AN ANALYSIS ON THE FACTORS ON CO2 EMISSION IN THE TOP FIVE CARBON EMITTING COUNTRIES

MOK JING WEI

BACHELOR OF ECONOMICS (HONOURS)
GLOBAL ECONOMICS

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT
DEPARTMENT OF ECONOMICS

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BY

MOK JING WEI

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the research project.

(4) The word count of this research report is ___13,195________.

Name of Student:	Student ID:	Signature:
_MOK JING WEI______	_21UKB01781___	__________________

Date: ___3 MAY 2024_____

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DEDICATION

This research is dedicated to those who have supported me throughout my journey of academic and personal growth.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey Fuller
CD	Cross-sectional Dependence
CO2	Carbon Dioxide
COP26	26th UN Climate Change Conference of the Parties
EC	Energy Consumption
EKC	Environmental Kuznet Curve
FEM	Fixed Effects Model
GDP	Gross Domestic Product
GLS	Generalized Least Squares
LM	Lagrange multiplier
NZE	Net Zero Emissions
POLS	Pooled Ordinary Least Squares Model
POP	Population Growth
REC	Renewable Energy Consumption
REM	Random Effects Model
Solar PV	Solar Photovoltaic
UNFCCC	United Nations Framework Convention on Climate Change
VIF	Variance Inflation Factors

PREFACE

The rapid rise of the global economy over the past few decades has led to extraordinary scientific and technical advancements, as well as social development. However, it has also posed a serious threat to the environment. The swift expansion of industrialization, urbanization, and transportation systems not only contributes to environmental degradation but also exacerbates the problem of global climate change. A continuous increase in CO_2 emissions has become one of the primary drivers of global warming. Given the growing global demand for green and renewable energy, developing these technologies has become a key strategy for reducing CO_2 emissions and addressing climate change.

Therefore, the motivation for this study arises from a deep concern about the environment issue. This research investigates the relationship between energy consumption, population growth, GDP per capita, renewable energy, and CO_2 emissions in five countries. The study aims to provide important insights and recommendations for reducing CO_2 emissions and promoting environmentally sustainable development worldwide.

ABSTRACT

Climate change is one of the global issues today. Carbon dioxide emission is one of the main causes of global climate change. This study investigates the effects of per capita GDP, population growth, energy consumption and renewable energy consumption on carbon dioxide emissions in the top five carbon emitting countries from 1990 to 2020. In this study, panel data was analyzed by using quantitative research design and second-hand data to evaluate the relationship between these variables and their impact on carbon dioxide emissions. The survey results show that population growth, energy consumption and per capita GDP have significantly increased carbon dioxide emissions, highlighting the key role of economic activities in environmental degradation. On the contrary, the increase of renewable energy consumption is associated with the decrease of carbon dioxide emissions. The results show that renewable energy can be effectively used as a strategy to slow down climate change. The significance of this study is very important for policy makers and stakeholders to formulate strategies to deal with the dual challenges of economic development and environmental sustainability in the context of global climate change.

CHAPTER 1: RESEARCH OVERVIEW

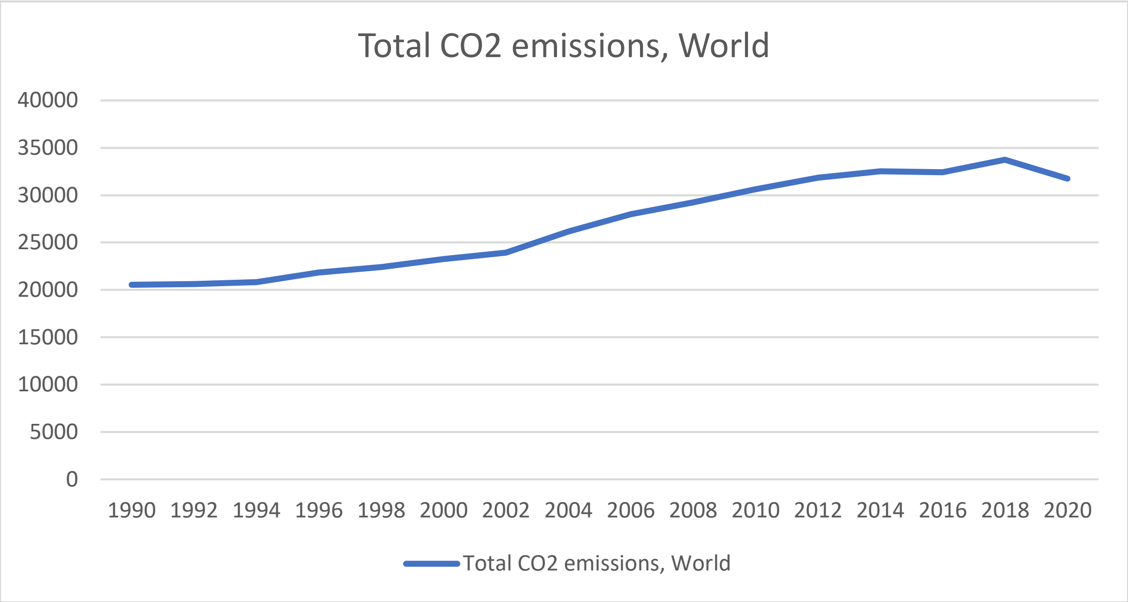
1.0 Introduction

The first chapter introduces the background on CO2 emissions in the top five carbon-emitting countries. It summarizes the current situation with CO2 emissions in the five nations. Additionally, it also discusses the problem statement, the objectives of the research, and the research questions. The significance of the study is explored in terms of its implications, particularly in shaping climate policy and economic strategies. Finally, the layout of the subsequent chapters is summarized to provide a roadmap of the investigation and its expected conclusions.

1.1 Research Background

In the past few years, global economic growth has been rapidly advancing due to industrialization and economic activities. According to World Bank data (2023), the global GDP has seen a significant increase, rising from $36 trillion in 1990 to $82.12 trillion in 2020 (constant 2015 US dollars). These developments are closely linked to human activities. The global population is also steadily growing, going from 5.29 billion in 1990 to 7.82 billion in 2020, which is 1.5 times the 1990 figure. One noticeable trend associated with this economic and population growth is a sharp rise in global energy consumption (Dong et al., 2018). The increasing population leads to a high demand for energy, primarily met through burning fossil fuels. Major global energy sources, including natural gas, coal, and oil, collectively make up over 80% of the total energy consumption (Kahouli et al., 2022). However, burning fossil fuels releases a significant amount of greenhouse gases.

