Energy innovation and ecological footprint: Evidence from OECD countries during 1990–2018

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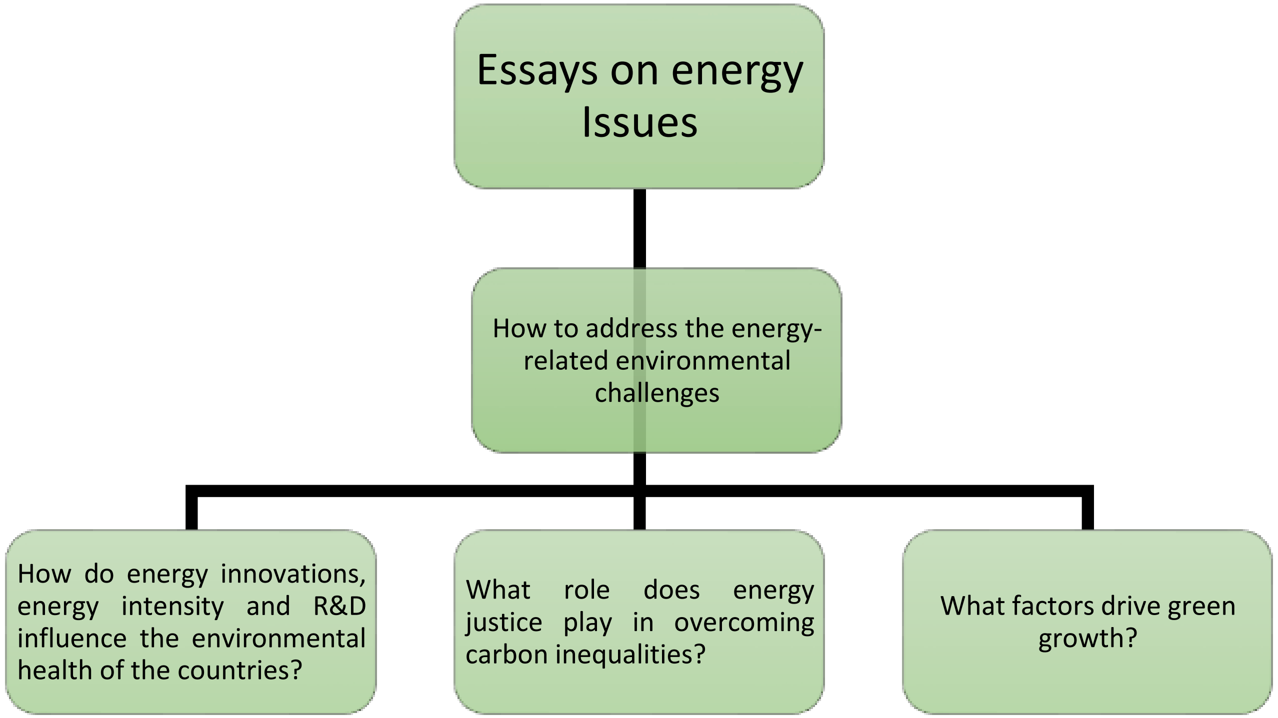
Thesis Objective

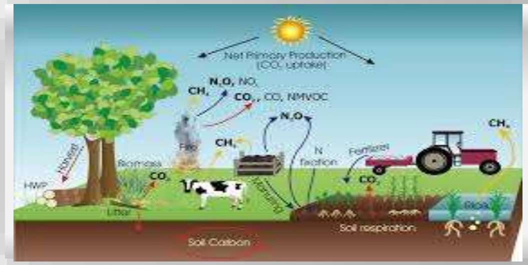
- The main objective of this PhD Dissertation is to highlight the energy challenges and explore how energy innovations, energy justice and environmentally friendly energy sources influence green growth processes.



Introduction (1/1)

- Human activities are the main driver of climate change

- Rising CO_2 emissions are increasing the global temperature



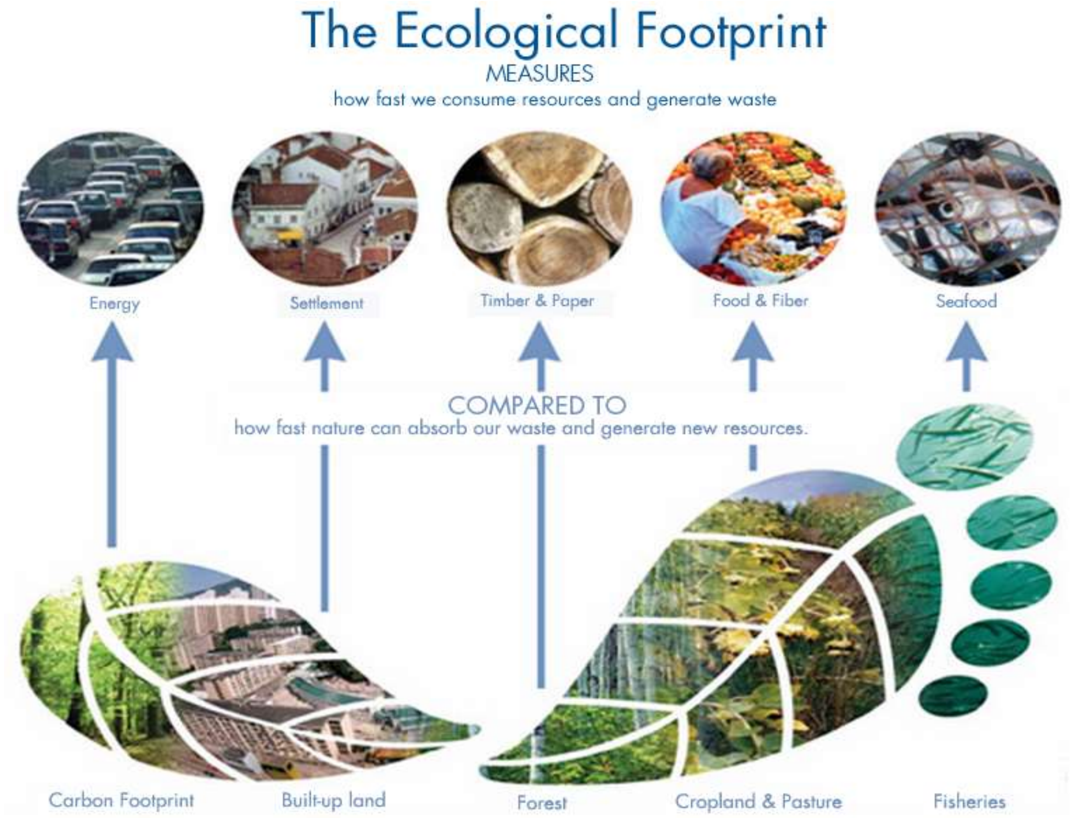
- Climate change threatens food security, water availability, health, and economic stability.

- Global call to limit warming to 1.5°C

Ecological Footprint

Total environmental pressure is divided into six indicators

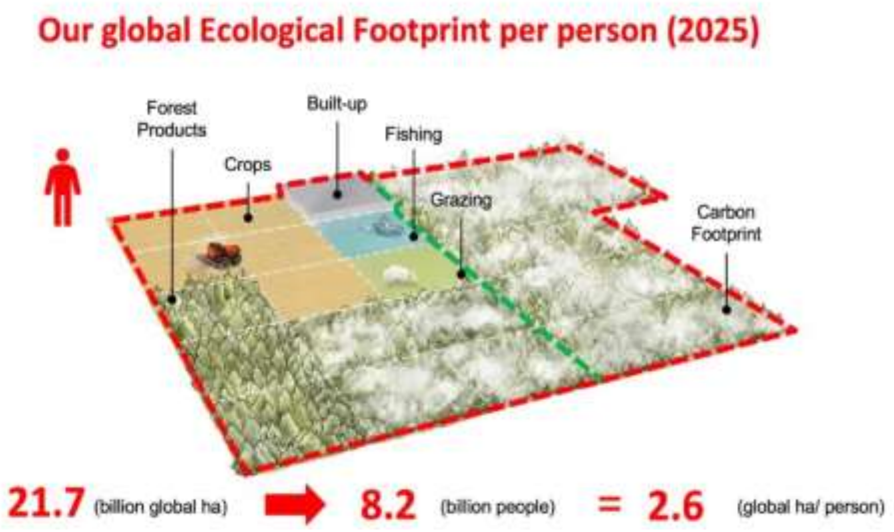
- **Ecological Footprint** is an accounting tool that measures how much natural resources people use to support their lifestyle, including land, water, and energy.
- (OECD, 2024).

