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Integrating Multifactorial Regression Models, Artificial Neural Networks, and Eco-Dynamic Simulations for Assessing Energy Sustainability in the European Union and Emerging Member States

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Abstract

This study aims to develop an integrated analytical framework for assessing energy sustainability in the EU and emerging member states. It examines the interrelationships between environmental quality—measured by greenhouse gas emissions—economic growth, and energy consumption from both renewable and non-renewable sources. Multifactorial linear regression models are employed and validated through artificial neural networks to enhance robustness and generalization capacity. Based on the identified correlations, the Environmental Kuznets Curve hypothesis is tested to assess patterns of environmental degradation. The analysis then advances to a dynamic framework using the Grey Lotka–Volterra model, which captures nonlinear effects and the mechanisms of competition and cooperation among variables. By exploring simultaneous and evolutionary interactions, the study reveals how these relationships shift over time, identifies inflexion points, and simulates public policy scenarios that may accelerate or hinder decarbonization. This approach provides a comprehensive and policy-relevant perspective on the dynamics of the energy transition.

Keywords: developing countries; energy sustainability; eco-dynamic modelling; artificial neural network; Environmental Kuznets Curve

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1. Introduction

According to the Glasgow Climate Pact [1], Europe is accelerating its search for alternatives to solid fossil fuels and aims to become the world's first climate-neutral continent by 2050, with the European Union (EU) leading this transition [2]. As outlined in the Paris Agreement [3] and reaffirmed in the 2021 Glasgow Climate Pact [1], the long-term global objective is to replace fossil energy sources to reduce emissions and ensure sustainable development for present and future generations.

To meet its climate goals, the EU adopted the European Climate Law [2], which makes the European Green Deal's 2050 climate-neutrality target legally binding for the Union and its member states [4,5]. Through the 2021 "Fit for 55" package, the EU raised its 2030 greenhouse gas (GHG) emissions reduction target from 40% [6] to at least 55% compared with 1990 levels. Globally, emissions are expected to fall by at least 7.6% annually during 2020–2030 [7], while the EU aims for a minimum 55% reduction by 2030 as part of its

pathway toward climate neutrality by 2050 [8]. In alignment with the Paris Agreement [3] and the Glasgow Climate Pact [1], Europe is accelerating its shift away from solid fossil fuels and seeks to become the first climate-neutral continent by 2050, with the EU at the forefront of this transition [2].

Under these circumstances, the impact of economic development on the climate remains highly significant. Economic growth, environmental protection (through GHG reduction), and increasing the share of renewable energy (REN) in total energy consumption are key objectives of EU economic policy [6]. To meet these climate and environmental goals, sustainability criteria have been strengthened. At the same time, the energy crisis triggered by the COVID-19 pandemic and the Russia–Ukraine conflict has pushed the EU to rely more heavily on domestic energy sources to reduce dependence on imported oil and gas. Since energy production and use account for 75% of EU emissions [9], the Union has set a 2030 target requiring that 40% of energy production come from renewable sources, imposing on member states an annual energy-saving obligation nearly double that of 2021 [9].

As a result of EU climate and energy legislation, the GHG emissions fell by 24% in 2021 [10] compared with 1990, while the EU economy grew by more than 60% over the same period—demonstrating a decoupling of economic growth from emissions. Consequently, forecasting future GHG emissions has become a major challenge for informing optimal policy decisions aligned with the EU's new climate objectives [9].

Economic growth—driven largely by long-term industrialization and measured through gross domestic product (GDP)—remains the main factor behind rising energy consumption [11] and the generation of millions of metric tons of GHG emissions [12,13]. In today's context of rapid economic expansion, GHG emissions have increased substantially [14,15], being widely recognized as a major contributor to global warming [16–18] and as a source of negative impacts on human health and national economies [19]. As GHG emissions are a key driver of climate change [20], their reduction has become a central objective of energy and environmental policies, with each country establishing clear national targets for lowering emissions [21].

In line with the European Commission's climate and energy priorities [6,22], EU member states have committed to combating climate change by reforming energy policy and transitioning from fossil fuels to renewable energy sources [20,23]. The combustion of traditional fuels is a major source of harmful emissions (COx, NOx, SOx, etc.) [24], making it essential for EU countries to shift toward an energy system increasingly based on renewables [25], thereby optimizing the existing energy mix while protecting the environment [26].

Consequently, several studies have projected future GHG emissions trends in Europe using various reference periods [27–29].

Based on the EU's climate and energy commitments, this study pursues the following main objectives:

- Analyze the relationship between economic growth and GHG emissions in the European Union and seven emerging member states (Bulgaria, Czechia, Hungary, Latvia, Romania, Slovenia, and Slovakia), assessing how GDP dynamics influence emission over the long-term.
- Evaluate the impact of renewable (REN) and non-renewable (NREN) energy consumption on GHG emissions, quantifying the contribution of each energy source to environmental degradation and progress toward EU climate targets.
- Test the Environmental Kuznets Curve (EKC) hypothesis within the EU context, examining whether economic growth initially increases environmental degradation before improvements occur at higher income levels.

- Validate and deepen the empirical findings using advanced analytical and computational methods. The study integrates multifactor linear regression to estimate direct effects, artificial neural networks (ANNs) to capture nonlinear interactions and variable importance, and the Grey Lotka–Volterra (GLV) model to explore long-term dynamic relationships of cooperation and competition among variables.
- Identify cooperative and competitive mechanisms linking GDP, energy consumption structure, and GHG emissions. The aim is to distinguish cooperative dynamics—such as investment-driven renewable energy expansion that reduces emissions—from competitive dynamics, such as GDP growth associated with increased fossil fuel use and import dependence.
- Provide a comprehensive analytical framework that supports evidence-based policymaking for sustainable development and energy transition. The findings aim to inform EU-level and national strategies by highlighting how economic growth can be reconciled with environmental protection and climate-neutrality goals.

The analysis is particularly relevant in the context of the ongoing energy crisis and the heightened risk of economic recession.

The seven countries examined are classified as emerging economies according to the criteria used by international institutions such as the IMF, the World Bank, credit rating agencies, and financial analysts. This classification does not imply "developing country" status in the traditional sense; rather, it reflects their rapid economic growth and the fact that they have not yet reached the economic stability, structural maturity, and income levels characteristic of advanced EU economies. The term is technical in nature, primarily used in financial and macroeconomic analysis, and carries no value judgement. International institutions also frequently employ the designation CESEE (Central, Eastern, and Southeastern Europe), which encompasses these countries.

They are grouped together because they share a common historical background—specifically the post-communist transition after 1990—a similar economic model based on foreign investment and export-led growth, generally higher-than-average EU growth rates during favourable periods, and comparable macroeconomic risks, including vulnerability to external shocks, inflationary pressures, and current account deficits.

The study's novelty lies in its interdisciplinary integration of mathematical ecology and sustainable economics to address the complexities of energy transition. It offers a robust framework for testing environmental hypotheses under real-world conditions. The initial regression analysis quantifies the contribution of each economic factor to GHG emissions, while neural networks uncover deeper nonlinear interactions, including substitution effects between energy sources. In this research, the GLV framework is employed as a dynamic modelling tool. It provides a compelling alternative to traditional linear approaches by offering enhanced sensitivity to structural shifts and complex interdependencies. The GLV model can be applied in future studies to analyze both cooperative scenarios (e.g., renewable energy expansion leading to emission reductions) and competitive scenarios (e.g., GDP growth driving increased fossil fuel consumption). These simulations can generate short- and long-term forecasts, providing valuable insights for environmental policymaking and sustainable development planning.

This topic is highly relevant from both scientific and policy perspectives, as it supports the design of effective environmental and energy strategies. By identifying cooperative and competitive relationships at both the EU and national levels, the study contributes to the development of balanced policies that reconcile economic growth with environmental protection. The findings indicate that GDP growth and investment are often aligned with renewable energy development, fostering cooperative dynamics. In contrast, fossil fuel

consumption and energy import dependence tend to conflict with emission-reduction objectives, highlighting competitive pressures that require targeted policy interventions.

The paper is structured as follows. After the Introduction and a concise Literature Review, the next section presents the Data Sources and Methodological Framework used in the analysis. The core findings are then detailed and interpreted in the Results and Discussion section. Finally, the paper concludes with a synthesis of the main insights, where research limitations are acknowledged and avenues for future investigation are proposed.

2. Literature Review

Numerous studies have examined the link between GHG and economic growth, recognizing its importance for sustainable development [30]. Developed economies, which rely more heavily on services and technology, tend to exhibit lower per capita emissions, whereas developing nations dependent on fossil fuels experience rapid economic expansion accompanied by higher emissions [31]. Urbanization and industrialization in emerging economies further intensify GHG emissions, underscoring the need for investment in low-emission infrastructure [32].

Economic growth often correlates with rising emissions, raising concerns that environmental policies may constrain development [33]. The Environmental Kuznets Curve (EKC) hypothesis has been widely tested, yet empirical results remain inconclusive [34,35]. Energy consumption—particularly from fossil fuels—continues to be a major driver of environmental degradation [18,36], and despite global mitigation efforts, fossil fuels still dominate national and regional energy mixes [37].

The COVID-19 pandemic temporarily reduced emissions, sparking renewed interest in renewable energy as a pathway to long-term sustainability [38]. Renewables energy sources, which are associated with lower GHG emissions, are essential for mitigating environmental harm [39–41]. Several studies highlight a bidirectional relationship between renewable energy use and GDP, underscoring their mutual interdependence [16,42,43]. However, barriers such as intermittency, limited accessibility, and insufficient infrastructure continue to constrain renewable energy adoption [44], prompting reliance on alternatives such as natural gas and hydropower [45].

Economic growth remains a key driver of fossil fuel consumption, thereby exacerbating environmental degradation [17,46]. The relationship between energy use, GDP, and pollution varies across countries [47]. Some studies report a positive association between GHG emissions and GDP, and a negative relationship between renewable energy consumption and GHG emissions [17,48], while others find GDP can either reduce or increase emissions depending on national circumstances [41]. Long-term increases in renewable energy consumption are consistently associated with GDP growth and lower emissions [30].

Countries rich in renewable resources—wind, solar, hydropower, biomass, and geothermal—have achieved both economic gains and emission reductions through targeted investments [16,49]. EU member states must prioritize renewable energy infrastructure and reduce dependence on fossil fuel to meet environmental objectives and advance sustainable development [50,51]. The EU's long-term strategy targets an 80% share of renewable energy by 2050, reinforcing the need for a progressive phase-out fossil fuels [5].

Despite the breadth of existing research, integrated approaches that combine econometric analysis, AI-based predictive modelling, and eco-dynamic frameworks remain largely absent—particularly for emerging EU economies—highlighting a clear gap that the present study addresses.

3. Data and Methodology

3.1. Data

The empirical analysis uses four macroeconomic and environmental indicators:

1. Total greenhouse gas emissions, CO_2 equivalent per capita (GHG) measured in tonnes per capita [52];
2. Gross domestic product at market prices per capita (GDP) expressed in thousand euro per inhabitant [53];
3. Non-renewable energy consumption (NREN);
4. Renewable energy consumption (REN).

Energy consumption data—final energy consumption (thousand tonnes of oil equivalent)—were extracted from the Eurostat energy balance dataset. Both REN and NREN represent aggregate energy consumption values rather than per capita measures. This choice follows Eurostat's reporting structure and avoids distortions that may arise from population-based scaling in short annual samples [54].

REN includes all renewable energy sources listed under Eurostat's "renewables" category: hydro, wind, solar, geothermal, biomass, biofuels, and other renewables.

NREN aggregates all non-renewable energy sources: coal and coal products, natural gas, oil and petroleum products, nuclear heat, and non-renewable waste).

Although Eurostat reports energy consumption in aggregate units, both REN and NREN were converted into per capita measures. Aggregate final energy consumption (in KTOE) was divided by the resident population from Eurostat's "Population on 1 January" dataset [55]. For comparability, KTOE values were transformed into kilograms of oil equivalent per capita using the standard Eurostat conversion factor: 1 ktoe = 1,000,000 kg of oil equivalent.

All variables were extracted from Eurostat using stable dataset identifiers and explicitly documented filters to ensure full reproducibility. The dataset covers the European Union (EU aggregate) and seven emerging EU member states—Bulgaria (BG), Czechia (CZ), Hungary (HU), Latvia (LV), Romania (RO), Slovenia (SI), and Slovakia (SK)—for the period 2010–2022.

The choice of the 2010–2022 period is motivated by both methodological and policy considerations. This interval captures a critical phase in the EU's climate and energy agenda, including the Europe 2020 Strategy, the launch of the European Green Deal, and the 2021–2022 energy crisis.

These developments provide meaningful variation for examining how European economies respond to structural pressures on their energy systems and greenhouse gas emissions.

