

**Shaping Sustainable Future: Investment
in Digital Transformation and
Environmental Pollution on Green
Innovation**

**Shaping Sustainable Future: Investment in Digital Transformation and Environmental
Pollution on Green Innovation**

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QUEST FOR EXCELLENCE

Letter of Transmittal

September 23, 2025

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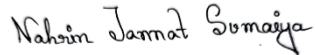
Dear Sir,

It is with great respect and genuine enthusiasm that I submit my project paper entitled “*Shaping Sustainable Future: Investment in Digital Transformation and Environmental Pollution on Green Innovation.*” This work reflects months of study, reflection, and analysis, and it has been prepared to fulfill the requirements for my Bachelor of Business Administration (BBA) degree, majoring in Finance, at United International University.

In this study, I have tried to explore how technology and environmental challenges come together to influence green innovation in today’s business world. Your kind guidance and support have been instrumental in shaping this work, helping me frame the research direction and refine my ideas with academic rigor.

I am truly grateful to United International University for providing me with the environment and facilities that made this study possible. I would also like to acknowledge the encouragement of my family and peers, whose constant support kept me motivated throughout this journey.

I sincerely hope that the insights shared in this paper will add value to ongoing discussions on sustainable business practices. Thank you very much for your valuable time and kind attention in reviewing my work. I look forward to your thoughtful feedback and guidance.

Sincerely,
Nahrin Jannat Sumaiya
ID: 111 201 099


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Abstract

The pursuit of sustainability in the twenty-first century compels researchers, policymakers, and industries to reconcile economic development with environmental protection. This study examines how digital transformation and environmental pressures—particularly per capita methane emissions—shape cross-national trajectories of green innovation. Using panel data from 54 countries (2000–2022), green innovation is operationalized through environmental patent counts, digital transformation through internet penetration rates, and environmental pressure through CO₂-equivalent methane emissions. Control variables include GDP per capita, exports, urbanization, and foreign direct investment. Employing Pooled OLS, Fixed Effects, and Random Effects models, with the Hausman test favoring Random Effects ($\chi^2 = 5.31$, $p = 0.622$), the analysis is validated through stationarity diagnostics and heteroskedasticity-robust checks.

Findings reveal that digital transformation exerts a strong, statistically significant positive effect on green innovation, highlighting the role of digital infrastructure in knowledge diffusion, R&D acceleration, and eco-technological advancement. By contrast, methane emissions show a negative yet statistically insignificant relationship, indicating that ecological pressures alone rarely catalyze innovation without supportive policies. Among controls, exports display a tentative positive association, while GDP, FDI, and urbanization remain largely insignificant once digitalization is accounted for.

The results underscore digital transformation as a critical enabler of sustainable technological progress, while emphasizing that environmental policies must complement pollution pressures with regulatory incentives and market mechanisms to stimulate eco-innovation. By integrating digital infrastructure expansion with environmental regulation, governments can accelerate the diffusion of green technologies and secure innovation as a cornerstone of sustainable development. This study contributes to both academic discourse and policy design by evidencing the transformative role of digitalization in advancing environmental sustainability and cautioning against reliance on pollution pressures alone to drive green innovation.

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List of Abbreviations

Abbreviations	Full Form
ADF	Augmented Dickey-Fuller
AI	Artificial Intelligence
BBA	Bachelor of Business Administration
CH ₄	Methane
CO ₂	Carbon Dioxide
CV	Critical Value
ESG	Environmental, Social, and Governance
EU	European Union
FDI	Foreign Direct Investment
FE	Fixed Effects
GDP	Gross Domestic Product
GI	Green Innovation
ICT	Information and Communication Technology
IoT	Internet of Things
ITU	International Telecommunication Union
OLS	Ordinary Least Squares
OECD	Organisation for Economic Co-operation and Development
PPP	Purchasing Power Parity
R&D	Research and Development
RE	Random Effects
RFE	Robust Fixed Effects
UN	United Nations
WDI	World Development Indicators

1.0 Introduction

In response to escalating environmental challenges and increasing demands for sustainability, green innovation has become a vital strategy for balancing ecological protection with economic development. It refers to the creation and use of technologies, processes, and services that help reduce environmental damage while supporting industrial progress (Klerkx & Rose, 2020; Li et al., 2025). The foundations of today's green innovation movement were laid by key historical developments, such as the construction of the Hoover Dam in 1936—one of the first major hydroelectric projects—and the early experimentation with electric vehicles (Junesand, 2021). Over time, the urgency of environmental issues and the growing awareness among consumers, especially younger generations focused on sustainability, have driven businesses to adopt greener strategies (*Betting on Technology to Help Turn Consumers Green*, n.d.; *What's the Price of a Green Economy?*, 2022; Nayal et al., 2022). These shifts are also supported by significant public and private investments in sustainable technologies and infrastructure. Major policy initiatives like the European Green Deal and the U.S. Inflation Reduction Act have further accelerated this transition, highlighting green innovation as a key tool for building a sustainable and resilient future (*2. European Green Deal Policies and Sustainability | Transforming Our World: Interdisciplinary Insights on the Sustainable Development Goals*, n.d.; *INFLATION REDUCTION ACT OF 2022*, n.d.).

Concurrently, digital transformation has emerged as a crucial enabler of sustainability in both developed and developing economies. The integration of advanced technologies such as artificial intelligence (AI), big data analytics, blockchain, and the Internet of Things (IoT) across industries has fundamentally reshaped how organizations approach decision-making, resource allocation,

and emissions monitoring (Klerkx & Rose, 2020; Nayal et al., 2022). These digital tools not only improve operational efficiency but also provide greater transparency and traceability across supply chains, which is essential for meeting sustainability targets and complying with regulatory frameworks. In agriculture, for instance, the use of precision farming techniques enabled by digital technologies has optimized irrigation, fertilizer application, and livestock management, thereby reducing methane emissions—a particularly potent greenhouse gas—and promoting more sustainable food production systems (Shukla et al., 2022). Similar applications can be seen in manufacturing, energy, and transportation, where digitalization supports the transition toward greener practices by minimizing waste, lowering carbon footprints, and fostering circular economy models.

According to the Intergovernmental Panel on Climate Change (*2023 Global Methane Pledge Ministerial: Decisive Action to Curb Emissions - European Commission*, n.d.), agricultural methane—largely produced through enteric fermentation in livestock and manure management—accounts for almost 40% of the sector’s total greenhouse gas footprint. This is especially concerning because methane is far more potent than carbon dioxide in trapping heat in the atmosphere, making it a critical driver of climate change. Although various mitigation strategies have been tested and applied, from improving feed quality to better manure handling, global per capita methane emissions remain stubbornly high. This reality suggests that traditional approaches alone may not be sufficient to address the scale of the challenge. What is increasingly needed are integrated frameworks that connect digital transformation with sustainability goals. By examining how digital tools can help track, reduce, and manage per capita methane emissions, researchers and practitioners can gain a clearer picture of the role technology plays in fostering green innovation. Such an approach not only highlights the urgency of tackling agricultural emissions

but also underscores the importance of aligning technological progress with pathways to sustainable development.

Although previous literature has explored these themes in isolation, limited attention has been paid to their interdependent effects—particularly concerning per capita methane emissions. This study seeks to address this gap by empirically examining how digital transformation and per capita methane emissions influence the development and diffusion of green innovation initiatives. The findings are expected to inform policymakers, corporate leaders, and sustainability practitioners in shaping coherent and scalable approaches to sustainable agriculture and climate resilience.

2.0 Literature Review

2.1 Digital Transformation as a Driver of Green Innovation

Digital transformation has emerged as a transformative force driving both organizational efficiency and environmental sustainability. It entails the application of technologies such as artificial intelligence, the Internet of Things (IoT), blockchain, and big data analytics, which collectively enhance the precision and responsiveness of green innovation initiatives (Huang & Lau, 2024; Xi & Wang, 2024). By fostering real time monitoring, data driven decision making, and streamlined operations, digital tools support the execution of ESG goals and promote corporate transparency—a link affirmed by corporate-level research (*ESG in the Age of AI*, 2024; Zhang & Huang, 2024)—which underscore how digital transformation enhances ESG effectiveness through live data insights and improved disclosure quality.

Recent high-end empirical studies confirm a statistically significant positive influence of digital transformation on green innovation outcomes (e.g., green patent counts, innovation quality, efficiency). These relationships are evident in large panel datasets spanning Chinese manufacturing and listed firms, and remain robust across alternative specifications, mediating pathways (e.g., via R&D intensity or regulatory support), and regional and ownership heterogeneities (e.g., stronger effects in eastern regions and state owned enterprises) (Dong et al., 2024; Feng et al., 2022; Jiang, 2025; Yang & Liu, 2024; Zhu et al., 2024).

