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A Cointegration Analysis of Real GDP and CO₂ Emissions in Transitional Countries

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Abstract: This paper analyses the relationship between real GDP and CO₂ emissions for 17 transitional economies based on a series of annual data from 1997 to 2014. The analysis was conducted using Dynamic Ordinary Least Squares (OLS) (DOLS) and Fully Modified OLS (FMOLS) approaches. The results clearly suggest the existence of a statistically significant long-run cointegrating relationship between CO₂ emissions and real GDP. A 1% change in GDP leads to around a 0.35% change of CO₂ emission on average for the considered group of countries. Close values of long-run coefficients for all estimations confirm the robustness of the estimated results. The authors state that transitional economies need to follow global policy incentives, and try to implement new mechanisms and instruments for the purpose of reducing CO₂ emissions, such as environmental taxes, emissions-trading schemes, and carbon capture and storage, if they want to achieve future CO₂ emission reductions, while attaining economic growth.

Keywords: real GDP; CO₂ emissions; DOLS; FMOLS; environmental degradation; economic growth; transitional countries

1. Introduction

The relationship between environmental degradation and economic growth is one of the most important areas in the literature of ecological economics, both theoretically and empirically [1–7]. Since the 1980s, the focus of scientific and technical discussion has been placed on the environment and its deterioration, which is a direct consequence of climate change and especially global warming. Environmental degradation is among the most serious problems confronting modern societies [8], and greenhouse gas (GHG) emissions, mainly containing carbon dioxide (CO₂), represent the principal cause of climate change. Sustainable economic development can be achieved by sustainable environmental development in any economy [9]. The relationship between environmental quality and economic growth is important because it allows policy-makers to understand the interaction between the environment and economic growth. The impact to the environment resulting from economic growth is crucial because the function of any economy is to maximize economic growth [1,10].

“The process of economic growth and sources of differences in economic performance across nations are some of the most interesting, important, and challenging areas in modern social science” [11] (p. xv). We can define economic growth as an increase in gross domestic product (GDP) over time, which is one of the main objectives of every national economy. Therefore, the most common parameter to measure economic growth of a country is its GDP growth.

Be that as it may, in the last decade or so, extensive discussions were conducted about the fact that GDP is not the most appropriate indicator of economic performance. A need to develop more adequate indicators to monitor global changes in the 21st century, such as poverty, climate change,

devastation of resources, quality of life, and health status of a nation, has been widely expressed [12]. Economic indicators, such as GDP, in general are not designed to be a comprehensive measure of well-being and prosperity [13–17]. Even Kuznets [18], one of the main creators of GDP, stated that the welfare of a nation can scarcely be inferred from a measurement of national income. However, GDP's clear methodology and a long history of its usage by economists and policymakers alike, make it a widely exploited indicator of economic activity. Therefore, GDP is used in this paper as an indicator of economic growth. "Without measures of economic aggregates like GDP, policymakers would be adrift in a sea of unorganized data" [19] (p. 3).

Abovementioned environmental degradation is caused by factors such as industrialization, population, transportation, poverty, congestion and traffic, soil erosion, exploitation of open access resource due to ill-defined property rights, etc. [20]. Intensive and excessive use of fossil fuels is one of the main reasons for the significant increase in anthropogenic GHG emissions that lead to climate change [21]. Boopen and Vinesh [7] also underline that CO₂ emissions have grown dramatically in the past century because of human activities, primarily by the use of fossil fuels and changes in land use. Generally, producers are prone to using non-renewable sources of energy such as carbon based fossil fuels. Combustion of these fuels produces CO₂ and other GHG emissions as a by-product. GDP grows with the growing increase in production, which consequentially means an increase in the use of fossil fuels and the growth of CO₂ emissions.

One possible solution is to create a low-carbon world economy, which in turn has technological, economic, engineering, and organizational obstacles. The biggest obstacle in creating a global agreement that takes into account the consequences of climate change is the strong negotiating position of countries with great reserves of fossil fuels, such as the United States, Russia, China, Canada, and the countries of the Persian Gulf [22]. Due to different levels of financial and technological development of countries, and different intensities of CO₂ emissions, a global instrument that takes into account all of these obstacles is essential.

The Kyoto Protocol is the first significant global agreement that took into account the characteristics of both developed and developing countries. Adopted in December 1997 as a protocol of the Convention on Climate Change, it came into force in 2005. The Protocol defined specific obligations of the Member States to limit or reduce GHG emissions, and stated that industrialized countries should implement action plans and quantify the reduction of GHG emissions to meet their targets primarily through national measures. Additionally, developed countries were to ensure a transfer of technology and financial resources to developing countries for these purposes. The Kyoto Protocol established three flexible mechanisms to assist countries with the aim of reducing the cost of limiting GHG emissions: (1) Clean development mechanism—CDM, (2) Joint implementation—JI, and (3) Emissions trading—ET [23].

However, the anticipated timeframe for the commitments countries have signed has not generally been fulfilled. The Kyoto Protocol expired in 2012, and its extension to 2020 was adopted at the UN Climate Conference in Doha (COP 18). Partially indeterminate decisions have been adopted concerning financial assistance to transitional and undeveloped countries that are confronted with problems caused by climate change. Another attempt to ensure the functioning of the mechanism for stopping unwanted climate change was held in Paris (COP 21) in 2015. "The Paris Agreement is the first global accord on climate change that contains policy obligations for all countries" [24]. Key elements of the Paris Agreement focused on facilitating the transition between today's policies and climate-neutrality before the end of the century. Regarding the reduction of emissions, governments agreed that a long-term goal is to keep the increase in global average temperature well below 2 °C, relative to pre-industrial levels, with the aim of limiting the increase to 1.5 °C, since this would significantly reduce risks and impacts of climate change. Furthermore, the Paris Agreement underlines the need for global emissions to reach a peak as soon as possible, while undertaking reductions in compliance with the best available science. It is acknowledged that developing countries will take

longer to achieve this [25,26]. A particular challenge is that the Agreement will become operational when at least 55 countries accounting for at least 55% of global emissions ratify it [24].

