DOI: 10.15838/esc.2023.5.89.15
UDC 330.15:502.335, LBC 65.28

Revisiting the Linkages Between Economic Growth, Human Capital and Environmental Quality

Funda DURGUN
Dicle University
Dıyarbakır, Türkiye
e-mail: funda.uncu@dicle.edu.tr
ORCID: 0000-0001-7254-227X

Aziz DAYANIR
Istanbul University
Istanbul, Türkiye
e-mail: aziz.dayanir@istanbul.edu.tr
ORCID: 0000-0001-7279-1487

Abstract. Various anthropogenic activities that cause the release of greenhouse gases have increased the problems caused by climate change. The increasing necessity of mitigating the damaging impacts of worldwide warming draws attention to the environmental degrading effects of fossil fuels. This empirical research explores the relationship among China's human capital (lhc), GDP growth (lgdp), energy intensity (lei) and environmental degradation (lco2) by using the data from 1990 to 2019. In this study, macroeconomic data of China is analyzed; the Bayer – Hanck test is employed in the analysis of cointegration, and the Toda – Yamamoto test is conducted for causality analysis. The following are the study's findings: the cointegration analysis shows that there exist a cointegrated relationship between lco2, lhc, lgdo and lei. In other words, it shows that the factors have a cointegrated relationship. According to the outcomes of FMOLS analysis, increases in energy intensity, GDP growth, and human capital

For citation: Durgun F., Dayanir A. (2023). Revisiting the linkages between economic growth, human capital and environmental quality. *Economic and Social Changes: Facts, Trends, Forecast*, 16(5), 262–278. DOI: 10.15838/esc.2023.5.89.15

increase carbon dioxide releases in the long term. As evidenced by the findings, improvement in energy efficiency is associated with favorable outcomes for the environment, though economic expansion and the augmentation of human capital are linked to adverse effects on environmental conditions. The Toda – Yamamoto causality test has yielded results indicating the presence of causality links between human capital and carbon emissions, as well as between human capital and energy intensity. Furthermore, it has been observed that the former variable exerts a unidirectional influence on the latter. There is also a unidirectional causality from all variables to carbon emissions, GDP growth and energy intensity, respectively.

Key words: economic growth, human capital, China, CO_2 emissions, Bayer – Hanck cointegration.

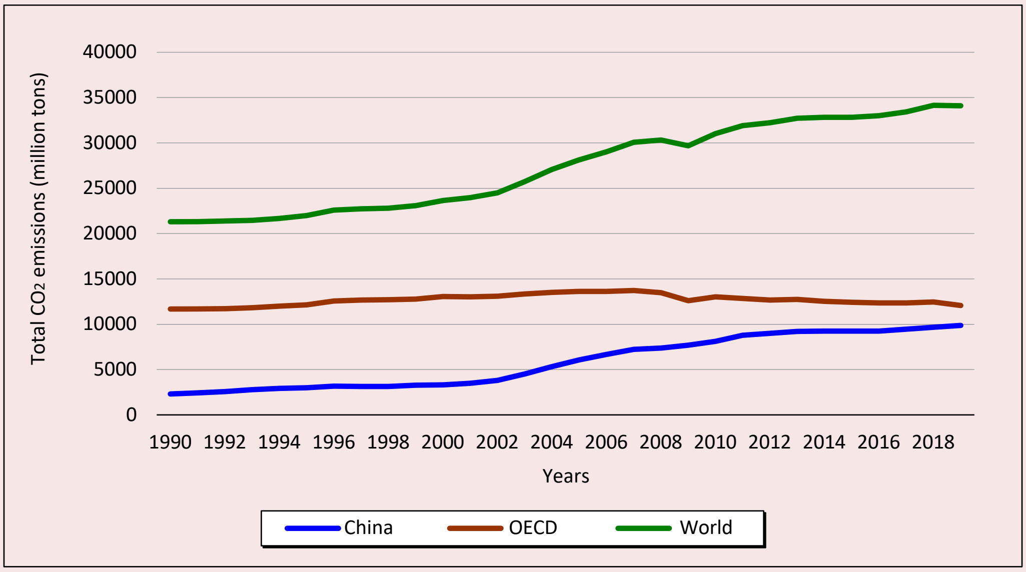
Introduction

The biggest factor leading to environmental degradation is the anthropogenic rise in greenhouse gas pollution. A vast majority of these anthropogenic emissions are because of the production of products with fossil-fuel-based energy. The issues of global warming and climate change continue to be widely discussed in modern scientific discourse, with a particular emphasis on the ecological impacts of human behavior. The antrhropogenic environmental pollution is a significant area of concern in this regard. Therefore, it has become very important and imperative to understand the relationship of deterioration of environment with the expansion of the economy and other factors that cause environmental degradation. The problem of reducing anthropogenic emissions has become more urgent than ever for policy makers to cope with environmental problems and thus ensure sustainable economic expansion. CO_2 emissions constitute the largest share among greenhouse gas emissions. Therefore, governments have taken measures to decrease CO_2 emissions. The fundamental goal of countries throughout the economic growth process is to boost output, which has led to environmental concerns reaching global proportions since the 1990s. The most prominent among these environmental problems are the unconscious consumption of natural resources, degradation of green areas, and global warming. Among these problems, the rapid and large-scale effects of global warming have brought global warming to the top of the list of problems to be solved. Greenhouse gas emissions originating from human-induced activities, which are important factors contributing to global warming, continue to increase every year *(Fig. 1, 2)*. According to BP Statistics, between 1990 and 2019, global total CO_2 emissions from energy and global per capita carbon emissions increased by 60% and 10%, respectively[1].