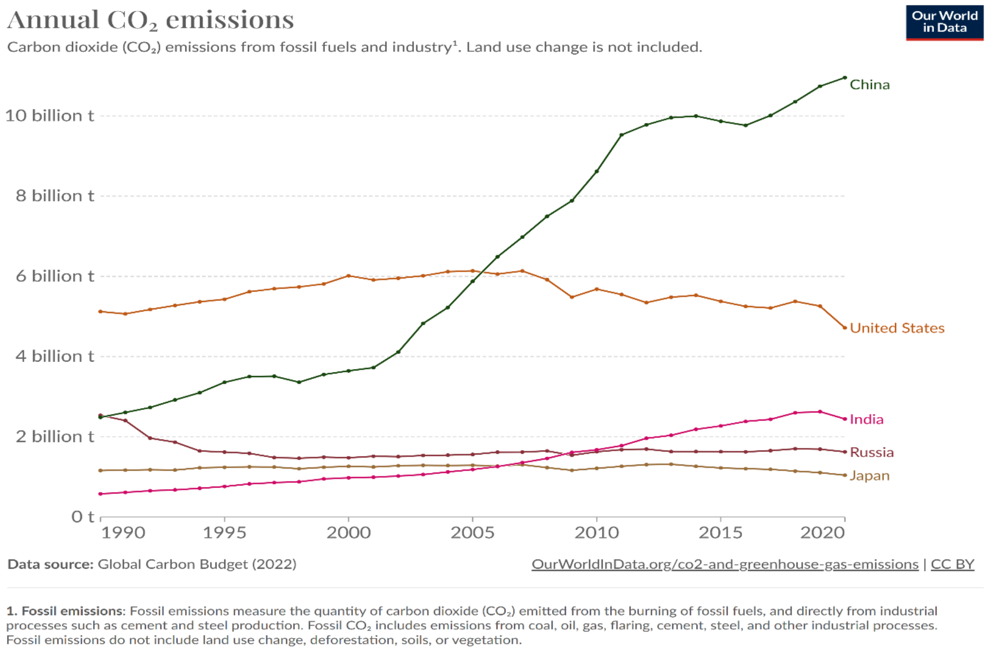
Figure 1.1 Atmospheric CO_2 levels from 1990 through 2020



Source: EIA (2023)

The increase in greenhouse gas emissions has had serious impacts on climate change. Among the various greenhouse gases contributing to climate change, the role of CO_2 is crucial. As shown in Figure 1.1, global CO_2 concentrations have been consistently rising since 1990. Due to the long atmospheric residence time of CO_2, the heat it absorbs leads to further warming of the earth, profoundly affecting the worldwide ecosystems. Adverse effects include rising sea levels, global temperature increases, droughts, and imbalances in precipitation (United Nations, 2023). The establishment of international organizations such as UNFCCC and the convening of international climate change conferences like the 2015 Paris Climate Conference are designed to bring more attention to the issue of climate change.

Figure 2.1 The Co2 emissions of top 5 emitting countries (1990 - 2020)



Source: Our World In Data

In the global context, the top five carbon-emitting countries included both developed and developing nations. China stands out as the largest emitter, drawing widespread global attention to its emission levels. The country has implemented numerous climate change strategies and actively participated in various climate change policies and action plans (Ng & Ren, 2018).

The United States has consistently been the second-largest greenhouse gas emitter since 2005. Approximately 81% of its greenhouse gas emissions are attributed to carbon dioxide, with 93.1% of CO2 emissions in 2018 originating from fossil fuel combustion (Jeon, 2022). Policies such as Clean Air Interstate Rule and Cross-State Air Pollution Rule have been employed by the U.S. government to establish tradable permit systems and restricting emissions.

India, a developing country with severe pollution issues in South Asia, ranks third globally in carbon emissions. Apart from adopting appropriate strategies to reduce annual carbon emissions, India committed to emission reductions at COP26, aiming for carbon neutrality by 2070. However, India has faced challenges in effectively implementing carbon reduction policies, leading to issues in fulfilling environmental commitments and substantial pressure on its environmental indicators (Alamo et al., 2023). Russia and Japan exhibit relatively stable carbon emissions. Japan's emissions have remained relatively steady since 1990, with a notable increase in 2011 primarily attributed to the Fukushima nuclear disaster (Ortega-Ruiz et al., 2022).

However, Bilgili et al. (2016) and Dong et al. (2018) indicate that renewable energy is the optimal choice to overcome the challenges of environmental degradation, reduce Co2 emissions and energy depletion. In the developed economies, the incorporation of renewable energy has been shown to reduce CO2 emissions. Renewable energy is a broadly accepted approach to environmental sustainability since it is an appropriate substitute for fossil fuels (Bhattacharya et al., 2017). In general, the demand for emission reduction has led to a major shift in favour of renewable energy rather than traditional energy. Therefore, researchers advocate the implementation of climate change policies in the economy, increased use of green energy and energy-efficient technology. It can successfully address issues such as temperature rise and climate change.

1.2 Problem Statement

The global Co2 concentration is rising. In 1990, the total emission was 20,540.49 million metric tons, which will increase to 31,739.55 million metric tons in 2020. Although the total emissions in 2020 will temporarily decline due to the pandemic, but this is only a short-term decline. Many countries have implemented climate change adaptation plans and strategies, and international agreements such as the Paris Agreement has also set binding emission reduction targets to curb national carbon emissions, but the global Co2 emissions are still increasing.

As the impact of climate change becomes more obvious, the global society is facing an urgent challenge: reducing Co2 emissions. Extensive research has established a clear relationship between climate change and greenhouse gas emissions. The results have provided evidence of the significant consequences related to CO_2 emissions. Unfortunately, the sustained expansion of economic activities leads to an increase in energy consumption (Ortega-Ruiz et al., 2022), this has aggravated the problem of Co2 emissions. This complex situation highlights the difficulties and barriers faced by emission reduction efforts. Although various measures have been taken by the international community, such as the formulating policies, advocating for sustainable practices, and promoting renewable energy, the continuous upward trend of carbon dioxide emissions shows that the current efforts are not enough.