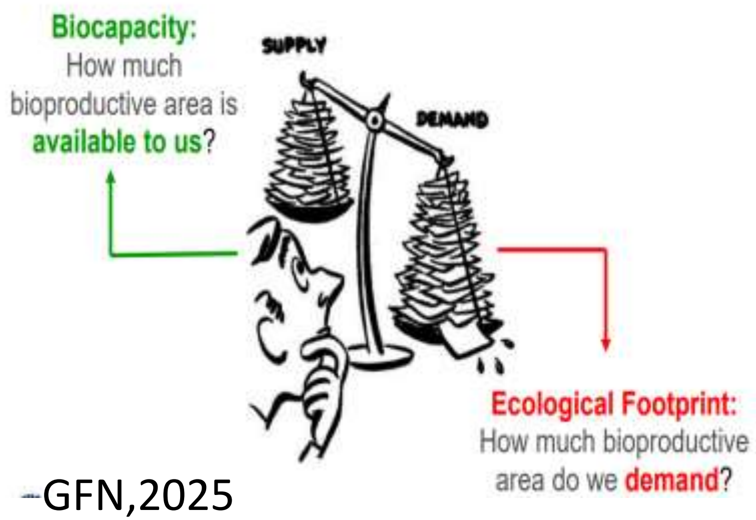


Source: (GFN, 2022)

Accounting Framework for Ecosystem Services

- Spending of natural resources against the “budget” that nature actually provides.
- 21.7 billion hectares = Total Human demand
- 2.6 hectares per person = Individual demand
- 12.2 billion hectares = the total biocapacity/total global budget(productive land and water) available on Earth.
- 1.4 hectares per person = the biocapacity available to each person.
- Demand> Supply





-GFN,2025

Project 1

- Fossil fuel-based energy production is a major contributor to global carbon emissions.
- Advances in renewable energy, storage, and efficiency lower a nation's ecological footprint.
- Renewable energy advancements need major R&D investments and coordinated financial support(Sherif et al., 2022).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ABSTRACT

Recent developments in energy engineering and state-of-the art technologies to increase eco-friendly energy production are receiving increasing attention in scientific debate as engines of growth. Although the energy-growth-environment nexus has been extensively studied, the ecological implications of innovative technologies in energy production are yet to be adequately addressed to provide adhoc social changes and policy perspectives. To bridge these gaps, the present study investigates the relationship between energy innovation (EIN), renewable energy production (REP), non-renewable energy production (NREP), energy intensity (EI), research and development (R&D) expenditures, GDP, and ecological footprint (EF) in 21 OECD economies during the period 1990–2018. This study applies advanced, rigorous, and robust econometric methodologies. The empirical outcomes reveal that REP, EIN, and EI, mitigate EF, while NREP, GDP, and R&D somehow accelerate the ecological deficit. This study advances the empirically proven validity of the Environmental Kuznets Curve hypothesis for OECD countries and provides valuable policy insights in terms of intensification of governmental budget spending on R&D, and boosting technological energy innovations and non-polluting energy projects. Of particular importance to trace a green energy growth is the development of comprehensive economic and energy policies with a specific focus on ecological wellbeing.

Literature Gap

- The current body of literature does not provide valuable insight about the emerging correlations between energy, technological advancements, economic growth and ecological footprints.
- Earlier scholars (Khan et al., 2019; Espoir et al., 2022) used CO_2 emissions as an indicator of environmental damage to capture air pollution.
- Earlier research focuses more on emerging economies than advanced OECD economies.
- The EKC hypothesis remains under-tested in OECD economies.
- Prior studies report mixed results due to conventional methods that ignore cross-sectional dependence and heterogeneity.

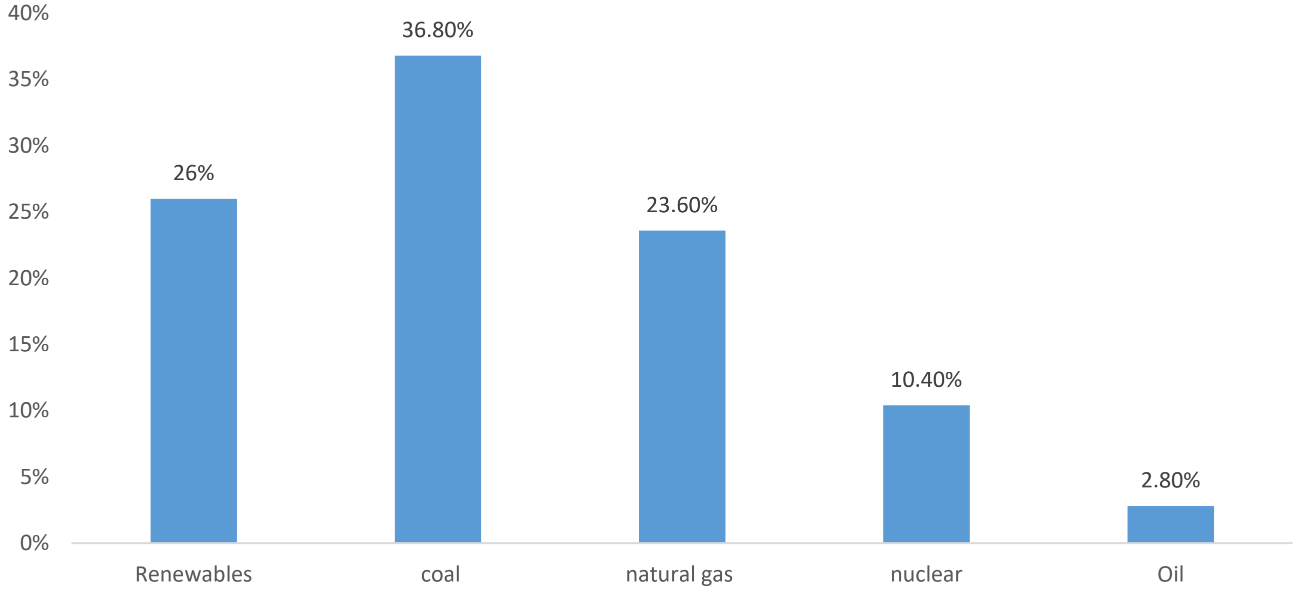


Figure 1. Worldwide sources of energy production (in %).
Source: International Energy Agency - IEA (2022).