Since the 1990s, the increase in CO_2 emissions from anthropogenic activities in newly industrialized countries has been greater than in industrialized countries (Kasman, Duman, 2015). Among the newly industrialized countries, China is the most important and the largest country that uses fossil fuel-based production methods and emits a very high amount of CO_2. China's economy has undergone a significant period of growth during the past thirty years, which has led to excessive CO_2 releases and consequent degradation of environment. In 2019, China, the world's largest energy related CO_2 emitter since 2006, emits a total of CO_2 around, 9868.5 million tones. China's total carbon emissions rosed from 10.8% of world in 1990 to 28.9% in 2019. BP Energy Statistics shows the annual growth rate of CO_2 emissions in China as

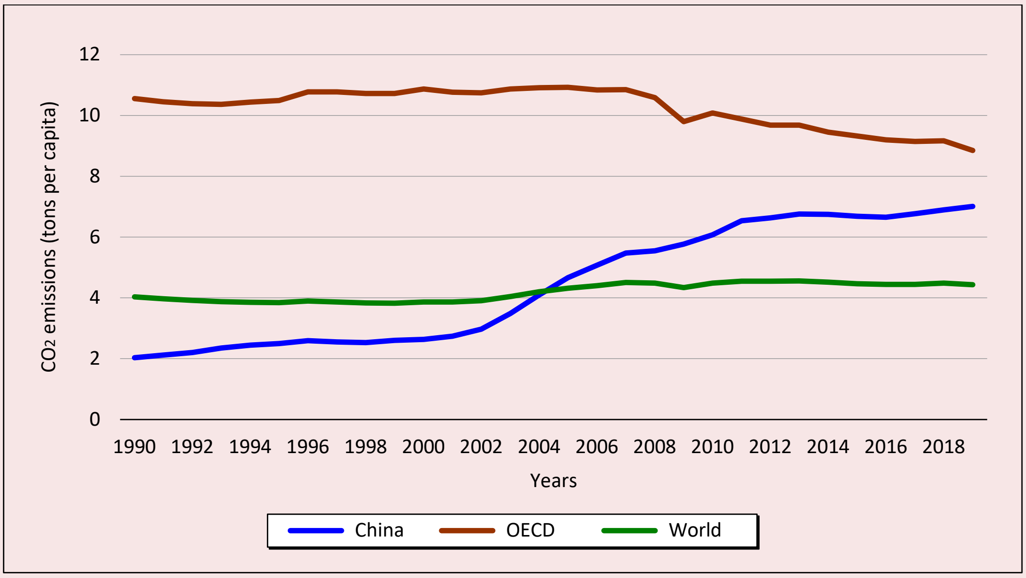
[1] BP Statistical Review of World Energy (2022). Data on Carbon Dioxide Emissions from Energy. Available at: http://www.bp.com/statisticalreview (accessed: August 19, 2022).

Figure 1. Total CO_2 emissions



Source: BP Statistical Review of World Energy (2022). Data on Carbon Dioxide Emissions from Energy. Available at: http://www.bp.com/statisticalreview (accessed: December 28, 2022).

Figure 2. CO_2 emissions per capita



Source: BP Statistical Review of World Energy (2022). Data on Carbon Dioxide Emissions from Energy. Available at: http://www.bp.com/statisticalreview (accessed: December 28, 2022).

10.9 for the period from 1990 to 2019[2]. As can be seen from the graph of total CO_2 emissions, the gap between China and OECD members is narrowing between 1990 and 2019. For this period, (although slightly declining in recent years) OECD members' total CO_2 emissions stayed virtually flat, while total CO_2 emissions in China nearly quadrupled.

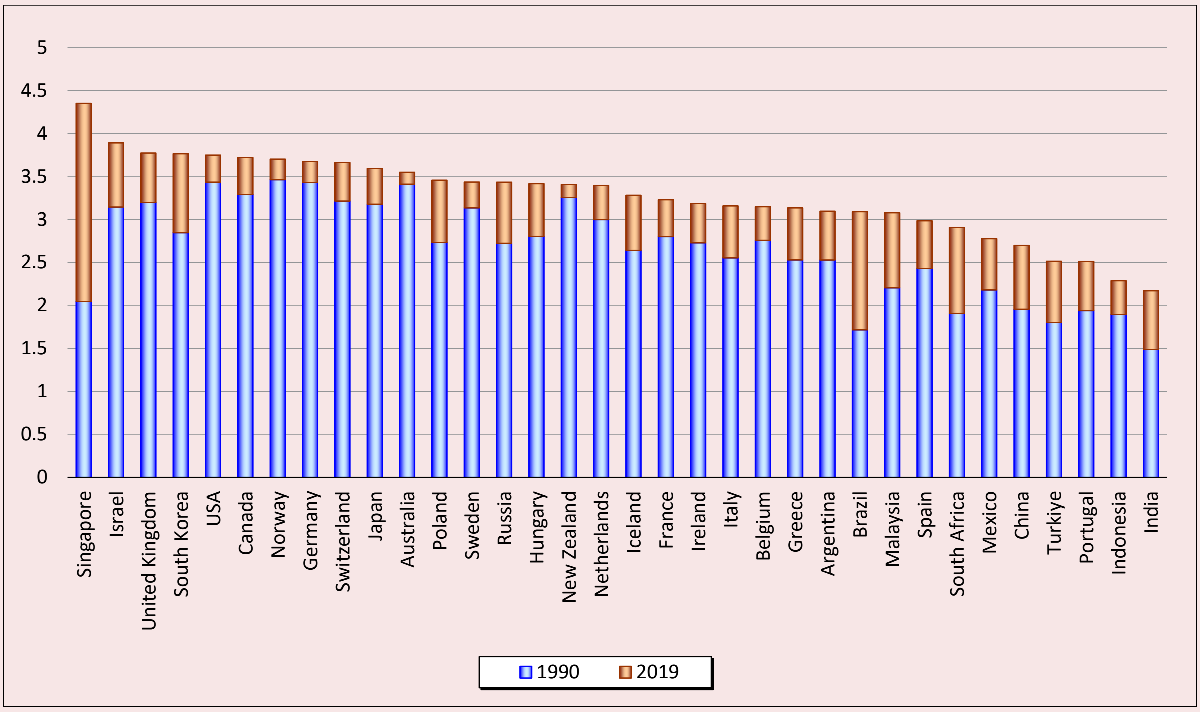
Figure 2 shows how the gap in per capita CO_2 emissions between China and the OECD countries continues to narrow. The per capita emissions of China exceed the mean of all other countries. Despite the decrease in average CO_2 emissions per capita in OECD member countries, the 10% growth in global emissions per individual, which followed almost a flat course throughout this particular period, was influenced by the great increase in China. China officially joined the WTO in December 2001 (Teng, 2004). As shown in the figures, China's membership to the WTO has increased the country's production, through the implementation of development strategy that prioritizes exports and increases both the amount of total CO_2 emissions and per capita emissions. The figures demonstrate China's CO_2 emissions have had a notable increasing trend since 2001.

The data presented in the figures depict the impact of the worldwide economic downturn on China, OECD member countries, and other regions across the globe. The 2008 global economic crisis severely affected the world economy and OECD members, but less so China. As of 2008, when the economic crisis was effective, CO_2 emissions decreased in OECD countries, and remained stable in the world due to the decrease in production. China, however, did not experience such a reduction in emissions level of CO_2 due to 2008 economic crisis.

