Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 10, No. 1, February, 2026

Time-Varying Impacts of Robust Determinants on Greenhouse Gas Emissions: Panel Data Evidence

Tho M. Nguyen [1], Kansuda Pankwaen [1], Pathairat Pastpipatkul [1], Worrawat Saijai [1*]

[1] *Faculty of Economics, Chiang Mai University, Chiang Mai 50200, Thailand.*

Abstract

Understanding the key drivers of greenhouse gas (GHG) emissions is crucial for designing effective and adaptable climate policies, particularly given the complex interplay among structural, institutional, and energy-related factors. This study examines the time-varying impacts of key determinants of GHG emissions across 29 countries from 1993 to 2018, with an emphasis on the shadow economy, energy security risks, and geopolitical volatility. The analysis follows a four-step framework: countries are classified using principal component analysis (PCA) and K-means clustering, robust covariates are selected via Bayesian Model Averaging (BMA), and their impacts are estimated with time-varying coefficient panel models. Model robustness is evaluated through grouped cross-validation, confirming the superior performance of the time-varying random effects (tvRE) specification. The results reveal that the shadow economy and energy security risk exert more dynamic and substantial impacts in the Higher-income group, while their effects are comparatively muted in the Lower-income group. Geopolitical risk, however, shows limited explanatory power for emissions in both contexts. This study provides a novel empirical framework for capturing the dynamic influences of emissions drivers and contributes actionable insights toward achieving sustainable development goals.

Keywords:

Time-Varying;

Random Effects;

Bayesian;

Greenhouse Gas Emissions.

Article History:

Received:	08	May	2025
Revised:	20	December	2025
Accepted:	03	January	2026
Published:	01	February	2026

1- Introduction

Scientific evidence overwhelmingly confirms that climate change, driven predominantly by GHG emissions, poses profound and escalating threats to ecosystems, economies, and public welfare [1]. According to the IPCC Sixth Assessment Report [2], emissions continue to rise, primarily due to fossil fuel combustion, industrial processes, and emissions from land-use change, deforestation, and non-CO_2 sources (Figure 1). These persistent and nonstationary trends underscore not only the urgency of mitigating emissions but also the necessity of deepening our understanding of the economic and structural determinants underpinning emissions growth over time.

Building on existing literature, numerous studies have examined the factors influencing environmental quality and CO_2 emissions, including demographic dynamics [3-5], affluence levels [6, 7], technological advancement [8, 9], energy structures [10, 11], and socio-political conditions [12, 13]. Beyond the commonly examined factors, this paper focuses on three additional variables—the shadow economy, energy security, and geopolitical risk—whose impacts on GHG emissions remain relatively underexplored in existing literature.

* **CONTACT**: worrawat.s@cmu.ac.th

DOI: http://dx.doi.org/10.28991/ESJ-2026-010-01-010

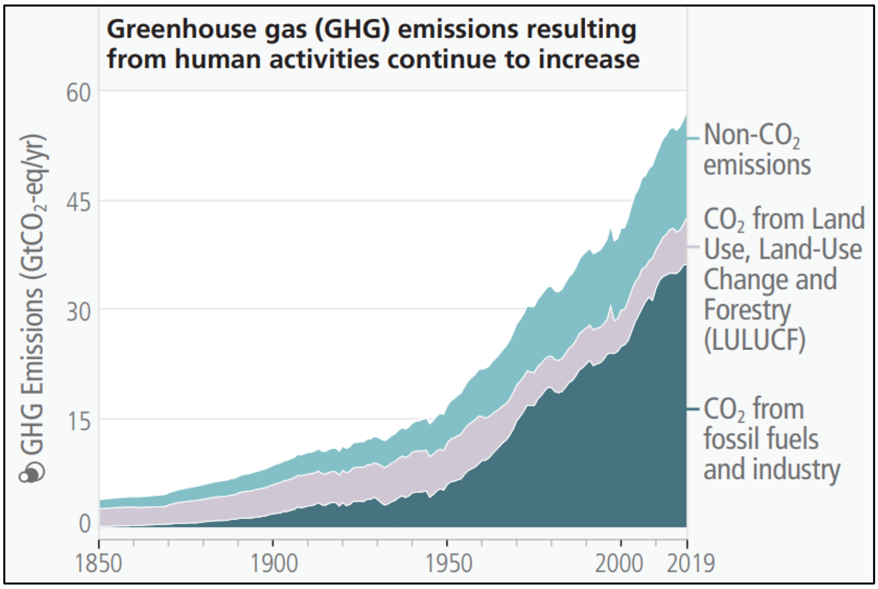


Figure 1. Increased emissions of GHGs

Previous studies often overlook the shadow economy due to severe measurement challenges. Shadow activities—such as black-market trade, undeclared work, and tax evasion—are intentionally hidden from authorities, making reliable data collection nearly impossible [14]. Moreover, distinguishing legal from illegal transactions in international data is a "quantitative nightmare" [15], so researchers mostly avoided these complexities until estimation techniques, such as those proposed by Medina & Schneider [16]. In this paper, we use the shadow economy derived from the Multiple Indicators, Multiple Causes (MIMIC) approach [17]. This determinant presents a paradox in environmental economics. On the one hand, it exacerbates emissions by enabling unmonitored industrial activity, inefficient energy use, and regulatory evasion. Informal sectors often rely on outdated technologies and bypass emissions standards, thereby disproportionately contributing to pollution [18, 19]. This challenge is particularly acute in developing economies, where the informal sector constitutes a substantial share of overall economic activity [20]. Nonetheless, the shadow economy does not necessarily exert a uniform detrimental effect. Some studies suggest that it may mitigate environmental pollution [21, 22]. Hence, the impact of the informal economy on GHG emissions remains a matter of debate.

In addition to the hidden economy, energy security risk (ESR) and geopolitical risk (GPR) are critical determinants of greenhouse gas emissions [23, 24]. However, the relationship between ESR and GHG emissions remains a subject of ongoing debate, with empirical evidence offering no clear consensus on whether ESR acts as a complement to or a trade-off against emission-reduction objectives [25, 26]. Several studies report that mitigating ESR can paradoxically lead to higher GHG emissions, as countries often resort to carbon-intensive energy sources to secure short-term supply stability [27-29]. Conversely, China's energy-saving and emission reduction policy illustrates a win–win outcome, improving energy security while cutting emissions [30]. Hence, the influence of ESR on GHG emissions remains open for further analysis.

With respect to GPR, although its relationship with GHG emissions has increasingly attracted scholarly attention, empirical findings remain mixed [31, 32]. Using the method of moments quantile regression (MMQR) and the augmented mean group (AMG) estimator, [33, 34] reported that GPR escalates emissions by disrupting energy transitions and prompting governments to revert to fossil fuel consumption, thereby amplifying climate threats. In contrast, employing wavelet quantile technique, Feng et al. [35] suggested that geopolitical risks can exert a short-term mitigating effect, either by suppressing economic activity or by slowing energy demand. This divergence highlights the complex and context-dependent nature of the GPR–GHG nexus [36], underscoring the need for further empirical investigation.

During the literature review, we also identified a methodological gap. Most previous studies rely on time-invariant estimation techniques that capture only average effects [37], implicitly assuming that the underlying relationships remain constant across time. However, several scholars [38, 39] argue that this approach is inappropriate for inherently time-varying variables, potentially producing biased estimates and failing to reflect actual dynamics.

While previous studies have yielded valuable insights, the evidence remains fragmented. To address these gaps, this study aims to answer two key research questions: (1) What are the main drivers of GHG emissions? and (2) How do their effects evolve over time, particularly in the context of structural shocks such as hidden economic activity, energy insecurity, and geopolitical tensions?

In doing so, this study offers several contributions to existing literature. First, it investigates the causal effects of a broad set of determinants on GHG emissions, thereby capturing the complexity of environmental pressures beyond conventional explanatory factors. Second, while most existing empirical evidence is largely static, this study emphasizes the importance of accounting for the dynamic nature of these relationships. Third, although some studies have employed dynamic approaches—such as linear/ nonlinear autoregressive distributed lag (ARDL/NARDL) or rolling-window quantile ARDL models [37, 40, 41]—these techniques are typically limited to distinguishing between short- and long-run effects, without fully capturing how the influence of key drivers evolves over time. To overcome these limitations, this study employs a time-varying parameter framework, offering a more flexible and realistic assessment of how GHG emissions respond to structural economic and political shocks over time.

The structure of this paper is as follows: Section 1 introduces the research context and objectives. Section 2 outlines the relevant theoretical foundations. Section 3 describes the dataset and details the country classification through clustering analysis. Section 4 outlines the methodological framework. Section 5 presents the empirical results and discusses the key findings. Finally, Section 6 concludes with policy implications and offers directions for future research.

2- Theoretical Framework

Understanding the determinants of GHG emissions requires the conceptual frameworks that can accommodate both environmental and socio-economic factors. In line with most existing research [42-44], this study draws primarily on two complementary concepts: (1) the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model, and (2) the Environmental Kuznets Curve (EKC) hypothesis. While the former offers a flexible structure for quantifying the elasticities of multiple socio-economic and structural drivers, the latter captures the potential non-linear dynamics of income–environment interactions. Together, these frameworks enable the present study to capture both the direct and evolving impacts of conventional and unconventional determinants over time, providing a richer understanding of the economic and structural processes that shape emissions trajectories.

2-1- The STIRPAT Model

The STIRPAT model, as extended by Dietz & Roza [45, 46], is an econometric reformulation of the IPAT identity proposed by Ehrlich & Holdren [3], which expresses environmental impact (I) as the multiplicative product of population (P), affluence—or economic activity per person—(A), and technology (T). While the original IPAT equation is deterministic, the extended STIRPAT model introduces stochasticity and allows for flexible estimation through logarithmic transformation:

$$I_{it} = a_{it}P_{it}^{b_1}A_{it}^{b_2}T_{it}^{b_3}e_{it} \tag{1}$$

where; I, P, A, T are the same variables as described in the IPAT identity for country i at time t. a represents the country-specific effect, $b_1, b_2,$ and b_3 are elasticities to be estimated. e is the error term. Taking the natural logarithm of both sides of Equation 1 yields the following expression:

$$lnI_{it} = a_{it} + b_1lnP_{it} + b_2lnA_{it} + b_3lnT_{it} + e_{it} \tag{2}$$

This formulation enables empirical testing of the magnitude and significance of the three main factors above, while accommodating additional explanatory variables beyond the original IPAT factors [47, 48].

In this study, the STIRPAT framework serves as the conceptual foundation for identifying and interpreting the causal drivers of GHG emissions. While retaining its core focus on demographic, economic, and technological factors, the framework is expanded to encompass a broad spectrum of determinants that capture the multi-dimensional nature of environmental pressures. These include demographic factors (total population, urban population), environmental resources (forest land, natural resource rents), structural economic measures (GDP/GDP^2, industry/agricultural value-added, and shadow economy), social development indicators (human development index), political and institutional indicators (democracy, corruption, and geopolitical risk index), global integration metrics (globalization index, trade openness, import/export trade), market-related factors (oil prices, energy security risk), energy-related variables (renewable energy consumption, energy intensity), and technological innovation (environmental patents). This enriched specification allows for a more comprehensive assessment of the diverse and evolving forces shaping GHG emissions.

