5/2023, sentabr-oktabr (№ 00067)

THE ANALYSIS OF ECONOMIC GROWTH AND ENERGY USE AND CO2 EMISSION IN UZBEKISTAN

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DOI: *https://doi.org/10.55439/EIT/vol11_iss5/a27*

Abstract
Greenhouse gas (GHG) emissions, in particular Carbon dioxide (CO_2) emissions, are the primary cause of global climate change, which poses extreme risks to the environment, development, and sustainability. Uzbekistan's economy and agriculture are developing steadily, which results in increasing energy demand and CO_2 emissions. For governments attempting to balance climate change mitigation and sustainable development, it is increasingly important to comprehend Uzbekistan's susceptibility to climate change. Minimizing environmental degradation in Uzbekistan can be achieved through analyzing pollution-development trade-offs. The relationship between economic growth, energy use, agricultural added value, and CO_2 emissions in Uzbekistan was thus empirically studied in the current study. This study used time series data for Uzbekistan from 1990 to 2020 to evaluate the short-run and long-run correlations between the variables using the autoregressive distributed lag (ARDL) technique. The empirical results showed that while energy consumption and economic expansion cause environmental degradation by raising CO_2 emissions, increasing agricultural added value actually enhances Uzbekistan's environmental quality by lowering CO_2 emissions over the long and short terms.
Keywords: Environmental degradation · Carbon emissions · Economic growth · Energy use Agriculture · Sustainability.

Introduction

Due to atmospheric GHG concentrations dominated by CO_2, which are mostly produced by human activities like burning fossil fuels and deforestation, global climate change is a pressing issue (Raihan et al. 2018, 2021a, 2022a; Jaafar et al. 2020). According to Raihan et al. (2019, 2022b; Isfat and Raihan 2022) and other researchers, the continued rise in CO_2 emissions will have profound effects on the world's climate system and have disastrous effects on all facets of society. In order to maintain sustainable development and lessen the negative effects of climate change, it is now a global issue to reduce CO_2 emissions and improve environmental quality (Ali et al. 2022; Raihan et al. 2021b, 2022c; Raihan and Said 2022). Therefore, identifying the primary sources of CO_2 is crucial to raising environmental quality. Environmental degradation will necessarily arise if the functional connection between natural resources and contemporary development processes cannot be avoided. These problems are especially prevalent in emerging nations like Uzbekistan where environmental sustainability, agricultural value addition, energy security, and economic growth are all equally crucial (Shahbaz et al. 2019).

In the past 30 years, Uzbekistan, a developing nation, has seen significant economic growth (Nguyen et al. 2021). In order to achieve economic growth that is compatible with long-term development, Uzbekistan has also developed methods. Uzbekistan has ratified international agreements including the Paris Agreement and the Kyoto Protocol that aim to combat climate change and cut CO_2 emissions. Uzbekistan has said in its most recent Intended National Determined Contributions (INDC) that it will use domestic resources to cut GHG emissions by 8% by 2030 compared to a business-as-usual scenario. Uzbekistan is now dealing with serious environmental problems. For policymakers looking to strike a balance between measures aimed at achieving sustainable development and policies targeted at mitigating climate change, as well as measures that achieve both, recognizing Uzbekistan's sensitivity to climate change is becoming more and more crucial. The hardest part of achieving this dual goal at once is the trade-off between pollution and development. Examining Uzbekistan's environmental factors will help us to find an important solution to the question of how Uzbekistan may cut CO_2 emissions. As one of the transitional economies with the greatest growth rates in the world, Uzbekistan has transformed from a low-income nation to a lower-middle-income nation (Nguyen et al. 2021). According to the World Bank, Uzbekistan's gross domestic product (GDP) expanded by about nine times from 30 billion USD in 1986 to 59 billion USD in 2020. With a 5% annual GDP growth rate in 2019 (according to the World Bank 2022). However, the spectacular economic growth of Uzbekistan is associated with a rise in energy consumption, which has led to several environmental problems (Al-Mulali et al. 2015; Tang and Tan 2015; CO_2 emissions significantly increase as a result of the increased usage of fossil fuels for energy (Raihan et al., 2022d). Uzbekistan's CO_2 emissions per person have exceeded the global average since 2018 (Nguyen et al. 2021). Because of this, the nation is quite concerned about the rising emission intensity, particularly from the energy sector. As a result, concerns about climate change have intensified discussions over Uzbekistan's implementation of energy conservation laws and the need to understand the relationship between economic growth, energy use, and CO_2 emissions. According to Raihan et al. (2023a), one of the main causes of environmental deterioration is agriculture. According to Raihan and Tuspekova (2022a), agriculture is linked to CO_2 emissions and is seen as being extremely susceptible to climate change. The second-largest source of CO_2 emissions and a significant driver of climate change, agriculture, forestry, and other land use (AFOLU) and land use, land-use change, and forestry (LULUCF) activities account for around one-fifth of annual worldwide CO_2 emissions (IPCC 2014).

