“CO2 emissions, industrial output, and economic growth nexus: Evidence from Nepalese economy”

AUTHORS	Arjun Kumar Dahal Ganesh Bhattarai Prem Bahadur Budhathoki

ARTICLE INFO	Arjun Kumar Dahal, Ganesh Bhattarai and Prem Bahadur Budhathoki (2023). CO2 emissions, industrial output, and economic growth nexus: Evidence from Nepalese economy. *Environmental Economics*, *14*(2), 1-12. doi:10.21511/ee.14(2).2023.01
DOI	http://dx.doi.org/10.21511/ee.14(2).2023.01
RELEASED ON	Thursday, 13 July 2023
RECEIVED ON	Sunday, 04 June 2023
ACCEPTED ON	Wednesday, 05 July 2023
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Environmental Economics"
ISSN PRINT	1998-6041
ISSN ONLINE	1998-605X
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Arjun Kumar Dahal (Nepal), **Ganesh Bhattarai** (Nepal),
Prem Bahadur Budhathoki (Nepal)

CO_2 EMISSIONS, INDUSTRIAL OUTPUT, AND ECONOMIC GROWTH NEXUS: EVIDENCE FROM NEPALESE ECONOMY

Abstract

This study aims to investigate the relationship between Nepal's industrial sector output, economic expansion, and CO_2 emissions. The analysis uses secondary data from various World Bank reports and covers the period from 1990 to 2022. It is founded on an exploratory and analytical research design. The relationship and effect of Nepal's GDP and manufacturing output on CO_2 emissions are investigated using various statistical and econometric tools, including descriptive statistics, Pearson correlation analysis, unit root testing, Granger causality test, Johansen co-integration test, and autoregressive regression model. The results show that the production of the industrial sector and CO_2 emissions are highly positively correlated, as is GDP. The GDP granger causes CO_2 emissions, but manufacturing output does not. Johansen's co-integration test shows a long-term relationship between predictor and response variables. The previous value of CO2 emission is also responsible for the present level of carbon emissions: a one percent increase in GDP leads to a 0.314 percent increase in CO_2 emissions in Nepal. The impact of industrial sector output is statistically insignificant. The condition of GDP and CO_2 emissions shows the initial phase of the environmental Kuznets curve (EKC). The study recommends adopting an environment-friendly production technique to overcome the problem of carbon emissions in Nepal.

Received on: 4th of June, 2023
Accepted on: 5th of July, 2023
Published on: 13th of July, 2023

Arjun Kumar Dahal, Lecturer, Faculty of Humanities and Social Science, Mechi Multiple Campus, Tribhuvan University, Nepal.

Ganesh Bhattarai, Lecturer, Faculty of Management, Nepal Commerce Campus, Tribhuvan University, Nepal. (Corresponding author)

Prem Bahadur Budhathoki, Lecturer, Faculty of Management, Saraswati Multiple Campus, Tribhuvan University, Nepal.

Keywords autoregressive analysis, environmental Kuznets curve, greenhouse gas, associations, variability

JEL Classification L16, Q13, Q43

INTRODUCTION

Carbon dioxide (CO_2) emissions refer to releasing CO_2 into the atmosphere due to human activities, mainly burning fossil fuels such as coal, oil, and natural gas. Carbon dioxide is released as a byproduct when these fuels are burned for energy production, transportation, industrial processes, or residential use (Liu et al., 2023). As a greenhouse gas, carbon dioxide (CO_2) contributes to climate change by trapping heat on the earth's surface, leading to global warming. Controlling and reducing CO_2 emissions is crucial in addressing climate change and mitigating its impacts (Cai et al., 2018). Among all the greenhouse gases, CO_2 emissions are the primary culprit for the damaging environmental quality of the community (Fernando & Lin Hor, 2017; Khan et al., 2019).

Climate change results from anthropogenic behavior and increasing greenhouse gas (GHG) emissions, leading to growing natural catastrophes that threaten biodiversity and future generation (Lewandowski & Ullrich, 2023). CO_2 emissions have increased over the past century due to the growing global population, industrialization, and the widespread use of fossil fuels (Saboori et al., 2012). Efforts are being made worldwide to reduce emissions and transition to clean energy sources such as renewable energy (solar, wind, hydroelectricity), adopting en-

Conflict of interest statement:
Author(s) reported no conflict of interest

ergy-efficient technologies, and promoting sustainable practices (Raihan & Tuspekova, 2022). Global warming due to CO_2 emission has been one of the challenging environmental problems (Zhang & Cheng, 2009).

The relationship between gross domestic product (GDP), industrial sector output, and CO_2 emission is complex and can vary depending on various factors. However, there are some general trends and patterns observed in many countries. As GDP and industrial sector output increase, so do CO_2 emissions. This is because economic growth and industrial activities often require energy consumption, and a significant pattern of the world's energy comes from fossil fuels, which release CO_2 when burned (Shahzad et al., 2020). Historically, there has been a strong correlation between GDP growth and CO_2 emissions, and some countries have started to experience a decoupling of economic growth from emissions. This means that they can achieve economic growth without a proportional increase in emissions. This can be attributed to increased energy efficiency, shifts toward cleaner energy sources, and changes in industrial practices.

Specifically, the impact of industrial sector output growth and carbon emissions in Nepal requires investigation. In addition, this study contrasts the effects of total GDP growth and manufacturing output growth on carbon emissions in Nepal.

