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THE ENVIRONMENTAL KUZNETS CURVE REVISITED: ECONOMIC COMPLEXITY AND ECOLOGICAL FOOTPRINT IN THE MOST COMPLEX ECONOMIES OF THE WORLD

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Abstract: The paper examines the Environmental Kuznets Curve (EKC) model in the panel of the most complex economies in the world by considering the ecological footprint as an indicator of environmental degradation and economic complexity - as a variable of interest and expression of structural changes in the economy. The study includes the first 48 complex economies in the world, with positive averages of the Economic Complexity Index (ECI) for 1995-2017. The model of cointegrating polynomial regression (CPR) includes also variables with impact on ecological footprints such as globalization, energy intensity and urbanization. The EKC model is validated in the panel of the 48 complex economies, suggesting that these countries have already reached a development stage enabling them to curb the increasing pollution expressed by ecological footprint. Globalization has a mitigating effect while urbanization and energy intensity have an extension effect on ecological footprint. Policy implications are also included.

Keywords: ecological footprint, economic complexity, panel data, EKC.

JEL Classification: Q5, Q56, P48, L16, O13, C33, F64.

1. Introduction

The rising levels of environmental degradation threaten sustainability and prosperity around the world in economies of different stages of development. The interest of the researchers' community is how to stop this environmental decline

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without affecting the economic progress. From a theoretical point of view, the Kuznets curve hypothesis seemed to give hope by indicating that a certain level of development of an economy, the reduction of environmental pressure can be attained. The original Kuznets Curve (KC) model postulates that an inverted U-shaped relationship between economic income and inequality could be validated (Kuznets, 1955). Starting with the introductory paper of Grossman and Krueger (1995), an impressive number of studies developed analyses on the quadratic dependency between pollution and income, taking into consideration diverse indicators of pollution or environmental degradation/quality. Most of the literature focused on Environmental Kuznets Curve (EKC) is based on the use of GDP/GDP per capita or its growth rate to measure the impact of income on CO2 emissions, GHG emissions, or other air emissions as indicators of pollution. These measurements are not including water and soil pollution. Recent studies use ecological footprint (EF) as a measure of environmental degradation. It was introduced by Wackernagel and Rees (1996) as a more inclusive and comprehensive indicator of environmental degradation, encompassing built-up land, grazing land, cropland, forest land, carbon footprint, and ocean. The ecological footprint (EF) is the expression of the total quantity of natural resources that a population consumes. It measures the area of productive land and water needed to support human activities and sequester the generated waste (Lin et al, 2019). For example, Al-Mulali et al. (2015) investigated the EKC hypothesis using ecological footprint as an indicator of environmental degradation and GDP as an explanatory variable in ninety-three countries.

An impressive amount of studies are examining the determinants of ecological footprint, i.e. energy intensity (e.g., Bilgili et al., 2017; Dogan et al., 2020; Chu&Le, 2021), globalization (e.g., Figge et al., 2017; Rudolph and Figge, 2017; Sabir and Gorus, 2019; Ansari et al. 2020; Nathaniel, 2021); urbanization (e.g., Al-Mulali, 2015: Ozturk et al., 2016; Bilgili et al., 2017; Bello et al., 2018; Ansari et al., 2020; Danish et al. 2020).

Moreover, recent studies revealed that not only income (expressed by GDP or GDP per capita) can curb the rise of pollution, but also structural changes in the economy, as products sophistication and diversification. In order to capture technological and structural changes in the economy and to measure the productive structure of a country, the economic complexity index (ECI) was introduced by Hidalog and Hausmann (2019). (ECI) reflects a country's productive structure meaning a combination of ”diversity” and ”ubiquity”. ”Diversity” means the number of exported products and ”ubiquity” states for the number of countries that export that product (Hidalgo and Hausman, 2009). In recent years, ECI has received attention from researchers, as an expression of a country's productive structure, economic complexity and as a robust predictor of economic growth (Hidalgo and Hausmann, 2009; Hausmann et al., 2014). Several recent papers highlighted that ECI has a significant impact on the environment, the literature on this issue revealing linear or non-linear dependency (i.e. EKC model) between ECI and pollution based on a large range of methodological approaches. But, the debate on this dependency is just begun and, moreover, despite its diversity, the literature includes very few studies of the EKC model using ECI squared as a variable of interest. Thus, our paper intends to cover this gap.

