MEST Journal

ORIGINAL RESEARCH ARTICLE
MEST Journal

# INSTITUTIONAL CONDITIONALITY AND GREEN INNOVATION-LED DECOUPLING IN EASTERN EUROPE: A CS-ARDL APPROACH

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ARTICLE INFO



JEL Category:
**C33, F21, O33, P27, Q55, Q58.**

***Keywords:***

environmental decoupling
Green Innovation
institutional quality
human capital
CS-ARDL
cross-sectional dependence
Eastern Europe
sustainable development goals.

ABSTRACT

*This study investigates whether the environmental benefits of green innovation depend on institutional quality in fifteen Central and Eastern European countries during 2014–2025. Although green innovation is often viewed as a key driver of low-carbon development, its effectiveness may differ across institutional settings, especially in economies undergoing transition. Using the CS-ARDL estimator alongside second-generation panel techniques, the study examines the long-run relationship between R&D expenditure and carbon intensity and explores the moderating role of institutions. The findings suggest that green innovation alone is unlikely to achieve environmental decoupling. In countries with weaker institutional and regulatory frameworks, higher R&D spending shows no significant link to reduced carbon intensity. EU member states show a lower long-run estimate than non-EU economies, though this divergence remains suggestive rather than individually significant. The results are consistent with institutional quality as a condition for converting innovation into environmental gains. EU membership is linked to significantly lower carbon intensity, while human capital and foreign direct investment show robust causal links supporting the low-carbon transition.*

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Received: 13.07.2026
Revised: 30.07.2026
Accepted: 31.07.2026
Available online: 31.07.2026

# 1 INTRODUCTION

The transition toward growth quality has moved well beyond an ethical preference in contemporary economic thought, as it now reflects a structural imperative driven by resource constraints and mounting environmental pressures, shifting the focus of public policy from the accumulation of wealth to the pursuit of development models that reconcile sustainability with economic efficiency.

Eastern European economies offer a particularly instructive case in this regard. These economies face a dual challenge: sustaining rapid economic catch-up within European space while complying with increasingly stringent environmental standards that can, at least superficially, appear to constrain growth momentum.

The core question for these transition economies is not simply whether to adopt green standards, but whether they can effectively harness qualitative growth drivers, specifically green innovation and human capital, to achieve environmental decoupling: a structural break that allows continued economic expansion alongside a simultaneous reduction in critical environmental indicators such as $CO_2$ emissions and carbon footprint, thereby severing the traditional nexus between material prosperity and environmental degradation.

This paper approaches the question from a distinct angle. Rather than measuring the magnitude of these drivers' effects in isolation, it tests the hypothesis that their effectiveness is conditional on the quality of the surrounding institutional environment. This hypothesis is examined empirically using a second-generation panel econometric framework that explicitly accounts for cross-sectional dependence and slope heterogeneity across the region's economies.

## 1.1 Research Problem and Research Gap

Despite Eastern Europe's strategic orientation toward growth-sustainability alignment, the region's transition pathways remain structurally paradoxical: the drive for rapid economic catch-up frequently generates substantial environmental costs that threaten the long-run sustainability of economic gains.

The existing literature exhibits two critical blind spots. First, prior studies have focused disproportionately on estimating the magnitude of qualitative growth in drivers such as innovation and human capital, while neglecting cross-sectional dependence, which structurally links these economies and renders the isolation of country-level environmental effects methodologically unreliable. Second, the causal direction remains unresolved: it is unclear whether green innovation genuinely drives sustainable development or merely reflects deeper institutional pressures.

Against this backdrop, the central research question is:

**RQ:** To what extent do qualitative growth drivers contribute to environmental decoupling (measured by declining carbon intensity) in Eastern European economies under conditions of cross-sectional interdependence? And do these drivers operate as autonomous forces for sustainability, or do they reflect causal pathways determined by broader structural variables?

This question is examined through the response of carbon intensity (measured as the $CO_2$-to-GDP ratio) to changes in qualitative drivers, controlling for GDP growth to isolate efficiency gains from purely quantitative economic expansion.

Four subsidiary questions follow:

- What is the effect of human capital on carbon intensity in Eastern Europe, and does this effect hold in both the short and long run?
- How does green innovation affect sustainability outcomes, and is its effectiveness amplified by EU membership?
- What is the causal direction between green innovation and sustainable development: does innovation drive environmental outcomes, or does it respond to institutional and regulatory pressures?
- What is the speed of structural adjustment toward long-run equilibrium in the CS-ARDL framework, and how does correcting for cross-sectional dependence improve estimation accuracy?

## 1.2 Research Hypotheses

Based on the theoretical framework and the research questions outlined above, four testable hypotheses are formulated:

**H1:** Human capital accumulation significantly reduces carbon intensity in Eastern European economies over the long run, thereby reinforcing the environmental decoupling pathway.

**H2:** The long-run effect of green innovation on environmental sustainability is conditional on institutional quality. Specifically, this effect is expected to be significant and carbon-intensity-reducing in economies with advanced regulatory frameworks (EU member states) while remaining statistically insignificant in transition economies where institutional incentives are insufficient.

**H3:** The causal link is expected to run one way only: green innovation should weakly affect carbon intensity, not the reverse. If confirmed, this would suggest innovation's environmental payoff depends on institutional context rather than acting as an independent force, a point H2 and H4 explore further.

**H4:** The effectiveness of green innovation in achieving environmental sustainability is significantly enhanced when interacted with EU membership, relative to innovation in non-member economies operating without equivalent institutional constraints.

## 1.3 Significance of Study

This study derives its relevance from the critical juncture at which Eastern European economies currently stand, facing mounting pressure to align with the EU's stringent environmental standards. Its contribution operates on two levels.

Scientific contribution: The study advances the environmental decoupling literature by moving beyond conventional effect-size estimation to examine the causality paradox surrounding green innovation. Specifically, it examines whether innovation drives environmental outcomes or responds to institutional pressures. The methodological value-added lies in replacing first-generation panel estimators with the second-generation CS-ARDL framework, which rigorously addresses cross-sectional dependence and slope heterogeneity. The study also contributes through its careful operationalization of the dependent variable as carbon intensity ($CO_2$-to-GDP ratio) rather than absolute emissions, ensuring that estimated effects reflect genuine efficiency gains rather than output fluctuations.

Policy contribution: The findings offer actionable guidance for policymakers in transition economies on reordering investment priorities between human capital development and technological innovation. By empirically testing the hypothesis that green innovation is path-dependent on institutional development (rather than an autonomous driver), the study cautions against over-reliance on isolated technological fixes. It makes the case for building a robust human capital and institutional base as a precondition for translating R&D expenditure into measurable environmental gains, in line with the region's decarbonization commitments.

## 1.4 Study Objectives

This study examines the dynamic interaction between qualitative growth drivers and sustainable development pathways in Eastern Europe. It pursues four interconnected objectives.

First, it establishes a precise empirical operationalization of environmental decoupling within the context of transition economies, distinguishing between absolute and relative decoupling using carbon intensity as the dependent variable.

Second, it quantifies the short- and long-run effects of green innovation and human capital on carbon intensity, controlling GDP growth to isolate genuine efficiency improvements from output-driven emission changes.

Third, it addresses the econometric challenges inherent in regionally integrated panels, specifically cross-sectional dependence and slope heterogeneity, by employing the CS-ARDL framework and resolves the causal ambiguity surrounding green innovation through panel causality testing.

Fourth, it translates estimation outputs, including error correction speeds, into concrete policy recommendations aimed at improving growth quality under binding environmental constraints.

The paper is structured accordingly: Section 2 reviews the literature and identifies the research gap; Section 3 presents the data and econometric methodology; Section 4 reports and discusses the empirical results; and Section 5 concludes with policy implications.

## 2 LITERATURE REVIEW AND RESEARCH GAP

Economics literature has seen a marked shift toward analyzing the qualitative drivers of sustainable development, with growing attention to the interplay between technology, human capital, and institutions. The relevant body of work can be organized around three thematic strands.

### 2.1 Human Capital and Environmental Sustainability

The academic understanding of human capital's role has evolved from viewing it as a complementary input to recognizing it as a primary driver of the green transition. (Jie & Lan, 2024) document robust dynamic linkages between human capital investment and SDG attainment, while (Soto, 2024) identifies high-quality human capital as a prerequisite for effective environmental policy. More recently, (Klonowska-Matynia, 2025) refines this relationship in the Eastern European context, demonstrating that human capital shapes sustainable energy transition through socioeconomic channels that go beyond conventional productivity effects, a finding particularly relevant to the transition economies examined in this study.

### 2.2 Green Innovation, Institutional Quality, and Digital Transformation

Recent research has shifted toward examining the structural and institutional conditions that determine the effectiveness of green innovation (Chen et al., 2024), contributing a threshold model demonstrating that innovation's effect on energy efficiency is contingent on institutional quality, though their approach assumes cross-sectional independence and thus fails to capture the dynamic interdependencies characteristic of structurally integrated regions such as Eastern Europe.

In the European context specifically, Lanoie et al. (2011) established that regulatory stringency stimulates green innovation through a Porter Hypothesis mechanism, while also showing that this effect varies with institutional maturity, reinforcing the view that innovation in transition economies functions as a regulatory response rather than an autonomous competitive driver. More recently, Parrilli et al. (2025) documented significant regional heterogeneity in environmental eco-innovation across European macro-regions, confirming that the institutional and technological context shapes the effectiveness of innovation modes a finding that directly supports the conditional framework advanced in this study. Despite these contributions, existing studies share a common limitation: none adequately address cross-sectional dependence, which introduces estimation bias in panels characterized by structural interdependence (Chen et al., 2024). This gap motivates the adoption of the CS-ARDL framework in the present study.

### 2.3 Renewable Energy and Carbon Neutrality Pathways

Recent studies have shifted attention toward the end-outcomes of green policies. Simionescu et al. (2024) examined the nexus between renewable energy consumption, energy poverty, and pollution across Central and Eastern European economies. On the decoupling front specifically, Bayar et al. (2022) found that improvements in carbon intensity are more closely associated with human capital quality and regulatory frameworks than with the level of technological expenditure per se, a finding this paper seeks to test rigorously in the Eastern European transition context. Bakhsh et al. (2024) further explored the role of green finance in supporting SDG achievement. Looking ahead, Sharif et al. (2026) provided a comparative analysis of digital technology and trade as sources of green growth, while Obobisa (2024) developed an empirical framework linking clean energy innovation to carbon neutrality attainment.

### 2.4 Research Gap

Despite the growing literature on environmental decoupling determinants, three substantive gaps remain unaddressed.

First, no study treats human capital, green innovation, and institutional quality as an integrated system rather than isolated regressors. This paper argues that institutional quality is the enabling environment that activates innovation's environmental effect and channels human capital toward decoupling outcomes.