The majority of studies on the relationship between carbon emissions and economic growth in developing countries are concentrated on Environmental Kuznets Curve (EKC) hypothesis. “Under this hypothesis, environmental degradation increases during the initial stage of economic growth until some threshold level or turning point in relations to income is reached, after which environmental degradation begins to decline” [27] (p. 785). This clearly suggests an inverted U-shape of the economic growth–environmental pollution relationship, and when we observe the existing literature on EKC, it is evident that different methodologies, indicators, and data are used to test its’ validity. Scientific papers that investigate the EKC hypothesis provide a wide range of results that often have diverging conclusions. Nevertheless, only a few research studies have gone the full distance to examine the relationship between CO₂ emissions and economic growth, beyond the postulates of EKC hypothesis [6].

In the process of changing from a centrally planned to a market based economy, “the transitional economies have experienced profound structural changes that continue to influence the evolution of regional CO₂ output” [28] (p. 137). In this paper, the authors try, at least partly, to provide answers about the factors that are underlying the relationship between CO₂ emissions and real GDP in transitional countries. The authors have studied the cointegrating relationship between CO₂ emissions and economic growth for 17 transitional economies (Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Croatia, Georgia, Kazakhstan, Kyrgyzstan, Macedonia (Republic of), Moldova, Montenegro, the Russian Federation, Serbia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan) over the period of 1997–2014. The authors chose the transitional economies because even though there is a vast amount of literature about this relationship, there is not sufficient research on this specific set of countries. Furthermore, the authors are not aware of any recent empirical study that comprehensively examines the long-run relationship between growth and environmental degradation in the countries regarded as transitional according to the most recent classification of United Nations. There is a serious doubt that developing countries have the ability to cope with climate change and disasters because they have weak economic foundations and outdated technology compared to developed countries [29]. This makes transitional economies an interesting research topic.

The empirical analysis in this paper is mostly based on the set of standard panel cointegration tools, such as Pedroni’s cointegration tests and the Fully Modified Ordinary Least Squares (OLS) (FMOLS)/ Dynamic OLS (DOLS) estimators, with two distinctive aspects. First, it is completely based on linear modelling because modelling of non-linear cointegration by simply extending linear to quadratic function is a tremendously popular choice among EKC researchers. However, this does not have strict theoretical grounds. For that reason, as a second aspect, traditional cointegration testing is enriched with the Westerlund approach, which is more flexible in counting the likely structural breaks and cross-sectional dependencies in economic and environmental performances of transition countries, which is often neglected in empirical studies. The results of this paper suggest the existence of a robust and statistically significant long-run cointegrating relationship between CO₂ emissions and real GDP.

The paper is organized in six sections. After the Introduction, Section 2 briefly presents a literature review on the relationship between CO₂ emissions and economic growth, both from a group and individual countries perspective. The data and methodology are discussed in Section 3. Section 4 gives a clear review of the research results. Discussion with policy implications and possible directions for further research is presented in Section 5, while Section 6 concludes.

2. Literature Review

There is a large number of papers empirically examining the issues of the relations between environmental degradation and economic development indicators, and more particularly the EKC hypothesis, using the tools of econometric analysis. Typically, the empirical models analysing EKC assert an indicator of environmental degradation as a dependent variable vis-à-vis indicators of

economic development and their squares (to control non-linearity) as the explanatory variables. One of the first papers to use such a format was [30], which found a significant association between income and environmental quality by applying the parsimonious econometric methodology. It also provided evidence on possible non-linearity in this relation, indicating that most environmental indicators deteriorate initially with a tendency to improve as countries approach middle-income levels.

The later empirical works have increased the complexity of the methodological approaches following the theoretical advances in econometric analysis of time series and especially panel data. The papers dealing with panel data can be roughly categorized with respect to the methodology to those applying panel cointegration analysis and those applying traditional panel estimation techniques. The main advantage of the panel cointegration approach is its focus on the long-run relationships, however, the format of the models limits the number of the accounted variables typically to CO₂ emissions, GDP, and electricity consumption. Lean and Smyth's [31] VECM (Vector Error-Correction Model) analysis for five ASEAN (Association of Southeast Asian Nations) countries over the period 1980–2006 is a typical example of such an approach. Based on quadratic specification, they concluded, among other, that there is a statistically significant non-linear relationship between emissions and economic growth in support of EKC. Arouri et al. [32] provided similar analysis and results for 12 MENA (Middle East and North Africa region) countries over the period 1981–2005. However, having found that single EKC turning points considerably vary across the countries, they expressed concerns regarding the validity of conclusions stemming from the panel analysis. Martinez-Zarzoso and Bengochea-Morancho [33] even extended the functional form to cubic specification in addressing the relationship between CO₂ and GDP for 22 OECD (Organisation for Economic Co-operation and Development) countries for the period 1975–1998. The cubic function indicated that a decline in CO₂ emissions when income is rising can be expected, but only up to a certain level, and then an increase of pollution can be expected again at higher incomes. Kapusuzoglu [34] uses variance decomposition within cointegration analysis to provide similar evidence on the causality from CO₂ emissions to GDP in developing economies, but not in OECD and European countries.

The use of a parsimonious empirical framework combining cointegration analysis and quadratic functional form tends to be a very popular solution in the analysis of non-linear association between CO₂ emissions and GDP in EKC testing. However, such an approach is loosely based on the theoretical grounds and may be a subject of certain critical appraisal in the broader context of non-linear cointegration testing. The theoretical solutions to non-linear cointegration and turning points determination are primarily based on the threshold vector equilibrium correction models (see for example [35]) for their summary. The power of the particular cointegration test in finite samples depends on the class of non-linear relation, and a priori misspecification of the nonlinear model is expected to create distortions in statistical inference [36]. Even in the case that the quadratic form meets the proper specifications, some of the standard parametric tests of cointegration are not straightforwardly applicable [37]. All of these issues are matters of further concern in the case of panel analysis, as the standard panel cointegration testing (described in the methodology section) assumes the use of linear models. It is worthwhile to mention that an extensive search of the literature beyond the subject of EKC testing revealed that cointegration panel analysis based on quadratic modelling is not frequently applied.

