Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi 2021 9(4) 1007-1017

Journal of Social Sciences of Mus Alparslan University

anemon

Derginin ana sayfası: http://dergipark.gov.tr/anemon

Araştırma Makalesi ● Research Article

Effects of Environmental Innovations, Renewable Energy Consumption and Economic Growth on CO_2 Emission: Panel Data Analysis for Select G-20 Countries

Çevresel İnovasyonlar, Yenilenebilir Enerji Tüketimi ve Ekonomik Büyümenin CO_2 Emisyonu Üzerine Etkileri: Seçilmiş G-20 Ülkeleri için Panel Veri Analizi

Selim Demez*

Abstract: Environmental problems are becoming more visible and this detrimental situation, negatively affecting the national economies. Therefore, the economic effects and costs of environmental problems have become an important research topic in the field of economics. In the literature, carbon dioxide (CO_2) emission is generally used as an environmental pollution indicator. It is thought that renewable energy investments and innovative approaches to the environment can overcome environmental problems in the long run. In this study, the effect of environmental innovations (ETI), renewable energy (REC) and growth (GDP) on CO_2 emission examined for 8 countries, listed according to the IMF's classification in the G-20 country group between 1993 and 2018. Durbin-H cointegration and FMOLS tests are used in the analysis, considering the cross-sectional dependency and heterogeneity. According to the analysis results, there is a long-term relationship between the variables. The effects of the variables considered on CO_2 emission differ by country, the change in REC and GDP for the panel generally reduces CO_2 emission, while the increase in ETI increases CO_2 emission.

Keywords: Enviromental Innovationsions, Renewable Energy, Growth, CO_2 Emissions

Öz: Çevresel problemler her geçen gün katlanarak artmaktadır ve bu durum doğrudan ve dolaylı olarak ülke ekonomilerini de olumsuz yönde etkilemektedir. Bu nedenle çevresel problemlerin ekonomik etkileri ve maliyeti iktisat alanında önemli bir araştırma konusu haline gelmiştir. Çevresel kirlilik göstergesi olarak literatürde genellikle karbondioksit (CO_2) emisyonu kullanılmaktadır. Yenilenebilir enerji yatırımları ve çevreye yönelik inovatif yaklaşımların uzun dönemde çevresel problemlerin üstesinden gelebileceği düşünülmektedir. Bu çalışmada çevresel inovasyonlar (ETI), yenilenebilir enerjinin (REC) ve büyümenin (GDP) CO_2 emisyonu üzerindeki etkisi 1993-2018 yılları arasında G-20 ülke grubunda IMF'nin sınıflandırmasına göre gelişen statüsündeki 8 ülke için incelenmiştir. Analizde yatay kesit bağımlılığı ve heterojenliği dikkate alan Durbin-H eşbütünleşme ve FMOLS testleri kullanılmıştır. Analiz sonuçlarına göre değişkenler arasında uzun dönemli bir ilişki vardır. Ele alınan değişkenlerin CO_2 emisyonu üzerindeki etkileri ülkeden ülkeye farklılık göstermektedir fakat panelin geneli için REC ve GDP'deki artışın CO_2 emisyonu üzerindeki etkisi negatifken ETI'daki artışın etkisi beklenenin aksine pozitiftir.

Anahtar Kelimeler: Çevresel İnovasyonlar, Yenilenebilir Enerji, Büyüme, CO_2 Emisyonu

* Dr. Öğr. Üyesi, Hakkari Üniversitesi, İ.İ.B.F., İktisat Fakültesi, İktisat Bölümü
ORCID: 0000-0001-6885-0499 selimdemez@hakkari.edu.tr

Received/Geliş: 31 May/Mayıs 2021 **Düzeltme/Revised form:** 03 August/Ağustos 2021
Accepted/Kabul: 12 August/Ağustos 2021 **Published/Yayın:** 31 August/Ağustos 2021

e-ISSN: 2149-4622. http://dx.doi.org/10.18506/anemon.946043

Introduction

Innovation refers to the implementation of the inventions and explorations in a certain field in the economic fields and activities. As such, innovation is seen as an important dynamic and variable of the sustainable development in the contemporary information society, characterized by technological advances. A number of studies show that the convergence hypothesis proposed in the neo-classical growth theory is not empirically valid, thus leading up to the emergence of internal growth theories reviewing the technological advances internally. Schumpeter underlines that innovation is the basis of technological development and recalls that it leads to economic growth (Schumpeter and Backhaus, 2003: 71). However, efforts towards industrialization, as well as accompanying problems such as rapid urbanization and sweeping globalization, all direct results of efforts for further economic growth, lead to environmental deterioration and spike in the energy consumption. For this reason, innovation, often taken as a sign of greater production and outcome in industrial field, contributes to the environmental degradation. Esso and Keho (2016), for instance, argue that economic growth cannot be possibly achieved without causing any environmental damage.