Over the past few decades, the rise of industrialization and its consequent global economic activities have resulted in significant advancements in GDP, the use of renewable energy technologies, energy consumption and population growth. However, the development has come along with an increase in CO_2 emissions, which poses a serious threat to global climate stability. This problem is particularly prominent in the top five carbon emitting countries, and their economic growth and energy consumption patterns have greatly influenced the global emission trend. In addition, the proportion of these countries in the global population is also very significant. The rapid growth of population may bring many challenges, such as the increase in energy demand (Al-multi et al., 2013). This might explain why the top five carbon emitting countries have seen a significant growth in energy consumption and CO_2 emissions in the last 30 years. In 2020, the share of renewable energy in the final use of energy in these nations was between 4% and 17%. (EIA, 2024). This is still a relatively small percentage. Fossil fuels remain the main energy sources for these countries.

The world's biggest economy is United States, accounting for about 24% of global GDP, followed by China with 18% of global GDP. Japan, Russia, and India are also important economies, which together contribute about 12% of the world's total GDP. These five major emitters are often chosen as the targets of academic analysis because of their prominent role in global economic growth, especially China and the United States. These countries are not only global carbon emitters, but also play a central role in global economy and environmental policies. Their policy choices and development trends have a far-reaching impact on the trend of global climate change and the international community's efforts to reduce emissions. Therefore, it is critical to understand and analyse the effects of economic, population, and consumption of energy patterns of these countries on Co2 emission for create effective climate strategies.

Although renewable energy has the capability to decrease the release of CO2, costs of investment and storage constraints limit its effectiveness (Chen, Pinar and Stents, 2022). Solar PV is the only renewable energy technology (NZE) that is expected to achieve zero emission by 2050 (IEA, 2024). During the period of 2023-2030, the annual consumption of renewable energy must increase by an average of 13% to achieve NZE. However, the consumption percentage of renewable energy in these five nations is relatively low (between 4% and 17%). The lack of policy and market support is a key factor restrict the development of renewable energy (Lehmann, 2012). For example, the lack of sufficient government incentives (such as subsidies and tax incentives) and the immaturity of the renewable energy market have limited the practical benefits of these technologies. Therefore, the effectiveness of renewable energy in reducing CO2 emissions can differ across diverse economic and demographic contexts.

The reason to choose these five countries is because of their significant contribution to global emissions, accounting for half of the world's total (China 31.07%, United States 13.73%, India 6.93%, Russia 4.61%, Japan 2.96%). They also represent key economic entities globally, especially the United States and China. Indeed, there are notable differences globally in terms of economic growth, carbon emissions, population size , and renewable energy consumption (Hoogwijk, 2004). These five countries encompass both developed and developing nations, with disparities in population and economic growth. Therefore, studying these five countries may yield insightful results.

1.3 Research Questions

1.3.1 General Research Question

What is the effect of GDP per capita, population growth, energy consumption, and renewable energy consumption on Co2 emission?

1.3.2 Specific Research Questions

i. How do the GDP per capita, population growth, energy consumption, and renewable energy consumption affect the CO2 emissions?

ii. What is the long run relationship between the significant factors and Co2 emission in top 5 carbon-emitting countries.

1.4 Research Objectives

1.4.1 General Research Objective

To identify the factors affecting Co2 emission in top 5 carbon-emitting countries.

1.4.2 Specific Research Objectives

i. To investigate the influences of per capita GDP, population growth, energy consumption, and renewable energy utilization on CO2 emissions in top 5 carbon-emitting countries (China, Japan, the United States, India, and Russia).

ii. To analyse the long run relationship between CO2 emissions, per capita GDP, population growth, energy consumption, and renewable energy utilization in top 5 carbon-emitting countries.

1.5 Significance of the Study

Based on the existing literature, this study further expands and deepens the analysis of the emission factors of the top five Co2 emitters in the world, and the time span extends to 2020. The study can be more comprehensively captures the evolution trends of CO2 emissions over the past thirty years in these major emitting countries through the detailed examination of this timeframe and reveal the main trends and influencing factors that may lead to emission changes. The extension of this time range has given a foundation for providing more timely and relevant data, thus the overall value and practicability of the research results can be enhanced.

Besides, the study also focuses on the macro background of global climate change. The increase in the concentration of Co2 and other greenhouse gases in the earth's atmosphere is closely related to the impact of major climate change such as rising global temperature, melting polar ice sheets and increasingly frequent extreme weather events. Therefore, it is very important to fully understand how these factors affect global climate change together. The study also analyzes the influence of renewable energy consumption on the emission status of these countries. It also predicts that it may become a key manner to reduce Co2 emissions. This expectation is based on the preliminary observation of the global energy consumption trend and the development of renewable energy technology. It is believed that the use of renewable energy will provide a new way to reduce the global carbon footprint.

1.6 Chapter Layout

Chapter 1: Introduction

The first chapter highlights emissions of carbon dioxide trends in global and the five largest emitters. This chapter also discusses the background of economy, energy consumption and population of the country. Besides, the problem statement, significance of study , research objectives and questions are discussed in 1.2, 1.3, 1.4 and 1.5 respectively. Moreover, the section 1.6 outlines the layout of the entire chapter.

Chapter 2: Literature Review

Chapter 2 covers the existing literature on various aspects related to CO2 emission. This chapter will cover a deeper literature study to clarify the relationships between both the emission of Co2 and the driving factors. It also analyses theoretical models such as the EKC theory and identifies gaps from existing research. In addition, this chapter also discusses conceptual framework and hypothesis development.

Chapter 3: Methodology

Chapter 3 introduces in detail the research design and data collection methods. The definition of the variables also covered in this chapter. Meanwhile, this chapter also explained the statistical models and tests adopted, including panel data model and diagnostic test to verify the hypothesis of econometric model.

Chapter 4: Data Analysis

The data analysis is performed in Chapter 4. It presents descriptive statistics, correlation analysis, and the results of panel model estimations. The chapter also includes diagnostic checks such as tests for heteroskedasticity, autocorrelation, and multicollinearity.