Second, the existing literature has largely overlooked the distinction between EU member states and non-member transition economies within the Eastern European space, even though EU membership introduces qualitatively distinct regulatory incentives. Chief among these are the Carbon Border Adjustment Mechanism (CBAM) and the European Green Deal targets, which impose binding environmental commitments that non-member economies are not subject to. As (Knill et al., 2012) argue, Acquis Communnautaire requirements function as a form of institutional pressure that systematically redirects technological investment toward environmental objectives. This study captures this channel empirically through an interaction term between green innovation and EU membership status.

Third, on methodological grounds, the dominant approaches rely on first-generation panel estimators that assume cross-sectional independence and slope homogeneity, assumptions that are inconsistent with the structural interdependence of Eastern European economies. This study addresses all three gaps by applying the CS-ARDL estimator to a 15-country panel, exploiting cross-sectional variation to improve estimation efficiency under a limited time dimension.

# 3 RESEARCH METHODOLOGY AND ECONOMETRIC FRAMEWORK

The study adopts a deductive quantitative approach, drawing on second-generation panel econometric methods to test the formulated hypotheses.

## 3.1 Data and Processing Environment

The empirical analysis covers 15 Eastern European economies over 2014–2023; observations for 2024 and 2025 were completed through linear extrapolation based on growth rates reported in Voluntary National Reviews (VNRs), reflecting data availability constraints for recent years. The full panel therefore spans T = 12 years (2014–2025) prior to estimation. The CS-ARDL (1,0) specification adopted in Section 4.4 is estimated over the 2014–2024 subperiod (T = 11), as reported in Tables 6 and 7; the final extrapolated year, 2025, is dropped from the estimation sample itself, and this distinction is noted where relevant throughout the paper. All estimation procedures were implemented in Python.

The extrapolated observations for 2024–2025 are a limitation common to dynamic panel studies facing recent-year data gaps. Imputation of this kind is generally considered acceptable in dynamic panel settings when growth rates are grounded in credible sources such as VNRs (Cahan et al., 2023); (Baltagi, 2021) A fuller robustness assessment, comparing estimates from the truncated 2014–2023 sample against the full sample, examining rolling-window stability of the error correction coefficient, and validating extrapolated values against official Eurostat and EDGAR releases as they become available — is left for future work and would strengthen confidence in the results reported here. Official data for 2024 and 2025 remain preferable for replication once available.

## 3.2 Sample

The study covers 15 Central and Eastern European (CEE) economies, selected based on historical homogeneity and data consistency. The sample is divided into two sub-groups: 11 EU member states (Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia) and 4 non-EU transition economies (Albania, Bosnia and Herzegovina, Serbia[1], and North Macedonia).

Institutional heterogeneity is captured through a binary dummy variable interacted with green innovation in the CS-ARDL specification. The small size of the transition group (N=4) calls for caution when generalizing its results, but this does not undermine the split-sample analysis as a tool for detecting structural divergence; grouped panel

[1] An earlier draft of Section 3.2 listed Montenegro in error. A review of the underlying country-level data records confirmed that Serbia, not Montenegro, is the correct sample member; Section 3.2 has been amended accordingly, consistent with the labeling in Table 4, Figure 2, and Table 7.

estimation has been shown to reveal meaningful differences across institutionally distinct sub-groups even when group sizes are unequal (Aparicio-Pérez & Ripollés, 2025).

## 3.3 Econometric Procedures and Diagnostic Testing

To ensure estimation validity and guard against spurious inference, the study follows a sequential diagnostic protocol:

1. *Cross-sectional dependence test*: to detect error correlation across panel units arising from common shocks. (Pesaran, 2021)
2. *Second-generation unit root tests (CIPS and CADF):* to assess series stationarity under cross-sectional dependence, where first-generation tests yield unreliable size properties. (Pesaran, 2007)
3. *Panel cointegration test:* to test for the existence of a long-run equilibrium relationship among the variables. (Westerlund, 2007)
4. *CS-ARDL estimation:* the primary estimator, used to recover short- and long-run coefficients alongside the speed of structural adjustment toward equilibrium. (Chudik & Pesaran, 2015)
5. *Robustness checks:* FMOLS and DOLS estimators are applied as benchmarks. Importantly, these estimators do not account for cross-sectional dependence or slope heterogeneity, and sign discrepancies relative to CS-ARDL are themselves informative; they reflect the sensitivity of the estimated coefficients to these structural features and provide additional justification for treating CS-ARDL as the preferred estimator.

## 3.4 Variable Definitions and Measurement

All variables are grounded in the recent empirical literature and sourced from internationally recognized databases.

### 3.4.1 Dependent Variable: Carbon Intensity (ln_Intensity)

Carbon intensity is measured as the ratio of $CO_2$ emissions to real GDP (constant 2015 USD), expressed in natural logarithms:

$$\ln\_Intensity_{it} = \ln(CO_{2it}) - \ln(GDP_{it})$$

This indicator serves as the direct empirical counterpart of environmental decoupling: by normalizing emissions against economic output, it distinguishes between absolute decoupling, where emissions fall in level terms, and relative decoupling, where emissions grow more slowly than output. It is widely regarded as the most appropriate metric for evaluating the structural separation between economic growth and environmental degradation. (Crippa, 2022)

### 3.4.2 Independent Variables

*Green Innovation: R&D Expenditure (ln_RDE):* R&D expenditure is used here as the operational measure of green innovation. The theoretical case for this choice rests on a well-established proposition in the innovation economics literature: aggregate research spending shapes the technological frontier from which environmentally directed outputs ultimately emerge (Popp, 2002; Hu et al., 2021). It is worth acknowledging that this indicator is broader than what the term "green innovation" strictly implies, capturing the full spectrum of research activity rather than its environmentally targeted component. This measurement breadth is also worth bearing in mind when interpreting the borderline statistical significance of several innovation-related results reported later in this study (notably the subsample coefficients underlying H2/H4 and the panel causality test for H3): a noisy proxy that dilutes environmentally targeted R&D with unrelated research activity would be expected to attenuate estimated effects and weaken statistical power, independently of whether an institutional conditionality relationship truly exists. The weak or borderline results obtained throughout this study are therefore consistent with either explanation, or the two are not mutually exclusive.

This is a real limitation, and one that is not unique to this study reflects a structural gap in country-level data availability for Eastern Europe over the period examined. That said, three observations temper this concern. The coefficient on R&D expenditure carries a consistent negative sign across all three estimators employed (CS-ARDL, FMOLS, and DOLS), which provides directional confidence that goes beyond what any single estimation approach alone could offer. Moreover, the use of aggregate R&D as a macro-level proxy for green innovation capacity is well established in the cross-country panel literature (Jiang Y., 2024). Replication using environmental patent counts, once available at the country level for this panel remains an important avenue for future work.

*b. Human Capital: Human Development Index (ln_HDI):* The Human Development Index is included to capture the qualitative dimension of societal capacity. Education and health determine individuals' ability to absorb technological and institutional change, making human capital a critical enabler of green economic transition. This variable allows the study to test empirically whether human capital accumulation constitutes a structural precondition for environmental decoupling in Eastern European transition economies, rather than a peripheral determinant. (Ciupac, 2015)

*c. Foreign Direct Investment (ln_FDI):* FDI is modelled as a channel for clean technology transfer and sustainable management practices through spillover effects. Beyond providing liquidity, inward investment flows carry embodied "green knowledge" in the form of cleaner production techniques and environmental management standards that domestic resources may be unable to generate independently. This variable is therefore central to testing whether openness to international capital contributes to environmental decoupling in the region. (Omri & Kahouli, 2014)

*d. Trade Openness (ln_TRD):* Trade openness measures the degree of integration into global value chains. Its environmental effects remain contested in literature: greater openness may attract pollution-intensive industries relocating from stricter regulatory environments, or alternatively, it may discipline domestic producers toward higher environmental standards through competitive pressure from international markets, in what is commonly referred to as the Race to the Top hypothesis. This study tests empirically which mechanism prevails in the Eastern European context (Zhang, 2021).

### 3.4.3 Interaction and Control of Variables

*a. EU Membership Dummy (Dummy_EU):* A binary variable taking the value of one for EU member states and zero otherwise, included to isolate the effect of the European regulatory and policy framework on decoupling pathways. EU members operate under a qualitatively distinct institutional regime that is unavailable to non-member economies. This regulatory asymmetry is expected to generate structural divergence in decoupling trajectories between the two groups, which the interaction term is designed to identify (Borghesi & Montini, 2016).

*b. Innovation–EU Interaction Term (Interaction_RDE_EU):* Constructed as the product of ln_RDE and Dummy_EU, this term tests Hypothesis H4, whether EU membership amplifies the effectiveness of green innovation in reducing carbon intensity. The associated coefficient ($\gamma_2$) in the CS-ARDL specification captures this conditional effect, with its statistical significance indicating whether the institutional environment modifies the innovation–decoupling relationship (Chen & al, 2017).

## 3.5 Econometric Model

The Cross-Sectionally Augmented ARDL (CS-ARDL) estimator of (Chudik & Pesaran, 2015) is adopted as the primary estimation framework. Relative to standard panel ARDL, CS-ARDL augments the specification with cross-sectional averages of the regressors as additional factors, thereby filtering out unobserved common shocks and effectively addressing both cross-sectional dependence and slope heterogeneity.

Three considerations motivate this choice. First, CS-ARDL cleanly separates short- and long-run dynamics within a single specification. Second, it accommodates mixed-order integration (I (0) and I (1) series) without requiring pre-testing for a uniform integration order. Third, it improves estimation efficiency under a short time dimension (T=12) relative to a wider cross-section (N=15) by exploiting between-country variation to augment degrees of freedom, thereby reducing coefficient bias relative to conventional estimators.