Over the past 25 years, the agriculture sector in Uzbekistan has made significant advancements. It is a significant producer and exporter of several agricultural goods, such as rice, peanuts, and coffee. Additionally, out of all economic sectors in Uzbekistan, agriculture employed more than 18.8 million Uzbekistanese in 2019 (Nguyen et al. 2021). However, for long-term development, both increasing agricultural value added and environmental quality are required. According to Raihan et al. (2023b), increased agricultural value added reduces poverty, improves income distribution, boosts food security, and encourages economic development. Economic studies have shown that agricultural value-added benefits the environment as well (Shahbaz et al. 2019; Prastiyo et al. 2020). Agriculture's value added is correlated with economic expansion, which boosts consumer demand for goods, services, and a cleaner environment as well as government enforcement of environmental laws (Borlaug, 2007). Several studies have looked at the contributing elements of environmental degradation over the previous three decades. A discussion about whether there is a connection between environmental deterioration and economic advancement was ignited by Grossman and Krueger's (1991) investigation. Empirical research on the effects of economic expansion on the environment was developed as a result of the influence this study had on many academics. As a result, several research using time series data looked at the relationships between economic growth and environmental pollution indicators such as CO_2 emissions (Adebayo et al. 2020; Begum et al. 2020; Raihan 2023a). Despite being a prominent topic among modern academics globally, there hasn't been much study on the interaction of CO_2 emissions and environmental factors in Uzbekistan.

Literature review

Empirical studies have extensively demonstrated the connection between economic development, energy use, and CO_2 emissions. There was a wide range of studies taken into account, covering several nations, elements, and approaches. Begum et al. (2015) used data from 1970 to 2009 for Malaysia to use the ARDL approach and DOLS technique, revealing the beneficial effects of economic growth and energy use on CO_2 emissions. Economic growth and energy usage lead to an increase in CO_2 emissions, according to research by Sehrawat et al. (2015) using the ARDL estimator for India from 1971 to 2011. By using the ARDL method, Liu and Bae (2018) demonstrated the beneficial effects of economic growth and energy consumption on CO_2 emissions in China from 1970 to 2015.

Akbota and Baek (2018) observed that CO_2 emissions rose as a result of economic expansion and energy demand for Kazakhstan between 1980 and 2011. Ahmed et al. (2019) found that CO_2 emissions in Indonesia are triggered by economic growth and energy use using an ARDL estimate and annual data from 1971 to 2014. Adebayo (2020) revealed that economic growth and energy usage have a beneficial impact on CO_2 emissions in Mexico by applying ARDL, FMOLS, and DOLS estimators using annual data from 1971 to 2016. By employing FMOLS and DOLS methodologies, Kirikkaleli and Kalmaz (2020) discovered beneficial effects of economic growth and energy utilization on CO_2 emissions in Turkey from 1960 to 2016.