2.2 Per Capita Methane Emissions as a Driver of Green Innovation

In parallel with technological advancement, rising per capita methane emissions have drawn significant global attention as a critical driver compelling the adoption of green innovation strategies. Methane (CH₄), a potent greenhouse gas with a global warming potential over 80 times greater than that of CO₂ over a 20-year period, accounts for a substantial portion of short-term climate forcing (Environment, 2021). Sector-specific activities—such as livestock farming, oil and gas extraction, and organic waste decomposition—are among the largest contributors to methane emissions per capita, particularly in both industrialized and rapidly developing economies (*Global Methane Tracker 2022 – Analysis*, 2022; *Understanding Methane Emissions – Global Methane Tracker 2023 – Analysis*, n.d.). This emissions profile has prompted urgent policy actions and regulatory pressures, including international agreements such as the Global Methane Pledge, which aims to reduce methane emissions by 30% by 2030 (*2023 Global Methane Pledge Ministerial: Decisive Action to Curb Emissions - European Commission*, n.d.). In response, industries are increasingly investing in methane-reducing technologies—such as anaerobic digesters, precision agriculture, and advanced leak detection systems—as part of broader green innovation agendas (*Methane | Climate & Clean Air Coalition*, n.d.). These investments not only mitigate environmental harm but also stimulate innovation ecosystems focused on sustainable solutions, thereby reinforcing the role of methane metrics as both a regulatory benchmark and an innovation catalyst in the transition to low-carbon economies.

Recent studies suggest that higher per capita methane emissions can drive green innovation, largely in response to environmental pressures and stricter regulations. Magazzino et al., (2024) found that rising methane levels are linked to increased innovation in natural resource

management. Similarly, Jianu et al., (2022) show that in EU countries, higher greenhouse gas emissions per capita are associated with advances in green energy and waste technologies. While direct studies on per capita methane emissions and green innovation remain limited, the evidence points to environmental degradation acting as a trigger for innovation.

2.3 Research Gaps

Furthermore, recent literature calls for a more holistic approach in assessing the interplay among digital transformation, global methane approach, and green innovation. While previous research has typically examined digital transformation and per capita methane emissions independently, their combined impact on fostering green innovation remains underexplored (Babar & Akan, 2025; Rocca et al., 2024). Recent evidence suggests that digital transformation not only promotes green innovation, enabling firms to balance sustainability with performance (Xia & Chen, 2025), but also enhances green innovation through the mediating role of green management disclosure (Jiang, 2025). In parallel, studies demonstrate that green innovation plays a critical role in reducing environmental pollution across regions (Han et al., 2025) and in mitigating environmental injustice by alleviating disproportionate pollution burdens on disadvantaged groups (Fan et al., 2025). Building on these insights, this study contributes by bridging the gap and offering an integrated framework that links digital transformation and per capita methane emissions with the advancement of green innovation.

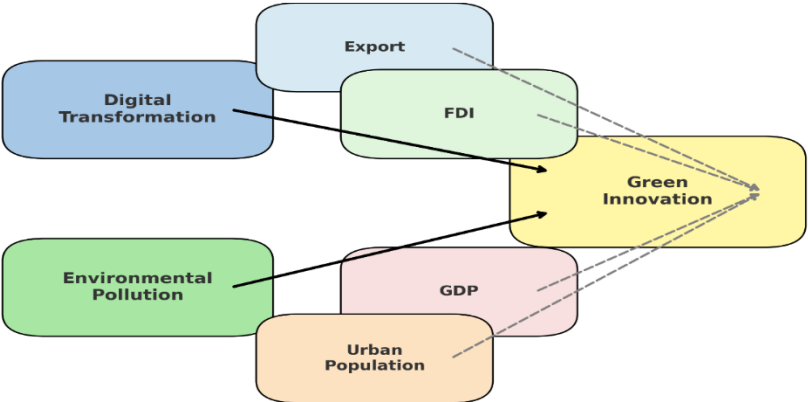
In summary, digital transformation and per capita methane emissions jointly shape the development of green innovation, supporting environmental stewardship, operational efficiency,

and sustainable practices. Future research should further explore this relationship to identify actionable strategies that drive innovation while advancing global resilience and low-emission outcomes.

2.4 Integrative Framework

Although prior research has examined digital transformation, per capita methane emissions, and green innovation individually, their joint effects remain largely unexplored. Evidence shows that digital transformation can stimulate green innovation (Jiang, 2025; Xia & Chen, 2025), while methane emissions critically shape environmental outcomes (Babar & Akan, 2025; Rocca et al., 2024). Green innovation has also been linked to reducing pollution spillovers and enhancing environmental justice (Fan et al., 2025; Han et al., 2025). Yet, challenges such as regulatory alignment, resource constraints, and uneven technology diffusion persist (Yang & Liu, 2024). Based on earlier studies that looked at these factors separately, we believe that digital transformation and environmental pollution both play important roles in shaping green innovation, and we propose a framework to examine how they interact.

Figure 1 Conceptual framework of the study



3.0 Methodology

3.1 Variable Definition and Data Sources

3.1.1 Dependent Variable

The dependent variable of this study is green innovation, which reflects a country's or firm's ability to produce environmentally sustainable technologies (Sova et al., 2024). This is measured through the number of patents on environmental technologies, a commonly accepted proxy in environmental economics and innovation research. These patents represent tangible outputs of eco-innovation and have been widely used in empirical studies to assess environmental technology advancement. In this study, patents on environmental technologies is denoted as *pat_env*. The data has been derived from the OECD database. For all the variables, including this, we have considered 54 countries and the time frame 2000-2022.

3.1.2 Independent Variables

To explore what drives green innovation, two independent variables are considered.

First, digital transformation is captured through the percentage of individuals using the internet in a given country and year. It refers to the proportion of the population who used the internet in the last three months, regardless of the device or location (home, work, mobile, etc.)(*Statistics*, n.d.). It is sourced by the International Telecommunication Union (ITU), a specialized agency of the United Nations. The ITU is responsible for collecting and standardizing global data on information

and communication technologies (ICTs), including internet usage, mobile access, and digital infrastructure. This variable reflects the diffusion of digital access and infrastructure across the population—factors that can significantly enhance a country’s innovation potential. A higher percentage indicates more widespread digital adoption, which may facilitate knowledge transfer and technology development. This variable is denoted as `int_usr`.

Second, environmental pollution is measured by per capita methane emissions, expressed in CO₂ equivalent metric tons. This variable reflects the environmental burden posed by an individual’s share of methane emissions, measured in tonnes of CO₂-equivalent per capita, illustrating the average greenhouse gas footprint per person—an indicator widely used to assess environmental pressure (*Per Capita Methane Emissions*, n.d.). The data was obtained from the Our World in Data database. A higher per capita methane emission level often signals environmental degradation, which may either constrain or incentivize green innovation efforts. This variable is denoted as `meth_em`.

3.1.3 Other Control Variables

In addition to the main predictors, a set of control variables is included to account for economic and structural influences on green innovation.

Export, denoted as `exp`, is measured by the exports of goods and services as a percentage of GDP. This variable captures the trade openness and global market integration of an economy. Such measures are widely used in empirical research examining how openness to international markets

can promote environmental innovation by facilitating competition and knowledge spillovers (Kim & Lin, 2022).

GDP, denoted as *gdp*, is measured through GDP per capita (PPP, current international \$). It is a measure of the average economic output per person, adjusted for differences in price levels across countries. It reflects the value of all goods and services produced in a country in a given year, divided by the population, and adjusted to account for the cost of living and inflation rates. This metric is expressed in current international dollars to enable more accurate cross-country comparisons.

In this study, urban population is used as a proxy for overall population structure because it better reflects the conditions that support both digital transformation and green innovation. It is represented by *urb_pop*. Urban areas typically have stronger access to digital infrastructure, research hubs, and governance systems—all of which play a key role in enabling innovation. They also tend to concentrate economic activity and environmental challenges, including methane emissions from sectors like transportation, industry, and waste. Using urban population (% of total population) offers more meaningful insight than total population alone, as it captures the density, scale, and capacity of cities to both generate and respond to innovation. This approach is consistent with previous research that links urbanization to the spread of digital technologies and the clustering of green innovation (*World Cities Report 2024*, n.d.).

Lastly, Foreign Direct Investment, denoted as *fdi*, is captured through FDI, net inflows (BoP, current US\$). As of the World Bank (*Glossary / DataBank*, n.d.-a), Foreign Direct Investment (FDI), net inflows (BoP, current US\$) represent the total incoming investment from foreign investors into a country, including equity capital, reinvested earnings, and intra-company loans.