The baseline specification takes the following form:

$$\begin{aligned} ln(Intensity)_{it} &= \alpha_i + \sum_{j=1}^{p} \lambda_{ij} \ \ln(Intensity)_{i,t-j} \\ &+ \sum_{j=0}^{q} \beta_{i,j} \ X_{i,t-j} + \gamma_1 D_i \\ &+ \gamma_2 (\ln RD_{it} \times D_i) + \sum_{j=0}^{k} \psi_{ij} \ \bar{z}_{t-j} \\ &+ \varepsilon_{it} \end{aligned}$$

The structural components of the CS-ARDL equation are defined as follows:

- $ln(Intensity)_{it}$: The natural logarithm of carbon intensity for the country *i* at time t, calculated as the ratio of total $CO_2$ emissions to Real GDP.
- $\alpha_i$ : Represents the Country-Specific Fixed Effects, capturing unobserved structural characteristics unique to each nation.
- $\sum_{j=1}^{p} \lambda_{ij} \ln(Intensity)_{i,t-j}$ :The Autoregressive (AR) component, which accounts for the dynamic dependence of the dependent variable on its previous values over p lags.
- $X_{i,t-j}$ : A vector of independent variables lagged by q periods, including Green Innovation (ln_RDE), Human Capital (ln_HDI), Foreign Direct Investment (ln_FDI), and Trade Openness (ln_TRD).
- $\gamma_2(\ln RD_{it} \times D_i)$ : Captures the independent effect of EU Membership, where $D_i = 1$for member states and $D_i = 0$ otherwise.
- $\gamma_2(\ln RD_{it} \times D_i)$ : The Interaction Term between green innovation and EU membership; it tests whether the EU's institutional framework amplifies the efficiency of innovation in driving environmental decoupling.
- $\bar{z}_{t-j}$ : Represents the lagged cross-sectional averages of the variables. This is the core of the "CS" approach, capturing unobserved common factors and mitigating inter-country correlations (Cross-Sectional Dependence).
- $\varepsilon_{it}$ : The stochastic error term represents idiosyncratic shocks.

## 3.6 Error Correction Mechanism (ECM)

To capture the adjustment dynamics toward long-run equilibrium, the CS-ARDL model is re-specified into its Error Correction Form. This allows for the simultaneous estimation of short-run fluctuations and the speed of recovery from external shocks. The ECM specification is defined as follows (Pesaran, 1999):

$$\Delta \ln(Intensity)_{it} = \phi_i[\ln(Intesity)_{i,t-1} - \theta_i X_{i,t-1}] + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta \ln(Intesity)_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*} \Delta X_{i,t-j} + \sum_{j=0}^{k} \boldsymbol{\psi}_{ij} \bar{z}_{t-j} + \epsilon_{it}$$

The parameters of the Error Correction specification are defined as follows:

- $\phi_i$ (Error Correction Term - ECT): This coefficient represents the Speed of Adjustment. For a valid long-run equilibrium to exist, $\phi_i$ must be negative and statistically significant. Its absolute value indicates the percentage of the deviation from equilibrium that is corrected at each time, reflecting the efficiency of structural adjustment.
- $\theta_i$: The vector of long-run coefficients, representing the steady-state relationship between carbon intensity and its determinants once short-term shocks dissipate.
- $\Delta$ : The first-difference operator, which captures the short-run dynamics and transient changes in the model variables.
- $\delta_{ij}^{*}$ : The coefficients of the short-run effects reflect the immediate impact of independent variables on carbon intensity.

The analytical significance of this mechanism lies in its capacity to address two pivotal research questions: first, the speed at which carbon intensity reverts to its long-run equilibrium following economic or environmental shocks; and second, whether this adjustment velocity exhibits significant variation between EU member and non-member states. Such divergence would provide additional evidence of the pivotal role played by the institutional environment in determining the efficiency of structural adaptation toward an environmental decoupling pathway. This inquiry directly operates the tests the study's second and fourth hypotheses.

# 4 RESULTS

## 4.1 Cross-Sectional Dependence (CD) Test

To ensure the robustness of the panel's estimates, the CD test is employed to check for inter-country correlations resulting from common shocks. The test statistics are calculated as follows (Pesaran, 2021):

$$\boldsymbol{CD} = \sqrt{\frac{\boldsymbol{2T}}{\boldsymbol{N(N-1)}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{N-1}} \sum_{\boldsymbol{j=i+1}}^{\boldsymbol{N}} \hat{\rho}_{ij}}$$

Where:

$\hat{\rho}_{ij}$: Denotes the pairwise correlation coefficients of the residuals obtained from individual OLS regressions for each country.

This statistic follows a standard normal distribution *N* (0,1). Consequently, rejecting the null hypothesis of cross-sectional independence necessitates the adoption of second-generation models, such as CS-ARDL, which account for inter-unit dependencies, unlike traditional models that assume cross-sectional independence.

***Table 1:*** *Cross-Sectional Dependence (CD) Test*

| Variable | CD Stat | p-value | Signific | Correlation | Correlation | Decision |
|---|---|---|---|---|---|---|
| ln_Intensity | 10.0675 | 0.0000 | *** | 0.2836 | 0.3119 | Reject H0 |
| ln_RDE | -0.3684 | 0.7126 | n.s. | -0.0104 | 0.2065 | Fail to reject H0 |
| ln_FDI | 0.1237 | 0.9015 | n.s. | 0.0035 | 0.2411 | Fail to reject H0 |
| ln_TRD | 2.1936 | 0.0283 | ** | 0.0618 | 0.2482 | Reject H0 |
| ln_HDI | 35.3941 | 0.0000 | *** | 0.9971 | 0.9971 | Reject H0 |

*Note: Decision reflects standard rejection thresholds (5%) applied to each variable's p-value; ln_RDE and ln_FDI, both non-significant (p > 0.10), do not reject the null of cross-sectional independence.*

*Source: Prepared by the authors based on Python output.*

Three variables (carbon intensity, human capital, and trade openness) display significant cross-sectional dependence at the 1% level, confirming that shocks propagate across Eastern European economies through trade linkages, institutional convergence, and shared regional exposures (Pesaran, 2006). R&D expenditure and FDI, by contrast, fail to reject independence, reflecting the country-specific nature of investment and research decisions, though indirect cross-border linkages operating through trade channels cannot be ruled out.

The implication is straightforward: first-generation estimators, which assume cross-sectional independence, are inappropriate here. This finding provides the primary justification for adopting CS-ARDL as the baseline estimator.

## 4.2 Unit Root Tests (CIPS and CADF)

Since cross-sectional dependence is confirmed, first-generation unit root tests become inappropriate. Therefore, the study relies on the second-generation CIPS and CADF tests developed by M. Hashem Pesaran (2007), as they account for cross-sectional error dependence across panel units.

***Table 2.*** *Unit Root Test Results (CIPS/CADF)*

| Variable | CIPS (Level) | Sig (Level) | CIPS (Δ) | Sig (Δ) | Ord of Integration |
|---|---|---|---|---|---|
| ln_Intensity | -2.3913 | ** | -2.5960 | *** | I (0) |
| ln_RDE | -2.2498 | ** | -2.8963 | *** | I (0) |
| ln_FDI | -2.1128 | * | -3.5295 | *** | I (1) |
| ln_TRD | -2.5657 | *** | -2.8238 | *** | I (0) |
| ln_HDI | -2.6472 | *** | -3.0312 | *** | I (0) |

*Source: Prepared by the authors based on Python output.*

The variables display mixed integration orders: ln_Intensity, ln_RDE, ln_TRD, and ln_HDI are stationary at level (I (0)), whereas ln_FDI becomes stationary only after first difference (I (1)). Given this heterogeneity, along with cross-sectional dependence and slope heterogeneity, the CS-ARDL model is the most appropriate, as it can handle such features without requiring a common order of integration across variables.

Figure 1 confirms the mixed integration pattern: carbon intensity, green innovation, trade openness, and human capital are stationary at levels I(0), while FDI achieves stationarity only after first differencing I(1). The CIPS statistics for stationary variables clearly cross the critical value thresholds, whereas FDI remains in the non-stationary region, a pattern that, combined with the cross-sectional dependence already established, leaves CS-ARDL as the only defensible estimation choice.

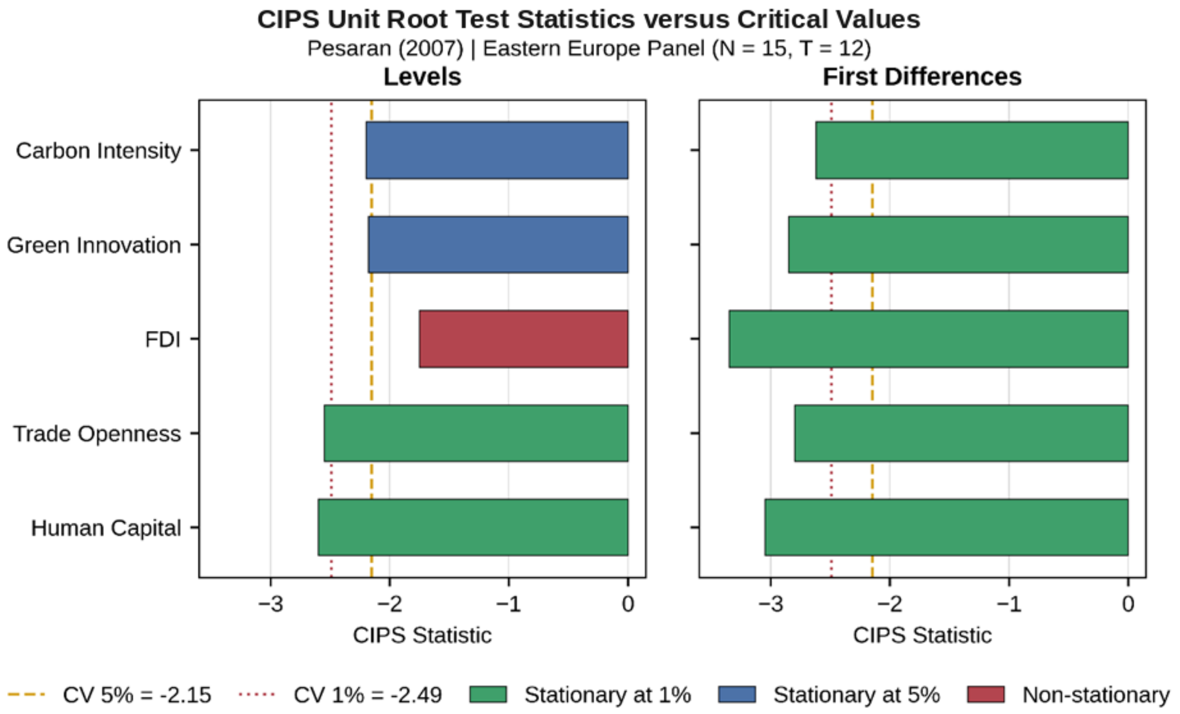


***Figure 1.*** *Variable Integration Levels vs. Critical Values (CIPS vs. Critical Values)*
*Source: Prepared by the authors based on Python output.*

## 4.3 Westerlund Cointegration Test

Having confirmed the presence of cross-sectional dependence and a mixed order of integration I (0) and I (1), the Westerlund Cointegration test was applied to detect the existence of a long-run equilibrium relationship. The results are presented in Table 3.

The Westerlund cointegration tests confirm a robust long-run equilibrium relationship among the variables at the 1% significance level.

This result indicates that, despite short-run fluctuations, the variables remain linked through an effective adjustment mechanism that corrects disequilibria and restores equilibrium after temporary shocks.