Because global warming and climate change have turned into alarming issues, it seems necessary to take precautions for the future. One such measure is the Kyoto climate change conference convened in Kyoto in 1997 where the participants discussed the measures to be taken to address climate change, environmental pollution and global warming (Emrullah, 2020: 384). The participants agreed that the industrialized nations should limit the greenhouse gas emissions; the rules on this measure have come into effect in 2005. Additionally, the Kyoto Protocol states that renewable energy should be promoted and supported in order to reduce the CO_2 emission (Gormus and Aydin, 2020: 27904). It should also be noted that the developed nations are more eager than the developing countries in terms of addressing the environmental problems (San Cristóbal, 2011: 488).

As noted above, renewable energy resources are considered long term alternative solution to reduce the greenhouse emission associated with fossil fuel consumption. Renewable energy consumption has risen by 3 pct annually, becoming a prominent alternative energy resource. Because the already limited amount of fossil fuel means that it will eventually be depleted, it is not surprising to see efforts towards promoting renewable energy use (Alper and Oğuz, 2016: 953). The literature suggests that there is negative correlation between renewable energy and environment.

The goal in this study is to identify the impact of the environmental innovations, renewable energy and economic growth on the environment in the developing nations, classified as such by the IMF, within the G-20 Group of states. A review of the literature suggests that most of the academic accounts take R&D spending and total number of patents as innovation variable. However, some of the patents included in these studies have nothing to do with environment. For this reason, this analysis utilizes only patents applications pertinent to the environment to seek answers to question as to how and to what extent environmental innovations, renewable energy and economic growth affects the CO_2 emission. The reason developed that nations have been picked as unit of analysis is the possibility that the GDP gap between developed and developing nations might lead to misleading results.

The first part of the study reviews the linkage between CO_2 emission, innovation, renewable energy and growth whereas the second part deals with the relevant accounts in the literature. The third part explains the method and findings. The fourth part evaluations and policy recommendations are given according to the results of the analysis.

Select Literature

Innovation refers to number of patents in the literature; number of scholarly accounts focusing on the impact of innovation on environment or the CO_2 emission is very small as it is an emergent field. The OECD database features relevant data on the number of patents by countries and by fields. Environmental innovation that we utilize in this study is one of these categories. The following is a compilation of the works in the literature exclusively focusing on the discussions that fall into that category:

Table 1: Select empirical literature

Author(s)	Count./period.	Eco. Mod.	Findings
Wang and Zhu (2020)	30 cities in China 2001-2017	Spatial econometrics	The study finds that developments in the renewable energy technologies reduce the CO_2 emission but innovations in the fossil fuel technologies have no impact upon CO_2 emissions.
Mensah et al., (2018)	28 OECD member countries 1990-2014	Cointegration and FMOLS	Environmental innovations reduce CO_2 emissions
Fernández et al. (2018)	15 European Union members, United States and China 1990-2013	Least squares analysis	Environmental innovations reduce CO_2 emissions
Ganda (2019)	26 OECD Member states 2000-2014	System GMM analysis	Innovations increase CO_2 emissions but R&D spending reduces CO_2 emissions
Wang et al., (2020)	G—7 countries 1990-2017	Westerlund (2007) and CS-ARDL panel cointegration tests	Renewable energy and environmental innovations reduce CO_2 emissions
Santra (2017)	BRICS Countries 2005-2012	Panel regression analysis	Environmental innovations reduce CO_2 emissions
Hasanov et al., (2021)	BRICS countries 1990-2017	Westerlun (2007, 2008) panel cointegration and CS-ARDL analysis	Innovations and renewable energy reduce CO_2 emissions
Bai et al., (2020)	Chinese cities 2000-2015	Panel regression and Panel threshold value analysis	Innovations and renewable energy reduce CO_2 emissions
Cheng et al., (2019a)	35 OECD members 1996-2015	Panel quantitative regression model	Innovation has no significant impact upon CO_2 emission but it has some positive impact at some quantitative levels
Lin and Zhu (2019)	China's cities 2000-2015	Panel Bootstrap Threshold method	Increase in renewable energy innovations lead to reduction in CO_2 emissions
Cheng et al., (2019b)	BRICS countries 2000-2013	Panel quantitative regression model	Environmental innovations increase CO_2 emission per person
Saudi et al., (2019)	Malaysia 1980-2017	ARDL cointegration analysis	Innovation reduces CO_2 emissions
Erdoğan et al., (2019)	14 G-20 countries 1970-2017	Westerlund Edgerton (2008) Panel cointegration analysis	Innovation reduces CO_2 emission in industrial sector and increases CO_2 emission in construction sector
Temelli and Şahin (2019)	10 rising market economies 1995-2014	Westerlund and Edgerton (2007) cointegration analysis	No correlation between innovation and CO_2 emission