The present paper explores the relationship between economic complexity and ecological footprint by using the EKC model where replaces the variable income with variable economic complexity in a panel data model including 48 complex economies for 1995 to 2017. It uses a cointegrated polynomial regression (CPR) that will be estimated with two models: standard fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS), respectively, in a heterogeneous panel data framework comprising of the 48 most complex economies, with tests of errors' cross-dependence, stationarity and variance ratio.

The present study intends to add to the existing knowledge through the following achievements: (1) it supports the beginning debates of the impact of economic complexity on the environment; (2) it documents the less explored dependency of an ecological footprint on the quadratic evolution of economic complexity. To the best authors' knowledge, this is the first attempt in the EKC literature to use ecological footprint as an indicator of pollution in a cointegrating polynomial regression with economic complexity index in a panel approach including the 48 most complex economies in the world.

The remainder of the paper is structured as follows. Section 2 discusses the relevant literature on the relationship between economic complexity and environment, section 3 explains Data and Methodology used in the paper and section 4 describes the findings of the analysis. Finally, section 5 is dedicated to the Conclusions.

2. Literature review on the relationship between economic complexity and environment

We will follow in the lines below two strands of studies: (1) those focused on the link between economic complexity and environment; and (2) those examining the EKC model with ECI squared as an indicator of structural changes in the economy.

2.1. Economic complexity and environmental degradation

Due to the interest given by researchers around the world to environmental concerns, the relationship between economic complexity and environmental degradation is studied and discussed in recent studies.

Can and Gozgor (2017) introduced ECI for the first time in the EKC model in the case of the French economy for the period of 1964-2014. They illustrated that, in the long run, higher economic complexity can suppress the level of pollution (CO2 emissions). Dogan et al. (2019) examined the impact of economic complexity on CO2 emission in the case of 55 countries for the period of 1971-2014. They concluded that the EKC hypothesis is validated in high-income countries and in lower and middle-income countries economic complexity has an extensive impact on environmental degradation. Lapatinas et al. (2019) found also that ECI has the potential to reduce total environmental pollution while it induces an increase of particular air quality indicators (i.e. fine particular matter and CO2 emissions) and validated the EKC hypothesis for 88 selected countries.

The relationship between ECI and GHG emissions within are positively associated within a panel of 25 European countries from 1995 to 2016 (Neagu and Teodoru, 2019). Dogan et al. (2020b) found that ECI affects CO2 emissions differently at various stages of development in their sample of 55 countries over the period 1971 to 2014: increasing environmental degradation in higher-middle and lower-income countries and abating CO2 emissions in high-income countries.

Swart and Brinkmann (2020) investigated the relationship between ECI, income level, and four different pollution indicators in the Brazilian economy. They found that the square of ECI is statistically insignificant and ECI reduces waste generation while it increases forest fires. They also revealed that economic complexity has no impact on deforestation and air pollution. The EKC hypothesis was validated in the case of deforestation and waste generation.

Similar results regarding the effect of economic complexity on the environment were obtained by Wang et al. (2021) in the top ten complex economies, suggesting that economic complexity is largely based on fossil fuel consumption.

Romero and Gramkov (2021) revealed that an increase of one unit of ECI generate a 23% decrease of CO2 kilotons per billion dollars of output, by using data of 67 countries for 1976-2012. In other words, the production of complex products is associated with reduced emission intensity.

Laverde-Rojas et al. (2021) examined the EKC model in the case of Columbia, introducing the ECI into the analysis as differentiating element of production volumes and found no validity.

Boleti et al. (2021) analyzed the relationship between economic complexity and environmental performance in the case of 88 developed and developing countries for 2002-2012 and found that higher levels of economic complexity induces better overall environmental performance measured through the Environmental Performance Index (EPI) and do not lead to environmental degradation (i.e. exposure to PM2.5, CO2, methane and nitrous emissions increases).

In their study on the top 18 economic complexity countries, based on data from 1990-2019, Abbasi et al. (2021) concluded that economic complexity increases CO2 emission in the short and long run.

