Environmental Science and Pollution Research (2021) 28:66930–66940
https://doi.org/10.1007/s11356-021-14410-7

RESEARCH ARTICLE

Role of economic growth and innovative technologies in the outlook of energy and environmental efficiency: a way forward for developing Asian economies

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Received: 19 February 2021 / Accepted: 10 May 2021 / Published online: 8 July 2021

Abstract

Energy consumption is widely regarded as the primary driver of economic development and environmental degradation. The current study examines how energy use is related to technological innovation, human resources, energy pricing, economic development, and trade openness. For this context, the data set of OECD economies' indicators as mentioned above has been compiled for the period 1991–2019. Three estimators were used in this study from the family of autoregressive distributed lag (ARDL): the mean group (MG), the dynamic fixed effect (DFE), and the pooled mean group (PMG). According to empirical research, technical advances, human resources, and energy pricing all have a negative impact on OECD countries' long-run energy consumption. In the short term, however, these variables have a negligible or inverse effect on energy consumption. On the other hand, economic growth and trade openness in OECD economies all contribute positively to energy demand in the short and long run. Based on the empirical findings, this study recommends a policy structure for emerging economies.

Keywords Eco-innovative technologies · Energy consumption · MG, DFE, PMG · Human capital · Energy pricing

Introduction

Global GDP has increased by more than 60% between 1990 and 2018, while the average increase is estimated at 3% between 2020 and 2050 (World Bank 2019). Therefore, the world's energy demand is projected to increase by 50% between 2018 and 2050. Therefore, the world's energy demand is projected to increase by 50% throughout 2018–2050 (U.S. Energy Information Agency 2019). Similarly, fuel consumption is the most significant segment of the world energy supply (34% of total energy usage), coal (27%) is second, while natural gas (23%) is the third biggest primary source of energy usage (BPSTATS 2019). Precisely 84% of the world's primary energy sources are non-renewable.

The OECD nations are composed of the world's most developed and advanced nations, which account for a sizable

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portion of global GDP. These nations account for most global energy use, and are leaders in promoting renewable energy, and have a value for human capital (Shafiei and Salim 2014). The OECD countries' contribution to global eco-innovation was 74% in 1990 and rose to 85% in 2016 (OECD 2019). In this case, it is critical to determine the effect of eco-innovation, human capital, energy prices, and foreign trade on OECD economies' energy use.

Rapid economic growth is a significant contributor to rising energy use, which has resulted in severe ecological concerns across the world (Wan Alwi et al. 2016). By 2040, energy demand will increase by 25%, mostly in non-OECD economies. By 2040, energy demand will increase by 25%, mostly in non-OECD countries (Liu et al. 2018). The primary drivers of this phenomenon are population growth from 7 billion to 9 billion people and a global economy that has grown by an estimated 150% because of greater flexibility and rapid urbanization (Jing et al. 2018; Doi and Production 2016). The forecasted growth would result in the addition of over a billion new automobiles and 229 million new commercial fleets in developed countries, equating to 29.4 billion metric tons of carbon dioxide emissions, a 51% rise over current levels (Topcu and Payne 2018; Mohsin et al. 2018). On the other hand, the OCED countries will increase their commercial vehicle fleet by 47 million, resulting in 13.8 billion metric tons of carbon emissions. Environmental deterioration caused by power production activities can be mitigated by increasing consumer performance and enacting successful policies (Yao et al. 2019).

Environmental sustainability needs energy efficiency which can contribute to CO_2 emission reductions. Additionally, unsustainable industrial energy use has resulted in a rise in ambient carbon dioxide levels, a negative sign for environmental sustainability. In highly developed countries, the standard of living has been reached, and it is critical to reducing energy consumption to preserve a healthy climate (Ahmad et al. 2016). CO_2 emission reduction is a proxy for collective output in terms of cleaner emissions, and so countries aim to measure emission reductions to determine the effectiveness of climate change mitigation targets and energy policies. Numerous economies have identified their commitment to global climate change mitigation strategies to reduce greenhouse gas emissions. Generally, it is known as the "United Nations Framework Convention on Climate Change."

CO_2 emissions rate is generally higher in developing economies than in industrial economies, owing to the lower GDP of developing economies. Other than that, it is derived from a portfolio of national energy-intensive services (World Bank 2019). Global warming is primarily caused by CO_2 emissions from fossil fuel burning, cement production, and land-use change (Basha et al. 2017). Although various global emissions account for approximately 72% of CO2, nitrous oxide, methane, and other gases account for a significant portion of 19%, 6%, and 3%, respectively. Additionally, global energy-related CO_2 emissions accounted for approximately 80% of total global GHG emissions (Meng et al. 2019). Simultaneously, fossil fuel combustion accounts for two-thirds of global carbon emissions, making it the single largest source of greenhouse gases. As a result, carbon emission reduction has become one of the most critical tasks for emerging economies' energy policies worldwide (Zhang 2019).