2-2- The EKC Hypothesis

The EKC hypothesis, originating from the work of Grossman & Krueger [49], posits a non-linear relationship between environmental degradation and economic growth. Specifically, it suggests that environmental pressure increases during the early stages of economic development, reaches a turning point, and subsequently declines as economies achieve higher-income levels and adopt cleaner technologies. This inverted-U pattern is commonly tested by including both income and income-squared terms (often GDP and GDP^2) in regression analysis. Empirical evidence for the EKC remains mixed, varying with the pollutant examined, the control variables included, and the estimation techniques applied [50-52]. In the context of GHG emissions, the EKC framework provides a basis for the investigation of whether economic expansion can eventually coincide with environmental sustainability or whether emissions continue to rise regardless of income growth. This approach offers insights that can guide well-targeted policy interventions that balance economic growth and environmental sustainability.

3- Data

This study utilizes a balanced panel dataset covering 29 countries spanning 1993-2018, constructed by merging multiple internationally recognized sources to ensure both cross-country comparability and temporal consistency. All explanatory variables are lagged by one year for several purposes. First, lagging mitigates mitigate simultaneity and reverse-causality concerns, ensuring that predictors reflect prior-year conditions rather than being contaminated by contemporaneous feedback from emissions. Second, this design reflects the inherent inertia in environmental and macroeconomic systems—driven by technological adaptation lags, infrastructure lock-in, and gradual policy effects—where changes in drivers often materialize with a delay. Third, applying a uniform one-period lag across all predictors facilitates comparability of coefficient trajectories and reduces the risk of overfitting, particularly in annual datasets with relatively short time spans. Combined with the time-varying parameter (TVP) framework, this setup enables the model to capture both the delayed transmission of effects and their evolving magnitude over time, without inflating complexity or compromising interpretability. The selection of sample countries is guided by several considerations. First, we include as many countries as possible from those that report the geopolitical risk index. Second, the sample is further constrained by the availability of data for other explanatory variables. Accordingly, the final country selection maximizes data coverage across all variables of interest and is based on annual observations. Lastly, to enable the semiparametric estimation procedure central to this study, a balanced panel is required. These criteria result in a panel dataset comprising 29 countries, which are subsequently divided into two clusters. Further details are provided in subsection 3.2.

3-1- Variable Descriptions

The study encompasses the potential variables, each of which is crucial for analyzing the determinants of GHG emissions. These variables cover economic, environmental, and policy-related sectors that collectively shape emission patterns over time. Given the complexity of emissions dynamics, incorporating a diverse set of explanatory variables allows for a more comprehensive assessment of their relative influences. Moreover, including both macroeconomic indicators and sector-specific measures ensures that the analysis captures cross-sectional variations in emission determinants. To facilitate a structured analysis, Table 1 provides a detailed description of these variables, including their symbols, measurement methods, and data sources. All variables are transformed using natural logarithms.

Table 1. Variables and their descriptions

Variable name	Symbol	Measurement	Source
Greenhouse gas emissions	GHG	GHG per capita ($tCO_2eq/cap/yr$)	EDGAR Community GHG Database
Shadow economy	INF	MIMIC estimates of informal output (% of official GDP) (higher values indicate larger informal sector, generally undesirable due to reduced tax revenue and regulatory oversight)	Elgin et al. [17]
Geopolitical risk	GPR	The index is calculated by counting the number of articles related to adverse geopolitical events in each newspaper for each month (a share of the total number of news articles) (higher values indicate greater geopolitical instability, generally undesirable for economic stability)	Caldara & Iacoviello [53]
Energy security risk	ESR	International index of energy security risk (higher values indicate higher vulnerability in energy supply, generally undesirable for energy stability)	Global Energy Institute
Agriculture value added	AGR	Agriculture, forestry, and fishing value added (% of GDP)	WDI
Corruption index	COR	Political corruption index (higher values indicate greater political corruption, generally undesirable)	OWID
Democracy index	DEM	Liberal democracy index (higher values indicate stronger democratic institutions, generally desirable)	OWID
Energy intensity	EI	The amount of energy consumed per unit of GDP produced (MJ per 2015 USD PPP)	SDG 7.3, IEA
Export trade	EXP	Exports of goods and services (% of GDP)	WDI
Forest area	FRS	Forest land square (sq. km)	WDI
Gross domestic product	GDP	GDP per capita, PPP (current international $)	WDI
Squared GDP	GDP^2	It is included to check the environmental Kuznets curve hypothesis and calculated by the squared natural logarithm of GDP	
Globalization index	GLO	KOF globalization index	KOF Swiss Economic Institute
Human development index	HDI	An average achievement in three dimensions: human development life expectancy, education, and GNI indices	UNDP
Import trade	IMP	Imports of goods and services (% of GDP)	WDI
Industry value added	IND	Industry (including construction) value added (% of GDP)	WDI
Oil price	OIL	World Brent Oil price (US per barrel)	BP
Population	POP	Total population	WDI
Patents	PAT	Environment-related technologies (% of inventions)	OECD
Renewable energy consumption	REC	The share of renewable energy in total final energy consumption (%)	WDI
Natural resources rents	REN	The sum of oil rents, natural gas rents, coal rents, mineral rents, and forest rents (% of GDP)	WDI
Trade openness	TRA	The sum of imports and exports (% of GDP)	WDI
Urban population	URB	Urban population (% of total population)	WDI

Note: All variables are transformed into their natural logarithmic form.

The descriptive statistics for all variables are presented in Table 2. This table provides an overview of the mean, standard deviation, minimum, and maximum values for each variable, providing insights into the data across the sample of countries.

Table 2. Summary statistics of variables

Variable	Mean	S.D.	Min	Max
GHG	2.076	0.636	0.540	3.360
GPR	-2.539	1.282	-5.630	1.470
ESR	6.904	0.240	6.340	8.130
COR	-1.943	1.678	-6.210	-0.030
DEM	-0.765	0.828	-3.240	-0.110
EI	1.517	0.392	0.530	2.840
FRS	11.75	2.149	6.11	15.91
GDP	9.724	0.825	7.220	11.130
GDP^2	95.24	15.66	52.14	123.88
GLO	4.243	0.191	3.430	4.510
HDI	-0.249	0.149	-0.810	-0.040
OIL	3.723	0.695	2.540	4.720
POP	17.52	1.309	15.28	21.06
INF	3.123	0.456	2.100	4.090
AGR	1.3261	0.940	-0.610	3.400
EXP	3.437	0.529	1.910	4.790
IMP	3.409	0.483	1.940	4.610
IND	3.358	0.253	2.850	4.200
PAT	3.211	0.904	0	4.610
REC	2.295	1.498	-4.610	4.260
REN	0.023	2.116	-6.960	4.010
TRA	4.121	0.497	2.750	5.400
URB	4.219	0.306	3.060	4.580

Note: All variables are transformed into their natural logarithmic form.

3-2- Clustering-Based Country Grouping

Instead of relying on conventional income classifications from the World Bank, countries were grouped using an unsupervised learning technique that combines Principal Component Analysis (PCA) and K-means clustering. The clustering was performed on lagged averages of the core variables listed in Table 1. This data-driven approach facilitates structural grouping based on latent similarities across economic, social, and energy-related indicators.

The PCA and K-means (with C clusters, where C=2) procedure identified two structurally coherent clusters as shown in Figure 2:

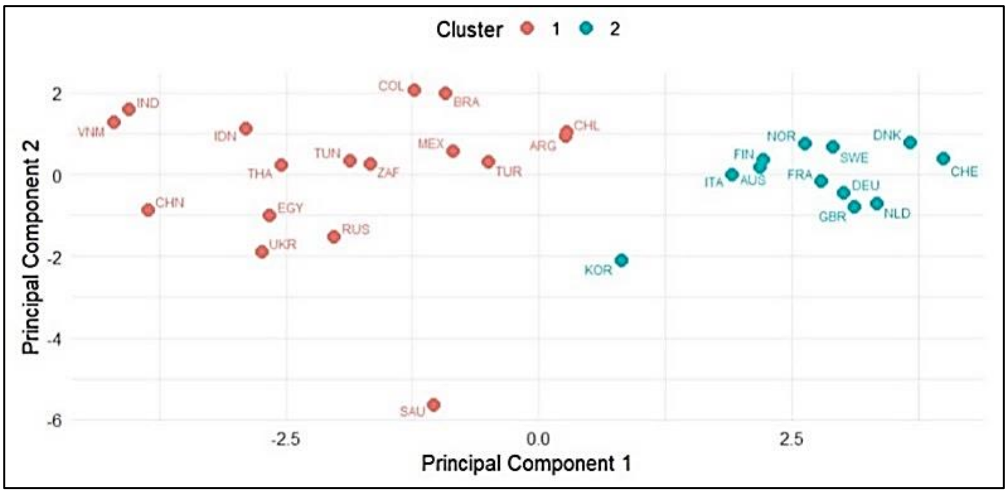


Figure 2. Country Clustering Using K-means (based on PCA projection of lagged economic indicators)

Cluster 1: Lower-income Group (Primarily Emerging and Developing Economies) consists of Argentina (ARG), Brazil (BRA), Chile (CHL), China (CHN), Colombia (COL), Egypt (EGY), Indonesia (IDN), India (IND), Mexico (MEX), Russia (RUS), Saudi Arabia (SAU), Thailand (THA), Tunisia (TUN), Turkey (TUR), Ukraine (UKR), Vietnam (VNM), and South Africa (ZAF). These nations tend to exhibit relatively lower HDI, ESR, and limited adoption of REC technologies. They are generally characterized by ongoing industrialization, urbanization, or transitional economic development. Elevated emissions levels may result from high EI or dependence on fossil fuels.

Cluster 2: Higher-income Group (Advanced Economies and High Performers) includes Australia (AUS), Switzerland (CHE), Germany (DEU), Denmark (DNK), Finland (FIN), France (FRA), United Kingdom (GBR), Italy (ITA), Korea (KOR), Netherlands (NLD), Norway (NOR), and Sweden (SWE). This cluster comprises primarily Organisation for Economic Cooperation and Development (OECD) or high-income countries. These nations are typically distinguished by better governance indicators (e.g., COR, DEM), more efficient energy intensity (EI), and lower natural resource rents (REN). They also exhibit more advanced institutional capacity, greater reliance on technological innovation, and more diversified economic structures.

This grouping strategy reflects underlying development and policy structures more accurately than static income classifications and supports heterogeneity-aware modeling. Specifically, while countries in Cluster 2 appear to be more homogeneous in terms of advanced infrastructure and environmental policy implementation, Cluster 1 represents a more heterogeneous mix of nations undergoing rapid industrialization or development challenges.

4- Methodology

Recognizing empirical uncertainty in covariate relevance and the evolving nature of environmental-economic relationships, we first apply the BMA approach for systematic variable selection. We then employ time-varying parameter (TVP) estimation in a panel data context to capture how explanatory effects evolve over time. To ensure model adaptability across country heterogeneity, both Fixed Effects (FE) and Random Effects (RE) versions of the TVP estimators are used, providing a flexible estimation framework. Model performance is evaluated through cross-validation and simulation-based validation techniques. Figure 3 illustrates the methodological steps undertaken in this study.

