Does economic growth reduce or increase pollution? An examination of Croatia's sector-specific Environmental Kuznets Curve

Srdelic, Leonarda and Barisic, Radoslav

December 2024

Does economic growth reduce or increase pollution? An examination of Croatia's sector-specific Environmental Kuznets Curve

Leonarda Srdelić*[a] and Radoslav Barišić[b]

[a]*Institute of public finance, Zagreb, Croatia*
[b]*Faculty of Economics & Business, University of Zagreb, Croatia*

December, 2024

Abstract

This paper investigates the existence of sector-specific Environmental Kuznets Curves (EKC) in Croatia from 1995 to 2021. Using Autoregressive Distributed Lag (ARDL) and Error Correction Models (ECM), the relationship between greenhouse gas (GHG) emissions and Gross Domestic Product (GDP) is analysed across key climate-policy relevant sectors (CPRS). A stable long-term relationship with significant short-term adjustments was found in the energy-intensive sector, which is regulated under the European Union Emissions Trading System (EU ETS). Long-term cointegration, but with non-significant short-term adjustments, was observed in the buildings, transportation, and utility/electricity sectors. Among sectors with a significant long-term relationship, an inverted U-shaped Environmental Kuznets Curve (EKC)—where emissions initially rise and then, after reaching a certain GDP threshold, decline—was identified in the buildings and energy-intensive sectors. In contrast, a U-shaped relationship was found in the utility/electricity sector, where emissions initially decrease but start to increase again as GDP grows. The transportation sector shows a positive linear relationship with GDP, with emissions rising consistently with economic growth, highlighting the need for targeted interventions like carbon pricing. Conversely, the fossil fuel sector shows no significant GDP-emissions relationship, pointing to external factors like geopolitical risks as primary influences.

Keywords: Environmental Kuznets Curve (EKC), greenhouse gas emissions (GHG), climate- policy relevant sectors (CPRS), European Union Emissions Trading System (EU ETS), Croatia.

JEL: Q53, Q56, O11.

* *Corresponding author*
Email address: `leonarda.srdelic@ijf.hr`

1 Introduction

The interaction between economic growth and environmental quality remains a pivotal area of research, sparking debates on the sustainability of economic development models. Seminal works by Simon Kuznets and Gene M. Grossman & Alan B. Krueger have laid foundational theories in this field. Kuznets, in "Economic Growth and Income Inequality," hypothesises that in the early stages of economic growth, income inequality tends to widen due to rapid industrialisation and urbanisation. This phase is characterised by significant shifts in population and industry that favour higher-income groups. However, as a country matures economically, factors such as political interventions, demographic changes, and the levelling influence of urban populations begin to narrow this inequality (Kuznets, 1955). Grossman and Krueger expand this inquiry into the environmental arena, and reveal a pattern where environmental quality initially deteriorates with economic growth but improves after reaching a certain income level, forming an inverted U-curve. The critical income levels for these turning points vary but are generally below 8,000 per capita. This research suggests that the relationship between economic development and environmental health is not linear or solely negative, highlighting the importance of economic growth for environmental protections once certain thresholds are surpassed (Grossman & Krueger, 1995).

Building upon this conceptual framework, the Environmental Kuznets Curve (EKC) hypothesis has been extensively tested, including within the Croatian context. Ahmad et al. (2016), who analysed the period from 1992 to 2011, provide empirical support for the EKC in Croatia, showing a long-run inverted U-shaped relationship between CO_2 emissions and economic growth, indicating that after reaching a certain level of economic output, further growth leads to environmental improvements. However, studies like those by Škrinjarić (2019) and Zmajlović and Pavelić (2019) suggest that the relationship is not uniform across all pollutants or waste outputs, with no clear EKC pattern found in all cases.

This paper contributes to the existing literature by applying a sector-specific approach to examine the EKC in Croatia, rather than relying solely on aggregate national data. This method enables a detailed assessment of the impact of environmental policies at the micro-level, pinpointing sectors that are particularly responsive to these policies. The core objective is to identify sectors in need of stricter environmental controls or enhanced mitigation strategies. Up to our knowledge, it is the first attempt to test sector-specific EKC for Croatia.

In assessing the EKC hypothesis across different sectors in Croatia, the Autoregressive Distributed Lag (ARDL) by Pesaran et al. (2001) was conducted to investigate the long-run relationship between greenhouse gas (GHG) emissions and economic growth (GDP) across climate-policy relevant sectors (CPRS), including agriculture, buildings, energy-intensive industries, fossil fuels, transportation, and utility/electricity. Furthermore, to explore how deviations from the long-run equilibrium are corrected over time, an Error Correction Model (ECM) was estimated to capture short-term dynamics. Following the methodology by Ahmad et al. (2016), several diagnostic tests were employed to ensure the robustness and reliability of the models (Breusch-Godfrey, Breusch-Pagan, Ramsey RESET, Jarque-Bera, CUSUM and CUSUM of Squares).

Studying Croatia's sector-specific EKC is internationally significant due to its unique position as a post-socialist transition economy that joined the European Union in 2013 and the EU ETS. Croatia's experience offers insights into managing economic growth alongside environmental sustainability, particularly relevant for other post-socialist nations in Eastern Europe, such as Bulgaria, Romania, and the Baltic states. These countries share similar economic structures and challenges, including industrial modernisation and integration into the EU's regulatory framework.

Additionally, Croatia's thriving tourism industry, a major contributor to its economy, provides a model for Mediterranean and other coastal nations dependent on tourism, such as Greece, Spain, and Portugal. These nations face the challenge of maximising tourism's economic benefits while mitigating its environmental impacts. Croatia's journey in aligning with EU environmental standards provides a model for how these nations can balance economic development with ecological commitments like those under the Paris Agreement.

The paper is organised as follows. Section 2 outlines the methodology, detailing the data and variables specification and the empirical strategy used to assess the EKC hypothesis across various sectors in Croatia. Section 3 presents the results of the analysis, highlighting sector-specific findings. Section 4 includes a robustness check, ensuring the reliability of the results through various statistical tests. Finally, Section 5 summaries the key findings and concludes with policy recommendations and suggestions for future research.

