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Foreign direct investment and greenhouse gas emissions: Evidence across income groups and technological contexts

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ABSTRACT

This paper examines the relationship between foreign direct investment (FDI) and greenhouse gas (GHG) emissions in middle- and high-income countries. Particular attention is paid to income-group heterogeneity and the context of green technology. Using an unbalanced panel of 74 countries from 1975 to 2021, we estimate static and dynamic panel data models. The static analysis includes pooled OLS, random effects and two-way fixed effects specifications, incorporating income group and FDI-patent interactions. To address dynamic persistence and potential endogeneity, we also employ one-step and two-step system GMM estimators with lagged dependent variables and income-specific FDI effects.

The results suggest a generally positive association between FDI and GHG emissions, although the magnitude and statistical significance of this relationship vary across different models. Dynamic system GMM estimations provide further evidence of a positive association between FDI and emissions. In the main interaction specifications, estimated effects are somewhat larger for middle-income economies than for high-income ones, though this difference is not consistent across all specifications and should be interpreted as suggestive rather than conclusive. Analysis of disaggregated green patent categories reveals substantial technological heterogeneity. Some patent classes are associated with a weaker FDI–emissions relationship, whereas others appear to strengthen it. In contrast, aggregate patent activity shows either positive or statistically insignificant relationships with emissions, suggesting that broad patent measures may obscure important technology-specific effects. Overall, FDI does not automatically lead to environmental improvement. Its consequences appear to vary with income-related structural conditions and the technological orientation of the host economy. These findings support broad policy caution: FDI attraction strategies should be evaluated together with environmental monitoring, and green innovation should be assessed at a more disaggregated technological level.

1. Introduction

Human activity and economic growth are inextricably linked to the development and use of resources. Economic development drives industrialization, which increases the value of extracted natural resources (Baloch et al., 2019). This is caused by the release of carbon dioxide (CO_2) and other greenhouse gases into the atmosphere.[1] In particular, the burning of fossil fuels contributes to the emission of large amounts of carbon and sulfur. These are trapped in the atmosphere and prevent some of the heat present on Earth from being radiated into space, causing global temperatures to rise. Of the greenhouse gas (GHG) emissions that have occurred since 1850, 30% have been caused by changes in land use and 70% by the burning of fossil fuels (Friedlingstein et al., 2022). Human activities undermine the temperature regulating effect by producing large amounts of GHGs that cause climate change (Manisalidis et al., 2020). Moreover, the energy demand of developing countries is expected to rise drastically in the following years (Wolfram et al., 2012), which means more pollution in the future is expected.

Most air pollution comes from the burning of fossil fuels, mainly for electricity generation, heating, and transportation (Mackenzie and Turrentine, 2016).[2] The boom in transportation, agriculture, and industry is introducing large amounts of nitrogen into the ecosystem (Zhong et al., 2019). In addition, sulfur dioxide (SO_2) and nitrogen oxides (NO_x) are major contributors to acid rain, which not only causes environmental pollution but also leads to significant economic impacts

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[1] Sources of pollution are usually divided into man-made and natural sources.

[2] Air pollution is determined as the presence of pollutants in the air in large quantities for long periods. Manisalidis et al. (2020)

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due to material damage (Mayerhofer et al., 1995). Large amounts of emissions lead to air pollution, which not only contributes to climate change, but also has a detrimental effect on public health (Manisalidis et al., 2020). In particular, these pollutants can lead to significant increases in mortality and loss of life expectancy due to cardiovascular disease (Lelieveld et al., 2020). Air pollution not only imposes severe costs, penalties, and consequences on human health, but also damages natural biological networks and ecosystems (Ashfaq and Sharma, 2012).

While global GHG emissions have been widely acknowledged as a pressing challenge, the drivers of these emissions remain multifaceted and context-specific. Among these, the role of foreign direct investment (FDI) has received increasing attention in both academic and policy circles. FDI can act as a double-edged sword: on one hand, it can facilitate the transfer of cleaner technologies; on the other hand, it may lead to a "pollution haven" effect, where multinational firms exploit weaker environmental standards in host countries (Eskeland and Harrison, 2003a). This study contributes to this ongoing debate by examining the impact of FDI on GHG emissions across countries at different income levels, with particular attention to middle- and high-income economies and to the role of green technological activity measured through aggregate and sector-specific green patent indicators.[3]

This paper contributes to the literature in several ways. First, unlike most existing studies that focus narrowly on CO_2, we examine a broader spectrum of GHGs, allowing for a more comprehensive environmental assessment. Second, we investigate whether the environmental effects of FDI differ systematically across middle- and high-income countries, where differences in income levels may reflect variation in regulatory capacity, institutional conditions, and absorptive ability. Third, we incorporate data on green patent applications, disaggregated by sector-specific $Y02$ categories, to capture the role of technological innovation more precisely. Fourth, we employ both static and dynamic panel estimation techniques including two-way fixed effects (TWFE) to account for country- and time-specific heterogeneity, and system Generalized Method of Moments (GMM) to address potential endogeneity and dynamic persistence, thereby enhancing the robustness of the findings. The analysis is based on an unbalanced panel dataset covering 74 countries over the period 1975–2021, combining environmental, economic, and innovation-related indicators.

The results suggest that FDI per capita is generally positively associated with GHG emissions, although the strength and statistical significance of this relationship vary across specifications. In the baseline dynamic specifications of the main GMM models, the FDI coefficient is positive but statistically insignificant. In the income-group interaction specifications, the estimated FDI coefficient is positive and statistically significant mainly for middle-income country-years, while the corresponding coefficient for high-income country-years is small and statistically insignificant. In the static interaction model, the FDI coefficient for high-income countries is positive and statistically significant at the 10% level, while the interaction term for middle-income countries is negative and only marginally significant.

The dynamic system GMM robustness specifications provide additional evidence of a positive association between FDI and GHG emissions. In these alternative baseline specifications, the FDI coefficient is positive and statistically significant in both the one-step and two-step models. In the corresponding income-group interaction specifications, the estimated FDI coefficients are positive and statistically significant for both middle- and high-income country-years, with somewhat larger coefficients for middle-income economies. However, the difference between the two income groups should be interpreted as suggestive rather than conclusive, as some robustness specifications yield weaker evidence.

The results for green patent categories point to substantial technological heterogeneity. In the fixed effects robustness specifications, some patent categories are positively associated with emissions, while others, particularly GHG capture and sequestration technologies, are negatively associated with emissions. When lagged patent variables are included, some categories display delayed negative associations, suggesting that the environmental effects of green technological activity may take time to materialize. Moreover, the FDI–patent interaction results indicate that the relationship between FDI and emissions is strengthened in some technological contexts and weakened in others. Overall, these findings suggest that the environmental consequences of FDI may depend not only on income status, but also on the technological composition and broader structural context of host economies.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on the relationship between FDI, environmental outcomes, and green innovation. Section 3 presents the conceptual framework guiding the empirical analysis. Section 4 describes the data and empirical methodology, including the static panel and dynamic system GMM specifications. Section 5 reports the main empirical results. Section 6 presents robustness checks, including specifications with grouped green patents, lagged patent variables, and FDI–patent interactions. Section 7 concludes by discussing the main findings, policy implications, and limitations of the study.

2. Related literature

A growing body of research examines the environmental consequences of FDI, often focusing on CO_2 emissions as a proxy for environmental degradation. However, the findings are mixed and depend on the context, particularly when it comes to different income groups, institutional settings and industrial compositions. Much of the literature centers around two competing hypotheses: the Pollution Haven Hypothesis (PHH), which posits that FDI inflows shift polluting industries to countries with weaker environmental regulations (Copeland and Taylor, 2004), and the Pollution Halo Hypothesis (PHaH), which suggests that FDI can improve environmental outcomes by transferring cleaner technologies and practices (Eskeland and Harrison, 2003b).

Several studies find evidence in support of the PHH, particularly in low- and middle-income countries. For example, Pham et al. (2025) use a dynamic system GMM model on a panel of 90 countries and report that FDI significantly increases CO_2 emissions, especially in countries with less stringent environmental policies. In particular, they find that FDI significantly increases CO_2 emissions across total, per GDP, and per capita measures. The negative environmental impact of FDI is strongest in low- and middle-income countries, which are more vulnerable due to their weaker environmental standards. Other contributions emphasize the importance of sectoral and regional heterogeneity. Caetano and Marques (2024) analyze the environmental effects of FDI in a sample of 25 high-income and 10 middle-income countries from 1995 to 2019. Their findings highlight that FDI has a dual effect depending on the income level of the country: in high-income countries, FDI contributes to environmental improvement, likely through the adoption of cleaner technologies and stricter regulatory compliance. In contrast, FDI increases environmental degradation in middle-income countries, supporting the PHH. Notably, this pattern does not hold uniformly for all pollutants; for example, nitrous oxide emissions do not follow the same country-income differentiation. The authors conclude that renewable energy expansion and electrification play a crucial role in mitigating the environmental consequences of economic openness and capital inflows.

Focusing on the Latin American context, Sapkota and Bastola (2017) analyze panel data for 14 countries from 1980 to 2010 using panel fixed and random effects estimators. Their results indicate that FDI inflows

[3] Initially, we also included low-income countries. However, due to the lack of patent data in these countries, in the end there were only two groups of countries.

significantly increase CO_2 emissions, providing evidence in support of the PHH. They also confirm the Environmental Kuznets Curve (EKC) hypothesis, where pollution initially rises with income but eventually declines beyond a certain threshold. Importantly, the authors estimate separate models for high- and low-income countries and find that the core results regarding the PHH remain robust across both groups. Mejia (2021) extends the literature on FDI and environmental harm by examining the relationship between foreign capital dependence and nitrous oxide (N_2O) emissions - a highly potent but under-researched GHG. Using fixed effects panel regression on 106 developing countries over the period 1990–2014, the study finds that FDI dependence is positively and significantly associated with higher N_2O emissions. Kastratović (2019) investigates the relationship between FDI and GHG emissions in the agricultural sector across 63 developing countries from 2005 to 2014. Using a dynamic panel model estimated via system GMM, the study finds that FDI inflows are positively associated with agricultural emission intensity, largely driven by extensive land use practices and fertilizer-related pollution. These results provide empirical support for the PHH in low-income countries.

On the other hand, some studies report more mixed or even positive environmental effects of FDI, conditional on country characteristics or firm behavior. Shabir et al. (2022) analyze a panel of 24 developed and developing countries over the period 2001–2019 and find that FDI actually improves environmental quality. Using second-generation panel techniques, the authors demonstrate that, although trade openness, economic policy uncertainty and energy consumption have an adverse environmental impact, FDI is associated with a reduction in CO_2 emissions. Solarin and Al-Mulali (2018) examine the influence of FDI on environmental degradation using a panel of 20 developed and developing countries. Employing Augmented Mean Group and Common Correlated Effects Mean Group estimators, the authors analyze three indicators: CO_2 emissions, carbon footprint, and ecological footprint. While the panel-level results show that FDI has no statistically significant impact on environmental degradation, the country-level analysis reveals a more nuanced picture. In developing countries, FDI and urbanization increase pollution, supporting the PHH, whereas in developed countries, both factors mitigate environmental harm, consistent with the PHaH. These findings underscore the importance of institutional quality and regulatory enforcement in shaping the environmental effects of FDI.

Recent research has expanded the analysis of FDI's environmental consequences by incorporating spatial dynamics, distributional heterogeneity, and institutional context. Using spatial Durbin models on Chinese provincial data, Lin et al. (2022) find that while FDI tends to reduce emissions at the national level, it simultaneously increases local CO_2 emissions and generates positive spillover effects in neighboring provinces. Le Quoc (2025) investigates the heterogeneous impact of FDI on environmental quality across 112 countries from 1990 to 2021 using a Bayesian Quantile Regression approach. The study finds that FDI improves environmental quality in countries with low to medium CO_2 quantiles (0.05–0.45), while it significantly deteriorates environmental quality in countries with medium to high CO_2 quantiles (0.50–0.95). These results emphasize the nonlinear and context-dependent nature of FDI's environmental impact. Institutional quality also emerges as a critical moderator: Boateng et al. (2024) find that FDI reduces emissions intensity only in countries with strong institutional frameworks, whereas in weak institutional environments, FDI either fails to improve or actively worsens environmental outcomes. Cole et al. (2017) provide a comprehensive review of the FDI–environment literature, highlighting the conditions under which FDI may either worsen environmental outcomes through pollution haven mechanisms or improve them through cleaner technologies and management practices. They also emphasize key empirical challenges, including endogeneity, measurement issues, and firm-level heterogeneity.

Another area of research focuses on the relationship between patents, green innovation, and environmental outcomes. Li et al. (2021) study the impact of patent activity on CO_2 emissions in China using panel data for provinces and sectors. They find an inverse U-shaped relationship between patents and emissions: at low levels, innovation tends to worsen environmental quality, but beyond a threshold, additional patenting helps reduce emissions. Their results also vary across sectors and province development levels, suggesting that the environmental impact of innovation is non-linear and context-dependent. Li et al. (2023) focus on green innovation in China's construction sector and find that green patent activity helps reduce CO_2 emissions, although the effect is non-linear and stronger under stricter environmental regulation. Their results further indicate that the emissions-reducing effect of green innovation varies across regions and development conditions. Similarly, Abbas et al. (2024) analyze the relationship between green patents and CO_2 emissions in Chinese low-carbon pilot cities and find that green patents contribute to lower emissions and support environmental sustainability, although the magnitude of the effect varies across quantiles and local conditions. These studies suggest that the environmental effects of patenting and green innovation are generally favorable but remain heterogeneous and context-dependent. At the same time, these contributions are based on evidence from a single-country setting, namely China, whereas our study examines these issues in a cross-country context.