Thus, this study aims to create the relationship between energy consumption and several critical variables such as human capital, technological innovation, energy pricing, and, of course, economic growth and trade openness in OECD economies as a guide for developing economies, especially in Asia.

The next portion of this paper will provide a systematic overview of the most recent studies in this field and will include the vocabulary of summarization on which this article will rely. The "Methodological background" section discusses the theoretical underpinnings of the research and testing procedures used. The "Results" section includes observations and broad hypotheses. Finally, consider the ramifications of the guidelines.

Literature review

The critical role of energy use in sustaining rapid economic growth while maintaining a sustainable environment has become a topic of discussion in published studies (He et al. 2020). Hanif et al. (2019) discovered a connection between energy sustainability and a safe environment, and an efficient energy system. The research analyzed the different predictors of energy usage; similarly, economic growth, ecological degradation, financial progress, population, trade openness, energy prices, and urbanization are all widely recognized as determinants of energy consumption. Economic growth (GDP or GNP), labor, and capital have been viewed as critical variables in determining energy demand over the last few years (Mohsin et al. 2019a).

Following that, various researchers introduced various environmental variables in examining the link between energy use and economic growth (Iqbal et al. 2020b). According to Xia et al. (2020), the primary factor contributing to environmental pollution is non-renewable energy use. Energy prices were included in the predictors of energy utilization (Sun et al. 2020b; Mohsin et al. 2020b). Conversely, Iqbal et al. (2020a) determined energy use using a factor such as research and development (R&D) as a proxy for green technologies. Public budgets for energy research, production, and exhibition have been used in some research as a substitute for green technologies (Asbahi et al. 2019). Comparably, the latest analysis determined the proportion of all inventions classified as technical advances. The correlation between energy use and ecological innovation is skewed in reverse (Anser et al. 2020). Correspondingly, Chandio et al. (2020) included human capital in the performance in terms of energy consumption and used it as a substitute for human capital development. Iram et al. (2020) incorporated the element of energy usage into the list of factors. Using energy costs and human resources, a new study (Mohsin et al. 2019b) explores energy usage. The effect of eco-innovation on energy use, on the other hand, is assiduously overlooked. It is a widely held belief that research and development (eco-innovation) accelerate economic growth by rerouting energy consumption away from polluted to renewable sources, allowing for a better climate (He et al. 2020). As a result, officials consider R&D efforts, which are critical during consumption and energy output (Sharif Hossain 2011).

Numerous studies have used various econometric methods to determine the correlation between energy use and environmental and economic sustainability. Wang et al. (2020) examined renewable energy usage factors using panel data techniques, including Pedroni co-integration, FMOLS, and Vector Error Correction Model (VECM) Granger causality. The dynamic ordinary least squares (DOLS) procedure was used by Bilgili et al. (2016). Abbas et al. (2020) used panel least square regression, panel fixed effect regression, and panel two-stage least square regression techniques to estimate non-renewable energy usage. FMOLS is primarily used for limited sample sizes and lags of the predictive variable's first differences. On the other hand, the Johansen co-integration test relies on assuming that parameters are merged into the first difference (Huang et al. 2020).

Correspondingly, the GMM estimator was constructed for a panel with a short period and a substantial number of panels. Other traditional panel co-integration methods are unsuccessful because they cannot handle the error term associated with cross-sectional (CS) dependence. As a result, the current study employs three primary ARDL estimation techniques, namely MG, DFE, and PMG, to determine the short and long-run dynamics (Bekhet et al. 2017).

As shown by the literature mentioned above, considerable research on energy use has concentrated on economic growth and other economic determinants. In terms of these possible advances, our research is unique. The impact of human capital, eco-innovation, and trade openness on total energy consumption is examined.

Furthermore, in the precedent, R&D investment was used as a proxy for technology. To the best of our understanding, there is still some uncertainty about whether this proxy produces consistent outcomes. There is vast literature on eco-innovations from various perspectives; however, little consideration has been devoted to the effect of eco-innovation on energy use. As a result, we implemented a new collection of independent variables that could influence energy usage to close this distance. Additionally, we calculated energy consumption using human capital and environmentally friendly technologies (Eco-innovation). Besides that, we use the most recent era.