1. LITERATURE REVIEW

The environmental Kuznets curve (EKC) is an economic hypothesis that suggests a relationship between environmental degradation and economic development. It posits that as per capita income rises, environmental degradation initially increases but eventually decreases, forming an inverted U-shaped curve. The theory implies that economic growth, technological advancement, and income redistribution can improve environmental quality (Grossman & Krueger, 1991). According to the EKC hypothesis, countries prioritize economic growth over environmental concerns in the early stages of economic development. This often leads to higher levels of pollution and resource depletion. However, as income levels continue to rise, societies become more aware of the environmental consequences and demand environmental regulations and cleaner technologies (Shafik & Bandyopadhyay, 1992). Consequently, pollution levels begin to decline. Therefore, the environmental Kuznets curve is formed as an inverted U-shaped curve.

The Porter (1991) Hypothesis argues that severe environmental regulations can stimulate innovation and competitiveness, ultimately leading to economic growth. According to this theory, environmental regulations incentivize firms to develop cleaner technologies and processes, reducing CO_2 emissions. Companies investing in green innovation can spur economic growth and enhance their competitive advantage in the global market. The decoupling theory suggests that economic growth can be 'decoupled' from CO_2 emissions through improvements in energy efficiency and the adoption of renewable energy sources. It posits that economies can continue to grow while reducing their carbon footprint. This theory highlights the importance of technological advancements and policy measures to promote sustainable development and transition to low-carbon economies.

The pollution haven hypothesis suggests that industries might relocate from countries with strict environmental regulations to countries with more lenient laws, leading to increased CO_2 emissions in the latter. This theory is explored by Cole et al. (2005) and Copeland and Taylor (2004). The environmental innovation hypothesis suggests that economic growth can stimulate the development and adoption of cleaner technologies, reducing CO_2 emissions. As economies expand, they invest in research and development, creating environmentally friendly technologies. This theory is supported by Galeotti et al. (2006) and Smulders and De Nooij (2003). The energy efficiency hypothesis argues that economic growth leads to technological advancements and

http://dx.doi.org/10.21511/ee.14(2).2023.01

increased energy efficiency, which in turn can reduce CO_2 emissions. As countries become more economically developed, they adopt cleaner and more efficient technologies, lowering carbon intensity. This theory is supported by Ang (2007) and Selden and Song (1994).

Zhang and Cheng (2009) examined the existence and direction of Granger causality in China between economic growth, energy consumption, and carbon emissions. They found that neither carbon emissions nor energy consumption contributed to economic expansion. Soytas et al. (2007) investigated the impact of energy consumption and output on carbon emissions in the United States. They discovered that output does not cause long-term CO_2 emissions, but energy consumption does.

Narayan et al. (2016) analyzed the dynamic relationship between economic growth and carbon dioxide emissions in 181 nations. Consistent with the environmental Kuznets curve (EKC) hypothesis, they revealed a positive cross-correlation between the current and past levels of CO_2 emissions and a negative cross-correlation between the current and future levels of CO_2 emissions. Therefore, CO_2 emission decreases with an increase in income over time. The relationship between economic growth, energy use, agricultural productivity, and CO_2 emissions was observed by Raihan and Tuspekova (2022). They discovered that a one percent increase in economic growth and fossil fuel energy consumption would increase CO_2 emissions by 0.61 and 0.67 percent, respectively.

Begum et al. (2015) examined the dynamic effects of GDP growth, energy consumption, and population growth on carbon dioxide emissions. According to the findings, both per capita energy consumption and per capita GDP positively affect per capita CO_2 emissions in Malaysia. Raihan et al. (2022) showed that economic growth is positively and significantly correlated with CO_2 emissions, with a one percent increase in economic growth being associated with a 0.9 percent increase in CO_2 emissions. Additionally, a one percent increase in the use of renewable energy is associated with a 0.3 percent reduction in long-term CO_2 emissions.

C. Tan and S. Tan (2018) discovered a long-term correlation between industrial output and carbon dioxide emissions in the Malaysian industrial sector. Ewing et al. (2007), Ray and Reddy (2007), and Hamit-Haggar (2012) examined the relationship between industrial sector growth and CO_2 emissions. The relationship between manufactured output and CO_2 emissions is highly positive, indicating that the expansion of the industrial sector contributes to CO_2 emissions. Khan et al. (2019) and Can et al. (2020) discovered that industrial product, export, and fossil fuel energy consumption are associated with elevated carbon emissions.

The causal link between GDP growth and carbon emissions was found by Chen et al. (2007), Tang (2008), Chandran et al. (2010), Ismail and Yunus (2012), Apergis and Tang (2013), Zakari and Shamsuddin (2016), Nuryartono and Rifai (2017), and Aller et al. (2021). Similar findings were made by Ahmed et al. (2016) for newly industrialized economies like Brazil, India, China, and South Africa. They discovered unidirectional causality between economic growth and CO_2 emissions. In addition to observing the considerable and favorable effects of economic expansion on CO_2 emissions, Ahmed et al. (2022) depicted a direct correlation between energy use and CO_2 emissions.

Shreezal and Adhikari (2021) observed the nexus between CO_2 emissions, energy use, and economic growth in Nepal. The finding shows that the carbon emissions level and economic growth are positively related in the short run. Aung et al. (2017) and Adu and Denkyirah (2018) concluded that CO_2 emissions increased with the increase in GDP in the short run, but their relationship was not strong in the long run. But Mohiuddin et al. (2016) showed no causality between GDP and CO_2 emissions in any direction.

Most research investigates GDP, energy consumption, export, trade openness, technology, and the installation of renewable energy as determinants of CO_2 emissions. Nonetheless, this study aims to ascertain the relationship between manufacturing output and CO_2 emissions, as well as Nepalese GDP growth. The study excludes agricultural, industrial, and tertiary production and CO_2 emissions. Finally, this paper investigates the effect of expanding manufacturing output on carbon emissions to close the gap.

2. METHODS

This study employs an analytical and exploratory approach to research. Various econometric instruments explore the relationships and effects between predictor and response variables.

