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ARTICLE INFO

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

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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”

NUMBER OF REFERENCES
41

NUMBER OF FIGURES
0

NUMBER OF TABLES
7

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Environmental Economics, Volume 14, Issue 2, 2023

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CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions are highly positively correlated, as is GDP. The GDP granger causes CO₂ 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 CO₂ emissions in Nepal. The impact of industrial sector output is statistically insignificant. The condition of GDP and CO₂ 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.

Keywords

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

JEL Classification

L16, Q13, Q43

INTRODUCTION

Carbon dioxide (CO₂) emissions refer to releasing CO₂ 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 (CO₂) contributes to climate change by trapping heat on the earth’s surface, leading to global warming. Controlling and reducing CO₂ emissions is crucial in addressing climate change and mitigating its impacts (Cai et al., 2018). Among all the greenhouse gases, CO₂ 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). CO₂ 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-
nergy-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
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.


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 ter-
tiary 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:

$$CO_2 EM = f(\text{GDP, ISY}).$$

(1)

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

$$LNCO_2 EM = f\left(LNGDNP, LNISY\right).$$

(2)

The general regression model is defined as follows:

$$LNCO_2 EM = \alpha + \beta_1 LNGDNP + \beta_2 LNISY + \mu_i.$$ \hspace{1cm} (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:

$$Y(t) = \alpha + \beta_1 \cdot Y(t-1) + \beta_2 \cdot Y(t-2) + ... + \beta_p \cdot Y(t-p) + \mu_t.$$ \hspace{1cm} (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:

$$Y(t) = \alpha + \beta_1 \cdot Y(t-1) + \beta_2 \cdot Y(t-2) + ... + \beta_p \cdot Y(t-p) + \gamma_1 \cdot X_{1(t)} + +\gamma_2 \cdot X_{2(t)} + ... + \gamma_n \cdot X_{n(t)} + \mu_t,$$ \hspace{1cm} (5)

where $Y(t)$ is the dependent variable at time $t$. $Y(t-i)$ 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 $\gamma_1, \gamma_2, ..., \gamma_n$ are the corresponding coefficients that capture the influence of the independent variables on the dependent variable. The coefficients $\beta_1, \beta_2, ..., \beta_p$ represent the autoregressive components, capturing the impact of past observations of the dependent variable on the current observation, and $\mu_t$ 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:

$$LNCO_2 EM(t) = \alpha + \beta_1 \cdot LNCO_2 EM(t-1) + +\gamma_1 \cdot LNGDNP + \gamma_2 LNISY + \mu_t.$$ \hspace{1cm} (6)
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: CO₂ emissions, GDP, and industrial output. Table 1 estimates the summary statistics of the response and explanatory variables.

<table>
<thead>
<tr>
<th>Headings</th>
<th>CO₂ Emissions</th>
<th>GDP</th>
<th>Industrial output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>5.589</td>
<td>14.635</td>
<td>0.846</td>
</tr>
<tr>
<td>Median</td>
<td>3.392</td>
<td>9.044</td>
<td>0.660</td>
</tr>
<tr>
<td>Maximum</td>
<td>15.224</td>
<td>37.450</td>
<td>1.720</td>
</tr>
<tr>
<td>Minimum</td>
<td>1.098</td>
<td>3.401</td>
<td>0.210</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>4.519</td>
<td>11.489</td>
<td>0.489</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.095</td>
<td>0.712</td>
<td>0.465</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.704</td>
<td>2.032</td>
<td>1.787</td>
</tr>
<tr>
<td>Coefficient of variation</td>
<td>80.86%</td>
<td>78.50%</td>
<td>57.80%</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>6.715</td>
<td>4.079</td>
<td>3.207</td>
</tr>
<tr>
<td>Probability</td>
<td>0.035</td>
<td>0.130</td>
<td>0.201</td>
</tr>
<tr>
<td>Sum</td>
<td>184.450</td>
<td>482.949</td>
<td>27.920</td>
</tr>
<tr>
<td>Sum Sq. dev.</td>
<td>653.501</td>
<td>4224.226</td>
<td>7.671</td>
</tr>
<tr>
<td>Observations</td>
<td>33</td>
<td>33</td>
<td>33</td>
</tr>
</tbody>
</table>

Note: CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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. CO₂ 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. CO₂ 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 CO₂ 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. CO₂ 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. CO₂ 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>
<thead>
<tr>
<th>Variables</th>
<th>LNCO_EM</th>
<th>LNGDPN</th>
<th>LNISY</th>
</tr>
</thead>
<tbody>
<tr>
<td>LNCO_EM</td>
<td>1.000</td>
<td>0.9481</td>
<td>0.9514</td>
</tr>
<tr>
<td>LNGDPN</td>
<td>0.9481</td>
<td>1.000</td>
<td>0.9837</td>
</tr>
<tr>
<td>LNISY</td>
<td>0.9514</td>
<td>0.9837</td>
<td>1.000</td>
</tr>
</tbody>
</table>
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$_2$EM (log-transformed CO$_2$ emissions), LNDGDPN (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$_2$EM, LNCO$_2$EM and LNDGDPN, LNISY and LNCO$_2$EM, and LNCO$_2$EM and LNISY.