It is important to apply nonconventional methods as well as conventional methods of combating environmental pollution. One of the nonconventional methods is human capital. Numerous studies show that raising the stock of human capital reduces carbon dioxide emissions. It is emphasized in the literature that investing in education is a channel to reduce CO_2 emissions. It is suggested that highly educated individuals will pay attention to using products with low CO_2 emissions. Regions with significant accumulation of human capital and thus technological capability have the potential to facilitate environmental amelioration because these regions can use sophisticated technologies (Lan et al., 2012). While higher-income consumers are spending more on green products, they are also demanding regulations to protect the environment (Dinda, 2004; Aytun, Akın, 2016). Highly educated and talented people are almost always more likely to earn more than others (Becker, 1994). People with increasing incomes care more about the environment, so regulators work more effectively and environmental degradation levels are reduced (Dinda, 2004). It has been demonstrated that the allocation of resources towards the development of human capital leads to a rise in labor productivity and serves as a catalyst for economic growth. There are very few examples of countries that have experienced a period of sustainable economic development without significant investments in the workforce. Most studies that attempt to quantitatively analyze the drivers of growth have identified that investment in human capital plays an important role (Becker, 1994). Research and development activities for environmental improvements increase with income (Komen et al., 1997). It is argued that skilled human capital is important for technological progress (Vandenbussche et al., 2006). With technological progress, old technologies that pollute the environment are replaced by new and cleaner technologies that contribute positively to environmental quality (Dinda, 2004).

[2] BP Statistical Review of World Energy (2022). Data on carbondioxide emissions from energy. Available at: http://www.bp.com/statisticalreview. Accessed 19/08/2022.

Figure 3. Human Capital Index in selected countries



Source: Feenstra R.C., Inklaar R., Timmer M.P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105(10), 3150–3182.

China's human capital level is given in *Figure 3*. As can be seen, China's human capital level is not very high. It is seen that China lags behind many industrialized countries in the ranking of human capital. Although China has increased its human capital level more than 2 times from 1990 to 2019, this is not enough for China to catch up with industrialized countries.

The major aim of this research is to investigate the possible impact of investing in human capital as an unconventional method to address air pollution by decreasing CO_2 emissions. The examination of the relationship between the human capital index, a comprehensive tool for assessing education, and environmental quality will provide significant suggestions for policymakers. Despite the fact that many research papers have investigated the correlation between a nation's education level and its impact on environment, the academic literature lacks a consensus regarding the specific direction of human capital's influence on the decline of the environmental conditions. Different results were obtained through the models developed by adding various control variables. We tried to contribute to the literature by adding energy intensity as a control variable. However, we did this by applying the Bayer – Hanck procedure.

The organization of subsequent sections of research is laid off in the following manner: First section contains a comprehensive review of literature pertaining the correlation between human capital and carbon dioxide emissions. After that, we will go on to a discussion of the data as well as the methodology. Subsequently, the main findings are presented and discussed. Finally, the article concludes with some recommendations on policy implications for China.

Literature review

Recent years have witnessed a substantial increase in academic research on the variables influencing environmental health. The literature on environmental quality has reached a very high volume, as the countries or groups of countries studied, the econometric techniques used and the models developed are quite different from each other. According to our knowledge, the prevailing body of research examining the influence of human capital on the quality of environment has produced results indicating a favorable correlation between education level and environmental quality. Numerous scholarly studies demonstrate, however, that an enhancement in human capital either degrades environmental conditions or has no significant impact on it.

Danish et al. conducted an Autoregressive Distributed Lag analysis of the interrelations among Pakistan's GDP expansion, ecological footprint, biodiversity, and education level between 1971 and 2014, revealing educational investments do not significantly increase ecological footprint (Danish et al., 2019). Using STIRPAT model, Yao et al. assessed the role of educaiton level on the release of CO_2 in OECD nations from 1870 to 2014, discovering that educational investments could potentially serve as aviable means of CO_2 mitigation (Yao et al., 2020).

Khan analyzed EKC hypothesis for 122 nations between 1980 and 2014 using the Hansen threshold model. He found that beyond a certain threshold level, CO_2 emissions decrease with an increase in human capital (Khan, 2020). Hao et al. (2020) utilized data on G-7 countries collected from 1991 to 2017 and the Cross-Sectionally Augmented Auto-regressive Distributive lag method to explore the link that exists between human capital and carbon dioxide emissions. They found that investing in people helps the environment by lowering carbon output (Hao et al., 2020). Mahmood et al. investigated the effects of renewable energy and reel GDP growth in Pakistan from 1980 to 2014 on CO_2 emissions by adding human capital and came to the conclusion that making better use of human capital can contribute to a reduction in the quantity of carbon dioxide that is discharged into the environment (Mahmood et al., 2019). The research of Beyene, which employs the STIRPAT model and examines 38 African nations from 2000 to 2018, reveals a positive and nonlinear relationship between the Human Development Index and health of the environment (Beyene, 2021). Khan et al. studied data of seven OECD countries from 1990 to 2018, indicating higher levels of human capital are associated with lower levels of carbon dioxide emissions and worsening environmental quality through CS-ARDL model (Khan et al., 2021).

By using panel quantile regression approach, Chen et al. explored the drivers of ecological footprints in 110 nations. According to the findings of Chen et al., human capital initially results in a larger ecological footprint and subsequently contributes to the footprint's reduction. In addition, according to the analysis of subsamples, Chen et al. point out that environmental degradation in high-income countries decreases with the increase in human capital, whereas environmental degredation in low income countries increases with human capital (Chen et al., 2021).

Aytun and Akin also investigated the causal relationships among environmental degredation, human capital, and Türkiye's energy usage by analyzing the data from 1971 to 2010. The results of bootstrap causality method found no association between enrollment in primary or secondary school and air pollution, while there exists a causal linkage between human capital measured by tertiary education and environmental degredation (Aytun, Akin, 2016). In a study for Pakistan, Li et al. emprically examined the effect of economic disparity on environmental quality by incorporating globalization and human capital for the period 1980–2015 and pointed out that human capital is a contributor of the contamination of the environment (Li et al., 2021).

Ahmed and Wang analyzed the influence of human capital on India's ecological footprint between 1971 and 2014 by deploying the cointegration test and auto-regressive distributed lag (ARDL) bound test, and noted that human capital improvement promotes environmetal quality via reducing the ecological footprint both in the short term as well as in the long term (Ahmed, Wang, 2019). Iorember et al. studied the relationship between South Africa's human capital and environmental quality during the period 1990–2016 based on Maki cointegration tests, Auto-regressive Distributed Lag (ARDL) model, and VECM causality tests, concluding that human capital development is essential for slowing South Africa's environmental deterioration through lowering ecological footprint (Iorember et al., 2020).