The literature also emphasizes that the environmental impact of FDI depends not only on host-country characteristics but also on the composition of foreign investment. Doytch and Uctum (2016), using a dynamic panel framework, show that FDI directed to manufacturing tends to increase pollution, whereas services-related FDI is more compatible with the PHaH. They further find that FDI inflows worsen environmental quality in low- and middle-income countries, while the effects are more favorable in high-income economies. Extending this logic, Ashraf et al. (2021) demonstrate that the environmental impact of FDI also varies by entry mode. They find that greenfield investment tends to increase pollution, while cross-border mergers and acquisitions are associated with lower emissions, especially in developed economies. These studies suggest that the FDI–environment nexus is heterogeneous and can depend on the level of economic development as well. By contrast, our paper examines whether the relationship between FDI and GHG emissions varies with green patent activity and host-country income level.

Although the relationship between FDI and environmental outcomes has been widely studied, the literature still leaves important questions open. First, most empirical studies focus primarily on CO_2 emissions, whereas broader measures such as total GHG emissions have received less attention. Second, while previous research has documented heterogeneity in the FDI–environment nexus across sectors, entry modes, institutions, and regional settings, less attention has been paid to the joint role of income-group differences and green technological activity. In addition, much of the literature on green technology and environmental outcomes is based on evidence from single-country settings, (for example, China), rather than cross-country comparisons. This paper addresses these issues by examining the relationship between FDI and total GHG emissions across middle- and high-income countries, while incorporating green patent indicators to capture the technological context of different economies.

3. Conceptual framework

Our conceptual framework is grounded in the multinational-enterprise theory articulated by Markusen (1995) and adapted from the partial-equilibrium environmental model of Doytch and Uctum (2016). We consider a host country i in year t, where $i = 1, \dots, N$ indexes countries and $t = 1, \dots, T$ indexes time. A domestic firm, denoted by superscript d, and a foreign multinational affiliate, denoted by superscript f, supply the local market with differentiated goods. Consistent with the literature on horizontal FDI, the foreign affiliate serves the host market through local production. Host-country GHG emissions arise from production undertaken within the economy. As in Doytch and Uctum (2016), the environmental effect of FDI operates through the foreign affiliate's local production activity.

Relative to their framework, however, we extend the analysis in two directions that are central to this study. First, the environmental outcome is total GHG emissions rather than CO_2 emissions alone. Second, the environmental effect of foreign production is allowed to vary with the host country's technological orientation and income group. In our application, technological orientation is proxied by green patenting activity in CPC classes $Y02A$, $Y02B$, $Y02C$, $Y02D$, $Y02E$, $Y02P$, $Y02T$, and $Y02W$, while income-group classification captures differences in regulatory capacity and absorptive ability across middle- and high-income countries.

Let total host-country GHG emissions be denoted by E_{it}. Total emissions are given by

$$E_{it} = \bar{D}_i + Z^d_{it} + Z^f_{it}, \tag{1}$$

where E_{it} denotes total GHG emissions in country i at time t, $\bar{D}_i$ is an exogenous country-specific baseline component of emissions that is independent of production decisions — capturing, for example, emissions from natural sources or pre-existing infrastructure — and Z^d_{it} and Z^f_{it} denote emissions generated by domestic and foreign-affiliate production, respectively. In the empirical implementation, $\bar{D}_i$ is subsumed by the country fixed effect μ_i, which absorbs all time-invariant country-specific factors.

Since the empirical analysis uses emissions per capita, we define

$$GHG_{it} = \frac{E_{it}}{Pop_{it}}, \tag{2}$$

where Pop_{it} denotes population. The dependent variable in the empirical models is therefore

$$\log(GHG_{it}) = \log\left(\frac{E_{it}}{Pop_{it}}\right). \tag{3}$$

Dividing total emissions by population yields the per-capita emissions measure used in the empirical analysis.

The domestic firm minimizes production cost subject to a target level of output:

$$\min_{K^d_{it}, L^d_{it}, Z^d_{it}} C^d_{it} = r_{it} K^d_{it} + w_{it} L^d_{it} + \tau_{it} Z^d_{it} \tag{4}$$

subject to

$$X^d_{it} = A^d(P_{it})\, G(K^d_{it}, L^d_{it})\, (Z^d_{it})^{\alpha}, \quad 0 < \alpha < 1. \tag{5}$$

Here, K^d_{it} and L^d_{it} denote capital and labor employed by the domestic firm, Z^d_{it} is the emissions level associated with domestic production, and X^d_{it} is target output. The parameters r_{it} and w_{it} are the domestic rental price of capital and wage rate, while τ_{it} denotes the effective cost of emissions under environmental regulation and enforcement. The term P_{it} is a vector of green patent indicators, and $A^d(P_{it})$ is a technology shifter for the domestic firm. The parameter $\alpha \in (0, 1)$ implies diminishing emissions returns to output scale: holding other inputs fixed, successive increases in output require proportionally smaller increases in emissions. $G(\cdot)$ is an increasing, concave production function in capital and labor.

The foreign affiliate solves

$$\min_{K^f_{it}, L^f_{it}, Z^f_{it}} C^f_{it} = r^*_t K^f_{it} + w_{it} L^f_{it} + \tau_{it} Z^f_{it} \tag{6}$$

subject to

$$X^f_{it} = A^f(P_{it}, s_i)\, G(K^f_{it}, L^f_{it})\, (Z^f_{it})^{\alpha}, \quad K^f_{it} = \kappa(FDI_{it}), \tag{7}$$

where K^f_{it}, L^f_{it}, and Z^f_{it} denote the foreign affiliate's capital, local labor, and emissions in the host country, and X^f_{it} denotes its target output. The parameter r^*_t is the foreign investor's cost of capital. The term $A^f(P_{it}, s_i)$ captures how technological orientation and income-group conditions jointly affect the productivity of the foreign affiliate, where $s_i \in \{M, H\}$ denotes the country's income group. The income-group indicator s_i enters A^f because middle- and high-income countries differ systematically in regulatory capacity, institutional quality, and absorptive ability, all of which shape how foreign affiliates operate and what technologies they deploy. By contrast, the domestic firm's technology shifter $A^d(P_{it})$ depends only on patents, reflecting the assumption that domestic firms respond primarily to the local technological environment rather than to the broader institutional conditions that differentiate income groups. The mapping $K^f_{it} = \kappa(FDI_{it})$, where $\kappa(\cdot)$ is an increasing function, links the capital employed by the foreign affiliate to FDI inflows. This is a simplifying assumption that abstracts from capital depreciation and accumulation dynamics; in particular, it does not distinguish between FDI as a flow and capital as a stock. This simplification is maintained for tractability and is standard in partial-equilibrium frameworks of this type.

Solving the firms' cost-minimization problems yields conditional emission-demand functions of the form

$$Z^d_{it} = z^d(X^d_{it}, P_{it}, \tau_{it}), \quad Z^f_{it} = z^f(X^f_{it}, FDI_{it}, P_{it}, s_i, \tau_{it}), \tag{8}$$

with higher output increasing emissions and a higher effective emissions cost reducing them. Substituting these expressions into the total-emissions identity implies that total host-country emissions can be written as

$$E_{it} = \bar{D}_i + z^d(X^d_{it}, P_{it}, \tau_{it}) + z^f(X^f_{it}, FDI_{it}, P_{it}, s_i, \tau_{it}). \tag{9}$$

Letting total host-country output be $Q_{it} = X^d_{it} + X^f_{it}$, this relationship can be summarized in reduced form as

$$E_{it} = H(Q_{it}, FDI_{it}, P_{it}, s_i, \tau_{it}), \tag{10}$$

where $H(\cdot)$ is an aggregate emissions function linking total emissions to production scale, foreign investment, technological orientation, income-group characteristics, and the effective cost of emissions. This is the reduced-form representation of the conceptual model: after substituting out the firms' optimal choices, total emissions depend directly on observable determinants rather than on the firms' internal optimization variables.

Because the empirical analysis is based on emissions per capita, the corresponding empirical outcome is

$$GHG_{it} = \frac{H(Q_{it}, FDI_{it}, P_{it}, s_i, \tau_{it})}{Pop_{it}}. \tag{11}$$

In mapping this reduced form to the empirical specifications in Sections 4.2.1 and 4.2.2, several bridging assumptions are made explicit. First, total output Q_{it} is proxied by GDP per capita, which is the standard approach in cross-country environmental economics. The inclusion of both GDP per capita and its squared term allows for a potentially non-linear relationship between income and emissions, consistent with the EKC hypothesis. Second, the effective emissions cost τ_{it} is not directly observable and is therefore subsumed by the country fixed effect μ_i and the year fixed effect λ_t, which together absorb time-invariant country-specific regulatory stringency and common year-specific shocks to environmental policy. Third, trade openness and demographic variables including population growth and urban population per capita are included as empirical controls to account for factors that influence emissions but lie outside the production-based framework. These variables do not have explicit counterparts in the theoretical model and are included to reduce omitted variable bias in the empirical specifications. Fourth, in the empirical implementation, the vector P_{it} is operationalized through the sector-specific $Y02$ patent indicators, so that $P_{it} = (Y02A_{it}, Y02B_{it}, Y02C_{it}, Y02D_{it}, Y02E_{it}, Y02P_{it}, Y02T_{it}, Y02W_{it})$.

Within this framework, the net effect of green patents on emissions is theoretically ambiguous. On the one hand, stronger green inventive activity may reduce emissions intensity by improving production techniques and absorptive capacity – a technique effect operating through A^d and A^f. On the other hand, it may accompany output expansion, structural change, or delayed technology diffusion, generating a scale effect that raises total emissions. The sign of the net effect depends on which channel dominates, and this is an empirical question. Likewise, FDI may raise emissions through scale and composition effects, as foreign affiliates expand production in the host economy, or reduce them through technology transfer and superior management practices embedded in $A^f(P_{it}, s_i)$. In the empirical implementation, these channels are captured through aggregate patenting, sector-specific green patent indicators, FDI–income interactions, patent–income interactions, and patent–FDI interactions. Because the patent variables used in this study are jurisdiction-based indicators of green inventive activity rather than direct measures of technology adoption, the framework should be interpreted as linking FDI to emissions through the technological orientation of the host economy, not through a literal measure of clean-technology deployment.

4. Data and method

4.1. Data

This study uses an unbalanced panel dataset covering 74 countries over the period 1975–2021. The dataset combines environmental, economic, and innovation-related variables. The dependent variable is the natural logarithm of GHG emissions per capita. The dependent variable in our analysis is in per capita, which is standard in the environmental economics literature (for example, Acheampong, 2018; Romero and Gramkow, 2021). The explanatory variables include FDI, trade, GDP and its square, urban population, population growth, and the number of green patent applications across sector-specific $Y02$ categories, with most variables expressed in per capita terms. All main variables are expressed in per capita terms to ensure consistency with the dependent variable (GHG emissions per capita) and to allow meaningful cross-country comparisons. This normalization controls for differences in country size and focuses on intensity rather than scale. While alternative measures, such as per worker or per firm, could capture different aspects of economic activity and innovation, comparable data for these measures are not consistently available across countries and over the full sample period. For this reason, per capita variables are used as a practical and standard approach in cross-country analysis.

The dataset integrates multiple publicly available international data sources. GHG emissions are taken from the Emissions Database for Global Atmospheric Research (EDGAR) (Crippa et al., 2023). GDP, trade, FDI, and population indicators are obtained from the World Bank's World Development Indicators (WDI) database (Bank, 2023). These sources have been widely used in studies examining the relationship between FDI, growth, and environmental outcomes (Grossman and Krueger, 1995; Dinda, 2004; Zhang, 2013; Baek and Kim, 2013; Antweiler et al., 2001; Wang et al., 2014; Shi, 2003; Dietz and Rosa, 1997; Johnstone et al., 2010; Popp, 2002; Lanjouw and Mody, 1996).

Patent data are drawn from the EPO PATSTAT Global database, which relies on the Cooperative Patent Classification (CPC) system (Office, 2023; European Patent Office, 2022; Cooperative Patent Classification, 2020). Green technological innovation is identified using the CPC $Y02$ subclass, which is specifically designed to capture technologies for climate change mitigation and adaptation. To move beyond an aggregate measure of green innovation, the analysis distinguishes among the main $Y02$ categories, namely $Y02A$ (adaptation to climate change), $Y02B$ (buildings), $Y02C$ (carbon capture, storage, sequestration, or disposal of greenhouse gases), $Y02D$ (information and communication technologies for mitigation), $Y02E$ (energy generation, transmission, or distribution), $Y02P$ (production and processing of goods), $Y02T$ (transportation), and $Y02W$ (waste and wastewater management).[4] Each subclass is included separately in order to capture sector-specific differences in the relationship between green innovation and emissions.

The use of patent classification systems, such as CPC, is standard in the empirical literature on green innovation. This is because alternative approaches, such as keyword searches, are highly sensitive to terminology, and manual identification is not feasible in large patent datasets. In this study, patent counts are therefore interpreted as proxies for green inventive activity and technological orientation, rather than as direct measures of clean-technology adoption. While patenting reflects codified innovative output and the legal protection of an invention, it does not necessarily imply immediate commercialization, diffusion or effective environmental deployment. In the present dataset, patents are assigned geographically based on the patent application authority recorded in PATSTAT.[5] For this reason, the patent indicators should not be interpreted as pure measures of domestic invention, but rather as office-based indicators of green patenting activity associated with a jurisdiction. This distinction is particularly important in a cross-country setting, where patenting intensity differs substantially across countries and where knowledge may spill over internationally through trade, licensing, multinational production, imitation, and FDI.