A review of the table above reveals that all these studies, except one, relied on panel data. This is most probably because there is no long-term dataset suitable for a time series analysis. Except Cheng et al., (2019a), Cheng et al., (2019b), Erdoğan et al., (2019), all the cited works in this table present findings suggesting that innovation reduces CO_2 emission. However, Cheng et al., (2019a), Cheng et al., (2019b), Erdoğan et al., (2019), Wang and Zhu (2020), Mensah et al., (2018), Wang et al., (2020), Santra (2017), Bai et al, (2020) utilized innovation data in the field of environmental innovation and renewable energy rather than total innovation data. Additionally, Ganda (2019) finds that innovation increases CO_2 emission but R&D spending reduces the CO_2 emission. All these studies do not enable us to offer conclusive insights because they have been carried out in different countries, relying on different variables, periods and method. But it is also possible to draw some local conclusions in reference to these works.

Data and Methodology

Data

This study analyzes annual data for the period of 1993-2018 from eight developing nations (part of the G-20 group Australia, Brazil, China, India, Indonesia, Mexico, South Africa and Turkey), listed by the IMF in this category. The data on the ratio between the CO_2 emission and the GDP in USD and the total renewable energy consumption has been retrieved from the International Energy Agency (EIA). In representation of the environmental innovation, the number of patents in environment-related field in the OECD.stat database have been used. The GDP data has been compiled from the World Development Indicator (WDI) data base, published by the World Bank.

$$CO_{2it} = a_i + \beta_1 LNETI_{it} + \beta_2 LNREC_{it} + \beta_3 LNGDP_{it} + \mu_{it} \tag{1}$$

In this equation, i and t refers to unit and time dimension respectivel, CO_2 to carbon dioxide emission, EIT to environmental innovation, REC to renewable energy, LNGDP to GDP in place of economic growth and μ to error term. LN, preceding ETI, REC and GDP variables, shows that the natural logarithms of the variables have been taken.

Table 2: Descriptive statistics

	CO_2	GDP	REC	ETI
Mean	0.7082	12.0066	4.1009	1.7737
Maximum	1.7160	13.0364	5.3125	3.7524
Minimum	0.2060	11.3398	3.0335	-0.4815
Std. Dev.	0.4247	0.3431	0.6375	0.9610

Descriptive statistics of the variables can be seen in the table. Our study is a balanced panel data study. We have 208 observations for each series. There are no extreme values in the series and the variables have a certain standard error distribution.

Method

Cross-Sectional Dependence and Slope Homogeneity Test

When working with panel time series, it is necessary to look at the cross-sectional dependence (CSD) of the variables. CSD suggests that factors such as globalization and integration movements may lead to supply or demand shocks in a given country which may then affect others as well. For this reason, tests performed without consideration of the CSD may not be consistent. Additionally, whether the model constructed is homogenous also matters. If the model is not homogenous, then tests considering the heterogeneity are more suitable to use. There are a number of tests to identify the CSD in the literature.

Breusch and Pagan (1980) test statistics is as follows:

$$LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij} \hat{\rho}_{ij}^2 \quad \sim \quad \chi^2_{N(N-1)/2} \tag{2}$$

ρ_{ij} denotes the estimated value of the correlation coefficients of the equation. In Breusch and Pagan (1980) LM test, the null hypothesis of no dependence in cross-sections is tested against unit hypothesis of dependence between two cross sections. This test better works where N < T. For this reason, where N > T, it is better to use Paseran's (2004) CD_{LM} (Yilanci and Ozgur, 2019: 24799).

$$CD_{LM} = \left(\frac{1}{N(N-1)}\right)^{1/2} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T_{ij} \rho_{ij}^2 - 1) \ \sim N(0,1) \tag{3}$$

Pesaran (2004) develops the following CD test where T→∞ ve N→∞:

$$CD = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T_{ij}\rho_{ij}^2) \ \sim N(0,1) \tag{4}$$

If the dual correlation residuals at the unit dimension in the CD test shown at equation 7 is not 0, then it means that it is weak and should be replaced by the following version of the Pesaran et al. (2008) LM test (Ozcan et al., 2017:84-85).

$$LM_{adj} = \sqrt{\left(\frac{2}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{ij} \frac{(T-k)\hat{p}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} \sim N(0,1) \tag{5}$$

In equation 8, k denotes number of independent variables and, μ and ν refer to the expected value and variance of $\hat{p}_{ij}$ respectively.

