.13	0.33	0.52	1.00			*DLEC*	0.69	0.11	0.30	0.07	1.00		
LPAT	0.48	0.18	0.33	− 0.10	0.58	1.00		*DLPAT*	0.09	0.01	0.03	− 0.04	0.05	1.00	
LREG	0.37	0.20	− 0.15	− 0.03	0.35	0.24	1.00	*DLREG*	− 0.11	0.01	− 0.02	− 0.07	− 0.14	− 0.03	1.00
VIF		1.15	1.35	2.41	3.66	2.42	1.37			1.02	1.13	1.04	1.15	1.01	1.03
VIF_{MEAN}		2.06				1.06									
CD-test	8.34***	3.34***	23.92***	10.18***	10.69***	1.21	1.71*		6.52***	2.79***	9.47***	7.60***	7.53***	− 1.44	2.51**

VIF statistics and cross-sectional dependence test (middle-income countries) – GHG emissions

***, **, and *State significance at 1%. 5%. and 10% level, respectively

Table 12 Correlation matrices

	LCO_2	FDI	$LGFCF$	LTO	LEC	$LPAT$	$LREG$		$DLCO_2$	$DLFDI$	$DLGFCF$	$DLTO$	$DLEC$	$DLPAT$	$DLREG$
LCO_2	1.00							$DLCO_2$	1.00						
FDI	0.09	1.00						$DLFDI$	0.15	1.00					
$LGFCF$	0.24	0.13	1.00					$DLGFCF$	0.24	0.09	1.00				
LTO	0.56	– 0.17	0.23	1.00				$DLTO$	– 0.02	– 0.02	– 0.13	1.00			
LEC	0.96	0.13	0.33	0.52	1.00			$DLEC$	0.50	0.11	0.30	0.07	1.00		
$LPAT$	0.44	0.18	0.33	– 0.10	0.58	1.00		$DLPAT$	0.08	0.01	0.03	– 0.04	0.05	1.00	
$LREG$	0.35	0.20	– 0.15	– 0.03	0.35	0.24	1.00	$DLREG$	– 0.09	0.01	– 0.02	– 0.07	– 0.14	– 0.03	1.00
VIF		1.15	1.35	2.41	3.66	2.42	1.37			1.02	1.13	1.04	1.15	1.01	1.03
VIF_{MEAN}		2.06				1.06									
CD-test	7.43***	3.34***	23.92***	10.18***	10.69***	1.21	1.71*		2.65***	2.79***	9.47***	7.60***	7.53***	– 1.44	2.51**

VIF statistics and cross-sectional dependence test (middle-income countries) – CO_2 emissions

***, **, and * state significance at 1%. 5%. and 10% level, respectively

Table 13 Correlation matrices

	LN_2O	FDI	$LGFCF$	LTO	LEC	$LPAT$	$LREG$		DLN_2O	$DLFDI$	$DLGFCF$	$DLTO$	$DLEC$	$DLPAT$	$DLREG$
LN_2O	1.00							DLN_2O	1.00						
FDI	− 0.03	1.00						$DLFDI$	0.09	1.00					
$LGFCF$	0.36	0.13	1.00					$DLGFCF$	0.35	0.09	1.00				
LTO	0.37	− 0.17	0.23	1.00				$DLTO$	− 0.01	− 0.02	− 0.13	1.00			
LEC	0.86	0.13	0.33	0.52	1.00			$DLEC$	0.54	0.11	0.30	0.07	1.00		
$LPAT$	0.64	0.18	0.33	− 0.10	0.58	1.00		$DLPAT$	0.07	0.01	0.03	− 0.04	0.05	1.00	
$LREG$	0.20	0.20	− 0.15	− 0.03	0.35	0.24	1.00	$DLREG$	− 0.07	0.01	− 0.02	− 0.07	− 0.14	− 0.03	1.00
VIF		1.15	1.35	2.41	3.66	2.42	1.37			1.02	1.13	1.04	1.15	1.01	1.03
VIF_{MEAN}		2.06				1.06									
CD-test	19.18***	3.34***	23.92***	10.18***	10.69***	1.21	1.71*		6.80***	2.79***	9.47***	7.60***	7.53***	− 1.44	2.51**

VIF statistics and cross-sectional dependence test (middle-income countries) – N_2O emissions