Measured in current U.S. dollars, it reflects the real financial commitment of foreign entities based on the Balance of Payments framework. In this study, FDI is used as a control variable due to its potential impact on green innovation. Foreign investment can support technology transfer, knowledge spillovers, and access to capital for environmental R&D. Multinational firms often bring cleaner technologies and sustainability standards, especially from countries with stricter regulations. Therefore, FDI inflows may indirectly promote green innovation by improving firms' access to new capabilities and financial resources needed for developing environmental technologies (*Glossary / DataBank*, n.d.-b).

The below table (Table 1) presents a detailed description of the variables.

Table 1 Summary of variables and data sources

Type of Variable	Name of Variable	Measurement	Notation	Source
Dependent variable	Green innovation	Patents on environment technologies	pat_env	OECD Database
	Digital transformation	Percentage of individuals using the internet	int_usr	ITU – ICT Indicators
Independent variables	Environmental pollution	Per capita methane emissions	meth_em	Our World in Data
	Export	Exports of goods and services (% of GDP)	exp	World Development

Control variables				Indicators (WDI)
	GDP	GDP per capita, PPP (current international \$)	gdp	World Development Indicators (WDI)
	Population	Urban population (% of total population)	urb_pop	World Development Indicators (WDI)
	FDI	Foreign direct investment, net inflows (BoP, current US\$)	fdi	World Development Indicators (WDI)

3.1.4 Data Scope and Country Coverage

This study employs a balanced panel dataset covering 54 countries over the period 2000–2022. The use of panel data enables the analysis to capture both cross-sectional and time-series variations, thereby allowing for a more robust estimation of the relationship between digital transformation, environmental pollution, and green innovation. The countries included in this study were selected based on the availability and consistency of data across key variables such as internet usage, per capita methane emissions, gdp, exports, urban population, and foreign direct investment. By incorporating a wide set of countries from different regions and income groups,

the dataset provides a comprehensive basis to examine the global dynamics of sustainability and innovation. A detailed list of the countries included in the analysis is presented below.

Table 2 Country coverage

Country	Country	Country
Algeria	Estonia	Netherlands
Argentina	Finland	New Zealand
Australia	France	Norway
Austria	Germany	Pakistan
Bangladesh	Greece	Philippines
Belarus	Hungary	Poland
Belgium	Iceland	Portugal
Brazil	India	Romania
Bulgaria	Indonesia	Saudi Arabia
Canada	Ireland	Slovenia
Chile	Israel	South Africa
China	Italy	Spain
Colombia	Japan	Sweden
Costa Rica	Kazakhstan	Switzerland
Croatia	Lebanon	Thailand
Cyprus	Malaysia	Ukraine
Czechia	Mexico	United Kingdom
Denmark	Morocco	United States

Table 1 defines the dependent, independent, and control variables with sources, while Table 2 lists the 54 countries included in the study.

3.2 Research Hypotheses

3.2.1 Digital Transformation and Green Innovation

Recent studies have shown that digital transformation—especially through increased internet use—can strongly support green innovation. It helps spread knowledge, improve efficiency, and make it easier to develop and adopt clean technologies. For example, (Lin & Ma, 2022) and (Wang et al., 2024) found that countries with better digital infrastructure often generate more green patents and move faster toward cleaner solutions. Based on these findings, this study expects a similar positive relationship and proposes the following hypothesis:

H₁: Digital transformation, measured by the percentage of individuals using the internet (int_usr), are positively associated with green innovation (pat_env).

3.2.2 Environmental Pollution and Green Innovation

Emerging research suggests that higher environmental pollution, especially in the form of methane emissions, can trigger a regulatory and societal push toward eco-innovation. (Magazzino et al., 2024) and (Wang et al., 2024) find that regions with elevated greenhouse gas emissions often exhibit increased efforts in green technology adoption and sustainable development. Based on this observed pattern, it is reasonable to hypothesize the following relationship:

H₂: Environmental pollution, measured by per capita methane emissions (meth_em), are negatively associated with green innovation (pat_env).

3.2.3 Control Variables and Robustness of Relationship

Previous studies highlight that macroeconomic variables such as export levels, income per capita, urbanization, and FDI can also affect innovation outcomes. Trade openness and foreign investment, in particular, are known to encourage knowledge spillovers and technology transfer (Kim & Lin, 2022; Yingjun et al., 2024). To ensure the effect of digital transformation is not confounded by these influences, the following hypothesis is proposed:

H₃: The positive relationship between digital transformation (int_usr) and green innovation (pat_env) remains significant after controlling for exp, gdp, urb_pop, and fdi.

3.3 Model Specification

3.3.1 Baseline Panel Regression Model

To empirically examine the impact of digital transformation and environmental pollution on green innovation, the study employs a linear panel regression framework. The dependent variable is green innovation (measured by pat_env), while the key explanatory variables are digital transformation (int_usr) and per capita methane emissions (meth_em). Several control variables are included to account for trade openness, economic development, urbanization, and foreign investment.

The baseline model is specified as follows:

$$\begin{aligned} pat_env_{it} = & \beta_0 + \beta_1 \cdot int_{usr_{it}} + \beta_2 \cdot meth_{em_{it}} + \beta_3 \cdot exp_{it} + \beta_4 \cdot gdp_{it} \\ & + \beta_5 \cdot urb_pop_{it} + \beta_6 \cdot fdi_{it} + \epsilon_{it} \end{aligned} \quad (1)$$

Where:

- i = country index
- t = time (year)
- β_0 = intercept
- $\beta_1 \dots \beta_6$ = coefficients estimating the effect of each explanatory variable
- ϵ_{it} = error term

3.3.2 Pooled OLS Model

In this model, all country and time data are pooled together, ignoring individual country differences. It gives initial estimates but may suffer from bias due to unobserved heterogeneity. It assumes all countries are the same, no individual-specific effects.

The pooled OLS model is specified as follows:

$$pat_env_{it} = \beta_0 + \sum_{k=1}^6 \beta_k X_{kit} + \epsilon_{it} \quad (2)$$

Where:

- β_0 = intercept
- X_{kit} = Represents each explanatory variable (int_usr, meth_em, exp, gdp, urb_pop, fdi)
- ϵ_{it} = error term

3.3.3 Fixed Effects (FE) Model

The FE model controls for country-specific unobserved heterogeneity and is appropriate when regressors are correlated with the unit effects, helping mitigate omitted-variable bias.

The fixed effects model is specified as follows:

$$\begin{aligned} pat_env_{it} = & \beta_0 + \beta_1 \cdot int_usr_{it} + \beta_2 \cdot meth_em_{it} + \beta_3 \cdot exp_{it} + \beta_4 \\ & \cdot gdp_{it} + \beta_5 \cdot urb_pop_{it} + \beta_6 \cdot fdi_{it} + \mu_i + \epsilon_{it} \end{aligned} \quad (3)$$

Where:

- i = country index
- t = time (year)
- β_0 = intercept
- $\beta_1 \dots \beta_6$ = coefficients estimating the effect of each explanatory variable
- ϵ_{it} = error term
- μ_i = Country-specific unobserved factors (e.g., cultural, institutional, or historical traits)

3.3.4 Random Effects (RE) Model

Unlike FE, the RE model assumes country-specific effects are random and uncorrelated with regressors. It is more efficient if the assumption holds true.

The random effects model is specified as follows:

$$\begin{aligned}
 pat_env_{it} = & \beta_0 + \beta_1 \cdot int_{usr_{it}} + \beta_2 \cdot meth_{em_{it}} + \beta_3 \cdot exp_{it} + \beta_4 \cdot gdp_{it} \\
 & + \beta_5 \cdot urb_{pop_{it}} + \beta_6 \cdot fdi_{it} + \mu_i + \epsilon_{it}, \quad \mu_i \sim N(0, \sigma_\mu^2)
 \end{aligned} \tag{4}$$

Where:

- i = country index
- t = time (year)
- β_0 = intercept
- $\beta_1 \dots \beta_6$ = coefficients estimating the effect of each explanatory variable
- ϵ_{it} = error term
- μ_i = Country-specific effect is random and uncorrelated with regressors
- σ_μ^2 = Variance of random effect

3.3.5 Hausman Test

The Hausman test compares FE and RE estimators. The test compares FE and RE estimates using the difference in coefficients and their variance–covariance matrices. A significant test statistic indicates that RE is inconsistent, so FE should be preferred.

The hausman test model is specified as follows:

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})' \cdot [Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})]^{-1} \cdot (\hat{\beta}_{RE} - \hat{\beta}_{FE}) \tag{5}$$

Where:

- $\hat{\beta}_{FE}$ = Estimated coefficients from the Fixed Effects (FE) model
- $\hat{\beta}_{RE}$ = Estimated coefficients from the Random Effects (RE) model
- $Var(\hat{\beta}_{FE})$ = Variance-covariance matrix of the FE estimates.
- $Var(\hat{\beta}_{RE})$ = Variance-covariance matrix of the RE estimates.
- If the test statistic is significant, FE is preferred; otherwise, RE is retained

3.3.6 Augmented Dickey-Fuller (ADF) Test

The ADF test checks for stationarity of variables. The null hypothesis assumes a unit root (non-stationary), while rejection implies stationarity.

