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RESEARCH

Green Investment, Renewable Energy Capacity and Climate Policy: An Econometric Analysis of Sustainable Development in Brazil, Canada, China and India (2005–2023)

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ABSTRACT

PURPOSE: This study analyses how green investment, renewable energy capacity and climate policy influence gross domestic product (GDP), employment and CO_2 emissions in Brazil, Canada, China and India (2005–2023).

DESIGN/METHODOLOGY/APPROACH: A deductive explanatory strategy is utilised. Autoregressive integrated moving average and system generalised method of moments are applied to annual panel data to estimate the short- and long-run effects.

FINDINGS: Renewable energy investment increases GDP and the short-run effect is negative. Climate policy is growth friendly but has limited employment effects.

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ORIGINALITY/VALUE: New empirical evidence on growth and environmental trade-offs that can guide sustainable policy choices.

PRACTICAL IMPLICATIONS: Green investment and policy can foster growth despite transitioning difficulties. Governments need to assist in clean energy transitions without hurting employment.

KEYWORDS: *Green Investment; Renewable Energy Capacity; Climate Policy; GDP; Employment; CO_2 Emissions; Panel Data.*

INTRODUCTION

The energy business needs to shift a lot to deal swiftly with climate change, harm to the environment, and the loss of resources. It is now beneficial for the environment to switch from fossil fuels to renewable energy (Scrieciu *et al.*, 2022). In 2023, there were 510 gigawatts more sources of renewable energy than in 2022 and now it is 50% greater than in 2023. A large part of this was the development of solar panels, and China was a big part of it (Petreski, 2024). It is estimated that by 2028, the world's ability to use renewable energy will reach more than 3,700 GW (Petreski, 2024). In 2020, over 12 million individuals worked in the renewable energy industry, and most of them worked with solar photovoltaic (PV). The world's GDP also grew by 10% in 2023 Simply enacting new regulations will not help to reach the global climate objectives. This study examines the impact of investments in renewable energy on the overall economy using historical data and econometric models.

LITERATURE REVIEW

Sustainable development is now a growing issue with extensive research proving the existing relationship between environmental conservation and economic expansion. Achieving sustainable economic growth involves analysing how green investments, renewable energy capacities, and climate policies interact. Extensive studies underpin theoretical and empirical links for green investments, GDP growth, employment and innovation in the global shift to renewable energy (Bargawi and Cozzi, 2017).

Green Economic Growth: Theoretical Foundations

Contemporary models of green growth include environmental limits and natural resources within the traditional model. The Solow-Swan model has also been extended to incorporate progress in renewable resource and pollution abatement, which makes it more pertinent particularly when long-term sustainability issues are considered (Michaelides, 2025). The endogenous Growth Theory of Romer underscores human capital, knowledge spillovers and innovation with implications that environmental technologies and green research and development have direct benefits to GDP as well as ecological sustainability (Scrieciu *et al.*, 2013). The Environmental Kuznets Curve (EKC) further explains the income emissions relationships. This shows an inverted U-shaped pattern in which emissions increase during early growth phases and decline as cleaner technologies emerge. This highlights how green investments contribute to low-carbon transitions and reshape employment and sustainability outcomes (Arumugam *et al.*, 2023).

Empirical Evidence on the Economic Potential of Green Investment

Empirical literature shows strong macroeconomic effects from green sectors. In the UK, the net-zero economy expanded by 10% in 2024, generating £83 billion in GVA and nearly one million jobs. In China, clean-energy investment reached 6.8 trillion yuan (about USD 940 billion), representing roughly 10% of national GDP, driven by solar PV and electric vehicles (Bethany *et al.*, 2025). Accelerated green transitions could increase advanced economies' GDP per capita by over 120% and lift more than 175 million people out of poverty in low-income nations within a decade (Musztyfaga-Staszuk, 2025).

Gaps in Research and Policy Relevance

Despite meaningful contributions, gaps remain. Many studies focus on single countries or sectors, limiting generalisation across diverse economies. Models from China or the EU may not reflect conditions in emerging markets due to differences in governance, infrastructure, or market maturity (Petreski, 2024). Research is also limited regarding how specific renewable energy technologies affect employment or economic growth. Addressing these gaps is essential for effective resource allocation and long-term sustainability planning.

This study contributes by building a predictive framework using econometric and computational methods to examine the economic impacts of green energy investments across multiple countries and policy contexts from 2005 to 2023.