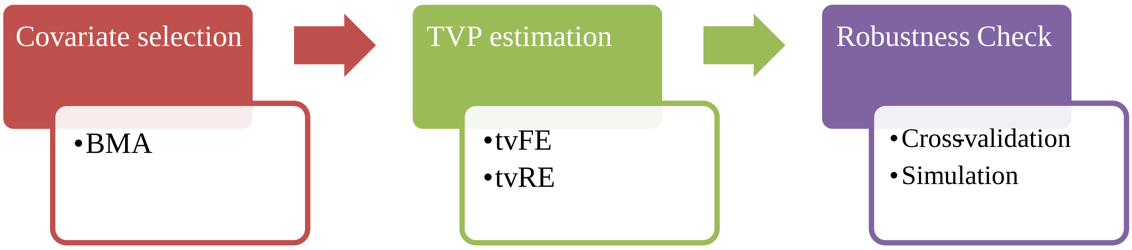


Figure 3. The process of the methodology

4-1- Covariate Selection Using Bayesian Model Averaging (BMA)

After establishing the clusters and data structure in Section 3, we proceed to identify statistically relevant variables using the Bayesian Model Averaging (BMA). Model uncertainty is a pervasive challenge in empirical studies on environmental determinants of GHG emissions, as different econometric specifications can lead to divergent results. Traditional model selection methods, such as stepwise regression or information-criteria-based approaches, are prone to overfitting and estimation instability [54]. To address this issue, BMA is employed to systematically evaluate multiple competing models, assigning weights based on posterior probabilities rather than relying on a single best model [55, 56]. This technique is particularly advantageous in environmental economics because it mitigates omitted variable bias and prevents over-reliance on specific model assumptions [57]. In addition, BMA helps reduce the impact of multicollinearity among explanatory variables by averaging over models that may exclude highly correlated predictors. Instead of forcing all variables into a single specification—which can inflate standard errors and distort coefficient estimates—BMA implicitly down-weights redundant predictors that offer little marginal explanatory power. This results in more stable and interpretable inference, as reflected in the posterior inclusion probabilities (PIP), which quantify the likelihood that a given variable significantly contributes to explaining GHG emissions. The posterior model probability (PMP) for a model M_p, given data y and covariates X, is computed as:

$$P(M_p|y,X) = \frac{P(M_p).P(y|M_p,X)}{\sum_{q=1}^{2^d} P(M_q).P(y|M_q,X)} \tag{3}$$

where, $P(M_p)$ is the prior probability assigned to the model M_p, $P(y|M_p,X)$ is the marginal likelihood of the data given the model M_p, d is the total number of predictors.

A key consideration in BMA is the selection of prior distributions. In line with best practices, this study employs three distinct priors—random, fixed, and uniform priors—to ensure the robustness in the variable selection process [58]. The rationale for this multi-prior approach is as follows:

- Random Priors: These allow for greater flexibility by dynamically assigning probabilities based on the data structure, making them particularly useful when prior knowledge about model specifications is limited.
- Fixed Priors: These introduce structure by incorporating theoretical justifications and empirical evidence, ensuring that key variables (e.g., economic growth and energy consumption) remain consistently included.
- Uniform Priors: These assume equal probability across all models, which reducing bias in variable selection by preventing excessive reliance on any single specification.

Following the empirical-Bayes approach, predictors with a PIP greater than 0.5 are retained for further analysis [59]. These selected variables form the basis for estimating time-varying coefficients in the subsequent modeling stage.

The use of BMA in this study is justified not only by its statistical rigor in handling model uncertainty but also by its alignment with the research objective of identifying structurally significant and consistently influential predictors of GHG emissions. While subsequent estimation is performed using frequentist time-varying models, BMA serves as an objective screening tool, narrowing the explanatory space and minimizing risks of overfitting or omitted variable bias. This modular integration leverages the strengths of both Bayesian variable selection and flexible frequentist estimation.

4-2- Time-Varying Parameter (TVP) Coefficient Models

Traditional econometric models—such as fixed-effects and random-effects panel estimators—assume time-invariant coefficients—implying that the relationship between explanatory variables and the dependent variable is constant over time. However, empirical evidence increasingly suggests that the economic and institutional drivers of GHG emissions evolve due to changing policies, technological shifts, and macro-structural transitions [60]. To capture these non-stationary dynamics, this study adopts a flexible non-static approach by employing TVP models.

Formally, the TVP structure is rooted in the varying coefficient model [61]:

$$Y = \boldsymbol{X}'\boldsymbol{\beta}(R) + \varepsilon \tag{4}$$

where, $X' = (X_1, \dots, X_d)'$ is the transpose of regressor vector with dimension d; $\beta = (\beta_1(R_1), \dots, \beta_d(R_d))$ is the vector of coefficient functions varying with an effect-modifying variable R; and ε is a mean-zero error term with constant variance. In this study, R corresponds to time, thereby allowing coefficients to evolve temporally. To estimate these time-varying coefficients, we minimize the expected squared error conditional on time:

$$minE[\{Y - X'\beta(R)|R\}^2|R = t] \tag{5}$$

The solution is the conditional expectation-based estimator:

$$\hat{\beta}(t) = E(XX'|t)^{-1}E(X'Y|t) \tag{6}$$

Extending this to a panel framework where heterogeneity exists across both individuals (i) and time (t), the TVP panel model is specified as follows:

$$Y_{it} = X'_{it}\beta(z_t) + \alpha_i + u_{it} \tag{7}$$

where, $\{(Y_{it}, X_{it})|i = 1, \dots, N, t = 1, \dots, T\}$ are observed data. Each regressor is modeled as an integrated process $X_{it} = X_{i,t-1} + v_{it}$, satisfying regularity conditions. Here, $\beta(.)$ Captures the unknown coefficient functions, z_t is the smoothing variable, and α_i represents individual fixed-effects. For notational convenience, the relevant expectation terms are denoted as follows: $S_{T,s}(z_t) = E(XX'|t)$ is the weighted sum of the regressors; $T_{T,s}(z_t) = E(X'Y|t)$ is the weighted sum of the regressors and the response variable. In which, s denotes the polynomial order used in the local linear approximation $(s = 0,1,2)$.

The kernel-weighted estimator becomes:

$$\hat{\beta}(z_t) = S_{T,s}^{-1}(z_t) T_{T,s}(z_t) \tag{8}$$

Both FE and RE specifications rely on this local smoothing framework [62, 63], differing in how they treat the unobserved heterogeneity α_i. While time-varying Fixed Effects (tvFE) estimator removes unit-specific means via kernel-based de-meaning techniques, time-varying Random Effects (tvRE) estimator incorporates unit-specific variances via an inverse covariance weighting matrix.

a) Time-Varying Fixed Effects Estimator (tvFE)

Identification requires the constraint $\sum_{i=1}^{N} \alpha_i = 0$. The kernel-weighted estimation proceeds as:

$$S_{T,s}(z_t) = X^T W_{b,t} X (Z - z_t)^s \tag{9}$$

$$T_{T,s}(z_t) = X^T W_{b,t} Y (Z - z_t)^s \tag{10}$$

where, $W_{b,t} = D_t^T K_{b,t}^* D_t$, is a kernel weighted matrix combining de-meaning with kernel weighting matrix according to bandwidth (b); $D_t = I_{NT} - D\left(D^T K_{b,t}^* D\right)^{-1} D^T K_{b,t}^*$ and $D = (-1_{N-1}, I_{N-1})^T \otimes 1_T$; $K_{b,t}^* = I_N \otimes diag\{K_b(z_1 - z_t), \ldots, K_b(z_T - z_t)\}$; $(Z - z_t)^s$ is the polynomial term that provides local weighting via a Taylor expansion centered at z_t, controlling for temporal distance in estimation.

b) Time-Varying Random Effects Estimator (tvRE)

The tvRE formulation adjusts for unit-level variance using:

$$S_{T,s}(z_t) = X^T K_{b,t}^{*1/2} \Sigma_t^{-1} K_{b,t}^{*1/2} X (Z - z_t)^s \tag{11}$$

$$T_{T,s}(z_t) = X^T K_{b,t}^{*1/2} \Sigma_t^{-1} K_{b,t}^{*1/2} Y (Z - z_t)^s \tag{12}$$

where, Σ_t denotes the estimated covariance matrix of the random effects, and $K_{b,t}^{*1/2}$ applies kernel-based temporal weights, ensuring local smoothing.

This study combines BMA with time-varying panel estimation (tvRE/tvFE) to capture evolving relationships between covariates and emissions. By allowing for both cross-country differences and within-country changes over time, the approach offers a flexible means of understanding how emission drivers shift across structural contexts. The bandwidth parameter for kernel smoothing, which controls the degree of temporal flexibility in the TVP models—was selected using grouped cross-validation to strike a good balance between bias and variance. While alternative clustering methods, such as hierarchical clustering, were considered, they were ultimately excluded from the final framework due to their limited capacity to handle time-varying relationships in high-dimensional panel data. Cross-validation therefore served both as a tuning method for bandwidth selection and as a tool for validating overall model robustness, leading into the next step of model performance evaluation.

4-3- Model Validation: Cross-Validation and Simulation

To evaluate performance and generalizability [64-66], we perform grouped 5-fold cross-validation using each country as the grouping unit to the preserve panel structure. Both MSE and MAE are computed to compare model types (static vs dynamic; Bayesian vs Frequentist), and this same cross-validation framework is applied to select the optimal bandwidth parameter for kernel smoothing in TVP estimation. Although an exhaustive grid search was not performed, several candidate bandwidths were tested to balance over-smoothing against responsiveness to temporal variation. While this cross-validation approach provides a solid empirical basis, it may still be insufficient for robust model validation [67]. Therefore, we additionally implement a Monte Carlo simulation procedure to assess whether estimated coefficients can accurately recover the true data-generating process. This entails testing parameter recovery using RMSE and correlation metrics on synthetic datasets. In terms of clustering design, although hierarchical clustering was initially considered, it was ultimately discarded due to its rigid structure, which does not align well with the overlapping and evolving emissions patterns observed across countries. As a result, both validation strategies confirm the superior out-of-sample performance of the tvRE model, particularly in capturing dynamic relationships over time, as discussed in subsection 5.3.

5- Estimation Results and Discussion

5-1- Covariate Selection

To evaluate the effectiveness of prior specifications in the BMA approach, we compare three types: fixed, random, and uniform priors. Among them, the random one consistently delivered the most stable and balanced variable selection performance across both country groups. Specifically, it selected the largest number of variables (15) in both groups, indicating a robust capacity to capture underlying structural relationships without overfitting. In contrast, the fixed and uniform priors selected fewer variables, with tendencies toward underfitting (fixed) or overfitting (uniform).

Based on the Posterior Model Size Distributions (Figure 4), the Random prior exhibits posterior model sizes that are neither too sparse nor overly dense, with means around 12-14 independent variables in both Higher- and Lower-income countries, respectively. These means are reasonable and reflect a balance between model complexity and parsimony. In contrast, the fixed and uniform priors both result in overly parsimonious models (means near 10–12 variables), potentially omitting influential covariates. Among the three types, the Random prior demonstrates the best behavior: its posterior aligns well with the empirical signal while preserving flexibility across income groups. Overall, the comparison confirms that the BMA results are only moderately sensitive to prior choice—while different priors naturally shift the prior model size distributions by design, the posterior distributions remain centered around a similar range. This indicates that the variable selection process is largely data-driven and robust to prior specification.