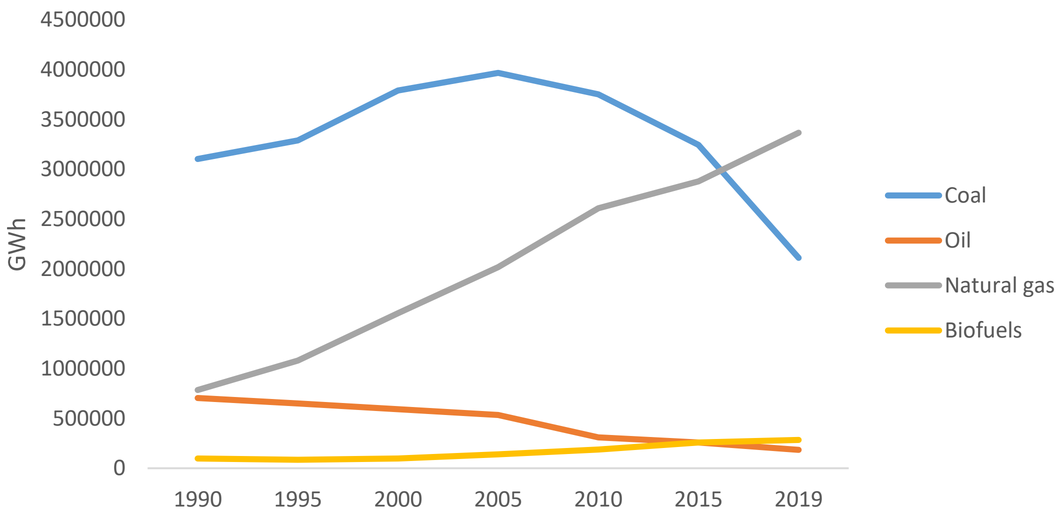


Figure 2. Energy production from non-renewable energy sources (Gwh).
Source: Authors' own computations based on OECD data.

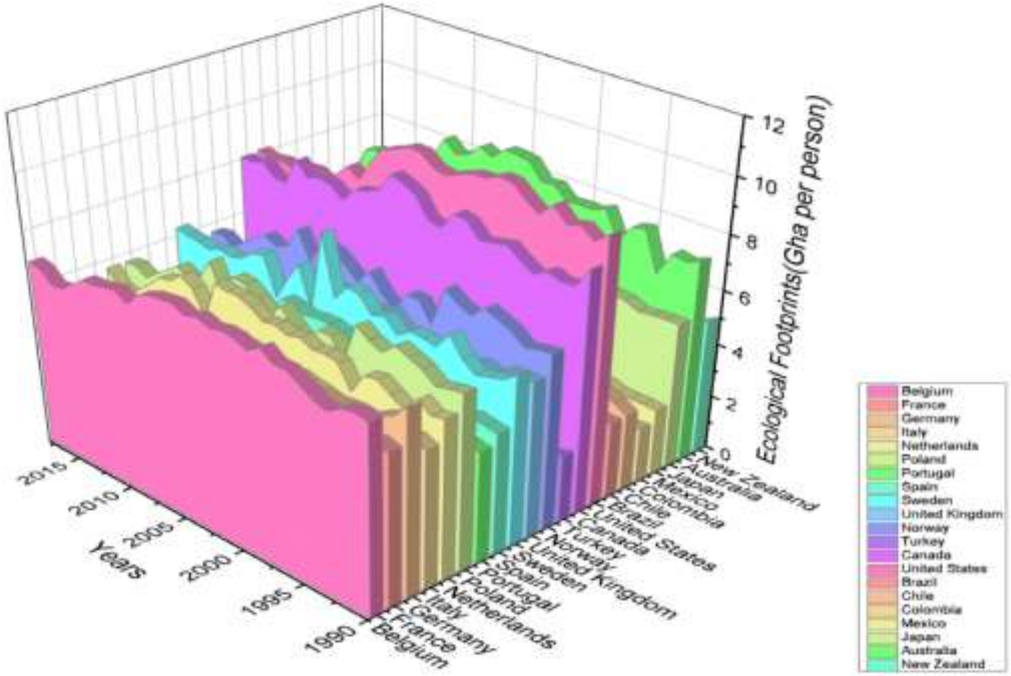


Figure 3. Glimpse of ecological footprints in the sampled OECD countries (in Gha/person).
Source: Authors' own computations based on OECD data.

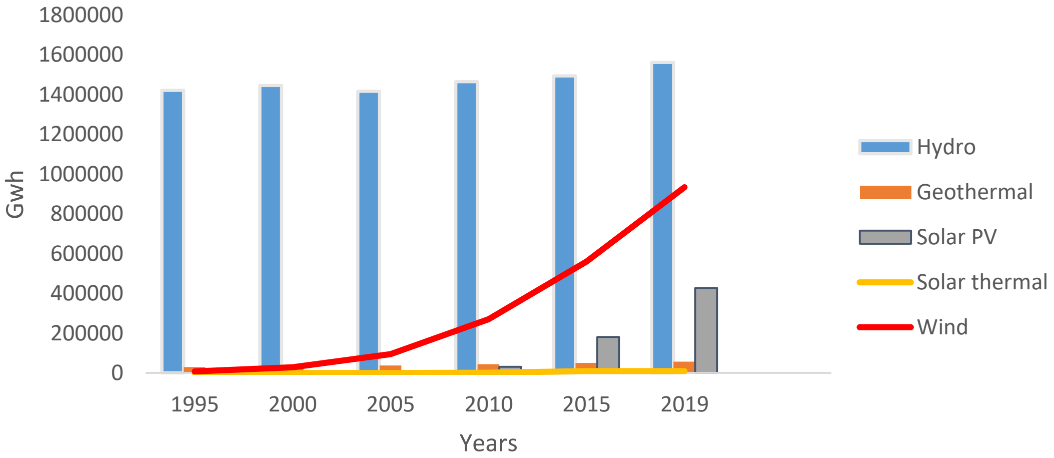


Figure 4. Energy production from renewable energy sources (Gwh).
Source: Authors' own computations on OECD data.

Contribution of the study

- The first contribution of this study lies in the use of a more comprehensive environmental indicator, the ecological footprint(EF).

- Second, the choice of this group of countries is supported by high levels of per capita EFs (Fig. 3), particularly due to high industrial growth and technological advancements.

- Thirdly, this study tests the existence of the Environmental Kuznets Curve (EKC) hypothesis in OECD countries

- Lastly, this study uses more recent data and modern econometric techniques

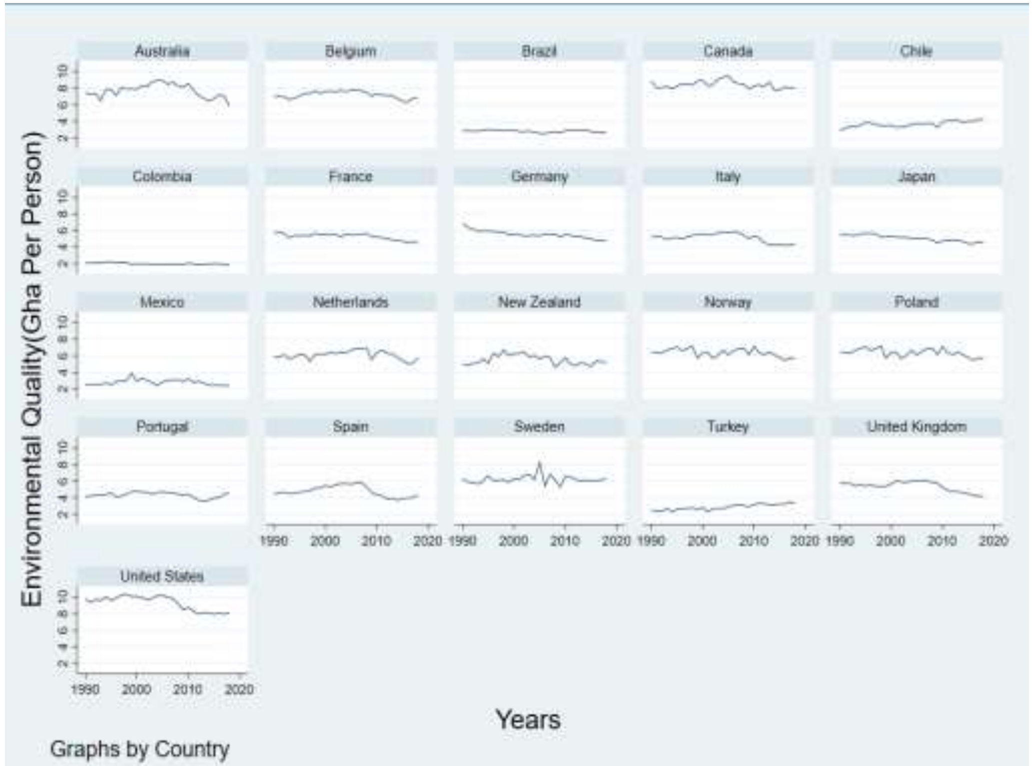


Figure 5. Glimpse of ecological footprints in the sampled OECD countries (in Gha/person).