2.1. Data and data analysis technique

The secondary data from 1990 to 2022 investigate the relationship and influence between the variables. The secondary data are compiled from numerous World Development Bank reports. Several statistical and econometric methods investigate the relationship and effect between independent and dependent variables, including summary statistics, unit root testing, correlation analysis, Ganger causality test, Johansen co-integration test, and autoregressive regression model. This model is evaluated using the serial correlation LM test, the heteroscedasticity test, and the normality test for diagnostic purposes.

2.2. Variable and model specification

Three variables (GDP, industrial sector output, and CO_2 emissions) are used in this study. CO_2 emissions is the dependent variable, and GDP and manufacturing output are taken as independent variables. The lagged one of the CO_2 emissions is created to avoid the problem of serial correlation in the ordinary least square method. Carbon emissions are affected by industrial activities and the overall economic activities of a nation. Economic activities determine the GDP and industrial sector output of the nation. In this sense:

CO_2 emissions = f(GDP, industrial sector output), in symbol,

$$CO_2EM = f\left(GDP,\ ISY\right). \tag{1}$$

After converting variables in logarithms, the equation first can be written as:

$$LNCO_2EM = f\left(LNGDPN,\ LNISY\right). \tag{2}$$

The general regression model is defined as follows:

$$\begin{aligned} LNCO_2EM &= \alpha + \beta_1 LNGDPN + \\ &+ \beta_2 LNISY + \mu_t. \end{aligned} \tag{3}$$

In this study, the autoregressive regression model is used. An autoregressive regression model is a statistical model that combines autoregression and regression techniques to analyze and forecast time series data. An autoregressive regression model combines these two concepts by incorporating both lagged values of the dependent variable and other independent variables as predictors in a regression framework.

The general form of an autoregressive regression model can be expressed as:

$$\begin{aligned} Y(t) &= \alpha + \beta_1 \cdot Y(t-1) + \beta_2 \cdot Y(t-2) + \\ &\dots + \beta_p \cdot Y(t-p) + \mu_t. \end{aligned} \tag{4}$$

The autoregressive regression model can be extended to include other independent variables, denoted as X_1, X_2, ..., X_n, resulting in a multiple autoregressive regression model:

$$\begin{aligned} Y(t) &= \alpha + \beta_1 \cdot Y(t-1) + \beta_2 \cdot Y(t-2) + \\ &\dots + \beta_p \cdot Y(t-p) + \gamma_1 \cdot X_{1(t)} + \\ &+ \gamma_2 \cdot X_{2(t)} + \dots + \gamma_n \cdot X_{n(t)} + \mu_t, \end{aligned} \tag{5}$$

where $Y(t)$ is the dependent variable at time t. $Y(t\text{-}i)$ represents the lagged values of the dependent variable up to order p. $X_{1(t)}$, $X_2(t)$, ..., $X_{n(t)}$ represent the independent variables at time t, and γ_1, γ_2, ..., γ_n are the corresponding coefficients that capture the influence of the independent variables on the dependent variable. The coefficients β_1, β_2, ..., β_p represent the autoregressive components, capturing the impact of past observations of the dependent variable on the current observation, and μ_t is the error term assumed to be independently and identically distributed with zero means. After introducing the variables of this study, the autoregressive regression model is specified as:

$$\begin{aligned} LNCO_2EM(t) &= \alpha + \beta_1 \cdot LNCO_2EM(-1) + \\ &+ \gamma_1 \cdot LNGDPN + \gamma_2 LNISY + \mu_t. \end{aligned} \tag{6}$$

http://dx.doi.org/10.21511/ee.14(2).2023.01

3. RESULTS AND DISCUSSION

3.1. Descriptive statistics

Descriptive statistics helps to understand the condition of variables. Furthermore, the descriptive statistics provide information about the distribution and characteristics of three variables: CO_2 emissions, GDP, and industrial output. Table 1 estimates the summary statistics of the response and explanatory variables.

Table 1. Viewing platform of summary statistics

Headings	CO_2 Emissions	GDP	Industrial output
Mean	5.589	14.635	0.846
Median	3.392	9.044	0.660
Maximum	15.224	37.450	1.720
Minimum	1.098	3.401	0.210
Std. dev.	4.519	11.489	0.489
Skewness	1.095	0.712	0.465
Kurtosis	2.704	2.032	1.787
Coefficient of variation	80.86%	78.50%	57.80%
Jarque-Bera	6.715	4.079	3.207
Probability	0.035	0.130	0.201
Sum	184.450	482.949	27.920
Sum Sq. dev.	653.501	4224.226	7.671
Observations	33	33	33

Note: CO_2 emissions are measured in megatons (Mt), and industrial sector output and GDP are estimated at billion USD.

The mean represents the average value of the data. For CO_2 emissions, the mean is 5.589 megatons (Mt); for GDP, it is 14.635 billion USD; and for industrial output, it is 0.846 billion USD. The maximum and minimum values represent the highest and lowest values in the data, respectively. The maximum CO_2 emissions are 15.224 Mt, the maximum GDP is 37.450 billion USD, and the maximum industrial output is 1.720 billion USD. The minimum CO_2 emissions are 1.098 Mt, the minimum GDP is 3.401 billion USD, and the industrial minimum production is 0.210 billion USD.

The standard deviation measures the dispersion or variability of the data around the mean. A higher standard deviation indicates a greater spread of the data points. For CO_2 emissions, the standard deviation is 4.519 Mt; for GDP, it is 11.489 billion USD; and for industrial output, it is 0.489 billion USD. The standard deviation of manufacturing output is less than others. So, the mean of Manufacturing output is more representative. Skewness measures the asymmetry of the distribution. Positive skewness indicates a longer tail on the right side of the distribution. CO_2 emissions have a positive skewness of 1.095, GDP has a positive skewness of 0.712, and industrial output has a positive skewness of 0.465. This confirms that the distributions of these variables are skewed to the right. The coefficient of variation (CV) is a relative measure of dispersion, calculated as the standard deviation divided by the mean. It is expressed as a percentage. CO_2 emissions have a CV of 80.8 percent, GDP has a CV of 78.50 percent, and industrial output has a CV of 57.80 percent. This indicates that CO_2 emissions have the highest relative variation compared to GDP and industrial output.