Methodological background

Since this study explores the dynamics of economic development, trade openness, technological advancement, and sustainable energy usage, we used a dynamic panel method to estimate the heterogeneous data using proper equipment and background. We used the autoregressive distributed lag (ARDL, p, q) method to perform error correction on three estimation methods using the visual features. Additionally, Pesaran and Smith (1995) and Pesaran et al. (1999) state that this process is initiated mean group (MG) and pooled mean group (PMG) quantitative measurements, as well as the dynamic fixed effect (DFE) model. The ARDL description is based on Loayza and Ranciere, as shown below (Loayza and Ranciere 2006). Assume the following feature for long-term energy usage:

$$EC_{it}^{*} = \beta_{0i} + \beta_{1t}GDP_{it} + \beta_{2t}CPI_{it} + \beta_{3t}Tech_{it} + \beta_{4t}hc_{it} + \beta_{5t}TOP_{it} + u_{it} \quad (1)$$

The autoregressive distributed lag (ARDL) ð1; 1; 1Þ dynamic panel specification of equation (1) is written as (Pesaran et al. 1999; Blackburne and Frank 2007):

$$\begin{aligned} EC_{it} = {} & \mu_i + \delta_{10i}GDP_{it} + \delta_{11i}GDP_{i,t-1} + \delta_{20i}CPI_{it} \\ & + \delta_{21i}CPI_{i,t-1} + \delta_{30i}Tech_{it} + \delta_{31i}Tech_{i,t-1} \\ & + \delta_{40i}hc_{it} + \delta_{41i}hc_{i,t-1} + \delta_{50i}TOP_{it} + \delta_{51i}TOP_{i,t-1} \\ & + \varepsilon_{it} \end{aligned} \quad (2)$$

Here, EC_{it} energy consumption, GDP_{it} is economic growth, CPI_{it} is consumer price index used as energy price variable, $Tech_{it}$ technological innovation, hc_{it} is human capital, TOP_{it} is trade openness, and u_{it} is error term.

Pesaran and Shin (2012) highlighted the hypotheses and showed many econometric advantages of the PMG and MG methods over alternative solutions. To begin, when investigators use the PMG and MG quantitative measurements, they escape the need for co-integration tests, the reliability of stationary or integration between factors, and the pre-test for unit roots.

This technique allows for the calculation of variables of varying degrees of stationarity, which means that it applies to variables of interest with an order of I (1) or I (0). Additionally, this method is effective for panel data with high N and T measurements. Second, this assessor makes possible estimation of the ARDL model's short- and long-term influences. Thirdly, the ARDL method addresses the limitations of struggling to evaluate predictions about endogenous constructs in the long run due to endogeneity issues in the Engle and Granger (2015) technique. Choosing between these explanatory variables, on the other hand, necessitates a general trade-off between performance and accuracy. Thus, the optimal solution is to become familiar with the conditions and assumptions underlying each estimation method.

Under the hypothesis of long-term homogeneity slope (Pesaran et al. 1999), the PMG estimation method offers an increase in measurement performance over the MG estimation techniques and thus serves the purpose of this review. Additionally, the Hausman test was used to determine the significance of variations between the PMG, MG, and DFE. The null hypothesis for this test is that the difference between PMG and MG estimations is not essential. If the null hypothesis is supported, there is no substantial difference, and thus the PMG estimation method is used due to its reliability. Alternatively, there may be a significant differentiation between PMG and MG. If the null hypothesis is rejected, this implies that a significant difference exists, and hence the average estimator is used. This definition is used to calculate the difference between the PMG and DFE or between the MG and DFE.

Additionally, we implement the following cross-sectional dependency (CD) tests: the Breusch and Pagan (1980) Lagrange multiplier (LM) test, the Pesaran (2021) scaled LM test, Pesaran (2021) CD test, and the Pesaran et al. (2008) bias-adjusted LM test. The test figures for each of the four cases are as follows:

$$LM = \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} T_{ij}\widehat{p}_{ij} \rightarrow X^2 \frac{N(N-1)}{2} \tag{3}$$

The test is asymptotically distributed under the null of X^2

$$LM_s = \sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T_{ij}\widehat{p}_{ij}-1\right)\rightarrow N(0,1) \tag{4}$$

The test is asymptotically distributed as $N(0, 1)$

$$CD_p = \sqrt{\frac{2}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} T_{ij}\widehat{p}_{ij}\rightarrow N(0,1) \tag{5}$$

$$LM_{BC} = \sqrt{\frac{1}{N(N-1)}} \times \sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T_{ij}\widehat{p}_{ij}-1\right)\rightarrow \frac{N}{2(T-1)} N(0,1) \tag{6}$$