The PIP distributions (Figure 5) further underscore the advantage of employing the random prior. Variables selected under this prior tend to cluster around the conventional decision threshold of 0.5, reflecting a more data-driven and adaptive model structure. The key strength of the random prior lies in its endogenous control of model complexity: selection emerges from patterns in the data rather than being dictated by fixed structural assumptions. This flexibility is especially valuable in high-dimensional panel settings involving intertwined socio-economic, environmental, and institutional variables—contexts where structural heterogeneity and interaction effects are both expected and informative. In detail, Figure 5 reveals both overlaps and divergences in the set of influential variables between the higher- and lower-income country groups. Several predictors, such as GDP, GDP^2, HDI, and INF, consistently exceed the 0.5 threshold in both groups, indicating their fundamental importance in explaining GHG emissions across diverse economic contexts. To examine the EKC hypothesis, GDP^2 is included to capture potential non-linearities; however, its coefficient remains near zero, suggesting minimal impact on the overall modeling outcome.

While several key features are common to both groups, group-specific patterns also exist. In the Higher-income group, variables like REC, ESR, and COR attain relatively high PIP values, reflecting a stronger role of energy transition, institutional integrity, and security-related risk mitigation in these countries. This aligns with expectations, given the advanced infrastructure and policy maturity in these economies. In contrast, the Lower-income group shows higher PIPs for variables such as IND, FRS, and URB, suggesting that industrial expansion, natural land-use patterns, and rapid urbanization remain dominant drivers in shaping emission patterns. Notably, REN and GPR appear less prominent, highlighting structural constraints in diversifying energy sources and responding to geopolitical risk management in developing countries.

Overall, these differences reinforce the need for differentiated modeling strategies and policy interventions. The random prior helps reveal these nuanced patterns by selectively emphasizing variables whose inclusion is statistically and theoretically supported within each group context. Considering all visual and quantitative indicators (Figure 5 and 6), the random prior emerges as the most robust choice for this study. It offers the best trade-off between parsimony and generalizability, capturing both well-supported and structurally meaningful variables across income groups. Accordingly, random prior is used as the basis for subsequent time-varying panel model estimation.

A notable feature of the proposed modeling framework is that all explanatory variables are included in their first-lagged form. This specification is theoretically motivated by the annual frequency of the data and the empirical context, where delayed responses to macroeconomic and policy shocks—such as those from international climate agreements—are more plausibly captured by a one-year lag rather than contemporaneous values. By uniformly applying a lag of one year to all predictors, the model accounts for inertia, adjustment periods, and policy implementation lags that typically characterize emissions–driver relationships in both high- and low-income contexts. This approach also helps mitigate simultaneity bias and potential endogeneity, since current emissions are less likely to directly influence explanatory variables from the previous year. Moreover, because variable selection is already addressed through BMA, which filters out irrelevant or collinear predictors via posterior inclusion probabilities, combining lagged variables with the time-varying coefficient framework preserves parsimony while enhancing interpretability. The resulting estimation strategy therefore captures both temporal evolution in effects and the realistic delayed impacts of drivers, providing a robust and policy-relevant view of emissions dynamics.

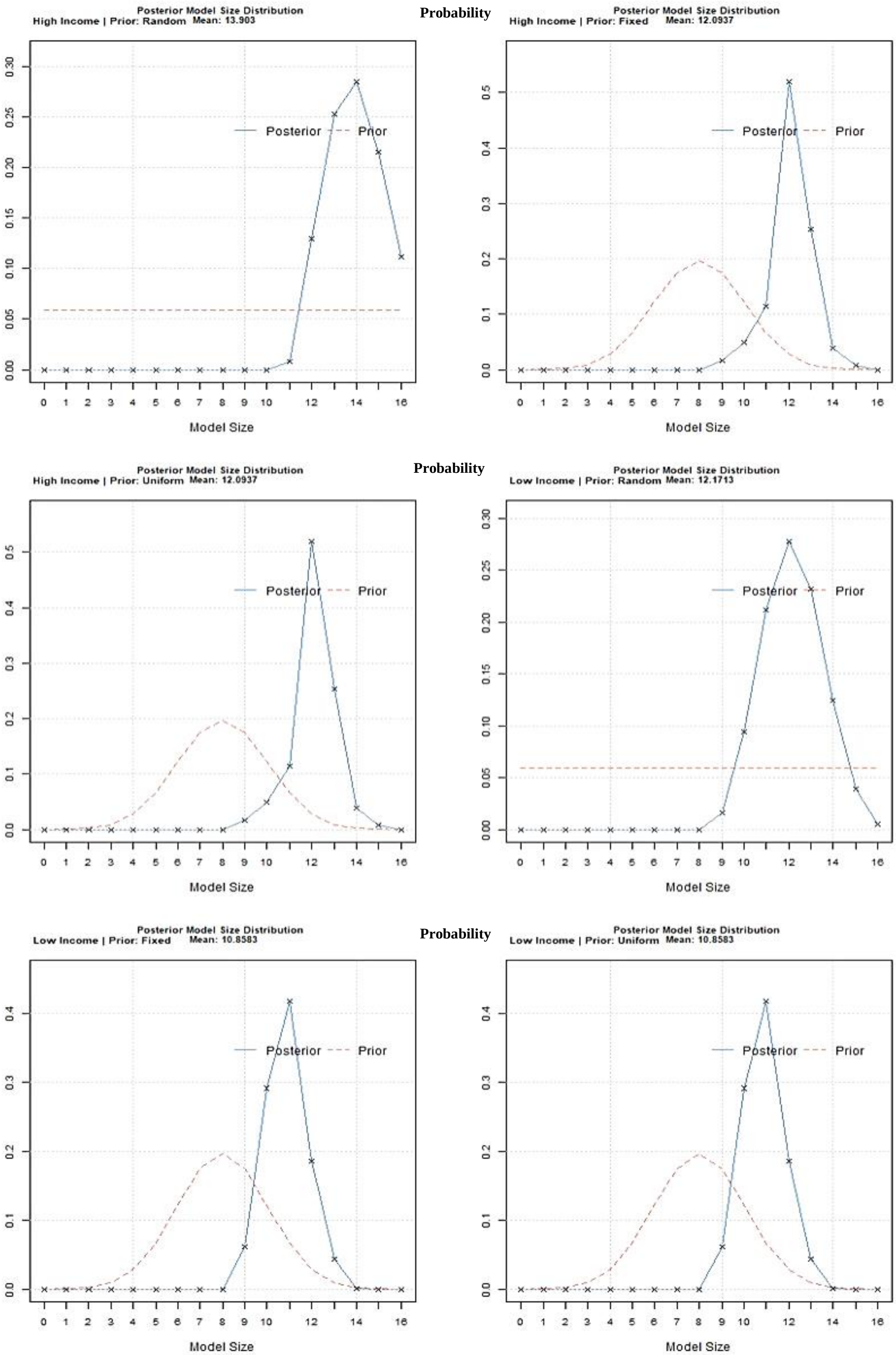
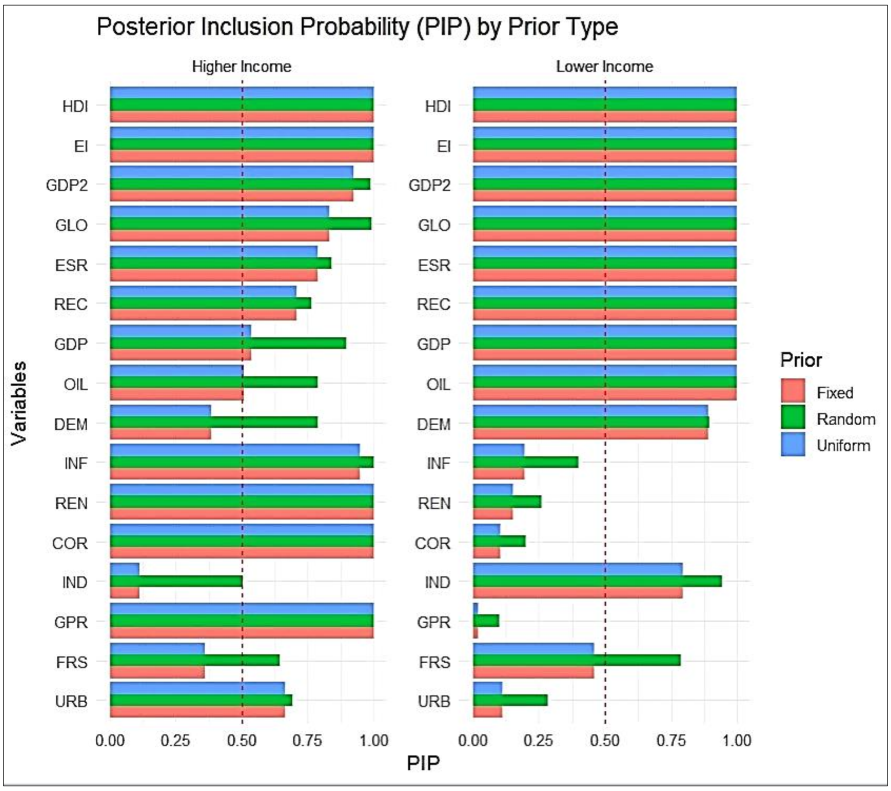


Figure 4. Posterior Model Size Distributions under Different Priors

Note: The dashed red line represents the prior distribution of model size (i.e., beliefs about model complexity before observing the data), while the solid blue line shows the posterior distribution derived from the data. A well-performing prior yields a posterior that is data-driven yet avoids extremes—striking a balance between underfitting and overfitting.



Note: The vertical dashed line indicates the threshold PIP = 0.5. Only variables with PIP>0.5 under the Random prior are selected. All variables are transformed into their natural logarithmic form.

Figure 5. Posterior Inclusion Probabilities (PIPs) by Prior Type for Each Country Group

5-2- Estimate the Time-Varying Coefficients

Table 3 reports the means and interquartile ranges (min–max) of time-varying coefficients estimated from the random effects specification. These summaries reflect not only the average magnitude of influence across time but also the extent of their dynamic variability. The results underscore several key patterns and provide new insights into group-specific emissions behavior.

Table 3. Time-Varying Coefficients and Model Diagnostics from tvRE Model

Variable	Higher-income Group						Lower-income Group					
	Min	Q1	Mean	Median	Q3	Max	Min	Q1	Mean	Median	Q3	Max
GDP	-1.9844	-0.8922	0.6565	0.4821	2.0065	2.9133	0.6188	0.6754	0.9772	0.8400	1.2977	1.4863
GDP^2	-0.1163	-0.0957	-0.0480	-0.0639	0.0118	0.0932	-0.0382	-0.0347	-0.0150	-0.0153	-0.0076	0.0160
INF	-0.3650	-0.2023	-0.0664	-0.1244	0.0161	0.0952	—	—	—	—	—	—
HDI	-0.2793	-0.1724	1.0876	0.3410	3.0871	8.5370	-0.1866	1.2241	1.4544	1.7022	1.9318	2.0515
ESR	-1.1872	-0.3880	-0.3856	-0.3472	-0.2708	-0.1524	-0.2443	-0.1982	-1.424	-0.1699	-0.1326	-0.0791
COR	0.1274	0.1724	0.1982	0.1928	0.2347	0.2707	—	—	—	—	—	—
REC	-0.1708	-0.0571	-0.0078	-0.0215	0.0432	0.0432	-0.0827	-0.0269	-0.0127	-0.0270	-0.0042	0.0181
EI	0.0069	0.0858	0.0952	0.1081	0.2417	0.2147	-0.6956	0.8653	0.8884	0.8884	0.9585	0.9918
GLO	-3.7862	-0.5513	-0.0480	-0.0626	0.0118	1.7497	-1.7266	-1.4503	-1.0753	-1.1716	-0.5069	-0.3908
DEM	-0.3229	-0.1106	0.1099	0.1099	0.2304	0.3405	-0.0016	0.0081	0.0299	0.0278	0.0511	0.0634
OIL	-0.2561	-0.1981	-0.0728	-0.0726	0.0528	0.2175	-0.3056	-0.0502	-0.0243	-0.0289	-0.0121	0.0417
IND	—	—	—	—	—	—	-0.3649	-0.3314	-0.2435	-0.2678	-0.1625	-0.0375
FRS	—	—	—	—	—	—	-0.0274	-0.0167	0.0022	-0.0084	0.0181	0.0292
Pseudo-R^2	0.9772						0.9909					
RMSE (Min)	0.0396						0.0632					
RMSE (Max)	0.1669						0.1255					
Mean Stability Score	1.66						2.47					

Note: "—" indicates the variable was not included or not estimated for the specified group. Data are presented in natural logarithms.