2 Methodology

2.1 Data and Variables Specification

Our analysis of sector-specific Environmental Kuznets Curves (EKC) begins by identifying relevant sectors. Following Battiston et al. (2017), we categorise economic activities into Climate Policy Relevant Sectors (CPRSs). CPRSs are essential for assessing climate transition risks—risks associated with the potential disruptions caused by transitioning to a low-carbon economy. These sectors are integral in evaluating both economic and financial risks for businesses and industries that may not comply with climate and decarbonization targets, such as those established by the Paris Agreement.

The identification of CPRSs is based on several key criteria:

1. Their direct and indirect contributions to greenhouse gas (GHG) emissions.
2. Their significance in the implementation of climate policies, particularly their cost sensitivity to changes in climate policy or regulation, such as the Carbon Leakage Regulation.
3. Their role within the energy value chain.

Using the NACE sector classification as a framework, we identify six primary CPRSs: fossil fuels, utilities, energy-intensive industries, buildings, transportation, and agriculture. These sectors are essential for understanding climate risk assessment and the strategic transition towards sustainable, low-carbon economies.

The CPRS methodology has been utilised in various studies, including those by Battiston et al. (2020), Battiston et al. (2019), Jun et al. (2020), and by financial regulatory bodies to assess climate-related transition risks on financial stability. For instance, the European Central Bank incorporated this methodology into its 2019 Financial Stability Report, which highlighted the exposure of financial institutions to CPRSs (European Central Bank, 2019). Similarly, the European Insurance and Occupational Pensions Authority (EIOPA) used the CPRSs methodology in its 2020 sensitivity analysis report to evaluate transition risks in sovereign bond portfolios (European Insurance and Occupational Pensions Authority, 2020). By adopting CPRS, regulators aim to identify potential vulnerabilities within financial systems arising from disorderly transitions in response to evolving climate policies.

After defining CPRSs, we collect emissions data for these sectors from the United Nations Framework Convention on Climate Change (UNFCCC), measured in millions of metric tonnes of CO_2-equivalent (Table 1). This data is then grouped according to the CPRSs classification. Additionally, we take Eurostat data on annual gross domestic product (GDP) in 2015's chain-linked volumes, measured in millions of euros.

Table 1: Mapping of CPRS, EUROSTAT NACE, and UNFCCC Classifications

CPRS	EUROSTAT NACE	UNFCCC
Agriculture	A01, A02, A03	3 Agriculture
Buildings	F, L68	1.A.4.a Commercial/Institutional 1.A.4.b Residential
Energy-intensive	C10-C12, C13-C15, C20, C21, C22, C23, C24, C25, C26, C27, C28, C31-C32	1.A.2 Manufacturing Industries and Construction 2 Industrial Processes and Product Use
Fossil fuel	B, C19, D35, H49, H50	1.A.1.b Petroleum Refining 1.A.1.c Manufacture of Solid Fuels and Other Energy Industries
Transportation	H49, H50, H51, H52, H53	1.A.3 Transport
Utility/electricity	D	1.A.1.a Public Electricity and Heat Production

2.2 Model

The Environmental Kuznets Curve (EKC) general form can be expressed as:

$$GHG_{it} = \beta_0 + \beta_1 GDP_t + \beta_2 (GDP_t)^2 + \epsilon_i \quad (1) \tag{1}$$

where GHG_{it} represents the dependent variable indicating the total emissions for a specific sector i and time period t, GDP_i is the independent variable reflecting the economic growth, and $(GDP_t)^2$ is added to capture the potential non-linear effects. ϵ_i is a white noise error term, with properties ensuring that it does not follow a predictable pattern and does not systematically influence the dependent variable, thus allowing for more accurate identification and assessment of the main effects within the model.

The coefficients β_1 and β_2 are pivotal in determining the shape of the curve: β_1 captures the initial linear impact of economic activity on emissions for the sector, while β_2, being the coefficient of the quadratic term, is essential for identifying the presence of an inverted U-shape as per the EKC hypothesis for each sector. If $\beta_1 = \beta_2 = 0$, it indicates a constant relationship. If $\beta_1 < 0$ and $\beta_2 = 0$, or $\beta_1 > 0$ and $\beta_2 = 0$, the relationship linearly decreases or increases, respectively. For $\beta_1 < 0$ and $\beta_2 > 0$, there is a U-shaped relationship, and for $\beta_1 > 0$ and $\beta_2 < 0$ it forms an inverted U-shape, typical of the EKC (Ahmad et al., 2016). The turning point, or peak, of real income is calculated as:

$$GDP = -\frac{\beta_1}{2\beta_2} \quad (2) \tag{2}$$

This equation helps identify the level of economic growth at which the environmental impact begins to decline, in line with the EKC hypothesis.

2.3 Empirical strategy

2.3.1 Dynamic ARDL Bounds testing for cointegration

Many economic and environmental variables, such as GDP and emissions, are non-stationary, meaning their mean and variance change over time. These variables often exhibit upward or downward trends, rather than fluctuating around a fixed mean. Applying traditional regression models to non-stationary variables can lead to spurious results. However, when non-stationary variables share a cointegration relationship—a stable relationship between two or more non-stationary time series over the long term—it suggests that, despite short-term fluctuations, these variables move together in a way that maintains a consistent and predictable relationship over time, i.e., they share a common stochastic trend. In other words, if two or more non-stationary variables are cointegrated, it implies that some linear combination of them is stationary.

In the context of EKC analysis, finding a long-run cointegration relationship would indicate that GDP and emissions maintain a stable equilibrium over time. The Autoregressive Distributed Lag (ARDL) model, introduced by Pesaran et al. (2001), is commonly used to identify such cointegration relationships and to estimate both short-term and long-term effects, as demonstrated by Ahmad et al. (2016).