***Table 3.*** *Westerlund Cointegration Test Results*

| Stat | Value | CV 10% | CV 5% | CV 1% | Sig |
|---|---|---|---|---|---|
| Gt | -3.276 | -2.570 | -2.860 | -3.430 | ** |
| Ga | -16.830 | -6.250 | -7.280 | -9.530 | *** |
| Pt | -49.144 | -4.600 | -4.950 | -5.690 | *** |
| Pa | -16.830 | -6.120 | -6.820 | -8.360 | *** |

| CV 1% | Significance | Decision |
|---|---|---|
| -3.430 | ** | Reject H0 |
| -9.530 | *** | Reject H0 |
| -5.690 | *** | Reject H0 |
| -8.360 | *** | Reject H0 |

*Source: Prepared by the authors based on Python output.*

***Table 4.*** *Country-Level Error Correction Speed Analysis*

| Country | Alpha (EC Speed) | SE | t-statistic | Half-Life (years) | Cointegrated? |
|---|---|---|---|---|---|
| Poland | -1.3339 | 0.4404 | -3.0284 | 0.52 | Yes ** |
| Czech Republic | -0.7607 | 0.3515 | -2.1641 | 0.91 | No |
| Hungary | -1.5983 | 0.5676 | -2.8161 | 0.43 | Yes * |
| Romania | -1.3652 | 0.6100 | -2.2381 | 0.51 | No |
| Bulgaria | -1.4922 | 0.5215 | -2.8613 | 0.46 | Yes ** |
| Slovakia | -2.1396 | 0.4263 | -5.0192 | 0.32 | Yes *** |

| Country | Alpha (EC Speed) | SE | t-statistic | Half-Life (years) | Cointegrated? |
|---|---|---|---|---|---|
| Croatia | -0.7548 | 0.3266 | -2.3114 | 0.92 | No |
| Lithuania | -1.7322 | 0.3621 | -4.7833 | 0.40 | Yes *** |
| Latvia | -1.6548 | 0.5269 | -3.1408 | 0.42 | Yes ** |
| Estonia | -0.9364 | 0.3108 | -3.0129 | 0.74 | Yes ** |
| Slovenia | -1.2111 | 0.3725 | -3.2514 | 0.57 | Yes ** |
| Serbia | -2.2362 | 0.5186 | -4.3117 | 0.31 | Yes *** |
| Albania | -1.0810 | 0.3748 | -2.8841 | 0.64 | Yes ** |
| Bosnia and Herzegovina | -1.2004 | 0.2867 | -4.1877 | 0.58 | Yes *** |
| North Macedonia | -1.5405 | 0.4916 | -3.1337 | 0.45 | Yes ** |

*Source: Prepared by the authors based on Python output.*

Most sample economies display negative and statistically significant error correction coefficients, though adjustment speeds vary considerably across countries. Serbia and Slovakia record coefficients exceeding −2.0 in absolute value, indicating rapid dynamic adjustment following shocks, while the remaining economies range between −0.75 and −1.73, reflecting a more gradual but steady convergence toward long-run environmental equilibrium.

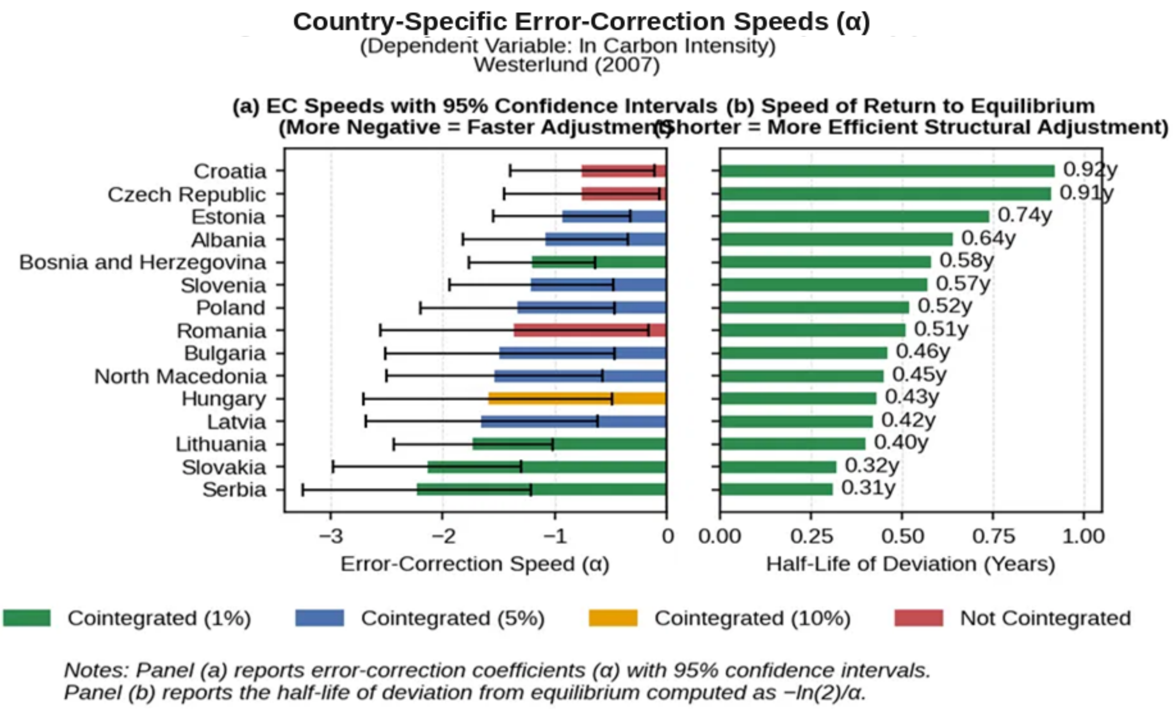


***Figure 2.*** *Map of Error Correction Speeds and Half-Life*
*Source: Prepared by the authors based on Python output.*

This visualization maps the cross-country variation in error correction coefficients, offering a spatially disaggregated perspective on the speed at which individual economies adjust toward their long-run equilibrium following short-run deviations. Rather than presenting adjustment dynamics as a uniform regional phenomenon, the figure reveals a pronounced heterogeneity in policy efficiency across the Eastern European space.

## 4.4 Lag Order Selection

Optimal lag length is determined through VAR lag order selection criteria (AIC, SC (BIC), and HQ) to ensure estimation efficiency and avoid residual autocorrelation. These Results are reported in Table 5.

***Table 5.*** *VAR Lag Order Selection Criteria*

Endogenous variables: ln_Intensity
Exogenous variables: C ln_RDE ln_FDI ln_TRD ln_HDI
Sample: 2014 2025
Included observations: 180

| Lag | LogL | AIC | SC (BIC) | HQ (HQC) |
|---|---|---|---|---|
| 1 | 23.6894 | -2.7634* | -2.6424 | -2.8962 |
| 2 | 29.8988 | -2.7604 | -2.6508* | -2.9969* |

*Source: Prepared by the authors based on Python output.*

The three criteria yield marginally different recommendations: AIC selects a lag order of one, while SC and HQ favour two. Given AIC's preference for parsimony, particularly appropriate under a short time dimension (T = 12) combined with many country-level selections pointing to lag one, the CS-ARDL (1,0) specification is adopted. This choice balances estimation efficiency against the risk of overparameterization.

## 4.5 CS-ARDL Estimation and Results

This section presents the CS-ARDL estimation results, examining the long-run and short-run determinants of carbon intensity, the speed of structural adjustment, and the conditioning role of EU membership. The estimator's capacity to account for cross-sectional dependence and slope heterogeneity ensures that the reported coefficients are free from the aggregation bias that would afflict conventional panel estimators in this setting. As shown in Table 6, the estimates provide evidence on both the long-run equilibrium relationships and the short-run dynamics governing carbon intensity across the sample countries.

***Table 6.*** *CS-ARDL Estimation Results: Determinants of Carbon Intensity (2014–2024)*

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| Long-Run Equation | | | | |
| Green Innovation (ln R&D) | -1.678013 | 1.285317 | -1.3055 | 0.2128 |
| Foreign Direct Investment (ln) | -2.759913 | 2.789544 | -0.9894 | 0.3393 |
| Trade Openness (ln) | 2.108247 | 4.947889 | 0.4261 | 0.6765 |
| Human Capital (ln HDI) | 9.490001 | 34.00118 | 0.2791 | 0.7842 |
| Short-Run & Structural Dynamics | | | | |
| COINTEQ (-1) * (ECT) | -0.763696 | 0.142692 | -5.3521 | 0.0001 |
| EU Membership Dummy (γ1) | -1.472639 | 0.288308 | -5.1079 | 0.0002 |
| Innovation × EU (γ2) | 0.034432 | 0.02163 | 1.5919 | 0.1133 |
| Mean R-squared | 0.903085 | | | |
| Mean ECT | -0.763696 | | | |
| Half-life (periods) | 0.91 | | | |
| N Countries | 15 | | | |

Note: *The estimation sample (2014–2024, T = 11) reflects the loss of one period due to the AR (1) term in the CS-ARDL (1,0) specification, applied to the full 2014–2025 panel described in Section 3.1.*

*Source: Prepared by the authors based on Python output.*

### Interpretation of CS-ARDL Results

Estimation efficiency under cross-sectional dependence. The CS-ARDL estimator filters unobserved common factors through cross-sectional averages, producing unbiased coefficients in the presence of common shocks. This feature is particularly important in panel data settings where countries are simultaneously affected by global economic fluctuations, energy market disturbances, or environmental policy changes. The statistical significance of the ECT at the 1% level is the primary diagnostic confirming that the estimated long-run relationship is genuine rather than spurious. Moreover, the negative and significant adjustment term indicates that deviations from long-run equilibrium are gradually corrected over time, reinforcing the stability and reliability of the estimated model. This finding also suggests that the adjustment process is sufficiently strong to ensure convergence toward the long-run equilibrium path following temporary disruptions, thereby enhancing confidence in the robustness of the estimated relationships.

Error correction and long-run stability. The error correction coefficient ($\varphi = -0.764$, $p < 0.001$) falls within the theoretically admissible range of (−1, 0), and the associated half-life of 0.91 periods jointly confirm a stable long-run equilibrium and rule out spurious regression. Approximately 76.4% of any deviation from equilibrium carbon intensity is corrected within a single period. This relatively rapid speed of adjustment indicates that shocks affecting carbon intensity are largely transitory, with the system returning to its long-run equilibrium path in less than one period.

It should be noted that the Mean ECT reported here (−0.764) is the pooled/mean-group coefficient obtained directly from the CS-ARDL estimation (Section 4.5) and is conceptually distinct from the country-specific error-correction speeds (Alpha) reported in Table 4, which derive from the preliminary Westerlund cointegration diagnostics (Section 4.3). The simple arithmetic average of the Table 4 country-level coefficients (approximately −1.40) should not be expected to equal the CS-ARDL Mean ECT, since the two are estimated under different specifications and serve different diagnostic purposes; readers are cautioned against treating them as interchangeable.