Although the dataset has a panel structure covering the EU and seven member states over the period 2010–2022, the empirical analysis does not employ pooled panel estimators such as fixed effects or random effects. Instead, all econometric procedures—unit-root tests, cointegration analysis, Granger causality, and the multifactor regression model—are conducted separately for each country. This country-by-country approach is motivated by the short annual time series and by the expectation that the relationship between economic activity, the energy mix, and greenhouse gas emissions may differ substantially across national contexts. Analyzing each country individually also avoids the bias that would arise from imposing homogeneous coefficients across structurally heterogeneous economies. The panel structure is therefore used only for data organization and comparability, not for estimating a pooled model.

These seven emerging EU members—Bulgaria, the Czechia, Hungary, Latvia, Romania, Slovenia, and Slovakia—share a common transition from planned to market economies and

face similar challenges in energy dependence, industrial modernization, and environmental performance. Their distinct energy and economic profiles make them well suited for studying links between emissions, economic growth, and energy use. Despite their differences, they remain comparable through the EU's unified regulatory and reporting framework.

The selected indicators and temporal coverage ensure consistency with EU climate-energy reporting standards and allow for a comparative assessment of structural dynamics across member states.

3.2. Methodology

This paragraph outlines the methodological framework employed to investigate the relationships among greenhouse gas emissions (GHG), economic growth (GDP), renewable energy consumption (REN), and non-renewable energy consumption (NREN) in the European Union (EU) and seven emerging EU member states over the period 2010–2022. The analysis integrates descriptive statistics, econometric modelling, artificial intelligence techniques, and nonlinear dynamic modelling to provide a comprehensive assessment of the energy–economy–emissions nexus.

The methodological design comprises four sequential stages:

1. Descriptive trend analysis of GDP, REN, NREN, and GHG for the EU and emerging member states.

The first stage consists of a descriptive analysis of the temporal evolution of the four key indicators: GHG emissions, GDP per capita, REN, and NREN. Annual data for 2010–2022 are examined to identify structural trends, turning points, and cross-country differences. This step provides the empirical context for subsequent modelling and allows for the identification of major events—such as the COVID-19 shock in 2020—that may influence the dynamics of the variables.

2. Regression estimation and neural network validation.

The second stage combines econometric estimation with neural network-based validation. Multifactor linear regression is used to identify the marginal effects of economic activity and energy consumption on emissions, while Multilayer Perceptron (MLP) networks assess nonlinearities and rank variable importance.

To quantify the marginal effects of economic activity and energy consumption on environmental degradation, the following country-specific time series regression is estimated for each of the eight economies:

$$GHG_{it} = \beta_{0i} + \beta_{1i}GDP_{it} + \beta_{2i}NREN_{it} + \beta_{3i}REN_{it} + u_{it}, \quad (1)$$

where i indexes countries and t indexes years. The coefficients $\beta_0, \beta_1, \beta_2, \beta_3$ are allowed to vary across countries, reflecting the structural heterogeneity of the economic–environmental relationship within the EU. This specification therefore represents a set of independent country regressions rather than a pooled panel estimator. The approach captures country-specific elasticities and allows an assessment of how the energy mix and economic activity relate to emissions in each national context.

Multicollinearity is evaluated using the Variance Inflation Factor (VIF). Stationarity and long-run relationships are examined using the econometric software EViews 9.5. The Augmented Dickey–Fuller (ADF) test determines the order of integration of each variable. When variables share the same order of integration, long-run causal relationships and the direction of causality are assessed through cointegration tests, error-correction models, and Granger causality tests. Model validity (cointegration equation) is evaluated using the White test to verify whether residuals exhibit homoscedasticity.

This formulation captures both the scale effects of economic growth and the structural effects of the energy mix.

To complement the econometric analysis and evaluate the predictive relevance of GDP, NREN, and REN for GHG emissions, a Multilayer Perceptron (MLP) artificial neural network is employed. The ANN serves strictly as a predictive validation tool, providing a nonlinear robustness check for the regression results rather than supporting causal inference.

The network incorporates GDP, NREN, and REN as input variables and GHG as the output. All variables were first converted to per capita values and subsequently standardized using z-score normalization:

$$X^* = \frac{x - \mu}{\sigma},$$

a procedure that ensures comparability across predictors and enhances training stability.

A single hidden layer MLP architecture was adopted uniformly across countries to maintain methodological consistency. The number of neurons in the hidden layer was selected through a grid search procedure testing configurations from one to five neurons, retaining the specification that minimized the validation error, measured using the Root Mean Square Error ($RMSE$) for both datasets [56].

$$RMSE = \sqrt{\frac{1}{N} \times SSE}$$

where SSE denotes the sum of squares error and N the number of observations.

The hidden layer employed the Hyperbolic tangent activation function, while the output layer used the Sigmoid function, both selected for their predictive performance.

Synaptic weight determines the strength and direction (positive or negative) of the connection between nodes, while the bias parameter ensures that the network architecture best fits the data. Prediction accuracy is evaluated using a train–test split with cross-validation [57].

Model training followed a standardized protocol. The network was trained using the Adam optimizer with a learning rate of 0.01, the Mean Squared Error (MSE) loss function, a batch size of 8, and a maximum of 1000 epochs. To prevent overfitting, early stopping with a patience parameter of 50 epochs was applied, together with L2 regularization ($\lambda = 0.001$). Reproducibility was ensured by fixing the random seed at 1234 and by conducting five independent training runs for each country, with final performance metrics computed as averages across repetitions.

A combined validation strategy was implemented in which grid search determined the optimal network size, repeated holdout training ensured robustness across random initializations, and early stopping prevented overfitting during model learning.

3. EKC hypothesis testing using the quadratic GDP specification.

The Environmental Kuznets Curve (EKC) hypothesis posits an inverted U-shaped relationship between GDP and environmental degradation.

To evaluate this hypothesis, the baseline model is augmented with a quadratic GDP term:

$$GHG_{it} = \alpha_{1i} GDP_{it} + \alpha_{2i} GDP_{it}^2 + \alpha_{3i} NREN_{it} + \alpha_{4i} REN_{it} + u_{it}, \quad (2)$$

where i indexes countries and t indexes years. Equation (2) is estimated both for the EU aggregate and for each country individually. The inclusion of squared GDP (GDP^2) term allows the identification of potential nonlinearities in the growth–emissions relationship.

The EKC hypothesis is assessed by examining the estimated coefficients of Equation (2) together with the corresponding GDP turning points for each country and for the EU as

a whole. The signs of the coefficients α_1 and α_2 determine the shape of the relationship. When $\alpha_2 < 0$, the relationship between GHG emissions and GDP follows an inverted U-shaped pattern. The GDP turning point is calculated as $GDP_0 = -\frac{\alpha_1}{2\alpha_2}$, representing the level of GDP at which GHG emissions reach their maximum, holding all other explanatory variables remain constant. The economic relevance of the turning point depends on whether it lies within the observed GDP range for each country.

4. GLV dynamic modelling for long-term cooperative or competitive relationships.

To identify long-term nonlinear interactions and cooperation–competition mechanisms between GHG emissions and each of the other indicators, the Grey Lotka–Volterra (GLV) model is employed.

This analysis is conducted at both the EU level and for each individual member state.

Economic systems often exhibit characteristics analogous to ecological systems:

- variables evolve over time,
- influence one another's growth trajectories,
- compete for limited resources,
- or reinforce each other through feedback mechanisms.

For example, economic expansion may stimulate emissions, renewable energy deployment may mitigate them, and fossil energy consumption may compete with renewable energy development.

The GLV model provides a deeper understanding of the long-term structural mechanisms governing the energy–economy–emissions system.

This approach offers several methodological advantages:

- It captures nonlinear and asymmetric interactions that linear models cannot represent.
- It accommodates short and uncertain datasets, which is particularly relevant for emerging EU economies.
- It provides insights into dynamic stability, identifying whether the system converges to equilibrium, oscillates, or exhibits dominance by one variable.
- It enables comparative analysis across countries, revealing structural differences in energy transitions and emission dynamics.

The GLV model extends the classical LV system by incorporating Grey system theory, which is specifically designed to handle short, incomplete, or uncertain time series—conditions frequently encountered in macroeconomic and energy-environmental data for emerging EU economies.

The original LV system (Equation (3)) models predator–prey interactions:

$$\begin{cases} \dot{y}_1 = y_1(a_1 - b_1 y_1 - c_1 y_2), \\ \dot{y}_2 = y_2(a_2 - b_2 y_1 - c_2 y_2), \end{cases} \tag{3}$$

where y_1, y_2 are functions of time t, and $a_i, b_i, c_i, (i = 1, 2)$ are real coefficients. The dot denotes differentiation with respect to the time.

This framework has been widely applied to characterize competitive and cooperative dynamics in economic and energy systems [58–63], including studies on emissions and economic growth [58], alternative energy [59], pollution [60], energy consumption and CO_2 emissions [61], and energy and electricity markets [62,63].

The evolution of each population is determined by its intrinsic growth rate and by interactions occurring both within and between variables. These dynamics can be expressed in discrete-time form [64]:

$$y_i(k+1) = \frac{\alpha_i y_i(k)}{1 + \beta_i y_1(k) + \gamma_i y_2(k)}, \text{ for } k = 1, \ldots, n-1, \ i = 1, 2, \tag{4}$$

where the parameters are defined as $\alpha_i = e^{a_i}, \beta_i = \frac{b_i}{a_i}(\alpha_i - 1), \gamma_i = \frac{c_i}{a_i}(\alpha_i - 1)$.

To estimate the coefficients of the Lotka–Volterra model (3), the Grey modelling framework is applied following [64]. The procedure begins with two original data sequences:

$$X_i = \{x_i(1),\ x_i(2), \ldots, x_i(k), \ldots, x_i(n)\};\ i = 1,\ 2, \tag{5}$$

From which the accumulating sequences are generated:

$$Y_i = \{y_i(1),\ y_i(2), \ldots, y_i(k), \ldots, y_i(n)\},\ \text{where } y_i(k) = x_i(1) + x_i(2) + \ldots + x_i(k),\ i = 1,2, \tag{6}$$

and the mean value sequences of consecutive accumulated terms:

$$Z_i = \{z_i(2),\ z_i(3), \ldots, z_i(k), \ldots, z_i(n)\},\ \text{where } z_i(k) = \frac{y_i(k-1) + y_i(k)}{2},\ k = 2,3,\ldots,n, i = 1,2. \tag{7}$$

Using these transformed sequences, the Grey approximation yields:

$$\begin{cases} x_1(k) \approx z_1(k)(a_1 - b_1 z_1(k) - c_1 z_2(k)), \\ x_2(k) \approx z_2(k)(a_2 - b_2 z_1(k) - c_2 z_2(k)), \end{cases} \tag{8}$$

which allows the parameters of model (3) to be estimated via least squares:

$$\begin{pmatrix} a_1^* \\ b_1^* \\ c_1^* \end{pmatrix} = ({B_1}^T B_1)^{-1} {B_1}^T M_1, \qquad \begin{pmatrix} a_2^* \\ b_2^* \\ c_2^* \end{pmatrix} = ({B_2}^T B_2)^{-1} {B_2}^T M_2, \tag{9}$$

where the matrices M_1, B_1, M_2, B_2 are defined as:

$$\begin{aligned} M_1 &= \begin{pmatrix} x_1(2) \\ \vdots \\ x_1(n) \end{pmatrix}, B_1 = \begin{pmatrix} z_1(2) & -z_1^2(2) & -z_1(2)z_2(2) \\ \vdots & \vdots & \vdots \\ z_1(n) & -z_1^2(n) & -z_1(n)z_2(n) \end{pmatrix}, \\ M_2 &= \begin{pmatrix} x_2(2) \\ \vdots \\ x_2(n) \end{pmatrix}, B_2 = \begin{pmatrix} z_2(2) & -z_1(2)z_2(2) & -z_2^2(2) \\ \vdots & \vdots & \vdots \\ z_2(n) & -z_1(n)z_2(n) & -z_2^2(n) \end{pmatrix}. \end{aligned} \tag{10}$$

The reconstructed values of the original sequences (5) are then obtained as:

$$x_i^*(k+1) = y_i^*(k+1) - y_i^*(k),\ k = 1,\ 2, \ldots \tag{11}$$

where $y_i^*(k+1)$ is computed using the Lotka–Volterra difference Equation (4).

Parameter estimation is carried out using the Grey modelling framework. The process begins by generating the original data sequences X_i (Equation (5)), followed by constructing the accumulated sequences Y_i (Equation (6)) and the mean sequences Z_i (Equation (7)). The Grey approximation in Equation (8) is then applied to obtain the model coefficients through a least squares estimation procedure (Equations (9) and (10)). The reconstructed series is subsequently produced using Equation (11), with the estimated values derived from the Lotka–Volterra difference equation (Equation (4)).

Model accuracy is assessed using the Mean Absolute Percentage Error (MAPE), interpreted according to commonly used thresholds: MAPE < 10% (high accuracy), 10–20% (good), 20–50% (acceptable).