The ARDL model is applicable when variables are stationary at level, i.e., I(0), purely I(1), or a mixture of both I(0) and I(1). It is rare for variables to require second differencing, i.e., I(2), and particularly in small samples, determining if a variable is second-difference stationary can be challenging. If a variable is found to be I(2), the solution is to take its difference and make it first-difference stationary. This flexibility allows ARDL to handle a wide range of variables, helping to avoid the need for traditional unit root testing. Moreover, ARDL models can be easily estimated even if all explanatory variables are endogenous, which is a significant advantage. Endogeneity is a common problem in econometrics, often leading to biased estimates. One of the most effective ways to address endogeneity is by introducing lags, which make the model dynamic (Borensztein et al. (1998)). The ARDL approach overcomes this issue by incorporating lags into the model, thus addressing endogeneity and ensuring more robust and reliable results.

To analyse the ARDL model and examine cointegration, we initially check for the stationarity of the variables involved. Stationarity in time series signifies that the statistical properties such as mean, variance, and covariance remain consistent over time, indicating the absence of trends, seasonal variations, or cycles within the observed period. We employ the Augmented Dickey-Fuller (ADF) test for testing stationarity, which effectively handles autocorrelation by incorporating lagged terms of the dependent variable and time trends in its regression model.

When a time series is non-stationary, it is standard to apply differencing or transformations like logarithmic and Box-Cox to achieve stationarity. Logarithmic transformations are employed for strictly positive data that exhibits exponential growth or heteroskedasticity; this approach is frequently used in Environmental Kuznets Curve (EKC) analyses to stabilize variance. In cases where logarithmic transformation is insufficient, the Box-Cox transformation, which both stabilizes variance and normalizes distribution, is used.

In this study, we applied logarithmic transformations to GDP and all greenhouse gas (GHG) emissions data, except for those from energy-intensive sectors and fossil fuels. The data from energy-intensive sectors were left unchanged, while GHG emissions from fossil fuels were subjected to Box-Cox transformations. These transformations were essential to achieve stationarity. We then conducted the ADF test to verify stationarity. The results indicated that all variables were stationary at level I(0), except for log-transformed GHG in agriculture, Box-Cox transformed GHG from fossil fuels, and GHG from energy-intensive sectors. For these, we applied first differencing to eliminate trends and achieve stationarity, after which log-transformed GHG from agriculture and Box-Cox transformed GHG from fossil fuels became stationary at I(1). GHG emissions from energy-intensive sectors required second differencing to reach stationarity at I(2). However, if any variable requires differencing to the second order to achieve stationarity, the solution involves taking its first difference to ensure it becomes stationary at the first difference level. Due to the loss of one data value with each differencing, we omitted the first observation from the GDP series to align the time series data for further analysis. The results of the stationarity tests are presented in Table A1.

Another aspect we addressed in our study involves tackling the issue of multicollinearity, which is common in EKC models. To mitigate this, we adjusted the data by subtracting the mean from GDP prior to creating polynomial terms. This method effectively reduces multicollinearity without compromising the integrity of the EKC relationship Kennedy (2008).

In mathematical terms, the ARDL model for the long-run relationship may be expressed as:

$$\begin{aligned}\Delta\mathrm{GHG}_{it} = \alpha_3 + \sum_{k=1}^{n} \beta_{1k}\Delta\mathrm{GHG}_{it-k} + \sum_{k=0}^{n} \beta_{2k}\Delta\mathrm{GDP}_{t-k} + \sum_{k=0}^{n} \beta_{3k}\Delta\mathrm{GDP}^2_{t-k} \\ + \Delta\mathrm{GHG}_{i(t-1)} + \Delta\mathrm{GDP}_{t-1} + \Delta\mathrm{GDP}^2_{t-1} + \epsilon_{3t}\end{aligned} \tag{3}$$

In this equation, $\Delta\mathrm{GHG}_{it}$ represents the change in greenhouse gas emissions for the sector i at time t. The symbols β_{1k}, β_{2k}, and β_{3k} are the coefficients corresponding to the lagged changes in GHG_{t-k}, GDP_{t-k}, and $(\mathrm{GDP}^2)_{t-k}$ respectively, capturing the impact of past values of these variables. The variable k represents the lag order of the variables. The terms GHG_{t-1}, GDP_{t-1}, and $(\mathrm{GDP}^2)_{t-1}$ refer to the lagged levels of greenhouse gas emissions, GDP, and the square of GDP, representing the long-term relationship in the model. The coefficients Δ_1, Δ_2, Δ_3 capture the adjustment dynamics for the lagged levels of these variables. The term ϵ_{3t} is the error term representing unexplained variations. In essence, the equation models how both the short-term changes and the long-term relationships between GDP, its squared values, and GHG emissions influence the overall change in emissions over time.

To conduct the ARDL model analysis and assess cointegration, we first employ vector autoregression (VAR) to determine the appropriate lag length. This selection is guided by the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC/BIC). If the AIC and BIC suggest different lag orders, we select the BIC's recommendation, as it is generally more conservative and better suited for small sample sizes (Lütkepohl, 2005, 2006).

Secondly, we estimate the ARDL model using the identified lag structure. Thirdly, we calculate F-statistics to test the null hypothesis that there is no cointegration. The critical values for this test, as outlined by Pesaran et al. (2001), are set as follows: at the 1% level between 4.13 and 5.00, at the 5% level between 3.10 and 3.87, and at the 10% level between 2.63 and 3.35. If the statistic exceeds the upper bound, it suggests the presence of cointegration. If it falls below the lower bound, there is no cointegration. If the statistic lies between these bounds, the results are inconclusive, necessitating further investigation into the significance of the error correction term (ECT).

2.3.2 Error Correction Model Testing

If cointegration is established, an Error Correction Model (ECM) can be employed to model the adjustments towards long-run equilibrium following short-term deviations. This approach illustrates the rate at which the system returns to equilibrium after a disturbance. To estimate the ECM, the initial step involves calculating the error correction term (ECT), which represents deviations from the long-run equilibrium.