Table 1 presents the descriptive statistics of the variables used in the analysis, all expressed after transformation as described in the table notes (the same summary table, reported separately for middle- and high-income countries, is provided in Appendix C). The average log-transformed GHG per capita across the sample amounts to approximately 9.17, with a relatively low standard deviation (0.58), indicating a concentrated distribution around the mean. The innovation indicator, measured as log-transformed patents per capita, exhibits a mean of 0.95 and a comparable standard deviation, pointing to substantial heterogeneity in patenting activity across countries. The signed log-transformed FDI per capita shows a wide range from approximately −26.9 to 26.3 reflecting considerable variation in both inward and outward FDI flows. Log-transformed trade openness displays moderate variation with a mean of 1.67 and a standard deviation of 1.28. Log-transformed GDP per capita averages 23.40 and ranges between 20.20 and 25.62, while its squared term is included to capture potential non-linearities in the income–emissions relationship. Signed log-transformed population growth has a relatively low mean (0.42) and modest dispersion (standard deviation of 0.51). In contrast, log-transformed urban population per capita shows greater variability (mean 1.74; standard deviation 1.15), reflecting differences in urbanization levels across countries.[6] Overall, the summary statistics suggest pronounced cross-country variation in environmental, economic, and demographic indicators, underscoring the appropriateness of employing panel estimation techniques that account for both within- and between-country heterogeneity.

Fig. 1 presents the Pearson correlation matrix for the variables used in the analysis. Several patterns stand out. GHG emissions per

[4] A detailed description of the essence of patents and $Y02$ patent classes are provided in Appendix B.

[5] Accordingly, the country dimension refers to the jurisdiction in which patent protection is sought rather than strictly to the inventor's or applicant's country of residence. The patent counts may therefore include both domestic and foreign-originated inventions filed in a given jurisdiction. Patent protection is territorial, and the location of filing does not necessarily coincide with the location of invention or eventual use.

[6] Prior to applying logarithmic transformations, all per capita variables are rescaled by multiplying by one million to improve numerical readability. Because the log and signed-log transformations are nonlinear, this rescaling factor enters the transformed values and affects their scale. In particular, $\log(\text{GDP per capita})$ values in Table 1 appear substantially larger than conventional log-GDP values because the rescaling adds $\log(10^6) \approx 13.8$ to the transformed values. Similarly, the wide range of the signed log-transformed FDI per capita variable from approximately -26.9 to 26.3 reflects both large inward and large outward FDI flows in the sample, with the signed transformation preserving the direction of net flows. Coefficient magnitudes throughout the paper should therefore be interpreted with reference to the rescaled and transformed variables as defined here, rather than to the original units.

Table 1
Descriptive statistics of variables.

Variables	Mean	Std. dev.	Min	Max	N
log(GHG per capita)	9.17	0.58	7.24	10.59	1844
log(Patents per capita)	0.95	0.95	0.00	4.06	1844
log(FDI per capita)	16.91	9.84	−26.92	26.30	1844
log(Trade per capita)	1.67	1.28	0.02	5.51	1844
log(GDP per capita)	23.40	1.06	20.20	25.62	1844
$(\log(\text{GDP per capita}))^2$	548.66	49.30	408.11	656.33	1844
log(Population growth)	0.42	0.51	−2.73	2.91	1844
log(Urban population per capita)	1.74	1.15	0.02	5.79	1844

Notes: All variables are expressed in per capita terms. Because the resulting per capita values were small, they were multiplied by one million to improve numerical readability. For strictly non-negative variables (GHG, patents, trade, GDP, and urban population), the natural logarithm of $(x+1)$ was applied. For variables that may take negative or zero values, namely FDI per capita and population growth, a signed logarithmic transformation $\text{sign}(x)\log(1+|x|)$ was used to preserve both direction and variation. This approach avoids distortions from large constant shifts while maintaining interpretability under logarithmic-type transformations. Rescaling is applied prior to the logarithmic transformations. Because the log and signed-log transformations are nonlinear, the rescaling factor enters the transformed values and affects their scale. Coefficient magnitudes should therefore be interpreted with reference to the rescaled and transformed variables as defined here, rather than to the original units.

capita are moderately and positively correlated with GDP per capita ($r = 0.57$) and its squared term ($r = 0.56$), indicating that higher income levels are generally associated with greater emissions, consistent with the upward segment of the EKC. A positive correlation also emerges between GHG emissions and patents per capita ($r = 0.38$), suggesting that higher innovation intensity does not necessarily coincide with immediate reductions in emissions. By contrast, FDI per capita shows a weak and slightly negative correlation with GHG emissions ($r = -0.06$), implying the absence of a systematic linear relationship between foreign investment and environmental outcomes at the aggregate level. Trade per capita exhibits a moderate positive correlation with GDP per capita ($r = 0.32$) and a very strong correlation with urban population per capita ($r = 0.94$), reflecting the expected co-movement between trade openness, economic development, and urbanization. Population growth remains largely uncorrelated with other variables, including emissions ($r = 0.03$), indicating limited direct influence on per capita outcomes. Overall, the correlation matrix highlights the interconnected nature of economic, innovation, and demographic factors in shaping emission dynamics, while also suggesting that the relationship between FDI and environmental performance is highly heterogeneous and likely context-dependent.

Fig. 2 displays the time trends in the average log of GHG emissions per capita across country income groups from 1975 to 2021 (the time trends for the other variables are in Appendix D). Two distinct trends emerge from the data. First, high-income countries consistently exhibit the highest levels of per capita GHG emissions throughout the sample period. However, there is a downward trend in emissions starting from the early 2000s, which may reflect the effects of environmental regulations, technological improvements, and structural shifts in their economies toward services and lower-emission sectors. Second, middle-income countries show volatility in per capita emissions, especially during the 1980s and 1990s. Nonetheless, a gradual decline is observed from the mid-2000s onward, although the levels remain substantially lower than in high-income countries. Overall emissions decline steadily from around 1995, suggesting some degree of global convergence in per capita emissions, albeit at different speeds across income groups. Thus, Fig. 2 highlights both the persistence of inequality in emissions and the global shift toward lower per capita emissions.

4.2. Method

This study employs both static and dynamic panel estimation techniques to investigate the determinants of GHG emissions per capita across countries. Following the empirical framework of Salari and Javid (2016), we begin with static models – pooled Ordinary Least Squares (OLS), Random Effects (RE), and TWFE – and subsequently proceed to dynamic estimation using the GMM to address potential endogeneity and dynamic persistence in emissions behavior. The TWFE specifications include both country and year fixed effects. By contrast, the system GMM specifications focus on dynamic persistence and potential endogeneity through lagged dependent variables and internal instruments. Year fixed effects are excluded from the GMM specifications for two reasons. First, including time dummies in the system GMM framework substantially increases the instrument count and can exacerbate instrument proliferation concerns. Second, the lagged dependent variable captures a substantial portion of the time persistence in emissions, reducing the need for year fixed effects to control for common trends.

4.2.1. Static panel estimation

To estimate the relationship between GHG emissions and their determinants, the analysis begins with three baseline panel estimators: pooled OLS, RE and TWFE. The dependent variable is the natural logarithm of GHG emissions per capita, $\log(\text{GHG}_{it})$. The baseline specification includes explanatory variables capturing technological innovation, FDI, trade, economic size and scale, demographic pressure, and urbanization:

$$\begin{aligned}\log(\text{GHG}_{it}) = \alpha &+ \beta_1 \log(\text{Patents}_{it}) + \beta_2 \log(\text{FDI}_{it}) + \beta_3 \log(\text{Trade}_{it}) \\ &+ \beta_4 \log(\text{GDP}_{it}) + \beta_5[\log(\text{GDP}_{it})]^2 + \beta_6 \log(\text{PopGrowth}_{it}) \\ &+ \beta_7 \log(\text{Urban}_{it}) + \varepsilon_{it}. \qquad (12)\end{aligned}$$

In this specification, $\log(\text{Patents}_{it})$ captures technological innovation, $\log(\text{FDI}_{it})$ measures FDI, and $\log(\text{Trade}_{it})$ reflects trade. Economic size and scale are represented by $\log(\text{GDP}_{it})$ and its squared term, $[\log(\text{GDP}_{it})]^2$, allowing for a potentially nonlinear relationship between economic development and emissions consistent with the EKC hypothesis. The remaining controls, $\log(\text{PopGrowth}_{it})$ and $\log(\text{Urban}_{it})$, account for demographic pressure and urbanization, respectively. Trade openness, population growth, and urbanization do not have explicit counterparts in the conceptual framework and are included as empirical controls to reduce omitted variable bias.

Pooled OLS is first estimated as a benchmark specification. The RE model is then employed to account for unobserved country-specific heterogeneity under the assumption that the individual effects are uncorrelated with the regressors. The Breusch–Pagan Lagrange Multiplier (LM) test is used to assess whether the RE estimator is preferred to pooled OLS. Under the null hypothesis of the Breusch–Pagan test, the variance of the individual-specific effects is zero, implying that pooled OLS is appropriate. Rejection of the null supports the use of the random effects estimator. Subsequently, a TWFE model is estimated to control for both unobserved country characteristics and common time shocks. The Hausman test is used to determine whether the FE estimator is

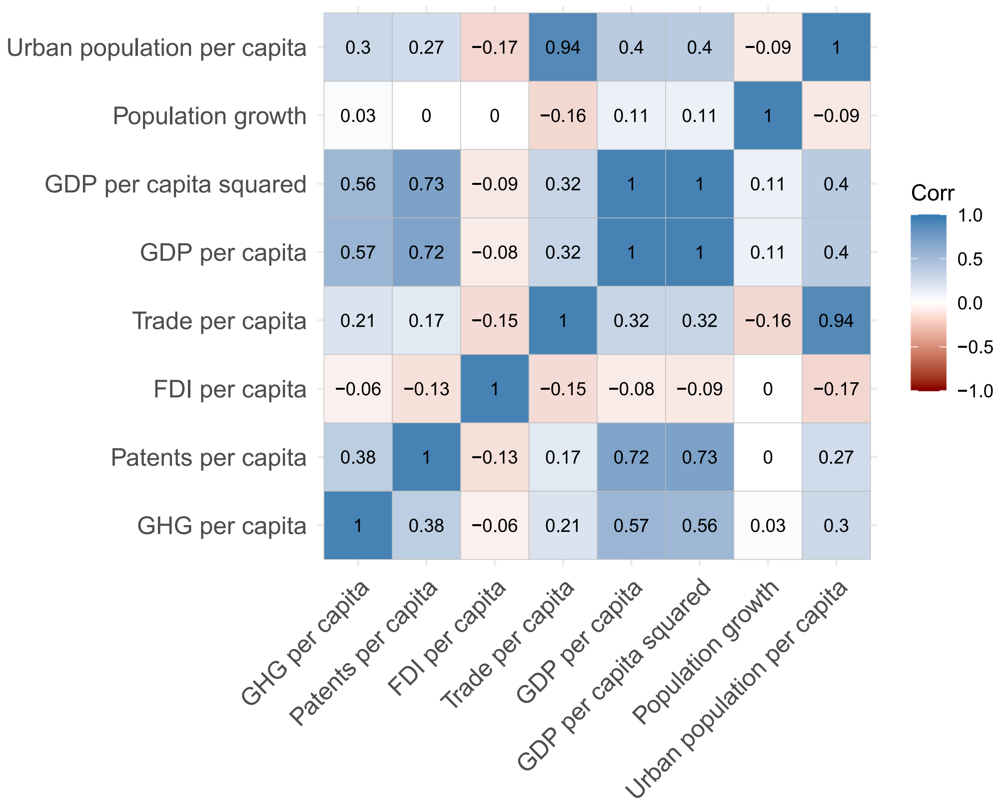

Fig. 1. Correlation matrix of the variables.

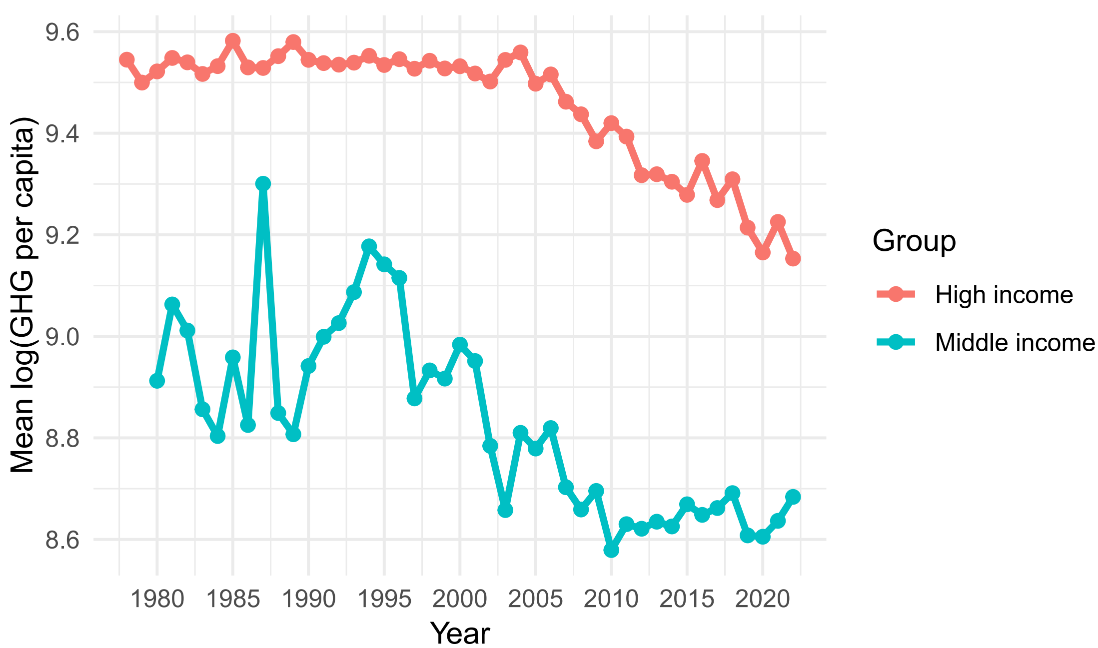

Fig. 2. Average GHG emissions per capita over time.

preferred to the RE estimator. Under the null hypothesis of the Hausman test, the individual effects are uncorrelated with the regressors and both estimators are consistent, with RE being more efficient. Rejection of the null indicates that the RE assumption is violated and that the FE estimator should be preferred. The strong rejection reported in Table 2 therefore supports the use of the TWFE specification as the preferred static estimator. Country-clustered robust standard errors are reported for the TWFE model.