Data and Methods

The current research uses an annual panel dataset of twenty-one OECD countries during the period from 1990 to 2018.

Variables	Description	Unit of measure	Data source
EF	Ecological footprint	Ecological footprints gha per person	GFN
REP	Renewable energy production	Renewable electricity production (kWh)	WDI
NREP	Non-renewable energy sources	Energy production from oil, coil and natural gas (% of total)	WDI
EI	Energy intensity	kg of per capita oil equivalent	WDI
EIN	Energy Innovation	Number of patent applications per thousand population	WDI
R&D	Research and development expenditures	% of government expenditures on research and development	WDI
GDP	Gross Domestic Product	GDP per capita (constant 2015$)	WDI

GFN - Global Footprint Network (https://data.footprintnetwork.org/#/ ↗); WDI - World Development Indicators (https://data.worldbank.org/indicator ↗).

Model specification

The Cobb-Douglas form of the environmental function is articulated in Eq. (1) as follows:

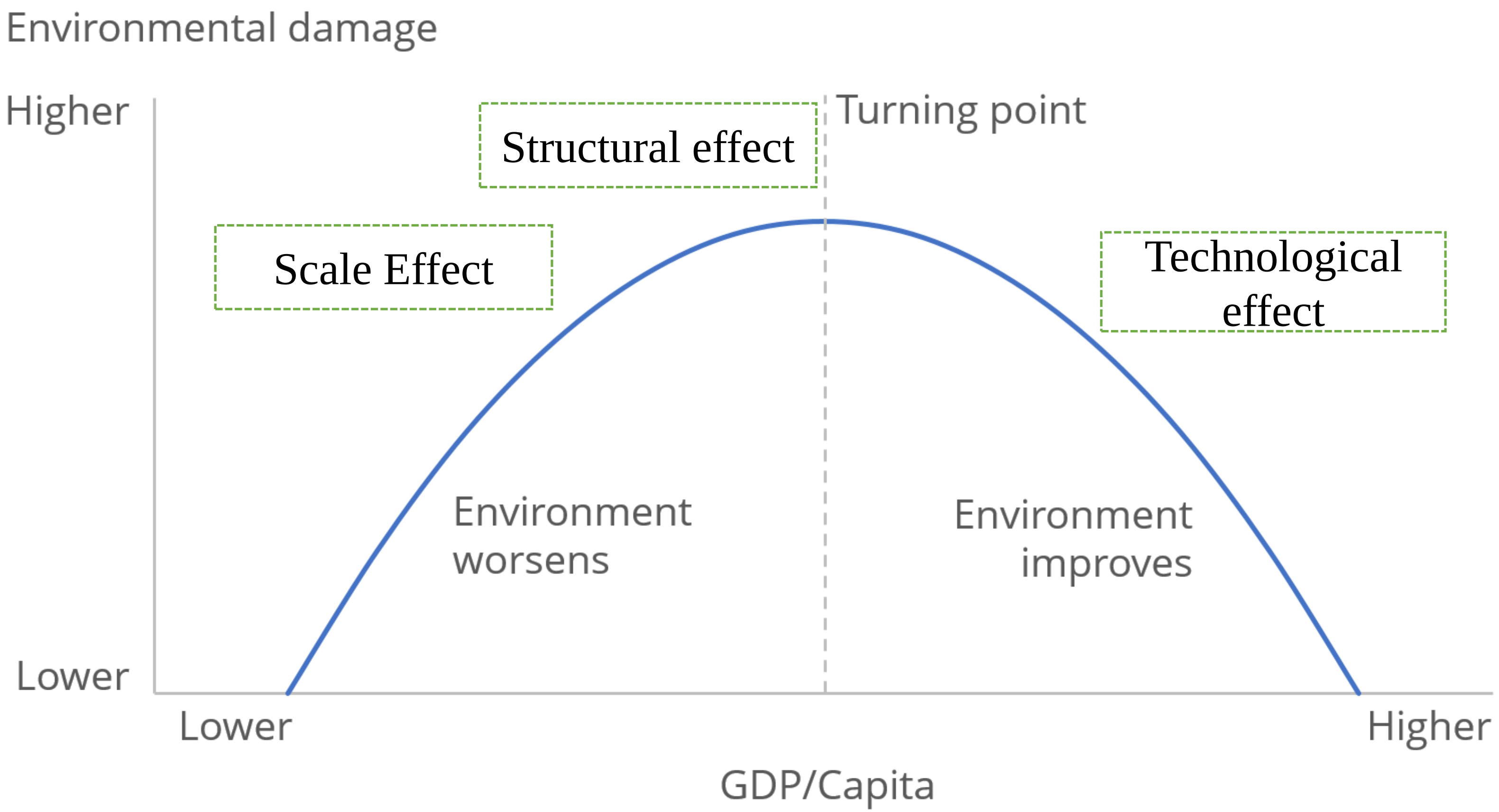
$$EF = f(REP_{it}, NREP_{it}, IE_{it}, EIN_{it}, R\&D_{it}, GDP_{it}, GDP_{it}^{2}) \quad (1)$$

Here, *i*,*t* and indicate the cross-sections and time periods
EF= Ecological footprint
REP = Renewable energy production
NERP = Non-renewable energy production
IE= Energy intensity
EIN= Energy Innovations
R&D= Research and Development
GDP= Gross domestic product.

To overcome data sharpness and heteroskedasticity, we take the natural log of the selected variables of Eq. (1), in the following notation:

$$LnEF = \alpha_0 + \beta_1 lnREP_{it} + \beta_2 NREP_{it} + \beta_3 lnEI_{it} + \beta_4 lnEIN_{it} + \beta_5 R\&D_{it} + \beta_6 \ln GDP_{it} + \beta_7 GDP_{it}^{2} + \mu_{it} \quad (2)$$