In Eqs. (1–4), $\widehat{p}_{ij}$ denotes the correlation coefficient, $i = 1, \ldots, N$ denotes cross-sectional units, $t = 1, \ldots, T$ denotes time-series measurements, $N(N-1)/2$ denotes degrees of freedom, χ^2 denotes that the test is asymptotically distributed under the chi-square null, and $N(0,1)$ denotes that the test is asymptotically distributed with mean nil and variance one. Second, we employ a structured version of the Swamy (1970) homogeneity test developed by Hashem Pesaran and Yamagata (2008) (delta tests). The Swamy (1970) test is first updated to account for the null of slope homogeneity.

$$\widetilde{S} = \sum_{i=1}^{N}\left(\widehat{\beta}_i-\widehat{\beta}_{WFE}\right)' X'_I \frac{M_\tau X_i}{\widetilde{\sigma}_i^2}\left(\widehat{\beta}_i-\widehat{\beta}_{WFE}\right) \tag{7}$$

where $\widehat{\beta}_i$ denotes a pooled OLS approximation, $\widehat{\beta}_{WFE}$ denotes a pooled weighted fixed effect estimation method, and $\widetilde{\sigma}_i^2$ denotes the estimation method. Following that, the standard dispersion statistics are computed:

$$\widehat{\Delta} = \sqrt{N}\left(\frac{N^{-1}\widetilde{S}-K}{2K}\right) \tag{8}$$

Additionally, a bias-adjusted variant of the standard dispersion statistics is measured in this manner:

$$\widehat{\Delta} = \sqrt{N}\left(\frac{N^{-1}\widetilde{S}-E(\widetilde{z}_{\mathrm{it}})}{\sqrt{\mathrm{var}(\widetilde{z}_{\mathrm{it}})}}\right) \tag{9}$$

where N denotes the cross-sectional dimension, $\widetilde{S}$ Denotes the dispersion statistic, and k refers to the number of regression coefficients?

$E(\widetilde{z}_{it}) = k$ and $var = \frac{2(T-k-1)}{T+1}$

Following that, we employ Pesaran (2007) cross-sectionally augmented IPS (Im et al. 2003) panel unit root tests, frequently alluded to as the CIPS test. Pesaran (2007) established this unit root test to account for cross-sectional dependency. Individual cross-sectionally augmented Dickey-Fuller (CADF) statistics and their simple averages are developed asymptotically (CIPS).

$$CIPS(N,T) = N^{-1}\sum_{i=1}^{N} t_i(N,T) = \frac{\sum_{i=1}^{N} CADP_i}{N} \tag{10}$$

where T is the time dimension and $t_i(N, T)$ ith cross-section CADF statistic associated with the ith cross-section? We implement the Durbin-Hausman (DH) co-integration techniques of Westerlund (2008) to consider cross-sectional dependence, slope heterogeneity, and hybrid pattern incorporation. These tests are applicable when cross-sectional dependence and slope heterogeneity are identified in the data series. Additionally, the experiments yield accurate measurements when components are present and added into the mixture, with the only requirement being that the dependent variable is non-stationary. Durbin-Hausman examinations include the following: $DH_p = \widehat{S}_n\left(\widetilde{\phi}-\widehat{\phi}\right)\sum_{i=1}^{n}\sum_{t=2}^{T}\widehat{e}_{it=1}^2$ and $DH_g = \widehat{S}_i\left(\widetilde{\phi}_i-\widehat{\phi}_i\right)\ {}^2\sum_{i=1}^{n}\sum_{t=2}^{T}\widehat{e}_{it=1}^2$ (11)where DH_p is the panel statistic and DH_g is the group mean statistic? Their null hypothesis of no co-integration

$\left(H_0 \quad : \widetilde{\phi}_i = 1, \text{for all } I = 1\right)$ is tested against the alternative of co-integration in all n units for DH_p $(H_i^p \quad : \phi_i = \phi, \text{and } \phi < 0)$ and against the alternative of co-integration in some of the cross-sectional units for $DH_g \qquad (H_i^p \quad : \phi < 1 \text{ for at least some } i)$.

Data description

The current article examines the effects of economic development, human resources, eco-innovation technology, energy pricing, and trade openness on energy usage in OECD countries. The annual dataset for 37 OECD countries from 1991 to 2019 was used for this reason. The factors are expressed, and their sources are mentioned in Table 1.

Results

The primary objective of this study is to evaluate eco-contribution innovations to the promotion of a sustainable environment in OECD countries between 1991 and 2019.