The second type of the panel studies, based on the traditional estimation methods, benefits from the greater flexibility in choice of explanatory variables and model specification, yet its focus is on the contemporaneous relationships between variables. For example, Tamazian and Rao [28] provided a comprehensive analysis supporting EKC for the panel of 24 transition economies, after controlling for unobserved heterogeneity, endogeneity, and impact of financial development and institutional quality. In a similar type of study, Azam [38] reversed the direction of causality and estimated the negative impact of environmental degradation by CO₂ emissions on the economic growth of 11 Asian countries between 1990 and 2011. Azomahou et al. [5] went beyond the standard parametric statistics using the non-parametric kernel-based estimator to assess the relationship between CO₂ emissions and GDP

for the panel of 100 countries during the period 1960–1996, and concluded that there is evidence of structural stability of the relationship.

Some other panel-wise empirical studies have examined the linkage between degradation and economic development on a non-econometric basis. For example, the report by Bacon et al. [39] provides a decomposition of the CO₂ emissions from fossil fuels for 70 countries in the period 1994–2004. Emissions per capita were only moderately positively correlated with GDP per capita and showed no evidence of an eventual decline in emissions per capita at higher per capita income. Additional research on the relationship between CO₂ emissions and economic growth using the panel datasets and estimation methods can be found in [40–47].

Furthermore, there is a copious amount of literature that investigates the relationship between CO₂ emissions and GDP on a national level in developing countries. Jalil and Mahmud [48] analysed China over the period 1975–2005 using the ARDL (Autoregressive Distributed Lag) methodology. A quadratic relationship between income and CO₂ emission was found. Nasir and Rehman [49] obtained the same results for Pakistan for the period 1972–2008, while Odhiambo [6] obtained the results of a distinct unidirectional causal flow from economic growth to carbon emissions for South Africa over the period 1970–1997. A unidirectional relationship between GDP and CO₂ emissions in the short term was proved for Tunisia by analysing data over the period of 1980–2010 [50]. A cointegration relationship between CO₂ emissions, real GDP squared, real GDP, energy use, and imports and exports of goods and services was proved for Algiers using ARDL over the period 1970–2010 [51]. The more recent studies on this subject pay particular attention to the effects of the external sector on the CO₂–GDP dynamic, like export in Anatasia's [52] study on Thailand and Malesia, or oil prices like in Al-Abdulahi's study [53] on Kuwait, Saudi Arabia, and the UAE, or Katricioglu's study [54] for Turkey.

Further research on the CO₂–GDP relationship for individual countries can be found in [55–62].

3. Materials and Methods

In this paper, 17 transition countries are observed for the period 1997–2014. Data on real GDP (*l_gdp*) were retrieved from UNCTADstat [63], while CO₂ emissions (*l_co2*) were retrieved from CDIAC [64].

In this paper, we follow the standard procedure of time series modelling, which consists of two methodological blocks: unit root testing as a prerequisite of the proper choice of modelling approach (VAR/VECM/ARDL—standard abbreviations of the Vector Autoregression, Vector Error-Correction, and Autoregressive Distributed Lag frameworks for modelling time series, respectively), and proper model specification and estimation within the selected modelling approach. However, instead of a single country, we use a panel dataset, whose analysis, in the context of time series modelling, differs to a univariate case in terms of unit root tests and estimation methods. The vast majority of the recent papers dealing with the empirical analysis of the intertwining effects between CO₂ emission and size of the economy use panel datasets and panel data estimation methods [3,44]. As emphasized by the Al-Mulali [3], the use of panel datasets over the individual time series data brings about several advantages in econometric modelling, such as the capability to control the unobserved heterogeneity, the increase in the degree of freedom, and the more stable parameter estimates. As the empirical results from the unit root testing suggest the use of the VECM and cointegration analysis approach, we provide detailed discussion on this methodological approach within the panel framework.

3.1. Panel Unit Root Tests—Methodology

According to Hossfeld [65], panel unit root tests can be categorized as “first generation” or “second generation”. The most notable tests of the first generation unit root tests are the Levin-Lin-Chu test (LLC) [66] and the Im-Pesaran-Shin [67] test (IPS). Basically, these tests are extensions of the traditional augmented Dickey-Fuller (ADF) unit root test for univariate time series modelling, under the very

restrictive assumption of individual cross-sectional independency. Univariate case of ADF unit root test for the stochastic process y_t is based on estimating the test equation:

$$\Delta y_t = \rho y_{t-1} + \sum_{p=1}^P \phi_p \Delta y_{t-p} + \gamma_l' D_l + \varepsilon_t, \quad t = 1, \dots, T \quad (1)$$

where D_l , $l = \{1, 2, 3\}$ is a vector of deterministic terms, which specifies whether the process has no constant term and time trend (empty set), only a constant term and no time trend, or a both constant term and time trend,

$$D_l = \begin{cases} \text{empty set} \\ 1 \\ 1, t \end{cases},$$

while ε_t is the error term identically independently normally distributed, $\varepsilon_t \sim N(0, \sigma^2)$. The ADF test statistics tests the null hypothesis that process y_t has the unit root against the alternative that y_t is stationary. In mathematical notation of the Equation (1), it is equivalent to testing $H_0 : \rho = 0$ against the alternative $H_1 : \rho < 0$.