MATERIALS AND METHODS

Data and Sources

This research uses annual panel data (2005–2023) for Brazil, Canada, China, and India to examine relationships between green economic indicators and macroeconomic outcomes. Data include GDP, employment (EMP), CO_2 emissions (CE), and Green Investments (GINV) from the World Bank (World Bank, 2025); Renewable Energy Capacity (REC) from IRENA; climate policy (CP) indicators from UNEP (Carrington *et al.*, 2024) and inflation and interest-related variables from the International Monetary Fund (IMF). All variables were log-transformed to enhance linearity (Apostol, 2022). Descriptive statistics and graphical analysis were performed using Stata 12 and Python, consistent with recent empirical research.

Modelling Framework

Various econometric and time-series models were applied using Stata 12 to evaluate short- and long-term relationships between green economic variables and macroeconomic outcomes (Arumugam *et al.*, 2023). Due to limited cross-sections (N=4), formal panel unit-root tests were not used; instead, graphical trend inspection and first-differencing were applied (Michaelides, 2025). Country-specific fixed effects were incorporated to address unobserved heterogeneity (Petreski, 2024). Year dummies were excluded to preserve degrees of freedom, a limitation acknowledged in line with previous studies (Noorunnahar *et al.*, 2023).

Correlation Analysis

Pearson correlation coefficients were calculated to explore initial relationships and detect multicollinearity (Apostol, 2022). The correlation matrix (see Table 4) shows mixed positive and negative associations, consistent with existing literature on renewable energy, employment, and sustainability in developing economies (Miot, 2018).

$$r_{xy} = \frac{\sum(x_i-\bar{x})\ (y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\ \sum(y_i-\bar{y})^2}}$$

Ordinary Least Squares (OLS) Regression

Initial models were estimated using OLS to assess the baseline relationships between independent variables (GINV, REC and CP) and dependent variables (GDP, EMP and CE), controlling for INF, IR, and BOP.

The standard OLS model is:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \epsilon_i$$

Where:
Y_i = dependent variable
X_{ki} = independent/control variables
ϵ_i = error term

Model fit was assessed using R2, and multicollinearity was examined using the Variance Inflation Factor (VIF).

Panel Data Regression

To account for unobserved heterogeneity across countries and time, the fixed effects (FE) and random effects (RE) panel regression models were estimated.

Fixed Effects Model (FE)

$$Y_{it} = \alpha_i + \beta X_{it} + \mu_{it}$$

Random Effects Model (RE):

$$Y_{it} = \alpha_i + \beta X_{it} + \mu_i + \epsilon_{it}$$

Using the Hausman test, the method of estimation between fixed effects (FE) and random effects (RE) models was established (Hahn *et al.*, 2011). The inclusion of country-specific effects aids in controlling the presence of unobserved heterogeneity, which helps prevent possible bias from omitted variables (Petreski, 2024). Nonetheless, time dummies are known to be excluded, which is a methodological weakness because the dataset is limited in time (Michaelides, 2025). A statistically significant Hausman test result ($p < 0.05$) supports the selection of the FE model over RE. Model performance was assessed using within, between, and overall R^2 values, consistent with standard econometric evaluation practices. Dynamic panel data model (System GMM) was used to address potential endogeneity and dynamic relationships; a two-step System-Generalised Method of Moments (GMM) model was estimated for GDP. Given the small cross-sectional dimension ($N = 4$), System GMM results should be interpreted cautiously. The following is the calculation of the model:

$$Y_{it} = \alpha Y_{it-1} + \beta X_{it} + \gamma Z_{it} + \epsilon_{it}$$

$Y(_{it\ 1})$ is the lagged dependent variable

X_{it} includes EMP and CE

Z_{it} includes instruments (lagged levels and differences)

Model validity was tested using: Arellano Bond tests for autocorrelation AR (1), AR (2)

Hansen tests for over identifying restrictions. To reduce instrument proliferation, the instrument matrix was collapsed; yet the number of instruments remained close to the number of observations, which may weaken the Hansen test reliability.

Time Series Modeling (ARIMA)

Country level time series trends for gross domestic product, employment (EMP), and CO_2 emissions (CE) were analysed using Autoregressive Integrated Moving Average (ARIMA) models, a widely applied approach for forecasting economic and environmental variables (Mondal *et al.*, 2014).