Table 2 summarizes the sample means for all variables. In the OECD, the average mean for EC is 8.7515, with a median of 10.9111 and a minimum of 6.6576. GDPP has an average value of 10.1833 with a median of 11.6256 and a minimum of 8.2269 in the OECD. While the CPI averages 4.3756, with a maximum of 5.4571 and a minimum of −0.9865, the average TECH value for the entire sample is 0.0240, while the lowest value reported is −5.7298. TECH has the highest average rate of 2.2076. In the case of HC, the average mean was 1.4155, with a high ratio of 1.6164 and a low ratio of −1.2024. Finally, the mean value of TOP is 25.4456, with the maximum and minimum values being 28.7985 and 21.7797, respectively.

The correlation analysis of the variables is summarized in Table 3. The results indicate that independent variables such as GDP growth per capita (GDPP), consumer price index (CPI), technological innovation (Tech), human capital (HC), and trade openness (TOP) all have a negligible correlation with energy use (EC). As a result, no issue of correlation between the variables has been identified.

To determine if the regressors GDPP, CPI, TECH, HC, and TOP are independent of one another, we examine their multicollinearity. The results of this test suggest that the variance inflation factor (VIF) values are less than 5, indicating that no multicollinearity exists between the regressors, implying that the factors mentioned above can be predictors for energy usage.

Table 4 also contains the results of Hashem Pesaran and Yamagata (2008) homogeneity test. Based on the calculated value of the delta and adjusted delta and their corresponding p-values, we can reject the null hypothesis that the slope coefficients are homogeneous and must therefore accept the alternative hypothesis that the slope coefficients are heterogeneous at the 1% level of significance. As a result, heterogeneous panel methods must be utilized.

In addition to the multicollinearity and homogeneity measures, we employ Pesaran (2004) cross-section independence test (CD). Table 5 summarizes the results of the test. As a result of these findings, we can confidently dismiss the null hypothesis of no cross-section independence for all parameters, as the p-value for these parameters is nearly zero, indicating that the results for these parameters are clustered across panel classes and there is cross-sectional dependency across the panel. As a result, we can use the panel unit root of the second generation.

Table 6 summarizes the results of the second-generation panel unit root evaluation. The CIPS test, which predicts cross-sectional dependency, reveals that all parameters with CD are non-stationary at their stages, which means we cannot reject the null hypothesis of non-stationarity. However, we may reject the null hypothesis when the variables are in their first differences. These findings indicate that the variables have a unit root at stages but not at their initial differences; thus, these series are I (1).

Due to the mixed order of integration of the analyzed parameters, we cannot use panel co-integration tests such as Pedroni or Westerlund panel co-integration; instead, we can use ARDL estimation. As a result, the pooled mean group (PMG), mean group (MG), and dynamic fixed effects (DFE) techniques were used.

Table 1 Variable description

Dimension	Indicator	Source
EC	Total energy uses (kg of oil equivalent per capita), fossil fuel energy consumption (percentage of total)	WDI
GDP	GDP per capita (constant 2010 US$)	WDI
CPI	Energy prices (CPI energy index)	OECD
Tech.	Eco-innovation technology energy prices (CPI energy index) are extracted from the OECD Statistic database	OECD
HC	Human capital data is collected from the Penn World Table version 9.0 database	PWT
TOP	Trade openness (sum of exports and imports as a share of GDP)	WDI

Table 2 Descriptive statistics

Panel A	EC	GDPP	CPI	TECH_	HC	TOP
Mean	8.75	10.18	4.37	0.02	1.41	25.44
Median	8.75	10.41	4.47	0.20	1.44	25.43
Maximum	10.91	11.62	5.45	2.20	1.61	28.79
Minimum	6.65	8.22	−0.98	−5.72	−1.20	21.77
Std. Dev.	0.72	0.73	0.51	0.81	0.17	1.41
Skewness	−0.08	−0.52	−4.90	−1.57	−5.81	−0.27
Kurtosis	3.63	2.49	37.39	8.34	70.29	2.70
Jarque-Bera	17.05	53.91	50,525.2	1521.24	184,230.7	15.16
Probability	0.00	0.00	0.00	0.00	0.00	0.00
Sum	8296.42	9653.76	4148.08	22.78	1341.98	24,122.43
Sum Sq. Dev.	498.2	509.75	252.96	626.07	27.65	1907.80
Observations	948	948	948	948	948	948

The following table contains the findings of PMG, MG, and FDE approximations for OECD countries using energy usage (EC) as the dependent variable and GDP per capita (gdpp), energy pricing (cpi), technical advances (tech), human capital (hc), and trade openness as the independent variables (top). The results provide a description of the long- and short-run coefficients.