In addition to the baseline specification, an extended TWFE model is estimated to examine heterogeneity in the relationship between green technological innovation, FDI and emissions. This specification replaces the aggregate patent variable with sector-specific green patent indicators and incorporates interaction terms between patents and income-group classification, as well as between patents and FDI. This extended specification is reported as a robustness check in Section 6 rather than as a main result, as it involves a large number of regressors relative to the available sample. High-income countries serve as the reference category. The extended specification is given by:

$$\begin{aligned}\log(\text{GHG}_{it}) = \alpha &+ \sum_{k\in\{A,B,C,D,E,P,T,W\}} \beta_k \log(\text{Y02}^k_{it}) \\ &+ \sum_{k\in\{A,B,C,D,E,P,T,W\}} \phi_k \left[\log(\text{Y02}^k_{it}) \times \text{MiddleIncome}_i\right] \\ &+ \sum_{k\in\{A,B,C,D,E,P,T,W\}} \psi_k \left[\log(\text{Y02}^k_{it}) \times \log(\text{FDI}_{it})\right] \\ &+ \theta \log(\text{FDI}_{it}) + \mathbf{X}'_{it}\delta + \mu_i + \lambda_t + \varepsilon_{it},\end{aligned} \tag{13}$$

where $\log(\text{Y02}^k_{it})$ denotes sector-specific green patent indicators, with $k \in \{A,B,C,D,E,P,T,W\}$. MiddleIncome_i is an income-group dummy, while high-income countries constitute the reference category. The coefficients on the patent–income interaction terms capture whether the association between sector-specific green patent activity and emissions differs between middle-income and high-income economies. The patent–FDI interaction terms indicate whether the relationship between green innovation and emissions varies with the level of FDI. $\mathbf{X}_{it}$ is a vector of control variables including $\log(\text{Trade}_{it})$, $\log(\text{GDP}_{it})$, $[\log(\text{GDP}_{it})]^2$, $\log(\text{PopGrowth}_{it})$, and $\log(\text{Urban}_{it})$, while μ_i and λ_t denote country and time fixed effects, respectively.

4.2.2. Dynamic panel estimation

Recognizing the dynamic nature of environmental degradation and the potential endogeneity of key regressors, particularly FDI, income, and innovation, we estimate a dynamic panel model using the Arellano–Bond-type system GMM estimator developed by Blundell and Bond (1998). This approach accounts for persistence in emissions and helps mitigate potential endogeneity, omitted variable bias, and reverse causality through internal instrumentation. To capture the dynamic adjustment of emissions, the model includes multiple lags of the dependent variable:

$$\begin{aligned}\log(\text{GHG}_{it}) = \alpha &+ \gamma_1 \log(\text{GHG}_{i,t-1}) + \gamma_2 \log(\text{GHG}_{i,t-2}) + \gamma_3 \log(\text{GHG}_{i,t-3}) \\ &+ \sum_{k\in\{A,B,C,D,E,P,T,W\}} \beta_k \log(\text{Y02}^k_{it}) \\ &+ \theta_M \left[\log(\text{FDI}_{it}) \times \text{MiddleIncome}_i\right] \\ &+ \theta_H \left[\log(\text{FDI}_{it}) \times \text{HighIncome}_i\right] \\ &+ \mathbf{X}'_{it}\delta + \varepsilon_{it},\end{aligned} \tag{14}$$

where $\log(\text{Y02}^k_{it})$ denotes sector-specific green patent indicators, MiddleIncome_i and HighIncome_i are income-group dummies, and $\mathbf{X}_{it}$ is a vector of control variables including $\log(\text{Trade}_{it})$, $\log(\text{GDP}_{it})$, $[\log(\text{GDP}_{it})]^2$, $\log(\text{PopGrowth}_{it})$, and $\log(\text{Urban}_{it})$. The coefficients γ_1, γ_2, and γ_3 capture the persistence of emissions over time. Since the estimation sample is restricted to middle- and high-income countries, the effect of FDI is modeled directly through group-specific interaction terms. Thus, θ_M gives the FDI effect for middle-income countries, whereas θ_H gives the FDI effect for high-income countries.

The number of lags of the dependent variable is set to three following standard practice in dynamic panel models of environmental outcomes (see, e.g., Doytch and Uctum, 2016; Salari and Javid, 2016), and to ensure that the persistence structure of GHG emissions is adequately captured. Including up to three lags allows for gradual adjustment dynamics while keeping the model parsimonious. The three-lag specification is nonetheless retained for consistency and to allow comparison across specifications.

This specification allows us to examine both the direct effect of green innovation on emissions and the heterogeneous effect of FDI across income groups. In contrast to the baseline model, the dynamic specification explicitly incorporates sector-specific patent categories and FDI–income interaction terms as core regressors. To address dynamic persistence and potential endogeneity, the lagged dependent variable and FDI are treated as endogenous and instrumented using internal lagged instruments within the Blundell–Bond system GMM framework. The remaining controls in $\mathbf{X}_{it}$ are included as additional covariates but are not separately instrumented as endogenous variables unless otherwise specified.[7]

To limit instrument proliferation, the instrument matrix is collapsed following Roodman (2009). The lagged dependent variable is instrumented using its second lag, and the number of instruments is kept below the number of countries in all specifications to reduce the risk of instrument proliferation bias. We report both one-step and two-step system GMM estimates and evaluate model validity using standard diagnostic tests. The Sargan test is used to examine the validity of overidentifying restrictions, while the Arellano–Bond tests are applied to detect first-order AR(1) and second-order AR(2) autocorrelation in the first-differenced residuals. We also report robust standard errors for both one-step and two-step models.

5. Empirical results

Table 2 reports static panel estimates of log(GHG emissions per capita). We present pooled OLS, RE, TWFE, TWFE with Arellano-type HAC standard errors clustered at the country level ("FE, robust"), and a TWFE specification with an interaction between FDI and the middle-income indicator ("FE, Int."). The income-group classification used in the interaction specification is measured annually using the World Bank income classification. Therefore, the middle-income indicator varies over time for countries that transition between middle- and high-income status during the sample period. The robust FE column reports the same coefficient estimates as the standard TWFE model but with country-clustered robust standard errors.

In the RE model, FDI per capita is positive and statistically significant, indicating that countries with higher FDI inflows tend to have higher per-capita GHG emissions. In terms of magnitude, however, the estimated effect is modest. Because FDI per capita is entered using a signed logarithmic transformation, $\text{sign}(x)\log(1 + |x|)$, the coefficient should not be interpreted as a conventional elasticity with respect to raw FDI. Rather, it reflects the approximate percentage change in GHG emissions per capita associated with a one-unit increase in the transformed FDI measure.[8] The estimated coefficient of approximately 0.001 in the RE model therefore implies that a one-unit increase in the transformed FDI variable is associated with about a 0.1% increase in GHG emissions per capita. In the TWFE models, the FDI coefficient remains positive and of a similar order of magnitude, but it is only weakly significant under conventional standard errors and becomes statistically insignificant once country-clustered robust standard errors are applied. Thus, the static results suggest a positive FDI–emissions association, but this relationship is not robust to more conservative inference.

In the TWFE interaction model, which allows the FDI–emissions relationship to differ across annual income-status categories, the main FDI coefficient refers to high-income country-years, which serve as the reference category. This coefficient is positive and statistically significant at the 10% level. The interaction term between FDI and the middle-income indicator is negative and only marginally significant. In

[7] In the system GMM estimations, the lagged dependent variable and FDI are treated as endogenous and instrumented using internal lagged instruments within the Blundell–Bond framework. The remaining controls are included as covariates but are not separately instrumented as endogenous variables unless otherwise specified. The instrument matrix is collapsed to limit instrument proliferation.

[8] This interpretation follows the broader literature on transformed dependent variables with zeros. For example, Fergusson and Molina (2019) use $\log(1 + y)$ for protest counts and explicitly discuss the implied semi-elasticities, while Bellemare and Wichman (2020) show more generally that coefficients under log-like transformations with zeros should be interpreted carefully and not automatically treated as conventional elasticities.

magnitude terms, the coefficient on log(FDI per capita) is about 0.001 for high-income country-years, while the interaction term is about -0.002. This implies that the estimated marginal association between FDI and emissions is weaker, and possibly slightly negative, for middle-income country-years in this static specification. However, given the marginal significance of the interaction term and the sensitivity of the FDI coefficient to robust inference, this result should be interpreted cautiously. The static interaction model therefore provides only limited evidence of income-status heterogeneity in the FDI–GHG relationship.

Patents per capita are positive and highly significant in the standard TWFE and TWFE interaction models, indicating that increases in patenting intensity are associated with higher per-capita emissions within countries over time. In terms of magnitude, the TWFE coefficient on log(Patents per capita) is approximately 0.036, implying that a one-unit increase in the transformed patent variable is associated with about a 3.6% increase in GHG emissions per capita. Since the patent variable is measured as $\log(x + 1)$, this effect is best interpreted as a semi-elasticity with respect to the transformed patent measure rather than as a conventional elasticity with respect to raw patent counts. When country-clustered robust standard errors are used, the patent coefficient loses statistical significance, suggesting that the within-country association between patenting and emissions is sensitive to robust inference. Nevertheless, the estimated sign remains positive across the fixed effects specifications.

Other covariates behave largely as expected. GDP per capita and its squared term are statistically significant with opposing signs across all models, providing evidence consistent with the EKC hypothesis (Grossman and Krueger, 1995). Urbanization is positively associated with emissions in the pooled OLS and RE models, but becomes negative and statistically significant in the fixed effects specifications. This suggests that, after controlling for time-invariant country characteristics and common year shocks, within-country increases in urbanization are associated with lower per-capita emissions. The effect of trade is negative and significant in the pooled OLS and RE models, but becomes positive and statistically insignificant in the fixed effects models, suggesting that its association with emissions is partly driven by unobserved country-level heterogeneity rather than reflecting a robust within-country relationship. The Breusch–Pagan LM test supports the use of random effects over pooled OLS, while the Hausman test favors the fixed effects estimator, indicating correlation between the regressors and unobserved country effects. The heteroskedasticity and Wooldridge tests indicate the presence of heteroskedasticity and serial correlation, justifying the use of the robust standard error specification.

Overall, the static panel results provide some evidence that FDI is positively associated with GHG emissions, although this relationship becomes statistically weaker under country-clustered robust inference. The interaction specification suggests that the FDI–emissions association may differ across annual income status, but the evidence from the static models is not strong enough to establish a robust difference between middle-income and high-income country-years. The positive association between aggregate green patenting and emissions should also be interpreted cautiously, as it loses statistical significance under robust inference and may reflect the fact that patent activity captures inventive intensity and technological orientation rather than actual deployment of emissions-reducing technologies.

This study also employs both one-step and two-step system GMM estimators, incorporating lagged dependent variables from one to three periods to capture the dynamic nature of GHG emissions. Table 3 reports the system GMM estimates for GHG emissions per capita across alternative model specifications. The GMM sample contains 3402 observations across 74 countries, compared with 1844 observations in the static panel models reported in Table 2. This difference arises because the GMM specifications draw on a broader set of country-year observations that include years for which patent data are unavailable, as the dynamic system GMM models incorporate sector-specific patent categories directly as regressors but do not require the same balanced coverage as the static fixed effects estimations. Using both estimators allows us to compare results under different weighting matrix assumptions and to assess the robustness of the main findings. In the reported specifications, the instrument matrix is collapsed in order to limit instrument proliferation, and the lagged dependent variable is instrumented using its second lag.

The lagged dependent variable shows strong persistence in GHG emissions. The first lag of log(GHG emissions per capita) is positive and statistically significant across all specifications, with coefficients slightly above one. This suggests a high degree of persistence in emissions over time. By contrast, the second and third lags are statistically insignificant in all models. The dynamic estimates therefore indicate that persistence is mainly captured by the first lag, with the second and third lags contributing negligible additional explanatory power.

The results for the green patent variables provide only limited evidence of a systematic relationship between green patenting activity and GHG emissions in the dynamic specifications. Most patent categories are statistically insignificant across the four models. The main exception is $Y02D$, which is positive and statistically significant in the one-step baseline model and the one-step interaction model, and weakly significant in the two-step interaction model. This suggests that patenting activity in climate-related information and communication technologies is positively associated with GHG emissions in some dynamic specifications. However, this result should be interpreted cautiously, both because the statistical significance is not fully robust across estimators and because patent counts capture technological orientation or inventive activity rather than actual technology adoption. Overall, the dynamic estimates do not provide strong evidence that green patenting activity is systematically associated with lower GHG emissions in the short run.

In the baseline GMM specifications, the coefficient on transformed FDI per capita is positive but statistically insignificant in both the one-step and two-step models. This means that, once the dynamic structure and the revised instrument strategy are taken into account, the baseline GMM results no longer provide strong evidence of a statistically significant aggregate association between FDI and GHG emissions.