The probability associated with the Jarque-Bera test determines the significance level of the test. A lower chance suggests a higher likelihood of the data not following a normal distribution. CO_2 emissions have a probability of 0.035, GDP has a possibility of 0.130, and industrial output has a potential of 0.201. These values indicate that the data for all three variables are statistically significant in deviating from a normal distribution. The probability associated with the Jarque-Bera test determines the significance level of the test. A lower chance suggests a higher likelihood of the data not following a normal distribution. CO_2 emissions have a probability of 0.035, GDP has a possibility of 0.130, and industrial output has a potential of 0.201. These values indicate that the data for all three variables are statistically significant in deviating from a normal distribution.

3.2. Relation analysis between variables

Correlation coefficients measure the strength and direction of the linear relationship between two variables. The values range from –1 to 1, where –1 indicates a perfect negative correlation, 0 shows no correlation, and 1 indicates a perfect positive correlation. The association between pairs of variables is measured in Table 2.

Table 2. Correlation between variables

Variables	*$LNCO_2EM$*	LNGDPN	LNISY
$LNCO_2EM$	1.000	0.9481	0.9514
LNGDPN	0.9481	1.000	0.9837
LNISY	0.9514	0.9837	1.000

http://dx.doi.org/10.21511/ee.14(2).2023.01

The correlation coefficient between CO_2 emissions and GDP is 0.9481. This indicates a strong positive correlation between these two variables. As the value of GDP increases, CO_2 emissions also tend to increase. It suggests a strong relationship between economic output (GDP) and CO_2 emissions. The correlation coefficient between CO_2 emissions and manufacturing output is 0.9514, indicating a strong positive correlation. As the value of industrial output increases, CO_2 emissions also tend to increase. This suggests that industrial sector output and CO_2 emissions are strongly correlated. C. Tan and S. Tan (2018) revealed a long-term correlation between Malaysia's industrial output and carbon dioxide emissions. Ewing et al. (2007), Ray and Reddy (2007), and Hamit-Haggar (2012) showed a strong positive correlation between manufactured output and CO_2 emissions, suggesting that industrial sector growth contributes to CO_2 emissions. Table 2 demonstrates that all three variables, CO_2 emissions, GDP, and industrial sector output, are highly correlated. Changes in one variable are significantly associated with variations in the other, as indicated by the high correlation coefficients.

3.3. Unit root testing

The Augmented Dickey-Fuller (ADF) test is commonly used to determine whether a time series has a unit root, which indicates non-stationarity. Non-stationary time series can exhibit trends and are more challenging to analyze and model. The ADF test compares the observed series with its lagged values to determine if it has a unit root. The results of the ADF test are presented in Table 3.

Table 3 provides the results of the Augmented Dickey-Fuller (ADF) unit root tests for three variables: $LNCO_2EM$ (log-transformed CO_2 emissions), LNGDPN (log-transformed GDP), and LNISY (log-transformed industrial sector output). All variables are non-stationary at the level because the p-values of the ADF test are more than 0.05. When $p > 0.05$, the analysis cannot reject the null hypothesis. Therefore, data are not stationary at the level form in intercept and trend and intercept. At the intercept form of the first difference, the ADF test p-values are less than 0.05 ($p < 0.05$). So, the data are stationary after the first difference. Data must be stationary for the operation of the system equation, which means some conclusions can be derived by analyzing these data.

3.4. Granger causality test

The Granger causality test is a statistical test used to determine if the one-time series variable can predict another time series variable. In Table 4, four pairs of variables are tested for Granger causality: *LNGDPN* and $LNCO_2EM$, $LNCO_2EM$ and *LNGDPN*, *LNISY* and $LNCO_2EM$, and $LNCO_2EM$ and *LNISY*.

The null hypothesis for the first pair (*LNGDPN* and $LNCO_2EM$) is that *LNGDPN* does not granger cause $LNCO_2EM$. The F-statistic is 3.5831, and the p-value associated with it is 0.0233. Since the p-value (0.0233) is less than the commonly used significance level of 0.05, the analysis rejects the null hypothesis. This suggests that GDP granger causes CO_2 emissions, meaning that GDP can be used to predict CO_2 emissions in Nepal. The

Table 3. Augmented Dickey-Fuller test to check stationary or non-stationary data

Variables	Criteria	Level		First intercept	
		Intercept	Trend and intercept	Intercept	Trend and intercept
$LNCO_2EM$	ADF test	–0.506	–2.631	3.344	–3.264
	P-value	0.874	0.271	0.022	0.092
	t-value	–2.981	–3.612	–2.967	–3.574
LNGDPN	ADF test	0.351	–2.845	–4.781	–4.784
	P-value	0.977	0.196	0.0006	0.003
	t-value	–2.957	–3.603	–2.960	–3.563
LNISY	ADF test	–0.906	–2.656	–5.393	–5.452
	P-value	0.768	0.260	0.0001	0.0006
	t-value	–2.992	–3.557	–2.960	–3.563

Note: $LNCO_2EM$ = Carbon dioxide (CO_2) emissions (in Kiloton, kt) after log transformation; *LNGDPN* = Gross Domestic Product (in 10 million USD) after log transformation; *LNISY* = Gross industrial sector output (in 10 million USD) after log transformation.