A group of recent studies uses ecological footprint as a measure of environmental degradation. For example, Ylanci and Pata (2020) investigated the EKC hypothesis for China considering the effect of economic complexity on ecological footprint. They found that economic complexity has an effect on the extension of ecological footprint in the Chinese economy in the period 1965-2016, in the short and long-term. Neagu (2020) revealed a harmful effect of complexity on the environment and proved that ECI induce an extension of ecological footprint in 48 most complex economies in the world for the time span of 1995 to 2017. Shahzad et al. (2021) investigated the impact of fossil fuels and economic complexity in the USA and revealed that ECI and fossil fuel positively contribute to ecological footprint. Ikram et al. (2021) found a cointegrated long-run bidirectional relationship between economic complexity and ecological footprint in Japan.

There are also studies using two proxies for environmental degradation: CO2 emissions and ecological footprint. For example, Nathaniel (2021) developed a study on ASEAN countries and found that globalization reduces the ecological footprint and economic complexity as well as energy consumption and economic growth increase ecological footprint and CO2 emissions. Moreover, the direction of causality flows from economic growth, economic complexity and energy consumption to ecological footprint. Similarly, Pata (2021) studied the impact of ECI, globalization, and non-renewable and renewable energy consumption on environmental pollution (expressed by CO2 emissions and ecological footprint) in the case of the US economy.

Rafique et al. (2021) examined the top 10 ECI economies for 1980-2017 and revealed that economic complexity has a positive and significant relationship with the ecological footprint.

2.2. EKC model using economic complexity as an indicator of economic activity

We identified only four studies investigating economic complexity as an explanatory variable instead of income, in a non-linear relationship (using ECI squared) and testing the EKC model.

For example, the EKC curve was validated by Neagu (2019) in a panel of 25 European countries as well as in 6 European countries (Belgium France, Italy, Sweden, Finland and the UK) considering the impact of economic complexity on CO_2 emissions.

Chu (2021) found also a nonlinear relationship between ECI and CO_2 emissions in 118 countries, validating an inverted U-shaped curve.

Pata (2021) included in the analysis of the effect of economic complexity on pollution other explanatory variables (i.e. renewable and non-renewable energy, globalization) and validated the inverted U-shaped relationship between economic complexity and pollution expressed by CO_2 emissions and ecological footprint. A similar study was conducted by Chu &Le (2021) for the G7 countries, by using economic complexity, renewable energy and energy intensity, as explanatory variables of environmental quality. The environmental Kuznets curve of economic complexity and environmental quality (measured by ecological footprint and CO_2 emissions) holds for these countries.

3. Data and methodology

The present study follows the quadratic model extensively used in the EKC literature (e.g. Cole, 1997; Apergis & Paine, 2010; Pao & Tsai, 2010; Orubu & Omotor, 2011; Wang et al., 2011; Saboori et al., 2012, Shahbaz et al., 2012; Al Mulali et al., 2015; Al Mulali & Ozturk, 2016; Bilgili et al., 2016; Neagu, 2019; Chu, 2020; Can et al., 2021).

In our model the variable income is replaced by "economic complexity" (following Neagu, 2019; Chu, 2021; Chu & Le, 2021; Pata, 2021):

$$\ln EFP_{it} = \alpha + \beta_{it} \cdot ECI_{it} + \delta_{it} \cdot ECI_{it}^2 + \lambda \cdot CV_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

where: $\ln EFP_{it}$ denotes Ecological Footprint of Production ECI_{it} means Economic Complexity Index, CV_{it} expresses the set of control variables (globalization expressed by the KOF globalization index, urbanization measured through the rate of urbanization and energy intensity, μ_i is country-specific effects, ε_{it} is the error term, while *i* and *t* stand for country and time indices, respectively.

In order to test the proposed model of the inverted U-shaped relationship between economic complexity and ecological footprint, both linear and quadratic terms of ECI are included. We expect that the coefficients β (ECI) and δ $(ECI)^2$ have positive and negative signs, respectively.

Ecological Footprint of Production (expressed in global hectares per capita) data series is collected from the Global Footprint Network database.

