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The Influence of Industrial Output, Financial Development, and Renewable and Non-Renewable Energy on Environmental Degradation in Newly Industrialized Countries

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Abstract: The prime objective of this study is to examine the impact of industrial output and financial development on carbon dioxide emissions for a panel of 10 newly industrialized countries, namely Brazil, China, India, Indonesia, Malaysia, Mexico, Philippines, South Africa, Thailand, and Turkey. The empirical analysis was conducted between 1982 and 2019 by employing various estimation tests and techniques. The different tests account for cross-sectional dependence in different series of the model. Therefore, the relevant panel unit root was conducted, and we found that all series become stationary after the first difference. The long run parameters were estimated, and we found that there is a significant long-run relationship between the industrial output, the financial development, and the carbon emissions. The carbon emissions are found to be significantly affected by both domestic income and industrial output, while being negatively affected by financial development. Industrial production coefficient estimates are highly elastic when compared to the other estimates. The results also indicate unidirectional short-run causality from the domestic output and trade openness to carbon emissions, urban population to domestic output, and financial development to industrial output. However, there is no evidence of bidirectional causality. The study concludes that sustainable economic growth can be achieved by using contemporary and efficient production techniques, using environmentally friendly inputs in industries, and increasing vigilance of both the public and private sectors. Both the public and private sectors should therefore be pushed to use more modern, eco-friendly, and productive processing techniques. It is recommended that both the public and commercial sectors be encouraged to embrace cutting-edge, environmentally friendly, and productive processing methods.

Keywords: financial development; industrial output; carbon emissions; newly industrialized countries; renewable energy; environmental degradation

1. Introduction

Global warming has become a challenge that the world is facing currently. The major factor behind global warming is CO_2 emissions that weaken the ecological state and lead to environmental degradation. On the other hand, energy is a prerequisite for economic activities today. In broad terms, a substantial amount of energy is used by four sectors: the transport sector, commercial sector, residential sector, and industrial sector. It is assumed that the industrial sector consumes 51% of the world's energy. A sector's success leads

to further energy consumption, which contributes to a rise in fossil fuels that have an adverse environmental impact, resulting in increased concern about the environmental consequences of industrial production [1]. In recent times, increased global focus has been presumed to curtail carbon emissions from energy production and industrial activities. The Kyoto Protocol (1997) and the Paris Agreement (2015) are fundamental steps towards reducing emissions of greenhouse gases (GHGs) to sustain a global temperature rise below 2 °C above pre-industrial levels and to explore the necessary steps further to restrict the increase in temperature to 1.5 °C.

The newly industrialized countries (NIC) contributed 42% to total global CO_2 emissions due to acceleration in their economic growth [2]. As time passed, the structure of the countries' economies shifted from agricultural to industrial or service-based economies. To attain high growth rates or compete with developed countries, new industrial countries are expanding their industrial sectors to produce more goods while disregarding pollution standards [3]. As a result, air pollution and ecosystem degradation are worse in newly industrialized countries (NIC) than in other countries [4]. CO_2 is a part of the atmosphere but has increased dramatically by one-third after the industrial revolution [2]. NASA data (2016) [5] show that atmospheric CO_2 remained below 300 parts per million (ppm) for 650,000 years but is now at 400 ppm. It depicted that CO_2 emissions grew with the industrial revolution. More energy use in industries is a key factor behind high CO_2 emissions. More energy use in sectors of the economy could be a major factor behind high CO_2 emissions, although it is not the only factor. In addition, financial development is an important determinant of CO_2 emissions. Financial development can, in many ways, impact CO_2 emissions. First, financial development improves stock market conditions, and listed companies can increase their monetary investment in new projects owing to financial growth. This feat raises installations and services that need more energy and result in high CO_2 emissions. Second, financial development motivates foreign direct investment in a country that promotes economic growth and aggravates CO_2 emissions. Third, an efficient financial development program positively affects purchasing expensive consumer goods such as bigger houses, air conditioners, automobiles, and other products. All of these considerations contribute to energy consumption and high CO_2 emissions.

The spike in individual activities triggers an increase in carbon dioxide (CO_2) emissions due to the acceleration of conventional energy sources. By 2025, the primary energy use in emerging economies is projected to reach an average of 3.2% per year [3,4]. In line with these realities, the International Energy Outlook (IEO) foresees a rapid rise in global access to low energy by 2025. This figure forecasts the terrifying situation of the contribution of traditional global energy demand, primarily from fossil fuels, which is between 80 and 95% [6]. It is, therefore, essential to incorporate modern and sustainable sources of energy to regulate pollution without harming economic development and the climate. For these purposes, economies worldwide strive to use modern renewable energy sources, such as biomass, tidal, wind, geothermal, solar, and hydroelectric power. Gielen et al. [7] pointed out that by 2050, renewable energy resources will reach two-thirds of the world's overall energy demand. This will drastically reduce greenhouse gas emissions.

The major objective of this research work is to empirically analyze the causal nexus between carbon emissions, GDP growth, industrial output, financial development, and renewable and non-renewable energy consumption from 1982 to 2019 for 10 NICs. This study contributes to the existing body of literature in many ways. First, this study analyzes the impact of industrial output and financial development in NICs. To the best of our knowledge, only a few studies have examined the causal nexus among carbon emissions and variables like GDP, energy consumption, trade openness, and urbanization in the case of NICs. However, industrial output and financial development have not garnered much attention from researchers. The variables included in this study overcome the omitted variable bias problem. Second, previous research has concentrated on the effects of energy use while ignoring the structure of energy usage (i.e., renewable and conventional energy). As a result, we include both types of energy use in this study, which can provide

essential information for successful energy policies that contribute to achieving sustainable development goals. Lastly, we applied advanced econometric techniques, i.e., cross-section dependency statistics and panel cointegration tests, to make our analysis economically appropriate. We used a panel data method for long-run regression, i.e., FMOLS and the Granger causality test are used to know the nature of causality between the variables of interest. From the standpoint of policy, these empirical procedures are essential for developing alternatives for policies that might encourage cleaner and more sustainable consumption and production patterns in NICs [8].

The rest of the paper unfolds as follows. Section 2 provides a review of the literature. Section 3 describes the model specification, econometric technique, and data and description. Section 4 explains the empirical analysis and discussion, and Section 5 concludes the study with policy implications.

2. Review of Literature

A brief overview of previous research on the relationships between financial development, industrialization, green energy, and carbon emissions is provided in the following section.