Model identification and selection were guided by the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to ensure optimal model fit and parsimony (Neath and Cavanaugh, 2012). The general ARIMA model is represented as follows, capturing autoregressive (AR), differencing (I), and moving average (MA) components to describe temporal dependence structures (Apostol, 2022).

$$Y_t = \alpha + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{j=1}^{q} \vartheta_j \epsilon_{t-j} + \epsilon_t$$

Where:
p: order of autoregression
d: degree of differencing
q: order of moving average
ϵ_t: White noise error term

Model fit was validated using Ljung Box Q tests for autocorrelation.

$$Q = n(n+2) \sum_{k=1}^{h} \frac{\hat{r}_k}{n-k}$$

Where $\hat{r}_k$ is the autocorrelation at lag k, and h is the number of lags tested.

The ARIMA models were used mainly for diagnostics and trend analysis rather than forecasting due to limited data. The methodology combines panel econometrics and time-series tools, capturing both cross-sectional and temporal dimensions, though small sample size may limit statistical power.

RESULTS

The mean of GINV is 3.81, SD is 0.69, showing slight left skewness. REC mean is 6.33, SD is 0.69, showing moderate negative skewness. CP and SD are 0.68, ranging from 0.00 to 2.30, showing skewness close to symmetrical, indicating that the data follow a normal distribution. In the case of dependent variables, GDP (log) has a mean of 28.61, SD is 0.81, showing near-zero skewness. EMP is 3.98, SD is 0.17, CE is 2.63 and SD is 0.92, showing slight left skewness. The variability of controls is moderate. Inflation is 1.86, SD is 0.71, Interest Rate is 1.65 and SD is 1.06, showing negative skew. Balance of Payments (BOP) has SD= 0.87. Overall, the data is appropriate to the panel econometric analysis, as the variability is sufficient, and the outliers are insignificant. Differences in some of the controls like BOP are minor which diminishes effective observations in some models (see Table 1).

Table 1: Descriptive statistics of key variables (2005–2023)

Variable Name	*N*	*Mean±SD*	*Median*	*Max*	*Min*	*Skewness*	*Kurtosis*
Independent variables							
GINV	72	3.81±0.69	3.97	4.59	1.34	1.56	5.28
REC	72	6.33±0.69	6.59	7.08	4.33	1.15	3.45
CP	72	1.31±0.68	1.39	2.30	0.00	0.51	2.24

Variable Name	N	Mean±SD	Median	Max	Min	Skewness	Kurtosis
Dependent variables							
GDP	76	28.61±0.81	28.22	30.47	27.72	1.17	2.85
EMP	72	3.98±0.17	3.97	4.25	3.70	0.02	1.66
CE	72	12.63±0.92	12.80	13.81	9.87	0.84	3.03
Control variables							
INF	72	1.86±0.71	2.02	2.70	0.00	0.78	2.71
IR	72	1.65±1.06	1.99	2.70	2.30	1.52	5.51
BOP	16	4.68±0.87	4.98	5.65	2.77	0.73	2.41

Source: Analysed by authors: Standard Deviation (SD), Maximum (Max) and Minimum (Min)

For BOP, N=16 reflects the available annual observations within the analysis window. The correlation analysis in Table 2 shows relationships among independent, dependent, and control variables. The only significant correlation at 5% is a moderate negative relationship between log GDP (lngdp) and BOP (lnbop) (−0.571, $p < 0.05$), suggesting higher surpluses may reduce output.

A positive, though non-significant, correlation exists between EMP (lnemp) and BOP (lnbop) ($r = 0.471$). There are weak correlations between carbon emissions (lnce) and the interest rates (lnir) (0.174), between GINV (lnginv) and CE (0.120), which reveal that there are not many short-term interactions among monetary, environmental and investment variables.

Overall, low to moderate correlations suggest limited multicollinearity, supporting the variables' suitability for regression modeling. Below, scatter plots of lngdp, lnemp, and lnce (Figures 1, 2, and 3) are provided for diagnostics only, not for causal inference.