The Lotka–Volterra model enables the identification of equilibrium points, stability conditions, and dynamic trajectories. These results reveal whether the relationship between variables tends toward stable coexistence, oscillatory behaviour, dominance of one variable, or mutual reinforcement.

The economic interpretation of the GLV model structure is as follows: each variable (e.g., GHG, GDP, REN, NREN) is treated as a dynamic process whose evolution depends on three components:

1. Intrinsic growth rate (a_i)

This parameter reflects the variable's natural tendency to grow or decline in the absence of external interactions.

- For GDP, it captures long-run economic expansion.
- For GHG, it reflects emissions growth driven by industrial activity.
- For REN, it represents endogenous expansion supported by technological progress, innovation, and policy support.
- For NREN, it may reflect structural decline under decarbonization policies or, conversely, persistence in economies still dependent on fossil fuels.

2. Self-limiting effects ($b_i y_i$)

These terms represent intra-variable constraints that reduce a variable's growth as its own level increases. In economic-energy systems, they capture mechanisms such as:

- diminishing returns in economic growth;
- regulatory limits on emissions;
- capacity constraints in renewable energy;
- structural decline in fossil energy use.

3. Interaction effects ($c_i y_i$)

These coefficients capture how one variable influences the growth of another.

- A negative coefficient indicates a cooperative or reinforcing effect (the presence of one variable supports the growth of the other).
- A positive coefficient indicates a competitive or inhibitory effect (the presence of one variable suppresses the growth of the other).

Through these interaction terms, the GLV model provides a flexible structure for identifying whether two economic variables exhibit competition, cooperation, dominance, or neutrality.

Based on signs of the interaction coefficients c_1 and b_2, relationships can be classified into standard ecological–economic categories such as competition, mutualism, commensalism, amensalism, or neutralism. GLV estimations are performed for each GHG–indicator pair across countries [65], and results for 2010–2022 are compared between the EU aggregate and the emerging member states. Modelling was implemented using Mathematica and Maple.

The signs of the interaction coefficients c_1 and b_2 allow the identification of the type of relationship between two variables.

These interaction patterns have clear economic interpretations:

- Pure competition (+/+). Both variables inhibit each other's growth. Example: GHG and REN may compete when emission reduction policies accelerate renewable deployment, while renewables reduce emissions.
- Predator–prey (−/+). Variable y_1 suppresses y_2, while y_2 enhances y_1. Example: GHG (predator) and REN (prey), where higher emissions stimulate renewable investment, but renewables reduce emissions.
- Prey–predator (+/−). The inverse of the above. Example: GDP (predator) and GHG (prey), where economic growth increases emissions, but emissions constrain growth through environmental regulation.

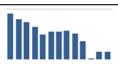
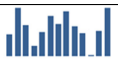
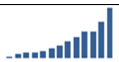
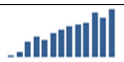
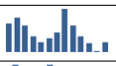
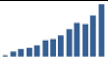
- Mutualism (−/−). Both variables reinforce each other. Example: GDP and REN may mutually support long-term sustainable development.
- Amensalism (+/0 or 0/+). One variable harms the other without being affected in return. Example: NREN may inhibit REN expansion without being significantly affected by renewable deployment in early transition stages.
- Commensalism (−/0 or 0/−). One variable benefits from the other, which remains unaffected. Example: GDP may benefit from REN expansion without immediate reciprocal effects.
- Neutralism (0/0). No interaction exists between the variables.

4. Empirical Findings and Results

4.1. Evolution of Macroeconomics Indicators (2010–2022)

A concise and descriptive analysis of the evolution of the four macroeconomic indicators is presented in Table 1.

Table 1. Analysis of economic indicators, 2010–2022.

	GHG			GDP			NREN			REN		
	Evol.	GR (%)	A	Evol.	GR (%)	A	Evol.	GR (%)	A	Evol.	GR (%)	A
EU		−18.7	8.9		41.7	28,722		−33.5	51.6		29.1	215
BG		11.2	8.3		144	7487		4.6	51.1		74.4	186
CZ		−18.9	11		72.1	18,222		−28.4	155		55.8	279
LV		−0.08	6.3		142	13,621		−90.3	23.7		19.0	510
HU		−2.26	6.9		76.2	12,633		−31.2	20.2		5.1	213
RO		1.17	6.2		137	9399		40.1	34.8		6.9	193
SI		−18.6	8.2		57.6	20,700		−61.5	19.0		−11.2	324
SK		−14.1	7.6		57.4	15,542		−48.4	86.2		127.7	139

Note: Evol. = Change in indicator between 2010 and 2022; GR (%) = Growth rate 2022/2010; A = Average value 2010–2022.

Between 2010 and 2022, GHG emissions fluctuated across the EU and the seven emerging member states. In 2020, emissions declined sharply due to COVID-19 restrictions.

The most pronounced reductions occurred in 2022: EU (−18.65%), CZ (−18.92%), SI (−18.59%), and SK (−14.13%). In contrast, BG and RO recorded increases of 11.22% and 1.17%, respectively. Over the full period, CZ exhibited the highest average GHG emissions (11.13 tons per capita), exceeding the EU average (8.89 tons per capita) (Table 1).

GDP increased steadily across all countries, with the exception of 2020. Slovenia recorded the highest average GDP (20,700 €/capita), followed by Czechia (18,222 €/capita) (Table 1).

In line with EU directives [6], NREN consumption declined by 33.5% at the EU level. Latvia, Slovenia, and Slovakia registered the largest reductions, while Bulgaria and Romania experienced increases. Despite Slovakia 's progress, its NREN levels remain above the EU average. Bulgaria is approaching the EU average, whereas Romania remains significantly below (Table 1).

REN consumption increased in most countries, with notable growth in Czechia, Latvia, and Slovenia. Although Slovenia recorded an 11.2% decline, its REN levels still exceed the EU average (Table 1).

4.2. Regression Analysis of GHG, GDP, and Energy Consumption

To assess the relationship between GHG emissions and key macroeconomic variables—GDP, NREN, and REN—a multifactor linear regression model was estimated (Equation (1)). The results are summarized in Table 2.

Table 2. Estimations for the regression coefficients in Equation (1).

Country	Coefficient		Standard Error	Probability	VIF
EU	C	2.738809	1.352899	0.0988	
	GDP	0.000890	0.044603	0.0949	9.636
	NREN	0.097917	0.012594	0.0006	6.678
	REN	−0.005117	0.004984	0.0351	9.169
BG	C	6.290620	3.147113	0.1021	
	GDP	0.377346	0.467252	0.0456	9.813
	NREN	0.023759	0.039533	0.0574	2.450
	REN	−0.008940	0.021739	0.0979	9.528
CZ	C	18.78457	1.426356	0.0000	
	GDP	0.123953	0.033082	0.0133	5.406
	NREN	−0.008037	0.004796	0.0154	5.164
	REN	−0.030845	0.003768	0.0004	9.584
HU	C	7.880751	1.209889	0.0013	
	GDP	0.023383	0.046741	0.0638	1.787
	NREN	0.043740	0.013637	0.0238	1.298
	REN	−0.010410	0.003822	0.0416	1.439
LV	C	4.370765	1.365963	0.0240	
	GDP	0.275685	0.118225	0.0671	9.739
	NREN	0.033023	0.019174	0.0145	7.422
	REN	−0.004699	0.003128	0.0193	1.970
RO	C	−2.973400	5.756649	0.0627	
	GDP	0.012720	0.073477	0.0869	2.826
	NREN	0.059186	0.038418	0.0184	1.180
	REN	−0.038268	0.024277	0.0175	2.870
SI	C	−8.749540	6.440788	0.0232	
	GDP	0.289456	0.139659	0.0929	5.902
	NREN	0.135016	0.061196	0.0785	4.971
	REN	−0.026608	0.01278	0.0918	1.487
SK	C	4.738586	1.766422	0.0437	
	GDP	0.116939	0.12427	0.0389	9.636
	NREN	0.016873	0.004917	0.0186	6.678
	REN	−0.001691	0.006435	0.0803	9.169

Across the EU aggregate and most emerging countries, the coefficients for GDP and NREN are positive, indicating that increases in economic activity and non-renewable energy use are generally associated with higher emissions. A notable exception is the Czechia, where NREN displays a negative coefficient, suggesting a distinct national energy structure. In contrast, REN consistently exhibits a negative coefficient across all countries, indicating that higher renewable energy consumption is associated with lower emissions. Variance Inflation Factor (VIF) values remain below the conventional threshold of 10, confirming the absence of problematic multicollinearity among regressors [66].

Before estimation, the stationarity properties of all variables were examined using the Augmented Dickey–Fuller (ADF) test. For each country and variable, the ADF regression

included either a constant or a constant and trend, depending on the observed data pattern, with a maximum lag length ($p$max) determined by the annual sample size. The optimal lag was selected using the chosen information criterion (AIC or SBIC). The results (Table A1 in the Appendix A section) indicate that all series become stationary after first differencing, satisfying the preconditions for cointegration analysis. All time series are stationary at the first difference at the 10% significance level.

Where appropriate, long-run relationships among the variables were assessed using Johansen's trace and maximum-eigenvalue tests, applied separately to each country.

The tests provide evidence of cointegration at the 10% significance level for several countries, suggesting the presence of stable long-run co-movements. Cointegration is interpreted as supporting the existence of long-run equilibrium relationships and the possibility of error-correction dynamics; however, it does not imply Granger causality on its own.

Granger causality was then examined using bivariate VAR or VECM models, depending on whether cointegration was detected. For non-cointegrated pairs, VAR models in levels or first differences were estimated with a constant term, and lag length was selected using AIC or SBIC. For cointegrated pairs, VECM models including the error-correction term were estimated. In each case, the null hypothesis states that variable X does not Granger-cause variable Y. The resulting F-statistics and p-values (Table A2 in the Appendix A section) capture predictive, rather than structural, causality:

1. Bidirectional causality:
    - GHG ↔ GDP: BG, HU, RO, SI
    - GHG ↔ NREN: All except CZ
    - GHG ↔ REN: BG, HU, LV, RO, SI
    - GDP ↔ NREN: CZ, HU, RO, SK
    - GDP ↔ REN: EU, HU, LV
    - NREN ↔ REN: BG, HU, LV, RO, SI
2. Unidirectional causality:
    - GHG → GDP: SK
    - GDP → GHG: LV
    - GHG → NREN: EU
    - NREN → GHG: CZ
    - GHG → REN: EU, SK
    - GDP → NREN: BG
    - NREN → GDP: LV
    - GDP → REN: BG, RO, SI
    - NREN → REN: EU, CZ, SK
    - REN → NREN: CZ
3. No causality:
    - GHG-GDP: EU, CZ
    - GDP-NREN: EU, SI
    - GHG-REN: CZ
    - GDP-REN: CZ, SK.

A country-level interpretation of the Granger causality results reveals substantial heterogeneity. In the EU aggregate, weak bidirectional causality between GHG and GDP appears at the 10% level, while both NREN and REN Granger-cause GHG, indicate that changes in the energy mix have measurable predictive power for emissions. Bulgaria shows limited evidence of causality, with only a marginal NREN → GDP effect. Czechia exhibits the richest causal structure, including bidirectional causality between GHG and

GDP, strong GDP → REN causality, and substitution patterns between REN and NREN. Hungary shows no significant causality, whereas Latvia displays marginal GHG → GDP and GDP → NREN effects. Romania presents only a weak GDP → REN relationship. Slovenia exhibits bidirectional causality between GDP and NREN, along with substitution from REN to NREN. Slovakia shows several meaningful relationships, including REN → GHG and bidirectional causality between GDP and REN.

The strongest causal structures appear in Czechia, Slovakia, Slovenia, and the EU aggregate, while Hungary, Bulgaria, and Romania exhibit weaker or less stable patterns. The most consistent findings across countries include: (i) renewable energy influencing emissions (EU, CZ, SK), (ii) economic activity driving renewable energy expansion (CZ, SK), and (iii) substitution between renewable and non-renewable energy sources (EU, CZ, SI, SK). These results suggest that the energy transition is more advanced and dynamically linked to economic and environmental indicators in Central European economies.

Model diagnostics for each country are reported in Table A3 in the Appendix A section.

The White test evaluates the null hypothesis of homoskedastic residuals, and the associated *p*-values—generally above 0.10—indicate no strong evidence of heteroskedasticity. The Durbin–Watson (DW) statistic provides a descriptive check for first-order serial correlation; values close to 2 suggest no pronounced positive or negative autocorrelation. Given the short annual samples, these diagnostics are interpreted cautiously, and no claims are made regarding higher-order serial correlation beyond what the tests can reliably detect.

The F-statistics of the multifactor regressions show *p*-values below 5% for most countries (with the exception of Bulgaria and Slovenia), indicating that the explanatory variables are jointly significant and that the overall model is statistically valid in the majority of cases. The coefficients of determination (R-squared) exceed 50% for most countries, suggesting that a substantial share of the variation in GHG emissions is explained by the included regressors. Together, the White and DW statistics confirm that the estimated models satisfy the key assumptions regarding residual behaviour for the available short annual samples.