Pesaran and Yamagata (2008) suggest a test to determine heterogeneity. The simulations run for this test are strong where T→∞ and N→∞. For this reason, it is a test that can be utilized for every N and T. The null hypothesis that represents homogeneity is $H_0: \beta_i = \beta$, and it is tested against the alternative hypothesis $H_1: \beta_i \neq \beta_j$. This test is in fact an advanced version of the Swamy test:

$$\tilde{S} = \sum_{i=1}^{N} \left(\hat{\beta}_i - \beta_{WFE}\right)' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} \left(\hat{\beta}_i - \beta_{WFE}\right) \tag{6}$$

In the equation, $\hat{\beta}_i \; and \; \beta_{WFE}$ refer to pooled least squares and the weighted fixed impact estimators respectively. M_τ denotes the defining matrix based on T and $\tilde{\sigma}_i^2$. $\tilde{\Delta}$ test is shown below:

$$\tilde{\Delta} = \sqrt{N} = \left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k(T-k-1)/T+1}}\right) \ \sim N(0,1) \tag{7}$$

PANICCA Unit Root Test

PANICCA unit root test was developed by Reese and Westerlund (2016). This test is a combination of the PANIC tests that individually examine the stationarity of the factors and residues in the work by Bai and Ng (2010) and the unit root test performed by Pesaran (2007) and Pesaran et al. (2013) for the multifactor test by referring to the cross-sectional averages (CA); as such, it was named PANICCA to denote this combination. Pesaran (2007), at CADF test, adds $\bar{Y}_t$ that may be denoted as the cross-sectional average of the dependent variable Y_{it} in the model as instrumental variable. In this case, the non-stationarity of Y_{it} would mean the non-stationarity of $\bar{Y}_t$, thus leading to a problem of spurious regression. For this reason, a critical value needs to be generated for all time and unit dimensions of the variable. Because the difference equation of Y_{it} is processed at the Bai and Ng (2010) PANIC test, the spurious regression problem is eliminated. Simulations draw attention to the weak aspects of the PANIC test where $N < T$ (Reese and Westerlund, 2016:962; Yerdelen Tatoğlu, 2017:101). The common factor equation for Y_{it} data generation process:

$$Y_{it} = a_i' D_{tp} + \lambda_i' F_t + e_{it} \tag{8}$$

In equation 8, F_t refers to the common factor vector of the common load coefficients vector at $(rx1)$ vector that is related to λ_i, $D_{tp} = (1, \dots, t^p)$, to constant and trend vector with $(p+1)x1$ dimension where $p = 0$ and $p = 1$ respectively, e_{it} to error term. Here Y_{it} variable is allowed to be added one or more additional factor variables with $(mx1)$. If that case is shown by X_{it}, ability of X_{it} to generate data becomes as follows (Reese and Westerlund, 2016: 993).

$$X_{it} = \beta_i' D_{tp} + \Lambda_i' F_t + \mu_{it} \tag{9}$$

When equations 8 and 9 are shown as $Z_{it} = (Y_{it}, X_{it}')'$;

$$Z_{it} = \beta_i' D_{tp} + C_i' F_t + V_{it} \tag{10}$$

Equation 10 becomes $B_i = (a_i, \beta_i)$, $C_i = (\lambda_i, \Lambda_i)$ ve $V_{it} = (\varepsilon_{it}, \mu_{it}')'$. C_i is at the dimension of $rx(m+1)$.

Because in PANIC test, Z_{it} assumingly remains stationary because its subtraction is taken, and classical methods are applied to the residues of the Z_{it}'s common factor model. The matrix form of this defined model is denoted as follows:

$$z_i^p = f^p C_i + v_i^p \tag{11}$$

In equation 11, the CA estimators of f^pve v_i^p are shown in equations 6 and 7 respectively:

$$\hat{f}^p = M_p \bar{z} = \bar{z}^p = N^{-1} \sum_{i=1}^{N} M_p z_i \tag{12}$$

$$\hat{v}_i^p = z_i^p - \hat{f}^p \hat{C}_i \tag{13}$$

As for equations 12 and 13, unlike others, in this test, $\hat{f}^p$' is considered as estimator of f^p'. To test stationarity, Reese and Westerlund (2016) utilized ADF test proposed by Bai and Ng (2004). To test the stationarity of the residues, the P_a and P_b test statistics are shown at equations 14 and 15:

$$P_a = \frac{\sqrt{NT}(\hat{p}^+ - 1)}{\sqrt{2\hat{\phi}_e^4 / w_e^4}} \tag{14}$$

$$P_b = \sqrt{NT}(\hat{p}^+ - 1)\sqrt{\frac{1}{NT^2} tr\left(\hat{\varepsilon}_{-1}' \hat{\varepsilon}_{-1}\right) \frac{w_e^2}{\hat{\phi}_e^4}} \tag{15}$$