Environmental Kuznets Curve (EKC) hypothesis

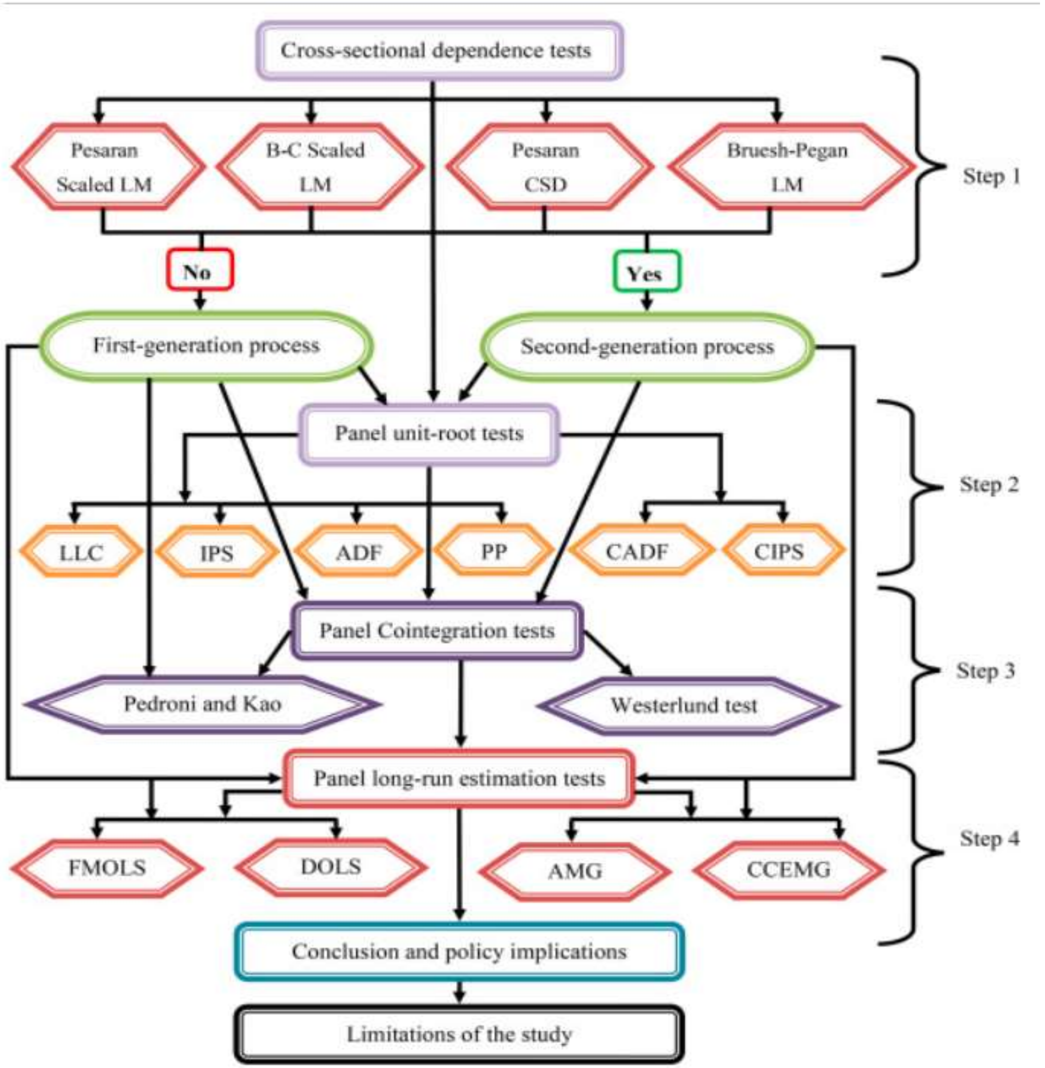


Study Hypothesis

- Based on the observed literature and the EKC hypothesis, the current study predicts a positive sign between EF, NREP, EI, and GDP as follows: $\beta_2 \frac{\Delta(EF)}{\Delta(NREP)} > 0$; $\beta_3 \frac{\Delta(EF)}{\Delta(EI)} > 0$; $\beta_6 \frac{\Delta(EF)}{\Delta(GDP)} > 0$.

- In contrast, a negative sign is likely to occur between EF, REP, EIN, and GDP^2: $'\Upsilon_1 \frac{\Delta(EF)}{\Delta(REP)} < 0, '\Upsilon_4 \frac{\Delta(EF)}{\Delta(EIN)} < 0; \ '\Upsilon_5 \frac{\Delta(EF)}{\Delta(R\&D)} < 0; \ and\ '\Upsilon_7 \frac{\Delta(EF)}{\Delta(GDP^2)} < 0.$

Methodological Flowchart



Cross-sectional dependency tests N<T

H_0: Cross-sectional independent.

H_1: Cross-sectional dependent.

Cross-sectional dependence refers to a situation in panel data where cross-sectional units (such as countries, firms, or regions) are correlated with each other due to common shocks or spillover effects.

Series	Pesaran Scaled CSD		Bias-corrected Scaled LM	
	Statistics	p-value	Statistics	p-value
LnEF	58.59	0.00	20.22	0.00
LnREP	244.80	0.00	72.13	0.00
NREP	86.95	0.00	9.65	0.00
LnEIN	91.72	0.00	15.20	0.00
LnEI	88.29	0.00	12.88	0.00
R&D	61.63	0.00	14.87	0.00
LnGDP	272.80	0.00	76.12	0.00
$LnGDP^2$	260.34	0.00	74.21	0.00

* ,**and *** indicates 10%, 5% and 1% level of significance, respectively.

Panel unit root *tests.*

H_0: The variables have a unit root(variables are wandering overtime)

H_1: The variables do not have a unit root

A **panel unit root test** examines whether variables in panel data are stationary or non-stationary.

Series	Level		First Difference		Integration Order
	CADF	CIPS	CADF	CIPS	
Ln_EF	81.33	-2.71	348.89***	-18.48***	I(1)
Ln_REP	14.57	7.01	211.47***	-18.97***	I(1)
NREP	38.80	3.48	292.44***	-14.11***	I(1)
Ln_EI	40.04	4.06	201.51***	-9.54***	I(1)
Ln_EIN	42.06	-4.54*	271.98***	-30.06***	I(1)
R&D	84.85	-0.26	206.56***	-17.77***	I(1)
Ln_GDP	23.25	2.73	255.28***	-13.97***	I(1)
Ln_GDP^2	14.69	-9.44	187.235**	-13.02***	I(1)

* ,**and *** indicates 10%, 5% and 1% level of significance, respectively.

Cointegration outcomes

H_0: Variables do not move together in the long run

H_1: Variables move together in the long run

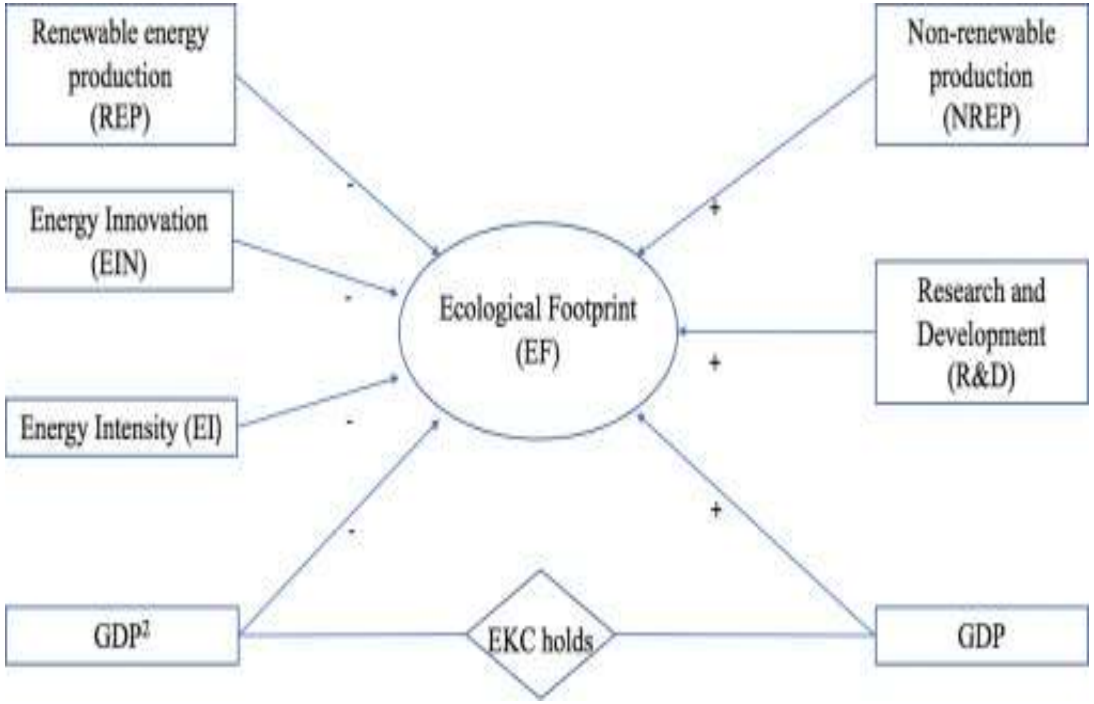
Statistics	Z-Values	P-value
Ga	-2.70***	0.00
Gt	-2.65***	0.00
Pa	-1.93**	0.00
Pt	-3.26***	0.00

* ,**and *** indicates 10%, 5% and 1% level of significance, respectively.