In their study based on data from sixteen countries in Central and Eastern Europe spanning from 1991 to 2014, Shujah-Ur-Rahman et al. revealed that human capital has the capacity to diminish the ecological footprint, thus leading to improvement in the quality of environment (Shujah-Ur-Rahman et al., 2019).

Pata and Caglar used data of China from 1980 to 2016 to emprically investigate how real GDP per capita, education level, globalization, use of renewable energy, and trade openness affect environmental quality. Their conclusion states that that the rate of environmental degredation decreases with a rise the country's human capital level in the long-term (Pata, Caglar, 2021). Li and Ouyang also specifically analyzed education level's role on air quality using Chinese data for the period between 1978 and 2015, with an ARDL approach. Their results unveiled that the association between human capital and CO_2 emissions exhibits a non-linear relationship, that in the begining, advancement in human capital lessens CO_2 emission levels until 1992, then increases emissions and lastly reduces it in the long-run (Li, Ouyang, 2018).

Zafar et al. also researched the effect of human capital on the ecological footprint in the U.S. over 1970–2015 through ARDL model and discovered improving human capital improve environmental outcomes through mitigating ecological footprint of the U.S. (Zafar et al., 2019). Jun et al. employed the Chinese provincal panel data from 1996 to 2008 to explore the link between economic disparity and CO_2 emissions by incorporating human capital, through the three-stage least square method, finding that human capital alleviates emmissions in China and helps to reduce the income inequality (Jun et al., 2011). Using a historical dataset for 11 EU transition economies from 2000 to 2018, Bayar et al. investigated the potential correlation between the level of human capital and the enhancement of environmental quality, specifically through the reduction of CO_2 emissions. In the study, they imply that higher human capital decreases CO_2 emissions considerably in certain countries, but increases CO_2 emissions in several other countries (Bayar et al., 2022). Sarkodie et al. examined the factors affecting environmental degradation in China from 1961 to 2016 via dynamic ARDL model, and revealing that the augmentation of human capital has a positive effect on China's ecological footprint (Sarkodie et al., 2020). The study conducted by Zhang and colleagues utilized the dynamic ARDL approach to examine the impacts of natural resources, human capital, and GDP growth on Pakistan's ecological footprint and carbon emission from 1985 to 2018. According to the findings of the research, it was discovered that in the short term, human capital is positively related with both CO_2 emissions and ecological footprint. In addition, human capital is negatively associated with CO_2 emissions and positively associated with ecological footprint, in the long run (Zhang et al., 2021).

In 2021, Williamson explored the relationships between education, government structure and carbon dioxide and methane emissions across 181 countries, finding that CO_2 emissions decrease with a rise in human capital, but only once certain threshold levels of human capital are reached. (Williamson, 2017). Hassan et al. studied the human capital's impact on Pakistan's environmental conditions during the time framework of 1970–2014 via ARDL bound test, noting that human capital had no statistically significant effect on Pakistan's ecological footprint (Hassan et al., 2019).

This extensive literature review examined 22 studies that addressed the link between education level and environment. Briefly, there are a variety of points of view about the environmental impact of a nation's education level.

Methods

The study's empirical framework suggests that environmental degradation is influenced by energy intensity, economic growth, and human capital. In the analysis, time series methods were employed to identify the link between the variables. First, the unit root test developed by Kwiatkowski et al. (Kwiatkowski et al., 1992) was used to identify the series' stationarity levels. The cointegration test proposed by Bayer and Hanck (Bayer, Hanck, 2012) was then utilized to determine the existence of a long-run relationship between the aforementioned variables. Long-term parameters were estimated by FMOLS method. In order to determine whether or not there was a causative relationship between the variables, the causality test that had been devised by Toda and Yamamoto (Toda, Yamamoto, 1995) was used.

KPSS unit root test

The KPSS unit root test, which was first introduced to the literature by Kwiatkowski, Phillips, Schmidt, and Shin (Kwiatkowski et al., 1992), has the opposite hypothesis compared to standard unit root tests. In the presence of a deterministic trend, the KPSS test is proposed as a means of testing the null hypothesis that a given observable series is stationary. In the KPSS test, the series consists of three structures: the series is a combination of the deterministic trend, random walk, and stationary error. The LM test is employed to test the null hypothesis that the variance of the random walk is equivalent to zero within the framework of the KPSS test (Kwiatkowski et al., 1992, p. 159).

Model:

$Y_t = \beta + \delta t + \alpha_t + \varepsilon_t$, $\alpha_t =$ constant, $\alpha_t = \alpha_{t-1} + u_t$, $u_t \sim WN(0, \sigma_\varepsilon^2)$ (Kozhan, 2010, p. 74).

The critical values used to test the hypotheses in the KPSS test were produced by using the Lagrange multiplier and $KPSS = \frac{\left(\frac{1}{T^2}\sum_{t=1}^{T}\hat{S}_t^2\right)}{\hat{\lambda}^2}$.

The equation here $\hat{S}_t = \sum_{j=1}^{t}\hat{\varepsilon}_j$, $\hat{\varepsilon}_t$, t and $\hat{\lambda}_t^2$ represents the residual of a regression on a(t).

The alternative hypothesis posits that a series is non-stationary and contains a unit root, in contrast to the null hypothesis which assumes the series is stationary and lacks a unit root.

Bayer – Hanck combined cointegration test

The Bayer – Hanck combined cointegration test, which was brought to the literature by Bayer and Hanck (Bayer, Hanck, 2012), proposes combined procedures by evaluating several tests together to provide stronger tests (meta tests) by combining the results of multiple scientific studies. In the first version of the test developed in 2008, a residual-based Engle–Granger test (Engle, Granger, 1987) and a system-based Johansen test (Johansen, 1988) were used together, while the version developed in 2012 also includes Boswijk (Boswijk, 1994) and Banerjee et al. (Banerjee et al., 1998) tests based on error correction. In the Bayer – Hanck combined cointegration test, the power of the test is based on metatests. Using metatests makes testing superior to other basic tests. Thus, it can be easily decided which one to use if individual test results are inconsistent. The test statistic of the test is obtained by adding the probability values of the cointegration tests calculated by the Fisher χ^2-test (Fisher, 1932; Bayer, Hanck, 2012). The statistics:

$\tilde{\chi}_I^2 = -2\sum_{i\in I} ln(p_i)$, where p_i = represents the p values of each tests or

$$EG - JOH = -2\left[ln(p_{EG}) + ln(p_{JOH})\right]$$
$$EG - JOH - BO - BDM = -2\left[ln(p_{EG}) + ln(p_{JOH}) + + ln(p_{BO}) + ln(p_{BDM})\right].$$

Probability values (p values) of the Engle – Granger, Johansen, Boswijk and Banerjee cointegration tests are shown as $p_{EG}, p_{JOH}, p_{BO}, p_{BDM}$ respectively (Govindaraju, Tang, 2013).