To examine heterogeneity across income-status categories, Columns 3 and 4 replace the aggregate FDI variable with separate coefficients for middle-income and high-income country-years. The coefficient for middle-income country-years is positive and statistically significant at the 10% level in the one-step interaction model and at the 5% level in the two-step interaction model. By contrast, the coefficient for high-income country-years is small and statistically insignificant in both interaction specifications. These results suggest that the positive FDI–GHG association is concentrated mainly among middle-income country-years, while there is no robust evidence of a corresponding relationship among high-income country-years.

Because FDI per capita is entered using the signed logarithmic transformation $\mathrm{sign}(x)\log(1 + |x|)$, the FDI coefficients should not be interpreted as conventional elasticities with respect to raw FDI. Rather, they indicate the approximate percentage change in GHG emissions per capita associated with a one-unit increase in the transformed FDI measure. In the baseline models, the estimated coefficient is approximately 0.0003 and statistically insignificant. In the interaction models, a one-unit increase in transformed FDI is associated with an increase in emissions of approximately 0.15–0.17% in middle-income country-years, while the corresponding estimate for high-income country-years is approximately 0.02% and statistically insignificant. Although the middle-income coefficient is larger than the high-income coefficient, Table 3 does not by itself provide a formal test of whether the difference between the two income-specific coefficients is statistically significant. Therefore, the income-status difference should be interpreted as suggestive rather than conclusive.

The remaining control variables are generally weaker in the GMM specifications than in the static models. Trade per capita is negative but statistically insignificant across all four models. In the baseline specifications, both GDP per capita and its squared term are statistically insignificant. In the interaction specifications, GDP per capita remains insignificant, while its squared term is positive and weakly significant at the 10% level. This pattern does not support the conventional EKC hypothesis, which would require a positive coefficient on GDP per capita and a negative coefficient on its squared term; the positive squared term here instead implies an upward-curving relationship between income and emissions, contrary to the EKC prediction. Population growth is negative and statistically significant at the 5% level in the one-step specifications and at the 10% level in the two-step specifications across all models, suggesting a negative conditional association with emissions. Urban population per capita is positive but statistically insignificant throughout.

The main interaction specifications classify countries according to their annual World Bank income status. This allows the models to capture variation for countries that move between middle- and high-income categories over time. However, annual income-status changes may not fully reflect persistent structural differences between middle- and high-income economies. Therefore, as a robustness check, Tables 4 and 5 re-estimate the static panel and dynamic system GMM specifications using a time-invariant income classification based on each country's latest available income status.

The results from the static panel models are broadly consistent with the main findings. The coefficient on FDI per capita remains positive in the fixed effects specifications, although its statistical significance remains sensitive to the choice of standard errors. Importantly, the interaction between FDI per capita and the time-invariant middle-income indicator is small and statistically insignificant. This suggests that, in the static specification, there is limited evidence that the FDI–GHG relationship differs systematically between structurally middle-income and high-income countries.

The time-invariant system GMM results present a more nuanced picture than the main specifications. The lagged dependent variable remains strongly significant, confirming the high persistence of GHG emissions over time. Notably, in the time-invariant baseline specifications, the aggregate FDI coefficient is positive and statistically significant in both the one-step and two-step models in contrast to the main specifications in Table 3, where the baseline FDI effect is insignificant. Furthermore, in the time-invariant interaction specifications, the high-income FDI coefficient is statistically significant in both the one-step and two-step models, while the middle-income coefficient is statistically significant only in the one-step model and insignificant in the two-step model. This pattern of mixed significance across income groups and estimators weakens the income-heterogeneity conclusion drawn from the main dynamic results and suggests that the stronger heterogeneity observed in Table 3 may be more closely linked to annual income-status variation than to permanent structural differences between economies. The time-invariant GMM results should therefore be interpreted as a robustness check that partially qualifies rather than simply confirms the main conclusions. In general, this analysis does not overturn the main conclusions. The results continue to suggest a positive association between FDI and GHG emissions, but the evidence for income-group heterogeneity is weaker when income status is defined as a fixed country-level characteristic.

6. Robustness checks

6.1. Two-way FE with Green patents grouped

Table 6 presents three TWFE specifications examining the relationship between disaggregated green patent categories ($Y02$) and GHG emissions per capita. All specifications include country and year fixed effects, thereby controlling for time-invariant country characteristics and common year-specific shocks. Income-group classification is measured annually using the World Bank income classification and is therefore allowed to vary over time. This means that countries that transition between middle- and high-income status during the sample period contribute within-country variation to the income-group indicators. In additional robustness checks, we also use a time-invariant country-level income classification in order to examine structural differences between middle- and high-income economies.

In the first specification, where no lagged patent variables are included, we observe that several categories of green patents are positively and significantly associated with GHG emissions. Notably, patents related to energy generation and distribution ($Y02E$), waste management ($Y02W$), and climate adaptation technologies ($Y02A$) are all associated with increased emissions. These results suggest that, in the short run, higher green patenting activity does not necessarily coincide with lower emissions. This is consistent with the broader literature emphasizing that the environmental effects of technology, foreign investment, and innovation may be ambiguous in the presence of scale effects, delayed diffusion, and heterogeneous regulatory conditions (Cole et al., 2017). By contrast, patents related to GHG capture, storage, sequestration, or disposal ($Y02C$) are negatively and statistically significantly associated with emissions in the contemporaneous specification.

This finding suggests that technologies directly targeting emissions capture and mitigation may be more closely associated with lower GHG emissions than broader categories of green patenting. The contrast between the negative coefficient on $Y02C$ and the positive coefficients on several other $Y02$ categories highlights the importance of distinguishing between different types of green technologies rather than relying only on aggregate patent measures. This is consistent with the argument that aggregated environmental or innovation indicators may conceal substantial heterogeneity across technological domains (Solarin and Al-Mulali, 2018).

Column (2) introduces 1-, 3-, and 6-year lags of each $Y02$ patent category. The results remain heterogeneous across technologies and lag structures. For transportation technologies ($Y02T$) and production or processing technologies ($Y02P$), the 6-year lag is negative and statistically significant, suggesting that these types of green technologies may be associated with emissions reductions only after a longer adjustment period. This delayed association is plausible, given that patented technologies may require time for commercialization, diffusion, adoption, and integration into production systems. Similarly, $Y02C$ continues to display a negative association with emissions, with the contemporaneous and 1-year lagged coefficients statistically significant and the 3-year lag marginally significant. These patterns suggest that some targeted mitigation technologies may be associated with lower emissions both contemporaneously and with delay.

However, not all lagged patent effects point toward emissions reductions. Waste-related patents ($Y02W$) remain positively associated with emissions across several lag structures, while adaptation-related patents ($Y02A$) also display positive and significant coefficients in the contemporaneous and 1-year lagged terms. Moreover, ICT-related mitigation patents ($Y02D$) are positive and statistically significant at the 3-year and 6-year lags. These findings indicate that the relationship between green patenting and emissions is not uniformly negative. Instead, it appears to depend strongly on the technological field and the time horizon considered. The positive coefficients may reflect transitional costs, rebound effects, or the possibility that some patent categories are more closely related to emissions-intensive economic activity than to immediate emissions abatement.

Column (3) adds income-group-specific FDI coefficients while retaining the disaggregated patent variables and their lag structures. Since income-group classification is measured annually, these coefficients refer to middle-income and high-income country-years rather than to time-invariant country groups. It should be noted that Column (3) is estimated on a reduced sample of 1270 observations, compared with 1871 and 1865 in Columns (1) and (2) respectively. This reduction arises because the income-group-specific FDI interaction requires complete data on both the income classification and the full set of

Table 2
Static panel estimations for GHG emissions per capita.

Variables	Pooled OLS	Random effect	Two-Way FE	Two-Way FE (Robust SE)	Two-Way FE (Int.)
log (Patents per capita)	–0.003 (0.019)	0.000 (0.008)	0.036*** (0.008)	0.036 (0.039)	0.036*** (0.008)
log (FDI per capita)	–0.001 (0.001)	0.001*** (0.000)	0.001· (0.000)	0.001 (0.000)	0.001* (0.000)
log (Trade per capita)	–0.161*** (0.027)	–0.072** (0.023)	0.014 (0.023)	0.014 (0.061)	–0.018 (0.023)
log (GDP per capita)	3.694*** (0.423)	3.063*** (0.160)	3.209*** (0.158)	3.209*** (0.615)	3.271*** (0.157)
log (GDP per capita)^2	–0.074*** (0.009)	–0.066*** (0.004)	–0.067*** (0.003)	–0.067*** (0.014)	–0.069*** (0.003)
log (Population growth)	–0.031 (0.023)	0.002 (0.012)	–0.047*** (0.011)	–0.047· (0.027)	–0.046*** (0.011)
log (Urban pop. per capita)	0.220*** (0.030)	0.135** (0.043)	–0.413*** (0.061)	–0.413* (0.198)	–0.416*** (0.061)
log(FDI per capita)× Middle income	–	–	–	–	–0.002· (0.001)
Constant	–36.866*** (4.833)	–26.354*** (1.814)	–	–	–
Observations	1844	1844	1844	1844	1844
R-squared	0.370	0.581	0.287	–	0.300
Breusch–Pagan LM test	13275.0*** (0.000)	–	–	–	–
Hausman test	–	548.81*** (0.000)	–	–	–
Heteroskedasticity test	–	–	203.77*** (0.000)	–	–
Wooldridge test	–	–	F=805.54***	–	–

Notes: Dependent variable: log(GHG emissions per capita). Standard errors in parentheses. All variables are in per capita terms. Non-negative variables are transformed as $\log(x+1)$; FDI per capita and population growth are transformed as $\mathrm{sign}(x)\log(1+|x|)$. "Two-Way FE (Int.)" adds an interaction between log(FDI per capita) and the annually measured middle-income indicator, with high-income country-years as the reference category. Because income classification is measured annually, countries that transition between middle- and high-income status contribute within-country variation to this interaction.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$. · $p < 0.15$.

Table 3
System GMM estimation results for GHG emissions per capita.

Variables	One-step	Two-step	One-step (Int.)	Two-step (Int.)
lag (log (GHG capita, 1))	1.076*** (0.175)	1.104*** (0.229)	1.084*** (0.177)	1.096*** (0.191)
lag (log (GHG capita, 2))	−0.002 (0.197)	−0.069 (0.236)	−0.001 (0.198)	−0.053 (0.202)
lag (log (GHG capita, 3))	−0.077 (0.058)	−0.028 (0.054)	−0.078 (0.054)	−0.037 (0.053)
log (Y02E capita)	−0.002 (0.007)	−0.001 (0.007)	−0.003 (0.007)	−0.002 (0.006)
log (Y02P capita)	−0.001 (0.007)	0.001 (0.009)	−0.001 (0.007)	0.003 (0.008)
log (Y02T capita)	−0.003 (0.005)	−0.005 (0.005)	−0.002 (0.005)	−0.004 (0.005)
log (Y02W capita)	0.003 (0.004)	0.005 (0.005)	0.003 (0.004)	0.005 (0.005)
log (Y02 A capita)	−0.008 (0.006)	−0.009 (0.006)	−0.008 (0.006)	−0.008 (0.006)
log (Y02B capita)	−0.003 (0.006)	−0.006 (0.006)	−0.003 (0.006)	−0.006 (0.005)
log (Y02C capita)	−0.004 (0.006)	−0.003 (0.005)	−0.005 (0.005)	−0.005 (0.004)
log (Y02D capita)	0.010*** (0.004)	0.007 (0.005)	0.009*** (0.003)	0.007* (0.004)
FDI (middle income)	–	–	0.0015* (0.0009)	0.0017** (0.0008)
FDI (high income)	–	–	0.0002 (0.0002)	0.0002 (0.0002)
log (FDI per capita)	0.0003 (0.0003)	0.0003 (0.0002)	–	–
log (Trade per capita)	−0.009 (0.010)	−0.008 (0.012)	−0.008 (0.009)	−0.009 (0.010)
log (GDP per capita)	−0.027 (0.026)	−0.033 (0.026)	−0.040 (0.027)	−0.039 (0.025)
log (GDP per capita)^2	0.001 (0.001)	0.001 (0.001)	0.001* (0.001)	0.001* (0.001)
log (Population growth)	−0.019** (0.009)	−0.017* (0.010)	−0.020** (0.009)	−0.017* (0.010)
log (Urban pop. per capita)	0.016 (0.013)	0.015 (0.015)	0.015 (0.012)	0.017 (0.013)
Observations	3402	3402	3402	3402
Countries	74	74	74	74
Instruments	31	31	33	33
Sargan test p-value	0.001	0.012	0.002	0.023
AR(1) test p-value	0.191	0.087	0.192	0.082
AR(2) test p-value	0.319	0.641	0.311	0.503
Wald test p-value	< 0.001	< 0.001	< 0.001	< 0.001

Notes: Dependent variable: log(GHG emissions per capita). Robust standard errors are in parentheses. All variables are expressed in per capita terms. Non-negative variables are transformed as $\log(x+1)$; FDI per capita and population growth are transformed as $\mathrm{sign}(x)\log(1+|x|)$.Columns (1)–(2) report baseline one-step and two-step system GMM estimates; columns (3)–(4) report income-status interaction specifications with separate FDI coefficients for middle- and high-income country-years. Income status is measured annually using the World Bank income classification. The instrument matrix is collapsed, and instruments are based on the second lag of the dependent variable. The Sargan test evaluates overidentifying restrictions; AR(1) and AR(2) are Arellano–Bond serial-correlation tests in first-differenced residuals. The Wald test reports joint significance of the regressors.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

Table 4
Static panel estimations for GHG emissions per capita: time-invariant income classification.