The ADF test model is specified as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^p \delta_i \Delta y_{t-1} + \epsilon_t \quad (6)$$

Where:

- y_t = Variable being tested (int_usr, meth_em, exp, etc.)
- Δy_t = First difference of the series
- t = Time trend
- γ = Coefficient testing for unit root
- Null: non-stationary ($\gamma = 0$); Alternative: stationary ($\gamma < 0$)

4.0 Empirical Results

4.1 Descriptive Analysis

Table 3 presents the descriptive statistics for the main variables used in this study. Green innovation (measured as *pat_env*) records an average of 11.37 patents, ranging from 0.84 to 48.69, with a positive skewness of 1.38, suggesting a concentration at lower values but with some highly innovative countries at the upper tail. Digital transformation (*int_usr*) averages 55.39%, with values ranging from nearly zero to universal access. This wide variation indicates significant digital divides across countries.

Table 3 Descriptive statistics

Variable	Mean	Median	Minimum	Maximum	Std. Dev.	Skewness
<i>pat_env</i>	11.3729	10.7074	0.8427	48.6924	5.2702	1.3812
<i>int_usr</i>	55.386	61.991	0.071	100	30.0511	-0.3801
<i>meth_em</i>	1.8947	1.4137	0.2444	9.8796	1.5324	2.5982
<i>exp</i>	41.0755	35.6887	8.2216	136.6844	22.1298	1.0764
<i>gdp</i>	28192.05	26432.89	1511.905	136104.45	18147.523	0.9255
<i>urb_pop</i>	70.8896	73.918	23.59	98.153	16.1529	-0.7271
<i>fdi</i>	2.71E+10	7.24E+09	-2.86E+11	7.338E+11	6.544E+10	3.8773

Environmental pollution (*meth_em*) averages 1.89, with a right-skewed distribution (skewness = 2.59), implying that most countries emit relatively low levels, while a few exhibit very high emissions. Control variables also show heterogeneity: exports average 41.08% of GDP, GDP

averages 28,192 USD but with high dispersion (min = 1,512; max = 136,104), urban population shares average 71%, and FDI inflows display extremely high variance due to global investment outliers.

Overall, the descriptive statistics highlight wide variation across the sample, supporting the use of panel econometric techniques.