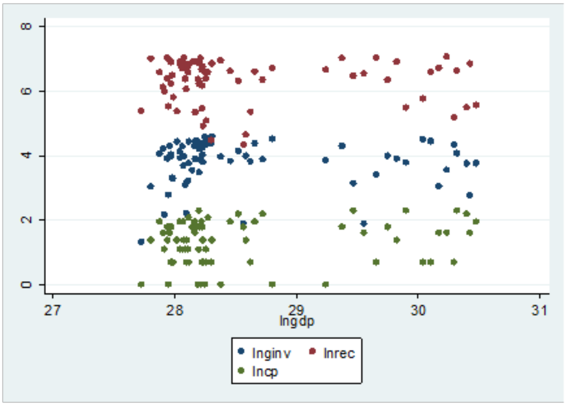

Figure 1: Scatterplot for Ln gross domestic product, Ln for green investment, Ln for Renewable Energy Capacity and Ln for Climate Policy
Source: Analysed by authors

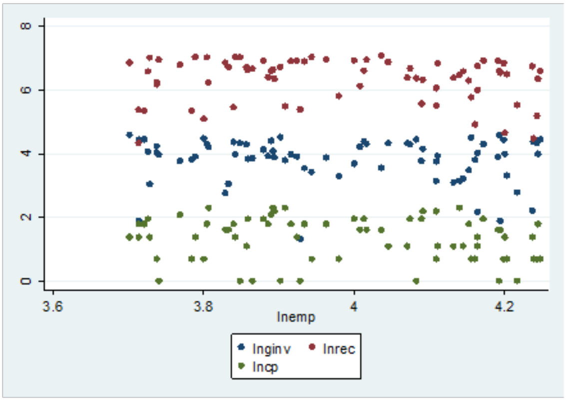

Figure 2: Scatterplot for Ln employment, Ln for green investment, Ln for Renewable Energy Capacity and Ln for Climate Policy
Source: Analysed by authors

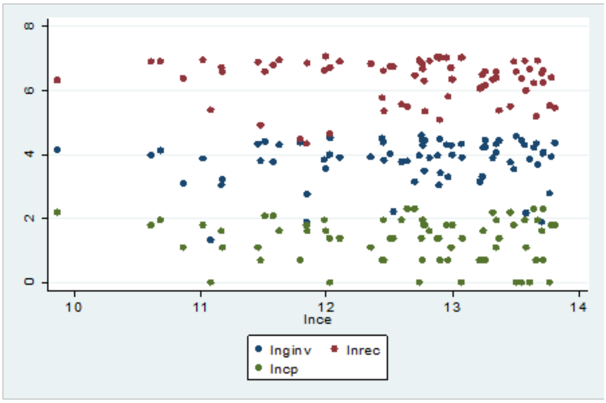

Figure 3: Scatterplots in CO_2 Emissions, Ln for green investment, Ln for Renewable Energy Capacity and Ln for Climate Policy
Source: Analysed by authors

Table 2: Correlation matrix of log transformed variables

Variable	*Lngdp*	*lnemp*	*lnce*	*lnginv*	*lnrec*	*Lninf*	*Lnir*	*lnbop*	*lncp*
Lngdp	1.000								
Lnemp	0.145	1.000							
Lnce	0.043	−0.001	1.000						
Lnginv	−0.016	−0.113	0.120	1.000					
Lnrec	−0.049	−0.095	−0.033	0.124	1.000				

Variable	Lngdp	lnemp	lnce	lnginv	lnrec	Lninf	Lnir	lnbop	lncp
Lninf	−0.062	0.030	0.176	−0.078	−0.111	1.000			
Lnir	0.055	0.116	0.174	0.082	−0.031	0.090	1.000		
Lnbop	−0.571*	0.471	0.101	0.161	−0.224	−0.225	0.389	1.000	
Lncp	0.175	−0.134	−0.129	0.020	0.121	−0.016	−0.010	−0.283	1.000

Source: Analysed by authors: Pearson correlation (p) coefficients are reported ($p < 0.05$).

Table 3 presents result from three baseline Ordinary Least Squares (OLS) regressions, each examining the relationship between three dependent variables, log-transformed GDP (lngdp), EMP (lnemp) and CE (lnce), and a standard set of independent variables such as GINV (lnginv), REC (lnrec), and CP (lncp). Models 2 and 3 also include macroeconomic controls (lninf, lnir, lnbop). When controls are added, the effective sample size drops (e.g., due to BOP availability), which explains the N=72 versus N=16 columns.