In the Higher-income group, variables such as GDP and HDI exhibit relatively high positive means and wide interquartile ranges; however, their effects on GHG emissions vary in sign across quantiles, suggesting that their influence is time-dependent and potentially nonlinear. Additionally, other factors (except COR and EI) also display sign reversals in their time-varying coefficients. Notably, COR and EI show consistently positive effects on environmental degradation.

For the Lower-income group, the robust determinants include GDP, HDI, EI, and GLO. Similar to the Higher-income group, this confirms the strong link between economic growth, affluence, and emissions. Interestingly, GLO exhibits consistently negative associations, suggesting that globalization may facilitate the transfer of cleaner technologies in developing countries. Meanwhile, the use of renewables (REC) is associated with negative coefficients, indicating its potential role in reducing GHG emissions, although the effects are not statistically significant. The differences between two groups reveal a central insight that emission drivers are not uniform across the development spectrum, and thus modeling approaches must respect such heterogeneity.

A key quantitative highlight is the higher pseudo-R^2 for the Lower-income group (0.9909 vs. 0.9772 for the Higher-income group). This implies that the model explains variation in GHG emissions more thoroughly in developing economies, likely because emissions are governed by more deterministic, observable variables. In contrast, advanced economies may involve more diffuse, lagged, or policy-dependent mechanisms that are harder to fully capture within the model. From a methodological standpoint, the application of time-varying coefficients across grouped panels provides novel empirical clarity into how the importance of different predictors evolves, both temporally and structurally. Unlike static panel models, this approach uncovers fluctuations and structural breaks in covariate influence that align with real-world policy events and economic cycles. The filtering of coefficients based on interquartile range and mean magnitude ensures interpretability and guards against overfitting. These elements collectively provide a more granular, dynamic, and policy-relevant understanding of emissions behavior across diverse national contexts.

The Root Mean Square Error (RMSE) distribution reveals that the models perform with relatively low prediction error over time. The Higher-income group's result shows a wider RMSE range (0.0396 to 0.1669), suggesting greater year-on-year variability in model fit—likely reflecting more complex dynamics and policy heterogeneity. In contrast, the Lower-income group demonstrates tighter RMSE bounds (0.0632 to 0.1255), which may imply more stable or deterministic emission pathways in developing economies. Additionally, the mean Stability Score (calculated as the inverse of relative variability of coefficients) is substantially higher for the developing countries (2.47) than for the advanced countries (1.66). This aligns with the estimated coefficients, which show less fluctuation and fewer sign reversals in the Lower-income group.

5-3- Robustness Check

5-3-1- Cross-Validation and Model Performance Comparison

To robustly evaluate model performance, we conducted grouped 5-fold cross-validation across five panel model frameworks: traditional static estimators (Frequentist RE and FE), Bayesian static models, and the time-varying specifications (tvRE, tvFE). Country-level grouping was applied to preserve panel structure and independence between folds.

Table 4. Cross-Validation Performance Comparison Across Panel Models

Model Type	Group	MSE	MAE	Time-Varying
tvRE	Higher-income	0.6458	0.5732	Yes
tvFE	Higher-income	6.8515	2.1257	Yes
Bayesian RE (Static)	Higher-income	11.8352	3.4368	No
Bayesian FE (Static)	Higher-income	52.4425	7.2401	No
RE (Static)	Higher-income	0.7498	0.6485	No
FE (Static)	Higher-income	12.3038	2.7994	No
tvRE	Lower-income	0.1071	0.2519	Yes
tvFE	Lower-income	0.2741	0.3200	Yes
Bayesian RE (Static)	Lower-income	22.1316	4.7032	No
Bayesian FE (Static)	Lower-income	20.1332	4.4857	No
RE (Static)	Lower-income	0.1161	0.3839	No
FE (Static)	Lower-income	0.4614	0.5211	No

Table 4 illustrates the predictive superiority of the tvRE model across both income groups. For the Higher-income group, tvRE achieves the lowest MSE (0.6458) and MAE (0.5732), outperforming all static and time-invariant models. A similar trend is observed in the Lower-income group, where tvRE yields the best performance with an MSE of 0.1071 and MAE of 0.2519. Compared to these dynamic models, static estimators—regardless of estimation paradigm—exhibit considerably higher prediction errors. Even the tvFE model underperforms relative to tvRE, likely due to its more restrictive ability to capture unobserved heterogeneity.

5-3-2- Simulation-Based Validation of Estimated Coefficients

While cross-validation emphasizes predictive power, it does not fully capture how well models recover the underlying data-generating structure. To complement this, we implemented a Monte Carlo simulation-based validation procedure to assess the structural reliability of estimated coefficient paths under each model. Using the actual panel data as a foundation, we generated 1,000 synthetic datasets per model and group. Each dataset was simulated by applying the model's estimated coefficients to the original predictors, followed by the addition of Gaussian noise. This setup preserved the original model structure while introducing stochastic variation to test its robustness.

For each synthetic dataset, the model was re-estimated, and the recovered coefficients were compared to the original ones. Two key metrics were used: (1) Average Correlation between estimated and true parameter values specified in the data-generating process to assess directional accuracy, and (2) Average RMSE to evaluate estimation precision. Table 5 reaffirms the robustness of the tvRE model, which consistently recovers coefficient structures with high fidelity across income groups. In the Higher-income group tvRE achieves an average correlation of 0.9782 and a low RMSE of 0.3354—clearly outperforming static and frequentist models. The Lower-income group exhibits slightly tighter performance across models, yet tvRE remains among the top in both correlation and error metrics.

Table 5. Simulation-Based Validation: Coefficient Recovery across Model Specifications

Model Type	Group	Avg Correlation	Avg RMSE
tvRE	Higher-income	0.9782	0.3354
tvFE	Higher-income	0.9346	0.3354
Bayesian RE (Static)	Higher-income	0.9746	0.3336
Bayesian FE (Static)	Higher-income	0.9746	0.3336
RE (Static)	Higher-income	0.9517	1.137
FE (Static)	Higher-income	0.9235	0.5527
tvRE	Lower-income	0.9898	0.0988
tvFE	Lower-income	0.9331	0.0988
Bayesian RE (Static)	Lower-income	0.9874	0.1129
Bayesian FE (Static)	Lower-income	0.9869	0.1129
RE (Static)	Lower-income	0.9932	0.0999
FE (Static)	Lower-income	0.9698	0.1987

To complement the summary statistics in Table 5, Figure 6 shows the full distribution of simulation-based metrics. The left panel (a) illustrates that tvRE consistently achieves the highest correlation across simulations with the narrowest interquartile range. In the right panel (b), tvRE also yields the lowest RMSE with minimal variation, further reinforcing its structural stability and estimation precision compared to tvFE, static Bayesian, and frequentist alternatives. In short, tvRE consistently outperforms all other models in both correlation and RMSE.

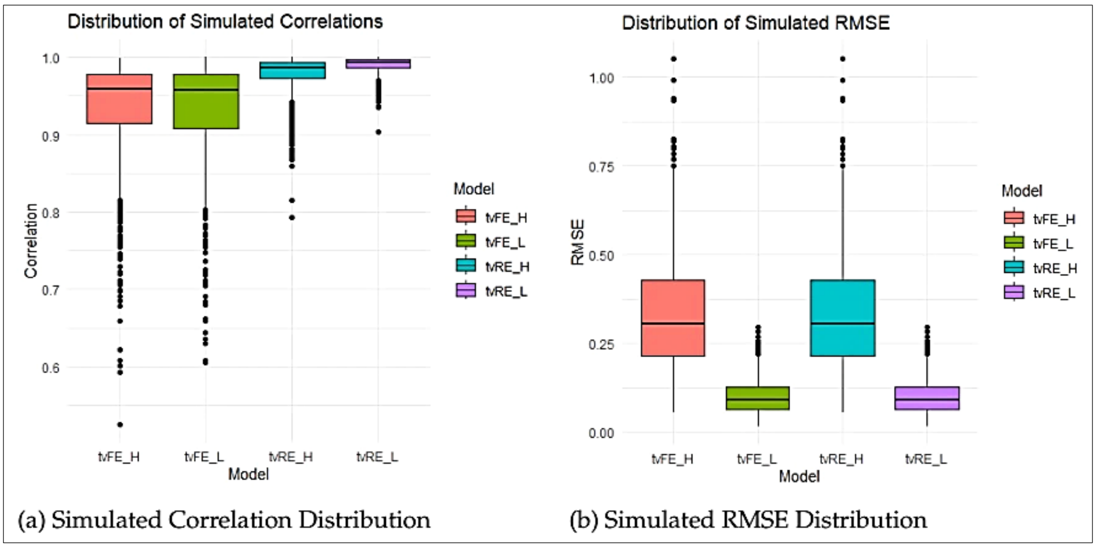


Figure 6. Distribution of simulation-based coefficient recovery metrics across model types

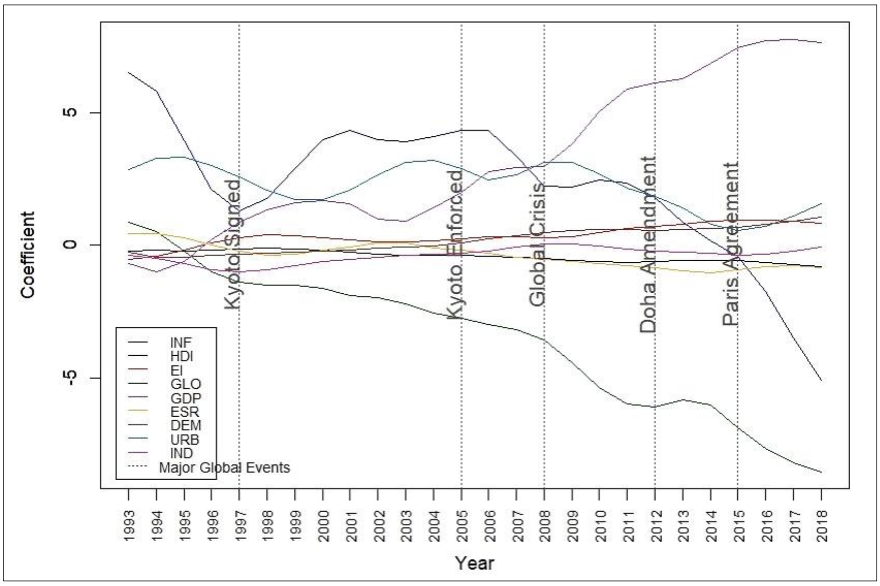
Taken together, the results from cross-validation and simulation studies consistently support the tvRE model as the most robust and methodologically defensible framework. It delivers superior out-of-sample accuracy, strong parameter recovery, and adaptability to dynamic causal mechanisms, making it an ideal tool for policy-oriented GHG modeling across diverse time and national contexts.