Data series of Economic Complexity Index (ECI) running from 1995 to 2017 for the 48 most complex economies in the world are sourced from the Observatory of Economic Complexity (OEC). The 48 countries were selected from the OEC database ranking by considering the positive average values of ECI for the period 1995-2017. The sample includes Japan, Switzerland, Germany, South Korea, Singapore, Czech Republic, Sweden, Austria, USA, Hungary, Finland, Slovenia, United Kingdom, Italy, France, Slovenia, Slovakia, Mexico, Ireland, Denmark, Netherlands, Israel, Spain, Poland, Brazil, Portugal, Norway, New Zealand, Canada, Estonia, Latvia, Lithuania, Croatia, Bulgaria, Romania, Belarus, Russia, Australia, Malaysia, Thailand, Greece, India, Turkey, South Africa, Saudi Arabia, Uruguay and Colombia.

Energy intensity of primary energy (EI) (the ratio between supply and gross domestic product measured at purchasing power parity) and urbanization (URB) (urban population as % of the total population) data series are extracted from the World Bank database.

The index of globalization (G) is calculated by the KOF Swiss Economic Institute and expresses the economic, social and political dimensions of globalization (Dreher, 2006; Savina et al., 2019).

The descriptive statistics of examined variables are displayed in Table 1.

Table 1 Descriptive statistics

	lnEFP	*ECI*	*ECI2*	*lnG*	*lnURB*	*lnEI*
Mean	1.5198	0.9229	1.2233	4.2974	4.2617	1.6587
Median	1.4621	0.8582	0.7367	4.3405	4.3049	1.6132
Maximum	2.6694	2.4638	6.0704	4.5106	4.6051	3.2846
Minimum	-0.2409	-0.3988	7.26E-07	3.6768	3.2811	0.6669
Standard deviation	0.5322	0.6091	1.314673	0.1521	0.2330	0.4124
Skewness	-0.0831	0.3545	1.2753	-0.0550	-1.7515	0.8023
Kurtosis	3.7789	2.2178	4.0206	3.9019	7.4699	4.0177
Observations	1104	1104	1104	1104	1104	1104

Source: authors' own computation using EViews 12.0 software.

We base our decision to use the ECI instead of income in the EKC model on the findings of several studies highlighting the fact that economic complexity could be used to explain differences in the level of income of countries (e.g. Chavez et al., 2017) and can predict future economic growth. A strong correlation has been found between economic complexity and income and the level of income tends to follow the productive structure of the economy (Hausmann et al., 2007; Hidalgo and Hausmann, 2009). High complexity is associated with high income (Ourens, 2012; Hartmann et al., 2014; Hausmann et. al, 2014; Fortunato et al., 2015; Demiral, 2016; Stojkoski et al., 2016; Zhu& Li, 2016; Hartmann et al., 2017; Britto et al., 2017; Tachella et al., 2018; Hausmann et al., 2020; Yalta & Yalta, 2020). A more complex productive structure is associated with a higher GDP per capita growth rate (Poncet & de Waldemar, 2013). Economic complexity is a driver of prosperity, not a symptom (Hausmann, et al., 2011) and a more complex productive structure enables countries to develop higher productivity activities that lead to faster development (Felipe et al., 2012). Economic complexity is seen as a significant predictor of long-term economic growth (Hidalgo, 2021, p.14).