The test's null hypothesis indicates that cointegration does not exist, while alternative hypothesis indicates that there is cointegration.

FMOLS

FMOLS is employed for the purpose of estimating the long-term coefficients, provided that the series exhibit cointegration. For the method to work, regression errors (w_t) of the independent variables should be calculated first, and then using the Least Squares method, the cointegrated regression errors (ε_t) need to be computed. Subsequently, long-run covariance matrix (Λ) from the regression errors of the independent variables and the covariance matrix (Ω) from the regression errors of the independent variables should be calculated. In order to eliminate the endogeneity problem, a transformation should be applied to the dependent variable. Thus, FMOLS estimators are obtained as:

$$\hat{\theta}_{FMOLS} = \begin{bmatrix}\hat{\alpha}\\ \hat{\beta}\end{bmatrix} = \left(\sum_{t=1}^{T} S_t y_t^{+} - T\hat{\gamma}_{12}^{+}\right)\left(\sum_{t=1}^{T} S_t S_t^{'}\right)^{-1}$$

(Phillips, Hansen, 1990).

Pedroni also examined the FMOLS method with his work in 2001 (Pedroni, 2001). With the simulation in the study, he obtained consistent, asymptotically unbiased and normally distributed results in his analysis. Based on the results, he concluded that the FMOLS method would also give good results in small samples.

Toda – Yamamoto casuality test

The Toda Yamamoto causality test is grounded on the VAR model and unlike the classical Granger causality test it does not detect the stationarity and cointegration relationship in the series. Prior to conducting the test, the optimal lag length of the VAR model and the maximum integration level in the series should be determined. Here, the condition $d_{max} \leq k$ must be met in order not to take the difference of the variables and thus to prevent loss of information by including the variables in the analysis at the level (Toda, Yamamoto, 1995).

The model is as follows:

$$Y_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \lambda_{1i} Y_{t-1} + \sum_{i=1}^{k+d_{max}} \lambda_{2i} X_{t-1} + \varepsilon_{1t} \quad (1)$$

$$X_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \gamma_{1i} X_{t-1} + \sum_{i=1}^{k+d_{max}} \gamma_{2i} Y_{t-1} + \varepsilon_{2t} \quad (2)$$

In order to perform the analysis, the VAR model with the lag length ($k + d_{max}$) must be estimated first, and then the parameters need to be estimated. However, when the Toda-Yamamoto test is applied to the stationary series at the level, no lagged variables can be added to the VAR model, so the test statistics obtained are the same as the Granger causality test based on the VAR model.

The hypothesis of the 1st equation of the test:

H_0: $\lambda_{2i} = 0$ X does not Granger cause Y.

H_1: $\lambda_{2i} \neq 0$ Granger causes Y.

The hypothesis of the 2nd equation of the test:

H_0: $\gamma_{2i} = 0$ Y does not Granger cause X.

H_1: $\gamma_{2i} \neq 0$ Y Granger causes X.

Here, the test statistics of the hypotheses are calculated with the Wald test, which is subject to the χ^2 distribution with k degrees of freedom (provided that $i \leq k$) (Toda, Yamamoto, 1995).

Data

The research investigates the influences of output expansion, energy intensity and human capital on CO_2 pollution in China between 1990–2019.

Table 1. Variable units and sources

Indicator	Definition	Measurement	Source
lco2	Carbon emissions	Million tonnes of carbon dioxide per capita	BP Statistical Review of World Energy, World Bank WDI (Population)
lei	Primary energy consumption intensity	Exajoules (GDP, constant indicator for 2015, USD)	BP Statistical Review of World Energy, World Bank WDI (GDP)
lgdp	GDP per capita	GDP per capita (constant indicator for 2015, USD)	World Bank, World Development Indicators
lhc	Human Capital Index	Based on years of schooling and returns to education	PennWorld Table 10.0

In the study, carbon emission data for environmental degradation indicator, real GDP for economic growth indicator, primary energy consumption per output for energy intensity indicator and human capital index data for human capital indicator are used. Carbon emission and income growth data have been divided by population data and converted to per capita data. The natural logarithms of the variables were computed prior to their incorporation into the model. *Table 1* contains details about the variables. The functional model utilized in the research is:

$$lco2 = f(lei, lgdp, lhc)$$

$$lco2_t = \beta_0 + \beta_1 lei_t + \beta_2 lgdp_t + \beta_3 lhc_t + \varepsilon_t .$$

In the model, β_0 represents the constant term or autonomous coefficient, β_1, β_2 and β_3 denote the independent variable coefficients, and ε_t denotes the error term. The positive β_1, β_2 and β_3 coefficients indicate that quality of environment worsens as energy intensity, income or human capital increase while negative β_1, β_2 and β_3 coefficients indicate that an increase in energy intensity, income or education level reduces pollution levels.

Descriptive statistics and correlation matrix of the series are given in *Table 2*. Each of the series consisting of 30-year data is normally distributed. All variables are highly correlated with each other. The variable *lei* is negatively correlated with all variables. Other correlations are positive.

Table 2. Descriptive statistics and correlation matrix

	lco2	*lei*	*lgdp*	*lhc*
Observations	30	30	30	30
Mean	1.396010	2.755635	8.100115	0.854279
Median	1.478849	2.744280	8.077781	0.870074
Maximum	1.941460	3.329926	9.232913	0.992877
Minimum	0.716422	2.296033	6.807969	0.670941
Std. Dev.	0.460667	0.278626	0.753663	0.089956
Skewness	-0.091036	0.323727	-0.082661	-0.407844
Kurtosis	1.282113	2.500363	1.738759	2.280940
Jarque-Bera	3.730356	0.836043	2.022575	1.477994
Probability	0.154869	0.658348	0.363750	0.477593
lco2	1.000000			
lei	-0.854411	1.000000		
lgdp	0.974300	-0.948065	1.000000	
lhc	0.924358	-0.978356	0.979951	1.000000
Source: own elaboration.				