***, **, and *State significance at 1%. 5%. and 10% level, respectively

Table 14 Unit roots tests

	High-income countries							
	Maddala-WU				CIPS			
	Without trend		Trend		Without trend		Trend	
	(0)	(1)	(0)	(1)	(0)	(1)	(0)	(1)
LCO_2	27.35	34.11	51.53	44.03	− 1.18	− 0.28	− 0.65	0.58
LN_2O	37.21	28.57	67.36*	66.11*	1.57	1.78	0.73	− 0.39
LGHG	15.73	28.50	66.43*	56.88	0.50	0.73	− 0.52	1.24
FDI	265.32***	147.27***	222.61***	111.89***	− 9.87***	− 3.38***	− 9.63***	− 2.80***
FDI^+	9.55	12.25	55.31	43.28	− 4.29***	− 1.74**	− 2.59***	0.29
FDI^-	5.85	6.84	60.24	48.91	− 3.62***	0.18	− 2.37***	1.75
LGFCF	65.18*	60.90	33.01	74.77**	0.41	− 1.39*	1.53	− 1.02
$LGFCF^+$	63.44	28.43	47.24	78.47***	0.77	− 1.55*	2.63	0.22
$LGFCF^-$	8.30	13.95	20.79	47.11	− 3.79***	− 2.88***	− 3.66***	− 1.84**
LEC	46.36	34.98	103.88***	83.40***	0.30	1.55	− 3.36***	− 2.56***
LEC^+	75.84	43.27	157.01***	78.56***	− 4.37***	− 2.91***	− 2.16**	− 0.69
LEC^-	5.65	8.68	32.14	35.66	− 2.20**	− 2.21**	− 1.24	− 2.44***
LTO	54.44	59.98	60.49	86.71***	1.07	− 1.72**	3.36	0.07
LTO^+	26.84	31.91	25.92	49.37	− 0.42	− 2.18**	2.74	0.99
LTO^-	9.11	11.25	51.12	62.24	0.71	− 0.95	3.21	1.15
LPAT	82.31***	77.11***	62.95	68.51**	0.26	0.06	− 0.34	0.18
$LPAT^+$	111.99***	85.49***	77.58***	57.40	− 2.84***	− 2.14**	− 0.37	0.47
$LPAT^-$	15.51	4.37	73.24**	43.23	− 0.93	− 0.37	− 0.15	− 0.08
LREG	51.55	47.23	66.18*	63.45*	− 0.47	0.04	0.61	1.13
$LREG^+$	79.72***	53.48	115.66***	70.77**	− 4.21***	− 3.78***	− 1.75**	− 0.09
$LREG^-$	19.74	32.12	21.18	29.72	0.60	1.45	0.72	2.32
$DLCO_2$	599.978***	261.06***	555.29***	235.13***	− 14.53***	− 7.67***	− 13.29***	− 5.49***

Table 14 (continued)