Taken together, the regression results, cointegration evidence, and Granger causality patterns indicate that the relationship between economic activity, the energy mix, and emissions is strongly country-specific. Renewable energy consistently exhibits a negative association with GHG emissions, while the strength and direction of predictive interactions differ across national contexts, reflecting heterogeneous stages of the energy transition. Although these findings do not establish structural causality, they align with prior studies [16–18,36,40,41,49] showing that greater reliance on renewable energy is associated with lower emissions. The diversity of long-run equilibria and predictive linkages across countries is also consistent with the literature documenting varying degrees of renewable energy integration within the EU [42,43].

To predict the GHG (endogenous variable) from GDP, NREN, and REN (exogenous variables), a Multilayer Perceptron (MLP) artificial neural network with a single hidden layer was constructed. The predictors GDP, NREN, and REN serve as the input nodes, while GHG forms the output node, as illustrated in Figure 1.

In constructing the ANN, hidden neurons were generated automatically. The Hyperbolic tangent activation function was used for the hidden layer and the Sigmoid function for the output layer for the EU and most countries (except Latvia, where the Hyperbolic tangent was also used for the output layer), as these configurations yielded the lowest Sum of Squared Error and Relative Error.

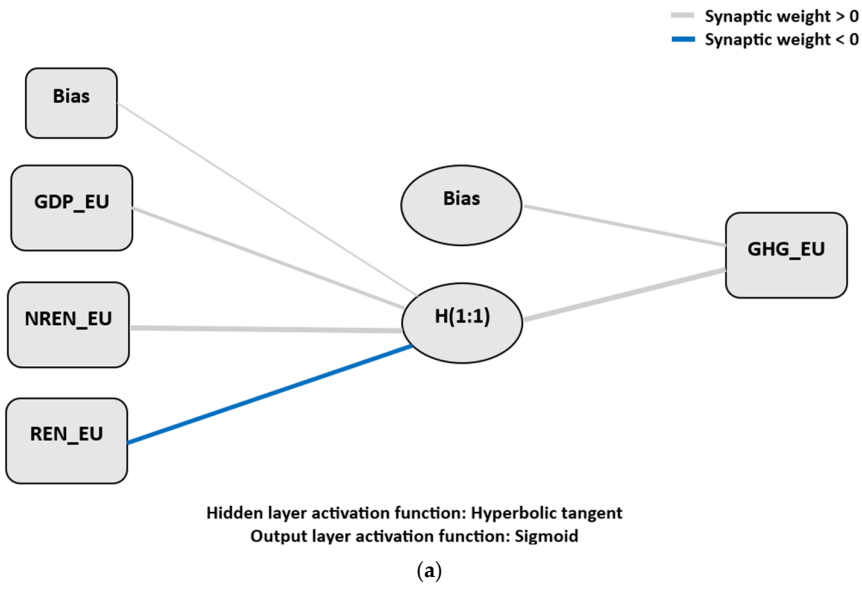
Table 3 and Figure 1 present the estimated parameters for the EU and each emerging country. The hidden layer exerts a substantial influence on model performance, confirming

a direct relationship between GHG and GDP, and an indirect one between GHG and REN across all countries. A direct link between GHG and NREN is observed in most cases, except for Czechia.

Table 3. Estimation of MLP parameters.

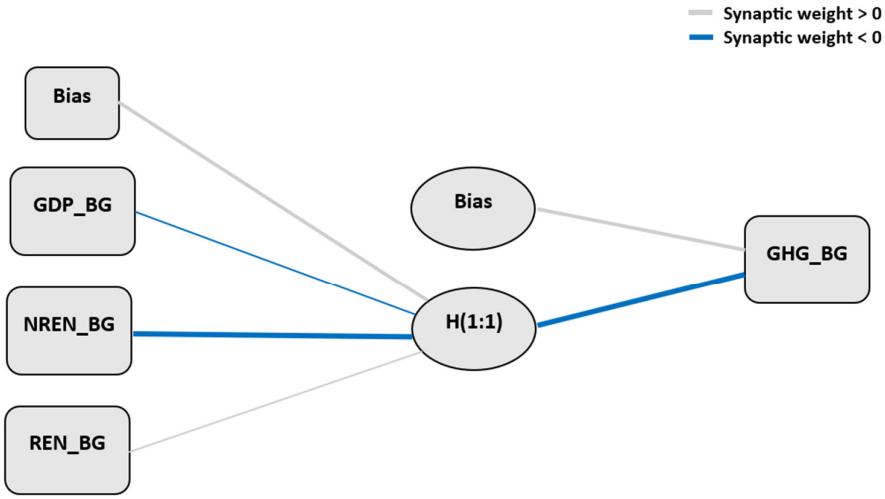
Exogenous Variable		Endogenous Variable: Hidden Layer1 H(1:1)	Endogenous Variable: Output Layer GHG	Region/ Country	Exogenous Variable		Endogenous Variable: Hidden Layer1 H(1:1)	Endogenous Variable: Output Layer GHG
Input Layer	(Bias)	0.007	-	LV	Input Layer	(Bias)	−0.007	-
	GDP	0.228	-			GDP	0.951	-
	NREN	0.765	-			NREN	0.463	-
	REN	−0.247	-			REN	−0.076	-
Hidden Layer1	(Bias)	-	0.301		Hidden Layer1	(Bias)	-	−0.149
	H(1:1)	-	2.140			H(1:1)	-	0.293
Input Layer	(Bias)	0.354	-	RO	Input Layer	(Bias)	0.162	-
	GDP	−0.007	-			GDP	−0.384	-
	NREN	−0.635	-			NREN	−0.554	-
	REN	0.305	-			REN	0.179	
Hidden Layer1	(Bias)	-	0.511		Hidden Layer1	(Bias)	-	−0.358
	H(1:1)	-	−0.760			H(1:1)	-	−0.182
Input Layer	(Bias)	0.159	-	SI	Input Layer	(Bias)	0.769	-
	GDP	0.489	-			GDP	−0.756	-
	NREN	−0.145	-			NREN	−1.951	-
	REN	−1.296				REN	0.156	-
Hidden Layer1	(Bias)	-	0.054		Hidden Layer1	(Bias)	-	−0.518
	H(1:1)	-	2.542			H(1:1)	-	−1.364
Input Layer	(Bias)	−0.586	-	SK	Input Layer	(Bias)	−0.635	-
	GDP	−0.504	-			GDP	0.955	-
	NREN	−0.626	-			NREN	1.026	-
	REN	0.372				REN	−1.323	
Hidden Layer1	(Bias)	-	−0.196		Hidden Layer1	(Bias)	-	0.445
	H(1:1)	-	−2.245			H(1:1)	-	2.254

Note: Positive weights strengthen the influence of an input on the output, whereas negative weights weaken it; larger absolute values represent stronger effects.

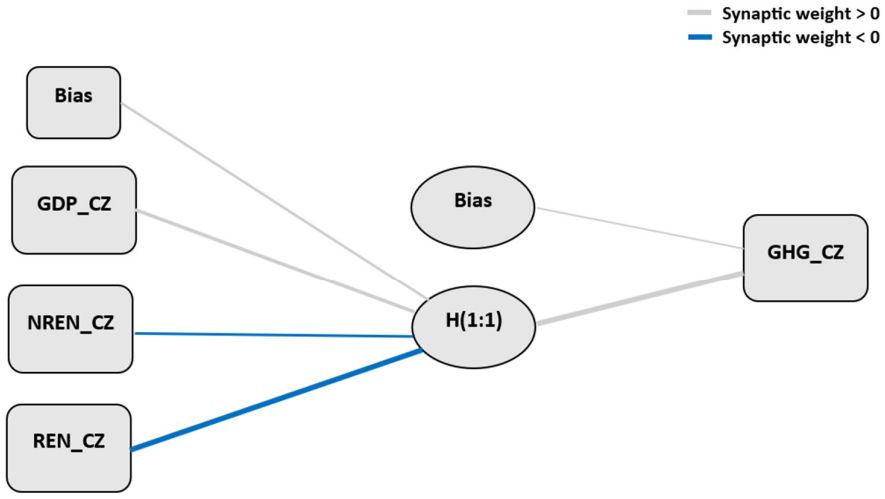


(**a**)

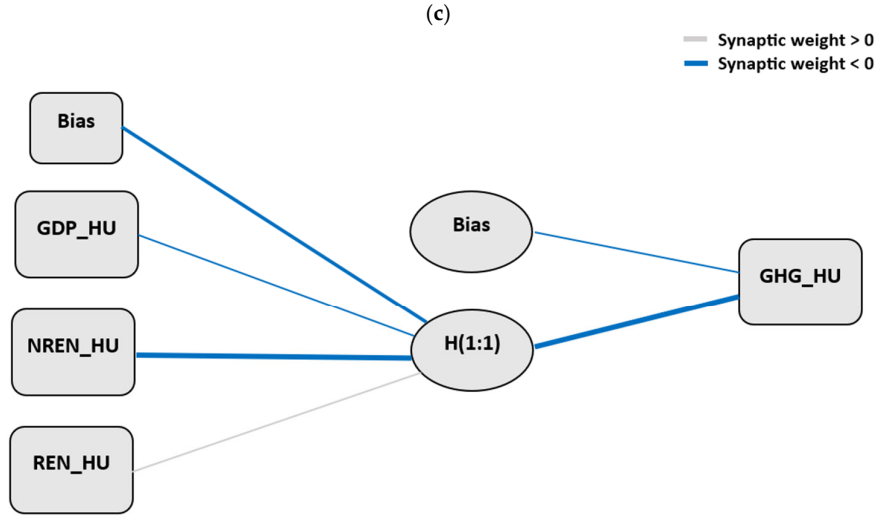
Figure 1. *Cont.*



(**b**)

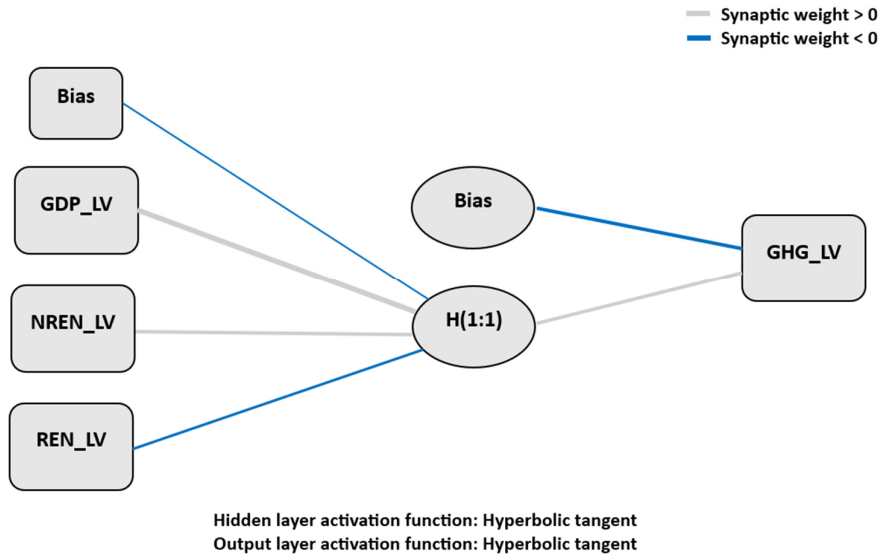


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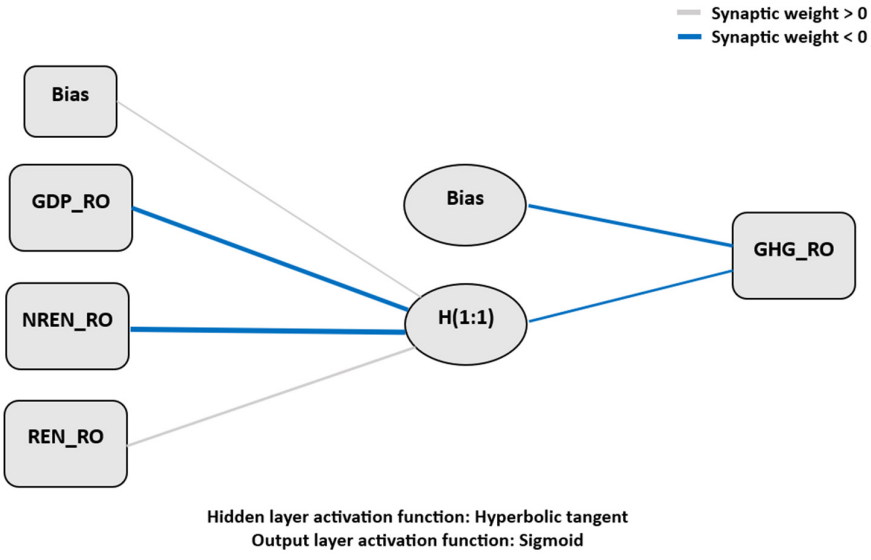