Chapter 5: Finding, Implication and Conclusion

The final chapter summarizes the findings from Chapter 4 and discusses the implications of the study. It also outlines the limitations of the current study as well as provides suggestions for future studies.

1.7 Conclusion

In summary, this chapter provides background information on CO2 emissions from the top five carbon emitters, as well as the problem statement, research objectives, and questions. Then, this chapter has outlined the chapter layout and conclusion. Next, Chapter 2 will discuss the literature reviews related to the study.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

In this chapter, the literature review presents the findings and analyses of other researchers on the factors affecting CO2 emissions. Additionally, this section will include the literature review on the impact of per capita GDP, energy consumption, population growth, and renewable energy consumption on CO2 emissions. It also summarizes the theoretical support for the study, the conceptual framework for CO2 emissions in this research, and the development of hypotheses.

2.1 Review of the Literature

2.1.1 Co2 Emission

Carbon dioxide is a gas that causes greenhouse effects. It may keep heat in the atmosphere, then contribute to the global warming. Human activities have greatly raised its concentration, such as open burning, deforestation, fossil fuel consumption and production activity. Although the pandemic has caused a slowdown in economic growth, the climate crisis still exists. In 2020, the COVID-19 pandemic significantly slowed down human activities, and lead to a temporary decrease in global Co2 emissions. Developed countries have the biggest decline, with an average decline of nearly 10%, and developing countries have also dropped by 4% compared with 2019 (United Nations, 2021).

The technical level, energy structure, economic structure, and population composition have the effect on carbon emission (Fan et al., 2006). The technology, population, and economics are the main variables affecting emissions, and these factors have different effects in different countries (Shi, 2003). Therefore, the main challenge in reducing carbon dioxide emissions lies in the connection between the economy and emissions. This means that it is necessary to balance economic growth and sustainable development goals to achieve emission reduction targets.

2.1.2 Energy Consumption and Co2 Emission

Energy is a critical input in the production process. It is widely utilized in a global scale. A stable energy supply is very important to maintain production and improving people's living standards in a country. Energy consumption is considered a prerequisite for sustainable development. In modern society, energy is not only the driving force of economic growth, but also an indispensable part of social operation and personal lifestyle. Therefore, it is very important to ensure a stable energy supply to maintain the normal operation of a country's economy and improving people's quality of life (Alam et al., 2016). Research by Dogan and Aslan (2017) indicated that energy consumption is a cause of CO2 emissions, because the increase in energy consumption will increase the emission level.

Some studies have found that increasing energy consumption leads to higher CO2 emissions (Begum et al., 2015; Zhou, 2023; Kanjilal and Ghosh, 2013). Additionally, Ertugrul et al. (2016), through VECM Granger Causality analysis of the top ten developing emitter countries, found that energy consumption stimulates environmental pollution, but long-term energy consumption does not result in economic growth. Wang et al. (2015) found that high energy intensity is a reason for the increase in carbon emission levels. Therefore, improving energy efficiency and reducing energy intensity through financial support can be achieved without increasing energy consumption. However, different results are found in other literature. Kanjilal and Ghosh (2013) revealed a long-run connection between consumption of energy and carbon emissions in India. Ghosh (2010) discovered no long-term connection between energy use and CO2 emissions in India, therefore invalidating the country's EKC theory.

Many studies have been conducted on energy use and carbon emissions, but there are still only a few papers available to test the hypothesis of the environmental

Kuznets curve based on the top five emitting countries, which indicates that conclusive evidence of a linear or nonlinear relationship between emissions of carbon dioxide and energy utilization has not been fully established.

2.1.3 GDP and Co2 Emission

In recent years, the positive relationship between GDP and Co2 emissions has been confirmed by many studies(Begum et al., 2015; Karaaslan & Çamkaya, 2022; Ahmad et al., 2018). Dong et al. (2018) investigated an imbalanced panel dataset of 128 countries from 1990 to 2014 and discovered that economic expansion had a positive relationship and significant influence on CO2 emissions at both global and regional levels. Souza Mendonça et al. (2020) examine the connection between CO2 and GDP in the 50 biggest economies. The result confirmed that GDP has a positive and significant influence on the emission of Co2.

Although the influence of GDP on CO2 emissions has been extensively investigated, certain empirical investigations on the EKC theory have shown different findings. Wang et al. (2017) and Liu et al. (2019) found that the EKC hypothesis is supported in China. Their findings reveal a reverse U-shaped trend in the connection between growth in the economy and carbon emissions. The research demonstrates that this inverted U-shaped relationship aligns with China's unique developmental characteristics during its actual economic growth stages. In recent years, the increasing demand for better environmental quality has prompted China to actively adjust its economic structure and increase the development of new energy sources, which has had a great impact on reducing Co2 emissions.

Furthermore, Begum et al. (2015) found a different conclusion for Malaysia. They found a U-shaped curve between Co2 emissions and per capita GDP by using ARDL boundary test, dynamic OLS and SLM U test. The results show that per capita Co2 emissions decrease with the increase of per capita GDP until a certain point, and then continue to increase with sustained economic growth. On the other hand, Li and Haneklaus (2022) found a non-linear EKC curve in the long term, which shows the complex relationship between CO2 and growth.

2.1.4 Population and Co2 emissions

Population growth is usually accompanied with an increased demand for resources, such as energy. More people may lead to more consumption and production activities, which will directly affect carbon emissions. The STIRPAT model developed by Rosa and Dietz (1998) suggests that population and economic activities are significant contributors to Co2 emissions. The population growth and environmental degradation pose challenges to the sustainable development of a country (Ohlan, 2015). Some literature supports the idea that population is a factor that contribute to an increase in Co2 emissions. The studies by Dong et al. (2018), and Souza Mendonça et al. (2020) indicate that Co2 emissions are positively affected by population.

A lot of EKC studies often has included linear variable specifications in research model to capture the impact of other important macroeconomic variables on environmental degradation measurement. For example, research by Begum et al. (2015), Alam et al. (2016), and Lantz & Feng (2006) used population as an explanatory variable to test the EKC hypothesis, but the results are inconclusive. In developing country, Begum et al. (2023) shows that in Malaysia, population growth does not significantly impact Co2 emissions. Alam et al. (2016) found a strong connection between CO2 emissions and growth in population.