	High-income countries							
	Maddala-WU				CIPS			
	Without trend		Trend		Without trend		Trend	
	(0)	(1)	(0)	(1)	(0)	(1)	(0)	(1)
DLN₂O	533.09***	294.29***	449.15***	227.69***	− 13.17***	− 7.98***	− 11.96***	− 6.44***
DLGHG	624.25***	260.50***	557.24***	210.04***	− 15.16***	− 7.39***	− 13.61***	− 4.88***
DFDI	1007.71***	381.28***	828.61***	271.97***	− 21.19***	− 13.54***	− 19.73***	− 11.13***
DFDI$^+$	636.77***	254.68***	522.90***	193.81***	− 17.60***	− 9.97***	− 16.23***	− 8.47***
DFDI$^-$	656.24***	244.84***	545.85***	171.85***	− 18.47***	− 8.26***	− 16.84***	− 6.09***
DLGFCF	231.83***	211.23***	159.61***	142.15***	− 8.89***	− 6.86***	− 6.46***	− 4.57***
DLGFCF$^+$	279.65***	210.49***	232.22***	164.89***	− 9.72***	− 6.90***	− 7.68***	− 5.13***
DLGFCF$^-$	279.55***	210.49***	191.27***	118.27***	− 11.90***	− 7.05***	− 9.81***	− 4.83***
DLEC	744.59***	319.01***	647.81***	244.68***	− 16.59***	− 10.95***	− 15.02***	− 8.77***
DLEC$^+$	775.84***	326.51***	663.00***	258.49***	− 15.98***	− 9.15***	− 14.28***	− 6.07***
DLEC$^-$	508.12***	208.78***	438.30***	167.00***	− 14.84***	− 9.11***	− 13.63***	− 8.35***
DLTO	505.65***	324.96***	404.49***	246.38***	− 9.38***	− 5.60***	− 7.90***	− 3.74***
DLTO$^+$	381.19***	275.65***	314.90***	227.41***	− 10.47***	− 6.32***	− 9.22***	− 4.56***
DLTO$^-$	502.01***	270.05***	387.92***	191.58***	− 11.01***	− 6.95***	− 9.27***	− 5.61***
DLPAT	480.29***	251.92***	424.75***	214.02***	− 13.70***	− 7.78***	− 12.74***	− 7.41***
DLPAT$^+$	490.66***	230.80***	451.62***	207.01***	− 14.75***	− 7.69***	− 13.78***	− 6.23***
DLPAT$^-$	550.05***	251.52***	462.69***	216.22***	− 13.16***	− 7.85***	− 11.19***	− 6.84***
DLREG	473.47***	233.26***	393.22***	179.33***	− 13.74***	− 6.41***	− 12.57***	− 4.96***
DLREG$^+$	589.78***	235.84***	502.33***	192.67***	− 14.99***	− 7.23***	− 12.99***	− 5.07***
DLREG$^-$	433.30***	222.23***	368.40***	187.14***	− 13.97***	− 7.92***	− 12.68***	− 6.89***

Table 14 (continued)

	Middle-income countries							
	Maddala-WU				CIPS			
	Without trend		Trend		Without trend		Trend	
	(0)	(1)	(0)	(1)	(0)	(1)	(0)	(1)
LCO_2	16.85	19.64	15.55	18.34	− 2.13**	− 1.73**	− 2.02**	− 1.29*
LN_2O	7.35	6.30	21.68	28.70*	− 0.54	− 2.39***	− 0.98	− 2.84***
LGHG	25.52	32.47**	8.83	19.42	− 1.19	− 2.87***	0.69	− 0.60
FDI	73.11***	50.96***	69.46***	49.69***	− 3.81***	− 3.28***	− 2.81***	− 2.08**
FDI^+	16.01	20.35	19.82	19.05	− 0.042	− 0.82	0.67	0.08
FDI^-	12.82	15.11	18.78	28.21	0.20	− 0.01	− 0.83	− 1.34*
LGFCF	22.59	61.65***	13.17	29.49*	− 1.35*	− 3.92***	− 0.38	− 2.79***
$LGFCF^+$	33.10**	58.32***	14.44	31.75**	− 2.09**	− 5.80***	− 0.43	− 3.99***
$LGFCF^-$	44.80***	26.45	72.37***	23.72	− 2.35***	− 1.92**	− 1.24	− 0.88
LEC	22.20	26.78	9.97	19.96	− 0.96	− 1.92**	1.20	0.02
LEC^+	15.86	12.10	11.05	13.63	0.42	− 0.20	1.41	0.57
LEC^-	13.09	19.63	17.77	25.42	− 0.54	− 2.02**	− 1.10	− 1.45*
LTO	25.20	18.05	25.73	22.84	0.21	0.41	0.13	0.55
LTO^+	12.79	13.86	18.56	14.55	− 1.65**	− 1.42*	0.21	0.80
LTO^-	6.62	11.38	16.95	17.92	0.22	0.10	2.07	2.04
LPAT	21.69	17.38	36.75**	16.49	− 0.84	0.44	− 1.00	0.13
$LPAT^+$	6.78	5.95	23.00	14.78	− 1.08	− 0.49	0.54	0.87
$LPAT^-$	28.67*	30.77*	23.05	74.35***	− 1.88**	− 2.21**	0.16	− 0.54
LREG	31.00*	63.00***	22.08	56.59***	− 0.47	− 2.84***	0.95	− 1.33*
$LREG^+$	28.11	37.58***	25.86	82.16***	− 1.69**	− 3.42**	0.98	− 1.06
$LREG^-$	5.88	4.23	22.71	15.83	0.67	1.58	0.34	0.07
$DLCO_2$	206.39***	119.96***	174.95***	95.76***	− 9.78***	− 6.60***	− 9.06***	− 5.70***