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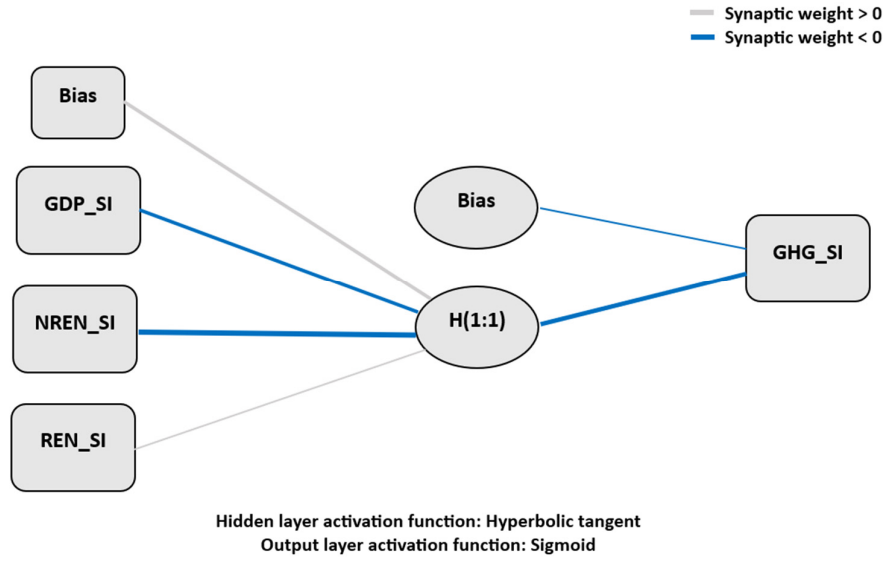
Figure 1. *Cont.*



(**e**)

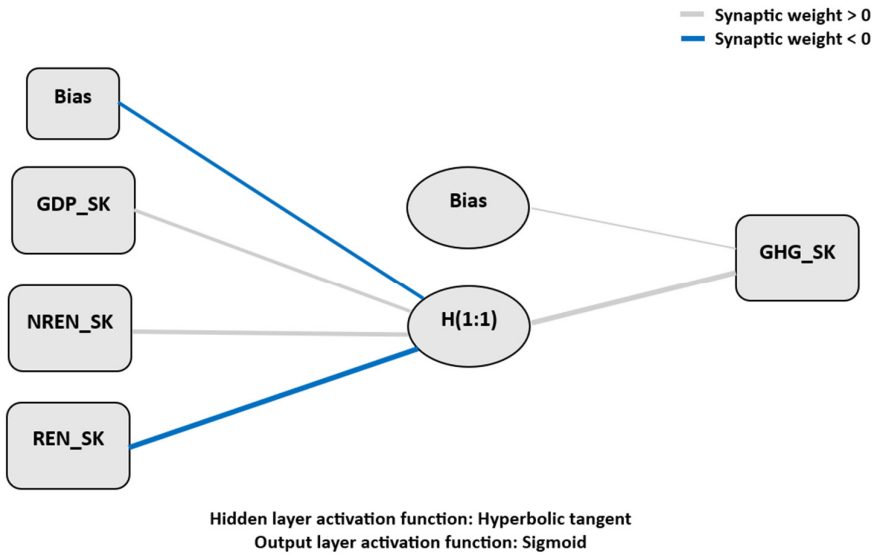


(**f**)



(**g**)

Figure 1. *Cont.*



(**h**)

Figure 1. Neural networks: (**a**) EU; (**b**) BG; (**c**) CZ; (**d**) HU; (**e**) LV; (**f**) RO; (**g**) SI; (**h**) SK.

The Hyperbolic tangent activation function indicates that the hidden layer (H(1:1))—which may be interpreted as capturing the influence of investments in infrastructure and environmental protection technologies—plays a substantial role in shaping the neural network's performance. The synaptic weight reveals a direct relationship between GHG emissions and GDP across the EU and all individual countries, as well as an indirect relationship between GHG emissions and renewable energy consumption. A direct link between GHG emissions and non-renewable energy consumption is also observed for the EU and most member states, with Czechia being the only exception.

The presence of the Bias parameter further confirms that the constructed neural network architectures are well adapted to the characteristics of the dataset. The effect exerted by economic growth and energy consumption on emissions can be made more efficient through increased environmental protection investments and the adoption of high-performance technologies.

The ANN findings reinforce the robustness of the regression model, showing that economic growth and energy consumption influence emission levels, while the magnitude of these effects is shaped by environmental investments and technological efficiency. Across the EU and emerging countries, the ANN confirms the main relationships identified by the regression model:

- GDP → GHG (direct effect): In all countries, GDP exerts a positive influence on the hidden layer or output, indicating that economic growth continues to exert upward pressure on emissions.
- REN → GHG (indirect mitigating effect): REN generally displays negative weights, confirming its role in reducing emissions. This pattern is consistent across all regions, although the magnitude varies.
- NREN → GHG (direct effect): NREN is positively associated with GHG in most countries, reflecting the structural dependence on fossil fuels. The exception is Czechia, where NREN shows a weaker or negative connection, suggesting partial decoupling between fossil energy use and emissions.

The strong influence of the hidden layer demonstrates that technological efficiency and environmental investments significantly shape the GHG response, beyond the linear effects captured by regression.

Given the interdependencies among the variables, interactions are expected to emerge; consequently, several ANN model specifications were estimated until the configuration that best captures these effects was identified. For model optimization, the dataset was partitioned into training and testing subsets, with the specific split proportions varying according to the parameter-tuning procedure (Table 4).

Table 4. RMSE values for the ANN model.

	EU		BG		CZ		HU		LV		RO		SI		SK	
	1	2	1	2	3	4	5	6	1	2	7	8	1	2	7	8
1	0.11	0.12	0.19	0.23	0.09	0.18	0.12	0.17	0.31	0.21	0.23	0.23	0.14	0.24	0.11	0.22
2	0.09	0.10	0.18	0.23	0.09	0.15	0.11	0.16	0.29	0.24	0.22	0.26	0.15	0.24	0.11	0.22
3	0.11	0.12	0.22	0.23	0.13	0.23	0.13	0.17	0.28	0.20	0.21	0.23	0.13	0.24	0.10	0.22
4	0.10	0.10	0.19	0.27	0.09	0.25	0.11	0.19	0.30	0.23	0.22	0.22	0.14	0.24	0.10	0.22
5	0.09	0.08	0.21	0.27	0.08	0.13	0.10	0.14	0.29	0.24	0.21	0.23	0.15	0.25	0.09	0.22
6	0.08	0.12	0.17	0.25	0.08	0.15	0.13	0.13	0.30	0.23	0.22	0.24	0.14	0.23	0.08	0.22
7	0.09	0.09	0.18	0.28	0.09	0.21	0.11	0.10	0.27	0.22	0.22	0.23	0.14	0.23	0.08	0.22
8	0.08	0.06	0.17	0.22	0.06	0.18	0.10	0.13	0.28	0.21	0.22	0.23	0.14	0.23	0.08	0.21
9	0.08	0.07	0.17	0.21	0.07	0.09	0.12	0.11	0.27	0.21	0.21	0.22	0.13	0.23	0.07	0.22
10	0.06	0.05	0.16	0.20	0.04	0.05	0.09	0.09	0.26	0.19	0.20	0.21	0.12	0.22	0.06	0.20
A	0.09	0.09	0.18	0.24	0.08	0.16	0.11	0.14	0.28	0.20	0.21	0.23	0.13	0.23	0.09	0.22

Note: [1] Training Dataset 61.5%; [3] Training Dataset 84.6%; [5] Training Dataset 76.9%; [7] Training Dataset 69.2%; [2] Testing dataset 38.5%; [4] Testing dataset 15.4%; [6] Testing dataset 23.1%; [8] Testing dataset 30.8%; A—Mean.

Given the limited number of annual observations, model validation relied on a repeated holdout cross-validation procedure. For each country, the dataset was randomly partitioned into a training set comprising 70 percent of the observations and a testing set comprising the remaining 30 percent. This partitioning was repeated five times using different splits generated under a fixed seed. Predictive accuracy was evaluated using the Root Mean Square Error (RMSE), defined as the square root of the average squared difference between observed and predicted values (Table 4). Across all countries, the tenth iteration (ANN10) consistently produced the lowest RMSE values, indicating high predictive accuracy and strong generalization performance [67].

The iterative training process shows that ANN10 consistently achieves the lowest RMSE across all countries, indicating high predictive accuracy, stable learning behaviour, and strong generalization across different training/testing splits. This reinforces the reliability of the ANN structure and validates the functional form of the regression model.

Using sensitivity analysis, the relative importance of GDP, NREN, and REN in predicting GHG emissions was ranked (Table 5).

Table 5. Normalized variable relative importance.

Predictors	**EU**			**BG**			**CZ**			**HU**		
	ARI	**NI**	**R**	**ARI**	**NI**	**R**	**ARI**	**NI**	**R**	**ARI**	**NI**	**R**
GDP	0.146	23.9	3	0.006	0.9	3	0.249	38.5	2	0.301	76.2	3
NREN	0.612	100.0	1	0.669	100.0	1	0.102	15.8	3	0.395	100.0	1
REN	0.241	39.4	2	0.325	48.6	2	0.648	100.0	1	0.304	77.1	2
Predictors	LV			RO			SI			SK		
	ARI	NI	R	ARI	NI	R	ARI	NI	R	ARI	NI	R
GDP	0.639	100.0	1	0.309	60.2	2	0.197	26.8	2	0.233	55.8	3
NREN	0.299	46.7	2	0.514	100.0	1	0.735	100.0	1	0.417	100.0	1
REN	0.062	9.7	3	0.177	34.3	3	0.068	9.2	3	0.350	84.0	2

Note: ARI—Average relative importance; NI—Normalized importance (%); R—Ranking.

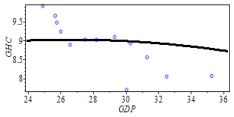
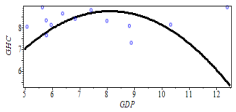
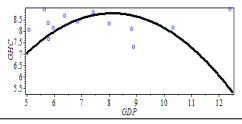
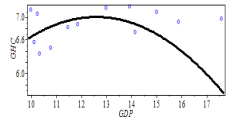
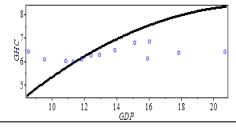
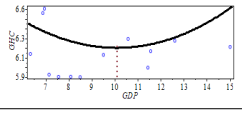
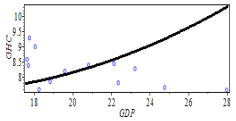
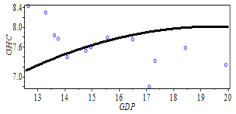
The relative importance of predictors reveals clear cross-country patterns. NREN is the dominant driver of GHG emissions in the EU and in most emerging economies (BG, RO, SI, SK, HU), confirming the structural dependence on fossil energy. GDP is the most influential predictor in Latvia, reflecting strong growth–emissions coupling, while REN is the leading predictor in Czechia, indicating rapid renewable integration. In several countries (EU, BG, HU, SK), REN ranks second, underscoring its growing strategic role. These results align with previous research [40,41,47], which shows that renewable energy expansion contributes to lower emissions and supports sustainable development [30,46,49].

The ANN models reinforce the regression findings by capturing nonlinear interactions between economic activity, energy use, and emissions. They show that GDP and NREN exert upward pressure on GHG, while REN consistently mitigates emissions, with effect sizes varying across countries. The hidden layer structure highlights the role of technological and environmental investments in shaping these relationships. These findings, consistent with earlier studies [41,48], strengthen the robustness of the regression model and underscore the strategic importance of renewable energy in advancing environmental sustainability.

4.3. Testing Environmental Kuznets Curve (EKC) Hypothesis

Given the cointegration of variables, the EKC hypothesis was tested using Equation (2), with the estimation results presented summarized in Table 6.

Table 6. Estimations of the coefficients for Equation (2).