The general form of the ECM can be expressed as follows:

$$\Delta\text{GHG}_{it} = \alpha_3 + \sum_{k=1}^{n} \beta_{1k}\Delta\text{GHG}_{it-k} + \sum_{k=0}^{n} \beta_{2k}\Delta\text{GDP}_{t-k} + \sum_{k=0}^{n} \beta_{3k}\Delta(\text{GDP}^2)_{t-k} + \theta_6\text{ECT}_{t-1} + \epsilon_{3t} \tag{4}$$

In this equation, ΔGHG_{it} represents the change in greenhouse gas emissions for the sector or group at time t. The terms β_{1k}, β_{2k}, and β_{3k} are the coefficients corresponding to the lagged changes in GHG_{it-k}, GDP_{t-k}, and $(\text{GDP}^2)_{t-k}$, capturing the short-run dynamic relationships between these variables. The summation symbols indicate that the model includes multiple lagged values (up to n) of these variables to capture their short-term impacts on the dependent variable. Additionally, the term ECT_{t-1} represents the error correction term, which reflects the deviation from the long-run equilibrium. The coefficient θ_6 associated with ECT_{t-1} shows how quickly the system adjusts back to its long-run equilibrium after a disturbance. The larger the magnitude of θ_6, the faster the adjustment towards equilibrium.

2.3.3 Diagnostic Tests

Finally, to validate the models, we perform several diagnostic tests. The *Breusch-Godfrey* test is used to check for serial correlation in the residuals. To assess whether the model is correctly specified, we apply the *Ramsey RESET* test. The *Jarque-Bera* test is employed to verify if the residuals are normally distributed, while the *Breusch-Pagan* test is used to check for heteroskedasticity in the residuals. Lastly, the *CUSUM* and *CUSUMSQ* tests are conducted to evaluate the stability of the coefficients over time and ensure the overall stability of the model.

3 Results

3.1 ARDL and ECM Results

The ARDL cointegration results are reported in Fig. 1, with model information (F-statistic, R-squared, and adjusted R-squared) available in Table A2. The ECM results, including coefficients and p-values for each sector's equation, are presented throughout the text, and additional model information is available in Table A3.

In the agriculture sector, the ARDL model did not indicate long-run cointegration among the variables (F-stat: 2.17), suggesting the absence of stable long-term equilibrium relationships. However, short-term dynamics assessed through the ECM highlighted significant adjustments towards equilibrium (ECT coeff: 1.0352, p-v: 0.031), indicating a robust short-term correction process despite the long-term absence.

The building sector showed a contrasting scenario. The ARDL results show a strong long-run cointegration (F-stat: 9.32), suggesting that variables move together over a longer period and maintain a stable relationship. However, the ECM results demonstrated that short-term deviations from this equilibrium are not significantly corrected (ECT coeff: 1.4012, p-v: 0.330), pointing to possible delays in adjustments following short-term shocks.

Similar robust long-term relationships were evident in the energy-intensive and utility/electricity sectors, where the ARDL models substantiated long-run cointegration with F-statistics of 6.49 and 11.84, respectively. The ECM for the energy-intensive sector notably corrected deviations efficiently (ECT coeff: 0.3969, p-v: 0.002), whereas the utility/electricity sector showed an insignificant short-term correction mechanism (ECT coeff: 0.0857, p-v:

0.915), suggesting that short-term fluctuations might persist without prompt alignment to the long-run equilibrium.

Conversely, the fossil fuel sector presented a unique case where neither long-term cointegration nor effective short-term error correction was evident (ARDL F-stat: 1.36, ECT p-value: 0.277). This lack of significant relationships in both long and short terms might reflect underlying structural differences in the sector or model specification issues.

Lastly, the ARDL model's high F-statistic of 151.83 (well above the upper bound) confirms a long-run cointegrating relationship among variables in the transportation sector. ECM results reinforce this, with an R-squared of 0.965 (adjusted R-squared: 0.958), indicating the model explains 96.5% of the variance in GHG emissions—a strong fit. The model's overall significance is underscored by an F-statistic of 137.1 (p-v: 3.09×10^{-14}). The ECT coefficient is 0.3448, implying that 34.48% of disequilibrium is corrected each period, though the ECT's p-value of 0.393 suggests this short-run adjustment lacks statistical significance.

3.2 Sectoral EKC Curves: Identifying GDP Turning Points

To understand how GDP impacts each sector based on the quadratic equations, we need to interpret the coefficients β_1 for GDP and β_2 for GDP squared and consider the shape of the curves (U-shaped or inverted-U-shaped), as shown in Figure 1. Moreover, we are now able to calculate the turning points. By examining both the shape of the curves and the calculated TPs, we can observe how different sectors respond to economic growth.