Table 14 (continued)

	Middle-income countries							
	Maddala-WU				CIPS			
	Without trend		Trend		Without trend		Trend	
	(0)	(1)	(0)	(1)	(0)	(1)	(0)	(1)
DLN_2O	185.40***	123.52***	153.27***	93.575***	− 7.81***	− 6.21***	− 7.19***	− 5.08***
DLGHG	179.91***	117.01***	158.60***	102.63***	− 8.59***	− 5.97***	− 8.20***	− 5.30***
DFDI	315.85***	198.54	252.58***	150.10***	− 11.27***	− 8.63***	− 9.79***	− 6.83***
$DFDI^+$	221.23***	113.85***	198.72***	85.76***	− 9.19***	− 5.50***	− 8.45***	− 3.61***
$DFDI^-$	194.69***	115.47***	166.16***	119.51***	− 9.57***	− 6.70***	− 8.22***	− 3.61***
DLGFCF	166.62***	78.16***	161.40***	56.97***	− 8.01***	− 3.03***	− 7.03***	− 1.14
$DLGFCF^+$	92.92***	87.14***	83.38***	58.01***	− 5.37***	− 4.51***	− 4.36***	− 2.50***
$DLGFCF^-$	126.87***	81.78***	98.19***	61.50***	− 8.47***	− 2.95***	− 7.91***	− 1.51*
DLEC	136.61***	92.14***	117.35***	79.24***	− 6.45***	− 5.20***	− 6.17***	− 5.49***
$DLEC^+$	165.45***	83.58***	148.76***	84.51***	− 8.21***	− 5.09***	− 7.67***	− 5.61***
$DLEC^-$	147.13***	85.15***	121.74***	69.18***	− 6.82***	− 4.89***	− 5.25***	− 3.17***
DLTO	236.32***	100.88***	192.88***	73.36***	− 9.24***	− 3.83***	− 7.97***	− 2.04**
$DLTO^+$	223.73***	85.75***	182.11***	65.14***	− 9.15***	− 4.18***	− 7.86***	− 2.56***
$DLTO^-$	223.11***	93.47***	187.41***	68.87***	− 8.92***	− 3.00	− 8.50***	− 2.08**
DLPAT	334.45***	124.46***	284.97***	100.79***	− 11.73***	− 6.60***	− 10.43***	− 5.44***
$DLPAT^+$	269.62***	104.95***	236.14***	84.43***	− 10.13***	− 5.51***	− 9.28***	− 5.02***
$DLPAT^-$	241.32***	107.64***	194.79***	81.97***	− 9.68***	− 5.33***	− 8.46***	− 4.19***
DLREG	186.34	135.01***	158.14***	112.32***	− 7.35***	− 4.68***	− − 6.74***	− 3.87***
$DLREG^+$	158.51***	125.15***	137.94***	98.81***	− 7.32***	− 3.92***	− 7.03***	− 3.02***
$DLREG^-$	196.76***	100.48***	151.08***	72.73***	− 7.59***	− 4.18***	− 6.03***	− 2.66***

(.) represents the lags order; ***, **, and * state significance at 1%. 5%. and 10% level, respectively