The literature on the influence of population growth on CO2 emissions varies across nations. Some research supports the idea that population growth increases the demand for resources such as energy, thereby directly impacting carbon emissions. Alternately, several studies use population as an explanatory variable in EKC models; however, the findings are inconclusive.

2.1.5 Renewable Energy Consumption (REC) and Co2 Emission

Several research examined the relationship between renewable energy use and CO2 emissions. Significant improvements have been made in renewable energy technologies and the costs have been consistently decrease with the increase in R&D investment in the past few years. However, as renewable energy technologies continue to advance and a country's consumption of this energy exceeds a particular threshold, renewable energy consumption will become an increasingly important element in lowering CO2 emissions (Chen, Pinar and Stengos, 2022). Numerous studies have investigated the relationship between renewable energy consumption and CO2 emissions.

Li and Haneklausb (2022) used ARDL panel to assess the G7 countries, the results demonstrated that an increase in clean energy utilization reduces the release of CO2 within G7 economies. Similarly, Karaaslan & Çamkaya's (2022) study on Turkey for the period 1980-2016 yielded similar results. However, the study discovered that increased renewable energy usage leads to a drop in CO2, but CO2 only marginally increases in the short term when both short and long run elements are included. This is due to the large start-up cost necessary for renewable energy, which is expensive and has a smaller storage capacity than non-renewable energy sources. Therefore, the high investment costs and storage issues may result in the impact of REC on CO 2 emissions not being significant in the short run.

Several studies have concluded that there is a negative correlation between CO2 emissions and renewable energy usage (Adebayo & Kirikkaleli, 2021; Nathaniel & Iheonu, 2019; Dong et al., 2018). Adebayo & Kirikkaleli (2021) suggest that increasing investment in renewable energy consumption by strengthening the framework for clean energy generation and consumption can enhance environmental quality to ensure sustainability. Sustainable development required a sustainable energy supply. The renewable energy can be obtained at reasonable prices in the long term without causing adverse social impacts (Dincer, 2000).

Some literature has also investigated the causality between CO2 and REC. Karaaslan and Çamkaya (2022) using the Toda-Yamamoto causality test found unidirectional connection between REC and CO2. Radmehr et al. (2021) analyzed the relationship between CO2 and REC in European Union nations from 1995 to 2014 and discovered a bidirectional causal link between renewable energy and CO2 emissions. Next, Menyah and Wolde-Rufael (2010) found no causation between REC to CO2 emissions but identified the opposite unidirectional causality. Ben Jebli et al. (2020) a bidirectional correlation between renewable energy use and CO2 emissions in 102 countries using the Granger causality test. This directional connectivity implies that carbon emissions may be minimized by generating energy from renewable sources.

2.2 Review of theoretical models

2.2.1 Environmental Kuznets Curve

This theory posits an inverted U-shaped relationship between environmental pollution indicators and economic growth. Pollution emissions rise during the early phases of economic expansion, resulting in a decrease in environmental quality. During the processes of social development and industrialization, substantial natural resource consumption occurs, accompanied by the generation of significant waste. At this stage, the individual income or economic growth has a positive correlation with environmental degradation. However, as the economy progresses beyond a certain point, the trend reverses, and economic growth reduces pollution, improving the environment (Karaaslan & Çamkaya, 2022). Therefore, As a result, the EKC provides as a framework for understanding the connection between energy use, economic growth, and the environment. The connections between CO2 emissions and economic development can take several forms, such as linear, U-shaped, or inverted U-shaped.

Nevertheless, numerous studies have supported the EKC hypothesis. Liu et al. (2019) and Han et al. (2018) provide evidence supporting the EKC hypothesis for the relationship between economic growth and CO2 emissions. However, there are also studies criticizing this assumption. Begum et al. (2023), Shafik (1994), Robalino-López et al. (2015) argue that the EKC hypothesis is invalid. These empirical findings, both in support of and against the EKC theory, reflect potential variations in its applicability across different regions and countries. Factors such as economic conditions, environmental policies, and technological levels can influence the theory's performance in specific geographic contexts.

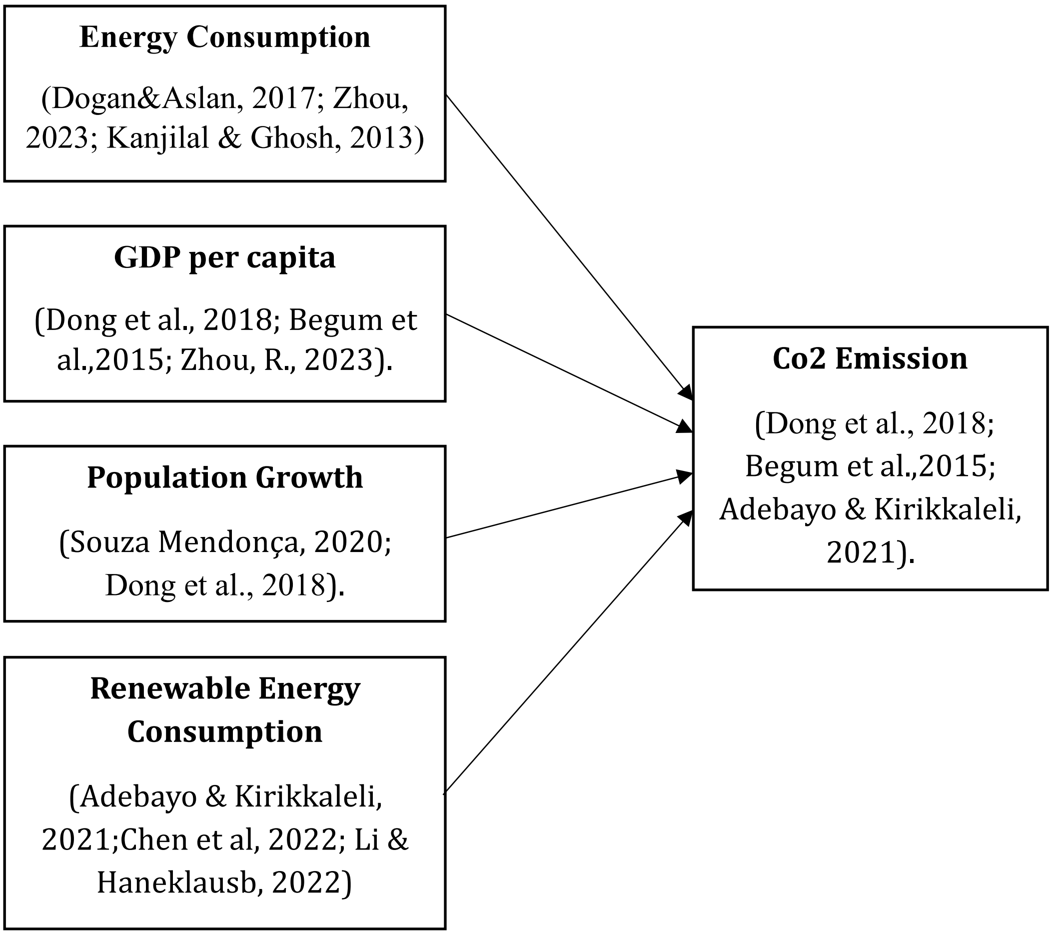
In numerous studies, Brock and Taylor's (2005) research illustrates three distinct mechanisms linking economic activities to pollution and emission measures: scale effect, composition effect, and technological effect. The scale effect suggests that as the economic scale increases, overall emissions may rise because larger-scale economic activities may trigger more production and resource usage, resulting in higher levels of pollution and emissions. Meanwhile, the composition effect emphasizes the significant impact of the composition structure of products and services in the economy on overall emission levels, with a shift toward more environmentally friendly products and services potentially reducing emissions. In this context, renewable energy becomes a key factor. The introduction of renewable energy involves the mechanism of technological effect. Technological effect works through improving emission reduction measures, enhancing energy efficiency, thereby lowering emissions per unit of output, which mean reducing emission intensity to mitigating adverse environmental impacts.