Table 3: Baseline Regression Model using OLS

Independent Variables	Dependent Variables					
	(1) lngdp		(2) lnemp		(3) lnce	
Lnginv	0.013 (0.140)	0.217 (0.331)	0.025 (0.030)	0.021 (0.063)	0.167 (0.159)	0.595 (0.276)
Lnrec	0.082 (0.142)	0.035 (0.466)	0.017 (0.030)	0.034 (0.089)	0.044 (0.162)	0.332 (0.389)
Lncp	0.217 (0.142)	0.432 (0.278)	0.031 (0.030)	0.008 (0.053)	0.171 (0.161)	0.289 (0.232)
Control Variables						
Lninf		0.199 (0.376)		0.035 (0.072)		0.498 (0.314)
Lnir		0.180 (0.311)		0.005 (0.059)		0.082 (0.260)
Lnbop		0.672 (0.329)		0.086 (0.063)		0.018 (0.275)
Constant	28.879	30.855	4.225	3.259	12.497	12.142
N	72	16	72	16	72	16
R2 value	0.036	0.552	0.035	0.274	0.033	0.498
Mean VIF	1.02	1.39	1.02	1.39	1.02	1.39

Source: Analysed by authors: Standard errors in parentheses. β = Coefficient estimate. *p<0.05. VIF = Variance Inflation Factor

OLS Regression Models

Model 1

lngdp=0.217*lnginv+0.035*lnrec+0.432*lncp 0.119 *lninf +0.180 *lnir 0.672*lnbop+30.855

Model 2

lnemp=0.021*lnginv+0.034*lnrec 0.008*lncp+0.035*lninf+0.005*lnir+0.086*lnbop+3.259

Model 3

lnce=0.595*lnginv 0.332*lnrec 0.289*lncp+0.498*lninf 0.082*lnir 0.018*lnbop+3.259+12.142

All the independent variables (lnginv, lnrec, lncp) have no statistically significant relationships with lngdp. The R-square of the model is low (0.036), which implies that these environmental variables do not significantly estimate the fluctuation of the GDP in the sample. The coefficient estimates are near to zero and imprecise (high standard errors), which support this conclusion.

Even though the coefficient of ln of climate policy (= 0.432) is relatively large, none of the predictors is significant. The model explicates a significant part of employment variance (R 2 = 0.552), which shows the stability and responsiveness of employment to policy as opposed to output. The coefficient of Lnbop (= -0.672) is negative (not statistically significant), indicating that it may have a negative relationship with employees, but this is not proven. This is estimated to be sensitive to the small sample size.

Lnginv is positively associated with lnce ($\beta = 0.595$), indicating that GINV may not yet reduce emissions. The estimate is not statistically significant, and the model fits moderately well (R^2 = 0.498).

Multicollinearity and Diagnostics

Mean Variance inflation factor value (1.02–1.39) indicates no significant multicollinearity, supporting OLS validity. Coefficient estimates are generally imprecise with large standard errors, and many variables are statistically insignificant, suggesting the need for model refinement or alternative methods. Boxplots of all variables are shown in figure 4.

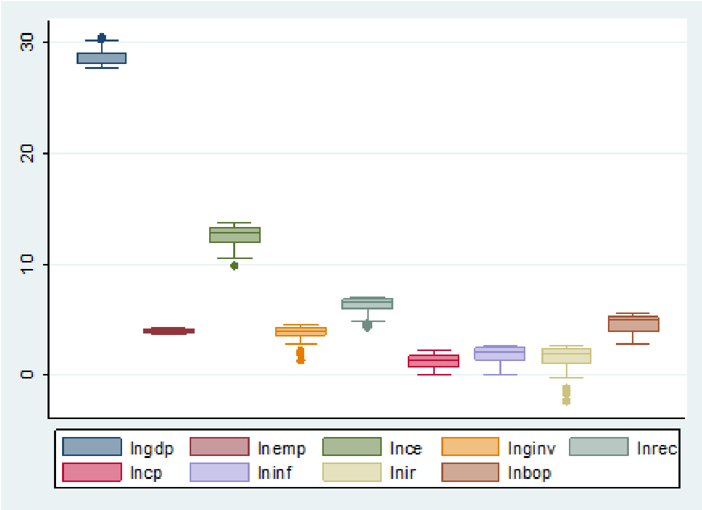

Figure 4: Boxplots of lngdp, lnemp, lnce, lnginv, lnrec, lncp, lninf, lnir and lnbop
Source: Analysed by authors

Table 4 presents baseline panel regression results assessing GINV, REC, and CP on GDP (lngdp), EMP (lnemp), and CE (lnce). Both FE and RE models are estimated, with the Hausman test determining the appropriate specification. All continuous variables are expressed in logarithms to correct skewness and allow elasticity-based interpretation of coefficients.