Table 15 Zivot and Andrews unit roots test

	Level						
	T-statistics			Time break			Conclusion
	(a)	(b)	(c)	(a)	(b)	(c)	
High-income countries							
Chile							
LGHG	– 3.46	– 3.97	– 4.31	2003	2000	2007	Unit root
LCO_2	– 3.42	– 4.14	– 3.34	2004	2001	2006	Unit root
LN_2O	– 3.77	– 4.74*	– 4.15	2004	2011	2011	Stationary
LFDI	– 3.17	– 3.48	– 3.90	2013	2015	2011	Unit root
LGFCF	– 2.57	– 2.92	– 2.60	2013	2005	2005	Unit root
LTO	– 4.89**	– 2.27	– 4.37	2008	2000	2009	Stationary
LEC	– 3.74	– 3.87	– 4.01	2007	2009	2008	Unit root
LPAT	– 4.69**	– 4.42	– 5.25**	2004	2002	2002	Stationary
LREG	– 3.37	– 3.48	– 3.12	2010	2004	2006	Unit root
Denmark							
LGHG	– 4.60**	– 5.72***	– 5.54**	2008	2003	2003	Stationary
LCO_2	– 4.58**	– 5.74***	– 5.62***	2008	2003	2003	Stationary
LN_2O	– 4.99***	– 6.56***	– 6.451***	2007	2009	2009	Stationary
LFDI	– 3.49	– 3.85	– 5.48**	2000	2002	2001	Stationary
LGFCF	– 3.23	– 6.36***	– 5.61***	2015	2009	2009	Stationary
LTO	– 3.79	– 3.59	– 4.12	2008	2000	2009	Unit root
LEC	– 4.80**	– 6.59***	– 7.26***	2008	2003	2003	Stationary
LPAT	– 4.19*	– 3.12	– 3.84	2001	1999	2001	Stationary
LREG	– 3.87	– 3.27	– 3.35	1999	2008	2008	Unit root
Estonia							
LGHG	– 2.13	– 0.31	– 2.08	2015	2005	2015	Unit root
LCO_2	– 3.18	– 3.19	– 3.21	2015	2007	2013	Unit root
LN_2O	– 4.06	– 2.38	– 3.72	2014	2015	2013	Unit root
LFDI	– 2.09	– 2.60	– 2.23	2006	2011	2003	Unit root
LGFCF	– 4.94***	– 4.06	– 8.23***	2007	2009	2009	Stationary
LTO	– 3.55	– 5.73***	– 5.11**	2001	2010	2010	Stationary
LEC	– 3.14	– 3.10	– 3.31	1999	2007	2003	Unit root
LPAT	– 3.70	– 4.62*	– 4.89*	2010	2012	2012	Stationary
LREG	– 3.45	– 4.30	– 4.04	2010	2013	2013	Unit root
Lithuania							
LGHG	– 2.37	– 3.25	– 3.49	2000	2004	2004	Unit root
LCO_2	– 3.31	– 3.77	– 3.67	2001	1999	1999	Unit root
LN_2O	– 3.82	– 3.33	– 3.56	2001	2000	2005	Unit root
LFDI	– 3.00	– 4.41	– 3.95	2006	2009	2009	Unit root
LGFCF	– 4.01	– 5.50***	– 6.35	2007	2009	2009	Stationary
LTO	– 3.05	– 3.09	– 3.34	2013	2014	2001	Unit root
LEC	– 2.46	– 4.38	– 4.22	2015	2010	2010	Unit root
LPAT	– 2.99	– 3.67	– 3.74	2001	1999	1999	Unit root

Table 15 (continued)

	Level						
	T-statistics			Time break			Conclusion
	(a)	(b)	(c)	(a)	(b)	(c)	
LREG	− 2.81	− 4.66*	− 3.93	2012	2005	2005	Stationary
Norway							
LGHG	− 4.04	− 3.96	− 4.42	2015	2003	2000	Unit root
LCO_2	− 4.15*	− 2.65	− 4.02	2008	2003	2007	Stationary
LN_2O	− 3.36	− 3.61	− 3.74	2015	2012	2012	Unit root
LFDI	− 2.49	− 3.23	− 3.19	2010	2006	2008	Unit root
LGFCF	− 4.88**	− 5.76***	− 5.71***	2008	2005	2006	Stationary
LTO	− 3.98	− 4.13	− 4.10	2015	2009	2012	Unit root
LEC	− 5.11***	− 4.74*	− 5.04*	2001	1999	2002	Stationary
LPAT	− 3.28	− 3.55	− 4.11	2004	2001	2001	Unit root
LREG	− 3.63	− 4.10	− 3.79	2013	2015	2015	Unit root
Spain							
LGHG	− 3.00	− 3.46	− 3.18	2000	2008	2008	Unit root
LCO_2	− 2.80	− 3.31	− 3.33	2000	2008	2008	Unit root
LN_2O	− 2.72	− 2.77	− 2.55	2000	2008	2013	Unit root
LFDI	− 4.40*	− 4.92**	− 5.04*	2001	2009	2009	Stationary
LGFCF	− 2.63	− 5.65***	− 2.85	2015	2009	2009	Stationary
LTO	− 3.16	− 3.08	− 3.28	2010	2003	2008	Unit root
LEC	− 3.16	− 3.90	− 3.14	2001	2008	2000	Unit root
LPAT	− 0.86	1.60	− 1.09	2013	2002	2013	Unit root
LREG	− 2.94	− 5.99	− 4.61	2010	2013	2013	Unit root
Middle-income countries							
Malaysia							
LGHG	− 4.36*	− 3.57	− 4.59	2008	2004	2009	Stationary
LCO_2	− 3.51	− 4.82**	− 4.69	2009	2003	2003	Stationary
LN_2O	− 3.34	− 4.71*	− 5.25**	2011	2013	2013	Stationary
LFDI	− 5.02***	− 3.73	− 4.38	1999	2010	2000	Unit root
LGFCF	− 7.82***	− 17.67***	− 14.66***	2015	2012	2012	Stationary
LTO	− 4.26*	− 2.76	− 2.64	1999	2008	2000	Stationary
LEC	− 4.35*	− 1.87	− 3.71	2006	2002	2005	Stationary
LPAT	− 3.30	− 2.16	− 4.17	2011	2015	2009	Unit root
LREG	− 3.82	− 1.65	− 4.25	2015	2005	2015	Unit root