http://dx.doi.org/10.21511/ee.14(2).2023.01

Table 4. Causality test of variables

Null hypothesis	F-statistics	P-value
LNGDPN does not Granger Cause *LNCO$_2$EM*	3.5831	0.0233
LNCO$_2$EM does not Granger Cause *LNGDPN*	1.4079	0.2675
LNISY does not Granger Cause *LNCO$_2$EM*	2.2736	0.0972
LNCO$_2$EM does not Granger Cause *LNISY*	1.0609	0.4015

null hypothesis for the second pair (*LNCO$_2$EM* and *LNGDPN*) is that *LNCO$_2$EM* does not granger cause *LNGDPN*. The F-statistic is 1.4079, and the associated p-value is 0.2675. In this case, the p-value (0.2675) is more significant than 0.05, so the study fails to reject the null hypothesis. This means there is not enough evidence to suggest that CO_2 emissions granger cause the GDP of Nepal. Soytas et al. (2007) also discovered that output does not cause long-term CO_2 emissions, but energy consumption does.

The null hypothesis for the third pair (*LNISY* and *LNCO$_2$EM*) is that *LNISY* does not granger cause *LNCO$_2$EM*. The F-statistic is 2.2736, and the associated p-value is 0.0972. The study fails to reject the null hypothesis since the p-value (0.0972) exceeds 0.05. Therefore, insufficient evidence suggests that industrial sector output granger causes CO_2 emissions in Nepal. The null hypothesis for the fourth pair (*LNCO$_2$EM* and *LNISY*) is that *LNCO$_2$EM* does not granger cause *LNISY*. The F-statistic is 1.0609, and the associated p-value is 0.4015. The analysis fails to reject the null hypothesis because the p-value (0.4015) exceeds 0.05. This indicates that insufficient evidence supports the idea that CO_2 emissions granger causes industrial sector output in the Nepalese setting.

3.5. Johnson co-integration test

The Johnson co-integration test determines the presence and number of cointegrating equations between variables. Co-integration refers to a long-term relationship between variables that exhibit a stable equilibrium. The test results indicate the number of cointegrating equations at a given significance level. Table 5 shows the unrestricted co-integration rank test in trace and maximum Eigenvalue methods.

The Unrestricted Co-integration Rank Test (Trace) determines the number of cointegrating equations between variables. Co-integration implies a long-term relationship between variables, and the test helps identify the presence and quantity of such relationships. In the given results, three hypotheses are tested: 'None' (no cointegrating equation), 'At most 1' (maximum of 1 cointegrating equation), and 'At most 2' (maximum of 2 cointegrating equations). The test results indicate that the eigenvalue associated with the 'None' hypothesis is 0.721, with a test statistic of 46.929. The critical value at the 0.05 level is 29.797. The probability (p-value) associated with this hypothesis is very low (0.0002), suggesting strong evidence to reject the hypothesis of no cointegrating equation. In

Table 5. Unrestricted co-integration rank test both in trace and maximum Eigenvalue method

Unrestricted Co-integration Rank Test (Trace)				
Hypothesized	**–**	**Trace**	**0.05**	**–**
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None*	0.721	46.929	29.797	0.0002
At most 1	0.185	7.347	15.495	0.538
At most 2	0.032	1.008	3.842	0.315
Unrestricted Co-integration Rank Test (Maximum Eigenvalue)				
Hypothesized	**–**	**Max-Eigen**	**0.05**	**–**
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None*	0.721	39.583	21.132	0.0001
At most 1	0.185	6.339	14.265	0.570
At most 2	0.032	1.008	3.841	0.315

Note: Trace test indicates 1 cointegrating equation(s) at the 0.05 level. Max-eigenvalue test indicates 1 cointegrating equation(s) at the 0.05 level. * Denotes rejection of the hypothesis at the 0.05 level; **MacKinnon-Haug-Michelis (1999) p-values.

the other two cases, the value is more than 0.05. So, there is insufficient evidence to reject the hypothesis of at most 1 and 2 cointegrating equations. In summary, there is evidence of one cointegrating equation at the 0.05 significance level. This suggests the presence of a long-term relationship between the variables being analyzed.

The Unrestricted Co-integration Rank Test (Maximum Eigenvalue) is another test used to determine the number of cointegrating equations between variables. It examines the eigenvalues associated with different hypotheses and compares them to critical values at a significance level of 0.05. The test results indicate that the eigenvalue associated with the 'None' hypothesis is 0.721, with a test statistic of 39.583. The critical value at the 0.05 level is 21.132. The probability (p-value) associated with this hypothesis is very low (0.0001), indicating strong evidence to reject the hypothesis of no cointegrating equation. There is insufficient evidence to reject the hypothesis of at most 1 or most 2 cointegrating equations.

3.6. Autoregressive regression analysis

The autoregressive regression model analyzes the relationship between the dependent variable, CO_2 emissions, and the independent variables, lagged CO_2 emissions and GDP industrial sector output, and a constant term, C. The coefficients represent the estimated effects of the independent variables on the dependent variable. The autoregressive regression model is displayed in Table 6.

Table 6. Outcomes of autoregressive regression model

Dependent Variable: *LNCO₂EM*				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
$LAGC_O2$	0.819	0.086	9.574	0.000
LNGDPN	0.314	0.189	2.665	0.017
*LNIS*Y	–0.221	0.269	–0.818	0.420
C	0.110	0.245	0.449	0.657
R-squared	0.977	Mean dependent var		8.379
Adjusted R-squared	0.974	SD dependent var		0.741
F-statistic	394.254	Durbin-Watson stat		2.045
Prob.(F-statistic)	0.000	–		

Note: $LAGCO_2$ = $LNCO_2EM$ (–1).