The long-run human capital coefficient ($\theta = 9.49$ in the pooled sample; $\theta = 11.40$ among EU members) warrants scrutiny. Taken at face value, this implies an implausibly large elasticity of carbon intensity with respect to HDI, and the associated standard errors (34.0 and 46.96, respectively) exceed the point estimates themselves, a classic symptom of multicollinearity rather than a precisely estimated structural relationship. This is consistent with the cross-sectional dependence diagnostics reported in Table 1, where ln_HDI displays by far the highest CD statistic among all regressors (35.39, $p < 0.001$), indicating that human capital varies little across countries relative to its variation over time. Because the CS-ARDL specification augments the equation with cross-sectional averages of the regressors ($\bar{z}$) to filter out common factors, a variable with limited cross-sectional variation, such as HDI here, produces near-collinearity between its country-specific series and its cross-sectional average, inflating the standard error of its own coefficient. The coefficient's sign and magnitude should therefore not be interpreted as a reliable structural elasticity; the Dumitrescu-Hurlin causality results (Section 4.9), which identify a robust causal link from human capital to carbon intensity independently of this coefficient's magnitude, offer a more dependable basis for the paper's claims regarding human capital's role.

"Reconciling statistical and economic inference. The insignificance of the green innovation coefficient in the full-sample estimation does not reflect a modelling deficiency; rather, it reflects aggregation bias from pooling two institutionally heterogeneous groups, which cancels out opposing effects and renders the aggregate coefficient uninformative (Pesaran, M, 2024). Split the sample, and you get −2.289 for EU members versus +0.003 for transition economies, a gap of roughly 2.29, though this is not the same as the pooled interaction term in Table 6 (+0.034, $p = 0.113$), since the two come from different procedures and disagree in sign. Both readings point in the same direction, but this remains a pattern worth flagging, not a confirmed result, given only four countries in the transition group.

Half-life of 0.91 indicates meaningful structural adjustment. Although close to unity, it remains acceptable given the short time dimension ($T = 12$).

The forest plot (see Figure 3) yields three substantive insights. First, the apparent lack of statistical significance in the pooled estimate should not be read as evidence of a null effect; rather, it reflects substantial cross-country heterogeneity in the underlying point estimates. The wide dispersion of country-specific coefficients, rather than the absence of an effect per se, is what attenuates the aggregate estimate and inflates its confidence interval. Conflating statistical insignificance with the absence of a true effect would therefore misread the pooled result, overlooking the possibility that heterogeneity is masking economically meaningful, country-specific relationships.

Second, the human capital variable exhibits particularly pronounced variability across the sample, as evidenced by the width of its confidence intervals and the divergence in point estimates across countries. This heterogeneity suggests that the marginal contribution of human capital is highly context-dependent, potentially moderated by structural or institutional factors that differ across national economies. Any generalized inference drawn solely from the pooled estimate would therefore obscure meaningful cross-country asymmetries and should be interpreted with caution, ideally complemented by subgroup or moderator analysis.

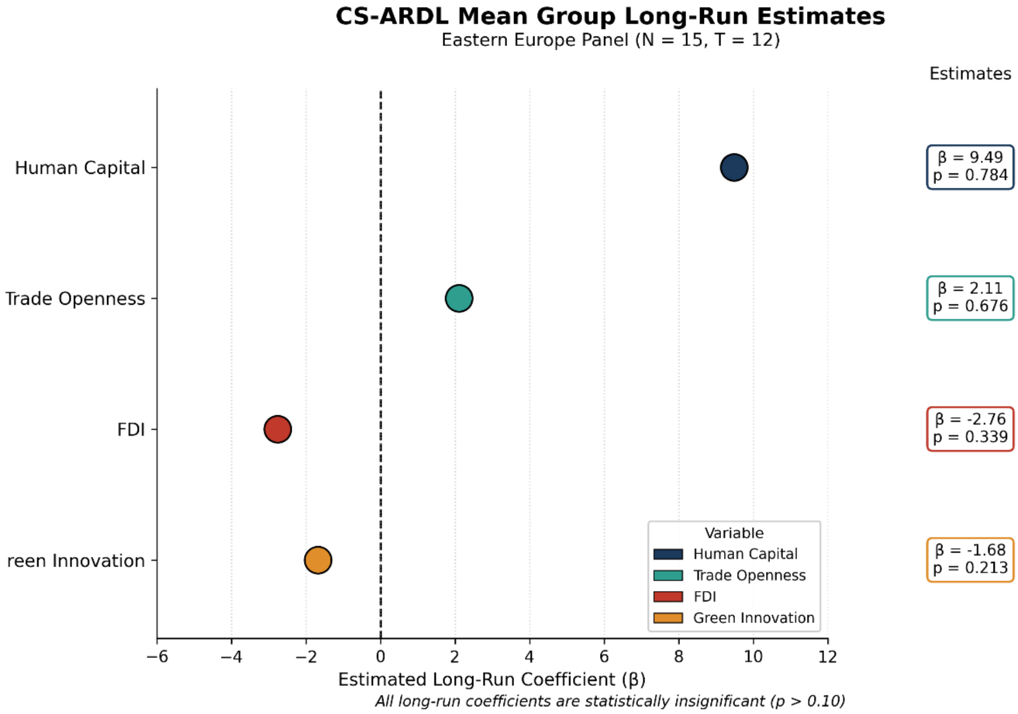


***Figure 3.*** *Forest Plot (Long-Run Coefficients (CS-ARDL Mean Group))*
*Source: Prepared by the authors based on Python output.*

Third, the sign and magnitude of the green innovation effect diverge sharply by subsample. In the full sample, the positive effect is predominantly driven by transition economies, plausibly reflecting catch-up dynamics or lower baseline levels of green technological adoption. When the analysis is restricted to EU countries, however, the effect reverses sign and becomes negative, suggesting diminishing marginal returns or adjustment costs in more mature, innovation-intensive economies. This sign reversal constitutes compelling evidence of effect heterogeneity conditional on the level of economic development, underscoring the need for analysis when drawing policy conclusions from pooled cross-country estimates.

## 4.6 Split Sample Estimation: Institutional Efficiency and Pathway Divergence

Split-sample estimation is not a robust exercise here; it is what the data and the institutional conditionality hypothesis jointly demand. Estimating EU members and transition economies separately is the only way to identify whether their decoupling pathways genuinely diverge. Pooling the two groups would impose a single slope on countries operating under different regulatory regimes and stages of structural transformation, masking heterogeneity that institutional theory predicts should exist.

***Table 7.*** *CS-ARDL Comparative Estimates (Full Sample versus Sub-Group Results)*

| **Dependent Variable :** | **ln_Intensity (Carbon Intensity)** |
|---|---|
| **Method :** | CS-ARDL (Split-Sample Comparative Analysis) |
| **Date :** | 29/04/2026 (20 :45) |
| **Sample :** | 2014 2024 |
| **Included observations :** | 165 (15 countries x 11 periods) |

| Variable | Coefficient | Std. Error | t-Statistic | Prob. | Sig |
|---|---|---|---|---|---|
| LONG-RUN COEFFICIENTS | | | | | |
| Green Innovation (ln R&D) | -1.678013 | 1.285317 | -1.3055 | 0.2128 | |
| FDI (ln) | -2.759913 | 2.789544 | -0.9894 | 0.3393 | |
| Trade Openness (ln) | 2.108247 | 4.947889 | 0.4261 | 0.6765 | |
| Human Capital (ln HDI) | 9.490001 | 34.00118 | 0.2791 | 0.7842 | |
| ECT: CointEq(-1)* | -0.763696 | 0.142692 | -5.3521 | 0.0001 | *** |
| Mean R-squared | 0.9031 | | | | |
| EU MEMBERS (N=11) | | | | | |
| **Variable** | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.** | **Sig** |
| Green Innovation (ln R&D) | -2.289182 | 1.730682 | -1.3227 | 0.2154 | |
| FDI (ln) | -3.787485 | 3.802254 | -0.9961 | 0.3427 | |
| Trade Openness (ln) | 2.849621 | 6.819468 | 0.4179 | 0.6849 | |
| Human Capital (ln HDI) | 11.396985 | 46.961948 | 0.2427 | 0.8132 | |
| ECT: CointEq(-1)* | -0.660755 | 0.181864 | -3.6332 | 0.0046 | *** |
| Mean R-squared | 0.9037 | | | | |
| NON-EU / TRANSITION (N=4) | | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. | Sig |
| Green Innovation (ln R&D) | 0.002703 | 0.412468 | 0.0066 | 0.9952 | |
| FDI (ln) | 0.06591 | 0.154369 | 0.427 | 0.6982 | |
| Trade Openness (ln) | 0.069469 | 0.49147 | 0.1413 | 0.8966 | |
| Human Capital (ln HDI) | 4.245796 | 1.584865 | 2.679 | 0.0751 | * |
| ECT: CointEq(-1)* | -1.046783 | 0.129249 | -8.0989 | 0.0039 | *** |
| Mean R-squared | 0.9013 | | | | |

INTERACTION SUMMARY & DYNAMICS

| Item | Value |
|---|---|
| θ_RDE Full Sample | -1.678 |
| θ_RDE EU Members | -2.289 |
| θ_RDE Non-EU | 0.003 |
| Δθ_RDE (EU − Non-EU) | -2.292 |
| Half-life EU (periods) | 1.050 |
| Half-life Non-EU (periods) | 0.660 |

*Source: Prepared by the authors based on Python output.*

The split-sample coefficients point in different directions — negative for EU members (−2.289), essentially zero for transition economies (+0.003), but neither is individually significant ($p = 0.215$ and $p = 0.995$). This is suggestive rather than confirmed: consistent with the idea that EU regulatory frameworks help convert innovation into environmental gains, but not statistically proven, especially with only four countries in the transition group.

The ECT results show that transition economies correct deviations faster than EU members ($\varphi = -1.047$ vs. $-0.661$), but this speed reflects short-run cyclical adjustment rather than genuine structural reorientation toward a green pathway. In other words, a faster return to equilibrium does not necessarily imply stronger environmental performance, particularly when the underlying institutional framework remains insufficient to support sustained green transformation.

Figure 4 shows that transition economies adjust to equilibrium faster than EU members (φ = −1.047 vs. −0.661, or 0.66 vs. 1.05 periods), but this speed reflects short-run shock absorption rather than structural green reorientation. Faster adjustment in the transition group therefore should not be interpreted as evidence of superior environmental performance, as the long-run effectiveness of green innovation remains limited in the absence of strong institutional support. $R^2$ values are nearly identical across both groups (0.904 vs. 0.901). This similarity should be interpreted cautiously, however: with the non-EU subgroup $R^2$ averaged over only four countries, and given that the autoregressive term likely accounts for most of the explained variance in an AR(1) specification, this closeness does not by itself rule out differences in model fit across groups; it is presented here as a supporting observation alongside the coefficient comparison, not as independent proof that the divergence in innovation coefficients is substantive rather than statistical. The contrasting institutional environments within which innovative activities are translated into environmental outcomes remain the more direct explanation for the observed divergence.