5-3-3- Discussion

This section interprets the temporal patterns of key coefficients from the tvRE model for both income groups. Figures 7 and 9 depict non-zero and fluctuating coefficients for selected drivers of GHG emissions, highlighting how the magnitude and direction of effects evolve alongside global policy events. Variables shown in these figures are selected using a filtering function that retains only those with either a high average effect (absolute mean > 0.3) or substantial temporal variability (standard deviation > 0.15). This selection strategy ensures attention on both experimental (policy-relevant) and control (structural) variables with meaningful time-varying influence. Variables omitted typically exhibit low magnitude and stability over time, with beta coefficients remaining close to zero—indicating minimal dynamic impact and limited policy relevance within this framework.

5-3-3-1- Structural Drivers and Constraints of GHG Emissions in the Higher-Income Countries

In wealthier nations, several predictors exhibit consistent positive effects on emissions (Figure 7). GDP remains a major driver, especially after the enforcement of the Kyoto Protocol in 2005, aligning with the EKC perspective linking income growth to environmental pressure. However, in our time-varying framework, the quadratic GDP term is excluded from the figure, as its estimated coefficient remains close to zero throughout the sample period. This suggests that any EKC-like curvature is weak or already captured within the temporal dynamics of the linear term, in line with recent evidence that EKC patterns are heterogeneous and highly context-dependent [68]. Other development-related predictors such as HDI and URB also show sustained positive effects. The plateauing of URB after 2012 parallels findings from Chinese cities where urban development's environmental impacts stabilize once regulatory frameworks mature [69]. ESR displays a mild but persistent positive trend, implying that energy vulnerability can increase emissions—particularly during periods of global energy instability—which is consistent with literature on renewable transitions and structural risk [70].

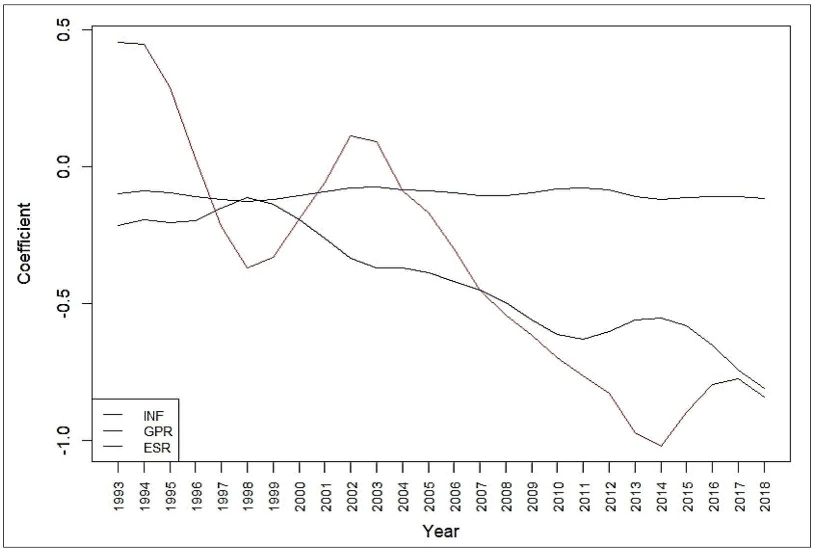


Note: Vertical dashed lines mark major global climate events (e.g., Kyoto, Paris). Variables shown in the figure are selected using a filtering function that retains only those with either a high average effect (mean > 0.3 in absolute value) or a large degree of fluctuation over time (standard deviation > 0.15). All series are in natural logs.

Figure 7. Time-Varying Coefficient Trajectories for Higher-income Group (tvRE)

The coefficient paths further indicate that EI remains persistently negative—especially after 2005—highlighting structural decoupling through improved energy efficiency and technology transitions in high-income economies. This aligns with [71] which documents China's decline in energy intensity as a key driver of reduced emissions during industrial transitions. The shadow economy (INF) also turns increasingly negative after 2010, suggesting that reductions in informality may enhance emissions monitoring and regulatory compliance. While larger shadow economies can elevate ecological footprints, they may also understate emissions due to reporting gaps, pointing to governance-dependent effects [72].

To provide a more detailed view of the three focal variables of this study—INF, GPR, and ESR—Figure 8 traces their individual coefficient trajectories. Among them, GPR does not meet the inclusion threshold for the main figure, whereas INF and ESR are retained in the baseline specification. INF shows a steadily strengthening negative effect after 2005, consistent with improved regulatory capacity and monitoring. GPR remains flat and close to zero across the sample, suggesting limited systemic influence on emissions for this income group. In contrast, ESR shows a mild positive effect before 2005 but declines sharply thereafter, implying that energy-related vulnerabilities may have initially driven carbon-intensive responses, which were later mitigated as energy systems stabilized. The inclusion of this figure therefore helps contextualize why these variables were filtered out, while still demonstrating that they exhibit interpretable, if modest, temporal shifts.

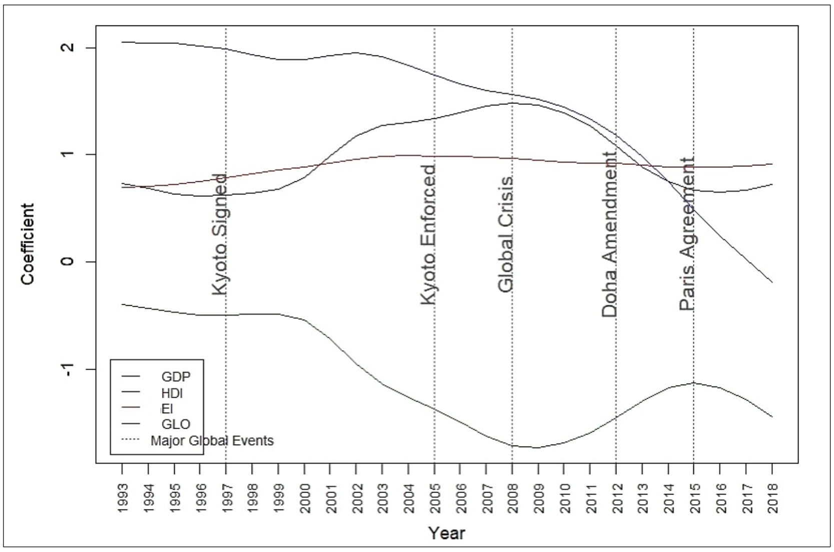


Note: All series are in natural logs.

Figure 8. The isolate the trajectories of INF, GPR, and ESR for the Higher-income Group

5-3-3-2- Structural Drivers and Constraints of GHG Emissions in the Lower-Income Countries

For the Lower-income group, GDP and HDI stand out as significant emission drivers, particularly between 2000 and 2010 during periods of rapid infrastructure expansion and economic growth (Figure 9). After 2015, the influence of GDP flattens and gradually declines, plausibly reflecting greater engagement with global climate commitments and incremental gains in economic efficiency. The quadratic GDP term is excluded from the final specification, as its time-varying coefficient remains close to zero throughout the sample. This suggests that nonlinear EKC dynamics are better captured through evolving effects of GDP over time rather than a fixed second-order term, consistent with evidence that EKC relationships vary across structural and institutional settings [68]. The persistently positive role of HDI underscores the emissions–development trade-off inherent in expanding human welfare within resource- and capacity-constrained contexts. The limited or insignificant effects of renewable energy and energy security variables in this group align with the structural and technological constraints faced by developing nations, particularly in accessing clean technologies and implementing effective policies [70]. Another city-level analysis—such as [69], further illustrates how spatial and sectoral heterogeneity in development pathways can yield divergent emission outcomes, underscoring the need for localized, group-specific strategies.



Note: Vertical dashed lines mark major global climate events (e.g., Kyoto, Paris). Variables shown in the figure are selected using a filtering function that retains only those with either a high average effect (mean > 0.3 in absolute value) or a large degree of fluctuation over time (standard deviation > 0.15). All series are in natural logs.

Figure 9. Time-Varying Coefficient Trajectories for the Lower-income Group (tvRE)

Energy intensity also maintains a negative association with emissions, albeit with lower magnitude and variability compared to Higher-income counterparts. This indicates that efficiency gains materialize more slowly where infrastructure and financing remain limited. Alam et al. [73] confirmed that in fast-developing economies, reductions in energy intensity can curb emissions, though the strength of this relationship depends on institutional quality and investment capacity. By contrast, INF shows inconsistent influence across countries, reflecting how informality's environmental impact depends on governance thresholds and data reliability. Similarly, the coefficient for ESR remains largely neutral, consistent with expectations that such concerns are less systematically measured or prioritized in developing economies due to data gaps and structural limitations.

In particular, for the Lower-income group, variables such as INF, GPR, and ESR are excluded from Figure 9 because their estimated time-varying parameters remain close to zero and display limited fluctuation across the study period. This pattern suggests that these variables exert neither any strong nor dynamic influence on emissions in these settings. In practical terms, their muted behavior may reflect structural limitations—such as data reporting gaps, institutional inertia, or lower policy responsiveness—that dampen the explanatory power of such variables. Their exclusion does not imply irrelevance in a broader context, but rather that within this specific empirical framework and sample, their contribution to explaining temporal emissions dynamics is negligible.

5-3-3-3- Shifting Influences and Global Events

The coefficient trajectories from our time-varying panel model exhibit distinct inflection points around three major global events, underlining the responsiveness of emissions drivers to policy, economic, and security shifts.

After the Kyoto Protocol's enforcement in 2005, coefficients on GDP accelerate markedly in the Higher-income group—an effect that may reflect rebound dynamics, where efficiency improvements are offset by increased economic activity. This pattern aligns with [68], which reports a robust N-shaped EKC across 214 countries, where the quadratic GDP effect turns negative but is often outweighed by stronger linear and cubic components.

During the Global Financial Crisis of 2008, GLO declined sharply in Lower-income countries, suggesting heightened vulnerability to capital and trade shocks. Guan et al. [71] documented how structural transformations in global energy and industrial systems during crises can significantly realign emissions trajectories, particularly in export-dependent economies.

Following the Paris Agreement in 2015, the effects of development-related variables—GDP, HDI, and URB—tend to stabilize or decline. This may reflect the early impacts of international climate commitments. Supporting this view, Wang & Cao [69] observed that urban development's effect on air pollution in China began to decelerate under more stringent environmental regulation. However, the more muted response in lower-income countries is consistent with findings from [72, 73], arguing that weak institutions and limited energy transition capacity dampen policy effectiveness in such contexts. Notably, ESR remains either weakly positive or neutral throughout. This suggests that energy security concerns can undermine decarbonization by pushing countries toward carbon-intensive fallback options. As Iyke [27] confirmed that climate-induced volatility can heighten ESR and disincentivize clean energy investment, Cevik [25] framed this as a critical policy trade-off between energy reliability and environmental sustainability.