Co/ Reg	Variable	Coef.	Std. Error	Prob.	R^2	SER	Curve in the (GDP, GHG) Plane	Critical Value
EU	GDP	0.1757	0.1002	0.0903	0.9467	0.1136		26.621
	GDP^2	−0.0033	0.0023	0.1042				
	NREN	0.0922	0.0160	0.0012				
	REN	0.0090	0.0070	0.0944				
BG	GDP	2.9253	0.9469	0.0214	0.5824	0.3088		8.122
	GDP^2	−0.1801	0.0541	0.0158				
	NREN	0.0149	0.0269	0.1007				
	REN	−0.0208	0.0161	0.0945				
CZ	GDP	2.2068	0.2475	0.0001	0.9495	0.1522		18.722
	GDP^2	−0.0589	0.0065	0.0001				
	NREN	−0.0050	0.0065	0.0975				
	REN	−0.0303	0.0054	0.0013				
HU	GDP	1.3277	0.2177	0.0009	0.7500	0.1923		12.597
	GDP^2	−0.0527	0.0104	0.0023				
	NREN	0.0435	0.0156	0.0320				
	REN	−0.0105	0.0048	0.0742				
LV	GDP	0.8494	0.2122	0.0071	0.5013	0.2667		22.932
	GDP^2	−0.0185	0.0075	0.0488				
	NREN	0.0579	0.0176	0.0168				
	REN	−0.0057	0.0040	0.0932				
RO	GDP	−0.3393	0.4831	0.0988	0.3536	0.2613		10.070
	GDP^2	0.0168	0.0269	0.0955				
	NREN	0.0550	0.0255	0.0744				
	REN	0.0311	0.0085	0.0106				
SI	GDP	−0.2866	0.4369	0.0954	0.6076	0.3810		12.346
	GDP^2	0.0116	0.0127	0.0995				
	NREN	0.1043	0.0558	0.1008				
	REN	0.0224	0.0121	0.1039				
SK	GDP	0.7190	0.1132	0.0007	0.8453	0.1718		19.503
	GDP^2	−0.0184	0.0072	0.0431				
	NREN	0.0195	0.0041	0.0032				
	REN	−0.0050	0.0029	0.1048				

The sign pattern of the estimated coefficients determines the shape of the income–emissions relationship:

- EKC (inverted U-shape): $\alpha_1 > 0$ and $\alpha_2 < 0$. Emissions rise with GDP until the turning point, after which they decline as GDP continues to grow.
- U-shaped curve (non-EKC): $\alpha_1 < 0$ and $\alpha_2 > 0$. Emissions initially fall or grow slowly, but, after the turning point, they increase again with GDP growth.

The economic relevance of the turning point depends on whether it lies within the observed GDP range for each country.

The EKC posits that GHG emissions initially rise with GDP growth and then decline once GDP surpasses a critical threshold. This inverted U-shaped relationship is confirmed for the EU and for most emerging countries—BG, CZ, HU, LV, and SK—where the estimated turning points fall within the observed data range. In contrast, RO and SI exhibit a U-shaped pattern, indicating that emissions continue to rise with GDP, thereby rejecting the EKC hypothesis in these cases.

The interpretation of the estimated turning points for the EU and for the emerging countries is as follows:

- European Union—EKC confirmed (turning point: 26.621). Below this GDP level, economic growth increases emissions; above it, further growth is associated with declining emissions. This suggests that the EU has entered a phase of relative decoupling, supported by technological improvements, energy-efficiency gains, and climate policy measures.
- Bulgaria—EKC confirmed (turning point: 8.122). Bulgaria reaches its emissions peak at a relatively low GDP level. Beyond this point, economic growth is associated with decreasing emissions, although the moderate R^2 suggests that additional structural factors also influence emissions.
- Czechia—EKC confirmed (turning point: 18.722). The EKC is strongly supported with high explanatory power and statistically significant coefficients. Emissions rise with GDP until the turning point, after which economic growth coincides with declining emissions. This reflects industrial modernization and progress in the energy transition.
- Hungary—EKC confirmed (turning point: 12.597). Hungary exhibits a clear transition: emissions increase with GDP up to the turning point, then begin to decline. This suggests that Hungary is moving toward a cleaner growth trajectory.
- Latvia—EKC confirmed (turning point: 22.932). The turning point is relatively high, indicating that only at higher GDP levels does Latvia begin to decouple emissions from economic growth. The lower R^2 suggests that factors beyond GDP and energy structure also shape emissions.
- Slovakia—EKC confirmed (turning point: 19.503). Slovakia follows a pattern similar to Czechia, with a well-defined EKC and a turning point at a medium high GDP level. This indicates progress toward cleaner economic expansion.
- Romania—EKC is not validated (U-shaped curve; turning point: 10.070, within the observed GDP range). For GDP levels below the turning point, emissions tend to decrease or grow slowly. Beyond this threshold, emissions increase again with GDP. This indicates that Romania's recent economic growth remains pollution-intensive, and that the country has not yet entered the EKC's descending phase.
- Slovenia—EKC is not validated (U-shaped curve (turning point: 12.346, outside the observed GDP range). Although the theoretical curve is U-shaped, the turning point lies outside the sample period. Empirically, Slovenia shows a monotonic increase in emissions with GDP during 2010–2022, meaning that the EKC hypothesis is not supported.

Role of NREN and REN around the turning points across the EU and most emerging countries:

- NREN coefficients are positive (except Czechia), confirming that fossil fuel consumption increases GHG emissions, regardless of the GDP level or position relative to the turning point.
- REN coefficients are negative in most countries (except EU, RO, SI), indicating that renewable energy consumption reduces emissions and can accelerate the transition to the descending part of the EKC. In Romania and Slovenia, the positive REN coefficients may reflect transitional inefficiencies, structural constraints, or the early stage of renewable integration.

The results reveal substantial heterogeneity among emerging EU economies:

- Several countries (EU, BG, CZ, HU, LV, SK) exhibit an inverted U-shaped EKC, suggesting that they are transitioning toward cleaner growth.
- Romania and Slovenia do not follow the EKC pattern, indicating that economic expansion continues to exert upward pressure on emissions.
- Fossil fuel consumption remains a dominant driver of emissions across all countries.
- Renewable energy plays a mitigating role, but its effectiveness varies depending on national energy structures and policy frameworks.

These findings highlight the heterogeneity among emerging EU states regarding the EKC hypothesis [35,36] and underscore the need for targeted national policies to accelerate renewable energy deployment and reduce dependence on fossil fuels [51], in line with EU climate objectives.

It can be concluded that GDP and NREN exert significant influence on GHG emissions, underscoring the need for national strategies that promote the adoption of renewable energy. In aligning with EU directives, such policies are essential for achieving sustainable economic growth and environmental protection.

4.4. Dynamic Estimation of Indicator Relationships Using the Grey Lotka–Volterra Model

The application of the Grey Lotka–Volterra (GLV) model to the pairs GHG-GDP, GHG-REN, and GHG-NREN across seven European countries and the EU provides a dynamic, interaction-based perspective on the drivers of greenhouse gas emissions. Unlike static regression models, the GLV framework captures competitive, cooperative, and predator–prey dynamics, revealing how economic activity and energy use shape emissions trajectories over time.

A more accurate interpretation of the interdependence among indicators requires examining the stability and position of the equilibrium points for each of the derived systems, as well as the initial conditions that shape the estimated trajectories.

The Lotka–Volterra model (2) has four equilibrium points when $b_1c_2(b_1c_2 - b_2c_1) \neq 0$:

- $E_0 = (0, 0)$: the trivial equilibrium, always a repeller.
- $E_1 = \left(\frac{a_1}{b_1}, 0\right)$, $E_2 = \left(0, \frac{a_2}{c_2}\right)$, axis equilibria.
- $E_3 = \left(\frac{a_1c_2 - a_2c_1}{b_1c_2 - b_2c_1}, \frac{b_1a_2 - b_2a_1}{b_1c_2 - b_2c_1}\right)$: the nontrivial equilibrium.

Because the variables have economic meaning, only equilibrium points located in the first quadrant are relevant for interpreting the dynamics. Based on the estimated coefficients in Table 7, we find that for each country, aside from the trivial equilibrium E_0, only one axis equilibrium and, in some cases, the non-trivial equilibrium lie in the economically meaningful region. Across the EU and the emerging countries, six distinct dynamic patterns were identified (Table 8, Figure 2). These patterns reflect differences in stability properties and interaction structures, offering a richer understanding of how economic activity and energy use dynamically influence GHG emissions.

Table 7. Estimated coefficients for pairs of indicators, using the *GLV* model.

Co/ Reg	Pairs	a_1^*	b_1^*	c_1^*	a_2^*	b_2^*	c_2^*	$MAPE_1/MAPE_2$	Type of Relationship
EU	GHG-GDP	0.483	0.017	−0.0042	0.490	0.016	−0.0041	12.3/11.3	Predator–Prey
	GHG-REN	0.464	0.016	−0.523	0.457	0.014	−0.480	12.4/11.7	Predator–Prey
	GHG-NREN	0.498	−0.034	6.582	0.499	−0.035	6.742	14.3/14.0	Prey–Predator
BG	GHG-GDP	0.457	0.012	−0.009	0.449	0.011	0.019	13.8/13.1	Predator–Prey
	GHG-REN	0.511	0.021	−0.778	0.517	0.019	−0.685	18.7/23.9	Predator–Prey
	GHG-NREN	0.250	0.022	−3.389	0.225	0.019	−2.941	14.5/13.8	Predator–Prey
CZ	GHG-GDP	0.462	0.009	−0.004	0.452	0.008	−0.004	13.0/14.1	Predator–Prey
	GHG-REN	0.460	0.011	−0.331	0.483	0.010	−0.321	21.1/17.3	Predator–Prey
	GHG-NREN	0.564	−0.058	4.422	0.580	−0.063	4.767	13.0/14.1	Prey–Predator
LV	GHG-GDP	0.442	0.017	−0.006	0.488	0.020	−0.007	12.1/11.0	Predator–Prey
	GHG-REN	0.314	0.024	−0.258	0.310	0.021	−0.233	14.7/16.6	Predator–Prey
	GHG-NREN	0.577	−0.003	2.565	0.595	−0.005	3.324	8.7/30.9	Prey–Predator
HU	GHG-GDP	0.447	0.019	−0.008	0.456	0.019	−0.008	13.1/12.9	Predator–Prey
	GHG-REN	0.438	−0.030	1.128	0.498	−0.044	1.585	17.1/15.9	Prey–Predator
	GHG-NREN	0.343	−0.004	2.554	0.353	−0.004	2.449	15.1/21.4	Prey–Predator
RO	GHG-GDP	0.494	0.019	−0.009	0.499	0.017	−0.008	12.6/11.9	Predator–Prey
	GHG-REN	0.424	0.065	−1.960	0.415	0.063	−1.888	13.8/12.3	Predator–Prey
	GHG-NREN	0.299	−0.031	6.191	0.310	−0.040	7.677	19.8/20.1	Prey–Predator
SI	GHG-GDP	0.449	0.015	−0.004	0.469	0.016	−0.005	13.2/12.1	Predator–Prey
	GHG-REN	0.299	−0.006	0.230	0.298	−0.008	0.271	15.0/14.8	Prey–Predator
	GHG-NREN	0.435	−0.006	4.205	0.455	−0.006	4.425	14.3/18.3	Prey–Predator
SK	GHG-GDP	0.488	0.020	−0.008	0.503	0.020	−0.008	12.7/11.3	Predator–Prey
	GHG-REN	0.423	0.008	−0.242	0.308	0.002	−0.040	21.1/17.3	Predator–Prey
	GHG-NREN	0.967	−0.049	5.141	0.960	−0.053	5.508	15.1/22.4	Prey–Predator

Table 8. Topological type of the equilibrium points of the estimated Lotka–Volterra models.