Results

It is imperative to ascertain the stationarity of the variables before delving into the investigation of the long-term relationship between them. KPSS unit root test is used for stationarity analysis. *Table 3* demonstrates that calculated test statistics for level values exceed the 5% and 10% critical values. As a result, the null hypothesis that the series is stationary is rejected. Upon conducting differencing, the null hypothesis cannot be rejected since computed test statistics are lower than the critical values. To put it differently, the analysis indicates that the series possess a unit root at the level and their first differences exhibit stationarity. Therefore, it can be investigated whether there is a long-term link between the variables. The integration of variables at I(1) level allows the Bayer – Hanck cointegration technique to be applied.

In time series analysis, test results are sensitive to lag length. Therefore, it is important to determine the appropriate lag length prior to cointegration test. *Table 4* shows the estimation results of the VAR model. According to all information criteria, the appropriate lag length is determined as 2.

Table 5 displays Bayer – Hanck cointegration analysis results. According to individual test statistics, a cointegrated relationship was found only in Johansen and Boswijk tests. The null hypothesis, which assumes the non-existence of cointegration, is rejected on the basis of the outcomes obtained

Table 3. Unit root analysis

	lco2	*lei*	*lgdp*	*lhc*
I(0)	0.673141	0.674352	0.712530	0.702510
I(1)	0.139412	0.151816	0.272310	0.341069
1%	0.739			
5%	0.463			
10%	0.347			
Source: own elaboration.				

Table 4. Lag length selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	155.9806	NA	2.27e-10	-10.85576	-10.66544	-10.79758
1	391.8342	387.4738	3.48e-17	-26.55959	-25.60801	-26.26868
2	440.9588	66.66907*	3.54e-18*	-28.92563*	-27.21280*	-28.40200*
Note: * represent significance level at 10 percent. Source: own elaboration.						

Table 5. Results of the Bayer – Hanck cointegration analysis

Estimated Models	Engle-Granger	Johansen	Banerjee et al.	Boswijk	EG-J	EG-J-BA-BO
lco2=f(lei, lgdp, lhc)	-3.2392	34.1885	-2.2132	29.2102	9.4236052	22.229473
	(0.4586)	(0.0196)	(0.7203)	(0.0023)	*	**
lei=f(lco2, lgdp, lhc)	-3.5709	34.1885	-3.3516	31.8766	10.342961	27.281768
	(0.2896)	(0.0196)	(0.2331)	(0.0009)	*	**
lgdp=f(lco2, lei, lhc)	-3.4407	34.1885	-2.4390	32.0999	9.9475925	25.132192
	(0.3529)	(0.0196)	(0.6304)	(0.0008)	*	**
lhc=f(lco2, lei, lgdp)	-4.2980	34.1885	-4.4299	45.7574	13.352843	76.203365
	(0.0643)	(0.0196)	(0.0225)	(0.0000)	**	***
Note: *, **, and *** represent significance level at 10 percent, 5 percent and 1 percent respectively. Values in parentheses represent significance values. The 1%, 5%, and 10% critical values for the EG-J test are 16263, 10711, 8352, respectively; the 1%, 5%, and 10% critical values for the EG-J-BA-BO test are 31742, 20788, and 16239, respectively. Source: own calculation.						

from the EG-J test and the EG-J-BA-BO test. It has also been determined that there is a cointegrated relationship in models where the dependent variables are growth, energy intensity and human capital. These findings revealed a cointegrated relationship between *lco2, lei, lgdp* and *lhc*. In other words, there is a long-run relationship between these variables.

After determining if the factors have a cointegrated relationship, the coefficients of their long-term relationship need to be figured out. *Table 6* demonstrates the estimation results that were obtained using the FMOLS testing approach. Statistical significance was observed for all variables in the model. According to the results, carbon emissions rise by 1.25% for every 1% increase in energy intensity, 1.38% for every 1% increase in GDP growth, and 1.32% for every 1% increase in human capital. All variables in the model exhibit a positive link with carbon related emissions, indicating a gworing influence. While the increase in energy efficiency affects the environment positively, advances in output and education level have a detrimental effect on environmental quality.

The error correction model is established by adding the lagged value of the residuals obtained from the estimation of the long-run coefficients to the model. The error correction model showing the short-run dynamics in the research is as follows:

$$\Delta lco2_t = \alpha_0 + \sum_{i=1}^{m} \alpha_{1i} \Delta lco2_{t-i} + \sum_{i=0}^{n} \alpha_{2i} \Delta lei_{t-i} + $$
$$+ \sum_{i=0}^{p} \alpha_{3i} \Delta lgdp_{t-i} + \sum_{i=0}^{q} \alpha_{4i} \Delta lhc_{t-i} + \beta ECT_{t-1} + \varepsilon_t .$$

In the equation above, Δ, α_0, β and ε_t, denote the difference operator, constant term, error correction term and error term, respectively. The estimation results of the error correction model are shown in *Table 7*. All coefficients in the model are significant at the 10% level. The effect of independent variables on dependent variables is positive in the short run as well as in the long run. The error correction term,

Table 6. Long run analysis

Indicator	Coefficient	Std. error	t-statistic	Prob.
lei	1.255213	0.050302	24.95356	0.0000
lgdp	1.384287	0.063256	21.88376	0.0000
lhc	1.328164	0.261181	5.085225	0.0000
c	-13.77963	0.507668	-27.14300	0.0000
@trend	-0.043432	0.005916	-7.341792	0.0000
R2	0.999415			
Source: own calculation.				

Table 7. Short run analysis

Indicator	Coefficient	Std. error	t-statistic	Prob.
Δlei	1.209813	0.049130	24.62493	0.0000
$\Delta lgdp$	1.266015	0.064732	19.55768	0.0000
Δlhc	0.578302	0.294373	1.964520	0.0617
ect(-1)	-0.265227	0.144540	-1.834978	0.0795
c	-0.027580	0.006269	-4.399177	0.0002
R2	0.982282			
Jarque – Bera normality test	2.129068			0.3448
Breusch – Godfrey LM test	2.626693			0.2689
BPG heteroskedasticity test	2.330506			0.6752
Ramsey RESET test	0.004112			0.9495
CUSUM	Stable			
CUSUMQ	Stable			
Source: own calculation.				