2.3 Research Gap

The current research reveals a concentration of studies on individual countries and groups such as OPEC, European Union and BRICS nations. However, there is still a gap in understanding the factors influencing CO2 emissions in the top five emitting countries. This research provides an opportunity for a more comprehensive investigation. Furthermore, while numerous studies have explored various factors contributing to CO2 emissions, there is insufficient literature specifically examining the relationships between GDP, population, energy consumption, renewable energy and CO2 emissions in these five countries. These four factors may exhibit variations due to differences in each country's economic structure, culture or consumption levels.

Moreover, there is still a gap in research that includes the latest data (up until 2020).. Given the significant global changes experienced in recent years, such as the COVID-19 pandemic and shifts in climate change policies, excluding the latest data may result in overlooking the latest trends and actual circumstances. To ensure the timeliness and comprehensiveness of our study, we aim to focus on the relationships between CO2 emission and GDP, population, energy consumption and renewable energy consumption in the top five emitting countries from 1990 to 2020.

2.4 Conceptual Framework



Source: Developed from the research

In this study, Co2 Emissions is the dependent variable. The research includes four independent variables, namely energy consumption (EC), population growth (POP), GDP per capita (GDP)and renewable energy consumption (REC). The research framework is employed to examine the impact of these four independent variables on CO2 emissions in the top 5 carbon-emitting countries.

2.5 Hypotheses Development

The hypothesis of the research**:**

H_{01}: There is no significant relationship between energy consumption and CO2 emissions.

H_{A1}: There is a significant relationship between energy consumption and CO2 emissions.

H_{02}: There is no significant relationship between GDP per capita and CO2 emissions.

H_{A2}: There is a significant relationship between GDP per capita and CO2 emissions

H_{03}: There is no significant relationship between population growth and CO2 emissions.

H_{A3}: There is a significant relationship between population growth and CO2 emissions.

H_{04}: There is no significant relationship between renewable energy consumption and CO2 emissions.

H_{A4}: There is a significant relationship between renewable energy consumption and CO2 emissions.

2.6 Conclusion

This chapter utilizes past research journals to explain the theoretical framework. It also explores the relationships between independent and dependent variables. Next, Chapter 3 will discuss the methodologies of the research study.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter discusses the research methodologies used in this study. Research design, data collection, data sources, research methodologies, residual diagnostics, and model evaluation are all covered in this chapter. Additionally, the research will use the secondary data from 1990 to 2020, and the definition of each variable is explained in this chapter. In this study, Co2 emissions serve as the dependent variable, while energy consumption, GDP per capita, population growth, and renewable energy consumption are the independent variables.

3.1 Research Design

This study has adopted two sorts of research which are descriptive and causal research. This study is presented as quantitative research. Quantitative research design is a structured approach used in empirical research to collect, analyse, and interpret numerical data (Hassan, 2022). It typically involves the collection of data in the form of numerical values, which are then analysed using statistical methods to identify patterns, relationships, and trends. The purpose of this research is to evaluate various variables, clarify their relationships, and confirm the hypotheses related to these relationships. A causal study is necessary to establish the nature and extent of causality among two or more variables. This method is suited for exploring causal connections between variables. In this case, the study is focused on examining relationships between variables.

3.2 Methods of Data Collection

Secondary data is used in this study. Secondary data are research data that has been collected and can be accessed by researchers. The advantage of these methods is that they are more convenient and economical than the primary data because there is no need to collect data by themselves so save time and cost. In addition, secondary data can provide a wide range of information sources and historical background and can understand the research objects more comprehensively. The research examines annual data from China, Japan, the United States, India, and Russia over the period 1990 to 2020. These countries have not only made great contributions to global emissions, accounting for half of the total emissions, but also are major economies in the world, especially the United States and China. The latest annual data for most variables we are studying are up to 2020, so we chose this year as the end time of the research period to ensure the use of the latest and most comprehensive available data.

3.3 Sources of data

Variable Specification	Variable	Description	Source
Dependent Variable	Co2 Emission	CO2 emissions (metric tons per capita)	WDI
Independent Variable	GDP	GDP per capita (constant 2015 US$)	WDI
	POP	Population Growth (annual %)	WDI
	EC	Primary energy consumption per capita (kWh/person)	U.S. Energy Information Administration
	REC	Renewable energy consumption (% of total final energy consumption)	WDI

3.3.1 Co2 Emissions

Data of CO2 emissions were collected from the WDI. The use of fossil fuels and the creation of cement both contribute to increased CO2 emissions. Co2 emissions include those caused by the use of gaseous petroleum products and the burning of gases.