Country/Region	Pairs	E_1	E_2	E_3	Generic Phase Portrait
EU	GHG-GDP	saddle	-	-	1
	GHG-REN	saddle	-	attractor	2
	GHG-NREN	-	saddle	attractor	5
BG	GHG-GDP	saddle	-	-	1
	GHG-REN	saddle	-	attractor	2
	GHG-NREN	saddle	-	-	1
CZ	GHG-GDP	saddle	-	-	1
	GHG-REN	saddle	-	-	1
	GHG-NREN	-	saddle	attractor	5
LV	GHG-GDP	attractor	-	saddle	3
	GHG-REN	saddle	-	attractor	2
	GHG-NREN	-	saddle	attractor	5
HU	GHG-GDP	saddle	-	-	1
	GHG-REN	-	saddle	attractor	5
	GHG-NREN	-	attractor	saddle	6
RO	GHG-GDP	saddle	-	-	1
	GHG-REN	saddle	-	-	1
	GHG-NREN	-	saddle	attractor	5
SI	GHG-GDP	attractor	-	saddle	3
	GHG-REN	-	saddle	attractor	5
	GHG-NREN	-	saddle		4
SK	GHG-GDP	saddle	-	-	1
	GHG-REN	saddle	-	attractor	2
	GHG- NREN	-	saddle	attractor	5

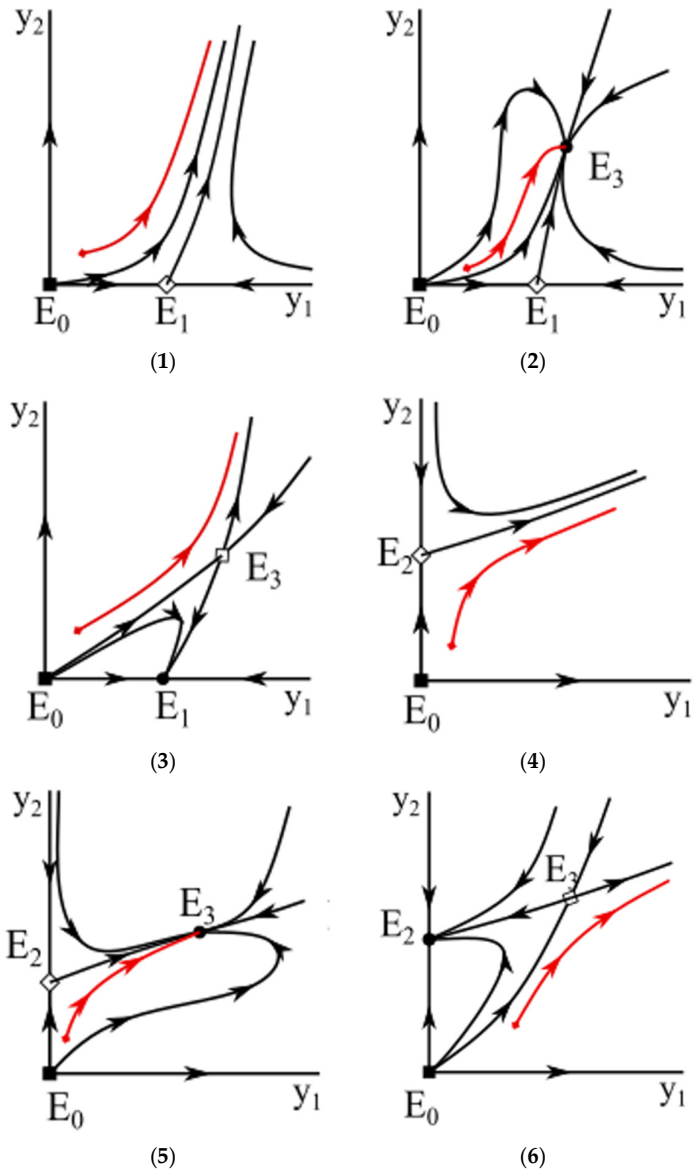


Figure 2. Generic phase portraits for the Lotka–Volterra model (**2**) (patterns (**1**)–(**6**)).

The analysis of the empirical results (Table 7) identifies several distinct types of dynamic relationships:

1. Predator–Prey Dynamics:
   - GHG-GDP: all regions;
   - GHG-REN: all regions except HU and SI.
2. Prey–Predator Dynamics:
   - GHG-NREN: all regions except BG.

Across all countries and the EU, the GHG-GDP pair exhibits a predator–prey relationship, with GDP acting as the "predator" and GHG as the "prey." Economically, this indicates that economic growth increases emissions, reflected in positive interaction coefficients. The negative values of c_1 imply that GDP exerts a reinforcing effect on emissions, consistent with the early stages of the Environmental Kuznets Curve (EKC). Most trajectories correspond to portrait type 1, where both GDP and GHG rise, but the growth rate of GHG slows over time. This suggests that economic expansion continues to place upward pressure on emissions, although structural changes—energy efficiency improve-

ments, technological upgrading, and EU climate policies—moderate the pace of GHG accumulation. Latvia and Slovenia follow a different configuration (portrait 3) yet display similar qualitative dynamic.

For four countries (BG, LV, RO, and SK) and the EU, the GHG-REN relationship is predator–prey, with REN acts as the "predator" that reduces GHG ("prey"). This reflects a strong negative impact of renewable energy on emissions, consistent with EU decarbonization goals. Several regions exhibit an attractor equilibrium (portrait 2), indicating long-term stabilization of emissions as renewable penetration increases. In Czechia and Romania, the dynamics resemble portrait 1, where REN still reduces GHG but with slower convergence. Hungary and Slovenia show prey–predator dynamics (portrait 5), meaning that the accumulations of both REN and GHG tend toward an equilibrium state.

For nearly all countries and the EU, the GHG-NREN pair exhibits a prey–predator relationship, where NREN acts as the "predator" and GHG as the "prey." Non-renewable energy consumption drives persistent increases in emissions, reflected in large positive c_1 and c_2 coefficients. Most countries converge toward a stable attractor (portrait 5), representing the most desirable configuration: the accumulation of both GHG emissions and non-renewable energy consumption tends toward an equilibrium, while annual changes converge toward zero.

The exception is Bulgaria, which shows a predator–prey dynamic (portrait 1), suggesting partial decoupling between NREN and GHG. Hungary exhibits portrait 6, a rare configuration in which NREN stabilizes but GHG fluctuates. Slovenia shows portrait 4, indicating unstable dynamics and potential transition.

Fossil fuel consumption remains the dominant structural driver of emissions. The attractor dynamics highlights the difficulty of reducing GHG without a decisive shift away from NREN sources.

MAPE values below 20 percent for most pairs indicate good predictive accuracy (Table 7), supporting the robustness of the GLV model. Higher MAPE values in a few cases (BG, CZ, and SK for REN; LV, HU, and RO for NREN) reflects greater volatility in renewable deployment, structural breaks in energy markets, and the 2021–2022 energy crisis.

Countries with saddle equilibrium face path dependence: without major policy intervention, emissions will converge to a high-GHG steady state. The most desirable configuration is the presence of an attractor, where GHG accumulation stabilizes and annual changes converge to zero.

The GLV model deepens the insights from the regression and ANN analyses by revealing the dynamic nature of interactions:

- GDP and NREN generally increase emissions, though with different dynamic patterns.
- REN reduces emissions, but the strength and stability of these effects differ across countries.
- Long-term trajectories depend on equilibrium stability, not merely on coefficient signs, illustrating how structural interactions shape emission paths.

In essence, the GLV framework shows that emissions trajectories emerge from competitive and cooperative dynamics between economic growth and energy choices. This provides a powerful tool for scenario-based policy design and long-term sustainability planning.

4.5. Concluding Remarks of Empirical Results

Across the four analytical components, the findings reveal substantial heterogeneity among the seven emerging EU member states and the EU as a whole. Between 2010 and 2022, the European Union, Czechia, Slovenia, and Slovakia achieved the largest reductions in GHG emissions, while Bulgaria and Romania experienced increases. NREN consumption declined markedly in Latvia, Slovenia, and Slovakia, but rose in Bulgaria and Romania,

reflecting divergent transition pathways. Renewable energy expanded in most countries, with Czechia, Latvia, and Slovenia showing the strongest growth.

The regression, ANN, and GLV analyses converge on the conclusion that GDP and NREN generally increase emissions, while REN consistently reduces them. Czechia is the only country where NREN shows a negative regression coefficient, pointing to structural particularities in its energy system. ANN variable importance rankings confirm NREN as the main driver in most countries, except Latvia and Czechia, where GDP and REN dominate.

Granger causality patterns also differ widely. Several countries (BG, HU, RO, SI) exhibit strong bidirectional causality between GHG and GDP, while others (EU, CZ) show no causal link. NREN displays bidirectional causality in most cases, whereas REN shows mixed patterns, reflecting different stages of renewable energy adoption. Cointegration tests confirm long-term equilibrium relationships in all countries.

The EKC hypothesis is validated for the European Union, Bulgaria, Czechia, Hungary, Latvia, and Slovakia, while Romania and Slovenia display U-shaped patterns, indicating continued growth-driven emissions.

GLV dynamics reveal six distinct interaction patterns, highlighting the structural diversity of energy–economy–environment linkages across the region.

Overall, countries such as Czechia, Slovenia, and Slovakia are more advanced in restructuring their energy mix and reducing emissions, while Bulgaria and Romania lag behind. Latvia and Hungary occupy intermediate positions, with progress in renewable energy adoption but persistent growth–emissions coupling. The EU shows a balanced profile, with declining emissions, strong REN effects, and a validated EKC pattern.

Taken together, the comparative evidence demonstrates that renewable energy expansion is the most consistent factor associated with emission reductions, while economic growth and fossil fuel consumption remain the primary sources of environmental pressure. These findings underscore the need for targeted, country-specific policies to accelerate the energy transition across emerging EU member states.

5. Conclusions

The COVID-19 pandemic and the Russian–Ukrainian conflict have accelerated the European Union's efforts to diversify away from fossil fuels. These developments have strengthened the EU's determination to reduce greenhouse gas emissions by at least 55 percent by 2030 (relative to 1990 levels) and to achieve climate neutrality by 2050 [5]. In this evolving context, the present study offers both theoretical and practical insights that are highly relevant for understanding the dynamics of the energy transition. The EU's shift is driven not only by environmental imperatives but also by the need to enhance energy security and support sustainable development.

This research contributes to the existing literature by moving beyond static correlations and examining dynamic interactions. It captures both cooperative dynamics—where GDP growth stimulates renewable energy development and reduces emissions—and competitive dynamics, where GDP growth increases fossil fuel consumption and drives emissions upward. These interactions are modelled as simultaneous and evolutionary processes, offering a more nuanced and realistic representation of the energy–economy–environment nexus.

Unlike classical models that require complete datasets, the Grey Lotka–Volterra (GLV) framework enables analysis under uncertainty, providing a realistic reflection of economic and ecological dynamics—particularly relevant in the context of climate change, where data are often fragmented or incomplete. Moreover, the testing of environmental curve hypotheses is conducted within an evolutionary framework, extending beyond static regressions to dynamic simulations. These simulations reveal how relationships evolve

over time, identify inflexion points, and explore policy scenarios that may accelerate or hinder decarbonization.

The analytical models employed in this study provide a comprehensive understanding of the complex interactions between the economy, the environment, and energy resources. They serve as tools for shaping public policies, guiding energy planning, and evaluating economic sustainability. The findings highlight both direct and indirect effects of economic growth and energy consumption on emissions, with varying intensities across countries. Economic growth and fossil fuel consumption exert the strongest upward pressure on emission, while renewable energy demonstrates a consistent mitigating effect, underscoring its central role in sustainable development.

Through multifactorial regression analysis, the study establishes correlations between GDP, energy consumption (fossil vs. renewable), and greenhouse gas emissions. It enables the simulation of energy transition scenarios and quantifies the effects on emissions through elasticity measures, capturing nonlinear, complex, and irregular relationships between variables. They also uncover subtle links between energy sources and GHG, offering valuable insights for decarbonization strategies.

The testing of environmental curve hypotheses provides an assessment of economic sustainability, showing that GHG tends to rise in the early stages of development but decline as GDP increases and green technologies are adopted. This highlights the need for differentiated policy approaches, as countries at different stages of development require tailored strategies.

The Grey Lotka–Volterra model further enriches the analysis by capturing competitive and cooperative dynamics between fossil and renewable energy sources and their impact on GHG. It facilitates the identification of optimal energy mixes and simulates how energy structures and emissions evolve in response to policy choices and investment patterns.

By integrating these modelling approaches, the study offers a holistic perspective on the interplay between economic growth, energy consumption, and environmental impact. This empowers policymakers to design sustainable energy strategies, evaluate the economic implications of the green transition, and anticipate climate-related risks. Researchers can calibrate these models using national or regional data to generate context-specific recommendations.

The empirical results carry several important policy implications for the European Union and the emerging member states examined.

The validation of the Environmental Kuznets Curve (EKC) for the European Union, Bulgaria, Czechia, Hungary, Latvia, and Slovakia suggests that, beyond a certain level of economic development, structural changes, technological progress, and environmental regulation can jointly contribute to the decoupling of economic growth from greenhouse gas emissions. However, the absence of an EKC pattern in Romania and Slovenia indicates that economic expansion in these countries remains closely tied to increased emissions, underscoring the need for more targeted and effective policy interventions.

First, the consistently positive coefficients associated with non-renewable energy consumption highlight the continued dependence on fossil fuels as a major driver of emissions. This finding reinforces the urgency of accelerating the phase-out of carbon-intensive energy sources. Policies should prioritize reducing fossil fuel consumption through carbon pricing, stricter emissions standards, and the gradual elimination of fossil fuel subsidies.

Second, the negative coefficients for renewable energy consumption in most countries demonstrate the effectiveness of renewable energy in mitigating emissions. Expanding renewable capacity—particularly in countries where REN still plays a limited role—should be central to national energy strategies. This includes increasing investment in renewable

infrastructure, improving grid flexibility, supporting decentralized energy systems, and strengthening regulatory frameworks that facilitate renewables integration. In countries where REN currently shows a positive association with emissions (EU, RO, SI), policymakers should investigate structural or transitional inefficiencies—such as reliance on biomass, outdated technologies, or insufficient grid capacity—that may limit the environmental benefits of renewable energy deployment.

Third, the variation in turning points across countries indicates that the transition toward cleaner growth is uneven. Countries with lower turning points (e.g., BG, HU) may require policies that consolidate recent progress and prevent regression, while countries with higher turning points (e.g., LV, SK) need to intensify efforts to reach the GDP levels at which emissions begin to decline. For Romania and Slovenia, where the EKC is not validated, policy interventions must focus on breaking the link between economic expansion and emissions through structural reforms, modernization of industrial sectors, and accelerated adoption of clean technologies.