2.1. Financial Development–Pollution Nexus

A plethora of studies empirically analyzed the role of financial development in affecting carbon emissions. For instance, many researchers (Acheampong, [9]; Adams & Klobodu, [10]; Al-Mulali, Ozturk, & Lean, [11]; Ganda, [12]; Nasir, Duc Huynh, & Xuan Tram, [13]; Shahbaz et al., [14]; Shoaib et al., [15]) have confirmed a positive impact of financial development on CO_2 emissions. In a similar vein, Y.-J. Zhang [16] studied the impact of financial development on carbon emissions for the Chinese economy over three decades. Based on the cointegration test and the variance decomposition method, the study found a positive and significant effect of financial development on carbon emissions. Likewise, Sadorsky [17] used panel data from 22 developing countries to analyze the nexus of financial development, energy consumption, and carbon emissions. The result shows that for these countries, financial development leads to more energy use that produces more carbon emissions. On the contrary, a growing body of literature has agreed that financial development reduces environmental degradation via the promotion of economic growth (e.g., Al-mulali, Tang, & Ozturk, [18]; Odhiambo, [19]; Shahbaz, Nasir, & Roubaud, [20]; Xing et al. [21]; Zafar, Saud, & Hou, [22]; Zaidi et al. [23], etc.). Besides, financial development promotes investment in the energy sector that assists in mitigating energy emissions [24]. Moreover, Nasreen and Anwar [25] reported a unidirectional causality from financial development to CO_2 emissions, whereas Shahbaz et al. [14] confirmed a bidirectional causality between the two variables. Boutabba [26] studied the Indian economy to identify the link between financial developments and carbon emissions. The results of the Johansen cointegration test and Error Correction Model (ECM) advocate that financial development contributes to environmental degradation. In addition, the Granger causality test identified one-way causality from financial development to carbon emissions. Ozturk and Acaravci [27] confirmed the long-run association between per capita carbon emissions, per capita real income, the square of per capita real income, and financial development in Turkey. The study revealed that a high level of per capita real income results in declining carbon emissions per capita. However, no significant impact of financial development on carbon emissions was found in the long term. The result further supported one-way causality from financial development to energy consumption in the short term.

Table 1 below provides a Chronological summary of the literature on financial development and CO_2 emissions.

Table 1. Chronological summary of the literature on financial development and CO_2 emissions.

Authors	Time Period	Region/Countries	Findings
Abid [28]	1996–2010	25 SSA countries	FD does not affect carbon emission
Abbasi and Riaz [29]	1971–2011	Pakistan	The effect of FD is insignificant on carbon emissions
Dogan and Turkekul [30]	1960–2010	USA	FD exerts no effect on CO_2 emissions
Saidi and Mbarek [24]	1990–2013	19 emerging countries	FD reduces CO_2 emissions
Shahbaz, Nasir, and Roubaud [20]	1955–2016	France	FD has a declining effect on carbon emissions
Paramati, Mo, and Gupta [31]	1991–2012	G-20 countries	FD increases environmental quality by reducing CO_2 emissions
Adams and Klobodu [10]	1985–2011	26 African countries	FD causes CO_2 emissions
Ganda [12]	2001–2012	OECD countries	FD increases CO_2 emissions
Charfeddine and Kahia [32]	1990–2015	MENA region	Inverted U-shaped relationship exit between FD and CO_2 emissions
Gokmenoglu and Sadeghieh [33]	1960–2011	Turkey	FD enhances carbon emissions
Shahbaz, et al. [14]	1975–2014	UAE	FD increases CO_2 emissions, and the relationship between financial development and CO_2 emissions is U-shaped and inverted N-shaped
Odhiambo [19]	2004–2014	39 SSA countries	FD unconditionally reduces CO_2 emissions
Shoaib et al. [15]	1999–2013	G8 and D8 countries	FD has a significant and positive impact on carbon emission in both panels in the long-run
Ahmad et al. [34]	1990–2017	90 Belt and Road countries	FD deteriorates the environmental quality by increasing the CO_2 emissions, and bidirectional causality exists between FD and CO_2 emissions
Ling et al. [35]	1980–2017	China	FD has important ramifications for carbon emissions
Shobande et al. [36]	1995–2018	OECD countries	FD reduces carbon emissions but increases energy use
Khan et al. [37]	1984–2018	15 emerging and growth-leading economies	FD development across all dimensions reduces environmental quality (CO_2 emissions)

Source: Authors' compilation.

2.2. Industrialization–Pollution Nexus

Some of the studies explored the industrialization impact on carbon emissions. Lin et al. [38] worked on data from 53 countries with different income levels, while Ma, Yan, and Cai [39], in the case of China, confirmed a significant association among financial development, industrialization, and CO_2 emissions. Wang, Shackman, and Liu [40] confirmed an association for Western developing countries; Abou-Ali, Abdelfattah, and Adams [41] affirmed this for Arab regions; and Rafiq, Salim, and Apergis [42] affirmed a positive impact of industrialization on CO_2 emissions for 53 countries based on the STIRPAT model. Likewise, Nejat et al. [43] and Tian et al. [44] in China, Salim and Shafiei [45] in 29 OECD countries, and Cherniwchan [46] in 157 countries concluded that industrialization has detrimental effects on CO_2 emissions. Besides, Shahbaz et al. [47] found the presence of the EKC hypothesis between industrialization and CO_2 emissions in the case of Bangladesh. Asumadu-Sarkodie and Owusu [48] studied the causal link between carbon emissions, energy use, industrialization, and financial development in Sri Lanka from 1971 to 2012. Based on the ARDL approach, the study established a long-run association among the variables. Furthermore, a unidirectional causal link was affirmed between carbon emissions to energy consumption, while a bidirectional causal link was found between industrialization and energy use (a strong determinant of CO_2 emissions). Asumadu-Sarkodie and Owusu [48] worked on the causal nexus between CO_2 emissions and industrialization for the period 1965–2011 in Rwanda. Based on the ARDL model, the study concluded a long-run association among the variables. Besides, the effect of industrialization on CO_2 emissions was found to be positive, adversely affecting health, air quality, and the environment. The study recommends environmentally friendly industrialization policies for Rwanda to reduce CO_2 emissions in the country. Zhao et al. [49] used the Log Mean Divisia

Index and concluded that the major factor behind high carbon emissions was industrial output in Shanghai. Appiah et al. [50] identified a causal link between industrialization and CO_2 emissions.

Concerning NICs countries, only a few studies (Ghazali & Ali, [51]; Sharif Hossain, [52]; S. Zhang, Liu, & Bae, [53]) have been carried out on the association of carbon emissions with other macroeconomic variables (economic development, urbanization, free trade, energy consumption), given the fact that NICs contribute 42% to global CO_2 emissions due to their rapid economic growth (IPCC, 2013) [2]. A summary of the more recent studies on the nexus of financial development, industrialization, and CO_2 emissions is provided in Table 2.

Table 2. Chronological summary of the literature on industrialization and CO_2 emissions.

Authors	Time Period	Region/Countries	Finding
Zhao et al. [49]	1996–2007	Shanghai	Industrial output positively contributes to CO_2 emissions.
Zhongping et al. [54]	1978–2008	31 industries in China	Heavy industrialization has a positive effect on CO_2 emissions
Kivyiro and Arminen [55]	2000–2012	Sub-Saharan Africa	Industrialization has a positive impact on CO_2 emissions.
Al-Mulali and Ozturk [11]	1962–2012	14 MENA countries	A causal link between industrialization, financial development, and CO_2 was revealed.
Gokmenoglu et al. [1]	1960–2010	Turkey	Cointegration exists between financial development, industrialization, and CO_2 emissions and unidirectional causality from financial development to CO_2 emissions.
Xu and Lin [56]	1990–2011	30 provinces in China	Industrialization with CO_2 emissions has an inverted U-shaped nonlinear relationship in 3 regions.
Sarkodie and Owusu [48]	1971–2013	Sri Lanka	A long-run association between industrialization and CO_2 emissions was affirmed, while a bidirectional causal link from industrialization to energy consumption was asserted.
Sarkodie and Owusu [57]	1965–2011	Rwanda	Industrialization accelerates CO_2 emissions
Appiah et al., [50]	1990–2014	Uganda	Industrialization has a positive effect on CO_2 emissions. A causal correlation between industrialization and CO_2 emissions was also found.
Opoku and Aluko [58]	2000–2016	37 African Countries	The industrialization has heterogeneous effects (decrease/increase) for different data quantiles.
Rehman et al. [59]	1971–2019	Pakistan	Industrialization has positive effects on carbon emissions

Authors' compilation.