Variables	Pooled OLS	Random effect	Two-Way FE	Two-Way FE (Robust SE)	Two-Way FE (Int.)
log (Patents per capita)	−0.010	−0.000	0.037***	0.037	0.037***
	(0.019)	(0.008)	(0.008)	(0.039)	(0.008)
log (FDI per capita)	−0.001	0.001***	0.001*	0.001·	0.001*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
log (Trade per capita)	−0.165***	−0.068***	0.027	0.027	0.027
	(0.026)	(0.022)	(0.022)	(0.060)	(0.023)
log (GDP per capita)	2.913***	2.954***	2.955***	2.955***	2.955***
	(0.345)	(0.132)	(0.130)	(0.468)	(0.132)
log (GDP per capita)^2	−0.057***	−0.064***	−0.062***	−0.062***	−0.062***
	(0.008)	(0.003)	(0.003)	(0.010)	(0.003)
log (Population growth)	−0.042*	0.001	−0.048***	−0.048*	−0.048***
	(0.022)	(0.012)	(0.011)	(0.027)	(0.011)
log (Urban pop. per capita)	0.222***	0.138***	−0.410***	−0.410**	−0.410***
	(0.029)	(0.043)	(0.061)	(0.202)	(0.061)
log(FDI per capita)× Middle income	–	–	–	–	−0.000
					(0.002)
Constant	−27.808***	−25.105***	–	–	–
	(3.898)	(1.482)			
Observations	1883	1883	1883	1883	1883
R-squared	0.419	0.580	0.363	–	0.363
Breusch–Pagan LM test	13,682.27***	–	–	–	–
	(0.000)				
Hausman test	–	719.41***	–	–	–
		(0.000)			
Heteroskedasticity test	–	–	146.20***	–	–
			(0.000)		
Wooldridge test	–	–	F=1056.49***	–	–

Notes: Dependent variable: log(GHG emissions per capita). Standard errors in parentheses. All variables are in per capita terms. Non-negative variables are transformed as $\log(x+1)$; FDI per capita and population growth are transformed as $\mathrm{sign}(x)\log(1+|x|)$."Two-Way FE (Int.)" adds an interaction between log(FDI per capita) and the time-invariant middle-income indicator, with high-income countries as the reference group. Because income classification is fixed at the country level, the direct middle-income indicator is absorbed by country fixed effects; therefore, the interaction coefficient captures whether the within-country association between FDI per capita and GHG emissions per capita differs between structurally middle-income and high-income countries.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$. · $p < 0.15$.

lagged patent variables, which restricts the usable sample. The results show that FDI is positive and statistically significant for both middle-income and high-income country-years, with both coefficients equal to approximately 0.013. This suggests that, in this specification, FDI is associated with higher GHG emissions in both annual income-status categories.

Since the two estimated coefficients are almost identical, the table does not provide evidence of a meaningful difference in the FDI–GHG relationship between middle-income and high-income country-years. Accordingly, these results do not support the view that high-income status, measured annually, is associated with an environmentally cleaner FDI–emissions relationship. Rather, they suggest that being classified as high income in a given year does not by itself guarantee that foreign investment is associated with lower emissions.

The patent coefficients in Column (3) also remain heterogeneous across technology categories. The contemporaneous coefficients for $Y02T$, $Y02W$, and $Y02A$ are positive and statistically significant or weakly significant, while $Y02C$ is negative and marginally significant. Several lagged coefficients are also significant. In particular, the 6-year lag of $Y02E$ becomes positive and significant, while the 1- and 3-year lags of $Y02B$ and the 3- and 6-year lags of $Y02C$ are negative and statistically significant. These results again suggest that the association between green technological activity and emissions differs substantially across patent categories and time horizons.

To further examine whether the environmental consequences of FDI depend on the country's technological profile, Table 7 reports an additional static TWFE specification with disaggregated $Y02$ patent categories, interactions between each patent class and the middle-income indicator, and interactions between each patent class and FDI per capita. Unlike the preceding specifications in Table 6, which report conventional standard errors, Table 7 reports Driscoll–Kraay standard errors (Driscoll and Kraay, 1998). These are robust to heteroskedasticity, serial correlation, and cross-sectional dependence, which is particularly relevant in this specification given the large number of interaction terms and the potential for spatial correlation in emissions across countries. The use of Driscoll–Kraay standard errors provides a more conservative basis for inference in this more demanding specification. The lagged dependent variable is excluded from this specification in order to avoid potential dynamic panel bias in the two-way fixed effects framework. The income-group indicator in this main specification is based on annual income classification. Therefore, the middle-income dummy is not necessarily absorbed by country fixed effects, because some countries transition between income categories during the sample period. The coefficient on the middle-income indicator should therefore be interpreted as reflecting within-country changes associated with annual income-status classification rather than permanent structural differences between countries.

The direct patent coefficients in Table 7 refer to high-income country-years at the reference value of FDI. Among these direct effects, $Y02P$ is negatively and significantly associated with emissions, while $Y02T$ and $Y02B$ are positively and significantly associated with emissions. The coefficients on $Y02E$, $Y02W$, $Y02A$, $Y02C$, and $Y02D$ are not statistically significant. These results suggest that, even within high-income country-years, the association between green patenting

Table 5

System GMM estimation results for GHG emissions per capita: time-invariant income classification.

Variables	One-step	Two-step	One-step (Int.)	Two-step (Int.)
lag (log (GHG capita, 1))	1.136*** (0.143)	1.211*** (0.201)	1.135*** (0.130)	1.229*** (0.198)
lag (log (GHG capita, 2))	−0.148 (0.139)	−0.205 (0.194)	−0.138 (0.126)	−0.221 (0.189)
lag (log (GHG capita, 3))	−0.007 (0.033)	−0.015 (0.050)	−0.001 (0.033)	−0.004 (0.048)
log (Y02E capita)	−0.012*** (0.003)	−0.011* (0.006)	−0.010*** (0.003)	−0.008 (0.005)
log (Y02P capita)	0.003 (0.006)	0.001 (0.006)	−0.001 (0.006)	−0.002 (0.007)
log (Y02T capita)	−0.006 (0.005)	−0.003 (0.007)	−0.002 (0.004)	0.001 (0.006)
log (Y02W capita)	0.001 (0.005)	0.003 (0.008)	0.001 (0.005)	0.001 (0.007)
log (Y02 A capita)	−0.000 (0.005)	0.001 (0.006)	−0.002 (0.004)	0.000 (0.006)
log (Y02B capita)	0.010 (0.007)	0.010 (0.009)	0.011* (0.006)	0.010 (0.008)
log (Y02C capita)	0.015 (0.010)	0.011 (0.010)	0.013 (0.010)	0.011 (0.010)
log (Y02D capita)	0.015* (0.008)	0.006 (0.009)	0.012* (0.007)	0.006 (0.009)
FDI (middle income)	–	–	0.001* (0.000)	0.001 (0.000)
FDI (high income)	–	–	0.000*** (0.000)	0.000* (0.000)
log (FDI per capita)	0.000*** (0.000)	0.000* (0.000)	–	–
log (Trade per capita)	−0.005 (0.004)	−0.005 (0.006)	−0.002 (0.003)	−0.002 (0.005)
log (GDP per capita)	0.014** (0.006)	0.007 (0.007)	0.005 (0.009)	0.001 (0.011)
log (GDP per capita)^2	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
log (Population growth)	−0.002 (0.004)	−0.003 (0.006)	−0.001 (0.004)	−0.002 (0.006)
log (Urban pop. per capita)	0.005 (0.005)	0.004 (0.007)	0.003 (0.004)	0.002 (0.006)
Observations	2735	2735	2735	2735
Countries	74	74	74	74
Instruments	31	31	33	33
Sargan test p-value	< 0.001	0.002	< 0.001	0.002
AR(1) test p-value	0.069	< 0.001	0.062	< 0.001
AR(2) test p-value	0.921	0.669	0.922	0.554
Wald test p-value	< 0.001	< 0.001	< 0.001	< 0.001

Notes: Dependent variable: $\log$(GHG emissions per capita). Robust standard errors are in parentheses. All variables are expressed in per capita terms. Non-negative variables are transformed as $\log(x+1)$; FDI per capita and population growth are transformed as $\text{sign}(x)\log(1+|x|)$. Columns (1)–(2) report baseline one-step and two-step system GMM estimates; columns (3)–(4) report income-status interaction specifications with separate FDI coefficients for middle- and high-income country-years. Income status is measured using a time-invariant country-level income classification based on each country's latest available income status. The interaction specifications therefore capture differences between structurally middle-income and high-income countries rather than annual changes in income status. The instrument matrix is collapsed, and instruments are based on the second lag of the dependent variable. The Sargan test evaluates overidentifying restrictions; AR(1) and AR(2) are Arellano–Bond serial-correlation tests in first-differenced residuals. The Wald test reports joint significance of the regressors.

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

and emissions varies across technology classes, with some categories displaying statistically significant associations while others do not.

The patent–income interaction terms indicate whether the association between each patent category and emissions differs in middle-income country-years relative to high-income country-years. The coefficient for $Y02P\times$Middle income is positive and statistically significant, indicating that production- and processing-related green patents are associated with relatively higher emissions in middle-income country-years compared with high-income country-years. The coefficient for $Y02W\times$ Middle income is also positive and statistically significant, suggesting a relatively stronger positive association between waste- and wastewater-related green patents and emissions in middle-income country-years. By contrast, the coefficient for $Y02C\times$ Middle income is negative and statistically significant, indicating that the association between GHG capture or sequestration patents and emissions is lower in middle-income country-years than in high-income country-years. The remaining patent–income interactions are not statistically significant, implying that the corresponding patent–emissions associations do not differ clearly between income groups.

The FDI–patent interaction terms provide evidence that the relationship between FDI and emissions varies across technological contexts. The insignificant coefficient on the common FDI term in Table 7 indicates that the association between FDI and emissions is not statistically different from zero when the interacted patent variables are equal to their reference values. However, several significant FDI–patent interaction terms show that the marginal association between FDI and emissions depends on the composition of green patenting activity.

The coefficients on $FDI\times Y02E$, $FDI\times Y02P$, and $FDI\times Y02A$ are positive and statistically significant. This suggests that in country-years with stronger patenting activity in energy-related technologies, production- and processing-related technologies, and adaptation-related technologies, the association between FDI and GHG emissions becomes more positive. In contrast, the coefficients on $FDI\times Y02T$, $FDI\times Y02B$, and $FDI\times Y02C$ are negative and statistically significant, indicating that the FDI–GHG relationship is weaker in country-years with relatively stronger patenting activity in transportation, buildings, and GHG capture or sequestration technologies. The interaction terms for $FDI\times Y02W$ and $FDI\times Y02D$ are not statistically significant.

6.2. Additional system GMM estimates with FDI–Income interactions

Table 8 presents additional system GMM estimates for GHG emissions per capita. The specifications include lagged dependent variables to account for persistence in emissions and compare baseline one-step and two-step system GMM estimators with specifications that allow the FDI coefficient to differ across annual income-status categories. As in the main income-interaction specifications, income-group classification is measured annually using the World Bank income classification. Therefore, the income-specific FDI coefficients refer to middle-income and high-income country-years rather than to time-invariant country groups. In the interaction specifications, the common FDI term is replaced by separate income-status-specific FDI coefficients.

The results show strong evidence of persistence in GHG emissions. The first lag of $\log$(GHG emissions per capita) is positive and statistically significant across all specifications. The second and third lags are positive and statistically significant in the one-step specifications, but lose statistical significance in the two-step specifications. Notably, the third lag reverses sign in the two-step models and the second lag also reverses sign in the two-step interaction model, which raises concern about the stability of the lag structure under the two-step estimator. This suggests that emissions are persistent over time, although the

Table 6
Two-way fixed effects estimates: Without lags, with lags, and with income interactions.

Variables	TWFE (No lags)	TWFE (With lags)	TWFE (With income interactions)
log (Y02E capita)	0.018** (0.006)	0.022*** (0.006)	0.007 (0.006)
lag (log (Y02E_1))	–	0.002 (0.005)	0.000 (0.006)
lag (log (Y02E_3))	–	0.001 (0.005)	0.009 (0.006)
lag (log (Y02E_6))	–	−0.004 (0.005)	0.018*** (0.005)
log (Y02P capita)	0.005 (0.006)	0.004 (0.006)	−0.008 (0.005)
lag (log (Y02P_1))	–	−0.004 (0.006)	0.004 (0.006)
lag (log (Y02P_3))	–	−0.005 (0.006)	0.001 (0.005)
lag (log (Y02P_6))	–	−0.014** (0.006)	−0.003 (0.005)
log (Y02T capita)	0.003 (0.006)	0.010* (0.006)	0.011* (0.005)
lag (log (Y02T_1))	–	−0.004 (0.006)	0.008 (0.005)
lag (log (Y02T_3))	–	−0.009 (0.006)	0.006 (0.005)
lag (log (Y02T_6))	–	−0.024*** (0.005)	−0.008 (0.005)
log (Y02W capita)	0.017** (0.006)	0.014* (0.006)	0.012* (0.005)
lag (log (Y02W_1))	–	0.011* (0.006)	0.015** (0.005)
lag (log (Y02W_3))	–	0.011· (0.006)	0.005 (0.005)
lag (log (Y02W_6))	–	0.012* (0.005)	0.009· (0.005)
log (Y02 A capita)	0.032*** (0.006)	0.024*** (0.006)	0.015** (0.006)
lag (log (Y02A_1))	–	0.016** (0.006)	0.011· (0.006)
lag (log (Y02A_3))	–	0.008 (0.006)	0.014* (0.006)
lag (log (Y02A_6))	–	0.008 (0.005)	0.016** (0.005)
log (Y02B capita)	0.003 (0.006)	0.004 (0.006)	−0.005 (0.005)
lag (log (Y02B_1))	–	−0.008 (0.006)	−0.011* (0.005)
lag (log (Y02B_3))	–	−0.006 (0.006)	−0.013* (0.005)
lag (log (Y02B_6))	–	0.003 (0.006)	−0.001 (0.005)
log (Y02C capita)	−0.030*** (0.007)	−0.021** (0.008)	−0.012· (0.006)
lag (log (Y02C_1))	–	−0.020** (0.007)	−0.010 (0.007)
lag (log (Y02C_3))	–	−0.011· (0.007)	−0.015* (0.007)
lag (log (Y02C_6))	–	−0.010 (0.006)	−0.014* (0.007)
log (Y02D capita)	0.002 (0.006)	0.001 (0.007)	−0.003 (0.006)
lag (log (Y02D_1))	–	−0.000 (0.007)	−0.004 (0.007)
lag (log (Y02D_3))	–	0.013* (0.006)	0.007 (0.007)
lag (log (Y02D_6))	–	0.016** (0.006)	0.008 (0.006)
FDI (middle income)	–	–	0.013*** (0.003)
FDI (high income)	–	–	0.013*** (0.003)
log (FDI per capita)	0.019*** (0.004)	0.019*** (0.004)	–
log (Trade per capita)	−0.001 (0.022)	0.013 (0.022)	0.089*** (0.025)
log (GDP per capita)	2.975*** (0.152)	2.502*** (0.163)	2.280*** (0.237)
log (GDP per capita)^2	−0.063*** (0.003)	−0.052*** (0.004)	−0.045*** (0.005)
log (Population growth)	0.043 (0.038)	0.058 (0.037)	0.041 (0.031)
log (Urban pop. per capita)	−0.414*** (0.059)	−0.362*** (0.059)	−0.544*** (0.077)
Constant	–	–	–
Observations	1871	1865	1270
R-squared	0.335	0.377	0.423