Fourth, the results of the Grey Lotka–Volterra (GLV) model reveal complex cooperation–competition dynamics between emissions, economic growth, and energy consumption. These nonlinear interactions imply that policy measures should not be designed in isolation. Instead, integrated policy frameworks are needed to simultaneously address economic development, energy transition, and environmental protection. For example, policies promoting renewable energy must be complemented by measures that enhance energy efficiency, encourage technological innovation, and support industrial restructuring.

The GLV model provides several actionable insights:

- Economic growth alone cannot deliver decarbonization. Even with efficiency gains, GDP growth continues to exert upward pressure on emissions.
- Renewables are effective but require scale and stability. Countries with attractor equilibria for GHG-REN show the strongest long-term mitigation potential.
- Fossil fuels create structural inertia. The attractor dynamics for GHG-NREN highlight the need for accelerated coal phase-out, diversification of energy sources, investment in grid modernization, and carbon pricing mechanisms.
- Transition pathways differ across countries. The six dynamic portraits reveal that one-size-fits-all policies are ineffective. Tailored strategies are needed depending on each country's equilibrium structure.

Finally, the heterogeneity observed across emerging EU economies suggests that a "one size fits all" approach is unlikely to be effective. While EU wide directives provide an essential framework, national governments must tailor their strategies to local economic structures, energy systems, and institutional capacities. Countries lagging in the transition—particularly those still heavily reliant on fossil fuels—should receive targeted support through EU cohesion funds, the Just Transition Mechanism, and other financial instruments aimed at reducing regional disparities in the energy transition.

In summary, the findings underscore the need for coordinated yet differentiated policy actions that accelerate the shift toward renewable energy, reduce fossil fuel dependence, and support sustainable economic development. Strengthening the alignment between national policies and EU climate objectives will be essential for achieving long-term decarbonization and ensuring that all member states progress toward climate neutrality.

This study acknowledges several methodological and contextual limitations. Conducted at the level of emerging EU member states and the EU as a whole, the research reflects regional economic characteristics that may differ significantly from those of countries on other continents. In emerging economies, the relatively low share of renewable energy in total consumption constrains comparative analysis with fossil energy and may distort the observed relationship between GDP and greenhouse gas emissions.

From a methodological perspective, the Multifactorial linear regression model may fail to capture nonlinear relationships and complex interdependencies. Artificial neural networks, while powerful, require extensive datasets and a degree of economic stability for effective training-conditions that may not be consistently met. Additionally, the assumption that GHG declines with GDP growth may not hold uniformly across all contexts. The Grey Lotka–Volterra model also presents challenges, as it depends on accurately estimated parameters, which are difficult to obtain in volatile or data-scarce environments.

Future research will extend the analysis to groups of countries across different continents to capture the impact of energy consumption and economic development on g emissions across diverse state categories. This broader scope will enhance the generalizability of findings and allow for comparative insights between regions. Additionally, the current study is limited to a sample of four macroeconomic indicators. Subsequent research will apply the same methodological framework, while incorporating a wider range of indicators that interact with and contribute to environmental degradation, thereby offering a more comprehensive understanding of sustainability dynamics.

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Appendix A

Table A1. Testing for stationarity of variables—ADF test results.

Country/ Region	GHG First Differences					GDP First Differences				
	t-Statistic	Prob.	Test Critical Values: 1% Level	5% Level	10% Level	*t*-Statistic	Prob.	Test Critical Values: 1% Level	5% Level	10% Level
EU	−3.197	0.048	−4.200	−3.175	−2.729	−2.827	0.089	−4.297	−3.213	−2.748
BG	−3.317	0.040	−4.200	−3.175	−2.729	−4.028	0.219	−5.295	−4.008	−3.461
CZ	−3.089	0.057	−4.200	−3.175	−2.729	−4.776	0.241	−5.522	−4.108	−3.515
HU	−3.314	0.046	−4.420	−3.259	−2.771	−2.856	0.082	−4.200	−3.175	−2.729
LV	−3.472	0.031	−4.200	−3.175	−2.729	−3.625	0.120	−4.297	−3.213	−2.748

Table A1. *Cont.*

Country/ Region	GHG First Differences					GDP First Differences				
	***t*-Statistic**	**Prob.**	**Test Critical Values:**			***t*-Statistic**	**Prob.**	**Test Critical Values:**		
			1% Level	**5% Level**	**10% Level**			**1% Level**	**5% Level**	**10% Level**
RO	−3.472	0.031	−4.200	−3.175	−2.729	−3.546	0.097	−5.522	−4.108	−3.515
SI	−2.298	0.027	−2.792	−1.978	−1.602	−3.49	0.096	−5.295	−4.008	−3.461
SK	−3.997	0.014	−4.200	−3.175	−2.729	−4.253	0.043	−5.522	−4.108	−3.515
Country/ Region	NREN First Differences					REN First Differences				
	t-Statistic	Prob.	Test Critical Values:			*t*-Statistic	Prob.	Test Critical Values:		
			1% Level	5% Level	10% Level			1% Level	5% Level	10% Level
EU	−1.632	0.095	−2.792	−1.978	−1.602	−4.408	0.007	−4.200	−3.175	−2.729
BG	−3.796	0.073	−5.522	−4.108	−3.515	−6.378	0.000	−4.421	−3.260	−2.771
CZ	−2.869	0.009	−2.792	−1.978	−1.602	−2.204	0.217	−4.421	−3.260	−2.771
HU	−2.870	0.009	−2.792	−1.978	−1.602	−3.456	0.003	−2.792	−1.978	−1.602
LV	−3.091	0.057	−4.200	−3.175	−2.729	−3.186	0.005	−2.792	−1.978	−1.602
RO	−5.478	0.000	−2.792	−1.978	−1.602	−5.104	0.000	−2.792	−1.978	−1.602
SI	−1.946	0.053	−2.792	−1.978	−1.602	−6.203	0.000	−2.792	−1.978	−1.602
SK	−3.802	0.001	−2.792	−1.978	−1.602	−3.48	0.003	−2.792	−1.978	−1.602

Notes: Annual data, sample period: [years]. The table reports *t*-statistics and *p*-values for Augmented Dickey–Fuller unit root tests applied to the first differences in each series. The ADF regressions include a [constant/constant and linear trend]. The maximum lag length is set to *p*max = [X] annual lags; the optimal lag for each country–variable combination is chosen by [AIC/SBIC]. "Test critical values" refers to MacKinnon critical values at the 1%, 5%, and 10% significance levels. The null hypothesis is that the series has a unit root.

Table A2. Granger causality between variables.

State	F-Statistic	Prob.	F-Statistic	Prob.	F-Statistic	Prob.	F-Statistic	Prob.
	Null Hypothesis 1 GHG Does Not Granger-cause GDP		**Null Hypothesis 2 GDP Does Not Granger-cause GHG**		**Null Hypothesis 1 GHG Does Not Granger-cause NREN**		**Null Hypothesis 2 NREN Does Not Granger-cause GHG**	
EU	4.20498	0.0722 *	4.7166	0.0588 *	0.18753	0.8337	13.2325	0.0063 ***
BG	1.07546	0.3989	0.03797	0.963	0.60345	0.577	0.79094	0.4956
CZ	9.45588	0.014 **	4.41556	0.0662 *	3.74952	0.0878 *	0.56039	0.5982
HU	1.03124	0.4121	2.63186	0.1511	0.14579	0.8673	0.39949	0.6873
LV	3.72312	0.0888 *	0.65808	0.5516	0.74018	0.516	3.20322	0.1131
RO	0.50978	0.6245	0.25922	0.7799	0.16721	0.8498	0.79046	0.4958
SI	1.31716	0.3356	0.60763	0.575	1.19661	0.3653	0.82088	0.484
SK	1.96377	0.2208	3.98733	0.0791 *	1.59215	0.2788	0.95497	0.4365
	Null hypothesis 1 GHG does not Granger-cause REN		Null hypothesis 2 REN does not Granger-cause GHG		Null hypothesis 1 GDP does not Granger-cause NREN		Null hypothesis 2 NREN does not Granger-cause GDP	
EU	0.21511	0.8124	6.4152	0.0324 **	3.70938	0.0894 *	4.93222	0.0541 *
BG	1.36257	0.3252	0.07682	0.927	2.67929	0.1474	5.07792	0.0512 *
CZ	6.3943	0.0326 **	7.44955	0.0237 **	1.32413	0.3339	1.99683	0.2164
HU	0.62756	0.5656	1.04566	0.4078	0.574	0.5914	0.48079	0.6402
LV	1.57111	0.2827	0.37123	0.7047	4.59248	0.0617 *	0.08223	0.9221
RO	0.62152	0.5684	2.77646	0.1401	2.13326	0.1996	0.52712	0.6153
SI	0.63477	0.5623	2.56722	0.1565	7.91117	0.0208 **	8.38683	0.0183 **
SK	0.20392	0.821	7.46067	0.0236 **	0.52382	0.6171	0.08311	0.9213
	Null hypothesis 1 GDP does not Granger-cause REN		Null hypothesis 2 REN does not Granger-cause GDP		Null hypothesis 1 NREN does not Granger-cause REN		Null hypothesis 2 REN does not Granger-cause NREN	
EU	1.84461	0.2375	0.14489	0.8681	2.56444	0.1567	14.898	0.0047 **
BG	4.53849	0.063 *	0.16786	0.8493	0.28383	0.7625	0.69189	0.5366
CZ	24.7511	0.0013 ***	3.86522	0.0834 *	0.22812	0.8026	9.88636	0.0126 **
HU	2.69638	0.1461	1.25681	0.35	0.04717	0.9543	0.22337	0.8062
LV	1.141	0.3802	0.72964	0.5204	0.4107	0.6805	3.0435	0.1223

Table A2. *Cont.*

State	F-Statistic	Prob.	F-Statistic	Prob.	F-Statistic	Prob.	F-Statistic	Prob.
	Null Hypothesis 1 GHG Does Not Granger-cause GDP		Null Hypothesis 2 GDP Does Not Granger-cause GHG		Null Hypothesis 1 GHG Does Not Granger-cause NREN		Null Hypothesis 2 NREN Does Not Granger-cause GHG	
RO	3.64044	0.0922 *	0.58676	0.5851	0.38264	0.6976	0.51195	0.6233
SI	4.43024	0.0658 *	0.39567	0.6896	2.91309	0.1306	1.79931	0.2442
SK	4.04314	0.0773 *	6.08659	0.036 **	0.89578	0.4566	3.69028	0.0902 *

Notes: Pairwise Granger causality tests are based on bivariate [VAR/VECM] models estimated for each country/region and variable pair. For non-cointegrated pairs, a VAR in [first differences/levels] with a [constant] is estimated; for cointegrated pairs, a VECM including the error-correction term is used. The maximum lag length is *p*max = [X] annual lags, and the final lag order is selected by [AIC/SBIC]. The null hypotheses are of the form "*X* does not Granger-cause *Y*". Reported F-statistics and *p*-values refer to these non-causality tests. Significance levels are denoted by [* for 10%, ** for 5%, *** for 1%]. Granger causality here is understood in the predictive sense and does not imply structural causality.

Table A3. Statistical indicators of multifactorial equations.

Country/ Region	R-Squared	F-Statistic	Prob (F-Statistic)	Durbin–Watson	Heteroskedasticity Test: White			
					F-Statistic	Prob. F(3,5)	Obs*R-Squared	Prob. Chi-Square
EU	0.969586	53.13263	0.000325	1.417312	2.832866	0.1457	5.66632	0.1290
BG	0.506477	0.736521	0.057374	1.974671	0.027983	0.9929	0.14861	0.9854
CZ	0.969847	53.60718	0.000318	2.066489	1.341111	0.3603	4.01293	0.2601
HU	0.851772	9.577266	0.016293	2.057035	0.774801	0.5561	2.85615	0.4143
LV	0.596598	2.464866	0.017733	1.799740	3.929831	0.0874	6.31975	0.0970
RO	0.564876	0.957491	0.048053	1.457129	0.643464	0.6195	2.50686	0.4741
SI	0.674852	3.459208	0.097501	1.256301	1.531240	0.3153	4.30943	0.2299
SK	0.834943	8.430834	0.021173	1.718085	0.661576	0.6103	2.55737	0.4650

Notes: The table reports goodness-of-fit and diagnostic statistics for the multifactor regressions by country/region. R^2 and the F-statistic (with its *p*-value) summarize overall fit and joint significance of the regressors. The Durbin–Watson statistic provides a descriptive check for first-order serial correlation in the residuals (values near 2 indicate no strong first-order autocorrelation). The White heteroskedasticity test is conducted under the null of homoskedastic residuals; the table reports the F-statistic and the Obs*R-squared statistic with their associated *p*-values.

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