Odugbesan and Adebayo (2020) used annual data ranging from 1981 to 2016 using ARDL, FMOLS, and DOLS methodologies to identify the beneficial effects of economic growth and energy consumption on CO_2 emissions in Nigeria. Nondo and Kahsai (2020) used the ARDL method to demonstrate the beneficial effects of economic growth and energy intensity on CO_2 emissions in South Africa from 1970 to 2016. Using data from 1971 to 2014, Adebayo and Kalmaz (2021) employed the ARDL, FMOLS, and DOLS methodologies to identify a favourable association between economic growth and energy use and CO_2 emissions in Egypt. Leito (2021) reported that energy consumption is directly related to climate change and environmental damage by increasing CO_2 emissions, while economic growth appears to support sustainable development practices over the long term. These models included ARDL, quantile regression, FMOLS, CCR, and DOLS, and were applied to annual data for Portugal between 1970 and 2016.

Additionally, a number of studies noted the beneficial effects of energy use and economic expansion on CO_2 emissions from a number of nations. Vo et al. (2019) found that the level of CO_2 emissions is positively correlated with economic growth and energy use in ASEAN countries using FMOLS and DOLS estimators with data from 1971 to 2014. Raheem and Ogebe (2017) discovered that economic expansion and energy use increased CO_2 emissions by utilizing time series data for 20 African nations from 1985 to 2013. Adebayo et al. (2020) used the ARDL model for MINT countries with a period range of 1980 to 2018 and discovered a positive correlation between economic growth and energy use on CO_2 emissions. Using the STIRPAT and ARDL techniques, Zmami and Ben-Salha (2020) reported the beneficial effects of economic growth and energy use on CO_2 emissions in GCC nations between 1980 and 2017. Wang et al. (2020b) used the DSUR approach with data for APEC nations from 1990 to 2014. According to Wang et al. (2020b), economic expansion and energy intensity both raise CO_2 emissions levels. According to Teng et al. (2021), energy consumption and economic growth have a favorable impact on CO_2 emissions in OECD nations.

The impact of agriculture on environmental deterioration has been a frequently debated topic during the past ten years. Recent studies have examined how agriculture affects environmental degradation using a variety of econometric approaches. Dogan (2016) found that CO_2 emissions in Turkey are positively associated with economic growth and adversely associated with agricultural productivity using data from 1968 to 2010 and the ARDL technique. Using data from 1970 to 2015 for Indonesia, Prastiyo et al. (2020) revealed positive affects of economic growth on CO2 emissions, but negative impacts of agriculture value added on CO_2 emissions. Using data from the ASEAN countries from 1970 to 2013, Liu et al. (2017) used the ARDL model to find that economic expansion has a positive impact on CO_2 emissions while agricultural value addition has a negative impact.

Using OLS, FMOLS, and DOLS methodologies, Jebli and Youssef (2017) found that while an increase in GDP influences CO_2 emissions, an increase in agricultural value added reduces CO_2 emissions in North African countries between 1980 and 2011. Wang et al. (2020a) discovered that, in the G7 countries, agricultural value added reduces CO_2 emissions whereas economic expansion increases CO_2 emissions using data for the years 1996–2017 and the ARDL model.

Methodology

Data: The World Development Indicator (WDI) dataset, which contains time series data for Uzbekistan from 1984 through 2020, was used in this study. The dependent variable in this study was CO_2 emissions, and the explanatory variables were economic growth, energy use, and agricultural value added. In this study, CO_2 emissions were expressed in kilotons, GDP (constant Uzbekistanese Dong), energy consumption was expressed in kilograms of oil equivalent per person, and agricultural value added was expressed as a share of GDP. To ensure that the data were normally distributed, the variables were finally transformed into a logarithm.

Table 1 lists the variables along with their logarithmic versions, measurement units, and data sources. In addition, Fig. 1 displays the annual trends of the studied variables in Uzbekistan. In addition, Fig. 1 displays the annual trends of the studied variables in Uzbekistan. It depicts how the GDP, energy consumption, agriculture value added, and CO_2 emissions are all rising steadily.

Empirical model

Theoretically, income and energy use are related to CO2 emissions. The following function is defined within the framework of the typical Marshallian demand function (Friedman 1949) at time t, assuming the market clearing condition, where CO_2 emissions match economic growth and energy use:

$$\mathrm{CO}_{2t} = f(\mathrm{GDP}_t; \mathrm{EUt})$$

where EUt is energy use at time t, GDPt is economic growth at time t, and CO_{2t} is the CO2 emissions at time t.