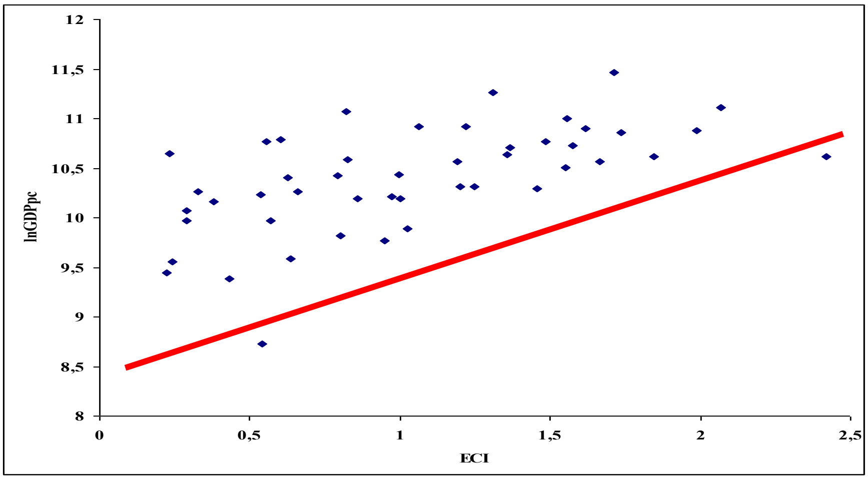

Figure 1 Dependency between lnGDPpc and ECI in 2017 (48 most complex countries) (corr lnGDPpc, ECI=0,53)
Source: authors' own computation.

Figure 1 displays the dependency between lnGDP and ECI in our sample of 48 economies in 2017. We can notice that countries are spread on both sides of the red regression line, illustrating a positive strong correlation between the two variables.
The paper uses the "cointegrated polynomial regression" (CPR), introduced by Wagner and Hong (2016). Such regression includes deterministic explanatory variables, with integrated processes as well as an integer of integrated processes. The main assumption states the stationarity of errors as well as an ergodic martingale difference sequence of errors. The martingale theory (Ibragimov and Philips, 2008) was used by Wagner and Hong (2016) to examine the behavior of the error. Martingale behavior of errors means that in the sequence of random variables the conditional expectation of the next value is equal to the present value, considering all prior values.
The paper's methodology consists of the following steps: (I) cross-sectional dependence is investigated; (II) stationarity of variables is examined through

second-generation unit root tests; (III) if the stationarity is identified for the I(1) level, the long-run relationship between the considered variables will be tested with the panel cointegration method; (IV) if the cointegration is revealed, the regression coefficients are estimated with the panel fully modified ordinary least square (FMOLS) and dynamic ordinary least square (DOLS) models and (V) cross-sectional dependence, stationarity and ratio variance of errors will be tested (as proposed by Müller-Fürstenberger and Wagner, 2007).

We will examine the cross-sectional dependence by using the following tests: Breusch-Pagan LM (1980), Pesaran scaled LM and Pesaran CD (2004). The null hypothesis states the no cross-section dependence and means a null correlation of disturbances between different cross-sections (countries). The alternative hypothesis states that this correlation is different from zero. The values of Prob lower than 0.05 will indicate the rejection of the null hypothesis, in other words, the presence of the cross-sectional dependence is detected.

When the cross-sectional dependence is detected, to ensure reliable and accurate results, second-generation unit root tests are recommended. We will apply two types of such tests, proposed by Pesaran (2007), namely, the cross-sectional ADF(PES-CADF) and the cross-sectional augmented IPS (CIPS). Within both tests, the null hypothesis states the nonstationarity of sections in the panel and the alternative indicates that at least one individual section is stationary.

In order to identify a cointegration relationship between the considered variables, we will apply the Pedroni test (1999, 2004). It assumes the cross-sectional dependence and allows for heterogeneous intercepts. If at least four values of Prob. corresponding to the seven (inter-and in-group) statistics are under 0.05, the null hypothesis is rejected, indicating the detection of a long-term relationship between the examined variables.

We will also apply the Westerlund (2005) cointegration test, in order to ensure accuracy and robustness of results. The test works with two assumptions of cointegration: in "some of the panels" or in "all the panels". The p-value of variance-ration (VR) statistics indicates the acceptance/rejection of the null hypothesis (of no cointegration). If the p-value is under 0.05, the null hypothesis is rejected, revealing a cointegration relation.

Equation 1 will be estimated through the panel fully modified ordinary square (FMOLS) and the panel dynamic ordinary least square (DOLS) models introduced by Pedroni (2001a, 2001b).

Finally, the cross-sectional dependence of residuals will be tested with Breusch Pagan LM Pesaran and Pesaran CD. If the cross-sectional dependence is detected, the stationarity of errors will be checked with second-generation unit root tests (PES-CADF and CIPS). Further, the heterogeneous Lo and MacKinlay (1988,

1989) variance ratio test will be also performed for the errors of both equations (FMOLS and DOLS). A value of Prob. higher than 0.05 indicates that the null hypothesis of a martingale sequence of errors is accepted.