Table 8. Toda – Yamamoto causality analysis

	Chi-sq	df	Prob.
lhc→ lco2	12.69879	2	0.0017
lgdp→ lco2	0.812548	2	0.6661
lei→ lco2	1.294541	2	0.5235
All→ lco2	**15.89347**	**6**	**0.0143**
lco2→ lhc	3.885790	2	0.1433
lgdp→ lhc	3.298155	2	0.1922
lei→ lhc	4.336021	2	0.1144
All→ lhc	**5.604208**	**6**	**0.4690**
lco2→ lgdp	0.836165	2	0.6583
lhc→ lgdp	3.995740	2	0.1356
lei→ lgdp	0.659725	2	0.7190
All→ lgdp	**15.92684**	**6**	**0.0142**
lco2→ lei	2.175016	2	0.3371
lhc→ lei	9.230317	2	0.0099
lgdp→ lei	2.007678	2	0.3665
All→ lei	**12.63654**	**6**	**0.0492**
Source: own compilation.			

which represents the speed of adjustment of short-term imbalances, was determined as negative and significant. Accordingly, 26% of that disequilibrium occurring in the short-term dissipates by the following period, thus approaching the long-term equilibrium. The diagnostic test results of the error correction model are also listed in Table 7. According to the results, the error terms are normally distributed; there are no autocorrelation and heteroscedasticity problems. Also, there is no model specification error and the coefficients are stable.

The Toda – Yamamoto causality test is utilized to examine the causal relationship among variables. *Table 8* displays the results of VAR analysis, wherein appropriate lag length is 2 and maximum degree of integration is 1. According to these outcomes, unilateral causal relation from human capital to carbon emission and from human capital to energy intensity has been determined. In addition, there is unilateral causality relation from all variables to carbon emissions, economic expansion, and energy intensity individually.

In the context of China, the prioritization of economic growth and the fast industrialization process has resulted in the relegation of environmental concerns to a secondary position. Insufficient implementations of environmental legislation and suboptimal practices have resulted in the occurrence of environmental pollution and deterioration. Moreover, it is expected that education would enhance environmental awareness and foster the preservation of the environment. However, it is often seen that there exists a positive association between greater levels of education and both increased wages and elevated levels of resource use. This phenomenon might potentially lead to a rise in energy consumption and the exhaustion of natural resources, thereby resulting in environmental damage. Furthermore, there is often a positive correlation between greater levels of education and increased levels of industry and technical advancement, leading to a potential rise in pollution and environmental degradation (Hou, 2022).

Conclusion

The current study examined how China's ecological deterioration between 1990 and 2019 was affected by the country's educational attainment, energy efficiency, and production expansion. The econometric analysis yielded results indicating the presence of a significant correlation between the variables in the long term. Moreover, elasticities suggest that each of the three independent factors has an influence that is damaging to the circumstances of the environment over the long-run. The increase in GDP also increases carbon emissions as it increases energy consumption, which is the main input of production. This relationship is an expected result for China, which has a low renewable energy utilization rate. The energy density analysis result was consistent with the anticipated outcome. As anticipated, the increase in energy density, which is also an indicator of energy efficiency, i.e., the increase in the quantity of primary energy consumed per output, results in environmental degradation and carbon emissions. The progress in human capital in China, which has a lower level of human capital compared to developed countries, increases its carbon emissions. The literature on developed countries commonly asserts that investing in education helps to favorably influence environmental conditions. China's relatively low level of human capital during development process does not have a mechanism to raise environmental quality. When we compare the short-term analysis results with the log-term results, the elasticities were also similar with the long-term analysis results. In the causality analysis, it was found that human capital causes carbon emissions.

These results provide useful information in the design of education and environmental policies for China in the development process. In this study, it has been determined that raising the education level of the society in China reduces the environmental quality and this requires more emphasis on environmental protection policies. Another method of improving environmental quality in China is to increase efficiency in energy use. Since reducing the energy intensity directly reduces the amount harmful emissions, increasing energy efficiency is a policy that can achieve rapid results. One of the effective policies to decrease primary energy intensity is to augment the the percentage of energy derived from renewable sources in total consumption. Although initial installation costs are high, it is a more reasonable policy to bear the high installation costs of renewable energies, as it has a reducing effect on carbon emissions and can prevent or reduce the emergence of major environmental problems that may be encountered in the future.

To make some useful policy recommendations regarding human capital for the prevention of environmental degradation, we can make the following recommendations: Initially, it is imperative to expeditiously elevate the mean educational attainment in China to the requisite level for environmental preservation, which is currently comparatively deficient in contrast to industrialized nations. Furthermore, training should be given to individuals at all levels of education that will increase their awareness of environmental protection and enable them to learn methods of using energy efficiently. Moreover, environmentally friendly technologies, renewable energy projects and efficiency-enhancing ideas and practices should be supported at higher education levels. Lastly, incentives and subsidies should be provided to the private sector to reduce carbon emissions.

The pre-university curriculum in China lacks emphasis on sustainability, sustainable development, and environmental responsibility. It is essential to enhance the environmental education curriculum in order to provide students with a more comprehensive understanding of sustainability issues (Wang, 2021). The establishment of collaborations at both local and national levels is crucial in the promotion and progression of environmental education.

By fostering collaboration among environmental groups, colleges, local governments, and other stakeholders, these partnerships have the potential to facilitate the advancement and execution of environmental education initiatives (Li et al., 2022).

Although this research is an original study in terms of its econometric model and methods, the subject can be handled in a different way with future studies in this field. The study's methodology does not account for structural breaks. In this study, structural breaks were not added to the models in the analysis, so future studies may consider the structural breaks. Lastly, the research model can be expanded by adding more control variables.

References

Ahmed Z., Wang Z. (2019). Investigating the impact of human capital on the ecological footprint in India: An empirical analysis. *Environmental Science and Pollution Researc*h, 26, 26782–26796.

Aytun C., Akin C. (2016). Relationship between CO_2 emissions, energy consumption and education in Turkey: Bootstrap causality analysis. *Eurasian Econometrics, Statistics & Emprical Economics Journal*, 4, 49–63.

Banerjee A., Dolado J., Mestre R. (1998). Error-correction mechanism tests for cointegration in a single-equation framework. *Journal of Time Series Analysis*, 19(3), 267–283.

Bayar Y., Smirnov V., Danilina M., Kabanova N. (2022). Impact of institutions and human capital on CO_2 emissions in EU transition economies. *Sustainability*, 14(1), 353.

Bayer C., Hanck C. (2012). Combining non-cointegration tests. *Journal of Time Series Analysis*, 34(1), 83–95.

Becker G.S. (1994). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. Third edition. Chicago: University of Chicago Press.

Beyene S.D. (2022). Human activities and environmental quality: Evidence beyond the conventional EKC hypothesis. *Heliyon*, 8(9), e10756.

Boswijk H.P. (1994). Testing for an unstable root in conditional and unconditional error correction models. *Journal of Econometrics*, 63, 37–60.

Chen Y., Lee C.-C., Chen M. (2021). Ecological footprint, human capital, and urbanization. *Energy & Environment*, 33(3), 487–510.