This study set out to determine how much agricultural value addition contributed to Vietnam's CO_2 emissions. So, Eq. (1) can be expressed as follows:

$$\mathrm{CO}_{2t} = f(\mathrm{GDP}_t; \mathrm{EU}_t; \mathrm{AVA}_t)$$

where AVAt is the agricultural value added at time t.

The following equation depicts the economic model:

$$\mathrm{CO}_{2t} = \tau_0 + \tau_1 \mathrm{GDP_t} + \tau_2 \mathrm{EU_t} + \tau_3 \mathrm{AVA_t}$$

Table 1 Variables with their logarithmic forms, units, and data sources

Variables	Description	Logarithmic forms	Units	Sources
CO_2	CO_2 emissions	LCO2	Kilotons	WDI
GDP	Economic growth	LGDP	Constant Vietnamese Dong	WDI
EU	Energy use	LEU	Kg of oil equivalent per capita	WDI
AVA	Agricultural value added	LAVA	Percentage of GDP	WDI

Stationary techniques for data

A unit root test is required to prevent erroneous regression. By comparing the variables in the regression and using stationary processes to estimate the relevant equation, it verifies that the variables are stationary (Raihan and Tuspekova, 2022b).

Before examining cointegration among variables, the empirical literature recognises the requirement to define the sequence of integration. Some studies claim that using more than one unit root test is essential when determining the integration order of a series since different unit root tests perform differently depending on sample size (Raihan and Tuspekova, 2022c, 2022d). The Augmented Dickey-Fuller (ADF) test, developed by Dickey and Fuller in 1979, the Dickey-Fuller generalized least squares (DF-GLS) test, developed by Elliott et al. in 1992, and the Phillips-Perron (P-P) test, developed by Phillips and Perron in 1988 were all used in the current study to find the autoregressive unit root. In order to confirm that no variable surpassed the order of integration and to support the use of the DOLS technique over conventional cointegration methods, the unit root test was utilized in this study.

Cointegration tests

The ARDL limits test suggested by Pesaran et al. (2001) was used in this work to identify the cointegration between the series. Comparing the ARDL bounds test to other one-time integer approaches, there are several benefits. First off, since the ARDL bounds test does not require any mandatory assumptions and requires that all variables be included in the analysis in the same order, it can be used when series have a mixed order of integration. Second, it is noticeably more trustworthy, especially given the tiny sample size. Thirdly, it provides an accurate long-term model estimation. Since the cointegration order occurs at I(0) or I(1), the ARDL limits testing approach can be applied regardless of whether the fundamental returning system is in sequence apart in the I(2). In Eq. (6), the ARDL limits test is shown as follows:

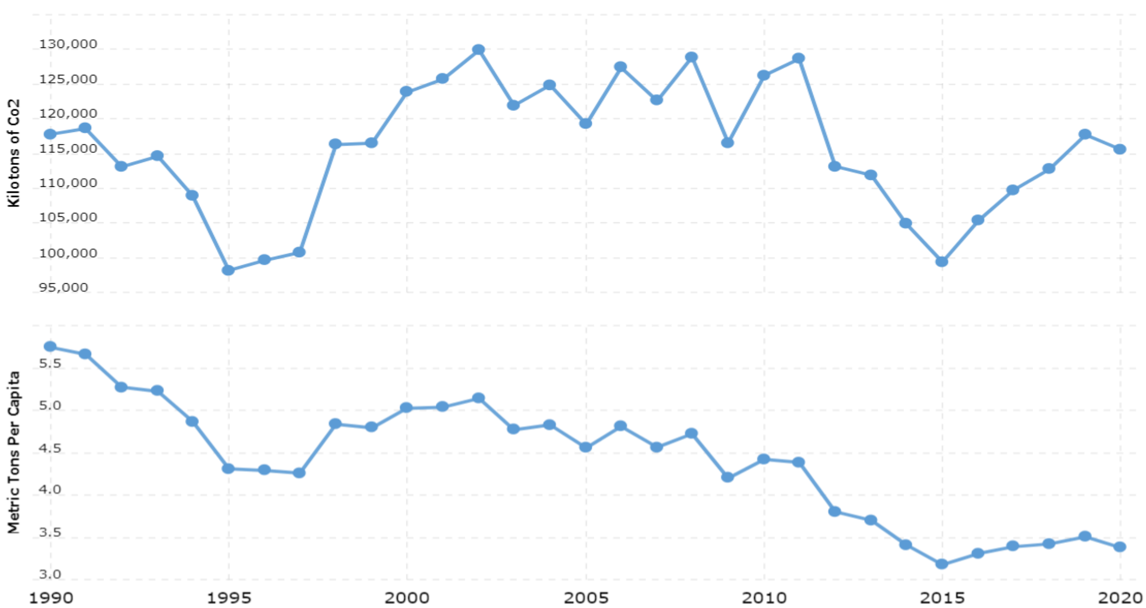
$$\begin{aligned}\Delta \mathrm{LCO2}_t = \tau_0 + \tau_1 \mathrm{LCO2}_{t-1} + \tau_2 \mathrm{LGDP}_{t-1} + \tau_3 \mathrm{LEU}_{t-1} + \tau_4 \mathrm{LAVA}_{t-1} \\ + \sum_{i=1}^{q} \gamma_1 \Delta \mathrm{LCO2}_{t-i} + \sum_{i=1}^{q} \gamma_2 \Delta \mathrm{LGDP}_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta \mathrm{LEU}_{t-i} \\ + \sum_{i=1}^{q} \gamma_4 \Delta \mathrm{LAVA}_{t-i} + \varepsilon_t\end{aligned} \tag{6}$$

where, in the aforementioned Eq. (6), q is the ideal lag length and is the first difference operator.

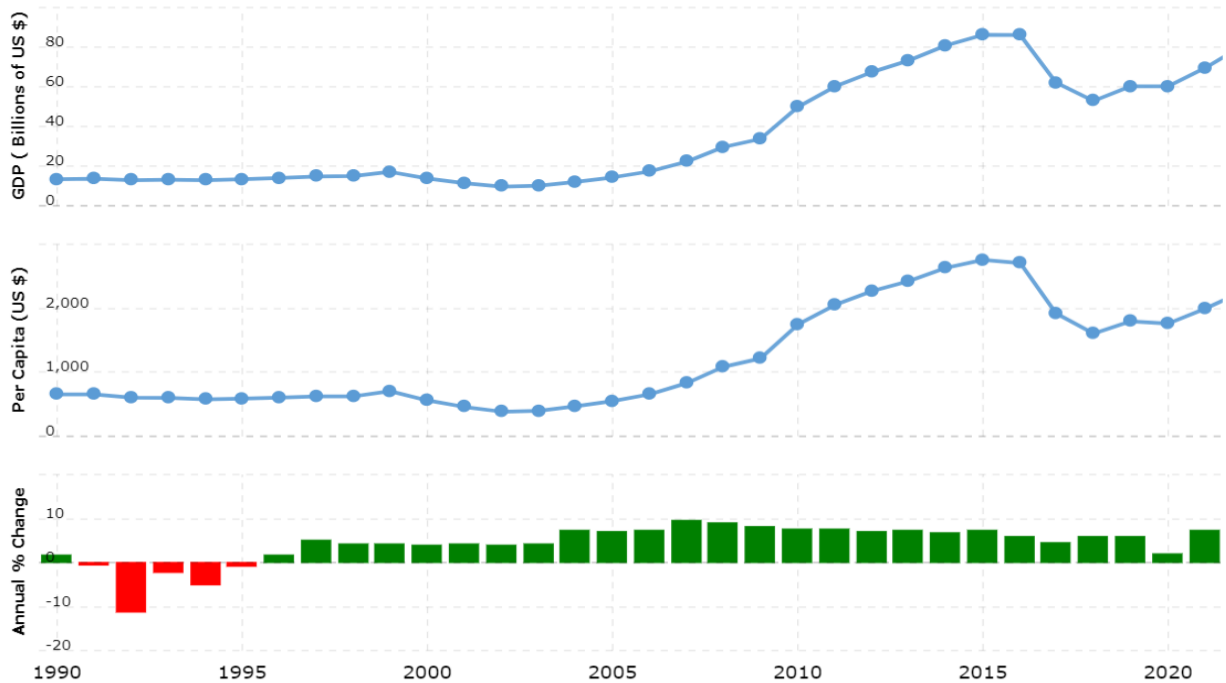
The critical values for the ARDL bounds test were put forth by Pesaran and Timmermann (2005), and it follows the F-distribution. Starting with Eq. (6), the estimate process employs OLS to enable the F-test to assess the combined significance of the coefcient of the lag variables. The main goal of this process is to assess the possibility of any potential long-term relationships between the different variables.