Figure 2 Skewness by variable

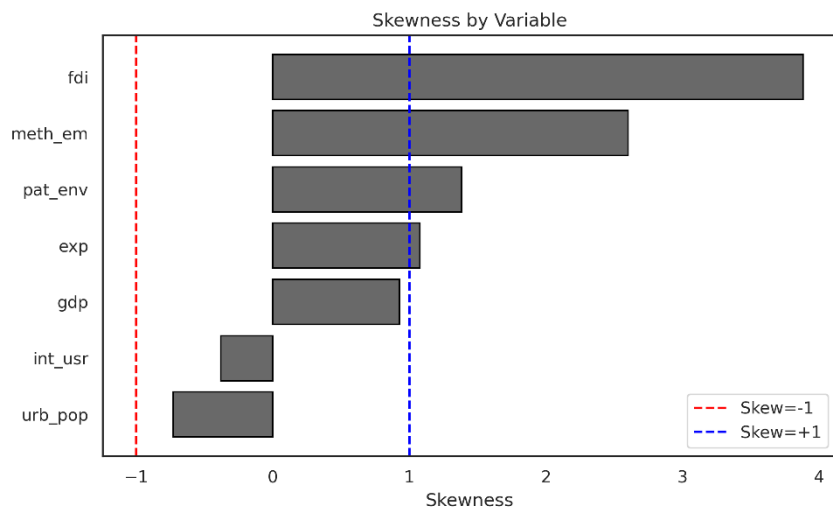


Figure 3 Range with median marker

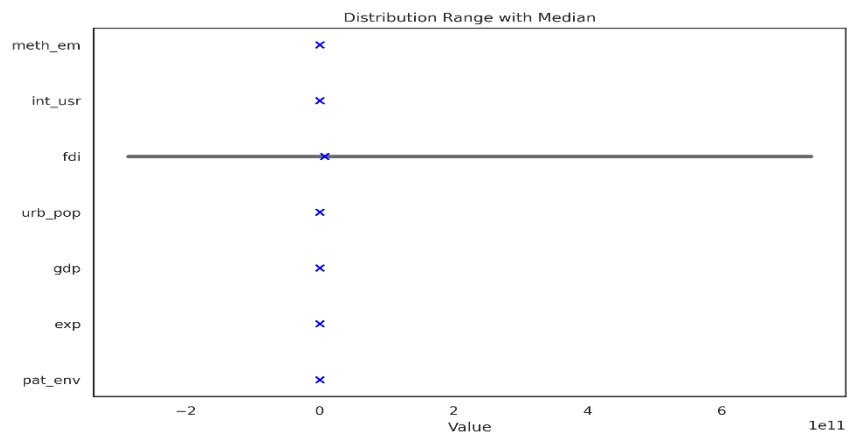


Figure 4 Coefficient of variation

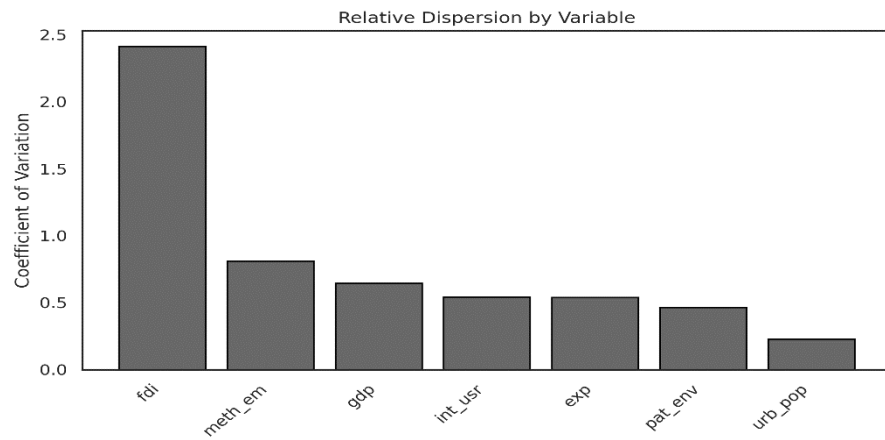


Figure 5 Scatterplot matrix

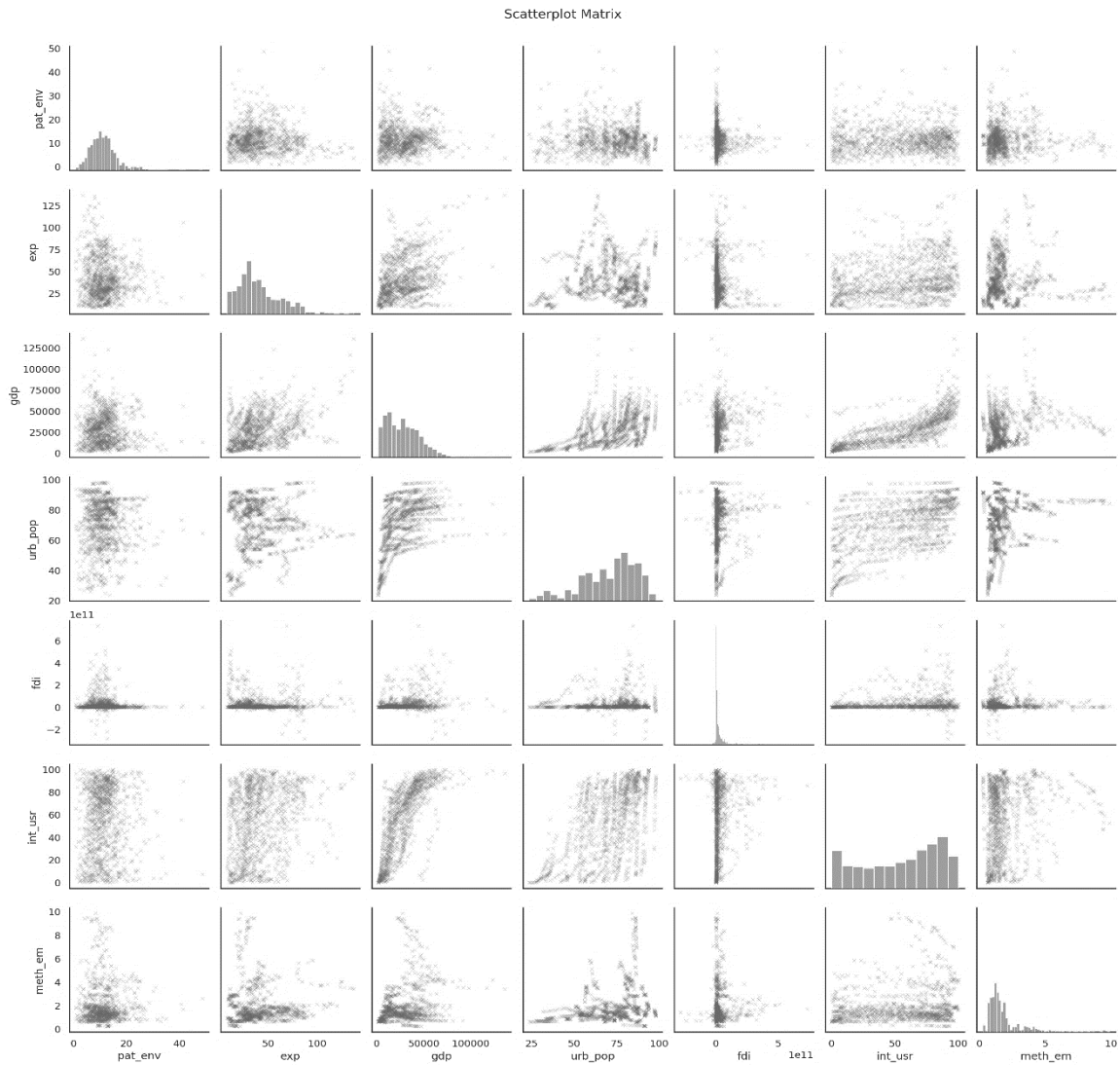


Figure 6 Correlation matrix heatmap

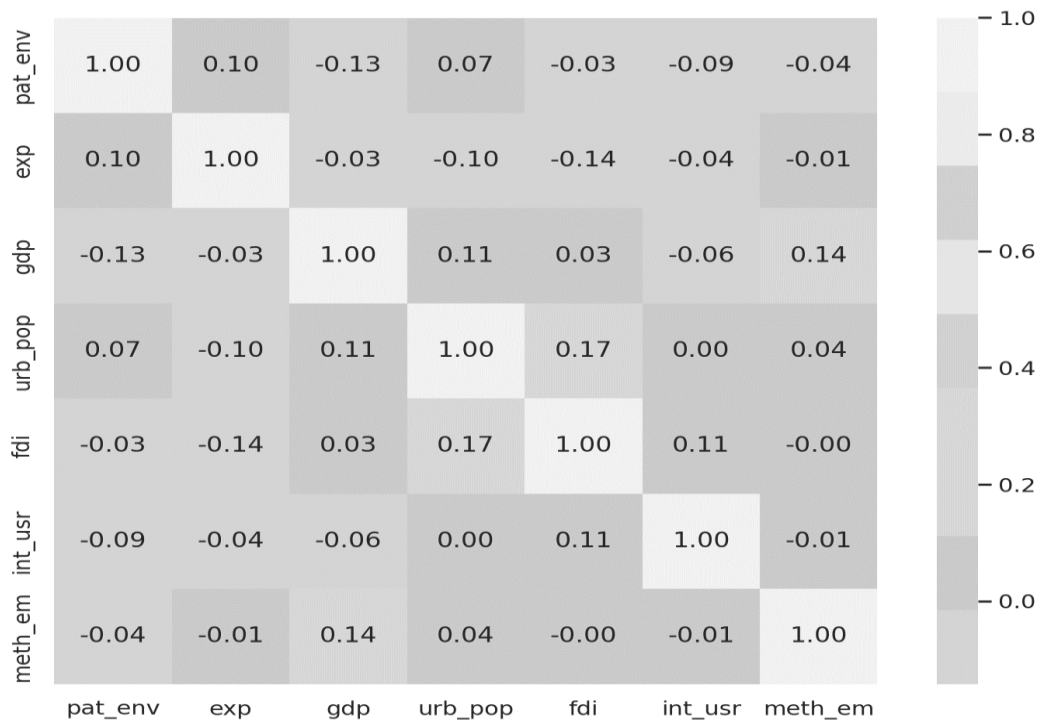


Table 3 shows descriptive statistics, highlighting wide cross-country variation. Figure 2 reports skewness, Figure 3 shows ranges with medians, and Figure 4 the coefficient of variation. Figures 5 and 6 present scatterplots and correlation heatmaps, summarizing inter-variable relationships.

4.2 Stationarity Test

The Augmented Dickey-Fuller (ADF) test was employed to examine the time-series properties of the panel data. At the 5% significance level, all variables—pat_env, int_usr, meth_em, exp, gdp, urb_pop—were found to be stationary. Only FDI failed the stationarity test (ADF = -2.45, p =

0.127). As non-stationarity can bias estimates, FDI is treated with caution in interpretation. This validation ensures that the regression models are free from false correlations.

Table 4 ADF unit root test summary

Variable	ADF Statistic	p-value	CV (1%)	CV (5%)	CV (10%)	Stationary (at 5%)
pat_env	-10.52589	0.00000	-3.43575	-2.86392	-2.56804	Yes
int_usr	-7.29693	0.00000	-3.43582	-2.86396	-2.56806	Yes
meth_em	-5.57085	0.00000	-3.43576	-2.86393	-2.56804	Yes
exp	-6.71513	0.00000	-3.43572	-2.86391	-2.56803	Yes
gdp	-5.90195	0.00000	-3.43582	-2.86396	-2.56806	Yes
urb_pop	-5.19305	0.00001	-3.43572	-2.86391	-2.56803	Yes
fdi	-2.45352	0.12720	-3.43582	-2.86396	-2.56806	No