2.3. Renewable and Non-Renewable Energy–Pollution Nexus

Numerous studies have examined the impact of renewable and non-renewable energy consumption on environmental quality. For instance, Apergis and Payne [60] analyzed the linkage between REC and CO_2 emissions from 1984 to 2007 in the case of 19 developed and developing countries. The Granger causality test findings show that REC does not lead to a short-term reduction in CO_2 emissions. In addition, for a group of 12 MENA countries, Farhani [61] explored the relationship between REC and CO_2 emissions for the period 1975–2008. The empirical findings show that, in the short-run, one-way causality ranges from REC to CO_2 emissions, while the long-term unidirectional causality ranges from CO_2 emissions to REC. Bölük and Mert [62] concluded that REC and NREC increase CO_2 emissions in the case of 16 European Union (EC) countries. Ben Jebli, Ben Youssef, and Ozturk [63] stated that, in 25 OECD countries, REC decreases CO_2 emissions while NREC increases environmental pollution. Bilgili, Koçak, and Bulut [64] found that REC positively reduced carbon emissions for a group of 17 OECD countries over the period 1977–2010. Zoundi [65] and Hu et al. [66] found that REC reduces carbon emissions in the case of 25 sub-Saharan African and 25 developing countries, respectively. Sharif et al. (2019) [67], in a sample of 74 countries, concluded that NREC increases while REC reduces CO_2 emissions. Danish, Ulucak, and Khan [68] affirmed the validity of the EKC hypothesis in BRICS countries and found that REC reduces ecological footprints. Similarly, Pham, Huynh, and Nasir [69] found that REC lowers CO_2 emissions in 28 Eu-

ropean countries. The overall evidence from past research related to renewable energy and non-renewable energy usage and environmental degradation provides mixed or inconclusive results. This merits further investigation to arrive at a novel conclusion for newly industrialized countries. Table 3 summarizes the recent literature that focuses on the relationship between REC, NREC, and carbon emissions.

Table 3. Chronological summary of the literature on REC, NREC, and CO_2 emissions.

Authors	Time Period	Region/Countries	Finding
Shafiei and Salim [45]	1980–2011	OECD countries	REC decreases while NREC increases carbon emission.
Bilgili, Koçak, and Bulut [64]	1977–2010	OECD countries	REC decreases carbon emission
Owusu and Asumadu-Sarkodie [48]	1971–2012	Sri Lanka	Unidirectional causality found from carbon emissions to NREC
Zoundi [65]	1980–2012	25 Sub-Saharan African countries	REC decreases CO_2
Bélaïd and Youssef [70]	1980–2012	Algeria	NREC has adverse effects, while REC has a positive effect on environmental quality
Hu et al. [66]	1996–2012	25 developing countries	Share of REC improves environmental quality
Pata [71]	1974–2014	Turkey	REC does not affect carbon emissions.
Chen et al. [72]	1980–2014	China	An increase in NREC increases carbon emissions, while a rise in REC reduces carbon emissions.
Danish, Ulucak, and Khan [68]	1992–2016	BRICS	REC has a positive impact on environmental quality
Pham, Huynh, and Nasir [69]	1990–2014	28 European countries	REC is found to reduce carbon dioxide emissions
Salahuddin, et al. [73]	1984–2016	33 Sub-Saharan African countries	Green energy reduces carbon emissions

Authors' compilation.

In brief, the extant literature shows numerous directions and impact strengths in the relationship between financial development, industrialization, renewable and non-renewable energy consumption, and CO_2 emissions. The high variability in results reflects the fact that the studies were performed for different regions, countries, development levels, and variable econometric techniques. In summary, the findings of empirical investigations remain mixed or uncertain, thereby investigating its impact on carbon emissions deserves further deliberation.

3. The Theoretical Framework of the Model, Data, and Methodology

3.1. Theoretical Framework of the Model

The STIRPAT model propounded by Dietz and Rosa [74] provides this study's theoretical and analytical reference framework. Based on the population, affluence, and technology, the model advocates that population and economic activities are essential sources of CO_2 emissions. The general form of the model can be written as follows:

$$I = f(P \ A \ T) \tag{1}$$

The STIRPAT model in nonlinear form can be written as

$$I_{it} = \beta_o P_{it}^{\beta_1} A_{it}^{\beta_2} T_{it}^{\beta_3} \mu_{it} \tag{2}$$

where the subscript ($i = 1, \ldots , N$) indicates the countries, and ($t = 1, \ldots , T$) shows the time span. β_o and μ_{it}, reflect country-specific effects and error terms, respectively. While β_1, β_2, and β_3 are the elasticities showing the impact on the environment with respect to P, A, and T (York, 2007) [75].

The STIRPAT model in Equation (2) is converted into a linear form by taking a natural log:

$$lnI_{it} = \beta_0 + \beta_1 lnP_{it} + \beta_2 \ lnA_{it} + \beta_3 lnT_{it} + \mu_{it} \tag{3}$$

Additional to the mentioned variables in Equation (3), in this study, we investigated the impact of economic variables (financial development and trade openness) and green energy (non-renewable and renewable energy) on CO_2 emissions. For this, we constructed two models, and these are structures as follows:

$$lnCO2_{it} = \gamma_{ot} + \gamma_{1t}lnY_{it} + \gamma_{2t}lnIO_{it} + \gamma_{3t}\text{lnUR}_{it} + \gamma_{4t}lnFD_{it} + \gamma_{5t}lnTO_{it} + e_{it} \quad (4)$$

$$\begin{aligned} lnCO2_{it} = \gamma_{ot} \quad &+ \gamma_{1t}lnY_{it} + \gamma_{2t}lnIO_{it} \\ &+ \gamma_{3t}\text{lnUR}_{it} + \gamma_{4t}lnFD_{it} + \gamma_{5t}lnTO_{it} + \gamma_{6t}lnNRE_{it} + \gamma_{it}lnRE_{it} + e_{it} \end{aligned} \quad (5)$$

In the given models, CO_2, Y, IO, and UR represent carbon dioxide emissions, total output, industrial output, and urbanization, representing I, A, T, and P in the STIRPAT model, respectively. The variables CO_2, Y, IO, and UR employed for I, A, T, and P are similar to earlier studies Al-Mulali, U. et al. (2015) [11], Saidi and Mbareak (2017) [24], and Appiah et al. (2019) [50]. In terms of additional variables, FD stands for financial development, TO stands for trade openness, NRE stands for non-renewable energy, and RE stands for renewable energy. The impact of these additional variables on CO_2 emissions have shown by different studies, where some of them include Shafiei and Salim (2014) [45], Zoundi (2017) [65], Ahmad et al. (2020) [34], Salahuddin et al. (2020) [73], and Khan et al. (2022) [37]. In the specification of the STIRPAT model, carbon emissions are widely used as a dependent variable. Following the studies of Saidi and Mbarek, 2017 [24]; Nasir et al. 2019 [13], and Arshad et al., (2022) [76], we replaced CO_2 emissions in metric tons per capita. The CO_2 emissions metric tons per capita is used as a dependent variable and the remaining as independent variables. In Equations (4) and (6), the last term e_{it} is the model's error term. Furthermore, the acronym and data source of all variables of the models are described in the Table 4. Data for all variables were retrieved from the World Development Indicators (WDI) for the period 1982–2019. However, the WDI lacked last year's data for renewable and non-renewable energy, which were obtained from the Energy Information Agency (EIA) and British Petroleum, respectively.