3.3.2 Energy consumption

By referring to the previous studies (Zhou, 2023; Kanjilal and Ghosh, 2013; Alam et al, 2016), we used the energy use (kilowatt-hours per person) to represent the energy consumption. The data is obtained from the EIA. Energy usage is the consumption of fundamental energy sources before they are changed into other end-use fuels (Robalino-López, 2014). Primary energy is the energy available as resources before undergoing transformation such as the fuels burned in power plants.

3.3.3 GDP per capita

Data is in constant 2015 US dollars and was gathered from WDI. This indicator is calculated by dividing it by the midyear population. GDP per capita refers to the total value added by all producers in the economy, plus product taxes and minus any non-product subsidies. The calculation of GDP per capita is not include the devaluation of industrial assets, as well as depletion of natural resources.

3.3.4 Population Growth

The data on population growth serves as the independent variable in this paper. It is sourced from WDI. The population comprises all residents, regardless of legal status or nationalities. The growth rate is indicated as a percentage. The annually population growth rate in year t is calculated using the mid-year population index growth rate from year t-1 to year t.

3.3.5 Renewable energy consumption

Data for this indicator were gathered from the World Development Indicators. Renewable energy consumption is expressed as a percentage of the total final usage of energy.

3.4 Model Specification

This study uses the data in natural logarithmic form to test and develop the panel data model. The equation covers China, India, Japan, Russia and United State, as illustrated below:

$$lnCO2_{it} = \beta_0 + \beta_1 lnGDP_{it} + \beta_2 lnEC_{it} + \beta_3 lnPOP_{it} + \beta_4 lnREC_{it} + \varepsilon_{it}$$

Where,

$lnCO2_{it}$ = CO2 emissions in natural logarithm (metric tons per capita)

$lnGDP_{it}$ = GDP per capita in natural logarithm (constant 2015 US$)

$lnEC_{it}$ = Primary energy consumption per capita in natural logarithm (kWh/person)

$lnPOP_{it}$ = Population Growth in natural logarithm (annual %)

$lnREC_{it}$ = Renewable energy consumption in natural logarithm (% of total final energy consumption)

β_0 = Constant coefficient

$\beta_1 \dots \beta_4$ = Coefficients of independent variables

ε_{it} = Error term

t (periods) = 1990-2020

3.5 Data Processing

The processing of data is the collection and transformation of raw data into usable information. The raw data is not suitable for analysis or interpretation. Before interpreting results, raw data must be gathered, filtered, classed, and stored. Data processing plays a vital role in analysis. Data cleaning can remove duplicate or incomplete entries in the data. Second, data processing may combine data from several sources and formats into a single data set, making it easier to evaluate and to interpret the information. Furthermore, data processing can change data to fulfill the objectives of analysis or modelling. Finally, statistical software analyzes the processed data and makes it visible. This paper will use statistical software package Eviews to analyze and test the data.

3.6 Panel Model

The panel data was employed in this paper. The panel data combines cross-sectional and time series data. A panel data set is a data set that tracks a given individual sample for a period, so each individual in the sample can be observed multiple times. There are extensive panel data in both developed and developing countries. In most econometric studies, the panel data model is the preferred model. The reason is that panel data estimation methods can deal with heterogeneity and allow individual-specific variables. Second, panel data has more samples, which can increase the degree of freedom and decrease the linear relationship between experimental variables. It enables researcher to study the dynamic changes more effectively and accurately detect and quantify the effects that cannot be seen in a single time series or cross-sectional data (Baltagi, 2008). The panel data model can diminish the effects of omitted variable bias in regression results (Hsiao, 2022).

The pooled ordinary least squares model (POLS), fixed effect model (FEM), and random effect model (REM) can be utilized for estimate the panel data. FEM controls the heterogeneity of individuals by introducing the fixed effect of individuals, and it is assumed that the intercept of each individual is fixed. Besides, the REM allows individual intercepts to be random variables, which means that the differences between individuals are random. Additionally, REM controls for individual heterogeneity by introducing individual random effects and allows for correlation between the random errors across individuals.

3.6.1 Pooled Ordinary Least Squares Model

The POLS is a statistical method used in econometrics to estimate the parameters of linear regression models. It is particularly suitable for processing panel data, which consists of observational data collected across multiple time periods from multiple individuals or entities. This model ignores the panel attribute of data and it has constant intercept and slope. The assumption holds that POLS is always "BLUE," which implies Best Linear Unbiased Estimator. In the POLS framework, "BLUE" is defined as minimizing the square of the residuals to get the estimate equation as near to the actual observed data as possible, hence improving the estimation model's accuracy.

The estimators of β_0 and β_1 that minimize the square of the residual will be selected by OLS and summed at all sample data points. The POLS model is presented as below:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \varepsilon_{it} \qquad (3.1)$$

where: Y_{it} = Dependent variable

β_0 = Constant intercept

β_1 = slope parameter

ε_{it} =stochastic error term

3.6.2 Fixed Effect Model

FEM is used to determine the impact of time-varying factors in a country. The model suggests that the level of the independent variable is assumed to be constant, while but the dependent variable vary in response to the level of the independent variable. The fixed effect model assumes that an individual's characteristics are unique and should not be associated with other individual characteristics (Torres-Reyna, 2007). One of the advantages of the FEM is to avoid the bias due to the ambiguous variables that do not change overtime. In addition, the model also assumes that the differences between individuals can be adjusted by different intercepts. To estimate the fixed effect model with intercept between different individuals, the dummy variable technique is adopted. This estimation model is usually called Least Squares Virtual Variable Technique (LSDV). Furthermore, the FEM can manage the time-invariant characteristics to make sure the effect does not affect the regression, thereby minimizing the deviation in the analysis results. The fixed effect equation is presented as below:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \alpha_i + u_{it} \quad (3.2)$$

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 D2_i + V_{it} \quad (3.3)$$

The V_{it} included error term (u_{it}) and unobserved impact of the time-invariant omitted variable (α_i).