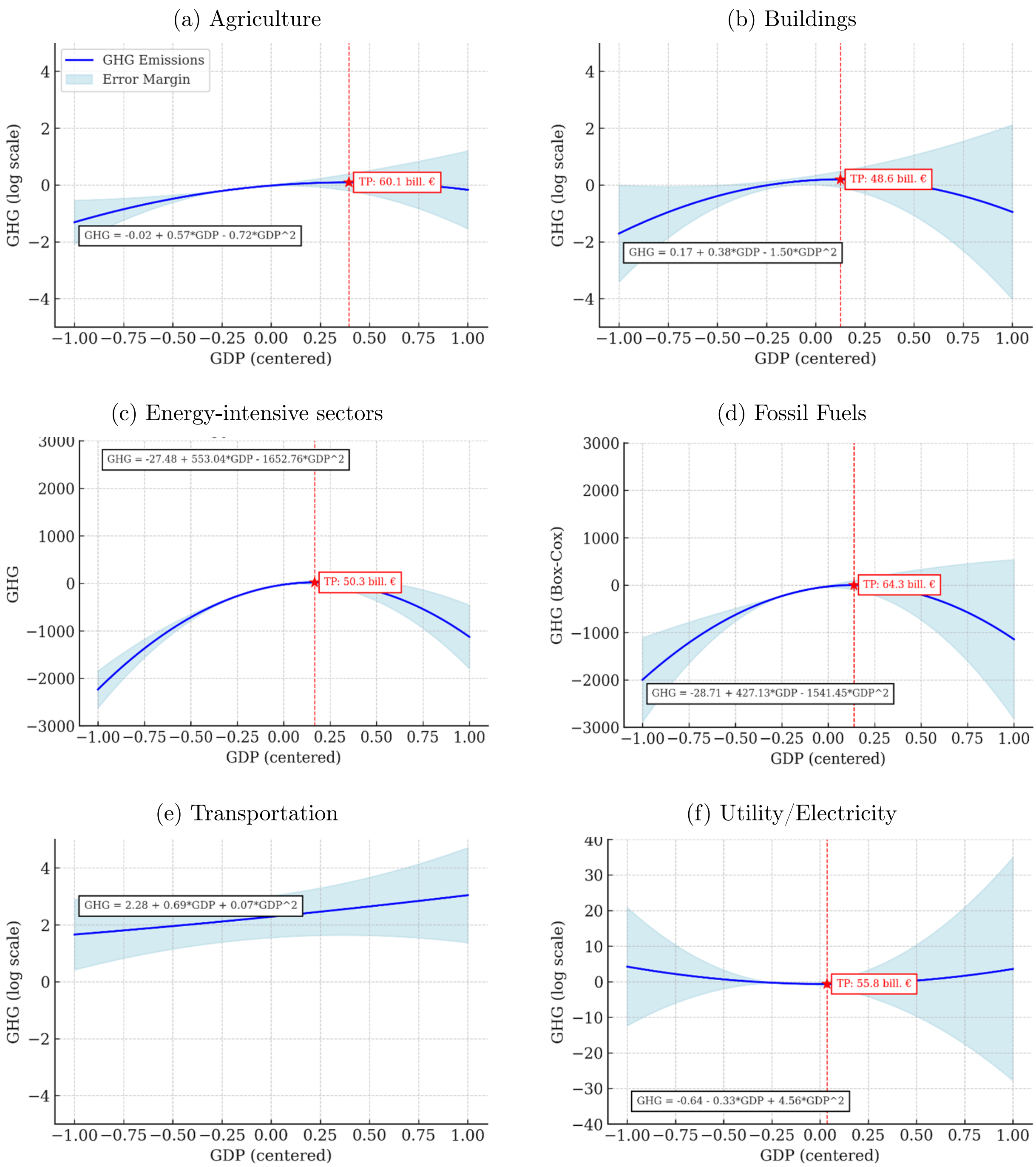
Analyzing each sector's curve, we see that Agriculture, Buildings, Energy-intensive, and Fossil fuels sectors all have negative β_2 coefficients, forming inverted-U-shaped curves. For these sectors, GHG emissions initially rise with GDP growth, reach a peak (the TP), and then begin to fall as GDP continues to grow. For instance, in the Agriculture sector, emissions reach a peak around a GDP of 60.2 billion euros; above this GDP level, emissions are expected to decrease. Similarly, Energy-intensive emissions peak around 50.3 billion euros, suggesting that further GDP growth in this sector may result in lower emissions, possibly due to technological advancements or more efficient energy usage.

In contrast, Transportation and Utility/electricity sectors have positive β_2 values indicating as GDP continues to increase, demands on transportation and utility services grow, leading to renewed emission increases. The Transportation sector also shows a TP at a negative GDP level, indicating emissions increasing steadily with GDP growth, likely driven by rising transportation needs in a growing economy.

3.3 Model diagnostics

Figure 1 illustrates an intriguing trend in GHG emissions variability as GDP increases, particularly for sectors Agriculture, Buildings, Energy-intensive, and Fossil-fuels. For these sectors, we observe emissions initially show a predictable pattern in response to GDP growth, as evidenced by the relatively narrow error bands on the left side of each graph. However, beyond the turning point, the error bands begin to widen significantly. This suggests that, up to a certain point, GDP alone is a strong explanatory variable for emissions in these sectors but beyond the TP, the widening of error bands indicates increased uncertainty or unexplained variability in emissions. In other words, while GDP growth remains a factor, it becomes less sufficient to explain changes in emissions. This suggests that, beyond a certain economic threshold, other factors begin to play a more significant role in influencing emissions levels.

Figure 1: ARDL test results for different sectors



Note: P-values for key terms in each sector's equation: Agriculture (GHG diff lag1: 0.029, GDP: 0.072, GDP^2: 0.502); Buildings (GHG lag1: 0.018, GDP: 0.588, GDP^2: 0.508); Energy-intensive (GHG diff lag1: 0.012, GDP: 0.029, GDP^2: 0.051); Fossil fuels (GHG diff lag1: 0.009, GDP: 0.305, GDP^2: 0.248); Transportation (GHG lag1: 0.172, GDP: 0.004, GDP^2: 0.928); Utility (GHG lag4: 0.080, GDP: 0.967, GDP^2: 0.856). P-values less than 0.05 are marked as significant.

For instance, in Energy-intensive sectors, changes in production processes, shifts toward energy-efficient technologies, or regulatory interventions might contribute to emissions variability. In Buildings, factors such as the adoption of energy-saving technologies, building materials, and new construction standards may become more significant influences on emissions independently of GDP growth.

The widening error margins underscore the limitations of using GDP as the sole explanatory variable for emissions, especially beyond certain economic thresholds. In high-GDP contexts, emissions models could benefit from incorporating additional variables, such as energy efficiency improvements, regulatory impacts, or sector-specific influences, to capture the true dynamics of emissions. This insight suggests that emissions reduction strategies may need to consider these other influencing factors, tailoring approaches to the unique drivers within each sector as GDP continues to grow.