Table 7 summarizes the findings of the mean group (MG), dynamic fixed effects (DFE), and pooled mean group (PMG) analyses. gdpp contributes significantly and positively to energy usage in the long term, according to the MG estimator's long-run data. The coefficient of gddp is 0.823, indicating that a one-unit increase in economic growth will increase energy consumption in the OECD economies by up to 0.82%. The parameter (gddp) is significant at the 1% stage, with a *p*-value of 0.001. Similarly, the DFE and PMG estimators exhibit the same pattern. In this case, the gdpp coefficient is 0.202 in DFE and 0.973 in PMG. Again, the sign of both coefficient estimators is positive, indicating that gdpp has a beneficial effect on energy consumption in the OECD region.

The cpi parameters (which are used to price energy) are statistically significant and have a negative relationship with energy consumption. According to the MG evaluator, a one-unit shift in energy prices will result in a 24% reduction in OECD economies' energy consumption. However, the MG coefficient has a significant level of 10%. The same pattern was observed in the DFE and PMG estimators, with energy pricing having a 25% effect on energy consumption in DEF and a 43% impact on energy consumption in PMG, respectively.

Technological innovation in the OECD economies has a negative and significant impact on aspects of energy use. In this case, a 9% reduction in energy consumption was observed using the MG estimator, a 3.3% reduction using the DFE estimator, and a 12.3% reduction using the PMG estimator. The same pattern has been observed in the coefficient of human capital (hc). It is statistically significant in all the given negative sign estimators. MG has a coefficient of −0.610, indicating a 61% reduction in energy consumption for every unit increase in human capital growth. This component has a coefficient of −0.345 and −0.685 for the DFE and PMG estimators, respectively.

Finally, the long-run findings indicate that trade openness (top) contributes positively and substantially to total energy consumption in OECD economies. The coefficient of the top

Table 3 Correlation analysis

	EC	GDPP	CPI	TECH_	HC	TOP
EC	1					
GDPP	0.10	1				
CPI	0.27	0.42	1			
TECH_	−0.08	−0.20	−0.13	1		
HC	0.31	0.39	0.80	−0.10	1	
TOP	0.14	0.45	0.39	−0.23	0.31	1

Table 4 Results of multicollinearity test and homogeneity test

VIF						
	EC	GDPP	CPI	TECH_	HC	TOP
EC	-					
GDPP	2.85	-				
CPI	1.08	1.22	-			
TECH_	1.00	1.04	1.01	-		
HC	1.11	1.18	2.78	1.01	-	
TOP	1.02	1.26	1.18	1.05	1.11	-
Pesaran and Yamagata (2008) test						
Delta tilde	*p*-value	Adjusted delta tilde	*p*-value			
11.195	0.000	14.161	0.000			

Table 5 Cross-section dependence and slope homogeneity test

Cross-section dependence test					Slope homogeneity test results	
Variables	LM	LMs	LMbc	CD	Delta	Bias-adjusted delta
EC	8186.79***	206.06***	205.42***	60.65***	5.12***	5.25***
	0.0000	0.0000	0.0000	0.0000		
GDP	17,101.74***	450.33***	449.69***	129.84***	2.70***	3.05***
	0.0000	0.0000	0.0000	0.0000		
CPI	16,396.43***	431.01***	430.37***	126.79***	2.19***	2.33***
	0.0000	0.0000	0.0000	0.0000		
Tech.	1643.59***	26.78***	26.148***	7.37***	3.90***	4.19***
	0.0000	0.0000	0.0000	0.0000		
HC	17,034.35***	448.49***	447.85***	129.85***	4.75***	4.94***
	0.0000	0.0000	0.0000	0.0000		
Top	18,582.83***	490.91***	490.28***	136.20***	4.35***	4.53***
	0.0000	0.0000	0.0000	0.0000		

Null hypothesis: No cross-section dependence (correlation)

Notes: Under the null hypothesis of cross-section independence, CD ~ $N(0,1)$

in DFE is 0.026, indicating that a one-unit rise in top results in a 26% increase in energy consumption. The same pattern has been observed in PMG estimates, which show a 21% rise in energy consumption. Although the MG coefficient is positive, it is not statistically significant.

Table 7 presents the short-run outcomes for the highlighted parameters. According to the findings, gdpp plays a significant and beneficial role in the OECD's energy use. Again, both estimators agree with a slight variation on the optimistic affirmation of gdpp in energy consumption. For instance, the coefficient of MG demonstrates the 37%, DFE 40%, and PMG 35% effect on energy consumption caused by a single unit shift in gdpp.