5-3-3-4- Policy Implications and Sustainable Development Goals Alignment

These dynamic patterns carry several important policy implications. For advanced economies, climate strategies should extend beyond improvements in energy efficiency to tackle lifestyle-related emissions, promote circular economy models, and strengthen governance over informal and unregulated pollutant sources. For emerging economies, priority should be placed on investments in clean infrastructure, policies that encourage the formalization of economic activity, and expanded access to green technologies to prevent long-term carbon lock-in.

These recommendations align closely with the Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action), SDG 8 (Decent Work and Economic Growth), SDG 11 (Sustainable Cities and Communities), and SDG 16 (Peace, Justice and Strong Institutions). Furthermore, the Principles for Sustainable Insurance (PSI) framework indicates pronounced temporal shifts in core drivers such as HDI and GLO among Higher-income countries, reflecting their evolving roles in shaping emissions dynamics. By contrast, Lower-income economies display consistently lower PSI performance, suggesting slower responsiveness to global climate objectives. This newly developed index offers a basis for differentiated policy design, enabling targeted interventions that account for both structural flexibility and time-varying adaptive capacity.

6- Conclusion

This study investigates the dynamic determinants of GHG emissions across 29 countries from 1993 to 2018, with particular attention to underrepresented yet structurally important drivers—namely the shadow economy, energy security risks, and geopolitical volatility. The empirical design follows a four-step framework in which countries are classified using principal component analysis and K-means clustering, robust covariates are selected through Bayesian Model Averaging, and their impacts are estimated using time-varying coefficient panel models, with robustness confirmed via grouped cross-validation. Results indicate the superior performance of the time-varying random effects specification and reveal distinct inflection points in the coefficient trajectories around three major global events. Following the Kyoto Protocol's enforcement in 2005, the influence of GDP on emissions accelerates markedly in the Higher-income countries, potentially reflecting rebound effects where efficiency gains are offset by expanded economic activity. During the 2008 Global Financial Crisis, the contribution of geopolitical and openness-related factors declines sharply in Lower-income economies, underscoring their vulnerability to capital and trade shocks. After the Paris Agreement in 2015, the effects of development-related variables—GDP, human development, and urbanization—tend to stabilize or decline, suggesting early impacts of international climate commitments, albeit with weaker responses in less developed contexts. Across the entire period, energy security risk remains either weakly positive or neutral, implying that concerns over energy reliability can undermine decarbonization by encouraging reliance on carbon-intensive fallback options. Collectively, these findings highlight the complex, event-sensitive, and often asymmetric nature of emissions drivers, highlighting the need for policy frameworks that integrate economic, environmental, and energy security considerations in a coherent and adaptive manner.

The findings point to a set of differentiated policy priorities. In the Higher-income economies, effective climate strategies should go beyond incremental energy efficiency gains to address consumption-driven emissions, embed circular economy principles, and enhance governance over informal or unregulated pollution sources. In emerging economies, policy efforts need to prioritize large-scale investment in clean infrastructure, promote the formalization of economic activity, and expand access to affordable green technologies to avoid long-term carbon lock-in. These priorities are relevant to the SDGs, particularly those relating to climate action, sustainable economic growth, urban resilience, and institutional capacity. Future research could extend this work along three main directions. First, broadening the geographical scope to include additional countries or regions would yield a more comprehensive understanding of cross-country heterogeneity in emissions drivers. Second, incorporating sector-specific emissions data could uncover industry-level pathways and inform more targeted mitigation strategies. Third, a notable limitation of the present study is its temporal coverage, restricted to 1993–2018 due to the availability and consistency of cross-country data. Updating the dataset to include more recent years would enable for the assessment of emerging global challenges, such as the impacts of post-2018 climate agreements, changes in energy market structures, the COVID-19 pandemic, trade wars, and shifting geopolitical dynamics, thereby enhancing the relevance and timeliness of the analysis. Taken together, these policy recommendations and further research directions underscore the importance of integrated, context-specific, and adaptive strategies for managing GHG emissions in an increasingly dynamic and interconnected global environment.

7- Declarations

7-1- Author Contributions

Conceptualization, T.M.N., K.P., P.P., and W.S.; methodology, T.M.N., P.P., and W.S.; investigation, T.M.N.; resources, W.S.; writing—original draft preparation, T.M.N., P.P., and K.P.; writing—review and editing, T.M.N. and K.P. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

Publicly available datasets were analyzed in this study, including the EDGAR Community GHG Database, World Bank (WDI), Our World in Data (OWID), Global Energy Institute, Sustainable Development Goal SDG 7.3 (IEA), KOF Swiss Economic Institute, UNDP, BP, and OECD.

7-3- Funding and Acknowledgments

This study was partially supported by the Faculty of Economics, Chiang Mai University. It was conducted as part of the Doctor of Philosophy Program in Economics, Faculty of Economics, under the CMU Presidential Scholarship.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

8- References

[1] Grubb, M., Hourcade, J. C., & Neuhoff, K. (2014). Planetary economics: energy, climate change and the three domains of sustainable development, Routledge, London, United Kingdom.

[2] IPCC. (2023). AR6 Synthesis Report: Climate Change 2023; Intergovernmental Panel on Climate Change: Geneva, Switzerland.

[3] Ehrlich, P. R., & Holdren, J. P. (1971). Impact of population growth. Science, 171(3977), 1212–1217. doi:10.1126/science.171.3977.1212.

[4] Le, T. H. (2021). Drivers of greenhouse gas emissions in ASEAN + 6 countries: a new look. Environment, Development and Sustainability, 23(12), 18096–18115. doi:10.1007/s10668-021-01429-6.

[5] Sudarmaji, E., Rubiul Yatim, M., Harsono, H., Masrio, H., & Azizah, W. (2024). Quantifying Drivers of GHG Emissions in ASEAN: Modeling CO2 Emissions Using LMDI and ARIMAX Approaches. International Journal of Energy Economics and Policy, 14(6), 426–435. doi:10.32479/ijeep.17186.

[6] Yamaka, W., Phadkantha, R., & Rakpho, P. (2021). Economic and energy impacts on greenhouse gas emissions: A case study of China and the USA. Energy Reports, 7, 240–247. doi:10.1016/j.egyr.2021.06.040.

[7] Le, T. H., & Nguyen, C. P. (2024). Determinants of Greenhouse Gas Emissions Revisited: a Global Perspective. Singapore Economic Review, 69(1), 141–167. doi:10.1142/S0217590820500514.

[8] Sakariyahu, R., Lawal, R., Etudaiye-Muhtar, O. F., & Ajide, F. M. (2023). Reflections on COP27: How do technological innovations and economic freedom affect environmental quality in Africa? Technological Forecasting and Social Change, 195, 122782. doi:10.1016/j.techfore.2023.122782.

[9] Gawrońska, D., & Mularczyk, A. (2025). Analysis of Greenhouse Gas Emissions Drivers in Poland and the EU: Correlation and Regression-Based Assessment. Sustainability (Switzerland), 17(10), 4345. doi:10.3390/su17104345.

[10] Bauer, F., & Sterner, M. (2025). Impacts of lifestyle changes on energy demand and greenhouse gas emissions in Germany. Renewable and Sustainable Energy Reviews, 207, 114944. doi:10.1016/j.rser.2024.114944.

[11] Lin, T. Y., Chiu, Y. ho, Chen, C. H., & Ji, L. (2025). Renewable energy consumption efficiency, greenhouse gas emission efficiency, and climate change in Europe. Geoenergy Science and Engineering, 247, 213665. doi:10.1016/j.geoen.2025.213665.

[12] Tsur, Y. (2025). The diverse impacts of democracy on greenhouse gas emissions. Ecological Economics, 227, 108411. doi:10.1016/j.ecolecon.2024.108411.

[13] Opoku, E. E. O., Dogah, K. E., & Aluko, O. A. (2022). The contribution of human development towards environmental sustainability. Energy Economics, 106, 105782. doi:10.1016/j.eneco.2021.105782.

[14] Gharleghi, B., & Jahanshahi, A. A. (2020). The shadow economy and sustainable development: The role of financial development. Journal of Public Affairs, 20(3), 2099. doi:10.1002/pa.2099.

[15] Gomis-Porqueras, P., Peralta-Alva, A., & Waller, C. (2014). The shadow economy as an equilibrium outcome. Journal of Economic Dynamics and Control, 41, 1–19. doi:10.1016/j.jedc.2014.02.006.

[16] Medina, L., & Schneider, F. (2018). Shadow Economies Around the World: What Did We Learn Over the Last 20 Years? In International Monetary Fund, IMF Working Papers, 2018(17), 1-76. doi:10.5089/9781484338636.001.

[17] Elgin, C., Kose, M. A., Ohnsorge, F., & Yu, S. (2021). Understanding informality. C.E.P.R. Discussion Paper 16497. Centre for Economic Policy Research, London, United Kingdom.

[18] Ahmad, W., & Hussain, B. (2024). Shadow Economy and Environmental Pollution Nexus in Developing Countries: What is the Role of Corruption? International Economic Journal, 38(2), 293–311. doi:10.1080/10168737.2024.2331463.

[19] Biswas, A. K., Farzanegan, M. R., & Thum, M. (2012). Pollution, shadow economy and corruption: Theory and evidence. Ecological Economics, 75, 114–125. doi:10.1016/j.ecolecon.2012.01.007.

[20] Canh, N. P., Thanh, S. D., Schinckus, C., Bensemann, J., & Thanh, L. T. (2019). Global emissions: A new contribution from the shadow economy. International Journal of Energy Economics and Policy, 9(3), 320–337. doi:10.32479/ijeep.7244.

[21] Butt, S., FAISAL, F., Chohan, M. A., Ali, A., & Ramakrishnan, S. (2024). Do Shadow Economy and Institutions Lessen the Environmental Pollution? Evidence from Panel of ASEAN-9 Economies. Journal of the Knowledge Economy, 15(1), 4800–4828. doi:10.1007/s13132-023-01217-9.

[22] Lobont, O. R., Doran, N. M., Vatavu, S., Barbulescu, M. A., Costea, F., & Badareu, G. (2025). The Dark Side of Growth: Are Shadow Economies Undermining the Global Climate Goal? Sustainability (Switzerland), 17(12), 5241. doi:10.3390/su17125241.

[23] Dhifaoui, Z., Ncibi, K., Gasmi, F., & Alqarni, A. A. (2023). The Nexus between Climate Change and Geopolitical Risk Index in Saudi Arabia Based on the Fourier-Domain Transfer Entropy Spectrum Method. Sustainability (Switzerland), 15(18), 13579. doi:10.3390/su151813579.

[24] Goldthau, A. C., & Youngs, R. (2023). The EU Energy Crisis and a New Geopolitics of Climate Transition. Journal of Common Market Studies, 61(S1), 115–124. doi:10.1111/jcms.13539.

[25] Cevik, S. (2024). Climate change and energy security: the dilemma or opportunity of the century? Environmental Economics and Policy Studies, 26(3), 653–672. doi:10.1007/s10018-023-00391-z.

[26] Brown, S. P. A., & Huntington, H. G. (2008). Energy security and climate change protection: Complementarity or tradeoff? Energy Policy, 36(9), 3510–3513. doi:10.1016/j.enpol.2008.05.027.

[27] Iyke, B. N. (2024). Climate change, energy security risk, and clean energy investment. Energy Economics, 129, 107225. doi:10.1016/j.eneco.2023.107225.