	First differences						
	T-statistics			Time break			Conclusion
	(a)	(b)	(c)	(a)	(b)	(c)	
High-income countries							
Chile							
LGHG	− 4.73**	− 4.64*	− 5.58***	2000	2004	2002	Stationary

Table 15 (continued)

	First differences						
	T-statistics			Time break			Conclusion
	(a)	(b)	(c)	(a)	(b)	(c)	
LCO_2	– 4.55**	– 4.33	– 5.89***	2001	2000	2002	Stationary
LN_2O	– 5.03***	– 5.92***	– 5.54**	2013	2014	2014	Stationary
LFDI	– 5.17***	– 6.64***	– 6.64***	2009	2013	2013	Stationary
LGFCF	– 4.85**	– 5.06**	– 5.06*	2006	2003	2000	Stationary
LTO	– 5.13***	– 6.75***	– 6.55***	2001	2009	2009	Stationary
LEC	– 5.91***	– 5.46***	– 5.80***	2000	2011	2000	Stationary
LPAT	– 6.18***	– 6.82***	– 6.75***	2011	2009	2009	Stationary
LREG	– 6.06***	– 8.70***	– 9.60***	2005	2001	2001	Stationary
Denmark							
LGHG	– 7.83***	– 8.44***	– 8.31***	2004	2008	2008	Stationary
LCO_2	– 7.78***	– 8.18***	– 8.13***	2004	2008	2008	Stationary
LN_2O	– 7.87***	– 8.47***	– 8.26***	2010	2008	2008	Stationary
LFDI	– 6.16***	– 7.55***	– 8.19***	2003	2001	2001	Stationary
LGFCF	– 3.19	– 3.49**	– 3.51	2010	2007	2008	Stationary
LTO	– 4.26*	– 5.48***	– 5.19**	2013	2009	2009	Stationary
LEC	– 8.31***	– 9.12***	– 8.91***	2004	2008	2008	Stationary
LPAT	– 5.00***	– 5.23***	– 5.26**	2006	2014	2007	Stationary
LREG	– 5.31***	– 5.92***	– 5.73***	2001	2010	2010	Stationary
Estonia							
LGHG	– 6.29***	– 6.56***	– 6.38***	2014	2003	2003	Stationary
LCO_2	– 6.06***	– 6.24***	– 6.11***	2013	2003	2003	Stationary
LN_2O	– 8.34***	– 9.18***	– 8.86***	2004	2001	2001	Stationary
LFDI	– 9.15***	– 10.51***	– 10.50***	2015	2006	2006	Stationary
LGFCF	– 4.59**	– 5.57***	– 5.56**	2010	2008	2008	Stationary
LTO	– 4.44**	– 4.73*	– 5.04*	2000	2010	2010	Stationary
LEC	– 6.26***	– 6.20***	– 6.11***	2004	2002	2003	Stationary
LPAT	– 4.97***	– 5.91***	– 5.34***	2007	2011	2011	Stationary
LREG	– 4.74**	– 4.30	– 4.650	2001	2015	2001	Stationary
Lithuania							
LGHG	– 4.50**	– 5.32**	– 5.38**	2005	2008	2001	Stationary
LCO_2	– 4.68**	– 5.21**	– 5.92***	2006	2001	2001	Stationary
LN_2O	– 3.87	– 4.72	– 4.78	2007	2008	2008	Stationary
LFDI	– 4.97**	– 6.34***	– 6.42***	2015	2009	2009	Stationary
LGFCF	– 4.54**	– 6.07***	– 6.13***	2010	2008	2009	Stationary
LTO	– 4.91**	– 4.74	– 4.68	2002	2014	2006	Stationary
LEC	– 4.71**	– 5.20**	– 5.27**	2011	2009	2009	Stationary
LPAT	– 4.93***	– 4.96**	– 6.35***	2000	2015	2001	Stationary
LREG	– 4.66**	– 4.76*	– 5.12**	2001	2000	2008	Stationary
Norway							
LGHG	– 6.23***	– 6.57***	– 7.05***	2001	2000	2002	Stationary