In this sense, the null hypothesis (H0) explains why the regressors don't have cointegrating correlations. According to Pesaran et al. (2001), the F-statistics can be compared to the upper and lower bounds' critical values. . On the other hand, the null hypothesis is accepted if the F-statistics are lower than the lower critical value. Alternatively, the test is inconclusive if the F-statistics are seen between the lower and upper critical values.

(a) CO2 emissions



(a) GDP of Uzbekistan



Source: Annual trends of the study variables in Uzbekistan. Macrotrends.net (2022)

$$CO_{2t} = \tau_0 + \tau_1 GDP_t + \tau_2 EU_t + \tau_3 AVA_t + \varepsilon_t \tag{4}$$

where τ_0 and ε_t stand for intercept and error term, respectively. In addition, τ_1, τ_2, and τ_3 denote the coefficients.

Furthermore, Eq. (4) can be arranged logarithmically as follows:

$$LOC2_t = \tau_0 + \tau_1 LGDP_t + \tau_2 LEU_t + \tau_3 LAVA_t + \varepsilon_t \tag{5}$$

Empirical findings

Table 2 displays the results of the summary measures among the variables together with the correlation between the variables and the statistical results of the various normality tests (skewness, probability, kurtosis, and Jarque-Bera). Each variable consists of 31 observations of time series data for Uzbekistan from 1990 to 2020. The unbalance

Values that are close to zero suggest that all the variables follow typical behavior. Furthermore, kurtosis was used in the study to determine whether the series' tails are light or heavy compared to a normal distribution. The empirical results show that all the series are platykurtic as their values are less than 3.

Additionally, the Jarque-Bera probability's lower values show that all the parameters are normal.

All of the variables are associated to one another, according to the results of the correlation analysis. LCO2, LGDP, and LEU all show very high positive correlations with one another, indicating that as one variable's value increases, so does the other and vice versa. However, LAVA exhibits a high but negative correlation with all the other variables, indicating that when agricultural value added increases, the value of the other variable tends to decrease and vice versa.

Table 2

Descriptive and correlation statistics

Variables	LCO2	LGDP	LEU	LAVA
Mean	9.08425	31.54545	5.312112	2.656
Median	8.656454	33.6454	5.97845	2.98452
Maximum	11.6556	33.7845	9.45695	3.121121
Minimum	8.65548	29.6541	5.48232	2.369852
Std. Dev	1.24556	0.94512	0.34844	0.256485
Skewness	0.087364	-0.061644	0.218547	0.31150
Kurtosis	1.565641	1.565986	1.921515	2.32644
Jarque-Bera	2.15544	3.154656	5.15564	3.56155
Probability	0.32668	0.248784	0.29794	0.78451
Sum	375.3154	1569.6454	253.1646	115.6484
Sum Sq. Dev	36.31511	16.16545	8.645411	6.264545
Observations	31	31	31	31
Correlation between the variables				
	LCO2	LGDP	LEU	LAVA
LCO2	1.000000	0.982454	0.941511	-0.93062
LGDP	0.984454	1.000000	0.936397	-0.979174
LEU	0.931811	0.979397	1.000000	-0.985043
LAVA	-0.97906	-0.938174	-0.945043	1.000000

Results of unit root tests

The results of unit root testing utilizing the ADF, DF-GLS, and P-P tests are shown in Table 3. In all three unit root tests, the results showed that LCO2, LEU, and LAVA were non-stationary at the level but became stationary at the first difference.