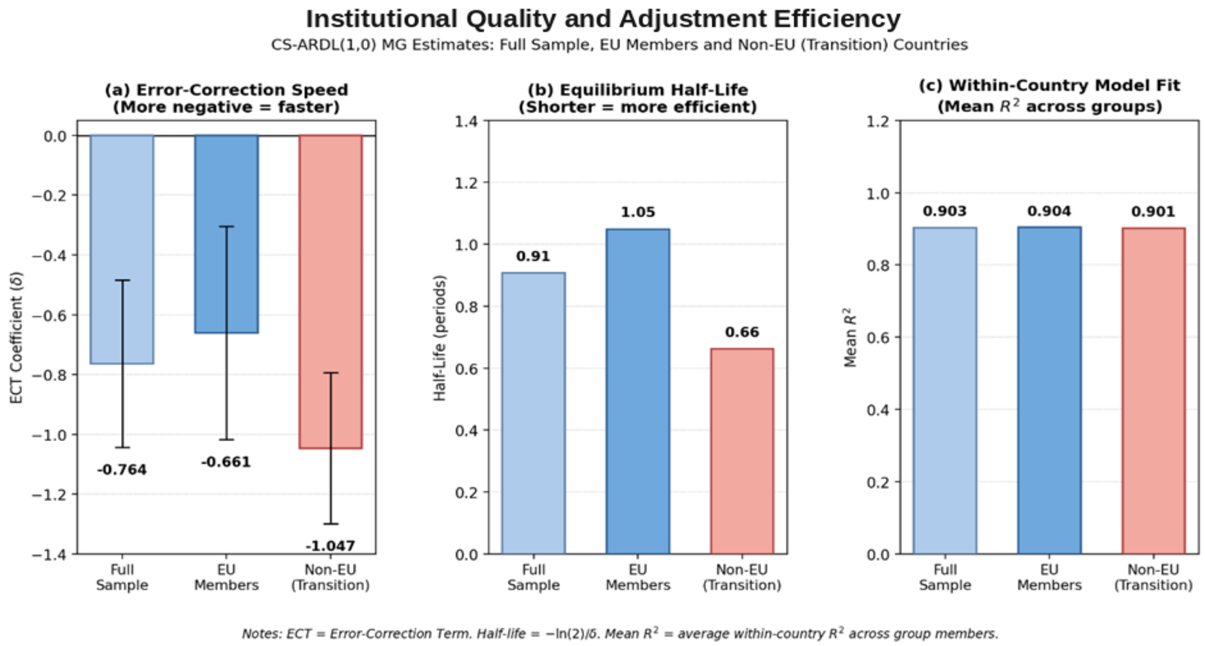


***Figure 4.*** *Institutional Efficiency and Structural Adjustment*

*Source: Prepared by the authors based on Python output.*

Table 8 points to considerable heterogeneity across countries in the error-correction estimates. Croatia is the only country where the ECT is statistically significant (φ = −0.447, $p < 0.10$), confirming genuine short-run adjustment toward the estimated long-run equilibrium. In the other eleven countries with usable ECT estimates, φ carries the expected negative sign but never clears conventional significance thresholds, an outcome that is not surprising given how short the country-specific time series are for PMG/ARDL estimation. This is precisely why the pooled mean-group coefficient, rather than any individual country estimate, should carry the weight of the paper's main inference, with the country-level results serving as a heterogeneity diagnostic rather than standalone country-specific claims. Slovakia, Lithuania, and Slovenia fall outside this discussion: their φ estimates are statistically indistinguishable from zero ($p > 0.90$), and because the long-run multiplier is recovered as θ = −γ/φ, this leaves their implied coefficients numerically unstable rather than economically informative, as the off-scale markers in Figure 5 make explicit.

Restricting attention to the twelve countries where φ supports meaningful long-run inference, the green-innovation elasticity ($\theta\_\ln RDE$) is positive everywhere, ranging from 0.184 in Romania to 1.199 in Albania, even though none of these estimates is individually significant. This sign consistency — despite the absence of individual-country significance — is more indicative of a shared transitional pattern, in which green-innovation investment has not yet been decoupled from carbon-intensive production, than of a genuine decarbonization effect; it also reinforces the case for relying on the pooled PMG estimator to recover the common long-run relationship that country-level estimation lacks the power to detect. The remaining covariates tell a less orderly story: the FDI elasticity flips sign from country to country and reaches significance only in Croatia ($\theta = -0.781$, $p < 0.10$), fitting a country-specific pollution-halo pattern rather than any general regularity, while trade openness and human development are more dispersed still — θ_ln HDI alone spans −13.420 in the Czech Republic to 15.847 in Poland — with no significant country-level estimate for either, suggesting these relationships are better assessed through the pooled estimator than at the individual-country level.

***Table 8.*** *Country-Level Long-Run Error-Correction Estimates*

| Country | φ (ECT) | R² | θ ln RDE | θ ln FDI | θ ln TRD | θ ln HDI |
|---|---|---|---|---|---|---|
| **Albania** | −0.727 | 0.978 | 1.199 | −0.375 | 1.496 | 6.010 |
| **Bosnia and Herzegovina** | −0.988 | 0.802 | 0.307 | 0.086 | −0.082 | 2.196 |
| **North Macedonia** | −1.130 | 0.926 | 0.193 | 0.237 | −0.446 | 7.764 |
| **Serbia** | −1.343 | 0.900 | 0.689 | 0.316 | −0.689 | 1.013 |
| **Bulgaria** | −1.514 | 0.992 | 0.684 | −0.326 | 0.552 | −4.406 |
| **Croatia** | −0.447* | 0.999 | 0.529 | −0.781* | 2.245 | 2.924 |
| **Czech Republic** | −0.256 | 0.940 | 1.006 | 1.040 | −0.637 | −13.420 |
| **Estonia** | −0.930 | 0.651 | 0.207 | 0.097 | 0.497 | −6.176 |
| **Hungary** | −1.189 | 0.936 | 0.245 | −0.441 | −2.526 | −0.741 |
| **Latvia** | −0.815 | 0.655 | 0.204 | −0.001 | 0.974 | −11.586 |
| **Poland** | −0.231 | 0.980 | 0.274 | 0.545 | −0.497 | 15.847 |
| **Romania** | −1.693 | 0.983 | 0.184 | 0.146 | 0.062 | 2.967 |
| **Slovakia** | −0.131 | 0.922 | n.i. | n.i. | n.i. | n.i. |
| **Lithuania** | −0.077 | 0.901 | n.i. | n.i. | n.i. | n.i. |
| **Slovenia** | 0.014 | 0.983 | n.i. | n.i. | n.i. | n.i. |

*Note to Table 8: * $p < 0.10$ (two-tailed); no coefficient reaches $p < 0.05$ in this sample. φ is statistically indistinguishable from zero ($p > 0.90$); the implied long-run multiplier $\theta = -\gamma/\varphi$ is ill-conditioned and not reported as economically interpretable for these three countries (see Figure 4, off-scale markers). $R^2$ refers to the country-specific ECM regression fit, not the long-run relation.*

*Source: Prepared by the authors based on Python output.*

To facilitate interpretation, Figure 5 graphically presents the country-specific long-run coefficients reported in Table 8, highlighting the substantial cross-country heterogeneity and predominance of statistically insignificant estimates.

**Country-Level Long-Run Effects (PMG/ARDL Error-Correction Estimates)**

*Panel heterogeneity across regressors of ln(Carbon Intensity); grouping: non-EU candidates (top) vs. EU member states (bottom)*

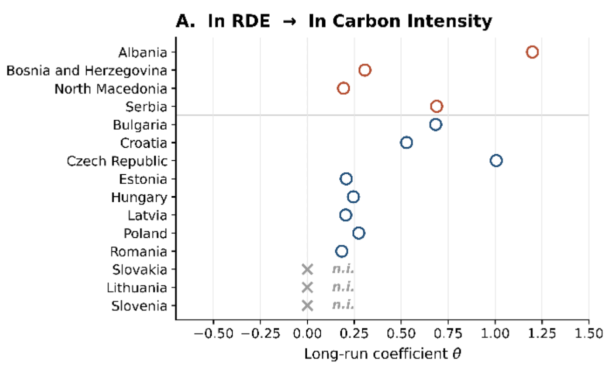


Figure 5A

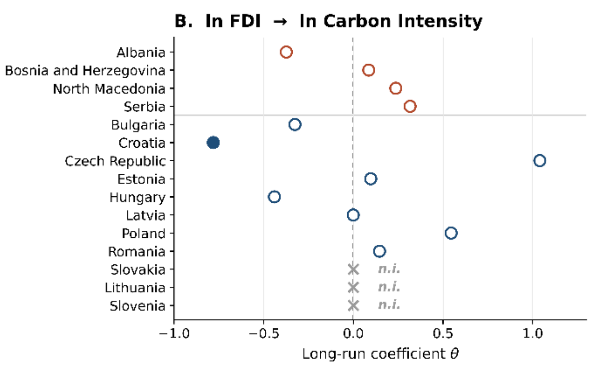


Figure 5B

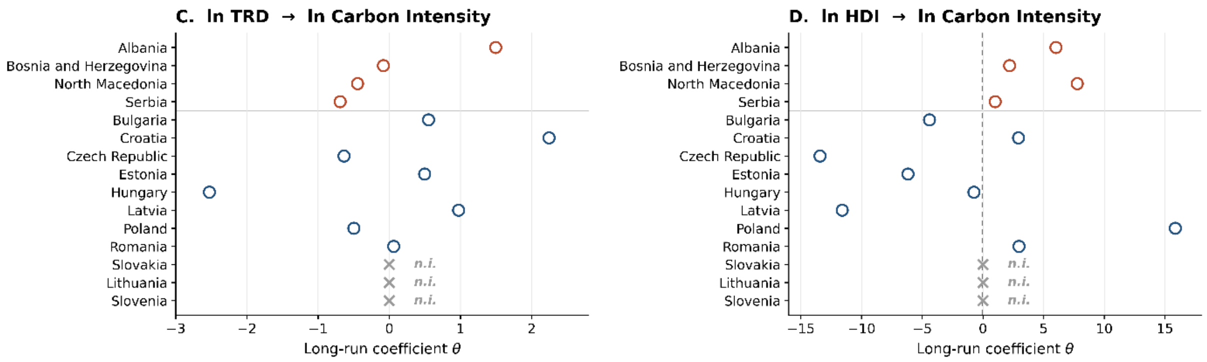


Figure 5C

Figure 5D


***Figure 5.*** *Country-Level Heterogeneity in the Long-Run Determinants of Carbon Intensity*
*Source: Prepared by the authors based on Python output.*