Table 4: Baseline Regression Model using Panel Data

Variables	*Dependent variables*					
	(1) Lngdp		*(2) Lnemp*		*(3) Lnce*	
	FE	*RE*	*FE*	*RE*	*FE*	*RE*
Independent Variables						
Lnginv	0.269 (0.119)	0.217 (0.331)	0.005 (0.061)	0.021 (0.063)	0.563 (0.303)	0.595* (0.276)
Lnrec	0.390 (0.186)	0.035 (0.466)	0.051 (0.094)	0.034 (0.089)	0.523 (0.473)	0.332 (0.389)
Lncp	0.201 (0.103)	0.432 (0.278)	0.019 (0.052)	0.008 (0.053)	0.354 (0.262)	0.289 (0.232)
Lninf	0.133 (0.182)	0.199 (0.376)	0.074 (0.092)	0.035 (0.072)	0.787 (0.462)	0.498 (0.314)
Lnir	0.200 (0.120)	0.180 (0.311)	0.037 (0.061)	0.005 (0.059)	0.234 (0.306)	0.498 (0.314)
Lnbop	0.168 (0.143)	0.672 (0.329)	0.111 (0.072)	0.086 (0.063)	0.162 (0.363)	0.082 (0.260)
Constant	31.764	30.855	3.740	3.259	12.359	12.143

Variables	Dependent variables					
	(1) Lngdp		(2) Lnemp		(3) Lnce	
	FE	RE	FE	RE	FE	RE
Model Statistics						
Observations	16	16	16	16	16	16
R^2 (Within)	0.742	0.349	0.377	0.199	0.585	0.529
R^2 (Between)	0.273	0.899	0.003	0.674	0.117	0.352
R^2 (Overall)	0.240	0.552	0.152	0.274	0.446	0.498
F statistic	22.28		1.43		0.62	
Hausman Test	8.79		5.54 (0.477)		1.63 (0.950)	
Decision			Random effect		Random effect	

Source: Analysed by authors: p<0.001, **p<0.01, *p<0.05; β (SE) = coefficient (standard error)

FE = Fixed Effects; RE = Random Effects. Hausman Test: If $p < 0.05$, Fixed Effects is preferred; otherwise, Random Effects. 'Observations = 16' refers to the number of annual time periods per country (T=16). With N=4 countries, the total panel comprises 64 countries–year observations.

Model 1: Economic Output (lngdp)

GINV (lnginv) is positively associated with GDP in both FE and RE models, statistically significant in FE with robust errors but not in RE. REC (lnrec) is negatively related to GDP in FE and slightly positive in RE, both insignificant. CP (lncp) is positive under RE but not significant. The Hausman test favours RE, which is presented as the preferred baseline while FE captures within entity variation. RE shows high overall R^2 (0.899), while FE within R^2 (0.742) indicates moderate temporal fit.

Model 2: Employment (lnemp)

No independent variables are statistically significant. GINV (RE $\beta = 0.021$) and renewable energy (RE $\beta = 0.034$) are positively associated with EMP; CP (RE $\beta = -0.008$) is slightly negative. FE shows similar patterns. Hausman test ($\chi^2 = 5.54$, $p = 0.477$) favours RE. Model fit is low (within $R^2 = 0.377$ in FE, overall $R^2 = 0.274$ in RE), suggesting employment effects may depend on additional factors like labour market dynamics or policy lags.

Model 3: Carbon Emissions (lnce)

GINV is positively and significantly associated with emissions ($\beta = 0.595$, $p < 0.05$), reflecting transitional or infrastructure related effects. RE (RE $\beta = -0.332$) and CP (RE $\beta = -0.289$) are negatively associated with emissions, though not significant. Hausman test ($\chi^2 = 1.63$, $p = 0.950$) supports RE. Within $R^2 = 0.585$ and overall $R^2 = 0.498$ indicate moderate model fit.

Model Selection and General Findings

Hausman tests favour RE, suggesting minimal correlation between regressors and unobserved heterogeneity. RE is the main specification, with FE confirming results. Green investment boosts GDP and short-term emissions, modestly affects employment, while renewable energy and climate policy reduce emissions without significance. Limited T = 16 restricts power and generalisation (see Table 5).