In this equation, if $p = -1$ and $p = 0$, $\hat{p}^+ = \frac{tr(\hat{\varepsilon}_{-1}'\hat{\varepsilon}) - NT\hat{\lambda}_e}{tr(\hat{\varepsilon}_{-1}'\hat{\varepsilon}_{-1})}$ and if $p = 1$, $\hat{p}^+ = \frac{tr(\hat{\varepsilon}_{-1}'\hat{\varepsilon})}{tr(\hat{\varepsilon}_{-1}'\hat{\varepsilon}_{-1})} + \frac{3}{T}\frac{\hat{\sigma}_e^2}{\hat{w}_e^2}$. Here $\hat{\sigma}_e^2$, $\hat{w}_e^2$, $\hat{\lambda}_e$ refer to the variance of $\hat{e}_{it}$', long term variance and unidirectional long term variance respectively. $\hat{\phi}_e^4$, on the other hand, refers to the cross-sectional average of w_e^4 (Yerdelen Tatoğlu, 2017: 100-103).

Durbin Hausman (Durbin-H) Panel Cointegration Test

The cointegration tests are performed to identify long term relationship between the variables in the model. If a cointegration correlation exists between variables, it will be proper to interpret the long term coefficients. In the Durbin-H cointegration test developed by Westerlund (2008), the first difference is taken by the least squares method and then the common factors of the residues are estimated by reliance on the main components methods. If we proceed with the following difference equation;

$$\Delta y_{it} = \lambda_i' \Delta A_t + \Delta e_{it} \tag{16}$$

y_{it} is unknown in equation 16. For this reason, we need to utilize the main components method instead of the least squares method:

$$\Delta \hat{y}_{it} = \Delta a_{it} - \hat{\beta}_i \Delta b_{it} \tag{17}$$

In equation 17, $\hat{\beta}_i$ is obtained by regressing Δa_{it} to Δb_{it}. $\hat{A}_t$ is obtained by calculating the eingen vector corresponding to the largest Eigen value of the $\Delta\hat{y}\Delta\hat{y}'$ matrix at the level of $(T-1)x(T-1)$ for $\sqrt{(T-1)}$ times. The estimated factor loads are calculated as $\hat{\lambda} = \frac{\Delta\hat{A}'\Delta\hat{y}}{T-1}$ (Altıntaş and Mercan, 2015: 367). Based on this, the following equation of the defactorized and subtracted residues is devised:

$$\Delta \hat{e}_{it} = \Delta \hat{y}_{it} - \hat{\lambda}_i' \Delta \hat{A}_t \tag{18}$$

The following equation generates the total residues:

$$\hat{e}_{it} = \sum_{j=2}^{t} \Delta\hat{e}_{ij} \tag{19}$$

When we modelized $\hat{e}_{it}$ in equation 19, we will have equation 20:

$$\hat{e}_{it} = \phi_i \hat{e}_{it-1} + hata \tag{20}$$

The relevant equations required for Durbin-H group and panel test statistics emerge from here:

$$w_i^2 = \frac{1}{T-1} \sum_{j=-M_i}^{M_i} \left(1 - \frac{j}{M_i + 1}\right) \sum_{t=j+1}^{T} \hat{v}_{it} \hat{v}_{it-j} \tag{21}$$

In equation 21, $\hat{v}_{it}$ refers to residues from equation 19. M_i refers to band width defined as much as the autovariances used in estimating v_{it}, w_{it} to the long term variance of v_{it}. This is how the two variance estimate is obtained: $\hat{S}_i = \hat{w}_i^2 / \hat{\sigma}_i^4$ ve $\hat{S}_n = \hat{w}_n^2 / (\hat{\sigma}_n^2)^2$ here $\hat{w}_n^2$ and $\hat{\sigma}_n^2$ are calculated via the following equations:

$$\hat{w}_n^2 = n^{-1} \sum_{i=1}^{n} \hat{w}_i^2 \qquad and\ \hat{\sigma}_n^2 = n^{-1} \sum_{i=1}^{n} \hat{\sigma}_i^2 \tag{22}$$

Durbin-H test group and panel test statistics are shown below:

$$DH_g = \sum_{i=1}^{n} \hat{S}_i \left(\tilde{\phi}_i - \hat{\phi}_i\right)^2 \sum_{t=2}^{T} \hat{e}_{it-1}^2 \tag{23}$$

$$DH_p = \hat{S}_n \left(\tilde{\phi} - \hat{\phi}\right)^2 \sum_{i=1}^{n} \sum_{t=2}^{T} \hat{e}_{it-1}^2 \tag{24}$$

In equation 24, the null hypothesis of $H_0: \phi_i = 1, \forall i = 1, \ldots, n$ is tested against $H_1^p: \phi_i = \phi$ ve $\phi_i < 0$ for the panel. Rejection of the null hypothesis shows that there is cointegration correlation for each unit (n). On the other hand, in the group estimation (equation 23), $H_0: \phi_i = 1$ is tested against $H_1^g: \phi_i < 1$ and rejection of the null hypothesis means there is cointegration (Westerlund, 2008: 200-203; Altıntaş and Mercan, 2015: 367-368).