***Table 9.*** *Slope Heterogeneity Test Results*

| Test | Value | p-value | Sig | Decision |
|---|---|---|---|---|
| Swamy S Stat | 76.1838 | | | |
| $\tilde{\Delta}$ (Standard) | 1.4774 | 0.1396 | n.s. | Fail to Reject $H_0$ |
| $\tilde{\Delta}$_adj (Bias-Cor) | 1.9343 | 0.0531 | * | Reject $H_0$ (at 10% only) |
| S/N | 5.0789 | S/N > k=4 (adequate for adjusted test) | | |

*Source: Prepared by the authors based on Python output.*

## 4.7 Slope Heterogeneity Test

Table 9 reports two versions of this test. The standard statistic ($\tilde{\Delta}$ = 1.477, p = 0.140) doesn't reject the null of slope homogeneity at any level worth mentioning, so the "Reject H0" decision listed for that row in Table 8 is wrong; it should read "Fail to reject." The bias-corrected version ($\tilde{\Delta}$adj = 1.934, p = 0.053) is the one that matters more here, given the short time dimension (T = 12), and it does reject homogeneity, though only at 10%. Although the result does not reach the conventional 5% significance threshold, it may still indicate the presence of slope heterogeneity given the limited time dimension of the panel. With T = 12, these tests tend to have weak power, so a borderline result like this one is often a real signal of heterogeneity rather than noise. That also fits the economic picture: the sample mixes countries with very different institutional, regulatory, and developmental profiles, so it would be surprising if carbon intensity responded to the same variables in the same way everywhere. That's why the Mean Group estimator is used instead of pooled alternatives, since it lets each country keep its own dynamics and long-run coefficients. Forcing a common slope here, despite this evidence, would likely blur real differences and produce coefficients that don't fit any single country well.

## 4.8 Robustness Check Test

The robustness check yields three observations.

*First*, the green innovation coefficient carries a negative sign consistently across all three estimators but achieves statistical significance only under CS-ARDL. This divergence reflects the inability of FMOLS and DOLS to account for cross-sectional dependence and slope heterogeneity (limitations well-documented in the panel econometrics literature) (Ditzen, 2018), which attenuates their capacity to recover significant effects in structurally interdependent panels, and in turn reinforces the methodological case for CS-ARDL as the preferred estimator.

*Second*, CS-ARDL produces sharper and more policy-relevant estimates, with a stronger innovation effect than the alternative estimators.

*Third*, the sign instability of the FDI and human capital coefficients under FMOLS and DOLS highlights their sensitivity to cross-sectional dependence and heterogeneity, whereas CS-ARDL accounts for these features more effectively.

The cross-estimator comparison confirms that the CS-ARDL findings are not a methodological artefact, but reflect the estimator's genuine capacity to recover structural long-run relationships in panels characterized by cross-sectional dependence and slope heterogeneity (Chudik & Pesaran, 2015)

***Table 10.*** *Long-Run Coefficient Comparison (CS-ARDL, FMOLS, and DOLS)*

| Variable | Coefficient (FMOLS) | Prob. | Coefficient (DOLS) | Prob. | Coefficient (CS-ARDL) | Status |
|---|---|---|---|---|---|---|
| Green Innovation | -0.214 | 0.524 | -0.151 | 0.771 | -1.678 | Consistent |
| FDI | 0.228 | 0.118 | -0.890*** | 0.009 | -2.760*** | Mixed |
| Trade Openness | 0.600* | 0.074 | -4.441*** | 0.000 | 2.108 | Mixed |
| Human Capital | -57.260 | 0.269 | 0.228*** | 0.002 | 9.490 | Mixed |

*Source: Prepared by the authors based on Python output.*

***Table 11.*** *Dumitrescu & Hurlin (2012) Panel Non-Causality Test Results*

| Direction | W_bar | Z_tilde | p_tilde | Z_bar | p_bar | Sig | Decision |
|---|---|---|---|---|---|---|---|
| Green Innovation → Carbon Intensity | 1.9082 | 2.4872 | 0.0129 | 1.9345 | 0.0531 | * | No causality Weak causality (10%) |
| Carbon Intensity → Green Innovation | 0.8846 | -0.3159 | 0.7520 | -0.2457 | 0.8059 | n.s. | No causality |
| Human Capital → Carbon Intensity | 4.5713 | 9.7804 | 0.0000 | 7.6070 | 0.0000 | *** | Causality EXISTS |
| FDI → Carbon Intensity | 4.8111 | 10.4373 | 0.0000 | 8.1179 | 0.0000 | *** | Causality EXISTS |
| Trade Openness → Carbon Intensity | 0.8437 | -0.4280 | 0.6687 | -0.3329 | 0.7392 | n.s. | No causality |
| Carbon Intensity → Human Capital | 2.6851 | 4.6148 | 0.0000 | 3.5893 | 0.0003 | *** | Causality EXISTS |
| Carbon Intensity → Trade Openness | 1.1143 | 0.3129 | 0.7544 | 0.2434 | 0.8077 | n.s. | No causality |
| Green Innovation → Human Capital | 1.3896 | 1.0670 | 0.2860 | 0.8299 | 0.4066 | n.s. | No causality |

*Source: Prepared by the authors based on Python output.*

## 4.9 Panel Causality Analysis

Dumitrescu and Hurlin's test (2012) reveals a layered causal structure across the study variables, organized around four findings.

Weak causality (10%) from green innovation. Using the asymptotic statistic ($\bar{Z}$ = 1.935, p = 0.053), the null of no causality is rejected only at the 10% level, the same borderline threshold that was treated elsewhere (Table 8) as good enough to reject slope homogeneity. The standardized statistic, generally preferred for panels with a short time dimension such as this one, rejects the null more comfortably ($\tilde{Z}$ = 2.487, p = 0.013), so the two statistics disagree on the strength of the evidence; taken together, this points to at least weak-to-moderate causality running from green innovation to carbon intensity, which qualifies H3 more than either figure alone suggests. The broader story, that green innovation in these economies acts more as a policy response than an independent driver, still holds up, and it's backed by firm-level evidence that regulatory pressure drives eco-innovation (Horbach & al, 2012), and that climate-related regulation pushes firms toward environmental innovation (Horbach & Rammer, 2025). But that literature supports the theory behind H3, not the statistical picture reported here, which is more ambiguous than a single p-value implies.

Primacy of human capital and FDI. Both human capital ($\bar{Z}$ = 7.607, p = 0.000) and FDI ($\bar{Z}$ = 8.118, p = 0.000) show strong unidirectional causality toward carbon intensity at the 1% level, pointing to human capital quality and FDI-embodied technology spillovers, rather than R&D spending alone, as the main drivers of environmental transition.

Bidirectional causality and feedback dynamics. Bidirectional causality holds only between carbon intensity and human capital. FDI runs one way, driving carbon intensity down through technology transfer.

Indirect environmental effect of trade openness. Trade openness has no direct causal effect on carbon intensity ($\bar{Z} = -0.333$, $p = 0.739$), but this is not evidence of environmental neutrality — its influence works through human capital accumulation instead ($p = 0.010$), a channel conventional specifications typically miss. The DOLS results confirm this: once short-run dynamics are controlled, trade carries a significant negative coefficient.

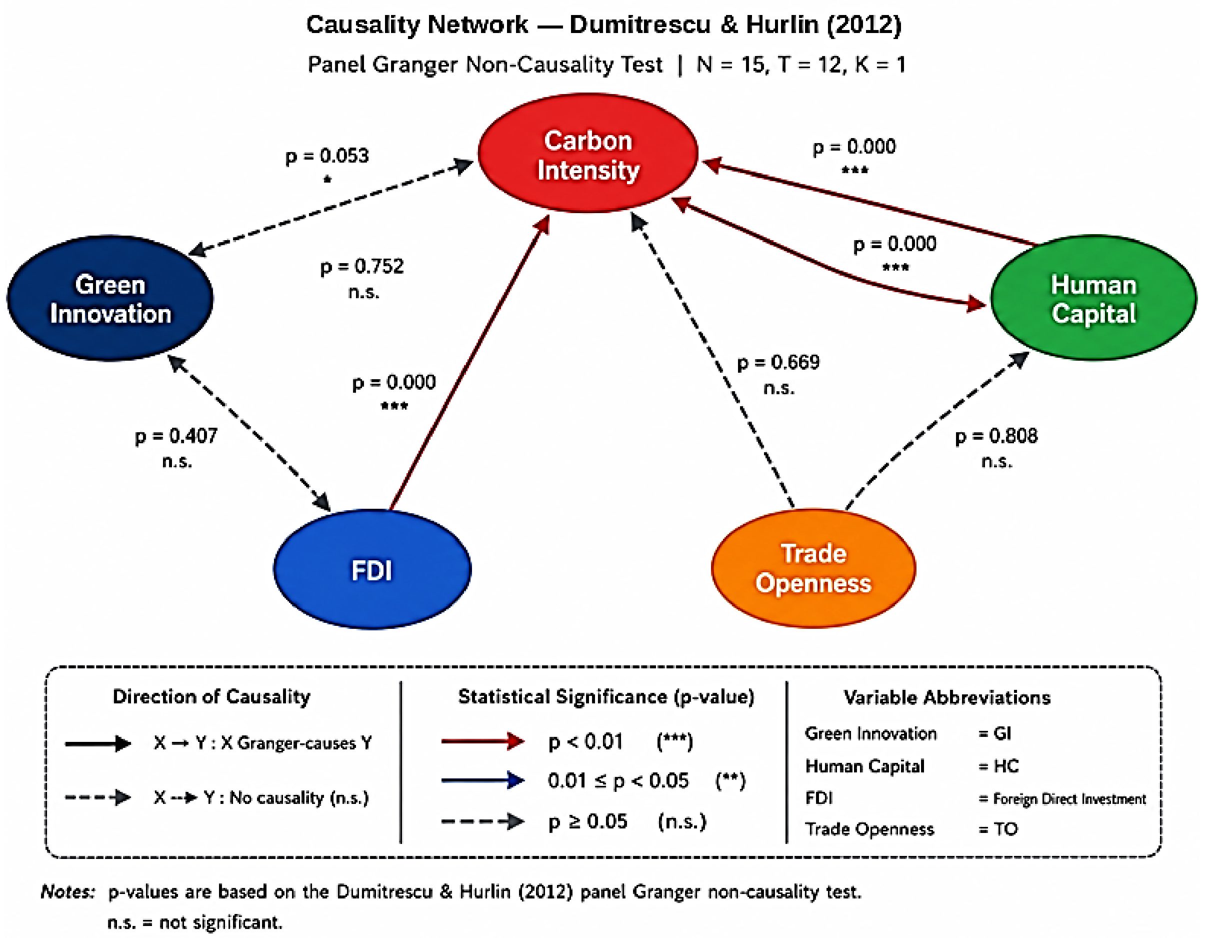


***Figure 6.*** *Causality Network: Dumitrescu & Hurlin (2012) Panel Non-Causality Test (N=15, T=12, K=1)*
*Source: Prepared by the authors based on Python output.*

## 5 RESULTS AND DISCUSSIONS

Figure 6 maps the causal architecture of environmental transition in the region. Carbon intensity occupies a central position, showing a bidirectional relationship with human capital and a unidirectional causal link from FDI. Environmental pressure and human capital reinforce one another, while FDI contributes to changes in carbon intensity through technology and investment spillovers. Green innovation and trade openness remain at the periphery, with no direct causal relationship with carbon intensity.