The ADF test for a panel case is based on estimating the following equation:

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{p=1}^{P_i} \phi_{ip} \Delta y_{i,t-p} + \gamma_{li}' D_{li} + \varepsilon_{it}, \quad t = 1, \dots, T, \quad i = 1, \dots, N \quad (2)$$

which is basically an extension of Equation (1) across individuals, denoted by subscript i . The errors $\varepsilon_{i,t} \sim N(0, \sigma^2)$ are assumed to be independent across the individuals. Vectors of deterministic components beside constant term (individual fixed effect) and time trend can also include time dummies θ_t .

The LLC test estimates ADF regression on the pooled panel data by the OLS (standard abbreviation of the Ordinary Least Squares estimator, the most frequently used in regression analysis), assuming the same auto-regressive process across individuals, which is an additional restriction. Under the assumption of common unit root, the LLC test is testing the null $H_0 : \rho_i = \rho = 0 \forall i$, against the alternative $H_1 : \rho_i = \rho < 0 \forall i$. The IPS test relaxes the latter assumption, allowing the possibility of varying autoregressive processes across individuals, and therefore uses the group-mean of individual t -statistics in statistical inference

$$\bar{t}_{NT} = N^{-1} \sum_{i=1}^N t_{iT}(P_i, \phi_{i1}, \dots, \phi_{iP_i}) \quad (3)$$

where $t_{iT}(P_i, \phi_{i1}, \dots, \phi_{iP_i})$ denotes the t -statistic for testing the unit root in the i th individual process (lag order P_i is typically selected according to some info criterion). Accordingly, \bar{t}_{NT} is used to test null $H_0 : \rho_i = 0 \forall i$ against the alternative $H_1 : \exists i \in \{1, \dots, N\}, \rho_i < 0$.

The issue of cross-sectional dependency between individuals may be partially impeded in the first generation tests, if the time fixed effects are included in the ADF specification (or equivalently, if the regression is run on cross-sectionally demeaned data). The second generation unit root tests offer some solutions in overcoming this issue, relaxing the assumption of cross-sectional independence [68]. The most notable test of the second generation, Cross-sectional IPS test (CIPS), was proposed by Pesaran [69]. Instead of the standard ADF regression, CIPS tests are based on the Cross-sectional ADF regression (CADF), which adds lagged cross-sectional means of individuals \bar{y}_t to control for effects of the common factor, while the computation of the test statistics and the inference follows the IPS procedure [65]. The CADF regression is specified as follows (for simplicity lagged differences of $y_{i,t}$ and \bar{y}_t are omitted)

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \phi_i \bar{y}_{t-1} + \psi_i \Delta \bar{y}_t + \gamma_{li}' D_{li} + \varepsilon_{it}, \quad t = 1, \dots, T, \quad i = 1, \dots, N \quad (4)$$

The CIPS statistic is then computed as group-mean of t -statistics obtained from particular CADF equations, as explained in (3).

3.2. Cointegration Analysis—Methodology

In this part of the paper, the methodology of cointegration is presented by testing partially the general procedure proposed by the recent work of Al-Mulali [3,44] for the econometric modelling of the interdependency between size of the economy and carbon-dioxide emissions. His procedure consists of cointegration testing and Granger causality testing, adjusted to acquire panel datasets analysis framework. We diverged from this approach in the last step, using a more explicit modelling approach, based on two OLS-wise estimation methods in the presence of panel cointegration: Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS) (see for example, Kao et al. [70]).

Similar to panel unit root tests, panel cointegration tests strive to provide more reliable results in testing of cointegration presence relative to those obtained by individual tests. The most frequently used panel cointegration tests are based on unit root testing of residuals from the OLS-wise regression, in the literature known under the umbrella term of t “Engle-Granger based” cointegration test. The name stems from the prominent Engle-Granger (EG) cointegration test for individual time series. The EG test is derived from the basic idea of cointegration models, that two non-stationary time series are cointegrated if there is some stationary linear combination of them. Consequently, under the null hypothesis that two series are cointegrated, residuals from their stationary linear combination are also stationary. Thus, the EG procedure requires two steps: the estimation of static OLS regression to obtain residuals, and then imposing some unit root testing to residuals (not necessarily ADF).

The broadest framework for a panel cointegration test based on the EG procedure was proposed by Pedroni [71]. The important advantage of Pedroni’s approach stems from the filtering of short-run parameters and individual-specific deterministic trends in the first step of the procedure [65]. Based on estimated residuals, Pedroni derived seven different test statistics. Similar to panel unit root tests based on ADF, Pedroni’s seven test statistics can be distinguished from those assuming a common process, typically referred to as “pooled” or “within-dimension” tests, and those assuming individual processes referred as “grouped” or “between-dimension” tests. The first group of Pedroni’s tests consists of panel semi-parametric ν -, ρ -, and t -statistics which corresponds to the variance ratio, and Phillip-Peron ρ - and t -statistics univariate analogues, respectively, and parametric panel ADF t -statistics. The second group consists also of Phillip-Peron ρ - and t -statistics and ADF t -statistics, but is computed according to the group-mean principle.

The starting point of the panel cointegration tests of Pedroni [71] is the cointegrating equation specified:

$$y_{i,t} = \beta_i' x_{i,t} + \gamma_i' D_{li} + \varepsilon_{i,t} \quad (5)$$

where $x_{i,t}$ is an independent variable, or in more general case, m -dimensional vector of independent variables

$$x_{i,t} = x_{i,t-1} + \epsilon_{i,t} \quad (6)$$

In line with the EG procedure, cointegration testing is based on the auxiliary regressions of residuals obtained from (5). Depending on the type of the test with respect to parameterization, two alternative specifications of auxiliary regressions are possible, (7) for semi-parametric and (8) for a parametric case

$$\hat{\varepsilon}_{i,t} = \rho \hat{\varepsilon}_{i,t-1} + \mu_{i,t} \quad (7)$$

$$\hat{\varepsilon}_{i,t} = \rho \hat{\varepsilon}_{i,t-1} + \sum_{p=1}^{P_i} \phi_{ip} \Delta \hat{\varepsilon}_{i,t-p} + \mu_{i,t}^* \quad (8)$$