4. Main findings

Table 2 displays the values of statistics for all three above-mentioned tests of cross-sectional dependence for all considered variables.

Table 2 Results of cross-sectional dependence tests of variables

	lnEFP	*ECI*	*ECI2*	*lnEI*	*lnG*	*lnURB*
Breusch-Pagan LM	8396.69*	10748.26*	10216.35*	16060.99*	23011.67*	19599.95*
Pesaran Scaled LM	153.03*	202.54*	191.34*	314.39*	460.73*	388.90*
Bias corrected Pesaran Scaled LM	151.94*	201.45*	190.25*	313.30*	459.64*	387.81*
Pesaran CD	18.01*	5.22*	5.49*	100.04*	151.51*	76.47*

Note: denotes Prob.< 1%

Source: authors' own computation using EViews 12.0 software.

The value of Prob. in all tests and for all variables is under 1%, indicating the rejection of the null hypothesis of no cross-sectional dependence.

Table 3 Results of stationarity tests

Variable	**PES-CADF test z (t-bar)**		**CIPS test CIPS statistic**	
	constant	*constant and trend*	*constant*	*constant and trend*
lnEFP	5.873	1.244	-1.447	-2.654*
ΔlnEFP	-9.159**	-7.233**	-4.972**	-5.169**
ECI	-5.814**	-0.558	-2,631**	-2.414
ΔECI	-9.42**	-6.341**	-4.175**	-4.196**
ECI2	-0.300	3.481	-1.819	-2.039
ΔECI2	-8.505**	-6.045**	-4.369**	-4.404**
lnG	-2.683**	0.081	-2.241**	-2.461
ΔlnG	-9.660**	-7.562**	-4.499**	-4.724**
lnURB	7.998	6.459	-0,056	-0.937
ΔlnURB	3.104	-4.677**	-1.325	-3.938**
lnEI	-3.473**	0.971	-2.494**	-2.406
ΔlnEI	-11.298**	-8.738**	-4.770**	-4.896**

**$p < 0.01$; * $p < 0.05$

Source: authors' own computation using EViews 12.0 software.

Given the presence of cross-sectional dependence of the panel variables, we can go further, to the next step, to examine the stationarity of variables with second-generation unit root tests (PESC-ADF and CIPS). Table 3 reports the results of the second-generation unit root tests which are robust in the presence of heterogeneity of cross-sections (countries) and cross-sectional dependence (detected above). Both tests indicate that the null hypothesis of the presence of a unit root cannot be rejected for the series of variables at their level, but a stationary process is detected in their first difference series (due to the value of Prob. under 1% and 5% respectively).

Given the fact that variables are integrated by their first order I(1), we perform the residual Pedroni and Westerlund cointegration tests. According to data displayed in table 4, the value of Prob. is less than 5% for the variables of equation 1, in five cases out of 11. This indicates the presence of one cointegration relationship, at least, between *lnEFP, ECI, ECI2, lnG, ln URB* and *lnEI*.

Table 4 Results of Pedroni cointegration test

Variables: *lnEFP, ECI, ECI2, lnG, lnURB, lnEI*					
Test	Statistic	Prob.	Statistic	Prob.	
Panel v-statistic	1.289526	0.0986	-3.553509	0.9998	common AR coefficients (within-dimension)
Panel rho-statistic	6.576684	1.0000	2.639334	0.9958	
Panel PP-statistic	3.051998	0.9989	-8.394718	0.000	
Panel ADF-statistic	−5.975307	0.0000	−7.810925	0.0000	
Panel rho-statistic	4.997455	1.000			individual AR coefficients (between-dimension)
Panel PP-statistic	−13.00519	0.0000			
Panel ADF-statistic	−5.714564	0.0000			

Source: authors' own computation using EViews 12.0 software.

The next table depicts the results of the Westerlund cointegration test. For both assumptions (*some panels are cointegrated* and *all panels are cointegrated*), the values of Prob. are less than 0.01. This suggests that the null hypothesis of no cointegration between *lnEFP, ECI, ECI2, lnG, lnURB, and lnEI for* a significance level of 1% under both assumptions is rejected.