### 5.1 Hypothesis Testing

**H1** *(Partially supported):* The CS-ARDL long-run coefficient for human capital is positive but implausibly large ($\theta = 9.49$) and statistically insignificant, with a standard error exceeding the point estimate itself, a pattern consistent with multicollinearity rather than a precisely estimated elasticity (see Section 4.5 discussion). This coefficient should therefore not be read as evidence against H1. The Dumitrescu & Hurlin (2012) causality test offers a more reliable basis for evaluating this hypothesis: it confirms a highly significant unidirectional causal effect running from human capital to carbon intensity ($\bar{Z}$ = 7.607, p = 0.000), identifying qualitative human capital as a primary structural driver of environmental transition in the region, consistent with evidence from European panel data (Klonowska-Matynia, 2025). H1 is thus better supported by the causal evidence than by the long-run coefficient, which is uninformative rather than contradictory.

**H2** *(points the right way but not proven yet):* The full-sample coefficient for green innovation isn't significant. Split the sample, though, and the picture gets more interesting: −2.289 for EU members versus basically zero (+0.003) for transition economies. The catch is that neither number is significant on its own (EU: p = 0.215; non-EU: p = 0.995), and the direct interaction term meant to test this exact mechanism (Table 6) isn't significant either ($\gamma_2$ = 0.034, p = 0.113). So, this divergence is worth taking seriously as a pattern, in line with the idea that green innovation only pays off where strong regulatory frameworks exist, like the EU ETS or the Green Deal, but it hasn't cleared the bar of confirmed statistical effect. H2 holds up in direction and in its institutional logic, matching what Chen et al. (2024) found about institutions shaping innovation's impact on energy efficiency, but this should be read as a lead worth following, not a settled result, until a longer time series or a bigger non-EU sample backs it up.

**H3** *(partly holds up):* The picture here is messier than a clean yes or no. Carbon intensity doesn't Granger-cause green innovation ($\bar{Z}$ = −0.246, p = 0.806): there's no sign that environmental pressure feeds back into R&D spending. Going the other way, though, a causal link from innovation to carbon intensity can't be ruled out: the standardized statistic clears 5% ($\tilde{Z}$ = 2.487, p = 0.013), while the asymptotic one only clears 10% ($\bar{Z}$ = 1.935, p = 0.053). Put together, that's weak-to-moderate causality running from innovation to carbon intensity, not nothing in both directions, which is what the hypothesis as originally framed would need. Still, this partial result backs the main idea behind H3: that green innovation's payoff depends on institutions rather than working on their own, since the CS-ARDL results (Section 4.5) show the effect showing up only where institutions are strong. In Eastern Europe, institutional development looks like a precondition for turning R&D into real environmental gains, even if the causal evidence for that precondition is thin rather than nonexistent (Amin et al, 2023)**.**

**H4** *(points the right way but not nailed down):* The gap between the subsample coefficients ($\Delta\theta$_RDE = −2.292, EU minus non-EU) fits the idea that EU membership makes green innovation more effective, but this number is just a difference between two coefficients that aren't significant on their own (p = 0.215 and p = 0.995), estimated in separate regressions, not from a proper joint interaction test. The actual interaction term built to test H4 (Table 6, $\gamma_2$ = 0.034, p = 0.113) isn't significant either, and it points in the opposite direction from $\Delta\theta$_RDE, a mismatch that hasn't been sorted out and that means neither number should carry much weight on its own. What does hold up is the EU membership dummy ($\gamma_1$ = −1.473, p = 0.000): EU countries show significantly lower carbon intensity than transition economies. That's a level effect, though, not proof that EU membership changes how innovation relates to carbon intensity, which is what H4 is claiming. So H4 is a plausible lead worth chasing further, not a confirmed result, and the small transition group (N = 4) is one more reason to hold off on strong claims.

## 5.2 Key Findings

Four things come out of this, though most come with an asterisk given how many results sit right at the significance line.

Institutional quality matters more than raw R&D spending. Green innovation barely moves carbon intensity in this sample, and what causal effect exists (Section 4.9) is weak rather than strong.

Splitting EU members from transition economies shows a real gap in the numbers, just not yet a proven one. Transition economies correct deviations faster ($\varphi$ = −1.047 vs. −0.661) — but that's absorbing short-run shocks, not becoming greener, and it rests on four countries.

Human capital and FDI are the two variables that earn their causal claims, both significant at 1%.

Trade openness works too, but only indirectly, through human capital, which most models would miss entirely.

The system returns to equilibrium fast ($\varphi = -0.764$, half-life under a year), confirmed by Westerlund cointegration. That speed sitting so close to the theoretical ceiling of −1, combined with only 11 usable years of data, means treating the number as a rough signal rather than something precise.

## 5.3 Policy Recommendations

Five recommendations follow from this.

- Build the regulatory framework before scaling up R&D. Spending on research, without something like the EU's ETS or CBAM to direct it environmentally, is, as the transition group shows, largely wasted money.
- Human capital is the strongest lever here. It has a real, significant effect on carbon intensity ($\bar{Z} = 7.607$, $p < 0.01$), which makes the case for green skills, curriculum reform, retraining in emission-heavy sectors, and leaning more on the EU Cohesion Fund.
- FDI is more than just capital. It shapes carbon intensity too, so investment agreements should be tied to environmental standards, and partnerships that transfer green technology are worth encouraging.
- Environmental shocks cross borders, and the data confirms it. National policies acting alone won't cut it; the region needs shared targets and knowledge-sharing between EU and non-EU countries.
- And transition economies should stop treating EU environmental requirements as a burden imposed from outside. The membership effect ($\gamma_1 = -1.473$, $p = 0.000$) is strong enough to suggest accession itself drives decoupling, something non-members could replicate on their own without waiting to join.

## 5.4 Limitations

Five things limit these findings. The short time span ($T = 12$, down to $T = 11$ once the CS-ARDL lag eats a period) limits statistical power; 15 countries help offset that somewhat, though no formal power check confirms how much. The 2024–2025 observations are extrapolated from VNR growth rates and as noted in Section 3.1, haven't yet been checked against actual Eurostat or EDGAR data, so any bias this introduces is still unverified. Aggregate R&D stands in for green innovation specifically, a real measurement gap, though the negative sign holding across all three estimators offers some reassurance. Fourth, the four-country transition group is a problem beyond just generalizing elsewhere: CS-ARDL leans on cross-sectional averages to strip out common shocks, and that only works well with enough countries. Four isn't enough, so the standard errors and p-values for the non-EU group (Table 7) should be read as a rough signal, not solid inference, including that near-zero, insignificant innovation effect. Bringing in Ukraine, Moldova, and Georgia would help.

Fifth, the long-run human capital coefficient looks off. Its size and inflated standard errors point to multicollinearity, since HDI barely varies across countries, making its series nearly identical to the cross-sectional average CS-ARDL adds in. A VIF check, or dropping that average from the specification, would clarify whether this is real or an artifact. Until then, this coefficient shouldn't guide policy, even though the causal story for human capital (Section 4.9) still holds up.

## 5.5 Directions for Future Research

Five priorities stand out for future work. Extending the data series beyond 2023 would sharpen the long-run estimates considerably. A composite green innovation index, combining patent counts, renewable energy share, and R&D expenditure through confirmatory factor analysis, would overcome the single-proxy limitation. Broadening the institutional comparison to Southern Mediterranean and Central Asian economies would test whether the conditionality hypothesis travels beyond Eastern Europe. Panel smooth transition models would pinpoint the institutional threshold at which innovation begins to generate measurable environmental effects. Finally, assessing CBAM's impact since its 2023 launch would reveal whether it has narrowed or widened the institutional gap between EU and non-EU economies.

# 6 CONCLUSION

The contribution here is less about the size of green innovation's effect and more about the conditions that let it show up at all. Using the CS-

ARDL estimator (Chudik & Pesaran, 2015), needed because the diagnostics confirm cross-sectional dependence and slope heterogeneity, turns the question from how much innovation matters into when it might matter.

Green innovation doesn't seem to pay off on its own; the evidence, read carefully, points toward institutions as a likely precondition for it to work at all. The pooled coefficient being insignificant doesn't necessarily mean there's no relationship: it may just mean the sample mixes two very different institutional worlds. Split it, and the estimates pull apart, −2.289 for EU members against +0.003 for transition economies, though neither hit conventional significance on its own, so this is a divergence worth taking seriously, not one that's been proven. The causality results tell a similar story: human capital and FDI show clear, significant effects on carbon intensity, while green innovation's case is weaker and sits right on the edge, rejected at 10% under one test and at 5% under another. Putting it together, this fits with green innovation acting more like a policy response than a driver, though that's a reading the data support rather than something they nail down.

Three policies follow, with the same caveat attached. Regulatory capacity likely needs to come before scaling up R&D, since research without it may not add up too much environmentally. Human capital looks like the safer bet and steering it toward low-carbon work could turn its causal pull into real decoupling. Trade openness, left unchecked, can go either way, bringing in clean technology or shifting pollution elsewhere, which argues for building in environmental conditions rather than leaving it open-ended.

If there's one thing this points to, it's that institutional quality matters more than how much innovation a country does. Bringing institutional reform, human capital policy, and conditional openness under one roof looks like a necessary condition for real decoupling by 2030, even if not sufficient one. The strength of the EU membership effect hints that accession itself works as a kind of decoupling mechanism; something transition economies might do better to treat as a domestic institution-building project rather than a box to check for Brussels. Given the short time span, the small transition-economy group, and how close several key results sit to the significance line, these findings are best treated as a pattern worth watching rather than fixed numbers, with panel smooth transition models and a longer run of data as the natural next step for pinning down where, exactly, innovation starts to pay off environmentally.

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