Table 5: Panel regression analysis results using fixed and random effect models (Robustness check)

Variables	*Dependent variables*					
	(1) Lngdp		*(2) Lnemp*		*(3) Lnce*	
	FE	*RE*	*FE*	*RE*	*FE*	*RE*
Independent Variables						
Lnginv	0.269* (0.069)	0.217 (0.147)	0.005 (0.064)	0.021 (0.050)	0.563* (0.108)	0.595*** (0.182)
Lnrec	0.390* (0.098)	0.035 (0.254)	0.051 (0.120)	0.034 (0.146)	0.523 (0.486)	0.332 (0.367)
Lncp	0.201* (0.054)	0.432 (0.262)	0.019 (0.062)	0.008 (0.076)	0.354 (0.339)	0.289 (0.279)
Lninf	0.133* (0.040)	0.199 (0.273)	0.074 (0.036)	0.035 (0.041)	0.787 (0.311)	0.498* (0.244)
Lnir	0.200 (0.083)	0.180 (0.112)	0.037 (0.074)	0.005 (0.070)	0.234 (0.338)	0.082 (0.293)
Lnbop	0.168* (0.042)	0.672*** (0.194)	0.111 (0.060)	0.086*** (0.016)	0.162 (0.231)	0.018 (0.071)
Constant	31.764	30.855	3.740	3.259	12.359	12.143
Model Statistics						
Observations	16	16	16	16	16	16
R^2 (Within)	0.742	0.349	0.377	0.199	0.585	0.529
R^2 (Between)	0.273	0.899	0.003	0.674	0.117	0.352
R^2 (Overall)	0.240	0.552	0.153	0.274	0.446	0.498

Source: Analysed by authors

FE (Fixed effect), RE (Random effect), $p<0.001$, $p<0.01$, $p<0.05$ and β (SE) represents the coefficient estimate with robust standard error in parentheses.

Model 1: Economic Output (lngdp): GINV (lnginv) is positively and significantly associated with GDP in the FE model ($\beta = 0.269$, $p < 0.05$), supporting the role of green investment in economic growth. Climate policy (lncp) also shows a positive significant effect ($\beta = 0.201$, $p < 0.05$), indicating that regulatory frameworks promote output. Renewable energy capacity (lnrec) has a negative significant association ($\beta = -0.390$, $p < 0.05$), possibly reflecting short-term adjustment costs during the energy transition. Inflation (lninf) ($\beta = -0.133$, $p < 0.05$) and BOP (lnbop) ($\beta = -0.168$, $p < 0.05$) negatively affect output. FE within $R^2 = 0.742$ indicates strong explanatory power for within entity variation.

Model 2: Employment (lnemp): No policy related variables are significant. There are weak positive effects on green investment and renewable energy whereas climate policy exhibits a slight negative effect. The BOP (lnbop) is substantially positive at RE (0.086, $p < 0.001$), which implies that improvements in the balance of trade can contribute to a rise in employment. The model fit is small (FE within R 2 = 0.377, RE total R 2 = 0.153) which means that the employment is determined by other structural or institutional factors.

Model 3: Carbon Emissions (lnce): Emissions in FE (0.563, $p = 0.05$) and RE (0.595, $p = 0.001$) share a positive and significant relation with green investment, and this could imply that at an early stage of development, carbon-intensive infrastructure could be involved in investments. Under RE (0.498, $p < 0.05$), we have a significant value of inflation (lninf). This suggests that the higher the inflation, the higher the chance that it is related to an increase in emissions. The fit is moderate (FE within R 2= 0.585).

Strength and Overall Conclusions

The primary findings are supported by strong standard errors. GINV has a good effect on GDP and increases emissions, which is a sign of a transitional effect. CP favours output yet has little short-term effect on EMP or CE. RE is better as it is consistent across the models and FE focuses on within-country dynamics. The sample size (N = 16) is too small to be generalised, and one should exercise caution when interpreting the results. Future research utilising a longer series, bigger datasets, and dynamic panel models should be employed.

Dynamic Panel Estimation

Table 6 shows a two stage-System GMM estimation where the GDP is the dependent variable. Explanatory variables are EMP and CE including one period lags. The panel consists of four cross-sectional units and 65 observations. The Arellano Bover/Blundell Bond model deals with endogeneity, autocorrelation and unobserved heterogeneity in this small panel.