Long run estimations

Variables		Long run Estimations		
	PMG		MG	
Long run	Coeff.	Prob	Coeff	Prob
LnREP	-0.10**	0.00	-0.06*	0.09
NREP	0.17**	0.00	0.57	0.12
LnEI	-0.15*	0.10	1.08	0.30
LnEIN	-0.12**	0.00	-0.07	0.92
LnR&D	-0 .08**	0.00	-0.02	0.76
LnGDP	2.20**	0.00	0.29	0.01
LnGDP ^{2}	-4.10**	0.00	0 .02	0.92
		Short Run Estimations		
ECM(-1)	-0.34	0.00	-0.92	0.00
LnREP	0.01	0.36	0.03	0.44
NREP	0.11	0.58	0.36	0.07
LnEI	0.25*	0.02	0.05	0.38
LnEIN	0.05	0.14	-0.00	0.92
LnR&D	0.05	0.34	0.16	0.36
LnGDP	0.51*	0.00	0.44	0.01
LnGDP ^{2}	-0.08	0.23	-0.18	0.51
Hausman test	Chi test=13.80	Prob. 0.06		

Conclusion and Policy Implications



Source: Source: Author's own elaboration

- Intensify investments and policy support for renewable energy sources.
- Increase R&D investment in green technologies.
- Implement comprehensive green economic policies.
- Encourage public-private partnerships for sustainable innovation.
- Provide financial incentives for clean energy projects.
- Educate and raise awareness about sustainable energy practices.

Project 3
The effect of macroeconomic PESTLE indicators on green growth: A spatial-temporal analysis in 30 European economies

- The Organisation for Economic Co-operation and Development (OECD) defines GG as an alternative measure of economic growth that goes beyond GDP, emphasising the importance of environmental quality.

- It enables economies to diversify and reduce their dependence on finite natural resources, making them more resilient to environmental shocks.

- By prioritizing resource efficiency, low-carbon technologies, and social inclusion, green growth helps mitigate climate change, create new economic opportunities, and improve overall well-being.

Contribution of the study

- Firstly, this study's novel contribution lies in the application of the PESTLE framework to macroeconomic dynamics.

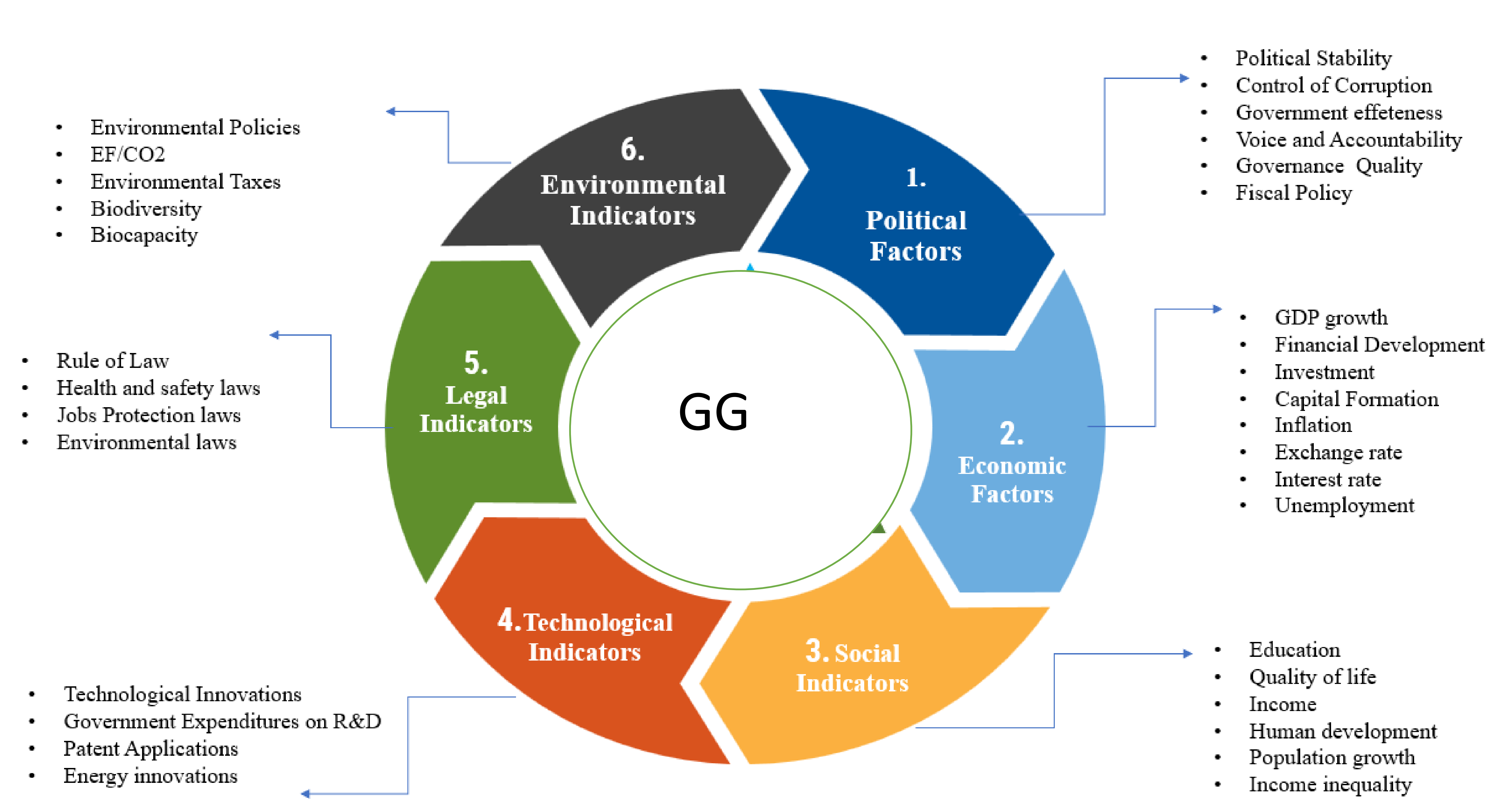
- To the best of our knowledge, no study has empirically and simultaneously explored the effect of PESTLE factors on Green growth(GG) in 30 EU economies.

- There are two rational reasons behind the selection of this group of economies:

  - European economies appear as the second largest investors in renewables, power grids, energy efficiency and use (International Energy Agency, 2024)
  - The close proximity across spatial units (Tobler, 1970), sharing common regulations and policies.

- On the other hand, it tests spatial dependence and spillover effects of the investigated framework through a Spatial Durbin Model (SDM).

Overview of the PESTLE framework (2/2)



Source: Source: Authors own elaboration

Data Description

Table 2. Description of data sources

Variables	Description	Unit of measurement	Data sources	Types of Variables
GG	Green growth	GDP per unit of energy-related CO2 emissions/ US dollars per kilogram, 2015	OECD	Endogenous
IQ	Institutional quality	Index	PCA self-estimated	Ind. var
FD	Financial Development Index	Index (0-1)	IMF	Ind. var
HDI	Human development	Government expenditures on education and health % of GDP	WDI	Ind. var
TI	Technological innovations	Number of Patent Applications per thousand population	WDI	Ind. var
EP	Environmental policy	Policy Stringency index (0-6)	OEDC	Ind. var
CC	Climate crisis	Ecological footprints gha per person	GFN	Ind. var
NRR	Natural resources rent	%of GDP	WDI	CV
GLO	Globalization	Index (0-10)	(Gygli et al., 2019)	CV
PGR	Population growth rate	% total population	WDI	CV
GE	Government expenditures	% of GDP	WDI	CV