Table 4. Variables of the study.

Variables	Description	Source
Per capita carbon emissions (CO_2)	CO_2 emissions metric tons per capita	WDI
GDP growth (GDPPC)	GDP per capita in USD $	WDI
Urbanization (UR)	Urban population growth in annual %	WDI
Financial Development (FD)	Domestic credit to private sector % of GDP	WDI
Trade Openness (TO)	the ratio of exports and imports as % of GDP	WDI
Industrialization (IO)	Value added by industry (% of GDP)	WDI
Renewable energy consumption (RE)	kg of oil equivalent	WDI and US Energy Information Administration (EIA 2020) [77]
Non-renewable energy Consumption (NRE)	kg of oil equivalent	WDI and British Petroleum Statistical Review of World Energy (BP 2019) [78]

3.2. Econometric Methodology

Given the variables, including carbon dioxide emission, domestic output, industrial output, urban population, financial development, and trade openness, we tried to establish their cointegration and causal association with the help of the panel cointegration and Granger causality test. Since the various econometrics tests and techniques used in this study are discussed in this section. Firstly, the independence test for cross-section developed by Breusch and Pagan [79] and M. H. Pesaran [80] is briefly discussed. Second, we describe the first- and second-generation panel unit root tests proposed by Levin, Lin, and James Chu [81]; Maddala and Wu [82]; and H. Pesaran [83]. Third, the panel cointegration tests suggested by Pedroni [84] and Kao [85] are introduced. Addition-

ally, the fully modified ordinary least square (FMOLS) method developed by Pedroni [86] is described to estimate the long-run relationship. Finally, the Granger causality tests procedure is introduced to test for the detection of the causal relationship between the study's variables.

3.2.1. Cross-Section Dependence Test

Cross-sectional dependence (CD) is one of the most important diagnostics that could be checked before panel cointegration analysis. Normally the problem arises in panel series due to unobserved common factors. The literature proposes that it must be tested before proceeding with the panel unit root to avoid bias and inconsistency in the results [79]. Therefore, first, we attempt to evaluate the CD among model variables by following the Bruech-Pagan LM test (Bruesch-Pagen, [79]) and the Pesaran CD test. Both tests considered the standard model of a panel given in an Equation (6) and tested for interdependence in the model's residuals.

$$y_{it} = \alpha_i + \beta_i x_{it} + \mu_{it} \tag{6}$$

Bruesch-Pagan LM test could be used to test cross-section dependence when the time dimension is greater than the cross-section. This proposes an LM statistic, which is significant for T > N and is given by the following equation:

$$CD_{LM} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{7}$$

where CD stands for cross-section dependence, T for time dimension, and N for panel dimension, and $\hat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of the regression residuals ($\hat{\mu}_{ij}$), and associated with Equation (6). This $\hat{\rho}_{ij}$ is calculated with the formula given below:

$$\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T} \hat{\mu}_{it} \, \hat{\mu}_{ji}}{\left(\sum_{t=1}^{T} \hat{\mu}_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} \hat{\mu}_{ji}^2\right)^{1/2}} \tag{8}$$

The stated CDLM test is asymptotically distributed as Chi-square with $N(N-1)/2$ degree of freedom under the null hypothesis, i.e., no relation exists between the cross-sections.

Pesaran [80] improved this test and considered when the time dimension is smaller than the cross-section or panel dimension. Pesaran proposed alternative CD test statistics as follows:

$$CD_P = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{9}$$

This test is applicable even N > T, and the null hypothesis is similar to that of the CDLM test.

3.2.2. Panel Unit Root Test

Next to the cross-section dependence test, the panel unit root must be tested to proceed with the cointegration analysis. The literature has divided panel unit root tests into two "first-generation" and "second-generation" tests. The first-generation tests could be used if we find no evidence for cross-section dependence, while the second-generation tests could be employed if we find evidence for cross-section dependence. The LLC and WU tests are the most widely applicable tests of the first-generation tests. The LLC test was developed by Levin, Lin, and Chu [81], while Maddala and Wu [82] introduced MW. Both tests are the extensions of the augmented Dickey–Fuller (ADF) test, under the restrictive assumption of "no relation between individual cross-section". For a panel data set, the LLC test is used as a modification of the ADF regression as follows:

$$\Delta Y_{i,t} = \rho_i Y_{i,t-1} + \sum_{k=1}^{n} \varnothing_i k \Delta Y_{i,t-k} + X'_{it}\delta + \mu_{it} \tag{10}$$

In which, Y_{it} ($i = 1, 2, \ldots , n$; $t = 1, 2, \ldots , T$) is a series for a country i over period t. The residual μit is white noise~N(0; σ2) and is assumed to be cross-section independent. The LLC test is conducted under the null hypothesis that "panels contain unit roots", while the alternative hypothesis indicates that "panels are stationary". The hypothesis may be written as follows:

$$H_0 : \rho_i = \rho = 0$$

$$H_1 : \rho_i = \rho < 0$$

Maddala and WU (MW, 1999) [82] is another panel unit root test of the "first generation". It is a non-parametric test and proposes a Fisher-type test that combines the logs of the *p*-values of each cross-section unit root test. The test statistics of MW have a χ^2 distribution with 2n degrees of freedom, where *n* represents the total countries in the panel. The following equation gives the MW test statistic:

$$\lambda = -2\sum_{i=1}^{n} log_e(\rho_i) \sim \chi^2 2nd(d.f) \tag{11}$$

where p_i stands for *p*-values from the test of ADF unit root for each unit *i*. Maddala and Wu (1999) [82] found that the test has certain advantages over the IPS panel unit test. It is superior to IPS because it does not depend on various lag lengths in the individual or cross-section ADF regressions.

In addition, the unit root is tested using a cross-sectional ADF (CADF). This is a notable test of the "second generation" of unit roots, which was proposed by Pesaran [83]. This test is popular to allow for the existence of cross-sectional dependence. Further, the test could be applied with N > T and gives strong results when T > N, and the test is based on the mean of individual ADF-test statistics of each unit in the panel. CADF test applies unit root for every cross-section forming panel and for the panel itself. The extended ADF regression of the test can be written as follows:

$$\Delta y_{it} = a_i + \rho_i y_{i,t-1} + \sum_{k=1}^{p} b_{ik} \Delta y_{i,t-k} + c_i \overline{y}_{t-1} + \sum_{k=0}^{p} d_{i,k} \Delta \overline{y}_{t-k} + \varepsilon_{i,t} \tag{12}$$

The null hypothesis assumes that all series contain a unit root, symbolically as, $H_0 : \rho_i = 0$ for all i . However, in the alternative hypothesis assume that at least one of the cross-sections in the panel is stationary, as symbolically, $H_1 : \rho_i < 0$ for at least one i.