In addition, LGDP was shown to be non-stationary at the level but became stationary at the first difference in the DF-GLS and P-P tests, whereas LGDP was stationary at the level and remained stationary after taking the first difference in the ADF test. The unit root test's findings demonstrate that the series is stationary at mixed levels of either level- or first-order integration, I(0) or I(1), making the ARDL technique appropriate. Additionally, the use of the Johansen and Engle-Granger cointegration tests to detect cointegration among the series is supported by the presence of mixed orders integration for variables estimated by the ADF, DF-GLS, and P-P tests.

Table 3

The results of unit root tests

Logarithmic form of the variables	LCO2	LGDP	LEU	LAVA	
ADF	Log levels	0.697771	-2.251133^{**}	2.954307	-0.731829
	Log first difference	-4.125315^{***}	-2.748702^{**}	-4.458685^{***}	-5.128078^{***}
DF-GLS	Log levels	0.569485	-1.141523	0.652350	0.899964
	Log first difference	-3.127161^{***}	1.450715^{*}	-3.561232^{***}	-5.218933^{***}
P-P	Log levels	-0.657771	-0.113099	2.134307	-0.461829
	Log first difference	-4.334584^{***}	-2.498702^{**}	-4.668685^{***}	875.360733^{***}

$*****$*, and* $*$ *denote significance at the* $1\%, 5\%$*, and* 10% *levels, respectively*

Cointegration with bounds testing

This study then went on to estimate the ARDL framework after the series' stationarity properties were confirmed. This analysis selected an acceptable lag period to measure the F-statistic built on the minimal values of the Akaike Information Criterion (AIC) in order to perform the ARDL bounds test for cointegration valuation. The results of the ARDL bounds test, which looked at the cointegration relationship between the variables, are shown in Table 4. If the estimated value of the F-test is greater than the values of both limits (lower and upper bound), then the existence of a long-run link between the parameters is confirmed. The results showed that the estimated F-statistic value (8.088212) is larger than 10%, 5%, 2.5%, and 1% of the critical upper limit in the order zero and one, rejecting the null hypothesis by demonstrating the existence of a long-term link between the relevant variables.

Table 4

The results of the ARDL bounds test

F-bounds test		Null hypothesis: No levels of relationship		
Test statistic	Value	Significance (%)	$\mathrm{I}(0)$	$\mathrm{I}(1)$
Value of F-statistic	8.088212	At 10	2.77	3.88
K	3	At 5	2.23	3.44
		At 2.5	2.98	3.98
	At 1	3.55	4.58	

Conclusion

The dynamic effects of economic growth, energy consumption, and agricultural value addition on CO_2 emissions in Uzbekistan were empirically examined in the current study. This study used the autoregressive distributed lag (ARDL) technique to examine the short- and long-term relationships between the variables, and it showed it through the Vector Error Correction Model (VECM) utilizing time series data.

Uzbekistan from 1990 to 2020. In this study, the unit root tests ADF, DF-GLS, and P-P were used to determine the integration order of the series. Test of ARDL limits demonstrated evidence of cointegration between the variables over time, including the Engle-Granger and Johansen cointegration tests were used to confirm this. The empirical results from ARDL estimation show that while increasing agricultural value added improves Uzbekistan's environmental quality by lowering CO_2 emissions in the long and short terms, economic expansion and energy use cause environmental deterioration by increasing CO_2 emissions. The estimated results stand up well to estimation by DOLS, FMOLS, and CCR. In order to identify the causative relationship between the variables, the Toda-Yamamoto causality test was also applied. By offering light on the potential for agricultural value added to reduce emissions in Uzbekistan, this study adds to the body of previous work. By building robust regulatory policy instruments to lessen environmental degradation, this essay made policy proposals for sustainable development.

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