For the variable $LAGCO_2$, the coefficient is 0.819, indicating that a one-unit increase in the lagged CO_2 emissions is associated with a 0.819-unit rise in CO_2 emissions. This coefficient is statistically significant, with a very low p-value of 0.000. For the GDP variable, the coefficient is 0.314, implying that a one-unit increase in GDP leads to a 0.314 unit increase in CO_2 emissions in Nepal. Raihan and Tuspekova (2022) also discovered that a one percent increase in economic growth would increase CO_2 emissions by 0.61 percent. Economic growth is positively and substantially correlated with CO_2 emissions, with a one percent increase in economic growth associated with a 0.9 percent increase in CO_2 emissions, as determined by Raihan et al. (2020). Also statistically significant, with a probability of 0.017, is this coefficient. In contrast, the coefficient for industrial sector output is –0.221, indicating that a one-unit increase in industrial sector output is associated with a –0.221-unit decrease in CO_2 emissions. This coefficient is not statistically significant, as its probability of 0.420 is relatively high.

The R-squared value (0.977) represents the proportion of the variation in CO_2 emissions explained by the independent variables. It suggests that around 97.7 percent of the variability in CO_2 emissions can be accounted for by the variables in the model. The Adjusted R-squared value (0.974) considers the number of variables and observations in the model, providing a more robust measure of model fit. The F-statistic (394.254) and its associated probability (0.000) indicate the overall significance of the model. The low probability suggests that the model as a whole is statistically significant. The Durbin-Watson statistic (2.045) is used to test for autocorrelation in the model's residuals. A value close to 2 suggests no significant autocorrelation. The autoregressive regression is estimated as follows:

$$LNCO_2EM = 0.110 + 0.819 \cdot LAGCO_2 + \\ +0.314 \cdot LNGDPN - 0.221 \cdot LNISY. \quad (7)$$

The diagnostic checking of the autoregressive regression model is presented in Table 7.

Breusch-Godfrey serial correlation LM test checks for serial correlation (autocorrelation) in the model's residuals. The observed R-square value of 4.458 suggests that the lagged residuals can ex-

http://dx.doi.org/10.21511/ee.14(2).2023.01

Table 7. Outcomes of various diagnostic checking

Methods	Observed R-square	P-value
Breusch-Godfrey serial correlation LM test	4.458	0.107
Heteroscedasticity	0.965	0.809
Normality test (Jarque-Bera)	–	0.933

plain 4.458 percent of the variation in the residuals. The associated p-value of 0.107 indicates that serial correlation is not statistically significant at a conventional significance level of 0.05. Therefore, no strong evidence suggests the presence of serial correlation in the residuals. The heteroscedasticity test assesses whether the variance of the residuals is constant across different levels of the independent variables. The observed R-square value of 0.965 suggests that the independent variables can explain 96.5 percent of the variation in the residuals. The associated p-value of 0.809 indicates no significant evidence of heteroscedasticity in the model's residuals. Normality test checks whether the residuals of the model follow a normal distribution. The p-value of 0.933 indicates no significant evidence to reject the null hypothesis of normality. This suggests that the residuals approximately follow a normal distribution. Based on the diagnostic tests, the model does not show significant issues with serial correlation, heteroscedasticity, or normality.

This study has several limitations. First, it is related to the secondary data, expanded from 1990 to 2022. It only includes three variables, GDP, industrial sector output, and CO_2 emissions. The manufacturing output and increase in GDP are taken as industrial sector output and economic growth, respectively. Some statistical and econometric tools like summary statistics, stationary checking, Granger causality test, Johansen co-integration test, and autoregressive model are used to explore the relation and impact between predictor and explanatory variables. It is necessary to study further using more data points, variables, tools, and techniques. It makes the study more comprehensive, reliable, and representative.

CONCLUSION

This study aimed to analyze the impact of industrial sector output and GDP on CO_2 emissions in Nepal. The industrial sector output is more consistent because it has the lowest value of the coefficient of variation than other variables. A high positive relationship exists between GDP growth and CO_2 emissions in Nepal. The correlation coefficient between industrial sector output and CO_2 emissions is 0.9514. So, manufacturing output and CO_2 emissions have a strong positive correlation. As the value of industrial sector output increases, CO_2 emissions tend to increase.

According to the results of the Granger causality test, it is concluded that CO_2 emissions do not granger cause the GDP of Nepal. However, GDP granger causes CO_2 emissions, meaning that the GDP can be used to predict CO_2 emissions in Nepal. The surprising finding is that the industrial sector output does not granger cause CO_2 emissions in the Nepalese setting. The Johansen co-integration test shows a long-term relationship between the variables. Previous carbon emissions have a positive and significant impact on present CO_2 emissions. One unit increase in the lagged CO_2 emissions is associated with a 0.819 unit increase in the CO_2 emissions ($LNCO_2EM$). The economic growth is statistically significant to explain CO_2 emissions in Nepal. It is found that a one percent increase in GDP leads to a 0.314 unit increase in CO_2 emissions in Nepal. The industrial sector output has no significant impact on CO_2 emissions in the Nepalese setting.

The analysis shows Nepal is in the initial environmental Kuznets curve (EKC) phase because CO_2 increases as GDP rises. Thus, policymakers can formulate an environmental policy to reduce CO_2 emissions. It aids in the development of environmentally favorable production techniques in the economy. The planning documents can be supplemented with appropriate policies from the circumstance analysis of the relationship and impact of GDP and manufacturing output on CO_2 emissions.

AUTHOR CONTRIBUTIONS

Conceptualization: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
Data curation: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
Formal analysis: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
Investigation: Arjun Kumar Dahal, Ganesh Bhattarai.
Methodology: Arjun Kumar Dahal, Prem Bahadur Budhathoki.
Project administration: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
Resources: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
Software: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
Supervision: Arjun Kumar Dahal, Prem Bahadur Budhathoki.
Validation: Ganesh Bhattarai, Prem Bahadur Budhathoki.
Visualization: Arjun Kumar Dahal, Ganesh Bhattarai.
Writing – original draft: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
Writing – review & editing: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.