3.2.3. Panel Cointegration Test

Two alternative approaches to panel cointegration have been used to provide more reliable estimates in cointegration testing. Panel cointegration tests show whether there is a linear association between the dependent and independent variables of the model in our panel or not. We employ two important panel cointegration tests, including the Pedroni (1999) [84] and Kao (1999) [85] tests. Both are residual-based cointegration tests that extend the Engle–Granger (EG) framework to test panel data. The Pedroni cointegration approach proposes several tests, and one can calculate the Pedroni's within the dimension and between dimension ADF and PP test statistics. We would also estimate these two in our study, as Pedroni [84] suggests that these two test statistics have the best properties if the samples have a small time dimension. The test's estimation method is an extension of the traditional EG methodology. Therefore, in two steps, estimate the desired panel cointegration. In the starting point, the dependent variable is regressed on explanatory variables, such as in our case, the cointegration equation specified as:

$$lny_{it} = a_i + \beta X_{i,t} + \epsilon_{i,t} \tag{13}$$

In this panel regression, for t = 1, 2, … T, i = 1, 2, … , N; where αi is constant or individual effects, y is the dependent variable (CO_2), and X is a vector of explanatory regressors includes domestic income (Y), industrial output (IO), urban population (UR), financial development (FD), trade openness (TO), non-renewable energy (NRE), and renewable energy (RE). The last term $\epsilon_{i,t}$ is a white noise term. Since then, after estimating Equation (8), the stationarity of $\hat{\epsilon}_{i,t}$ is examined with either the Dickey–Fuller test or the Phillips–Perron test. For the hypothesis test, the structure of estimated residuals may be as given, $\epsilon_{i,t} = \rho \epsilon_{i,t-1} + \varepsilon_{it}$. Pedroni describes the null hypothesis of no cointegration ($\rho_i = 1$); however, the author proposes two alternative hypotheses, i.e., the homogenous alternative as $\rho_i = \rho < 1$ for all i (for panel statistic test or within dimension), and the heterogeneous alternative as $\rho_i < 1$ for all i (for the group statistic or between dimensions). Finally, the decision of cointegration is made if the test statistic value rejects the null hypothesis and accepts the alternative hypothesis.

Kao [85] also tests the Kao test of panel cointegration. Kao proposes different DF-type and ADF-type tests to test the null hypothesis of no cointegration. This approach tests for cointegration in homogenous panels. In Kao tests, it is assumed that all the cointegration vectors in every cross-section are identical.

3.2.4. Fully Modified OLS

As a next step, we used a fully modified ordinary least square to determine the long-run relationship between variables of the model in Equation (3). Phillips and Hansen [87] first developed FMOLS to provide an optimal estimate of the cointegrating regression model. However, we estimate long-run relationships using the FMOLS suggested by Pedroni [86]. According to Ozcan [88], FMOLS has the advantage of correcting both the serial correlation and endogeneity bias. The FMOLS is the most appropriate estimation technique if the panel contains heterogeneous cointegration. Most importantly, using this approach, more consistent and unbiased estimates are generated even in small samples where the time dimension is not less than the cross-section (Pedroni, 2001) [86]. In this respect, FMOLS assume a regression of the panel as given:

$$y_{i,t} = a_i + \beta x_{i,t} + \mu_{i,t} \tag{14}$$

$$x_{i,t} = x_{i,t-1} + \xi_{i,t} \tag{15}$$

In which a_i is country-specific fixed effects, and β is a cointegrating vector. Therefore, the $\varepsilon_{i,t} = (\mu_{i,t} + \xi_{i,t})$ vector error process is also a stationary process. Using relevant notations, the FMOLS estimator for group means can be defined as:

$$\hat{\beta}*_{GFM} = N^{-1} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} (x_{i,t} - \overline{x}_{i,})^2 \right)^{-1} \left(\sum_{t=1}^{T} (x_{i,t} - \overline{x}_i) y *_{i,t} - T \hat{\gamma}_i \right) \tag{16}$$

where, $y*_{i,t} = (y_{i,t} - \overline{y}_i) - \frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}} \Delta y_{i,t}$; $y*_{i,t}$ is the transform variable of y_{it}; $\hat{\gamma}_i = \hat{\Gamma}_{21i} + \hat{\Omega}^o_{21i} - \frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}} \left(\hat{\Gamma}_{22i} + \hat{\Omega}^o_{22i} \right)$; and $\hat{\gamma}_i$ is the serial correlation correction term.

3.2.5. Panel Granger Causality Analysis

It is pertinent to mention that the purpose of the cointegration relationship is not to indicate the direction of the causal relationship among variables of the model. The causality tests could be used to identify the direct causal linkages, which are normally carried out after the appearance of cointegration. In this research, we analyze causality through the pairwise directions by the Granger causality tests for panel data introduced by Engle and Granger [89]. Additionally, we employ the DH causality approach proposed by Dumitrescu and Hurlin [90]. This DH approach offers more useful information and is

suitable for analyzing the panel's cross-sectional dependencies. The Granger equation for the panel data model is considered as follows:

$$\Delta Y_{i,t} = a_i + \sum_{i=1}^{k} \varphi_i^{(k)} Y_{i,t-k} + \sum_{i=1}^{k} \beta_i^{(k)} X_{i,t-k} + \varepsilon_{it} \tag{17}$$

where, in Equation (15), k denotes optimum lags, Y and X are the variables in which causality will be estimated, the intercept (α) represents fixed individual effects, $\varphi_i^{(k)}$ and $\beta_i^{(k)}$ respectively denote autoregressive parameters and regression coefficients, and the last term ε is the white noise error term. This test was used to detect whether or not pairwise causality exists between X and Y. As stated above, it should be noted that the Granger test coefficients are assumed to be the same across countries, while DH assumes differences across the cross-sections [88,89]. Both approaches have the same null hypothesis, i.e., H_0: X does not cause Y.

4. Empirical Analysis

The empirical analyses were carried out for the balanced panel dataset, and all variables were transformed into a natural logarithm. The results are reported in the following sub-sections accordingly.

4.1. Descriptive Statistics, Correlation Matrix, and Cross-Section Dependency Test

The study used descriptive statistics, a correlation matrix, and a cross-section dependence test before applying the panel unit root. The descriptive statistics and correlation matrix were conducted to describe the characteristics of the model's variables and correlation analysis, and their results are shown in Table 5.

Table 5. Descriptive statistics and correlation matrix results of study variables' descriptive statistics.

Variables	Mean	Std. Dev.		Skew	Kurt	J-B		Obs.
$lnCO_2$	3.554	2.660		0.928	2.769	51.207 *		351
lnY	7.788	1.054		−0.482	2.424	18.472 *		351
lnIO	3.495	0.212		−0.172	2.378	7.391 **		351
lnUR	3.903	0.383		−0.492	2.119	25.528 *		351
lnFD	3.937	0.748		−0.160	1.772	23.561 *		351
lnTO	3.902	0.674		0.119	2.479	4.797 ***		351
lnNRE	4.289	0.242		−0.844	2.641	43.564 *		351
lnRE	3.095	0.692		−0.640	3.178	24.431 *		351

Correlation Matrix

Variables	$lnCO_2$	lnY	lnIO	lnUR	lnFD	lTO	lRE	lNRE
$lnCO_2$	1							
lnY	0.582	1.000						
lnIO	0.413	0.844	1.000					
lnUR	0.527	0.236	−0.072	1.000				
lnFD	0.361	0.376	0.128	0.439	1.000			
lnTO	0.186	−0.160	−0.253	0.457	0.432	1.000		
lnRE	−0.696	−0.668	−0.490	−0.315	−0.651	−0.324	1	
lnNRE	0.719	0.553	0.312	0.345	0.476	0.271	−0.826	1

Note: Table 5 reports mean, standard deviation (Std. Dev.), skewness (Skew), kurtosis (Kurt), and Jarque–Bera (J-B) test statistics for respective variables. The *, **, and *** represent 1%, 5%, and 10% levels of significance, respectively. In the first column, ln stands a natural log, and in the last column, obs. stands for observation.