The null hypothesis for the first pair (LNGDPN and LNCO$_2$EM) is that LNGDPN does not granger cause LNCO$_2$EM. 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.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Criteria</th>
<th>Level</th>
<th>Intercept</th>
<th>Trend and intercept</th>
<th>First intercept</th>
<th>Intercept</th>
<th>Trend and intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td>LNCO$_2$EM</td>
<td>ADF test</td>
<td>−0.506</td>
<td>−2.631</td>
<td>3.344</td>
<td>−3.264</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.874</td>
<td>0.271</td>
<td>0.022</td>
<td>0.092</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>t-value</td>
<td>−2.981</td>
<td>−3.612</td>
<td>−2.967</td>
<td>−3.574</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LNGDPN</td>
<td>ADF test</td>
<td>0.351</td>
<td>−2.845</td>
<td>−4.781</td>
<td>−4.784</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.977</td>
<td>0.196</td>
<td>0.0006</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>t-value</td>
<td>−2.957</td>
<td>−3.603</td>
<td>−2.960</td>
<td>−3.563</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LNISY</td>
<td>ADF test</td>
<td>−0.906</td>
<td>−2.656</td>
<td>−5.393</td>
<td>−5.452</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.768</td>
<td>0.260</td>
<td>0.0001</td>
<td>0.0006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>t-value</td>
<td>−2.992</td>
<td>−3.557</td>
<td>−2.960</td>
<td>−3.563</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: LNCO$_2$EM = 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.
null hypothesis for the second pair (LNCO₂EM and LNGDPN) is that LNCO₂EM 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 CO₂ emissions granger cause the GDP of Nepal. Soytas et al. (2007) also discovered that output does not cause long-term CO₂ emissions, but energy consumption does.

The null hypothesis for the third pair (LNISY and LNCO₂EM) is that LNISY does not granger cause LNCO₂EM. 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 CO₂ emissions in Nepal. The null hypothesis for the fourth pair (LNCO₂EM and LNISY) is that LNCO₂EM 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 CO₂ 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

<table>
<thead>
<tr>
<th>No. of CE(s)</th>
<th>Hypothesized</th>
<th>Unrestricted Co-integration Rank Test (Trace)</th>
<th>Unrestricted Co-integration Rank Test (Maximum Eigenvalue)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><strong>Trace</strong></td>
<td><strong>0.05</strong></td>
</tr>
<tr>
<td>None*</td>
<td>0.721</td>
<td>46.929</td>
<td>29.797</td>
</tr>
<tr>
<td>At most 1</td>
<td>0.185</td>
<td>7.347</td>
<td>15.495</td>
</tr>
<tr>
<td>At most 2</td>
<td>0.032</td>
<td>1.008</td>
<td>3.842</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. error</th>
<th>t-statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAGC$_2$</td>
<td>0.819</td>
<td>0.086</td>
<td>9.574</td>
<td>0.000</td>
</tr>
<tr>
<td>LNGDPN</td>
<td>0.314</td>
<td>0.189</td>
<td>2.665</td>
<td>0.017</td>
</tr>
<tr>
<td>LNISY</td>
<td>−0.221</td>
<td>0.269</td>
<td>−0.818</td>
<td>0.420</td>
</tr>
<tr>
<td>C</td>
<td>0.110</td>
<td>0.245</td>
<td>0.449</td>
<td>0.657</td>
</tr>
</tbody>
</table>

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.

For the variable LAGC$_2$, 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:

$$LNCO_2EM = 0.110 + 0.819 \cdot LAGCO_2 + 0.314 \cdot LNGDPN - 0.221 \cdot LNISY.$$  (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-
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$_2$EM). 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.

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**Table 7. Outcomes of various diagnostic checking**

<table>
<thead>
<tr>
<th>Methods</th>
<th>Observed R-square</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breusch-Godfrey serial correlation LM test</td>
<td>4.458</td>
<td>0.107</td>
</tr>
<tr>
<td>Heteroscedasticity</td>
<td>0.965</td>
<td>0.809</td>
</tr>
<tr>
<td>Normality test (Jarque-Bera)</td>
<td>–</td>
<td>0.933</td>
</tr>
</tbody>
</table>
AUTHOR CONTRIBUTIONS

Conceptualization: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
Data curation: Arjun Kumar Dahal, Ganesh Bhattarai, Prem Bahadur Budhathoki.
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