Notes: OECD - Organization of Economic Cooperation and Development (https://search.oecd.org/greengrowth);
IMF - International Monetary Fund (https://data.imf.org);
WDI -World development indicators (https://databank.worldbank.org);
GFN - Global Footprint Network (https://www.footprintnetwork.org/);
CV - Control variable;

$$Production\ based\ CO_2\ productivity =$$

$$\frac{Real\ GDP}{CO_2};\frac{USD\$}{kg}.$$

The Framework of Green Growth Mechanisms

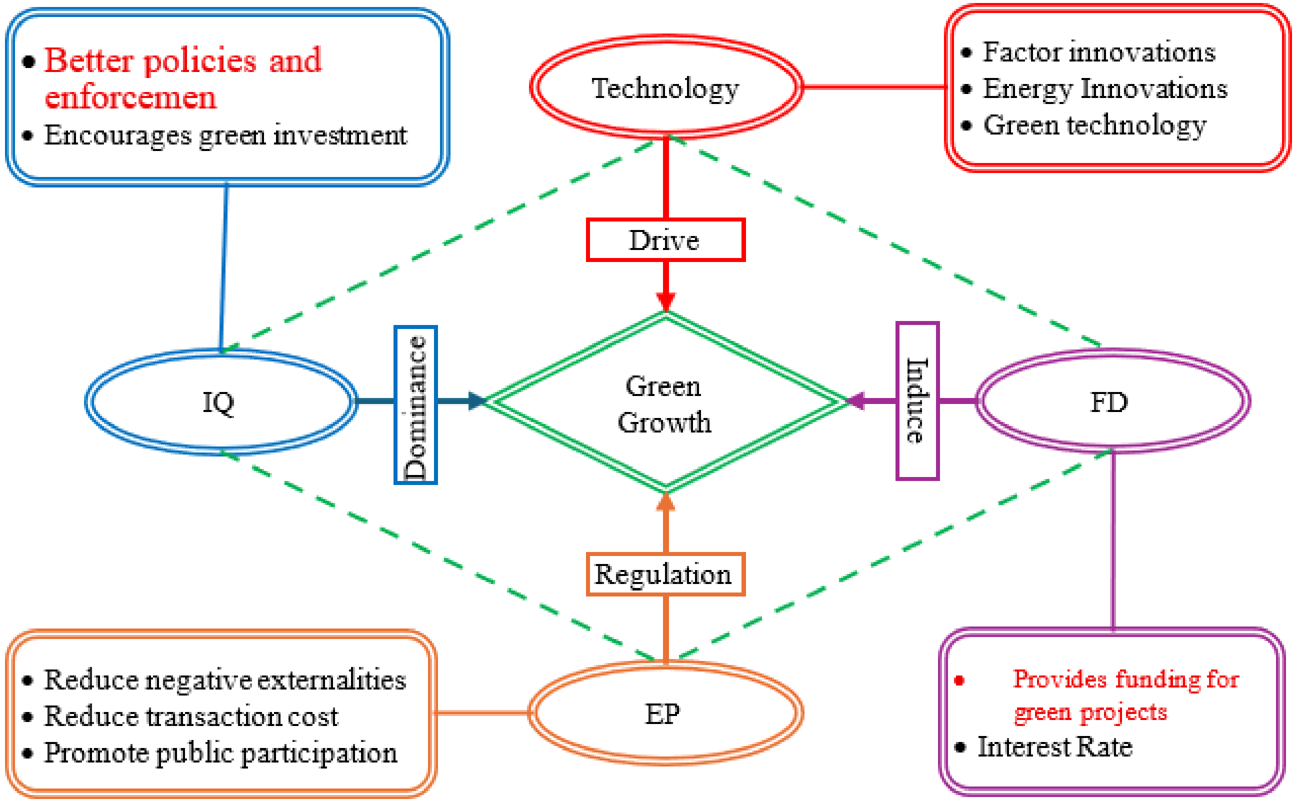


Figure 2.3 The Framework of Green Growth Mechanisms

(Source: Drawn by the author)

Methodology

- Model equation

$$GG_{it} = \alpha_{it} + \theta_1 IQ_{it}^{P} + \theta_2 FD_{it}^{E} + \theta_3 HD_{it}^{S} + \theta_4 TI_{it}^{T} + \theta_5 EP_{it}^{L} + \theta_6 ES_{it}^{E} + \vartheta_7 POP_{it} + \vartheta_8 GLO_{it} + \vartheta_9 TNR_{it} + \vartheta_{10} GE_{it} + \eta_i + \tau_t + \mu_{it}$$

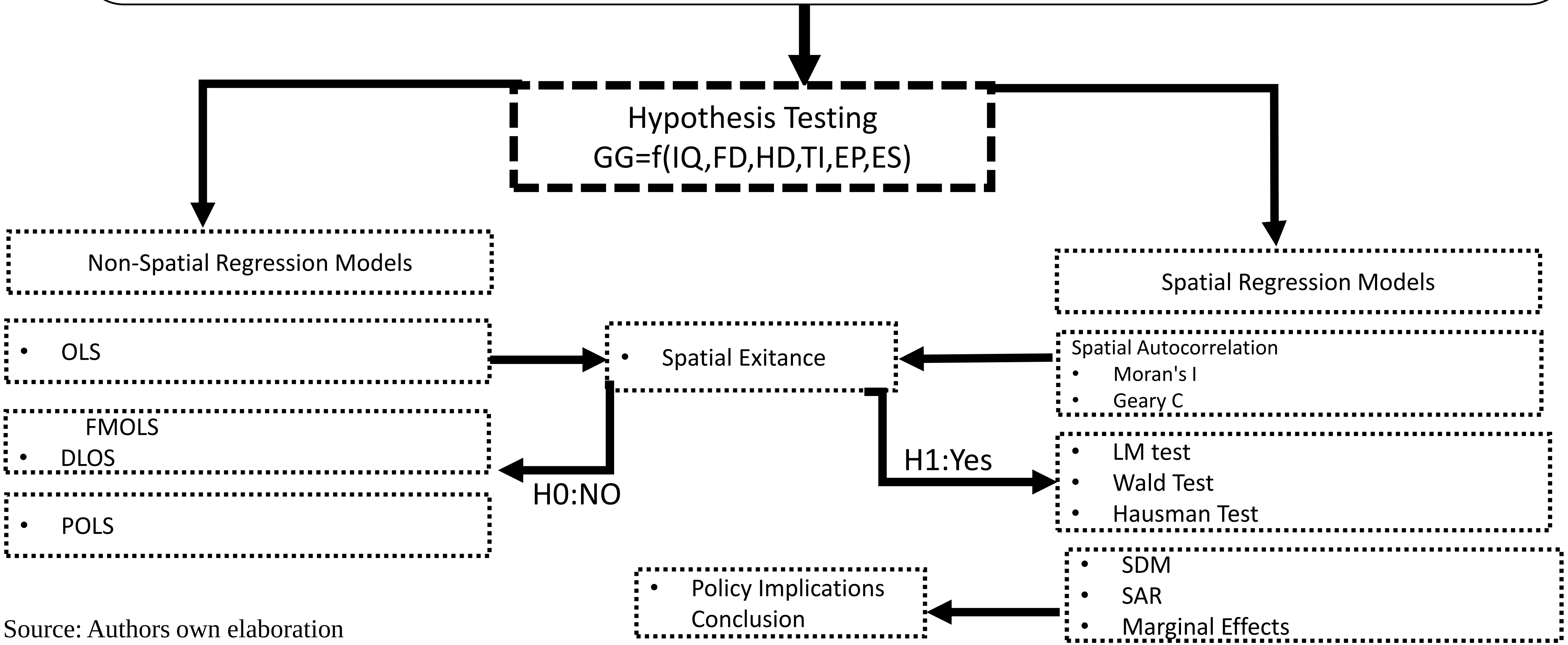
- Spatial Durban Model (SDM)

$$Y_{it} = \dot{\rho} \sum_{j=1}^{N} w_{ij} y_{it} + X_{it}\beta + \sum_{j=2}^{N} w_{ij} X_{jt} \theta + \varepsilon_{it}$$