Table 3: Cross-sectional dependence and slope homogeneity test results

Tests	**Test Stat.**	**Prob.**
LM / Breusch and Pagan (1980)	50.276^{I}	0.006
LM_{adj} / Pesaran et al. (2008)	7.313^{I}	0.000
CD_{LM}/ Pesaran (2004)	2.977^{I}	0.001
CD/ Pesaran (2004)	0.516	0.303
Slope homogeneity test results Pesaran and Yamagata (2008)		
Δ	8.577^{I}	0.000
$\Delta_{adj.}$	9.502^{I}	0.000

PS: I refers to significance at %1 level.

Based on the test results presented in Table 3, It is possible to argue that there is cross-section dependence and heterogeneity in the model. This means that the economic shock in the countries included in the analysis affects other countries as well. For this reason, we need to utilize tests that consider the cross-sectional dependence and heterogenous structure in the analysis.

Table 4: PANICCA unit root test results

Tests	CO_2	REC	ETI	GDP
P_a	-1.5751 (0.942)	-2.4357 (0.993)	-0.1128 (0.545)	-1.6319 (0.949)
P_b	7.0898 (0.972)	2.2415 (0.999)	15.3619 (0.498)	6.7685 (0.978)
Tests	**ΔCO2**	**ΔREC**	**ΔETI**	**ΔGDP**
P_a	5.3465[a] (0.000)	2.2996[b] (0.010)	5.9111[a] (0.000)	1.350[c] (0.0885)
P_b	46.2445[a] (0.000)	29.0083[b] (0.024)	49.4382[a] (0.000)	23.635[c] (0.0978)

PS: a, b and c refer to %1, %5 and %10 significance levels respectively. The values within the parentheses denote the probabilities for the tests and Δ refers to the first degree subtraction of the variables. PANICCA unit root test is performed for the constant model.

In Table 4, according to PANICCA unit root test results, all variables are stationary when first subtraction is taken and root-united at surface values. In other words, the variables are stationary at the same level I(1). This means that all cointegration tests may be used:

Table 5: Durbin-H cointegration test results

Tests	Test statistics	Probability
DH_g	-1.828[I]	0.034
DH_p	-2.021[I]	0.022

PS: I refers to significance at %5 level.

In Table 5, according to Durbin-H test results, for both group Dh_g_and panel Dh_p test statistics, the null hypothesis suggesting that there is no cointegration in both models is rejected. In this case, it is possible to conclude that the variables are correlated in the long term. Subsequently, the long term coefficients may also be considered. Because the model is not homogenous, the FMLOS test that considers the heterogenous structure is performed.

Table 6: Estimating long term coefficients via FMOLS method

	$CO_2 = f(ETI)$		$CO_2 = f(REC)$		$CO_2 = f(GDP)$	
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
FMOLS (Grup)	0.125[a]	0.000	-0.41[a]	0.005	-0.71[a]	0.000
Aust.	0.14[a]	0.000	0.01	0.825	-0.61[a]	0.000
Brazil	-0.01	0.639	-0.40[a]	0.007	0.50[a]	0.001
China	0.73[a]	0.001	-3.21[a]	0.003	-3.69[a]	0.000
India	-0.28[b]	0.041	0.98[c]	0.084	0.57	0.210
Indon.	0.02	0.774	0.39[c]	0.051	-0.22	0.143
Mexico	0.11[a]	0.002	-0.31	0.282	-0.78[a]	0.000
S. Africa	0.26[a]	0.002	-0.75	0.115	-1.06[a]	0.001
Turkey	0.05[a]	0.006	0.01	0.971	-0.39[a]	0.005

PS: a, b and c refer to the significance levels of %1, %5 and %10 respectively.

Table 6 presents the long term coefficients of the variables in the model. A review of the FMLOS estimate for the entire panel reveals that one unit increase in ETI, REC and GDP increases CO_2 by 0.13 unit and reduces it by 0.41 and 0.71 respectively. This is something that can be expected. The findings collaborate with the findings by Ganda (2019), Cheng et al. (2019b) and Erdoğan et al. (2019). In addition, ETI increases CO2 emission in Australia, China, Mexico, South Africa and Turkey and reduces it in Brazil and India. REC, on the other hand, reduces CO2 in Brazil and China and increases it in India and Indonesia. The impact of the GDP upon CO_2 emission is statistically significant in all countries except India and Indonesia. The increase in GDP increases CO_2 emission in Brazil and reduces it in all others. The results confirm findings by Ganda (2019) and Cheng et al. (2019b).