Danish H.S.T., Baloch M.A., Mahmood N., Zhang J.W. (2019). Linking economic growth and ecological footprint through human capital and biocapacity. *Sustainable Cities and the Society*, 47, 101516. https://doi.org/10.1016/j.scs.2019.101516.

Dinda S. (2004). Environmental Kuznets Curve hypothesis: A survey. *Ecological Economics,* 49(4), 431 –455.

Engle R.F., Granger C.W.J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2), 251–276.

Feenstra R.C., Inklaar R., Timmer M.P. (2015). The next generation of the Penn World table. *American Economic Review*, 105(10), 3150–3182.

Fisher R. (1932). *Statistical Methods for Research Workers*. London: Oliver and Boyd.

Hao L.-N, Umar M., Khan Z., Ali W. (2021). Green growth and low carbon emission in G7 countries: How critical the network of environmental taxes, renewable energy and human capital is? *Science of the Total Environment*, 752, 141853.

Hassan S.T., Xia E., Khan N.H., Shah S. (2019). Economic growth, natural resources, and ecological footprints: Evidence from Pakistan. *Environmental Science and Pollution Research*, 26(3), 2929–2938.

Hou G. (2022). How to promote the environmental education among young people in China. In: *Proceedings of the 2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022)*. Available at: https://www.atlantis-press.com/proceedings/icssed-22/125973938 (accessed: August 12, 2023).

Iorember P.T., Jelilov G., Usman O. et al. (2021). The influence of renewable energy use, human capital, and trade on environmental quality in South Africa: Multiple structural breaks cointegration approach. *Environmental Science and Pollution Research*, 28(11), 13162–13174.

Johansen S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12, 231–254.

Jun Y., Zong-kui Y., Peng-fei S. (2011). Income distribution, human capital and environmental quality: Empirical study in China. *Energy Procedia*, 5, 1689–1696.

Kasman A., Duman Y.S., (2015). CO_2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: A panel data analysis. *Economic Modelling,* 44, 97–103.

Khan M. (2020). CO_2 emissions and sustainable economic development: New evidence on the role of human capital. *Sustainable Development*, 28(5), 1279–1288.

Khan Z., Ali S., Dong K., Li R.Y.M. (2021). How does fiscal decentralization affect CO_2 emissions? The roles of institutions and human capital. *Energy Economics,* 94, 105060.

Komen R., Gerking S., Folmer H., (1997). Income and environmental R&D: empirical evidence from OECD countries. *Environment and Development Economics,* 2(4), 505–515. DOI:10.1017/S1355770X97000272

Kozhan R. (2010). *Financial Econometrics – with Eviews*. Roman Kozhan & Ventus Publishing ApS.

Kwiatkowski D., Phillips P.C.B., Schmidt P., Shin Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that the economic time series have a unit root? *Journal of Econometrics*, 54, 159–178.

Lan J., Kakinaka M., Huang X. (2012). Foreign direct investment, human capital and environmental pollution in China. *Environ Resour Econ.,* 51(2), 255–275.

Li G., Xi Y., Zhu Z. (2022). The way to sustainability: Education for sustainable development in China. *Asia Pacific Education Review*, 23(4), 611–624.

Li P., Ouyang Y. (2019). The dynamic impacts of financial development and human capital on CO_2 emission intensity in China: An ARDL approach. Journal of Business Economics and Management, 20(5), 939–957.

Mahmood N., Wang Z., Hassan S.T. (2019). Renewable energy, economic growth, human capital, and CO_2 emission: An empirical analysis. *Environmental Science and Pollution Research*, 26, 20619–20630. DOI: https://doi.org/10.1007/s11356-019-05387-5

Pata U.K., Caglar A.E. (2021). Investigating the EKC hypothesis with renewable energy consumption, human capital, globalization and trade openness for China: Evidence from augmented ARDL approach with a structural break. *Energy*, 216, 119220.

Pedroni P. (2001). Fully modified OLS for heterogeneous cointegrated panels. In: Baltagi B.H., Fomby T.B., Carter Hill R. (Eds.). *Nonstationary Panels, Panel Cointegration, and Dynamic Panels (Advances in Econometrics, Vol. 15)*. Bingley: Emerald Group Publishing Limited.

Phillips P.C., Hansen B.E. (1990). Statistical inference in instrumental variables regression with I(1) processes. *Review of Economic Studies*, 57(1), 99–125.

Sarkodie S.A., Adams S., Owusu P.A. et al. (2020). Mitigating degradation and emissions in China: The role of environmental sustainability, human capital and renewable energy. *Science of the Total Environment*, 719, 137530.

Shujah-ur-Rahman Chen S., Saud S., Saleem N., Bari M.W. (2019). Nexus between financial development, energy consumption, income level, and ecological footprint in CEE countries: Do human capital and biocapacity matter? Environmental Science and Pollution Research, 26*,* 31856–31872.

Teng B.-S. (2004). The WTO and entry modes in China. *Thunderbird International Business Review*, 46, 381–400.

Toda H.Y., Yamamoto T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, 66(1-2), 225–250.

Vandenbussche J., Aghion P., Meghir C. (2006). Growth, distance to frontier and composition of human capital. *Journal of Economic Growth,* 11(2), 97–127.

Wang A. (2021). *Enhancing Sustainability Education in China's Secondary Schools*. Available at: https://news.climate.columbia.edu/2021/05/04/sustainability-education-china/ (accessed: August 12, 2023).

Williamson C. (2017). Emission, education, and politics: An empirical study of the carbon dioxide and methane environmental Kuznets curve. *The Park Place Economist*, 25(1), 21–33.

Yao Y., Ivanovski K., Inekwe J., Smyth R. (2020). Human capital and CO_2 emissions in the long run. *Energy Economics*, 91, 104907.

Zafar M.W., Zaidi S.A.H., Khan N.R. et al. (2019). The impact of natural resources, human capital, and foreign direct investment on the ecological footprint: The case of the United States. *Resources Policy*, 63, 101428.

Zhang L., Godil D.I., Bibi M. et al. (2021). Caring for the environment: How human capital, natural resources, and economic growth interact with environmental degradation in Pakistan? A dynamic ARDL approach. *Science of the Total Environment*, 774, 145553.

Information about the Authors

Funda Durgun – PhD in Econometrics, Lecturer, Dicle University (İİBF, Fetih Mah., Sur, Dıyarbakır, Türkiye; e-mail: funda.uncu@dicle.edu.tr)

Aziz Dayanir – PhD in Economics, Research Assistant, Istanbul University (Main Campus, 34452, Beyazıt, Fatih, Istanbul, Türkiye; e-mail: aziz.dayanir@istanbul.edu.tr)

Received May 26, 2023.