In Table 5, it is obvious that the mean value of all variables, except the income level and non-renewable energy, is less than 4. The CO_2 variable, however, shows a wide dispersion as its standard deviation is relatively greater and has a value of 2.66. The skewness value is negative for all variables except CO_2 and trade openness (TO). The negative values show a skew towards the left while the positive skew towards the right. The positive and greater skewness value for CO_2 than zero indicates that the right tail is longer than the left. Kurtosis is positive for all variables, indicating a fat-tailed phenomenon.

Additionally, the results of the J-B tests look significant, showing that the data for all variables are not from the normal distribution. Furthermore, results show that all variables positively correlate with carbon emissions except renewable energy. Renewable energy is negatively correlated with carbon emissions. Notably, income level, renewable energy, and non-renewable energy show a high correlation with carbon emissions, whereas industrial output shows relatively less correlation.

Proceeding further, the model's cross-sectional dependency is tested. Two tests were used for this purpose, i.e., Breusch and Pagan (1980)'s [79] LM and M. H. Pesaran (2004)'s [80] CD tests. The models' results are based on a fixed effect estimator, derived from Equations (4) and (5), in which CO_2 is a dependent variable and Y, IO, UR, FD TO, NRE, and RE are explanatory variables. The test results are shown in Table 6.

Table 6. Cross-sectional dependency test results.

	Model-1 (Excludes Green Energy)		Model 2 (Includes Green Energy)	
Test	**Test-Statistic**	***p*-Value**	**Test-Statistic**	***p*-Value**
Bruesch-Pagen LM	245.82	0.000	388.76	0.000
Pesaran CD	−3.46	0.000	−3.42	0.000

Note: H_O: no cross-section dependence. Significance level; $p < 0.001$.

As we can see, the *p*-value is significant in the case of both LM and CD tests, indicating a strong cross-sectional dependence. Pesaran's test, however, could normally be used when the cross-section is larger than time. In our case, therefore, the LM test should be taken as T is > than N. This suggests that it is safe to reject the null and accept the alternative hypothesis and concludes that our models contain cross-sectional dependence under a fixed-effects assumption. We can also conclude that second-generation panel unit roots would produce a more consistent result than first-generation panel unit roots.

4.2. Panel Unit Root Results

Table 5 reports the results of panel unit root tests at the level and first difference for all study variables. In this paper, we applied unit root tests from both the "first-generation" and "second-generation" viewpoints. As discussed in the Methodology Section, we tested unit roots using LLC, MU, and CADF. Table 5 shows that the results of the panel unit tests are mixed, especially in the case of LLC. In the case of first-generation unit roots tests, the LLC test indicates that some of the variables are stationary at both levels and the first difference.

Similarly, the MU test suggests that all panels are non-stationary at the level, except the urbanization and non-renewable energy. However, all panels are stationary at the first difference, even at a 1% significance level. In the second-generation test case, the CO_2, income level (Y), and urbanization (UR) are stationary at a 5% significance level, while the other variables are non-stationary. In the first difference, except for the urban population (UR), CADF suggests stationarity with a strong significance level at the first difference. Consequently, all variables are first difference stationary. However, because of the clear cross-sectional dependency reported in Table 6, we decided to give more importance to the CADF test relative to the IPS and MU. Table 7 represents the panel unit root test statistics.

4.3. Results of the Panel Cointegration Test

This was found in unit root results, that all panel series are stationary at first difference. The panel cointegration is therefore tested to determine whether or not cointegration exists between the model variables. First, we employed Pedroni's panel cointegration [86]. The model includes intercept only and intercept and trend, and no-cointegration is assumed as the null hypothesis. The test results are reported in Table 8. The estimated results of Pedroni's test suggest rejecting the null hypothesis and accepting the alternative, supporting the presence of cointegration in cases of "intercept only" and "intercept and trend". In the first case, only two tests, i.e., ADF and PP, confirm cointegration with a significance level of 1%. However, in the second case, even modified PP test results conclude that the cointegration relation between variables is significant at 5%. We have also tested Kao panel cointegration, where Kao introduced parametric residual-based panel cointegration. Thus, Kao's test results also show that model variables are cointegrated and have a long-run relationship, irrespective of the test statistics (see Table 9). There is enough evidence to reject the null hypothesis of no cointegration at a 1% significance level since the results show that cointegration exists between variables.

Table 7. Results of panel unit root test statistics.

Variables	LLC		CADF Unit Root		MW Unit Root	
	Level	1st-Diff.	Level	1st-Diff.	Level	1st-Diff.
$lnCO_2$	0.77 (0.781)	−7.55 * (0.000)	−2.10 ** (0.018)	−12.11 * (0.000)	11.11 (0.889)	320.99 * (0.000)
lnY	1.23 (0.891)	−8.08 * (0.000)	−1.79 ** (0.037)	−11.42 (0.000)	2.21 (1.000)	187.06 * (0.000)
lnIO	−2.05 (0.019) **	−7.19 * (0.000)	0.59 (0.725)	−11.13 * (0.000)	24.580 (0.136)	250.66 * (0.000)
lnUR	0.65 (−0.743)	−2.99 * (0.001)	−4.52 * (0.000)	0.89 (0.812)	337.02 * (0.000)	16.72 (0.542)
lnFD	−1.37 (0.085) ***	−7.62 * (0.000)	0.15 (0.561)	−9.97 * (0.000)	18.49 (0.417)	216.92 * (0.000)
lnTO	−1.66 (0.048) **	−8.61 * (0.000)	−1.99 (0.139)	−8.54 * (0.000)	19.81 (0.343)	203.38 * (0.000)
lnNRE	−3.66 (0.000)	−7.61 (0.000)	−1.58 (0.057)	−11.11 * (0.000)	29.71 (0.040) **	297.61 * (0.000)
lnRE	2.64 (0.996)	−7.46 (0.000)	−1.47 (0.071)	−10.09 * (0.000)	4.38 (0.999)	255.13 * (0.000)

Note: A model with a constant for all variables was selected as a test model. The bracket values are *p*-values. The *, ** and *** indicate significance levels at 1% 5% and 10%, respectively. The MU test results are based on Chi-square test statistics. In the CADF test suggested by Pesaran, H_0 for all tests is that the variables are I(1), and used the STATA routine pescadf. In Maddala and Wu (MW) [82], H_0 is the unit root and we used the STATA routine xtfisher.

Table 8. Pedroni test results for cointegration (Pedroni, 1999 and 2001) [84,86].

Test Statistic	Included Intercept	Included Intercept and Trend
Modified Phillips-Perron t	−1.173 (0.120)	2.168 ** (0.015)
ADF t Statistics	−3.371 * (0.000)	−4.379 * (0.000)
PP t Statistics	−3.309 * (0.000)	−3.774 * (0.000)

Note: the null hypothesis is that the variables are not cointegrated, while the alternative assumes 'that all panels are cointegrated. The * and ** indicate the rejection of the null hypothesis at 1% and 5%, respectively.

Table 9. Kao test results for panel cointegration (Kao, 1999). [85].

Test Statistic	Statistic	*p*-Value
Modified Dickey-Fuller	−2.366 *	0.009
Dickey-Fuller t	1.740 **	0.041
Augmented Dickey-Fuller t	−1.953 **	0.025
Unadjusted modified Dickey-Fuller t	−2.200 **	0.014
Unadjusted Dickey-Fuller t	−1.672 **	0.047

Note: The model includes constant only. The null hypothesis is that the variables are not cointegrated, while the alternative. The * and ** indicate the rejection of the null hypothesis at 1% and 5%, respectively.