In the Transportation sector, emissions increase in a linear pattern with GDP, with relatively narrow error bands throughout the range of GDP. This steady relationship implies that GDP remains a strong predictor of transportation emissions across all levels of economic growth, with fewer influential external factors impacting emissions. The lack of a turning point in this sector indicates that, unlike other sectors, transportation emissions continue to rise consistently with GDP without significant shifts or increased uncertainty.

The results of the model diagnostic tests are presented in Table A4. In summary, all models passed the diagnostic tests, indicating they are well-specified. The residuals are normally distributed, with no evidence of serial correlation or heteroskedasticity. Additionally, the CUSUM and CUSUMSQ tests, shown in Figure A1, confirm that the models remain stable over time, as both tests fall within the critical bounds.

4 Discussion

The ARDL cointegration test was conducted to investigate the long-run relationship between greenhouse gas (GHG) emissions and economic growth (GDP) across climate policy relevant sectors (CPRS), including agriculture, buildings, energy-intensive industries, fossil fuels, transportation, and utility/electricity. A statistically significant long-term relationship between GDP and sector-specific GHG emissions was identified in the transportation, utility/electricity, energy-intensive, and buildings sectors. In this relationship, transportation and GDP exhibit a positive linear trend, energy-intensive and buildings sectors follow an inverted U-shaped curve, and the utility/electricity sector displays a U-shaped relationship with GDP.

To explore how deviations from the long-run equilibrium are corrected over time, an Error Correction Model (ECM) was estimated to capture short-term dynamics. The ECM accounts for short-run deviations and the speed at which variables return to their long-run equilibrium. A significant Error Correction Term (ECT) was found in both the energy-intensive and agriculture sectors. In the energy-intensive sector, which is covered by the European Union Emissions Trading System (EU ETS), the significant ECT suggests that short-term deviations from the long-run equilibrium are corrected relatively quickly. The EU ETS, as a market-based approach to controlling industrial GHG emissions, imposes a cap on emissions and requires companies in energy-intensive industries to buy or trade allowances for their emissions. The presence of long-term cointegration and meaningful short-term adjustments in this sector indicates that emissions respond effectively to changes in economic activity, likely driven by the EU ETS's carbon pricing mechanism (Dechezleprêtre et al., 2023).

This suggests that policies targeting economic growth and emissions reductions within the framework of the EU ETS could be highly effective in managing emissions in energy-intensive sectors. The system already provides a financial incentive to reduce emissions, and additional short-term interventions—such as increasing the price of carbon allowances or gradually reducing the number of free allowances—could further accelerate emissions reductions. By tightening the allowance cap or adjusting market regulations, policymakers could create stronger incentives for industries to invest in cleaner technologies and energy efficiency.

Indeed, the study by Dechezleprêtre et al. (2023) shows that regulated entities under the EU ETS achieved emissions reductions of roughly 10% without significant negative impacts on economic performance, reinforcing the effectiveness of market-based mechanisms like the EU ETS in driving both emissions control and economic stability. This finding supports the argument that policies targeting economic growth and emissions reductions within the EU ETS framework can be highly effective for managing emissions in energy-intensive sectors.

Another study that provides evidence regarding the role of non-GDP factors like regulatory policies and technological improvements that influence emissions is by Shapiro and Walker (2018) on pollution reduction in U.S. manufacturing. Shapiro and Walker (2018) highlight that the 60% reduction in air pollution emissions from U.S. manufacturing from 1990 to 2008 was primarily driven by within-product reductions in emissions intensity, rather than by changes in output or the composition of products. This trend reflects that as industries reach certain productivity or regulatory thresholds, further emissions reductions are achieved largely through improvements in pollution abatement techniques and regulatory pressures. They argue that environmental regulations, such as those under the Clean Air Act, significantly increased the implicit cost or "shadow price" of pollution for manufacturers, thus encouraging them to adopt cleaner production methods. This further aligns with Škrinjarić (2019) where technological changes (like emission control in refineries) had a substantial impact on SO_2 emissions.

The agriculture sector exhibited significant short-term adjustments in response to economic changes, though it did not display a long-term cointegration with GDP. This indicates that while economic shocks and rapid GDP changes may lead to temporary fluctuations in agricultural emissions, these effects do not persist over the long run. This pattern suggests that emissions in the agriculture sector are more sensitive to immediate economic conditions rather than sustained economic growth. Consequently, implementing targeted, short-term policies—such as promoting sustainable farming practices and improving resource efficiency—could be effective strategies for managing and reducing emissions in this sector.

The transportation sector exhibits a statistically significant positive relationship with GDP, which has important policy implications. The European Environment Agency (EEA) Report (2021) highlights that road transport remains one of the most difficult sources of emissions to manage and that, without aggressive, targeted policy interventions, short-term adjustments in emissions are unlikely to occur.

Supporting this, Andersson (2019) found that in Sweden, carbon pricing for road transport, which had previously been outside the EU ETS, led to notable emissions reductions. This evidence strengthens the argument that expanding carbon pricing to cover road transport across the EU could significantly reduce emissions in this sector.

Similarly, the slow adjustment in the utility/electricity and buildings sectors may point to the need for more aggressive policies promoting energy efficiency and the adoption of renewable energy. These trajectories have been recognized by the EU, which is why the ETS2, a new emissions trading system, was created. ETS2, which will become fully operational in 2027 and operate separately from the existing EU ETS, will cover GHG emissions from fuel combustion in buildings, road transport, and additional sectors (mainly small industries not currently covered by the existing EU ETS).