Figure 7 ADF test statistics with critical value references

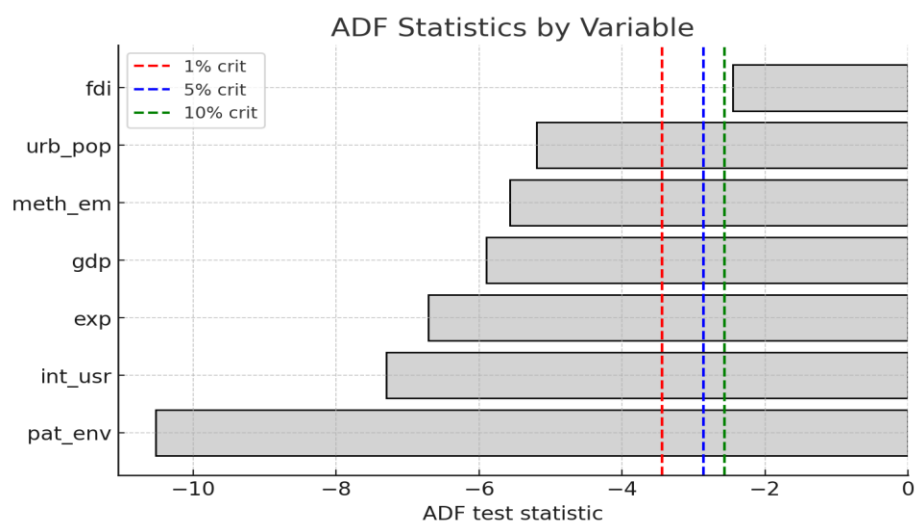
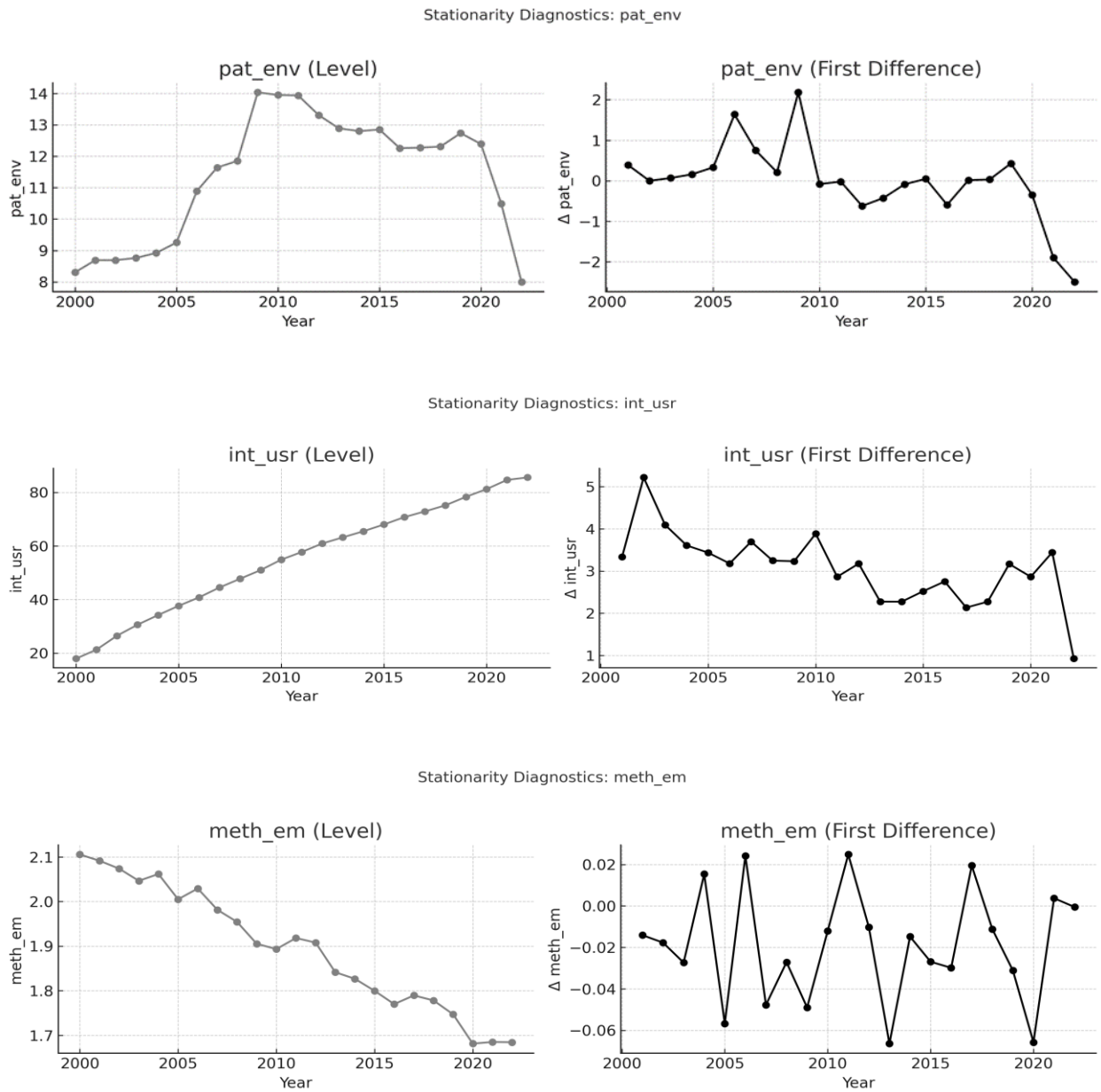
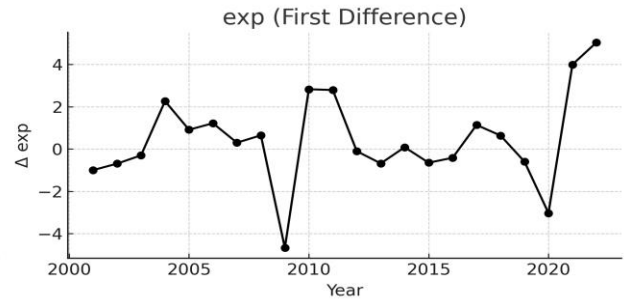
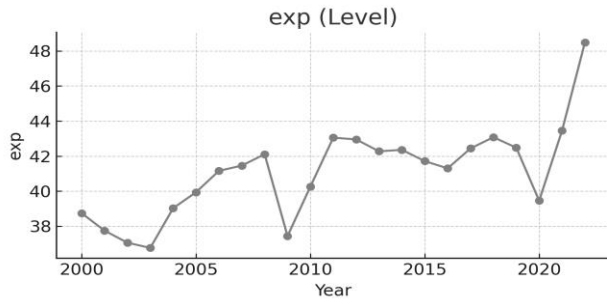


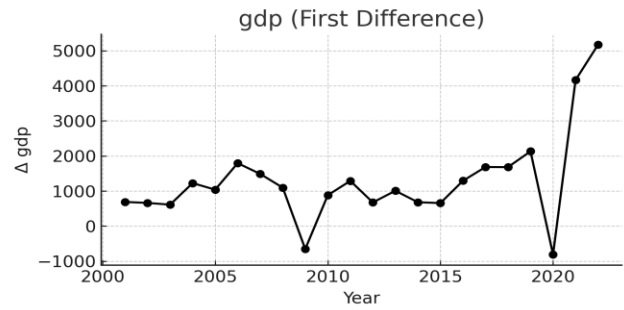
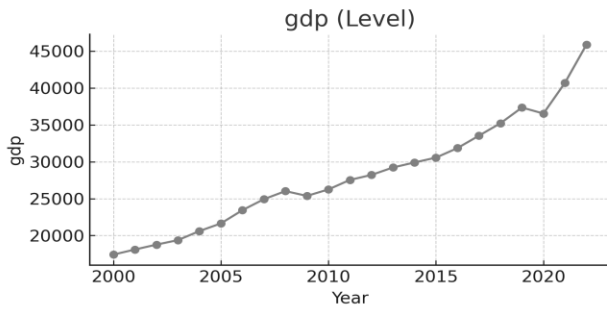
Figure 8 Time series plots (levels vs. first differences)



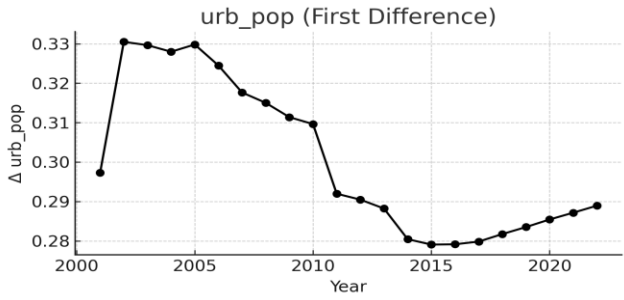
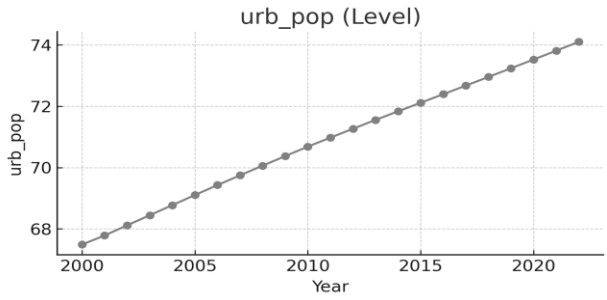
Stationarity Diagnostics: exp



Stationarity Diagnostics: gdp



Stationarity Diagnostics: urb_pop



Stationarity Diagnostics: fdi

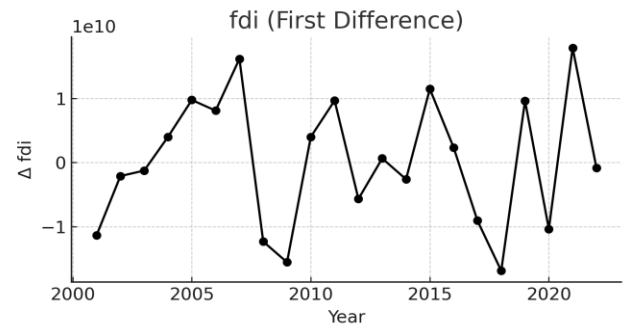
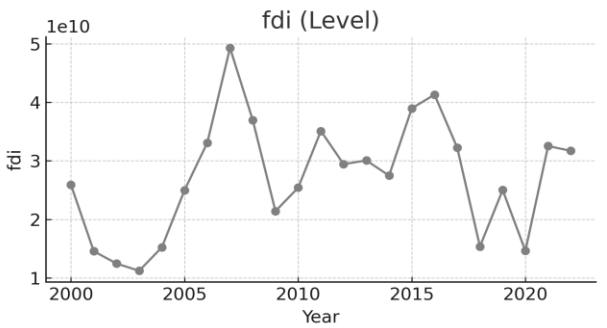


Table 4 reports ADF unit root results, showing most variables are stationary. Figure 7 compares test statistics with critical values, while Figure 8 plots time-series in levels and differences, confirming stability.

4.3 Regression Results

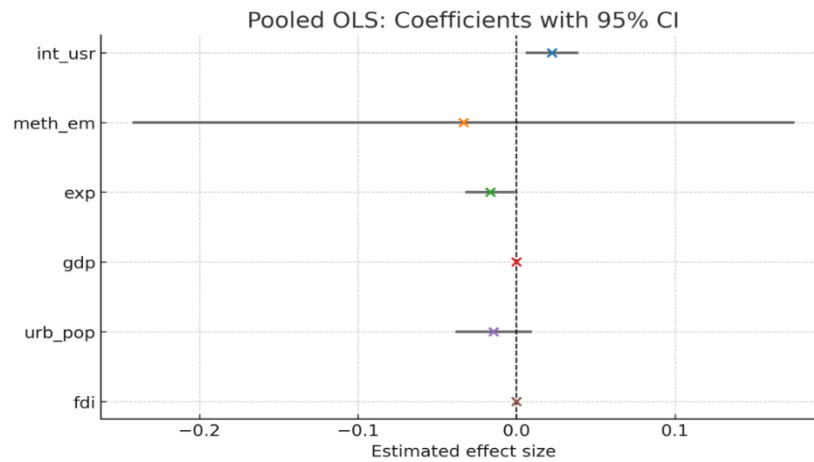
4.3.1 Pooled OLS

The baseline Pooled OLS regression provides an initial estimate without controlling for country-specific heterogeneity. Results indicate that `int_usr` exerts a positive and significant effect on green innovation. Exports show a negative and statistically significant association in Pooled OLS, though the sign turns positive (and weaker) in FE/RE. While `meth_em` enters with a negative but insignificant coefficient. However, because Pooled OLS ignores unobserved country effects, the estimates may be biased.