To derive properties of the cointegration testing, Pedroni [71] assumes that partitioned vector $z_{i,t} = [y_{i,t}, x_{i,t}]$ describes the true data generating process $z_{i,t} = z_{i,t-1} + \zeta_{i,t}$, where the vector error process $\zeta_{i,t} = [\varepsilon_{i,t}, \epsilon_{i,t}]$ is stationary with $(m+1) \times (m+1)$ asymptotic covariance matrix Ω_i . Covariance matrix Ω_i can be depicted in the partitioned form as:

$$\Omega_i = \begin{bmatrix} \Omega_{11i} & \Omega_{12i} \\ \Omega_{21i} & \Omega_{22i} \end{bmatrix}, \quad (9)$$

where Ω_{11i} is a long-run variance of $\epsilon_{i,t}$, Ω_{22i} is a long-run covariance matrix of $\epsilon_{i,t}$, and $\Omega_{21i} = \Omega'_{12i}$ is a vector giving long-run covariance between $\epsilon_{i,t}$ and $\epsilon_{i,t}$. Under the assumption of the invariance principle, Ω_i can be decomposed to the sum of contemporaneous Ω_i^0 and dynamic covariance Γ_i ,

$$\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i' \tag{10}$$

In addition, Pedroni did a triangularization of the Ω_i matrix for the sake of convenience in cointegration test statistics derivation ending up with lower triangular matrix L_i , with the partition given as

$$L_i = \begin{bmatrix} L_{11i} & L_{12i} \\ L_{21i} & L_{22i} \end{bmatrix}, \tag{11}$$

where $L_{11i} = (\Omega_{11i} - \Omega'_{21i}\Omega_{21i}^{-1}\Omega_{21i})$, $L_{12i} = 0$, $L_{21i} = \Omega_{21i}\Omega_{21i}^{-1/2}$, $L_{22i} = \Omega_{21i}^{1/2}$.

Under the assumption of cross-sectional independence or errors, $E[\zeta_{i,t}, \zeta_{k,l}] = 0 \forall i, t, k, l$, the following cointegration test statistics are derived:

Panel ν -statistic

$$Z_{\nu NT} = \left(\sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{\epsilon}_{i,t-1}^2 \right)^{-1} \tag{12}$$

Panel ρ -statistic

$$Z_{\rho NT-1} = \left(\sum_{i=1}^N \sum_{t=1}^T \hat{\epsilon}_{i,t-1}^2 \right)^{-1} \sum_{i=1}^N \sum_{t=1}^T (\hat{\epsilon}_{i,t-1} \Delta \hat{\epsilon}_{i,t} - \hat{\lambda}_i); \tag{13}$$

Panel t -statistic (semi-parametric)

$$Z_{tNT} = \left(\hat{\sigma}_{NT}^2 \sum_{i=1}^N \sum_{t=1}^T \hat{\epsilon}_{i,t-1}^2 \right)^{-1/2} \sum_{i=1}^N \sum_{t=1}^T (\hat{\epsilon}_{i,t-1} \Delta \hat{\epsilon}_{i,t} - \hat{\lambda}_i) \tag{14}$$

Panel t -statistic (parametric)

$$Z_{iNT}^* = \left(\hat{s}_{NT}^{*2} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{\epsilon}_{i,t-1}^2 \right)^{-1/2} \sum_{i=1}^N \sum_{t=1}^T \hat{L}_{11i}^{-2} \hat{\epsilon}_{i,t-1} \Delta \hat{\epsilon}_{i,t}; \tag{15}$$

Group ρ -statistic

$$\tilde{Z}_{\rho NT-1} = \sum_{i=1}^N \left[\left(\sum_{t=1}^T \hat{\epsilon}_{i,t-1}^2 \right)^{-1} \sum_{t=1}^T (\hat{\epsilon}_{i,t-1} \Delta \hat{\epsilon}_{i,t} - \hat{\lambda}_i) \right]; \tag{16}$$

Group t -statistic (semi-parametric)

$$\tilde{Z}_{tNT} = \sum_{i=1}^N \left[\left(\hat{\sigma}_i^2 \sum_{t=1}^T \hat{\epsilon}_{i,t-1}^2 \right)^{-1/2} \sum_{t=1}^T (\hat{\epsilon}_{i,t-1} \Delta \hat{\epsilon}_{i,t} - \hat{\lambda}_i) \right]; \tag{17}$$

Group t -statistic (parametric)

$$\tilde{Z}_{iNT}^* = \sum_{i=1}^N \left[\left(\hat{s}_i^{*2} \sum_{t=1}^T \hat{\epsilon}_{i,t-1}^2 \right)^{-1/2} \sum_{t=1}^T (\hat{\epsilon}_{i,t-1} \Delta \hat{\epsilon}_{i,t}) \right], \tag{18}$$

where $\hat{\lambda}_i$, \hat{s}_i^2 , $\hat{\sigma}_i^2$, $\hat{\sigma}_{NT}^2$, \hat{s}_i^{*2} , \hat{s}_{NT}^{*2} denote estimates of the nuisance parameters derived from residuals obtained in (7) and (8): dynamic covariance, contemporaneous variance, and long-run variances of $\hat{\mu}_{i,t}$ and contemporaneous and long-run variance of $\hat{\mu}_{i,t}^*$, respectively, as given by the following set of equations:

$$\begin{aligned} \hat{\lambda}_i &= T^{-1} \sum_{s=1}^{K_i} \omega_{sK_i} \sum_{t=s+1}^T \hat{\mu}_{i,t} \hat{\mu}_{i,t-s}; \hat{s}_i^2 = T^{-1} \sum_{t=1}^T \hat{\mu}_{i,t}; \hat{\sigma}_i^2 = \hat{s}_i^2 + 2\hat{\lambda}_i; \\ \hat{\sigma}_{NT}^2 &= N^{-1} \sum_{i=1}^N \hat{L}_{11i}^{-2} \hat{\sigma}_i^2; \hat{s}_i^{*2} = T^{-1} \sum_{t=1}^T \hat{\mu}_{i,t}^*; \hat{s}_{NT}^{*2} = N^{-1} \sum_{i=1}^N \hat{s}_i^{*2}, \end{aligned} \tag{19}$$

where ω_{sK_i} denotes linearly decaying weights, $\omega_{sK_i} = (1 - k/(K_i + 1))$, of the Newey-West kernel-based estimator with lag window K_i (weights for all lags beyond K_i are zero). Nuisance estimates \hat{L}_{11i}^{-2} are derived from the estimated long-run covariance Ω_i also using Newey-West weights.