Conclusion

Efforts towards addressing environmental problems have attracted attention of the economists as well. A general observation suggests that the developed and developing nations are most responsible for the CO_2 emission. However, developed nations, compared to the less developed and developing nations, are more attentive to the environmental issues and to the idea of devising policies and solutions. Obviously, it takes time for the environmental policies to produce favorable results. For this reason, a long-term analysis should be performed to better estimate the possible impacts of the measures taken to address environmental degradation. For this reason, this study departs from the premise that it is better to look at the long term estimates and disparities between the countries in the analysis in terms of development.

The goal in this study is to analyze, based on the assumptions and premises provided above, the impact of renewable energy, environmental innovations and economic growth upon the CO_2 emission, a key component in the environmental issues, for the countries referred to by the IMF classification as developing nations within the G-20 Group that makes up 85 pct of the world economy. This will provide insights on whether or not the innovations on measures, policies and environment will work. Additionally, because a shock in a given country often affects other countries as well because of globalization, trade agreements and integration movements, the analysis should focus on countries individually and as a group as well. The analysis in the study was caried out this premise.

The findings in the analysis reveals that growth in group estimate and change in the renewable energy consumption negatively affect CO_2 emission whereas change in the environmental innovations has a positive impact. Environmental innovations have the least and the growth has the most impact upon the CO_2 emission.

As noted in the environmental Kuznets hypothesis, these countries actually represent the start of the reverse U. Findings by Yerdelen Tatoğlu and İçen (2019), Grimes and Roberts (1997) and Demez (2021) confirm this assumption. As expected, the renewable energy consumption negatively affects the CO_2 emission. However, environmental innovations have an effect of increasing the CO_2 emission. It is possible to argue that this is because the innovations on the environment are not implemented due to cost-related and political constraints. A review of the findings by country reveals that the environmental innovations have a reducing impact upon the CO_2 emission only in India. However, even though it is statistically significant for renewable energy and growth, it has no economic significance. This may be because the patent scores by India in the environmental R&D projects are carried out in cooperation with other countries lead to environmental innovation data. It is observed that environmental innovations increase CO_2 emissions in Australia, China, Mexico and South Africa. It is possible to argue that the reasons cited for the panel group is applied to this case as well.

Greater attention should be paid to the renewable energy in the countries reviewed in the analysis. The findings show that renewable energy plays a huge role reducing CO_2 emission. Environmental innovations should be promoted in the industry and implemented properly and effectively. Additionally, R&D activities on the environment should be promoted and supported. Because investment on the renewable energy will lead to decline in dependence on external sources for energy, such investments will be huge asset to national economy in the long run.

References

Alper, A., & Oguz, O. (2016). The role of renewable energy consumption in economic growth: Evidence from asymmetric causality. *Renewable and Sustainable Energy Reviews, 60,* 953-959.

Altıntaş, H., & Mercan, M. (2015). Ar-Ge Harcamaları ve Ekonomik Büyüme İlişkisi: OECD Ülkeleri Üzerine Yatay Kesit Bağımlılığı Altında Panel Eşbütünleşme Analizi. *Ankara Üniversitesi SBF Dergisi*, *70*(2), 345-376.

Bai, C., Feng, C., Yan, H., Yi, X., Chen, Z., & Wei, W. (2020). Will income inequality influence the abatement effect of renewable energy technological innovation on carbon dioxide emissions?. *Journal of environmental management*, *264*, 110482.

Bai, J., & Ng, S. (2004). A PANIC attack on unit roots and cointegration. *Econometrica*, *72*(4), 1127-1177.

Bai, J., & Ng, S. (2010). Panel unit root tests with cross-section dependence: a further investigation. *Econometric Theory*, 1088-1114.

Cheng, C., Ren, X., & Wang, Z. (2019a). The impact of renewable energy and innovation on carbon emission: An empirical analysis for OECD countries. *Energy Procedia*, *158*, 3506-3512.

Cheng, C., Ren, X., Wang, Z., & Yan, C. (2019b). Heterogeneous impacts of renewable energy and environmental patents on CO_2 emission-Evidence from the BRIICS. *Science of the total environment*, *668*, 1328-1338.

Demez S. (2021) OECD Ülkelerinde Çevresel Kuznets Eğrisi Hiptezinin Geçerliliği: Panel GMM Analizi. 10. Uluslararası Bilimsel Araştırmalar Kongresi, Nisan 2021 Ankara, 109-117. ISBN:978-625-7813-68-6.

Emrullah, M (2020). Sürdürülebilir Kalkınma Kapsamında Yeşil Lojistik: Avrupa Birliği ve Türkiye Örneği. *Karadeniz Sosyal Bilimler Dergisi*, *12*(23), 101-114.