Notes: Dependent variable: log(GHG emissions per capita). Standard errors in parentheses. All columns report two-way fixed effects estimates with country and year fixed effects. Column (1) includes contemporaneous green patent variables by Y02 category. Column (2) additionally includes 1-, 3-, and 6-year lags of the Y02 patent variables. Column (3) reports the specification with income-group-specific FDI coefficients for middle- and high-income country-years. In this column, the common FDI term is replaced by separate coefficients for the two annual income-status categories. Income-group classification is measured annually; therefore, countries that transition between middle- and high-income status during the sample period contribute within-country variation to the income-group indicators. Constants are omitted because they are absorbed by the fixed effects.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$. · $p < 0.15$.

strength and duration of this persistence are somewhat weaker under the two-step estimator.

FDI per capita is positive and statistically significant in both the baseline one-step and two-step GMM models. In the one-step model, the coefficient of approximately 0.004 implies that a one-unit increase in the transformed FDI variable is associated with an increase of about 0.4% in GHG emissions per capita. The two-step model yields a slightly larger and also statistically significant coefficient of approximately 0.006 (significant at the 5% level). This indicates that the positive FDI–emissions relationship is robust across both GMM specifications in this robustness exercise, though the two-step standard errors should be interpreted with caution given the potential for downward bias.

Columns (3) and (4) examine whether the FDI–emissions relationship differs between middle-income and high-income country-years. In the one-step interaction model, both income-status-specific FDI coefficients are positive and statistically significant at the 1% level, with both coefficients equal to approximately 0.004, suggesting no meaningful difference in magnitude between income groups. In the two-step interaction model, both income-specific FDI coefficients are also positive and statistically significant at the 1% level, with coefficients of approximately 0.029 for middle-income and 0.027 for high-income country-years. However, these two-step magnitudes are substantially larger than the one-step estimates, raising concerns about the stability of the two-step estimator in this specification – a concern reinforced by the AR(2) violations discussed below. The two-step interaction results should therefore be interpreted with considerable caution.

Trade per capita is positive and statistically significant in the one-step models, but becomes negative and statistically insignificant in the two-step specifications. This sign reversal between estimators is consistent with the broader pattern of instability in the two-step estimates identified throughout this table. In the one-step specifications, GDP per capita is positive and statistically significant at the 5% level, while

Table 7
Static two-way fixed effects estimates with income-group and FDI–patent interactions.

Variables	TWFE (Income and FDI–Patent Interactions)
log (Y02E capita)	−0.006 (0.011)
Middle income	0.264 (0.225)
log (FDI per capita)	0.003 (0.003)
log (Y02P capita)	−0.033*** (0.011)
log (Y02T capita)	0.038*** (0.012)
log (Y02W capita)	−0.009 (0.018)
log (Y02 A capita)	0.011 (0.011)
log (Y02B capita)	0.031*** (0.010)
log (Y02C capita)	0.002 (0.009)
log (Y02D capita)	−0.004 (0.007)
log (Trade per capita)	−0.009 (0.037)
log (GDP per capita)	2.667*** (0.481)
log (GDP per capita)^2	−0.056*** (0.010)
log (Population growth)	−0.032* (0.019)
log (Urban pop. per capita)	−0.437*** (0.131)
Y02E × Middle income	0.005 (0.011)
Y02E × FDI	0.0012*** (0.0004)
Y02P × Middle income	0.037*** (0.009)
Y02P × FDI	0.0013* (0.0007)
Y02T × Middle income	0.015 (0.012)
Y02T × FDI	−0.0019*** (0.0006)
Y02W × Middle income	0.038** (0.017)
Y02W × FDI	0.0005 (0.0007)
Y02 A × Middle income	0.006 (0.008)
Y02 A × FDI	0.0010** (0.0004)
Y02B × Middle income	−0.009 (0.017)
Y02B × FDI	−0.0013*** (0.0005)
Y02C × Middle income	−0.051*** (0.015)
Y02C × FDI	−0.0009* (0.0005)
Y02D × Middle income	−0.016 (0.021)
Y02D × FDI	0.0004 (0.0004)
Observations	1844
R-squared	0.3820

Notes: Dependent variable: $\log(\text{GHG emissions per capita})$. Driscoll–Kraay standard errors are reported in parentheses. The table reports static two-way fixed effects estimates with country and year fixed effects. The lagged dependent variable is excluded in order to avoid potential dynamic panel bias in the two-way fixed effects framework. Income-group classification is measured annually and is therefore allowed to vary over time. Consequently, the middle-income indicator is not fully absorbed by country fixed effects when countries transition between income categories during the sample period. High-income country-years are the reference category. The specification includes green patent variables by Y02 category, interactions between each patent class and the annual middle-income indicator, and interactions between each patent class and FDI per capita. Because the specification includes patent–FDI interactions, the coefficients on the Y02 variables refer to high-income country-years at the reference value of FDI. The coefficients on Y02 × Middle income capture differential associations for middle-income country-years, while the coefficients on Y02 × FDI indicate how the patenting–emissions relationship varies with FDI. Patent variables measure jurisdiction-based inventive activity rather than actual technology adoption or deployment. Constants are omitted because they are absorbed by the fixed effects.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$

its squared term is negative and significant, consistent with the EKC hypothesis. However, this pattern does not hold uniformly across all two-step specifications. In the two-step baseline model, both GDP per capita and its squared term are statistically insignificant. In the two-step interaction model, the sign pattern reverses entirely: GDP per capita is negative and statistically significant while its squared term is positive and significant the opposite of the EKC prediction. These sign reversals between estimators further underscore the instability of the two-step results in this table. Urban population per capita is positive and statistically significant at the 10% level in the one-step specifications, but positive and statistically insignificant in the two-step specifications. Population growth is not statistically significant in any specification.

Overall, Table 8 provides partial support for a positive association between FDI and GHG emissions. The positive FDI effect is statistically significant in both one-step and two-step baseline specifications. The interaction results do not indicate a meaningful difference between middle-income and high-income country-years, since both income-specific coefficients are nearly identical in the one-step model. An important caveat, however, concerns the serial correlation diagnostics. The Arellano–Bond AR(2) test yields p-values of 0.019 and 0.010 in the two-step baseline and interaction specifications, respectively, both significant at the 5% level. By the standard criterion applied throughout this paper, significant AR(2) in the differenced residuals indicates a violation of the moment conditions underlying the GMM estimator. The AR(1) test results also warrant attention: while the two-step and interaction specifications show significant AR(1) as expected in a well-specified dynamic panel model, the one-step baseline specification yields an AR(1) p-value of 0.988 – an unusual absence of first-order autocorrelation in the differenced residuals that is difficult to interpret and provides an additional reason to treat those estimates with caution. The Sargan test further rejects the null of valid overidentifying restrictions across all four specifications, with p-values ranging from 0.000 to 0.009, among the most severe Sargan rejections reported in this study. Furthermore, the Wald test of joint significance yields a p-value of 0.084 in the two-step baseline model, indicating only marginal joint significance of the regressors at the 10% level. Combined, these diagnostics indicate that the two-step results in Table 8 are unreliable, and the one-step estimates are the more credible reference point within this robustness exercise. These findings should nonetheless be interpreted as a robustness check rather than as definitive evidence, and do not overturn the main conclusions drawn from Tables 3 and 5.

7. Conclusion and discussion

7.1. Conclusion

This paper examines the relationship between FDI and GHG emissions across middle- and high-income countries. The study contributes to the literature on FDI and environmental outcomes by focusing on total GHG emissions rather than only CO_2 emissions, and by incorporating income-group heterogeneity and disaggregated green patent indicators. In doing so, the paper contributes to the ongoing debate on the pollution haven hypothesis, which suggests that multinational firms may shift emissions-intensive activities to countries with weaker environmental regulations (Copeland and Taylor, 2004; Pham et al., 2025; Caetano and Marques, 2024; Sapkota and Bastola, 2017) .

The empirical analysis combines static and dynamic panel estimators. The static models include pooled OLS, random effects, two-way fixed effects, a robust fixed effects specification with Arellano-type HAC standard errors clustered at the country level, and extended fixed effects specifications incorporating income-group and FDI–patent interactions. The dynamic analysis uses one-step and two-step system GMM estimators with lagged dependent variables to account for the persistence of GHG emissions and to address potential endogeneity concerns.

Across the main specifications, FDI per capita is generally positively associated with GHG emissions. In the static models, this association is statistically significant in the random effects and conventional fixed effects specifications, but becomes weaker once country-clustered robust standard errors are applied. The dynamic system GMM results provide additional evidence of a positive FDI–emissions relationship, although the strength and significance of this association vary across estimators and robustness specifications. These findings suggest that foreign investment is often associated with higher emissions, but the magnitude and robustness of the effect depend on the estimation strategy.

The results also provide some evidence of income-group heterogeneity. In the main dynamic interaction specifications of Table 3, the estimated FDI coefficient is positive and statistically significant mainly

Table 8
Additional system GMM estimates with FDI–income interactions.

Variables	One-Step GMM	Two-Step GMM	One-Step (Interactions)	Two-Step (Interactions)
lag (log (GHG per capita)) L1	0.516***	1.394***	0.516***	1.360***
	(0.042)	(0.277)	(0.042)	(0.237)
lag (log (GHG per capita)) L2	0.068*	0.047	0.067*	−0.010
	(0.030)	(0.055)	(0.030)	(0.068)
lag (log (GHG per capita)) L3	0.155***	−0.479	0.155***	−0.359
	(0.029)	(0.304)	(0.029)	(0.244)
FDI (middle income)	—	—	0.004***	0.029***
			(0.001)	(0.007)
FDI (high income)	—	—	0.004***	0.027***
			(0.001)	(0.007)
log (FDI per capita)	0.004***	0.006**	—	–
	(0.001)	(0.002)		
log (Trade per capita)	0.126***	−0.008	0.126***	−0.006
	(0.028)	(0.011)	(0.027)	(0.010)
log (GDP per capita)	0.776**	0.013	0.781**	−0.066**
	(0.290)	(0.018)	(0.289)	(0.025)
log (GDP per capita)^2	−0.016**	−0.000	−0.016**	0.002**
	(0.006)	(0.000)	(0.006)	(0.001)
log (Urban pop. per capita)	0.421*	0.008	0.412*	0.008
	(0.205)	(0.013)	(0.205)	(0.011)
log (Population growth)	0.013	−0.039	0.013	−0.049
	(0.026)	(0.069)	(0.025)	(0.087)
Observations	2725	2725	2725	2725
Countries	74	74	74	74
Instruments	17	17	20	20
Sargan test p-value	0.000	0.006	0.001	0.009
AR(1) test p-value	0.988	< 0.001	0.002	< 0.001
AR(2) test p-value	0.199	0.019	0.257	0.010
Wald test p-value	< 0.001	0.084	< 0.001	< 0.001

Notes: Dependent variable: $\log(\text{GHG emissions per capita})$. Robust standard errors are reported in parentheses. The table reports system GMM estimates with collapsed instruments. Columns (1)–(2) report the baseline one-step and two-step models, while columns (3)–(4) replace the common FDI coefficient with separate FDI coefficients for middle- and high-income country-years. Income-group status is measured annually using the World Bank income classification. All models include lagged dependent variables. Constants are not reported.
*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$

for middle-income country-years, while the corresponding coefficient for high-income country-years is smaller and statistically insignificant. However, this income-group difference is not robust across all specifications: in the time-invariant GMM results both income groups show significant FDI coefficients, and in the additional robustness GMM estimates the one-step interaction model yields nearly identical coefficients for both groups. Income level appears to matter, but it does not fully explain cross-country variation in the environmental consequences of FDI.

The findings for green patents point to substantial technological heterogeneity. Aggregate patent indicators provide limited evidence of emissions-reducing effects, while the disaggregated $Y02$ patent categories reveal more nuanced patterns. Some patent classes are associated with lower emissions, particularly those more directly related to mitigation, while others are positively associated with emissions or become significant only after several lags. The FDI–patent interaction results further suggest that the relationship between FDI and emissions depends on the technological profile of the host economy. In some patenting contexts, FDI is associated with a stronger positive emissions relationship, whereas in others this association is weaker. Because the patent variables capture jurisdiction-based inventive activity rather than actual technology adoption or deployment, these results should be interpreted as evidence of heterogeneity in technological orientation rather than direct proof of clean-technology use.