[28] Borozan, D., & Pirgaip, B. (2025). Does uncertainty in climate policy play a role in shaping renewable energy use? Evidence from the USA. Environment, Development and Sustainability, 27(1), 2259–2284. doi:10.1007/s10668-023-03965-9.

[29] Bollen, J., Hers, S., & van der Zwaan, B. (2010). An integrated assessment of climate change, air pollution, and energy security policy. Energy Policy, 38(8), 4021–4030. doi:10.1016/j.enpol.2010.03.026.

[30] Wu, G., Liu, L. C., Han, Z. Y., & Wei, Y. M. (2012). Climate protection and China's energy security: Win-win or tradeoff. Applied Energy, 97, 157–163. doi:10.1016/j.apenergy.2011.11.061.

[31] Wang, K. H., Kan, J. M., Jiang, C. F., & Su, C. W. (2022). Is Geopolitical Risk Powerful Enough to Affect Carbon Dioxide Emissions? Evidence from China. Sustainability (Switzerland), 14(13), 7867. doi:10.3390/su14137867.

[32] Hafner, M., & Tagliapietra, S. (2020). The geopolitics of the global energy transition. Springer Nature, Cham, Switzerland. doi:10.1007/978-3-030-39066-2.

[33] Acheampong, A. O., Opoku, E. E. O., & Aluko, O. A. (2023). The roadmap to net-zero emission: Do geopolitical risk and energy transition matter?. Journal of Public Affairs, 23(4), e2882. doi:10.1002/pa.2924.

[34] Anser, M. K., Syed, Q. R., & Apergis, N. (2021). Does geopolitical risk escalate CO2 emissions? Evidence from the BRICS countries. Environmental Science and Pollution Research, 28(35), 48011–48021. doi:10.1007/s11356-021-14032-z.

[35] Feng, Y., Pan, Y., Lu, S., & Shi, J. (2024). Identifying the multiple nexus between geopolitical risk, energy resilience, and carbon emissions: Evidence from global data. Technological Forecasting and Social Change, 208, 123661. doi:10.1016/j.techfore.2024.123661.

[36] Hoffart, F. M., D'Orazio, P., Holz, F., & Kemfert, C. (2024). Exploring the interdependence of climate, finance, energy, and geopolitics: A conceptual framework for systemic risks amidst multiple crises. Applied Energy, 361, 122885. doi:10.1016/j.apenergy.2024.122885.

[37] Huang, Y., Wu, H., & Chen, X. (2024). The asymmetric and dynamic effects of oil price shocks and geopolitical risks on carbon prices in China. Applied Economics, 1–19. doi:10.1080/00036846.2024.2423900.

[38] Cai, Y., & Wu, Y. (2021). Time-varying interactions between geopolitical risks and renewable energy consumption. International Review of Economics and Finance, 74, 116–137. doi:10.1016/j.iref.2021.02.006.

[39] Ding, S., Wang, K., Cui, T., & Du, M. (2023). The time-varying impact of geopolitical risk on natural resource prices: The post-COVID era evidence. Resources Policy, 86, 104161. doi:10.1016/j.resourpol.2023.104161.

[40] Ahmed, N., Xinagyu, G., Alnafissa, M., Ali, A., & Ullah, H. (2025). Linear and non-linear impact of key agricultural components on greenhouse gas emissions. Scientific Reports, 15(1), 5314. doi:10.1038/s41598-025-88159-1.

[41] Guermazi, I., Smaoui, A., & Chabchoub, M. (2025). Analysis of factors mitigating greenhouse gas emissions (GHG) in Saudi Arabia. Society and Business Review, 20(3), 470–487. doi:10.1108/SBR-09-2024-0313.

[42] Chu, L. K., Doğan, B., Ghosh, S., & Shahbaz, M. (2023). The influence of shadow economy, environmental policies and geopolitical risk on renewable energy: A comparison of high- and middle-income countries. Journal of Environmental Management, 342, 118122. doi:10.1016/j.jenvman.2023.118122.

[43] Gravina, A. F., & Lanzafame, M. (2025). 'What's your shape?' A data-driven approach to estimating the Environmental Kuznets Curve. Energy Economics, 148(731), 108649. doi:10.1016/j.eneco.2025.108649.

[44] Li, Q. (2025). Revisiting the determinants of CO2 emissions: The role of higher education under the extended STIRPAT model. PLoS ONE, 20(3 March), 319930. doi:10.1371/journal.pone.0319930.

[45] Dietz, T., & Rosa, E. A. (1994). Rethinking the environmental impacts of population. Human Ecology Review, 1(2), 277–300.

[46] Dietz, T., & Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. Proceedings of the National Academy of Sciences of the United States of America, 94(1), 175–179. doi:10.1073/pnas.94.1.175.

[47] Martínez-Zarzoso, I., & Maruotti, A. (2011). The impact of urbanization on CO2 emissions: Evidence from developing countries. Ecological Economics, 70(7), 1344–1353. doi:10.1016/j.ecolecon.2011.02.009.

[48] York, R., Rosa, E. A., & Dietz, T. (2003). STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. Ecological Economics, 46(3), 351–365. doi:10.1016/S0921-8009(03)00188-5.

[49] Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. Quarterly Journal of Economics, 110(2), 353–377. doi:10.2307/2118443.

[50] Lau, L. S., Yii, K. J., Ng, C. F., Tan, Y. L., & Yiew, T. H. (2025). Environmental Kuznets curve (EKC) hypothesis: A bibliometric review of the last three decades. Energy and Environment, 36(1), 93–131. doi:10.1177/0958305X231177734.

[51] Mutascu, M. (2025). Beyond the EKC: Economic development and environmental degradation in the US. Ecological Economics, 232, 108567. doi:10.1016/j.ecolecon.2025.108567.

[52] Zhao, L., Zhong, W., & Jin, Y. (2025). Using Regression Model to Fit EKC Curve to Analyze the Sustainable Development of Environment and Economy. International Journal of Knowledge Management, 21(1), 1–15. doi:10.4018/IJKM.366584.

[53] Caldara, D., & Iacoviell, M. (2022). Measuring Geopolitical Risk. American Economic Review, 112(4), 1194–1225. doi:10.1257/aer.20191823.

[54] Koop, G., & Tole, L. (2013). Forecasting the European carbon market. Journal of the Royal Statistical Society. Series A: Statistics in Society, 176(3), 723–741. doi:10.1111/j.1467-985X.2012.01060.x.

[55] Raftery, A. E., Madigan, D., & Hoeting, J. A. (1997). Bayesian Model Averaging for Linear Regression Models. Journal of the American Statistical Association, 92(437), 179–191. doi:10.1080/01621459.1997.10473615.

[56] Sammut, C., Webb, G.I. (2017). Bayesian Model Averaging. Encyclopedia of Machine Learning and Data Mining, Springer, Boston, United States. doi:10.1007/978-1-4899-7687-1_100038.

[57] Prempeh, K. B. (2025). Do renewable energy and fiscal policy impede or promote carbon emissions in Ghana? Empirical evidence from Bayesian and quantile-on-quantile regression approaches. Cogent Economics and Finance, 13(1), 2507133. doi:10.1080/23322039.2025.2507133.

[58] Zeugner, S., & Feldkircher, M. (2015). Bayesian model averaging employing fixed and flexible priors: The BMS package for R. Journal of Statistical Software, 68, 1–37. doi:10.18637/jss.v068.i04.

[59] Scott, J. G., & Berger, J. O. (2010). Bayes and empirical-Bayes multiplicity adjustment in the variable-selection problem. Annals of Statistics, 38(5), 2587–2619. doi:10.1214/10-AOS792.

[60] Mikayilov, J. I., Hasanov, F. J., & Galeotti, M. (2018). Decoupling of CO2 emissions and GDP: A time-varying cointegration approach. Ecological Indicators, 95, 615–628. doi:10.1016/j.ecolind.2018.07.051.

[61] Hastie, T., & Tibshirani, R. (1993). Varying-Coefficient Models. Journal of the Royal Statistical Society Series B: Statistical Methodology, 55(4), 757–779. doi:10.1111/j.2517-6161.1993.tb01939.x.

[62] Casas, I., & Fernandez-Casal, R. (2019). tvReg: Time-varying Coefficient Linear Regression for Single and Multi-Equations in R. SSRN Electronic Journal, 1-43. doi:10.2139/ssrn.3363526.

[63] Sun, Y., Carroll, R. J., & Li, D. (2009). Semiparametric estimation of fixed-effects panel data varying coefficient models. Nonparametric econometric methods, 101-129. doi:10.1108/S0731-9053(2009)0000024006.

[64] Seraj, A., Mohammadi-Khanaposhtani, M., Daneshfar, R., Naseri, M., Esmaeili, M., Baghban, A., Habibzadeh, S., & Eslamian, S. (2022). Cross-validation. Handbook of HydroInformatics: Volume I: Classic Soft-Computing Techniques, 89–105. doi:10.1016/B978-0-12-821285-1.00021-X.

[65] Stone, M. (1974). Cross-Validatory Choice and Assessment of Statistical Predictions. Journal of the Royal Statistical Society Series B: Statistical Methodology, 36(2), 111–133. doi:10.1111/j.2517-6161.1974.tb00994.x.

[66] Zhang, X., & Liu, C. A. (2023). Model averaging prediction by K-fold cross-validation. Journal of Econometrics, 235(1), 280–301. doi:10.1016/j.jeconom.2022.04.007.

[67] Keevers, T. L. (2019). Cross-validation is insufficient for model validation. Joint and Operations Analysis Division, Defence Science and Technology Group: Victoria, Australia.

[68] Wang, Q., Li, Y., & Li, R. (2024). Rethinking the environmental Kuznets curve hypothesis across 214 countries: the impacts of 12 economic, institutional, technological, resource, and social factors. Humanities and Social Sciences Communications, 11(1), 292. doi:10.1057/s41599-024-02736-9.

[69] Wang, Y., & Cao, J. (2023). Examining the Effects of Socioeconomic Development on Fine Particulate Matter (PM2.5) in China's Cities Based on Spatial Autocorrelation Analysis and MGWR Model. International Journal of Environmental Research and Public Health, 20(4), 2814. doi:10.3390/ijerph20042814.

[70] Alola, A. A., Yalçiner, K., Alola, U. V., & Akadiri, S. Saint. (2019). The role of renewable energy, immigration and real income in environmental sustainability target. Evidence from Europe largest states. Science of the Total Environment, 674, 307–315. doi:10.1016/j.scitotenv.2019.04.163.

[71] Guan, D., Meng, J., Reiner, D. M., Zhang, N., Shan, Y., Mi, Z., Shao, S., Liu, Z., Zhang, Q., & Davis, S. J. (2018). Structural decline in China's CO2 emissions through transitions in industry and energy systems. Nature Geoscience, 11(8), 551–555. doi:10.1038/s41561-018-0161-1.

[72] Hassan, S. T., Xia, E., Khan, N. H., & Shah, S. M. A. (2019). Economic growth, natural resources, and ecological footprints: evidence from Pakistan. Environmental Science and Pollution Research, 26(3), 2929–2938. doi:10.1007/s11356-018-3803-3.

[73] Alam, M. M., Murad, M. W., Noman, A. H. M., & Ozturk, I. (2016). Relationships among carbon emissions, economic growth, energy consumption and population growth: Testing Environmental Kuznets Curve hypothesis for Brazil, China, India and Indonesia. Ecological Indicators, 70, 466–479. doi:10.1016/j.ecolind.2016.06.043.