Eventually, Pedroni [71] shows that all cointegration test statistics after standardization asymptotically converge to standard normal distribution, so they can be used to test $H_0 : \rho_i = 1 \forall i$ against the alternative $H_1 : \rho_i = \rho < 1 \forall i$ in case of within-dimension tests or $H_1 : \rho_i < 1 \forall i$ in case of between-dimension tests. However, “a limitation of the Pedroni test is that it cannot accommodate structural breaks that have been a common place in energy consumption and GDP” [72] (p. 2332). According to the [4], the panel cointegration test proposed by Westerlund [73] copes with this issue by determining structural breaks endogenously. Even more the Westerlund approach accounts for cross-sectional dependency by using bootstrapping to compute errors [74]. Estimation of the panel regression in the presence of cointegration is usually conducted using two methods of OLS-based estimators—FMOLS and DOLS. Using the same notation from cointegration section, the standard pooled OLS panel estimator is given as:

$$\hat{\beta}_{NT} = \left(\sum_{i=1}^N \sum_{t=1}^T (x_{i,t} - \bar{x}_i)^2 \right)^{-1} \sum_{i=1}^N \sum_{t=1}^T (x_{i,t} - \bar{x}_i)(y_{i,t} - \bar{y}_i) \quad (20)$$

Use of FMOLS in panel cointegration analysis has been suggested by Pedroni [75,76]. The pooled FMOLS estimator as a modification of standardized OLS is given as:

$$\hat{\beta}_{FM} = \left(\sum_{i=1}^N \hat{L}_{22i}^{-1} \sum_{t=1}^T (x_{i,t} - \bar{x}_i)^2 \right)^{-1} \sum_{i=1}^N \hat{L}_{11i}^{-1} \hat{L}_{22i}^{-1} \left(\sum_{t=1}^T (x_{i,t} - \bar{x}_i) y_{i,t}^* - T \hat{\delta}_i \right) \quad (21)$$

where $y_{i,t}^* = (y_{i,t} - \bar{y}_i) - \left(\frac{\hat{L}_{21i}}{\hat{L}_{22i}} \right) \Delta x_{i,t} + \left(\frac{\hat{L}_{21i} - \hat{L}_{22i}}{\hat{L}_{22i}} \right) \beta (x_{i,t} - \bar{x}_i)$ and $\hat{\delta}_i \equiv \hat{\Gamma}_{21i} + \hat{\Omega}_{21i}^0 - \left(\frac{\hat{L}_{21i}}{\hat{L}_{22i}} \right) (\hat{\Gamma}_{22i} + \hat{\Omega}_{22i}^0)$, and other variables are defined as in (9)–(11).

Pedroni [76] emphasized that the main reasons for concern in estimating dynamic cointegrated panels are heterogeneity issues with differences in means among the individuals and differences in individuals' responses to short-run disturbances from cointegrating equilibrium. The FMOLS that he proposed deals with these two issues by including into regression individual specific intercepts and by allowing serial correlation properties of the error processes to vary across individual members of the panel.

The DOLS estimator has been extended to panel analysis by Kao and Chiang [77], who develop finite sample properties of the OLS, DOLS, and Pedroni's FMOLS. The DOLS estimator in a panel case is obtained by running the following regression

$$y_{i,t} = \beta_i' x_{i,t} + \sum_{j=-q}^q \zeta_{ij} \Delta x_{i,t+j} + \gamma_{li}' D_{li} + \varepsilon_{i,t} \quad (22)$$

where q denotes the numbers of leads/lags typically chosen using some info criterion. Based on Monte Carlo simulations, they concluded that the DOLS outperforms both the OLS and the FMOLS estimators in finite samples in terms of unbiased estimation. The DOLS estimator also has an additional advantage in controlling the endogeneity in the model, as augmentation with the lead and lagged differences of the regressor suppress the endogenous feedback [31]. Thus, the DOLS estimation method provides a robust correction of endogeneity in the explanatory variables [78].

4. Results

4.1. Results of Panel Unit Root Tests

We applied the abovementioned methodology to the strongly balanced panel dataset. Both variables were transformed to logarithmic terms before analysis.

Before running the panel unit root tests, we looked for the presence of cross-dependency in our panel dataset. The literature offers a vast number of tests for the detection of cross-sectional

dependency. We applied some of the most frequently used: Breusch-Pagan LM (1980), Pesaran scaled LM (2004), Pesaran (2004), and Baltagi, Feng, and Kao bias-corrected scaled LM (2012). Results of the tests are presented in Table 1. The results of all four tests applied clearly indicated the strong presence of cross-sectional dependency, indicating that panel unit root tests of the second generation should provide more reliable inference.

Table 1. Cross-section dependence tests.