Table 5 Pooled OLS regression results

Variable	Coef.	Std.Err.	t	P> t 	[0.025	0.975]
<code>int_usr</code>	0.0223	0.0081	2.7710	0.0057	0.0065	0.0381
<code>meth_em</code>	-0.0334	0.1059	-0.3156	0.7524	-0.2413	0.1744
<code>exp</code>	-0.0165	0.0075	-2.1958	0.0283	-0.0313	-0.0018
<code>gdp</code>	0.0000	0.0000	-0.6023	0.5471	0.0000	0.0000
<code>urb_pop</code>	-0.0144	0.0118	-1.2169	0.2239	-0.0376	0.0088
<code>fdi</code>	0.0000	0.0000	-2.7165	0.0067	0.0000	0.0000

Figure 9 Coefficient estimates with 95% confidence intervals for Pooled OLS



4.3.2 Fixed Effects Model

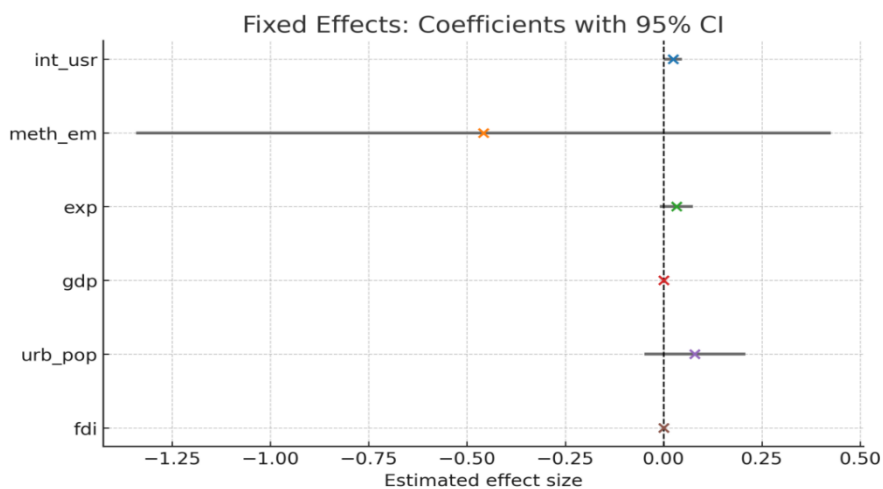
The Fixed Effects (FE) model, which controls for country-specific unobserved heterogeneity, is reported as the benchmark specification. While it provides valuable insights, subsequent model testing indicates that Random Effects (RE) offers the more appropriate framework for this dataset. Results reveal that digital transformation (*int_usr*) remains strongly positive and significant (Coef = 0.024, $p = 0.011$), supporting the hypothesis that greater internet penetration enhances green innovation. Methane emissions (*meth_em*), although negatively signed, are not statistically significant, suggesting that pollution alone does not directly suppress innovation once fixed effects are accounted for.

Table 6 Fixed effects regression results

Variable	Coef.	Std.Err.	t	P> t	0.025	0.975
<i>int_usr</i>	0.0241	0.0095	2.5310	0.0115	0.0054	0.0428
<i>meth_em</i>	-0.4581	0.4480	-1.0223	0.3068	-1.3371	0.4210

exp	0.0326	0.0195	1.6758	0.0940	-0.0056	0.0708
gdp	0.0000	0.0000	-0.0803	0.9360	0.0000	0.0000
urb_pop	0.0794	0.0635	1.2512	0.2111	-0.0451	0.2039
fdi	0.0000	0.0000	-0.0208	0.9834	0.0000	0.0000

Figure 10 Coefficient estimates with 95% CI for FE



Among controls, exports (exp) display a positive and marginally significant effect ($p \approx 0.094$), implying trade openness could stimulate innovation diffusion. By contrast, GDP, FDI, and urban population are statistically insignificant, indicating that macroeconomic scale, investment inflows, and urbanization do not directly drive innovation outcomes once digitalization is controlled for.

Notably, several country dummy coefficients are negative and significant (e.g., Argentina, Austria), capturing structural differences in baseline innovation performance relative to the reference group.

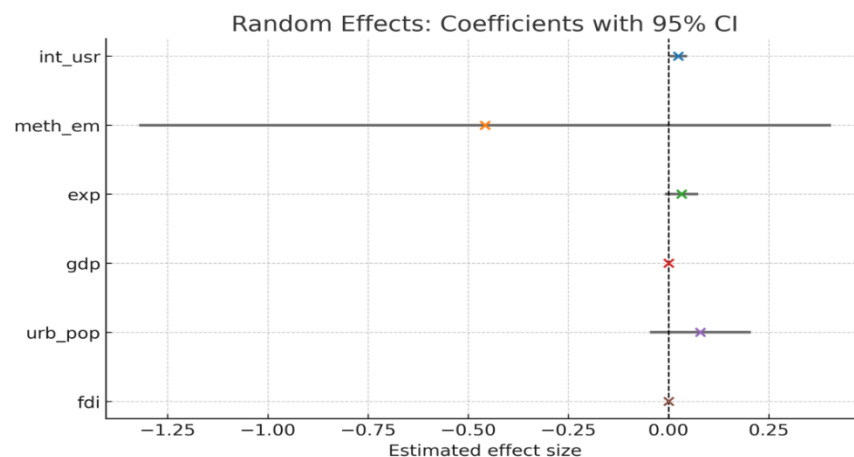
4.3.3 Random Effects Model

The Random Effects (RE) estimates, which assume orthogonality between regressors and individual effects, yield broadly similar coefficients. Digital transformation remains positive and significant, while environmental pollution remains negative and insignificant. The consistency across FE and RE models strengthens the validity of the findings. However, small differences in magnitude highlight the importance of testing model suitability.

Table 7 Random effects regression results

Variable	Coef.	Std.Err.	z	P> z	0.025	0.975
int_usr	2.41E-02	9.32E-03	2.59E+00	9.76E-03	5.84E-03	4.24E-02
meth_em	-4.58E-01	4.38E-01	-1.05E+00	2.96E-01	-1.32E+00	4.02E-01
exp	3.26E-02	1.90E-02	1.71E+00	8.69E-02	-4.73E-03	7.00E-02
gdp	-1.89E-06	2.31E-05	-8.21E-02	9.35E-01	-4.71E-05	4.34E-05
urb_pop	7.94E-02	6.21E-02	1.28E+00	2.01E-01	-4.24E-02	2.01E-01

Figure 11 Coefficient estimates with 95% CI for RE



4.3.4 Hausman Test

The Hausman specification test (Table 8) fails to reject the null hypothesis ($\chi^2 = 5.31$, $df = 7$, $p = 0.622$). This indicates that there is no statistical evidence of correlation between the regressors and the individual-specific effects. Consequently, the Random Effects model is preferred, as it is both consistent and more efficient than the Fixed Effects estimator in this context.

Table 8 Hausman test results

Test Statistic	Degrees of Freedom	p-value	Decision
5.307972	7	0.622435489	Fail to reject $H_0 \rightarrow$ Random Effects preferred

Table 5 with Figure 9 (OLS), Table 6 with Figure 10 (FE), and Table 7 with Figure 11 (RE) all confirm digital transformation's positive effect. Table 8 (Hausman test) supports RE, while Table 9 with Figure 12 (robust FE) validates result consistency.