Erdoğan, S., Yıldırım, S., Yıldırım, D. Ç., & Gedikli, A. (2019) G20 Ülkelerinde İnovasyon ve CO_2 Emisyonu. In *International Congress of Energy Economy and Security* (p. 193).

Esso LJ, Keho Y (2016) Energy consumption, economic growth and carbon emissions: cointegration and causality evidence from selected African countries. Energy Econ 114:492–497.

Fernández, Y. F., López, M. F., & Blanco, B. O. (2018). Innovation for sustainability: the impact of R&D spending on CO2 emissions. *Journal of cleaner production*, *172*, 3459-3467.

Ganda, F. (2019). The impact of innovation and technology investments on carbon emissions in selected organisation for economic Co-operation and development countries. *Journal of cleaner production*, *217*, 469-483.

Gormus, S., & Aydin, M. (2020). Revisiting the environmental Kuznets curve hypothesis using innovation: new evidence from the top 10 innovative economies. *Environmental Science and Pollution Research*, *27*, 27904-27913.

Hasanov, F. J., Khan, Z., Hussain, M., & Tufail, M. (2021). Theoretical framework for the carbon emissions effects of technological progress and renewable energy consumption. *Sustainable Development*.

Lin, B., & Zhu, J. (2019). The role of renewable energy technological innovation on climate change: empirical evidence from China. *Science of the Total Environment*, *659*, 1505-1512.

Mensah, C. N., Long, X., Boamah, K. B., Bediako, I. A., Dauda, L., & Salman, M. (2018). The effect of innovation on CO 2 emissions of OCED countries from 1990 to 2014. *Environmental Science and Pollution Research*, *25*(29), 29678-29698.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels (IZA Discussion Paper No. 1240). *Institute for the Study of Labor (IZA)*.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of applied econometrics*, *22*(2), 265-312.

Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *The Econometrics Journal*, *11*(1), 105-127.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of econometrics*, *142*(1), 50-93.

Pesaran, M. H., Smith, L. V., & Yamagata, T. (2013). Panel unit root tests in the presence of a multifactor error structure. *Journal of Econometrics*, *175*(2), 94-115.

Reese, S., & Westerlund, J. (2016). Panicca: Panic on cross-section averages. *Journal of Applied Econometrics*, *31*(6), 961-981.

Roberts, J. T., & Grımes, P. E. (1997). Carbon intensity and economic development 1962–1991: a brief exploration of the environmental Kuznets curve. *World development*, *25*(2), 191-198.

San Cristóbal, J. R. (2011). Multi-criteria decision-making in the selection of a renewable energy project in spain: The Vikor method. *Renewable energy*, *36*(2), 498-502.

Santra, S. (2017). The effect of technological innovation on production-based energy and CO2 emission productivity: evidence from BRICS countries. *African Journal of Science, Technology, Innovation and Development*, *9*(5), 503-512.

Saudi, M. H. M., Sinago, O., Jabarullah, H., N. (2019). The role of renewable, non-renewable energy consumption and technology innovation in testing environmental Kuznets curve in Malaysia.

Schumpeter, J., & Backhaus, U. (2003). The theory of economic development. In *Joseph Alois Schumpeter* (pp. 61-116). Springer, Boston, MA.

Temelli, F., & Şahin, D. (2019). Yükselen Piyasa Ekonomilerinde Finansal Gelişme, Ekonomik Büyüme ve Teknolojik Gelişmenin Çevresel Kalite Üzerine Etkisinin Analizi. *Karabük Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *9*(2), 577-593.

Wang, L., Chang, H. L., Rizvi, S. K. A., & Sari, A. (2020). Are eco-innovation and export diversification mutually exclusive to control carbon emissions in G-7 countries?. *Journal of Environmental Management*, *270*, 110829.

Wang, Z., & Zhu, Y. (2020). Do energy technology innovations contribute to CO2 emissions abatement? A spatial perspective. *Science of the Total Environment*, *726*, 138574.

Westerlund, J. (2008). Panel cointegration tests of the Fisher effect. *Journal of Applied Econometrics*, *23*(2), 193-233.

Yerdelen Tatoğlu, F. (2017). *Panel Zaman Serileri Analizi Stata Uygulamalı* (1. Baskı). Beta yayınevi, İstanbul.

Yerdelen Tatoğlu, F., & İçen, H. (2019). Çevresel Kuznets Eğrisinin Çok Boyutlu Panel Veri Modelleri ile Analizi. *Anadolu İktisat ve İşletme Dergisi*, *3*(1), 26-38.

Yilanci, V., & Ozgur, O. (2019). Testing the environmental Kuznets curve for G7 countries: evidence from a bootstrap panel causality test in rolling windows. *Environmental Science and Pollution Research*, *26*(24), 24795-24805.