REFERENCES

1. Adu, D. T., & Denkyirah, E. K. (2018). Economic growth and environmental pollution in West Africa: Testing the environmental Kuznets curve hypothesis. *Kasetsart Journal of Social Sciences, 40*(2), 281-288. Retrieved from https://so04.tci-thaijo.org/index.php/kjss/article/view/242142
2. Ahmed, J., Raies, Farooq, U., & Subhani, B. H. (2022). The moderating role of information and communication technology in the nexus between financial development, economic growth, and energy consumption. *OPEC Energy Review, 46*(4), 399-412. https://doi.org/10.1111/opec.12262
3. Ahmed, K., Shahbaz, M., & Kyophilavong, P. (2016). Revisiting the emissions-energy-trade nexus: Evidence from the newly industrializing countries. *Environment Science and Pollution Research, 23,* 7676-7691. https://doi.org/10.1007/s11356-015-6018-x
4. Aller, C., Ductor, L., & Grechyna, D. (2021). Robust determinants of CO2 emissions. *Energy Economics, 96,* 105154. https://doi.org/10.1016/j.eneco.2021.105154
5. Ang, J. B. (2007). CO_2 emissions, energy consumption, and output in France. *Energy Policy, 35*(10), 4772-4778. https://doi.org/10.1016/j.enpol.2007.03.032
6. Apergis, N., & Tang, C. F. (2013). Is the energy-led growth hypothesis valid? New evidence from a sample of 85 countries. *Energy Economics, 38,* 24-31. https://doi.org/10.1016/j.eneco.2013.02.007
7. Aung, T. S., Saboori, B., & Rasoulinezhad, E. (2017). Economic growth and environmental pollution in Myanmar: An analysis of environmental Kuznets curve. *Environmental Science and Pollution Research, 24*(25), 20487-20501. https://doi.org/10.1007/s11356-017-9567-3
8. Begum, R. A., Sohag, K., Abdullah, S. M. S., & Jaafar, M. (2015). CO2 emissions, energy consumption, economic and population growth in Malaysia. *Renewable and Sustainable Energy Reviews, 41,* 594-601. https://doi.org/10.1016/j.rser.2014.07.205
9. Cai, Y., Sam, C. Y., & Chang, T. (2018). Nexus between clean energy consumption, economic growth, and CO2 emissions. *Journal of Cleaner Production, 182,* 1001-1011. https://doi.org/10.1016/j.jclepro.2018.02.035
10. Can, M., Dogan, B., & Saboori, B. (2020). Does trade matter for environmental degradation in developing countries? New evidence in the context of export product diversification. *Environment Science Pollution Research International, 27,* 14702-14710. https://doi.org/10.1007/s11356-020-08000-2
11. Chandran, V. G. R., Sharma, S., & Madhavan, K. (2010). Electricity consumption-growth nexus: The case of Malaysia. *Energy Policy, 38*(1), 606-612. https://doi.org/10.1016/j.enpol.2009.10.013
12. Chen, T. S., Kou, H. I., & Chen, C. C. (2007). The relationship between GDP and electricity consumption in 10 Asian countries. *Energy Policy, 35*(4), 2611-2621. https://doi.org/10.1016/j.enpol.2006.10.001
13. Cole, M. A., Elliott, R. J., & Shimamoto, K. (2005). Industrial characteristics, environmental regulations and air pollution: An analysis of the UK manufacturing sector. *Journal of Environmental Economics and Management, 50*(1), 121-143. https://doi.org/10.1016/j.jeem.2004.08.001
14. Copeland, B. R., & Taylor, M. S. (2004). Trade, growth, and the environment. *Journal of Economic Literature, 42*(1), 7-71. https://doi.org/10.1257/002205104773558047
15. Ewing, B.T., Sari, R., & Soytas, U. (2007). Disaggregate energy consumption and industrial output in the United States. *Energy Policy, 35*(2), 1274-1281.