The control variables generally behave in line with expectations, though with some variation across estimators. GDP per capita and its squared term provide evidence broadly consistent with the EKC hypothesis in the static and one-step dynamic specifications, although this pattern is not uniform across all estimators. Trade openness shows mixed results: it is negative and insignificant in the main dynamic GMM models, but positive and significant in the one-step estimates of the additional robustness specifications. Urbanization shows different signs across estimators, suggesting that its relationship with emissions depends on whether the analysis captures cross-country differences or within-country changes over time. It should also be noted that the Sargan test rejects the null of valid overidentifying restrictions across all GMM specifications, and the AR(2) test flags moment condition violations in the two-step models of the additional robustness table. The dynamic GMM results should therefore be read with these diagnostic limitations in mind. Overall, the results lend partial support to the pollution haven hypothesis. FDI is repeatedly associated with higher GHG emissions in several specifications, particularly for middle-income country-years in the main dynamic interaction models, but the evidence is not uniform across all models. The findings therefore suggest that FDI does not automatically generate environmental upgrading. Its environmental consequences appear to vary with income status, broader structural conditions, and the technological orientation of the host economy.

The policy implications of these findings should be interpreted in a cautious and evidence-based manner. The empirical results indicate that FDI is generally positively associated with GHG emissions in several specifications, although the strength and statistical significance of this relationship vary across models. This suggests that attracting FDI should not be treated as environmentally neutral. Foreign investment may contribute to economic development, but it may also be associated with higher emissions. Therefore, rather than discouraging FDI, the results point to the importance of considering the environmental profile of foreign investment alongside its economic benefits.

The evidence also suggests that income level may matter for the FDI–emissions relationship, but this conclusion should not be overstated. In the main dynamic interaction specifications, the positive association between FDI and emissions appears stronger for middle-income country-years, while the corresponding effect for high-income country-years is smaller and statistically insignificant. However, this difference is not robust across all specifications, especially when time-invariant income classifications are used. Therefore, the findings do not support a strong claim that middle-income countries are systematically more vulnerable to FDI in all cases. Instead, they suggest that income status may be one relevant factor, but not the only determinant of the environmental consequences of FDI. Other structural and institutional conditions, such as sectoral composition, regulatory capacity, energy structure, and absorptive ability, may also help explain this heterogeneity and should be examined more directly in future research.

The results for green patents further imply that policy should avoid treating green innovation as a single uniform category. Aggregate patent activity does not consistently show an emissions-reducing association, while the disaggregated $Y02$ patent categories reveal substantial technological heterogeneity. Some technology classes are associated with lower emissions, particularly those more directly related to mitigation, whereas others are positively associated with emissions or show effects only after several lags. This suggests that broad support for green innovation may not be sufficient by itself. Policy evaluation should pay closer attention to the technological composition of innovation and to whether specific types of green technologies are likely to translate into actual emissions reductions.

At the same time, the policy implications should remain limited by the nature of the empirical evidence. The patent variables used in this study measure jurisdiction-based green inventive activity rather than actual technology adoption or deployment. Similarly, the FDI variable is an aggregate measure and does not distinguish between sectors, entry modes, or source countries of investment. For this reason, the results cannot identify which specific regulatory instruments, investment-screening mechanisms, or innovation subsidies would be most effective. The findings instead suggest the need for more targeted evaluation of FDI and green technological activity, particularly in relation to sectoral composition and technology-specific emissions outcomes.

Overall, the results indicate that FDI and green innovation are not automatically associated with environmental improvement. The environmental consequences of FDI appear to depend on the technological and structural context of the host economy. The results are consistent with the view that FDI attraction strategies may need to be complemented by careful environmental monitoring, and that green innovation policies should be evaluated at a more disaggregated technological level. Because the analysis relies on aggregate FDI measures and patent indicators that capture jurisdiction-based inventive activity rather than actual technology adoption or deployment, the results should be interpreted as broad policy considerations rather than direct prescriptions for specific regulatory, investment, or innovation-policy instruments. Future research using sectoral FDI data, direct measures of technology adoption, and more detailed institutional indicators would be useful for deriving more specific policy recommendations.

7.2. Discussion and limitations

Some limitations should be considered when interpreting the findings. First, the patent indicators used in this study should be interpreted as proxies for green inventive activity and technological orientation rather than as direct measures of clean-technology adoption. Although patenting reflects novelty and codified technological output, it does not necessarily imply commercialization, widespread diffusion, or effective environmental deployment. This distinction is particularly important in a cross-country setting, where patenting intensity differs substantially across countries, especially between middle- and high-income economies, and may partly reflect broader disparities in innovative capacity, institutional development, and access to patenting systems. Moreover, the patent variables are jurisdiction-based indicators of patenting activity. They therefore capture the country in which patent protection is sought, rather than necessarily the country where the invention originated or where the technology is eventually adopted. Knowledge embodied in patented technologies may also spill over internationally through trade, licensing, multinational production, imitation, and FDI. Accordingly, the patent variables used in this study are informative about green innovation effort and technological composition, but they do not directly capture domestic technology adoption or the location where environmental benefits ultimately materialize.

Second, endogeneity remains an important concern in estimating the relationship between FDI and environmental outcomes. FDI may respond to environmental regulation, institutional quality, market size, energy prices, or macroeconomic conditions, while emissions may themselves influence foreign investors' location decisions. In addition, omitted country-specific factors may affect both FDI inflows and environmental performance. To address these concerns, this study employs the Blundell–Bond system GMM estimator, which is well suited to dynamic panel settings characterized by persistent dependent variables, unobserved heterogeneity, and potentially endogenous regressors. By combining equations in first differences and in levels, and by using lagged values of the variables as internal instruments, the estimator helps mitigate simultaneity and omitted variable bias while preserving both the time-series and cross-country dimensions of the data. This approach is consistent with the broader empirical literature on the FDI–environment nexus, including Doytch and Uctum (2016). However, it should be acknowledged that the Sargan test of overidentifying restrictions rejects the null of instrument validity across all GMM specifications reported in this study. While the number of instruments remains below the number of countries in all cases — limiting concerns about instrument proliferation — and the Arellano–Bond AR(2) tests are satisfactory in the main specifications, the Sargan test results indicate that the internal instrument strategy may not fully resolve endogeneity concerns. The GMM estimates should therefore be interpreted as providing suggestive rather than definitive causal evidence.

Third, the analysis relies on aggregate FDI measures. However, the environmental effects of FDI may depend strongly on the sectoral composition of investment, the entry mode of foreign firms, the source country of investment, and the environmental standards of multinational enterprises. For example, manufacturing FDI may have different environmental consequences from services-related FDI, and greenfield investment may differ from mergers and acquisitions.

Fourth, while the analysis distinguishes between middle- and high-income countries, income classification is only a broad proxy for deeper structural and institutional differences. Countries within the same income group may differ substantially in environmental regulation, energy structure, industrial composition, governance quality, and absorptive capacity. These factors may shape both the environmental consequences of FDI and the effectiveness of green technological activity. This concern is partially reflected in the empirical results themselves: the income-heterogeneity finding identified in the main dynamic specifications weakens considerably when a time-invariant country-level income classification is used instead of the annual World Bank classification, suggesting that the result may be sensitive to how income status is operationalized rather than reflecting deep structural differences between economies. Future work could therefore examine more detailed institutional and sectoral channels through which FDI and green innovation affect GHG emissions.

Fifth, a further limitation concerns the comparability of the static and dynamic estimation samples. The GMM specifications draw on a broader set of country-year observations than the static fixed effects models, as the dynamic models do not require the same coverage of patent data. As a result, the two sets of estimates are not based on identical samples, and direct comparisons across static and dynamic results should be made with this in mind. Future work could examine whether restricting both sets of models to a common balanced sample materially affects the findings.

Table A.9
List of countries used in the analysis.

Australia	Algeria
Austria	Argentina
Belgium	Armenia
Canada	Azerbaijan
Chile	Belarus
Croatia	Brazil
Czechia	Bulgaria
Denmark	China
Estonia	Colombia
Finland	Costa Rica
France	Dominican Republic
Germany	Ecuador
Greece	Egypt
Hong Kong SAR China	Georgia
Hungary	India
Iceland	Indonesia
Ireland	Iran
Israel	Kazakhstan
Italy	Kenya
Japan	Malaysia
Latvia	Mexico
Lithuania	Moldova
Luxembourg	Morocco
Netherlands	Peru
New Zealand	Philippines
Norway	South Africa
Oman	Sri Lanka
Poland	Thailand
Romania	Tunisia
Russia	Turkey
Saudi Arabia	Ukraine
Singapore	Uruguay
Slovakia	Vietnam
Slovenia	
South Korea	
Spain	
Sweden	
Switzerland	
United Arab Emirates	
United Kingdom	
United States	

CRediT authorship contribution statement

Narek Mirzoyan: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jennifer Brodmann:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization. **Mahmoud Salari:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Sunghoon Joo:** Writing – review & editing, Validation, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used "ChatGPT" and "DeepLWrite" for checking the grammar of English language. After using these tools, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication. "ChatGPT" was also used in the coding to improve the code.

Appendix A. List of countries

See Table A.9.

Appendix B. Types of Green patents

Patents are widely recognized as a form of intellectual property right (OECD, 2009) that incentivizes inventors to disclose their technical solutions to the public while retaining exclusive control over their use for a defined period (Abbas et al., 2014; Bonino et al., 2010; EPO, 2022; Baumann et al., 2021). As a result, patents function not only as legal protection mechanisms but also as "indicators of new technology and technological progress safeguarding markets and therefore indicators of market interest" within a given technological domain (Frietsch and Schmoch, 2010). In both academic research and economic practice, patents are therefore widely employed as "invention indicators" (Albino et al., 2014), based on the simplifying assumption that a higher number of patents reflects a higher level of inventive activity (OECD, 2009). Although this assumption is debated, given the substantial role of exogenous factors shaping innovation, the empirical literature generally finds a strong correlation between patenting activity and underlying innovation dynamics (Phelps, 2015). Besides, patents can help identify "technological trends", "strategic technology planning", or find "technological hotspots" (Abbas et al., 2014). Patents protect inventions (EPO, 2018).

Green patents play a central role in measuring and promoting green innovation, but their definition varies across studies. Dechezleprêtre (2013) restricts green patents to technologies aimed at climate change mitigation or adaptation, whereas Hall and Helmers (2013) classify patents as green if they generate direct or indirect environmental benefits and fall within environmentally relevant IPC subclasses. Their analysis shows that many such patents relate to reducing environmental harm from industrial processes rather than climate change per se. Hoang et al. (2020) treat green patents and environmentally friendly technological innovations as equivalent concepts. By contrast, Kesidou and Wu (2020) define green patents more broadly as patents associated with green technologies, identified through IPC classifications and including inventions, utility models and industrial designs.

For empirical analysis, distinguishing green patents from all patents requires a systematic approach. Three main methods exist: patent-classification based identification, keyword searches, and manual reading (Haš̌ cič and Migotto, 2015). Keyword searches are sensitive to terminology and require deep technological knowledge (Oltra et al., 2010), while manual reading is infeasible for large datasets (Haš̌ cič and Migotto, 2015). For these reasons, the use of patent-classification systems such as IPC or CPC is generally recommended and is the dominant approach in empirical research (Arundel and Kemp, 2009). Across the studies provided, green patents are consistently operationalized using the CPC $Y02$ subclass, explicitly designated for "technologies for mitigating or adapting to climate change". This subclass is further divided into domains corresponding to key climate-policy sectors: (see Table B.10).

Appendix C. Summary statistics by income group

See Table C.11.

Appendix D. Evolution of the variables across time by income group

See Fig. D.3.

Appendix E. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2026.109525.

Data availability

The data presented in this study are available upon request.

Table B.10
Climate change mitigation and adaptation technologies.

CPC code	Description
Y02 A	Technologies for adaptation to climate change.
Y02B	Climate change mitigation technologies related to buildings.
Y02C	Capture, storage, sequestration or disposal of greenhouse gases.
Y02D	Climate change mitigation technologies in information and communication technologies.
Y02E	Reduction of GHG emissions, related to energy generation, transmission or distribution.
Y02P	Climate change mitigation technologies in the production or processing of goods.
Y02T	Climate change mitigation technologies related to transportation.
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management.

Table C.11
Descriptive statistics by income group.

Variables	Middle income					High income				
	Mean	Std. dev.	Min	Max	N	Mean	Std. dev.	Min	Max	N
log(GHG per capita)	8.75	0.57	7.24	9.95	705	9.42	0.41	8.56	10.59	1139
log(Patents per capita)	0.22	0.24	0.00	1.79	705	1.39	0.95	0.02	4.06	1139
log(FDI per capita)	17.90	4.16	−19.71	21.73	705	16.29	12.04	−26.92	26.30	1139
log(Trade per capita)	1.21	1.03	0.02	4.68	705	1.96	1.34	0.05	5.51	1139
log(GDP per capita)	22.30	0.69	20.20	23.72	705	24.08	0.58	22.22	25.62	1139
$(\log(\text{GDP per capita}))^2$	497.83	30.54	408.11	562.41	705	580.12	27.71	493.84	656.33	1139
log(Population growth)	0.40	0.61	−2.73	1.58	705	0.42	0.44	−1.66	2.91	1139
log(Urban population per capita)	1.21	0.88	0.02	3.95	705	2.06	1.18	0.22	5.79	1139

Fig. D.3. Average per capita values of all variables over time.

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