α → constant term $\theta_1 - \theta_8$ → coefficients of explanatory variables η_i → country-specific effect τ_t → time-specific effect μ_{it} → error term

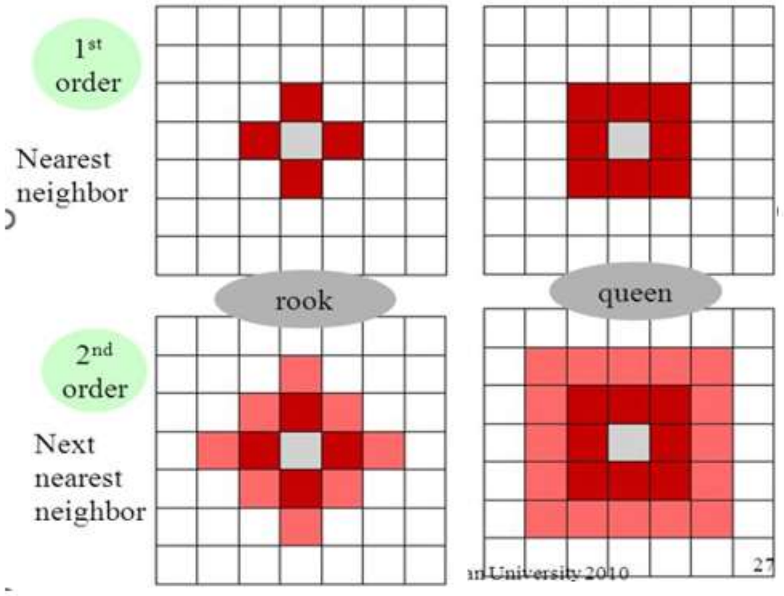
Methodology (1/3)

P: How does institutional quality shape green energy transition pathways?
E: How do economic disparities and financial development drive renewable energy adoption?
S: How do norms, perception, and human development affect the investment in green growth?
T: How do technology and R&D shape the green energy transition?
L: How do laws and regulations impact energy green growth?
E: How does ecosystem stress influence the pace of green growth?

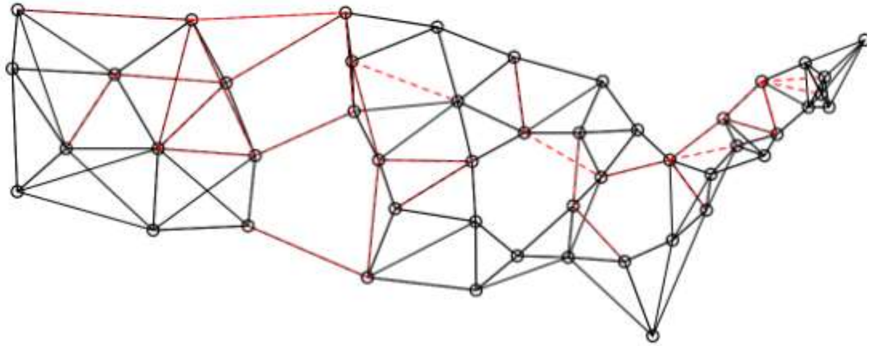


Source: Authors own elaboration

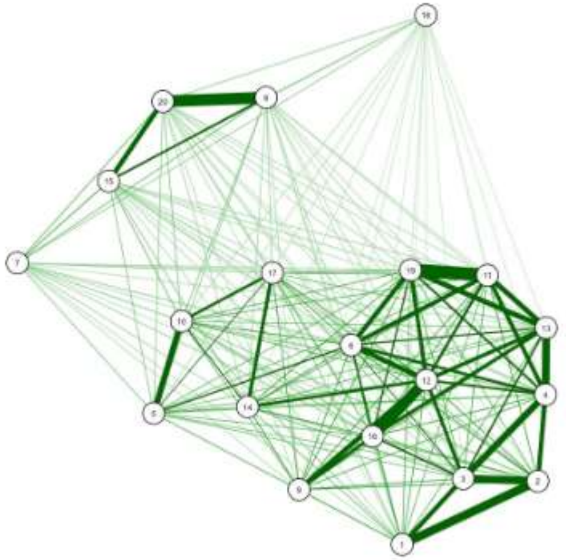
Types of Weight Matrix



K Nearest Neighbours



Distance Based WM



Moran’s I and Geary’s C

	I	p-values	C	p-values
GG	0.37	0.00	0.29	0.00
IQ	0.57	0.06	0.31	0.00
FD	0.59	0.05	0.50	0.00
HDI	0.65	0.07	0.40	0.00
TI	0.76	0.00	0.59	0.00
EP	0.71	0.01	0.51	0.00
GLO	0.46	0.00	0.53	0.00
POP	0.53	0.00	0.25	0.00
TNR	0.33	0.00	0.20	0.00
GE	0.24	0.00	0.60	0.00

Results and discussion (5/7)

Spatial model selection tests

Tests	Statistics	Prob
Likelihood ratio test	138.82	0.00
Wald test	47.00	0.00
Housman Tests	94.92	0.00
AIC	2349.06	2230.24
SBIC	2404.97	2332.75

Source: Authors' own computations

Results and discussion (6/4)

Cumulative marginal long-run effects

Long Run Effect			
IQ	0.19***	0.54***	0.76***
	(3.18)	(3.64)	(4.73)
FD	0.33***	0.47**	0.81***
	(4.01)	(2.41)	(3.98)
HD	0.07**	0.21**	0.28***
	(2.35)	(2.48)	(3.07)
TI	0.04	0.02*	0.06**
	(0.56)	(1.89)	(2.01)
EP	0.28***	0.021	0.30*
	(5.07)	(0.15)	(1.85)
CC	-0.12**	-0.28***	-0.40***
	(-2.31)	(-2.98)	(-3.97)
TNR	-0.11**	-0.28**	-0.40***
	(-2.45)	(-2.48)	(-3.18)
GLO	-0.04	-0.03	-0.06
	(-1.05)	(-0.44)	(-0.87)
GE	-0.06***	-0.14***	-0.07
	(-2.95)	(-3.00)	(-1.59)

Notes: ***, ** and * illustrate 1%, 5% and 10% significance, t-statistics in parentheses. *Source*: Authors' computations.

Conclusion

- Moran's I and Geary’s C test statistics confirm the presence of spatial autocorrelation among sample regions.

- This twofold perspective enriches our understanding of how local policies, economic landscapes, social interactions, technological advancements, legal regulations, and environmental factors jointly affect the transition to sustainable energy.

- The main findings reveal that IQ, FD, technological advancement, and environmental policies produce positive spillover effects, while ecosystem stress intensifies differences across spatial units.

Policy implications

- **Promote Renewable Energy**: Offer financial incentives (subsidies, tax breaks) and invest in renewable energy infrastructure (solar, wind, etc.) to boost clean energy adoption.

- **Enhance Energy Efficiency**: Implement stringent efficiency standards for buildings, industries, and vehicles, and promote public programs to reduce energy consumption across sectors.

- **Decarbonize the Energy Sector**: Introduce carbon pricing mechanisms (e.g., carbon taxes or cap-and-trade systems) and phase out fossil fuels through gradual restrictions and alternative energy investments.

- **Strengthen Institutional Quality**: Enhance governance, transparency, and legal frameworks to boost investor confidence and support financial development.

- **Promote Financial Development**: Facilitate better access to capital for sustainable and green projects through financial innovation and green finance mechanisms.

- **Foster Technology and Innovation**: Encourage research and development, particularly in green technologies, through public-private partnerships and targeted incentives.

- **Cross-Border Collaboration**: Strengthen international cooperation to share best practices, transfer technology, and support neighbouring countries in their green growth efforts.

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