The fossil fuel sector shows no significant long-term or short-term link between GDP and emissions, likely due to external factors like global market fluctuations, geopolitical instability, and transitional risks from the shift to a low-carbon economy. One critical external factor has been the Russia-Ukraine conflict, which has significantly impacted energy markets. In response to the conflict, the European Union has accelerated efforts to reduce reliance on Russian energy imports, advancing initiatives for energy diversification and the adoption of renewable energy sources. Jin et al. (2023) further substantiate this by demonstrating the significant dynamic spillover effects between geopolitical risk, climate risk, and energy markets. Their study shows that geopolitical events, particularly involving Russia, have an immediate and pronounced impact on energy prices and market stability, suggesting that energy sector emissions are closely tied to external geopolitical factors rather than solely to economic growth metrics. Zhigolli and Fetai (2024) found similar patterns in the Western Balkans, where CO_2 emissions were more influenced by external pressures than by GDP or production levels, supporting the idea that fossil fuel emissions are driven largely by external factors.

5 Conclusions

In light of these external factors, policymakers in Croatia must carefully navigate the challenges of energy security and the low-carbon transition. The war in Ukraine and its associated energy disruptions have highlighted the importance of energy independence and the need to accelerate the transition to renewable energy. However, the path forward is complicated by the transitional risks faced by fossil fuel industries.

To mitigate these risks, Croatia could focus on diversifying its energy sources to reduce its reliance on volatile fossil fuel markets. Increased investments in renewable energy infrastructure and energy efficiency would help buffer the economy from global market fluctuations and support long-term emissions reductions. Additionally, policies that provide clear guidance for industries on how to transition away from fossil fuels—such as phased reductions in fossil fuel subsidies, clearer timelines for decarbonization, and incentives for clean energy investments—would help businesses manage transitional risks more effectively.

To enhance the understanding of the EKC and the effectiveness of policy interventions, future research should expand the study to include additional socio-economic and environmental variables, such as population density, technological innovation, and regulatory changes, using more sophisticated models such as Bayesian Model Averaging (see, for example, Aller et al. (2021); Gravina and Lanzafame (2024)). This approach will help in better identifying the factors influencing the relationship between economic growth and emissions.

References

Ahmad, N., Du, L., Lu, J., Wang, J., Li, H.-Z., & Hashmi, M. Z. (2016). Modeling the CO_2 emissions and economic growth in croatia: Is there any environmental kuznets curve? *Energy*, *109*, 38–48.

Aller, C., Ductor, L., & Grechyna, D. (2021). Robust determinants of co2 emissions [Received 19 October 2020; Received in revised form 22 January 2021; Accepted 26 January 2021; Available online 6 February 2021]. *Energy Economics*, *96*, 105154. https://doi.org/https://doi.org/10.1016/j.eneco.2021.105154

Andersson, J. J. (2019). Carbon taxes and co_2 emissions: Sweden as a case study. *American Economic Journal: Economic Policy*, *11*(4), 1–30. https://doi.org/10.1257/pol.20170144

Battiston, S., Guth, M., Monasterolo, I., Neudorfer, B., & Pointner, W. (2020). Austrian banks' exposure to climate-related transition risk. *Financial Stability Report*, *40*, 31–44.

Battiston, S., Jakubik, P., Monasterolo, I., Riahi, K., & van Ruijven, B. (2019). Climate risk assessment of the sovereign bond portfolio of european insurers. *Financial Stability Report*, 69–79.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, *7*, 283–88. https://doi.org/10.1038/NCLIMATE3255

Borensztein, E., De Gregorio, J., & Lee, J.-W. (1998). How does foreign direct investment affect economic growth? *Journal of International Economics*, *45*(1), 115–135. https://doi.org/10.1016/S0022-1996(97)00033-0

Dechezleprêtre, A., Nachtigall, D., & Venmans, F. (2023). The joint impact of the european union emissions trading system on carbon emissions and economic performance. *Journal of Environmental Economics and Management*, *118*, 102758. https://doi.org/10.1016/j.jeem.2022.102758

European Central Bank. (2019). *Special feature on climate change and financial stability* (Financial Stability Report). European Central Bank.

European Insurance and Occupational Pensions Authority. (2020). *Sensitivity analysis of climate-change related transition risk* (tech. rep.). European Insurance and Occupational Pensions Authority.

Gravina, A. F., & Lanzafame, M. (2024). What's your shape? a data-driven approach to estimating the environmental kuznets curve [Paper presented at the 2024 ADB Economists' Forum and the ERDI seminar]. *SSRN Electronic Journal*.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The Quarterly Journal of Economics*, *110*(2), 353–377.

Jin, Y., Zhao, H., Bu, L., & Zhang, D. (2023). Geopolitical risk, climate risk and energy markets: A dynamic spillover analysis. *International Review of Financial Analysis*, *87*, 102597. https://doi.org/10.1016/j.irfa.2023.102597

Jun, M., Caldecott, B., & Volz, U. (Eds.). (2020). *Assessing forward-looking climate risks in financial portfolios*. Central Banks; Supervisors Network for Greening the Financial System (NGFS).

Kennedy, P. (2008). *A guide to econometrics* (6th). Blackwell Publishing.

Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review*, *45*(1), 1–28.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media. https://doi.org/10.1007/978-3-540-27752-1

Lütkepohl, H. (2006). Structural vector autoregressive analysis for cointegrated variables. *Allgemeines Statistisches Archiv*, *90*(1), 75–88. https://doi.org/10.1007/s10182-006-0222-4

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326. https://doi.org/10.1002/jae.616

Shapiro, J. S., & Walker, R. (2018). Why is pollution from u.s. manufacturing declining? the roles of environmental regulation, productivity, and trade. *American Economic Review*, *108*(12), 3814–3854. https://doi.org/10.1257/aer.20151272

Škrinjarić, T. (2019). Environmental kuznets curve in croatia: Panel data approach with croatian counties. *Journal of Central European Agriculture*, *20*(2), 712–740. https://doi.org/10.5513/JCEA01/20.2.2131

Zhigolli, G., & Fetai, B. (2024). The relationship between co2 emissions and gdp per capita, energy consumption, industrial production in the case of western balkan countries. *Ekonomska misao i praksa*.

Zmajlović, M., & Pavelić, I. (2019). Relation between economic growth and total waste production - testing the environment kuznets curve on the example of croatia. *39th International Scientific Conference on Economic and Social Development*, 504–514.