Table 6: Dynamic Panel Estimation Results Using Two Step System GMM

Variable	*Coefficient (β)*	*Std. Error*	*z Value*	*p Value*	*95% Confidence Interval*
lnemp	1.131	0.597	1.89	0.058	[−0.039, 2.300]
lnce	−0.111	0.075	−1.48	0.139	[−0.257, 0.036]
L1.lnemp	0.325	0.150	2.17	0.030	[0.031, 0.618]
L1.lnce	0.173	0.071	2.42	0.015	[0.033, 0.313]
L1.lngdp	(Omitted)				
Constant	(Omitted)				

Variable	*Coefficient (β)*	*Std. Error*	*z Value*	*p Value*	*95% Confidence Interval*
Model Diagnostics and Specification Tests					
Statistic/Test			Result		
Number of observations			65		
Number of groups			4		
Instruments used			65		
Wald χ^2 (5)			41.76		
p value (Wald test)			< 0.001		
Arellano Bond test for AR(1)			$z = -0.92$, $p = 0.356$		
Arellano Bond test for AR(2)			$z = -2.21$, $p = 0.027$		
Sargan test (overid. restrictions)			$\chi^2 = 119.33$, $p = 0.000$		
Hansen test (robust overid.)			$\chi^2 = 0.00$, $p = 1.000$		
Difference in Hansen (levels instruments)			$\chi^2 = 0.00$, $p = 1.000$		

Source: Analysed by authors

Two step system-GMM was used. Robust standard errors are reported. Instruments were collapsed for the difference and level equations.

Main Coefficients and Dynamic Effects

Employment (lnemp) positively affects GDP ($\beta = 1.13$, $p = 0.058$), while carbon emissions (lnce) have a negative but insignificant effect ($\beta = -0.111$, $p = 0.139$). Lagged employment and emissions are significant and positively associated with current GDP ($\beta = 0.325$, $p = 0.030$; $\beta = 0.173$, $p = 0.015$), indicating delayed effects from past labour and industrial activity.

Model Diagnostics and Specification

TestsAR (1) shows no first order autocorrelation ($p = 0.356$), but AR (2) indicates second order serial correlation ($p = 0.027$), suggesting possible model misspecification. Sargon test is against overidentifying restrictions ($p = 0.0001$), and Hansen test is in favour of instrument validity ($p = 1.000$). The number of instruments is nearly equal to the number of observations, which creates a risk of overfitting. Findings indicate that employment has instantaneous and time lagged positive impacts, whereas the impact of emissions on GDP is a time-dependent effect.

Residual Diagnostics Using Ljung–Box Test

Residuals from ARIMA are usually white noise. There is no major autocorrelation in India, Canada, and China. One of the diagnostics in Brazil exhibits slight autocorrelation. ARIMA only captures autocorrelation and persistence but it is not applied as a forecasting model rather, it is applied in diagnostic mode.

ARIMA Model Performance

GDP ARIMA models work effectively and lagged GDP predicts the present GDP strongly. Employment and consumption models demonstrate poorer performance; the AR and terms of MA are mostly insignificant. There is remaining variance that indicates unaccounted variation.

DISCUSSION

ARIMA has still been useful in the macroeconomic analysis where the series under consideration is stable and univariate such as the GDP. The institutional, social and policy factors make EMP and CE less predictable. GINV positively affects GDP but may increase short-term emissions, partially supporting the Environmental Kuznets Curve. EMP outcomes are weakly predicted, suggesting the need for hybrid or integrative forecasting frameworks. Innovation, while unmodeled, likely complements green investment and growth.

LIMITATIONS

Limited time dimension (T = 16) and small cross section (N = 4) reduce statistical power. System GMM shows second order autocorrelation and high instrument count. Annual data limits short-term dynamics, and institutional and socio-demographic factors are missing. GINV increases GDP but also short run CO_2 emissions; employment effects are weak.

CONCLUSIONS

This study examines how GINV, REC, and CP are related to GDP, EMP, and CO_2 emissions using data from Brazil, Canada, China, and India (2005–2023). Panel data from the World Bank, IRENA, UNEP, and IMF were analysed through OLS, fixed and random effects models, two-step System GMM, and country-level ARIMA diagnostics.

ARIMA models performed reliably for GDP, providing stable and interpretable insights for macroeconomic planning. Panel models confirmed that GINV positively affects GDP but also increases CO_2 emissions in the short term. REC has a minor negative impact on output whereas CP favours GDP. The impact on employment is still poor, and the effects of structural and institutional elements are not limited to macroeconomic indicators.

The results indicate that sustainable growth policies ought to encompass GINV, faster implementation of clean technologies, and increased environmental regulation to reduce short-term increment in emissions. Although green policies are economically beneficial, the gains to the environment may be achieved through other countermeasures like investment sequencing and regulation as well as the use of cleaner technologies.

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