Test	l_co2	l_gdp
Breusch-Pagan LM	858.3353 ***	2255.909 ***
Pesaran scaled LM	42.76723 ***	127.5076 ***
Bias-corrected scaled LM	42.26723 ***	127.0076 ***
Pesaran CD	14.20806 ***	47.47031 ***

Note: Null hypothesis: No cross-section dependence. Levels of significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Basically, specification of the ADF functional form depends on the characteristics of the time series analysed. When the ADF test is applied to the series levels, it is common to check both ADF versions with intercept only and intercept and trend (see e.g., Al-Mulali [44]). We applied LLC, IPS, and CIPS panel unit root tests to GDP and carbon-dioxide levels and first differences, considering both versions of ADF specification. In the case of LLC and IPS tests, time series were cross-sectionally demeaned to impede the effects of cross-section dependence. Results are provided in Table 2.

Table 2. Unit root tests.

		Level		First Difference	
		Intercept	Intercept and Trend	Intercept	Intercept and Trend
l_co2	LLC	−3.7864 ***	−7.159 ***	−6.9140 ***	−5.6412 ***
	IPS	−1.8709 **	−1.8709 ***	−4.9425 ***	−4.9329 ***
	CIPS	−1.984	−2.095	−2.222 **	−2.229
l_gdp	LLC	−2.1855 **	−3.6908 ***	−7.1496 ***	−8.5949 ***
	IPS	−0.7983	−1.8554	−3.2694 ***	−3.5160 ***
	CIPS	−1.670	−2.293	−2.678 ***	−3.485 ***

Note: Null hypothesis: Panels are stationary; IPS and CIPS tests based on ADF and CADF group-mean t-test statistics, respectively. Levels of significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. LLC, Levin-Lin-Chu test; IPS, Im-Pesaran-Shin test; CIPS, Cross-sectional IPS test; ADF, augmented Dickey-Fuller; CADF, Cross-sectional ADF regression.

Results of the panel unit root testing are mixed, especially in case of carbon-dioxide, where LLC and IPS tests indicate stationarity in both levels in first differences, while CIPS mostly suggests that some panels are not stationary. In the case of GDP, the situation is clearer, as IPS and CIPS suggest non-stationarity in levels and stationarity in differences, and these two tests are more reliable, keeping in mind that LLC restriction on common autoregressive processes for all panels is too restrictive. We decided to give more power to the CIPS test in the case of carbon-dioxide relative to LLC and IPS, due to the clear presence of cross-sectional dependence documented in Table 1. Also, we neglected non-stationarity in l_co2 differences as suggested by the CIPS when trend is included, as in this ADF specification it may be less relevant—differentiation of the series usually eliminates deterministic trends. Eventually, we considered both GDP and carbon-dioxide being non-stationary in levels and stationary in differences.

4.2. Results of Cointegration Analysis

As in Al-Mulali's work [44], we started with the regression equation where CO₂ is a dependent variable, and GDP is an explanatory variable. Then we applied seven Pedroni's tests of panel

cointegration. We considered both cases of deterministic trend and intercept only. The null hypothesis for all tests assumes no cointegration between variables. Results are presented in the Table 3.

Table 3. Panel cointegration tests.

Dimension	Test Statistics	Intercept	Intercept and Trend
Within-dimension	Panel v -Statistic	3.1553 ***	0.6033
	Panel rho-Statistic	−3.4333 ***	−0.2595
	Panel PP-Statistic	−5.1231 ***	−3.0995 ***
	Panel ADF-Statistic	−5.5646 ***	−4.1467 ***
Between-dimension	Panel rho-Statistic	−1.8934 **	0.8565
	Panel PP-Statistic	−6.4690 ***	−4.3839 ***
	Panel ADF-Statistic	−7.9836 ***	−6.1632 ***

Note: Alternative: common AR coefficients for within-dimension, individual AR coefficients for between dimension. Levels of significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

“It can be regarded as a sign of robustness if different test statistics lead to the same test decision, because evidence based on Monte Carlo simulations has shown that the various test statistics perform differently depending on the panel dimension and the assumed data generating process” [65] (p. 16). In our case, the majority of tests clearly suggest rejecting the null hypothesis and presence of cointegration, both in cases of deterministic trend and no trend included.

To provide additional cointegration testing that is robust to structural breaks and cross-sectional dependence, we use the Westerlund [73] approach. It provides four panel-based statistics testing the null of no cointegration by inferring whether the error-correction term in a conditional panel VECM is equal to zero [74]. The results of the Westerlund cointegration testing are presented in Table 4. Based on bootstrapped robust critical values, three of four tests reject the null, additionally confirming the presence of cointegration.

Table 4. Westerlund Panel cointegration tests.

Test Statistics	Value
Gt	−1.615 ***
Ga	−2.294
Pt	−4.416 ***
Pa	−1.584 *

Note: Alternative: the panel is cointegrated as a whole for G-tests, at least one unit is cointegrated for P-tests. Levels of significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, we estimated the cointegrating relationship between carbon-dioxide and GDP using both the FMOLS and DOLS estimators. In the case of the FMOLS, we included the deterministic trend into the cointegrating relationship, while the trend in the DOLS estimation was suppressed by the specification of the regression in dynamic terms. In both cases, we used pooled and grouped versions of the FMOLS and DOLS estimators, where grouped mean estimations computed the cross-section average of the individual cross-section estimates. The results are presented in Table 5. Estimates of short-run relationships and lagged variables were suppressed.

Table 5. Estimation of cointegrating relationship.

Estimation Method	FMOLS		DOLS	
	Polled, Trend	Grouped, Trend	Pooled	Grouped
Long-run coefficient	0.3448 *** (0.0405)	0.3782 *** (0.0252)	0.3484 *** (0.0454)	0.3770 *** (0.0284)
No. of observations	289	289	255	255
R-squared adj.	0.9941		0.9958	

Note: Standard errors in parentheses. Levels of significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. FMOLS, Fully Modified OLS; DOLS, Dynamic OLS; OLS, Ordinary Least Squares.

The results clearly suggest the existence of the long-run cointegrating relationship between CO₂ emissions and real GDP that is statistically significant. For all four versions of the estimations, it is approximately 0.35, meaning that, on average, a 1% change in GDP leads to a 0.35% change in CO₂ emission for the considered group of transition countries. The close values of long-run coefficients for all estimations confirm the robustness of the estimated results.