Table 5 Result of Westerlund cointegration test

Assumptions:			
"some panels are cointegrated"		*"all panels are cointegrated"*	
statistic	p-value	Statistic	p-value
−2.87805	0.0027	−4.9193	0.0000

Source: authors' own computation using EViews 12.0 software.

The cointegration coefficients are validated for both (FMOLS and DOLS) equations for a 1% level of significance, except ECI in the FMOLS models, where the level of significance is 5% (Table 6). This means that a quadratic dependency between *lnEF* and *ECI*, in the long run, is validated, representing an inverted U-shaped curve, for a 5% level of significance. The coefficient of ECI is positive (0.425; 0.494) and of ECI2 is negative (-0.149; -0.166) (respectively. The effect of other explanatory variables is as follows. Energy intensity has a statistically validated influence on the extension of ecological footprint; for a rise of 10% of energy intensity, ecological footprint increases by 2.55% (FMOLS estimation) and 2.16% (DOLS estimation). Urbanization rate has a similar effect on ecological footprint: for an increase of 10% in urbanization rate, the response of environmental degradation is of 6.08% increase of (FMOLS equation) and 6.23% (DOLS equation) of ecological footprint. A reducing effect of globalization on environmental degradation was also identified as statistically significant. When the globalization index increases by 10%, the reduction effect on ecological footprint is 3.72% (FMOLS estimation) and 4.5% (DOLS estimation).

Table 6 Estimation of coefficients of cointegrating polynomial regression

			FMOLS		
	ECI	***ECI2***	***lnG***	***lnURB***	***lnEI***
Coeff.	0.425**	-0.149*	-0.372**	0.608**	0.255**
Stat.	3.091	-2.383	-3.400	5.646	4.461
R-sq			0.1869		
Obs.			1104		
			DOLS		
Coeff.	0.494**	-0.166**	-0.405**	0.623**	0.216**
Stat.	3.610	-2.657	-3.729	5.838	3.831
R-sq			0.2076		
Obs.			1104		

** p<0.01; *p<0.05

Source: authors' own computation using EViews 12.0 software.

In order to ensure the robustness of the results, we check the cross-sectional dependence of errors (Table 7).

Table 7 Cross-section dependence test for FMOLS and DOLS equations residuals

	FMOLS		DOLS	
Test	**Statistic**	**Prob**	**Statistic**	**Prob**
Breusch-Pagan LM	7730.030	0.0000	8056.396	0.0000
Pesaran scaled LM	142.998	0.0000	145.869	0.0000
Bias-corrected scaled LM	141.879	0.0000	144.778	0.0000
Pesaran CD	21.101	0.0000	19.303	0.0000

Source: authors' own computation using EViews 12.0 software.

Due to the fact the cross-sectional dependence is identified for both sequences of errors (Table 7), in order to ensure the robustness of results, we test their stationarity through second-generation unit root tests. The results displayed in Table 8 show that the residuals follow a stationary process (the values of Prob. are under 0.05).

Table 8 Results of residuals stationarity

	PES-CADF test z (t-bar)		CIPS test CIPS statistic	
	constant	*constant and trend*	*constant*	*constant and trend*
FMOLS residuals	-2.515**	-4.649**	-2.531*	-3.677**
DOLS residuals	-1.343	-2.933**	-2.172	-3.173**

**p<0.01; * p<0.05

Source: authors' own computation using EViews 12.0 software.

The value of Prob. in the variance ratio test for residuals of FMOLS and DOLS equations is higher than 0.05 (Table 9). This indicates the presence of a martingale sequence of errors, meaning that, given all prior values, at a given moment, the conditional expectation of the next value in the sequence, will be equal to the present value.

Table 9 Variance ratio test of FMOLS and DOLS residuals

Fisher combined test	FMOLS		DOLS	
	$\max\lvert z\rvert$	Prob.	$\max\lvert z\rvert$	Prob.
asymptotic normal	91.104	0.5654	110.16	0.1532
wild bootstrap	11.585	1.000	106.30	0.2219

Source: authors' own computation using EViews 12.0 software.