A Appendices

Table A1: Stationarity test results

Variable	ADF Statistic	p-value	Critical Values	Stationary
log_GHG_Agriculture	-0.9979	0.7540	{’1%’: -3.7112, ’5%’: -2.9812, ’10%’: -2.6301}	FALSE
log_GHG_Buildings	-2.8643	0.0497	{’1%’: -3.8591, ’5%’: -3.0420, ’10%’: -2.6609}	TRUE
log_GHG_Energy_Intensive	-0.6282	0.8645	{’1%’: -3.7112, ’5%’: -2.9812, ’10%’: -2.6301}	FALSE
log_GHG_Fossil	3.6248	1.0000	{’1%’: -3.8092, ’5%’: -3.0216, ’10%’: -2.6507}	FALSE
log_GHG_Transportation	-3.2807	0.0158	{’1%’: -3.7884, ’5%’: -3.0131, ’10%’: -2.6464}	TRUE
log_GHG_Utility	-3.5478	0.0068	{’1%’: -3.8893, ’5%’: -3.0544, ’10%’: -2.6670}	TRUE
log_GDP	-3.8785	0.0022	{’1%’: -3.8893, ’5%’: -3.0544, ’10%’: -2.6670}	TRUE
log_GDP_Squared	-3.8785	0.0022	{’1%’: -3.8893, ’5%’: -3.0544, ’10%’: -2.6670}	TRUE
log_GDP_Cubed	-3.8785	0.0022	{’1%’: -3.8893, ’5%’: -3.0544, ’10%’: -2.6670}	TRUE
log_GHG_Agriculture_Diff	-6.9721	8.610e-10	{’1%’: -3.7239, ’5%’: -2.9865, ’10%’: -2.6328}	TRUE
log_GHG_Energy_Intensive_Diff	-1.3983	0.5831	{’1%’: -3.8591, ’5%’: -3.0420, ’10%’: -2.6609}	FALSE
log_GHG_Fossil_Diff	1.1370	0.9955	{’1%’: -3.8893, ’5%’: -3.0544, ’10%’: -2.6670}	FALSE
GHG_Energy_Intensive	-0.7530	0.8325	{’1%’: -3.7112, ’5%’: -2.9812, ’10%’: -2.6301}	FALSE
GHG_Energy_Intensive_Diff	-1.3822	0.5908	{’1%’: -3.8591, ’5%’: -3.0420, ’10%’: -2.6609}	FALSE
GHG_Energy_Intensive_Diff2	-6.1853	6.310e-08	{’1%’: -3.7529, ’5%’: -2.9985, ’10%’: -2.6390}	TRUE
GHG_Fossil_Boxcox	-1.1252	0.7049	{’1%’: -3.7239, ’5%’: -2.9865, ’10%’: -2.6328}	FALSE
GHG_Fossil_Boxcox_Diff	-9.2429	1.565e-15	{’1%’: -3.7239, ’5%’: -2.9865, ’10%’: -2.6328}	TRUE

A.1 Table A2: ARDL results of F-test for the existence of cointegration

Sector	F-Statistic	R-squared	Adjusted R-squared
Agriculture	2.1666	0.3631	0.1955
Buildings	9.3225	0.8234	0.7350
Energy-intensive	6.4925	0.9735	0.8236
Fossil fuels	1.3643	0.5770	0.1541
Transportation	151.8318	0.9743	0.9679
Utility	11.8393	0.9805	0.8977

Note: The critical value ranges of F-statistics according to Pesaran et al. are 4.13-5.00, 3.10-3.87, and 2.63-3.35 at 1%, 5%, and 10% levels of significance, respectively.

Table A3: The ECM Results of F-test

Sector	F-Statistic	R-squared	Adjusted R-squared
Agriculture	2.3249	0.3286	0.1873
Buildings	19.9623	0.8078	0.7673
Energy-intensive	3.4361	0.4782	0.3390
Fossil fuels	3.2382	0.4324	0.2989
Transportation	137.1493	0.9648	0.9578
Utility	23.9512	0.8569	0.8211

Table A4: Diagnostic Tests Results

Sector	Test	Test Statistic	p-value	F-Statistic	F-test p-value
Agriculture	Breusch-Godfrey	2.9394	0.2300	1.1863	0.3294
	Ramsey RESET	2.4890	0.1146	2.4890	-
	Jarque-Bera	1.0221	0.5999	-	-
	Breusch-Pagan	4.4286	0.3511	1.0748	0.3965
Buildings	Breusch-Godfrey	0.9654	0.6171	0.3563	0.7054
	Ramsey RESET	0.4873	0.4851	0.4873	-
	Jarque-Bera	1.5900	0.4516	-	-
	Breusch-Pagan	7.3271	0.1196	2.0874	0.1225
Energy-intensive	Breusch-Godfrey	1.2822	0.5267	0.4453	0.6501
	Ramsey RESET	4.9988	0.0254	4.9988	-
	Jarque-Bera	0.2717	0.8730	-	-
	Breusch-Pagan	3.0201	0.5545	0.6670	0.6247
Fossil fuels	Breusch-Godfrey	2.0843	0.3527	0.7849	0.4740
	Ramsey RESET	0.0401	0.8414	0.0401	-
	Jarque-Bera	0.6417	0.7255	-	-
	Breusch-Pagan	3.4548	0.4848	0.7917	0.5466
Transportation	Breusch-Godfrey	0.2660	0.8755	0.0968	0.9082
	Ramsey RESET	0.5263	0.4682	0.5263	-
	Jarque-Bera	1.4851	0.4759	-	-
	Breusch-Pagan	6.9203	0.1402	1.9138	0.1474
Utility	Breusch-Godfrey	5.8115	0.0547	2.6784	0.1035
	Ramsey RESET	0.0346	0.8524	0.0346	-
	Jarque-Bera	0.1041	0.9493	-	-
	Breusch-Pagan	2.0626	0.7242	0.4357	0.7810