5. Discussion

Cointegration analysis for 17 transitional economies was conducted using DOLS and FMOLS approaches developed by Pedroni [71] and Kao and Chiang [77], respectively. The results perspicuously present the existence of a statistically significant long-run cointegrating relationship between CO₂ and real GDP. For all versions of estimations, the coefficient was approximately 0.35, which means, on average, that a 1% change in GDP leads to around a 0.35% change in CO₂ for transitional economies. This result corresponds to the estimates in [28], which examined GDP and CO₂ relationships for a similar panel of countries. The main difference between [28] and our work is that [28] estimates static and dynamic contemporaneous relationships of GDP and CO₂, while our work provides long-run cointegration assessment.

However, it is of the utmost importance to emphasize that this result does not shed light on the factors behind the observed relationship. There is a variety of factors which need to be considered if we want to try to understand the nature of the relationship between environmental degradation and economic growth.

Firstly, inadequate allocation of resources in transitional economies frequently leads to their inefficient use, which, in turn, results in the increase of pollution as a negative externality of production processes [79]. Furthermore, one of the main characteristics of a transitional economy is that it uses energy that is largely based on fossil fuel combustion. The share of energy used from renewable energy sources is increased only in later stages of the transition process of these economies.

Outdated knowledge and deficient expertise of the management function in production companies can also be examined as a contributing factor to increasing pollution, although an indirect one. This is primarily due to the insufficient understanding of the significance of investing in modernization of production processes [80] which have much smaller negative ecological impacts. Outdated and deficient use of technology is therefore a significant source of pollution, and, as such, it is crucial that both the management function and policymakers have to recognize the importance of investing in new technologies. In relation with the abovementioned points, state-owned enterprises in transitional economies are able to use their political power and/or a monopoly position to their advantage and may, to a certain extent, ignore environmental protection legislation [27]. Sometimes, these companies are so large and strategically important that they can block certain regulations in environmental protection when and where their interests are at stake.

In the discussion about the characteristics of transitional economies in terms of ecology, we cannot ignore the social component, especially in terms of general environmental awareness, which can significantly contribute to reducing pollution [79]. Overall, the populations in transitional countries

are less aware about environmental problems than the populations in developed countries, and consequently, the community pressure on manufacturers to reduce pollution is diminished.

Moreover, transitional economies in general need to follow global policy incentives, such as COP 21, and make additional efforts to achieve the targets established by this and other international agreements. To this date, all transitional countries have signed the COP 21, except Uzbekistan [81]. Furthermore, they have to revise and update the existing policies and laws, as well as to create new environmental policies and laws that will go towards reducing pollutant emissions, primarily anthropogenic ones. One of the specific ways to reduce CO₂ emissions is by capture and storage, which is considered to be a pivotal strategy for meeting CO₂ emission reduction targets [82]. It consists of technologies “being developed to allow CO₂ emissions from fossil fuel use at large point sources to be transported to safe geological storage, rather than being emitted to the atmosphere” [83,84] (p. 4317). Transitional economies can consider implementing technologies for CO₂ capture and storage, but a main limitation is that this process is relatively expensive.

The abovementioned regulations should also further develop mechanisms such as environmental taxes and emissions-trading schemes. Environmental tax, ecological tax, eco-tax, pollution tax, or green tax are all “synonyms” describing every form of taxation in which the tax base is expressed in physical units of substance or matter that has a proven negative impact on the environment [85]. These taxes can substantially contribute to efforts to reduce pollutant emissions, especially if the tax revenue is directed towards addressing environmental issues. Taxes on environmentally harmful behaviour have the potential to raise revenues for developing and transitional governments in general [86]. On the other hand, carbon-trading schemes (cap and trade) are based on the principle that an increase in pollution from a single source must be accompanied by an equivalent reduction of pollution from other sources. Developed countries have these schemes to try to limit pollutant emissions and provide incentives for those who decide to pollute less. The European Union’s Emissions Trading Scheme (EU ETS) is the world’s first large scheme for trading CO₂ emissions [87,88], and transitional economies can find a satisfactory know-how from these countries on creating and/or developing an emissions-trading scheme.

In the context of future research, new variables can be introduced into the CO₂–GDP nexus, such as: foreign trade, energy consumption, renewables, capital investments, financial development, agricultural, industrial, social and sustainable indicators and indices, etc. Additionally, factors such as composition of GDP, level of technological development, and environmental awareness can be further examined as decisive factors in the relationship between CO₂ emissions and economic growth.

6. Conclusions

The nexus between the environment and economic growth is one of the most important relationships, for policy makers, academia, and industry alike. As early as the 1980s, this relationship has been the focal point of theoretical and empirical research, because a direct consequence of pollutant emissions is climate change and especially global warming.

The cointegrating relationship was estimated by using panel DOLS and FMOLS estimators for 17 transitional economies. Results suggest the existence of a long-run cointegrating relationship between CO₂ emissions and real GDP that is statistically significant. For all four versions of estimations the observed calculated coefficient was approximately 0.35, which means that, on average, a 1% change in GDP leads to a 0.35% change in CO₂ emission for the considered group of countries. Close values of long-run coefficients for all estimations confirm the robustness of the estimated results.

Furthermore, it is necessary to state that this result does not explain the factors behind the observed CO₂–GDP relationship. Future research should introduce new variables into the CO₂–GDP nexus. Transitional economies need to follow global policy incentives to implement new mechanisms and instruments for the purpose of reducing CO₂ emissions, such as environmental taxes, emissions-trading schemes, and carbon capture and storage.

In addition, inadequate allocation of resources and the increased use of renewable energy must be taken into consideration in the efforts to battle increasing pollution. Knowledge of the management structure and the importance of investing in new technologies must be acknowledged, as well as the need to raise ecological awareness.

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