Based on the results of all the above tests, we can conclude that the "cointegrating polynomial regression" (CPR) is validated, based on the assertions of Wagner and Hong (2016). It reflects a quadratic dependence of ecological footprint on economic complexity when other explanatory variables (globalization, energy intensity and urbanization rate) are included.

5. Conclusions and policy implications

The paper intended to check the validity of the Environmental Kuznets Curve hypothesis by replacing the variable "income" with the "economic complexity" index (ECI) as a proxy for economic activity for the 48 most complex economies in the world and using ecological footprint as indicator of environmental degradation. The study uses the model of cointegrating polynomial regression (CPR) that includes other explanatory variables of environmental degradation such as urbanization, energy intensity and globalization. Second-generation unit root for stationarity and cointegration tests, under cross-sectional dependence of panel data, were used to examine the long-run relationship between the variables under examination. A validated long-run cointegration relationship was identified between the considered variables. A panel cointegrating polynomial regression (Wagner, 2015; Wagner and Hong, 2016) is statistically validated and the inverted U-shaped curve is validated in the panel of the 48 complex economies. Considering the economic complexity index, the EKC hypothesis holds for this panel analysis. The EKC model was also validated in similar studies using ECI as an explanatory variable (Neagu (2019); Pata (2021); Chu& Le (2021). In the early stages of economic complexity, the diversification and sophistication of products have as a result an increasing pressure on the environment. At a certain level of economic complexity, when the production structure is well diversified and the economy has resources and capacity to innovate, develop and use clean and efficient technologies less pollutant accompanied with effective policy measures meant to limit environmental depreciation, the effect of economic complexity progress on ecological footprint became beneficial, the pressure on the environment being diminished.

The present analysis on the panel of 48 most complex economies in the world suggests the way these countries are able to manage the balance between the increasing complexity of their productive structure and environmental concerns. It is highlighted also the fact that economic complexity can contribute to the overall improvement of environmental performance when a certain level of products' sophistication and diversification is reached. This is related to a stage of economic development when the economy has the capacity can to uptake innovation, mainly green innovation for new complex products as suggested by Gala et al. (2018).

An increasing effect of urbanization and energy intensity on ecological footprint was identified in the examined panel of countries. This result is consistent with other studies regarding urbanization (Ozturk et al., 2016; Bilgili et al., 2020; Ahmed et al., 2020a; 2020b; Ansari et al., 2020; Danish et al., 2020) and energy intensity (e.g., Bilgili et al., 2017; Dogan et al., 20200a and 2020b; Chu &Le, 2021) as determinants of ecological footprint increase. This is justified by the fact that the countries in the examined sample have a high rate of urbanization, economic progress, intensive industrial and transport activities based on fossil fuels and other non-renewable energy sources.

It is also revealed the reducing impact of globalization on the ecological footprint in accordance with findings of several authors (e.g. Figge et al., 2017; Rudolph and Figge, 2017; Sabir and Gorus, 2019; Ansari et al., 2020; Gormus and Aydin, 2020; Nathaniel, 2021).

The paper's findings have several policy implications as follows: (1) energy intensity must be further monitored mainly in chemical, machinery and energy production sectors and appropriate policy measures (regulations or financial incentives) are need continually needed to increase the energy efficiency and effectiveness of the resources use ; (2) these complex economies possess high quality human capital and R&D resources to introduce innovation and new technologies in these sectors; thus globalisation, the process supporting the connection between researchers and knowledge networks can be taken as an advantage; but the import of pollution-intensive technologies and other non-renewable energy sources must be put under control; (3) structural changes are needed in industrial and manufacturing sectors which must be largely based on cleaner and renewable energy sources that help reduce pollutant emissions through appropriate energy-mix policies; (4) in the sector of urbanisation further progress must be also made on the path to reduce pollution through the development of hybrid and electrical means of transport and extensively promoting the smart and clean city concepts.

As limits of the study, we mention the short time span of the data series (1995-2017). Further directions of research may include: (1) to include in the dimensions of globalization (social, economic, political) in the analysis; (2) to include other explanatory variables of environmental pressure (energy structure, renewable, non-renewable energy consumption, green economy index, the share of green products; (3) to extend the study to another group of countries based on geographical or income criteria; (4) to develop analyses of the EKC model on individual countries when longer time data series will be available.

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