4.4. Fully Modified OLS Results

Given that the selected model variables are cointegrated, next to that we estimated the long-run relationship. For this, we employed Pedroni's FMOLS estimator and included the only constant in the cointegration relationship using FMOLS. The study variables are stationary in a different order of integration. Therefore, FMOLS is used as a robust test. The FMOLS test results are reported for both pooled and weighted estimation in Table 10.

Table 10. Panel of fully modified OLS results.

	Dependent Variable = LN_CO$_2$			
Method	**FMOLS (Pooled)**		**FMOLS (Weighted)**	
Variable	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
lnY	0.603 *(3.25)	0.061 (0.34)	0.519 * (35.47)	0.076 * (3.47)
lnIO	1.901 * (4.16)	1.257 * (3.14)	1.728 * (77.75)	1.408 * (57.31)
lnUR	5.746 * (7.74)	4.912 * (7.13)	5.747 * (1744.70)	4.739 * (729.02)
lnFD	−0.292 (−1.42)	−0.368 ** (−2.06)	−0.197 * (−25.16)	−0.307 * (−30.91)
lnTO	−0.884 (−3.67)	−0.845 * (−3.63)	−0.634 * (−29.94)	−0.778 * (−83.18)
lnNRE		0.885 (1.38)		0.687 * (41.09)
ln RE		−1.599 * (−5.58)		−1.560 * (−111.72)
R^2	0.958	0.968	0.958	0.967
Adj. R^2	0.956	0.966	0.957	0.966

Note: the * and ** indicate 1% and 5% significance levels, respectively. The bracket values are *t*-test values. Only intercept is included in the model. Bartlett kernel with Newey–West fixed bandwidth is used.

To estimate the specified regression given in Equations (4) and (5), we ran FMOLS, and the results are reported in Table 10. Almost all coefficient estimates are statistically significant, regardless of the panel method. It should be noted that Pedroni (2001) [86] proposed pooled weighted FMOLS estimates. When the models are estimated with a weighted panel method, the elasticity coefficient varies from −01.59 to 4.91 and from −1.56 to 4.73, respectively. Irrespective of the models, the main results confirm the significant positive relationship between domestic income level and CO$_2$, industrial output and CO$_2$, and urban population and CO$_2$. The results show that the Y, IO, and UR coefficient values are in the ranges 0.06–0.60, 1.25–1.90, and 4.73–5.75, respectively. These positive results are consistent with the findings of various previous studies, see for instance (Al-mulali et al. [11]; Salahuddin & Gow, [91]; Yang et al. [16]). Instead, Yao et al. [92] and Shuai et al. [93] found a negative association between urbanization and emissions of CO$_2$. In contrast, there is a negative relationship between financial development and CO$_2$ and trade openness and CO$_2$, and the coefficient values in pooled estimation are −0.36 and −0.84 for financial development and trade openness, respectively. These negative effects of the FD are consistent with studies conducted by Khan et al. [37], and our results corroborated with Sinha and Shahbaz [94], Afridi et al. [95], Syed [96], and Syed et al. [97] for trade openness. Furthermore, the results from FMOLS (pooled) indicated that NRE is positive but insignificant in explaining the CO$_2$ of the panel. If we consider this in FMOLS (weighted), then non-renewable energy is positive and significant in explaining the CO$_2$ of the panel. This implies that non-renewable energy is insufficient in reducing CO$_2$ in selected nine new industrialized countries. Instead, the coefficient of renewable energy (RE) is negative and significant in both cases. The coefficient of RE is around 1.59 and significant at the 1% level, indicating that a 1% increase in RE contributes to reducing CO$_2$ emissions by 1.59% in the long run for nine NICs.

Proceeding further, it is observed that a strong positive relationship runs from GDP per capita, industrial output, and urbanization to CO$_2$ emissions, and a negative relationship runs from financial development and trade openness to CO$_2$ emissions. The coefficient estimates are highly elastic for urbanization in the models. It is also elastic for industrial output and renewable energy, whereas it is less elastic for financial development. Hence,

by applying the method of FMOLS, we investigated the long-run relationship between variables of the model. Our methodology is in line with the study by Neagu [98] on European countries that used FMOLS (see also, Mitić et al. [99]). However, for the robustness and validity of the results, we extracted the residuals and tested them for white noise to ensure that our long-run model results are not spurious (see Table 11). The results indicate that in both cases, the residuals are stationary at that level, indicating that our results are consistent and unbiased and that the long-run regression model is not spurious.

Table 11. Test for residuals of regression model.

Model	Method	Statistic	Prob.
FMOLS (Pooled)	LLC test	−4.212	0.000
FMOLS (Weighted)	LLC test	−4.304	0.000

4.5. Panel Causality Tests Results

The directions of causality are tested using the Engle–Granger approach and DH approach. Table 12 represents the results of Equation (5) causality tests, including all the variables that have causality with CO_2 emissions. The full test pairwise significant results are given in Appendix A. If the *p*-values of the respective test statistic are significant at 1% and 5%, then reject the null hypothesis of non-causality and accept the alternative. In Granger causality, industrial output, urbanization, financial development, trade openness, non-renewable energy, and renewable energy are significant at 1%, while GDP per capita is significant at 10%, so we reject H_0, which indicates unidirectional causality.

Table 12. Panel causality test results (Granger causality and Dumitrescu–Hurlin).

Statement of Null Hypothesis	Granger Causality		Dumitrescu–Hurlin		
	F-Stat	Prob.	W-Stat	Zbar Stat	Prob.
Y does not Granger cause CO_2	2.628 ***	0.073	4.634 *	3.288 *	0.001
CO_2 does not Granger cause Y	0.097	0.907	1.893	0.315	0.752
IO does not Granger cause CO_2	5.143 *	0.006	5.801 *	4.824 *	0.000
CO_2 does not Granger cause IO	0.959	0.384	2.697	9.741	0.458
UR does not grange cause CO_2	4.679 *	0.009	4.494 *	3.106 *	0.002
CO_2 does not Granger cause UR	1.329	0.266	5.462 *	4.379 *	0.000
FD does not Granger cause CO_2	6.930 *	0.008	2.900	1.009	0.313
CO_2 does not Granger cause FD	0.775	0.379	3.275	1.503	0.133
TO does not Granger cause CO_2	5.642 *	0.004	4.421	2.974 *	0.003
CO_2 does not Granger cause TO	0.907	0.405	3.254 ***	1.578 ***	0.094
NRE does not Granger cause CO_2	4.749 *	0.009	4.409 *	2.994 *	0.0003
CO_2 does not Granger cause NRE	0.738	0.478	2.602	0.617	0.537
RE does not Granger cause CO_2	4.988 *	0.007	4.426 *	3.016 *	0.002
CO_2 does not Granger cause RE	0.607	0.512	3.301	1.536	0.124

Note: the * and *** denote that the null is rejected at 1%, and 10%, respectively.