Table 6 Panel unit root test

Variables	Without trend	With trend
Pesaran (2007) (CIPS)		
EC	−1.13	−2.53
DEC	−4.45***	−5.26***
GDP	−1.98	−2.40
DGDP	−3.99***	−4.04***
CPI	−1.36	−2.26**
DCPI	−4.02***	−4.24***
Tech.	−3.58***	−3.97***
D.Tech.	−5.91***	−6.09***
HC	−2.09*	−2.07
DHC	−3.19***	−3.35***
Top	−2.38***	−2.65**
D.Top	−4.53***	−4.60***

Notes: MW test assumes cross-section independence. CIPS test assumes cross-section dependence. ***$p<0.01$, **$p<0.05$, *$p<0.1$

All three estimators for the energy pricing variable produce inconsistent results. For example, MG demonstrates a positive and statistically significant effect of cpi on energy consumption in the short run. At the same time, the DFE estimator assumed a negative and statistically significant effect of cpi on energy consumption in the short run. PMG again observes a statistically significant and beneficial effect of cpi on energy use in OECD economies in the short run.

The vector of technical innovation (tech) also has a short-run negative effect on energy use, but the coefficients of all three estimators are statistically insignificant in the OECD's short-run dynamic. The human capital component exhibits the same pattern. While it contributes positively to energy use, none of the estimators considered it statistically significant.

Finally, the variable of trade openness continues to positively affect energy consumption in the short run and with statistical significance. According to the MG estimator, the top is responsible for 11% of the increase in energy usage. The DFE estimator estimated it at 49%, while PMG confirms it at 10%.

Economic growth and trade openness have contributed substantially and positively to the OECD's energy usage in the long and short run. In the long run, energy pricing, technical advancements, and human capital contribute negatively and statistically significantly to OECD economies. However, in the short term, these metrics are either statistically insignificant or have the opposite sign.

Discussion

The current research analyzes the impact of economic development, human capital, eco-innovation, energy pricing, and trade openness on energy consumption. This study examines

Table 7 Results of MG, PMG, and FDE estimator

Variables	MG	Dynamic fixed effects	Pooled mean group regression
Long-run results			
gdpp	0.823*** (0.001)	0.202*** (0.000)	0.973*** (0.000)
cpi	−0.240* (0.062)	−0.256*** (0.000)	−0.436** (0.024)
tech	−0.009** (0.046)	−0.033*** (0.237)	−0.123*** (0.003)
hc	−0.610*** (0.009)	−0.345* (0.068)	−0.685*** (0.000)
top	0.117 (0.154)	0.026*** (0.000)	0.214*** (0.000)
_cons	3.401 (0.001)	−0.053*** (0.000)	0.018 (0.001)
Short-run results			
D1. gdpp	0.374*** (0.000)	0.400*** (0.000)	0.355*** (0.001)
D1. Cpi	0.285** (0.034)	−0.053*** (0.000)	0.084 (0.404)
D1. Tech	−0.002 (0.401)	−0.002 (0.124)	−0.002 (0.174)
D1. Hc	0.018 (0.860)	0.000 (0.977)	0.078 (0.365)
D1.top	0.116*** (0.003)	0.049*** (0.007)	0.106*** (0.002)
_cons	0.024 (0.943)	0.622 (0.000)	0.202 (0.000)

annual data from 37 OECD countries between 1991 and 2019. To begin, this study examined cross-sectional dependence among the variables examined, which revealed that the OECD countries are inextricably related. Thus, the CIPS test result demonstrates a mixed order of parameter integration. This study validated the concept using three distinct estimation techniques: MG, DFE, and PMG.

Economic growth is positively related to energy usage, as shown by this research. The economic expansion would increase the OECD region's energy usage. Additionally, Malik et al. (2009) and Mohsin et al. (2020a) discovered a relationship between economic growth and energy use.

This research aimed to determine the effect of eco-innovation on energy usage in OECD countries, using a recent study by Sun et al. (2020a). Nonetheless, our study indicates that eco-innovation will result in a decrease in energy usage. These results suggest that a concerted effort to promote sustainable energy usage is essential. These technologies allow the conversion of energy from non-renewable to renewable sources to be more economical and sustainable. Additionally, the COP21 international environmental framework demonstrates the beneficial effect of eco-innovations on the ecosystem our results are also supported by the recent research by (Zafar et al. 2019; Šprajc et al. 2019).

Consequently, the OECD finds a negative correlation between human resources and energy use. In comparison to a population with less education, a more educated and qualified population consumes less resources. Similarly, modern businesses with experienced and professional managers, employees, and labor would have increased energy efficiency (Zhang et al. 2020; Nadimi 2019). Although human capital concentrates collective clean energy consumption into a single individual, it also increases renewable energy consumption while decreasing non-renewable energy consumption (Ali et al. 2021). Shahbaz et al. (2019) demonstrate the mechanism by which human capital decreases energy consumption (Mohsin et al. 2020a; López-González et al. 2019).