http://dx.doi.org/10.21511/ee.14(2).2023.01

https://doi.org/10.1016/j.enpol.2006.03.012

16. Fernando, Y., & Lin Hor, W. (2017). Impacts of energy management practices on energy efficiency and carbon emissions reduction: A survey of Malaysian manufacturing firms. *Resources, Conservation and Recycling, 126,* 62-73. https://doi.org/10.1016/j.resconrec.2017.07.023
17. Galeotti, M., Lanza, A., & Pauli, F. (2006). Reassessing the environmental Kuznets curve for CO2 emissions: A robustness exercise. *Ecological Economics, 57*(1), 152-163. https://doi.org/10.1016/j.ecolecon.2005.03.031
18. Grossman, G. M., & Krueger, A. B. (1991). *Environmental impacts of a North American free trade agreement* (Working Paper Series No. 3914). National Bureau of Economic Research. https://doi.org/10.3386/w3914
19. Hamit-Haggar, M. (2012). Greenhouse gas emissions, energy consumption, and economic growth: A panel co-integration analysis from Canadian industrial sector perspective. *Energy Economics, 34*(1), 358-364. https://doi.org/10.1016/j.eneco.2011.06.005
20. Ismail, M. A., & Yunus, M. M. (2012). *Energy use, emissions, economic growth and trade: A Granger non-causality evidence for Malaysia* (MPRA Paper No. 38473). Munich Personal RePEc Archive. Retrieved from https://mpra.ub.uni-muenchen.de/38473/
21. Khan, M. K., Teng, J., Khan, M. I., & Khan, M. O. (2019). Impact of globalization, economic factors and energy consumption on CO2 emissions in Pakistan. *Science of the Total Environment, 688,* 424-436. https://doi.org/10.1016/j.scitotenv.2019.06.065
22. Lewandowski, S., & Ullrich, A. (2023). Measures to reduce corporate GHG emissions: A review-based taxonomy and survey-based cluster analysis of their application and perceived effectiveness. *Journal of Environmental Management, 325*(B), 116437. https://doi.org/10.1016/j.jenvman.2022.116437
23. Liu, X. L., Jin, X. B., Luo, X. L., & Zhou, Y. K. (2023). Multi-scale variations and impact factors of carbon emission intensity in China. *Science of the Total Environment, 857*(1), 159403. https://doi.org/10.1016/j.scitotenv.2022.159403
24. Mohiuddin, O., Asumadu-Sarkodie, S., Obaidullah, M., & Dubey, S. (rev.ed.). (2016). The relationship between carbon dioxide emissions, energy consumption, and GDP: A recent evidence from Pakistan. *Cogent Engineering, 3*(1), 1210491. https://doi.org/10.1080/23311916.2016.1210491
25. Narayan, P. K., Saboori, B., & Soleymani, A. (2016). Economic growth and carbon emissions. *Economic Modelling, 53,* 388-397. https://doi.org/10.1016/j.econmod.2015.10.027
26. Nuryartono, N., & Rifai, M. A. (2017). Analysis of causality between economic growth, energy consumption, and carbon dioxide emissions in 4 ASEAN countries. *International Journal of Energy Economics and Policy, 7*(6), 141-152. Retrieved from https://www.econjournals.com/index.php/ijeep/article/view/5707
27. Porter, M. E. (1991). Towards a dynamic theory of strategy. *Strategic Management Journal, 12*(52), 95-117. https://doi.org/10.1002/smj.4250121008
28. Raihan, A., & Tuspekova, A. (2022). Nexus between economic growth, energy use, agricultural productivity, and carbon dioxide emissions: New evidence from Nepal. *Energy Nexus, 7,* 100-113. https://doi.org/10.1016/j.nexus.2022.100113
29. Raihan, A., Begum, R. A., Said, M. N. M., & Pereira, J. J. (2022). Relationship between economic growth, renewable energy use, technological innovation, and carbon emission toward achieving Malaysia's Paris Agreement. *Environment Systems and Decisions, 42,* 586-607. https://doi.org/10.1007/s10669-022-09848-0
30. Ray, B. K., & Reddy, B. S. (2007). *Decomposition of energy consumption and energy intensity in Indian manufacturing industries* (Working Paper No. WP2007-020). Indira Gandhi Institute of Development Research, Mumbai. Retrieved from http://www.igidr.ac.in/pdf/publication/WP-2007-020.pdf
31. Saboori, B., Sulaiman, J., & Mohd, S. (2012). Economic growth and CO_2 emissions in Malaysia: A co-integration analysis of the Environmental Kuznets Curve. *Energy Policy, 51,* 184-191. https://doi.org/10.1016/j.enpol.2012.08.065
32. Selden, T. M., & Song, D. (1994). Environmental quality and development: Is there a Kuznets curve for air pollution emissions? *Journal of Environmental Economics and Management, 27*(2), 147-162. http://dx.doi.org/10.1006/jeem.1994.1031
33. Shafik, N., & Bandyopadhyay, S. (1992). *Economic growth and environmental quality: Time series and cross-country evidence* (Working Paper No. 904). World Bank Policy Research. Retrieved from http://documents.worldbank.org/curated/en/833431468739515725/Economic-growth-and-environmental-quality-time-series-and-cross-country-evidenc
34. Shahzad, U., Ferraz, D., Dogan, B., & Rebelatto, D. A. N. (2020). Export product diversification and CO_2 emissions: Contextual evidence from developing and developed economies. *Journal of Cleaner Production, 276,* 124146. https://doi.org/10.1016/j.jclepro.2020.124146
35. Shreezal, G. C., & Adhikari, N. (2021). Nexus between CO_2 emissions, energy use, and economic growth in Nepal. *Quest Journal of Management and Social Sciences, 3*(2), 138-161. https://doi.org/10.3126/qjmss.v3i2.41524
36. Smulders, S., & De Nooij, M. (2003). The impact of energy conservation on technology and

economic growth. *Resource and Energy Economics, 25*(1), 59-79. https://doi.org/10.1016/S0928-7655(02)00017-9

37. Soytas, U., Sari, R., & Ewing, B. T. (2007). Energy consumption, income, and carbon emissions in the United States. *Ecological Economics, 62*(3-4), 482-489. https://doi.org/10.1016/j.ecolecon.2006.07.009

38. Tan, C. C., & Tan, S. (2018). Energy consumption, CO2 emissions, and economic growth: A causality analysis for Malaysian industrial sector. *International Journal of Energy Economics and Policy, 8*(4), 254-258. Retrieved from https://www.econjournals.com/index.php/ijeep/article/view/6451

39. Tang, C. F. (2008). A re-examination of the relationship between electricity consumption and economic growth in Malaysia. *Energy Policy, 36*(8), 3077-3085. https://doi.org/10.1016/j.enpol.2008.04.026

40. Zakaria, Z., & Shamsuddin, S. (2016). Electricity consumption and economic activity in Malaysia: Co-integration, causality and assessing the forecasting ability of the vector error correction model. *International Journal of Energy Economics and Policy, 6*(4), 706-713. Retrieved from https://www.econjournals.com/index.php/ijeep/article/view/2711

41. Zhang, X. P., & Cheng, X. M. (2009). Energy consumption, carbon emissions, and economic growth in China. *Ecological Economics, 68*(10), 2706-2712. https://doi.org/10.1016/j.ecolecon.2009.05.011

http://dx.doi.org/10.21511/ee.14(2).2023.01