Similarly, the DH causality test results show that GDP per capita (Y), industrial output (IO), non-renewable energy (NRE), and renewable energy (RE) are significant at 1%, indicating unidirectional causality from GDP per capita, industrial output, non-renewable energy, and renewable energy to CO_2 emissions. Urbanization (UR) has significant values of 1%, so we reject the null hypothesis, and the results indicate a bidirectional causality relationship between urbanization and CO_2 emissions. The CO_2 and trade openness (TO) are significant at 10%, indicating weak bidirectional causality. The DH test results are insignificant for financial development (FD) and CO_2, so accept the null hypothesis of non-causality. Consequently, unidirectional causality was found between domestic output, industrial output, non-renewable energy, and CO_2 emissions, while bidirectional causality

runs from urbanization and renewable energy to CO_2 emissions. The causality between CO_2 emissions and financial development is not significant. For complete significant results of the panel causality tests see Appendix A.

5. Conclusions and Policy Implications

The prime objective of the study is to find the long-run estimates of CO_2 emissions and the causal relationship between industrial output, financial development, gross domestic product, trade openness, non-renewable energy, renewable energy, and CO_2 emissions for the panel of NIC countries using data for the period from 1980 to 2019. To the best of our knowledge, only a few studies have investigated the causal relationship between carbon emissions and variables like GDP, energy consumption, trade openness, and urbanization in the case of new industrialized countries. In this research, the omitted variable bias is addressed by focusing on variables like industrial production and financial development, which have attained little attention in previous research work. Furthermore, previous research has concentrated on the energy use effects without considering the energy consumption structure (i.e., renewable and conventional energy). Thus, our study covers both forms of energy usage, which can provide essential information for successful energy policies that contribute to attaining long-term development goals.

We tested the model's variables for cross-sectional dependence, unit root, and long-run relationship before estimating for the long-term effects of GDP, energy consumption, trade openness, and urbanization on carbon emissions. The findings show that all variables become stationary after the first difference and that the model variables in the panel of newly industrialized countries have a long-run relationship. Economic growth, industrial output, urbanization, and non-renewable energy have long-term positive effects on CO_2 emissions, while financial development, trade openness, and renewable energy have negative effects on CO_2 emissions during the period of analysis. Furthermore, industrial output, urbanization, and renewable energy strongly influence CO_2 emissions in the countries analyzed.

Additionally, a significant bidirectional causality was found between CO_2 emissions and urbanization. Instead, significant pairwise unidirectional causality was found between domestic output and CO_2, industrial output and CO_2, non-renewable energy and CO_2, and renewable energy and CO_2 emissions, while insignificant unidirectional causality between CO_2 emissions and financial development. The results indicate that increasing effects of industrial output and urbanization rises CO_2 emissions, while the increase in trade openness and renewable energy leads to reducing CO_2 emissions.

The study results propose some policy implications as follows. The industrial output has a positive relationship with carbon emissions. Therefore, governments of newly industrialized nations can set emission standards to control carbon dioxide and other pollutants during production. Furthermore, it is suggested that governmental and commercial sectors focus on ecologically friendly, contemporary processing, and efficient production methods. Likewise, the newly industrialized countries must use environmentally friendly resources as their inputs to achieve economic growth without degrading the environment. Financial development has a negative association with emissions of CO_2. The study recommended that newly industrialized countries extend their financial resources to achieve high economic output.

Future research on the theme should focus on the variables, such as democracy and population, as well as the relationship between industrial production, financial development, and the environment, using disaggregated data from other developing/emerging blocs. Finally, circumstances in different developing countries may differ significantly. As a result, future research should examine broadening the analysis to include the cases of other emerging areas, such as South Asia, East Asia, and the Pacific; the Middle East and North Africa; and Latin America and the Caribbean. Such extensive evaluations can significantly contribute to reaching a broad conclusion about the influence of industrial activity and financial development on CO_2 emissions.

Appendix A Complete Significant Results of the Panel Causality Tests

Table A1. Panel Granger causality and DH causality test results for all variables.

Null Hypothesis Test	Granger Causality Test		Dumitrescu–Hurlin Causality Tests		
	F-Stat	*p*-Value	W-Stat.	Zbar-Stat.	*p*-Value
Y does not Granger cause CO_2	2.628 ***	0.074	4.633 *	3.288 *	0.001
IO does not Granger cause CO_2	5.1423 *	0.006	5.801 *	4.824 *	0.000
UR does not Granger cause CO_2	4.679 *	0.009	4.494 *	3.106 *	0.002
CO_2 does not Granger cause UR	1.329	0.266	5.463 *	4.379 *	0.000
TO does not Granger cause CO_2	5.642 *	0.004	4.421 *	2.974 *	0.003
NRE does not Granger cause CO_2	4.749 *	0.009	4.409 *	2.994 *	0.003
RE does not Granger cause CO_2	4.987 *	0.007	4.426 *	3.016 *	0.002
Y does not Granger cause IO	4.802 *	0.008	3.739 **	2.112 **	0.035
UR does not Granger cause Y	1.984	0.139	9.500 *	9.691 *	0.000
Y does not Granger cause UR	3.681 **	0.026	5.606 *	4.568 *	0.000
Y does not Granger cause FD	3.789 **	0.024	5.568 *	4.518 *	0.000
TO does not Granger cause Y	2.409	0.091	8.016 *	7.739 *	0.000
Y does not Granger cause TO	0.331	0.718	5.691 *	4.679 *	0.000
NRE does not Granger cause Y	1.022	0.3609	3.678 **	2.033 **	0.042
RE does not Granger cause Y	1.241	0.290	3.859 **	2.269 **	0.023
Y does not Granger cause RE	0.435	0.647	3.706 **	2.069 **	0.039
UR does not Granger cause IO	3.554 **	0.029	5.639 *	4.612	0.000
FD does not Granger cause IO	9.340 *	0.000	5.788 *	4.808 *	0.000
IO does not Granger cause FD	0.179	0.836	4.143 *	2.644 *	0.008
IO does not Granger cause TO	0.312	0.732	4.169 *	2.678 *	0.007
IO does not Granger cause NRE	0.172	0.842	5.622 *	4.589 *	0.000
IO does not Granger cause RE	1.217	0.297	4.288 *	2.834 *	0.005
FD does not Granger cause UR	4.055 **	0.018	5.229 *	4.073 *	0.000

Table A1. *Cont.*

Null Hypothesis Test	Granger Causality Test		Dumitrescu–Hurlin Causality Tests		
	F-Stat	*p*-Value	W-Stat.	Zbar-Stat.	*p*-Value
UR does not Granger cause FD	0.206	0.814	4.284 *	2.829 *	0.005
TO does not Granger cause UR	1.518	0.221	4.768 *	3.466 *	0.000
UR does not Granger cause TO	0.740	0.478	7.317 *	6.819 *	0.000
NRE does not Granger cause UR	5.659 *	0.004	4.851 *	3.574 *	0.000
UR does not Granger cause NRE	4.764 *	0.009	8.113 *	7.866 *	0.000
RE does not Granger cause UR	2.010	0.135	9.311 *	9.442 *	0.000
UR does not Granger cause RE	0.782	0.45	4.604 *	3.249 *	0.001
TO does not Granger cause FD	0.936	0.39	4.084 **	2.566 **	0.010
FD does not Granger cause TO	1.035	0.356	4.094 *	2.579 *	0.009
FD does not Granger cause NRE	1.208	0.299	3.675 **	2.029 **	0.042
RE does not Granger cause FD	0.197	0.821	3.965 **	2.410 **	0.016
NRE does not Granger cause TO	2.514 ***	0.082	4.934 *	3.685 *	0.000
RE does not Granger cause TO	2.346 ***	0.097	5.006 *	3.779 *	0.000

Note: the */**/*** represent 1%, 5%, and 10% significance levels, respectively. The lag length specified is 2.

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