Table 15 (continued)

	First differences						
	T-statistics			Time break			Conclusion
	(a)	(b)	(c)	(a)	(b)	(c)	
LCO_2	– 7.29***	– 7.74***	– 7.76***	2001	2014	2014	Stationary
LN_2O	– 5.01***	– 5.13**	– 5.44**	2001	2015	2003	Stationary
LFDI	– 5.56***	– 5.78***	– 6.23***	2015	2010	2013	Stationary
LGFCF	– 3.88	– 4.65*	– 4.58	2015	2008	2008	Stationary
LTO	– 5.06***	– 6.25***	– 6.19***	2003	2009	2009	Stationary
LEC	– 6.88***	– 7.28***	– 7.39***	2004	2001	2005	Stationary
LPAT	– 6.57***	– 6.53***	– 7.32***	2015	2004	2015	Stationary
LREG	– 5.01***	– 5.24***	– 5.45**	2015	2013	2001	Stationary
Spain							
LGHG	– 5.20***	– 5.44***	– 5.84***	2010	2014	2008	Stationary
LCO_2	– 4.72**	– 5.23**	– 5.12**	2010	2014	2008	Stationary
LN_2O	– 5.46***	– 6.80***	– 6.50***	2014	2015	2015	Stationary
LFDI	– 6.10***	– 6.86***	– 6.82***	2010	2009	2009	Stationary
LGFCF	– 3.65	– 3.60	– 5.01*	2010	2014	2008	Stationary
LTO	– 4.74**	– 6.16***	– 5.84***	2003	2010	2010	Stationary
LEC	– 5.51***	– 5.30***	– 5.82***	2010	2015	2008	Stationary
LPAT	– 5.05***	– 4.04	– 4.93*	2015	2002	2014	Stationary
LREG	– 4.66**	– 5.27**	– 6.74***	2002	2010	2013	Stationary
Middle-income countries							
Malaysia							
LGHG	– 5.84***	– 6.74***	– 6.57***	2005	2009	2009	Stationary
LCO_2	– 6.96***	– 6.03***	– 8.88***	2003	2001	2006	Stationary
LN_2O	– 5.62***	– 5.96***	– 7.252***	2015	2013	2013	Stationary
LFDI	– 6.81***	– 7.01***	– 6.84***	2005	2002	2002	Stationary
LGFCF	– 5.69***	– 5.24***	– 5.95***	2013	2015	2012	Stationary
LTO	– 5.30***	– 5.58***	– 6.74***	2010	2008	2008	Stationary
LEC	– 6.47***	– 7.94***	– 7.72***	2002	2008	2006	Stationary
LPAT	– 6.89***	– 7.15***	– 7.44***	2004	2011	2012	Stationary
LREG	– 7.78***	– 6.34***	– 8.28***	2015	2004	2015	Stationary

The lag selection criteria of Zivot and Andrews test is based in a TTest; (a), (b), and (c) mean trend, intercept, and both, respectively; ***, **, and * state significance at 1%. 5%. and 10% level, respectively

Table 16 Test of overall significance PARDL

High-income countries	GHG emissions	–
	CO_2 emissions	17.57***
	N_2O emissions	5.64**
Middle-income countries	GHG emissions	–
	CO_2 emissions	–
	N_2O emissions	–

***, and ** denote statistical significance at 1% and 5% level, respectively. H0: var = 0

Table 17 Test of overall significance NPARDL

High-income countries	GHG emissions	32.10***
	CO_2 emissions	25.49***
	N_2O emissions	21.65***
Middle-income countries	GHG emissions	–
	CO_2 emissions	–
	N_2O emissions	13.28***

***Denotes significance at 1% level. H0: var = 0

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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