In the OECD, trade openness is positively correlated with energy usage. This finding indicates that there is a distinct increase in energy demand because of increased trade. Additionally, it is a well-known fact that the trade will be impossible without vehicle transportation, as fuel is needed. Mass transit is the industry that consumes the most electricity (Baloch et al. 2020; Mandova et al. 2019). There is a strong link between the use of renewable energy and the development of new markets. However, due to trade liberalization policies, non-renewable energy use has declined (Mohsin et al. 2021; Šprajc et al. 2019).

According to this report, human resources and eco-innovation help countries in the OECD reduce their reliance on fossil fuels and promote energy efficiency (Halicioglu and Ketenci 2018). Clean energy and non-renewable resource usage must be accompanied by innovation and human capital growth. Although this study is limited to OECD economies, future researchers should replicate it for other developed (BRICS, G20, and emerging economies) and developing regions to increase the reliability of the analysis (Manan et al. 2018). The researcher discovered that human resources, eco-innovation, and energy pricing could all work together to help reduce energy consumption while also facilitating the transition to renewable fuels (Salim et al. 2017). To establish an appropriate policy for the nation, researchers must understand the marginal effects of emerging technologies such as alternative energy sources, human capital growth, and energy pricing (Yu et al. 2016).

Conclusions

Over the period 1991–2019, the impact of human resources, trade openness, energy prices, and economic growth on total energy consumption was examined in 37 OECD countries. Eco-innovative technologies require a considerable number of resources. Usually, they arise because of the advancement of eco-innovative technologies. It decreases emissions from non-renewable resources, lowers the cost of renewable energy production and usage, and ultimately results in lower product costs. In OECD countries, using human capital development also reduces energy usage. It results in a decrease in non-renewable resource use and total energy use. Ecological sustainability is achieved by increased awareness, experience, training, and management emphasis on eco-innovative technological applications, sustainable energy use, and the avoidance of non-renewable dirty energy sources such as fossil fuels. High energy prices are due to decreased demand for energy and the use of non-renewable energy sources.

It is, however, favorably associated with encouraging renewable energy use and mitigating ecological issues. Economic development accelerates the use of energy and waste, as well as the process of environmental pollution. However, by developing environmentally sustainable technologies, this economic development process will remain healthy and prosperous.

Policy suggestions

- Considering the above empirical findings, eco-innovation and human capital are valuable and efficient policy tools for increasing energy efficiency and environmental sustainability by converting non-renewable energy to clean energy. As a result, the current study recommends that developing economies, especially those in Asia, increase their R&D in eco-innovation technologies. To accomplish this, such economies should provide low-interest loans to energy-efficient manufacturers and households that can easily encourage emerging technology, such as electric cars and solar system installation in their homes and businesses.
- As with the OECD, developing world countries should provide incentives for renewable energy to promote sustainable energy use and increase taxes on non-renewable energy to discourage dirty energy use. Human capital plays a significant role in total energy consumption; thus, policymakers should invest in the nation's human capital, which reduces reliance on fossil fuels and promotes the use of renewable energy.
- Emerging economies should take measures to make space for renewable energy growth, such as reducing their reliance on fossil fuels, which is a critical step toward reducing energy-related CO_2 emissions and promoting a green economy. Additionally, tracking fossil fuel development to ensure that there is ample space for low-carbon energy. Simultaneously, rising energy efficiency would be considered the most cost-effective way to mitigate energy production's environmental impact.
- Emerging economies can pioneer commercial services in energy markets to address energy crises, including energy efficiency, energy infrastructure outsourcing, energy supply, risk management, power generation, and energy efficiency project implementation.

Availability of data and materials The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author contribution This research paper contributed by the abovementioned authors in the following way: the conceptualization, done by Teng Su and Abdul Qayyum; methodology, form by Ishtiaq Ahmad; software and validation; formal analysis performed by Weihua Yin; investigation, resources, data curation, performed by Saeed ur Rahman; writing–original draft preparation done by Rana Muhammed Adeel-Farooq; writing–review and editing; visualization, and supervision by Teng Su.

Funding This work is funded by "Strategy Research on Using Big Data to improve Government's Governance (GXZKLM-2019-08)" and "Research on the Target Index of Economic and Social Development Planning of Guangxi Zhuang Autonomous Region in the "14th Five-Year Plan" Period (GXZC2019-24891-GXYL)"

Declaration

Ethics approval and consent to participate We declared that we do not have human participants, human data, or human tissue.

Consent for publication We do not have any person's data in any form.

Competing interests The authors declare no competing interests.

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