4.4 Robustness Test

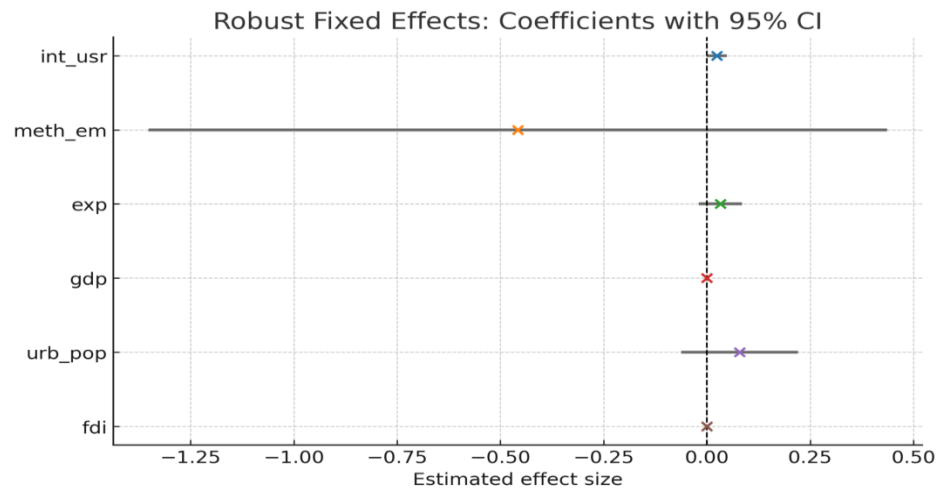
As a robustness check, we estimated Fixed Effects regressions with heteroskedasticity-consistent standard errors. Results confirm that digital transformation (*int_usr*) retains its positive and statistically significant impact on green innovation (Coef = 0.024, $p = 0.018$), while per capita methane emissions (*meth_em*) remain negative but insignificant. Control variables, including exports, GDP, urban population, and FDI, continue to show weak or null effects. These robustness

results reinforce the stability of our findings, even though the Hausman test indicates that Random Effects is the most appropriate specification for the main analysis.

Table 9 Robustness test results

Variable	Coef.	Std.Err.	z	P> z	[0.025	0.975]
int_usr	0.0241	0.0102	2.3592	0.0183	0.0041	0.0442
meth_em	-0.4581	0.4541	-1.0086	0.3132	-1.3481	0.4320
exp	0.0326	0.0246	1.3270	0.1845	-0.0156	0.0808
gdp	0.0000	0.0000	-0.0839	0.9331	0.0000	0.0000
urb_pop	0.0794	0.0700	1.1344	0.2566	-0.0578	0.2166
fdi	0.0000	0.0000	-0.0452	0.9640	0.0000	0.0000

Figure 12 Coefficient estimates with 95% CI for RFE



4.5 Comparative Interpretation

Across all specifications—Pooled OLS, Fixed Effects, Random Effects, and Robust Fixed Effects—the evidence consistently shows that digital transformation significantly enhances green innovation. Environmental pollution, while negatively associated, does not attain statistical significance, suggesting its role may be indirect or conditional on other moderating factors. Control variables (exports, GDP, urban population, and FDI) have limited or inconsistent effects, with exports showing the only tentative positive contribution.

The Hausman test confirms that Random Effects estimation is appropriate, and robustness checks reinforce the reliability of the results. Collectively, these findings provide strong empirical support for the hypothesis that digital transformation is a key driver of green innovation across countries, while traditional macroeconomic factors play secondary roles.

5.0 Discussion

The empirical results provide strong support for the first hypothesis. Across Pooled OLS, Fixed Effects, Random Effects, and robustness checks, digital transformation consistently shows a positive and statistically significant effect on green innovation. This finding highlights the crucial role of digitalization as a driver of eco-innovation, enabling the diffusion of knowledge, strengthening research and development, and supporting the adoption of sustainable technologies. Table 10 summarizes hypotheses and outcomes, while Table 11 condenses regression findings, confirming digital transformation as a consistent driver of green innovation.

Table 10 Summary of hypotheses

Hypothesis	Statement (as posed)	Empirical finding (direction & significance)	Verdict
H ₁	Digital transformation (int_usr) positively influences green innovation (pat_env).	Positive & statistically significant across Pooled OLS (p=0.0057), FE (p=0.0115), RE (p≈0.0098), and Robust FE (p=0.0183).	Supported
H ₂	Environmental pollution (meth_em) negatively influences green innovation.	Coefficient is negative but not statistically significant in Pooled OLS (p=0.7524), FE (p=0.3068), RE (p=0.296), Robust FE (p=0.3132).	Not supported

H ₃	The positive effect of digital transformation on green innovation remains after controlling for exp, gdp, urb_pop, fdi.	Remains positive & significant in FE (p=0.0115), RE (p≈0.0098), Robust FE (p=0.0183) with controls included.	Supported
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By contrast, the second hypothesis is not supported. Although methane emissions exhibit a negative coefficient, the relationship is statistically insignificant in all model specifications. This suggests that environmental pressures alone do not automatically stimulate green innovation unless accompanied by targeted regulatory or policy interventions.

Table 11 Summary of empirical results

Variable	Sign	Significance (main results)	Easy takeaway
int_usr	+	Significant in all models (p < 0.05)	Strong positive driver of green innovation
meth_em	-	Not significant in any model (p > 0.30)	No clear effect detected
exp	+	Weakly significant in some models (p ≈ 0.09)	Possible positive effect, but weak evidence
gdp	±	Not significant in any model	No effect
urb_pop	±	Not significant in any model	No effect
fdi	±	Not significant; also non-stationary (ADF p = 0.127)	No effect; results should be treated with caution

The third hypothesis is supported. Even after including control variables, the positive effect of digital transformation on green innovation remains significant. Among the controls, exports display a weak and marginally positive effect, while GDP, FDI, and urban population remain largely insignificant. These results reinforce the robustness of the digital transformation effect. Importantly, the Hausman test indicates that the Random Effects estimator is more appropriate, meaning that unobserved country-specific heterogeneity is not strongly correlated with the explanatory variables and that Random Effects provides the most efficient and consistent estimates for this dataset.

Recent studies reviewed in the literature have consistently highlighted the positive role of digital transformation in fostering green innovation, often emphasizing how information and communication technologies (ICTs) improve efficiency, reduce transaction costs, and enable environmentally sustainable technologies. Similarly, many articles reported that environmental pressures, including carbon and methane emissions, can act as drivers for innovation by compelling firms and countries to adopt greener practices. In line with this, my study confirms the strong and significant positive impact of digital transformation on green innovation, echoing earlier findings. However, in contrast to much of the existing work, I find that per capita methane emissions do not have a statistically significant effect, suggesting that environmental pressures alone are insufficient to trigger innovation without broader institutional and technological support. Moreover, while previous research has primarily focused on advanced economies or single-country contexts, my cross-country analysis across 54 diverse economies adds new global evidence. The robustness checks further strengthen this contribution by showing that the digital transformation effect holds across specifications. Thus, the study both validates prior insights and

extends them by challenging the assumed universal effect of pollution pressures while highlighting the central role of digital infrastructure as a consistent enabler of green innovation worldwide.

6.0 Conclusion and Future Recommendations

This study examined how digital transformation, environmental pollution, and selected macroeconomic factors shape green innovation across 54 countries between 2000 and 2022. The hypotheses focused on whether digital transformation positively influences green innovation, whether environmental pollution negatively affects green innovation, and whether the digital transformation effect remains significant after controlling for macroeconomic variables such as exports, GDP, FDI, and urban population.

In summary, the findings affirm that digital transformation is a central enabler of green innovation, while environmental pollution plays at most a secondary role. Policymakers should recognize that, in the absence of deliberate policy incentives, pollution pressures are unlikely to generate eco-innovation responses.

The findings carry important implications for both policy and future research. Governments should prioritize expanding digital infrastructure, including internet connectivity, ICT capacity, and digital literacy, since broadening access to digital technologies has the potential to accelerate the diffusion of knowledge and stimulate higher levels of green patenting. At the same time, environmental pollution must be linked to policy incentives. Because pollution on its own does not foster innovation, regulatory measures such as carbon pricing, methane taxation, or targeted subsidies for green research and development are necessary to transform ecological pressures into meaningful innovation drivers. Trade also emerges as a possible channel for green spillovers. The tentative positive role of exports suggests that trade openness can enhance technology transfer and knowledge exchange. Policy frameworks that promote green trade partnerships, sustainable value

chains, and international collaboration in research and development may therefore amplify this effect. Although foreign direct investment did not show significance in aggregate form, its impact could be strengthened if it is directed specifically toward renewable energy, clean manufacturing, and circular economy sectors.

Finally, this study highlights avenues for further research. Future work could extend the analysis by including other pollutants, such as carbon dioxide or nitrous oxide, to capture a broader set of environmental pressures. Employing dynamic panel models such as the Generalized Method of Moments (GMM) would also allow for the assessment of lag effects from digitalization on innovation. In addition, exploring moderating factors like institutional quality, environmental regulation, or renewable energy adoption could deepen our understanding of how contextual conditions influence the green innovation process. Examining regional differences across advanced and emerging economies may also reveal context-specific drivers and constraints.

Taken together, the results demonstrate that although environmental challenges remain pressing, digital transformation currently stands out as the most effective lever for accelerating sustainable innovation. The future of green innovation lies in combining digital strategies with targeted environmental and economic policies that together foster a comprehensive ecosystem for sustainability.

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