If substitute Equation 3.3 into Equation 3.2, the new equation is shown as below:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 D2_i + \alpha_i + u_{it} \quad (3.3)$$

After that, the average Equation 3.4 over time for each observation is show as below:

$$\bar{Y}_{it} = \beta_0 + \beta_1 \bar{X}_{it} + \beta_2 D2_i + \alpha_i + \bar{u}_{it} \quad (3.4)$$

If minus Equation 3.3 from Equation 3.4, the model is seen as below:

$$Y_{it} - \bar{Y}_{it} = \beta_1(X_{it} - \bar{X}_{it}) + (u_{it} - \bar{u}_{it}) \quad (3.5)$$

In the process, both β_0, $\beta_2 D2_i$ and α_i will be removed because these variables remain constant over time. Therefore, the fixed effects model will not suffer from bias caused by time-invariant omitted variables.

3.6.3 Random effect model

The REM assumes that variations among countries are randomized and unrelated to the model's dependent or independent variables. This method is usually appropriate when differences between countries are expected to affect dependent variables. Compared with the fixed effect model (FEM), REM provides more degrees of freedom, which is particularly beneficial for large data sets with a large number of cross-sectional elements. The advantage of this model is time-invariant variable. In the random effect model, it tends to consider personal characteristics that may affect the predicted variables. REM preserves the degree of freedom by estimating the parameters describing the intercept distribution between elements, so the model parameters can be estimated more effectively. The model also assumed that the error term is unrelated to the independent variable, and the time-invariant variable are allowed to be the explanatory variable. The equation for REM can be expressed as:

$$Yit = \beta_0 + \beta_1 Xit + u_{it} + \varepsilon_{it}$$

where: Yit is the dependent variable for country i at time t.

Xit is the vector of independent variables for country i at time t.

β_0 is the intercept.

β is the coefficients for the independent variables.

u_{it} is the country-specific error term

ε_{it} is the cross-section error term that inconstant and random

3.7 Hausman Test

Hausman Test evaluates the misspecification of econometric models by comparing the estimated values of two different model parameters estimators. It allows researchers to examine heterogeneity by testing which model is more accurate between REM and FEM. The hypothesis of Hausman test are as follows:

Hypothesis	H_0= Random Effects Model is preferred H_1= Fixed Effects Model is preferred

The decision rule of the test is reject the null hypothesis if the p-value is less than 0.05 significant level. This may indicate that if the null hypothesis is rejected, FEM is more suitable for this model. Otherwise, do not reject the null hypothesis if the p-value is more than the 0.05 significant level, REM is more preferred.

3.8 Panel Unit Root Test

Many panel unit root tests are based on the ADF framework (Lau et al., 2019). The unit root test determines if there is a unit root in a time series. The presence of a unit root indicates a nonstationary time series. The Levin, Lin, and Chu Test may be used to evaluate the unit root for panel data. Levin et al. (2002) found that the panel unit root test may be very beneficial in assessing industry-level and cross-country data. Below are the hypotheses of unit root test.

Hypothesis	H_0= The time series data is nonstationary H_1= The time series data is stationary

Decision rule for the unit root test is reject the null hypothesis if the p-value is smaller than the 0.05 significant level. Thus, time series data is stationary.

Otherwise, do not reject the null hypothesis if the p-value is greater than the 0.05 significant level and the time series data is nonstationary.

3.9 Panel Cointegration Test

The cointegration test determines if there is a long run relationship among variables in panel data. Traditional cointegration tests usually only consider time series data, while panel co-integration tests consider both horizontal and vertical dimensions. This method is particularly suitable for analysing data sets observed cross-sectional and time series dimensions. The Kao Test can be used to test the panel cointegration. Below are the hypotheses of cointegration test:

Hypothesis	H_0= The variables are not cointegrated H_1= The variables are cointegrated

The decision rule of the panel cointegration test is reject null hypothesis if the p-value is smaller than the 0.05 significant level. Therefore, the variables are cointegrated and have long run relationship. Otherwise, the null hypothesis fails to be rejected if the p-value is greater than the 0.05 significant level.

3.10 Diagnostic Test

3.10.1 Heteroskedasticity Test

Heteroscedasticity occurs when the variance of the residual in a regression model is not constant across every independent variable. The test is used to identify heteroscedasticity in linear regression models. When heteroscedasticity exists, it will lead to the inefficiency and partial standard deviation of parameter estimation in regression model. The causes of heteroscedasticity may be the misspecification of model and the existence of outliers. Thus, the result of the model is not reliable. Below are the hypotheses of heteroscedasticity.

Hypothesis	H_0= Residuals are homoskedasticity H_1= Residuals are heteroskedasticity

The decision rule for heteroskedasticity test is reject the null hypothesis if the p value is smaller than the 0.05. Therefore, the residuals are heteroscedasticity. However, if the p-value is larger than 0.05, do not reject the null hypothesis. The residuals indicate homoskedasticity.

3.10.2 Autocorrelation Test

Autocorrelation measures the relationship between current value and its past values of the variable. It is a statistical measure of the similarity between a particular time series and its lagging version in a continuous time interval. The residuals have an autocorrelation means that the model is no longer BLUE. Autocorrelation is very important in econometrics because it affects the accuracy and reliability of statistical inference. In regression analysis, autocorrelation in residuals violates the assumption of errors are independently and distributed identically, which will lead to the deviation of parameter estimation and wrong inference of the relationship between variables. The Durbin-Watson D test is used to detect the presence of autocorrelation in the model. Below are the autocorrelation test hypotheses.

Hypothesis	H_0= Residuals have no autocorrelation H_1= Residuals have autocorrelation

The decision rule is if the Durbin Waston statistic value approaches 2, it indicates that the residuals have no autocorrelation, and the null hypothesis should not be rejected. Otherwise, if the value is less than 2, it indicates the residuals have positive autocorrelation, while if it is greater than 2, it indicates the residuals have negative autocorrelation, and the null hypothesis can be rejected.

3.10.3 Cross-Section Dependence Test

Cross-section dependence refers to the existence of correlation or interdependence between individual units in a panel data collection. This dependence violates the assumption of independence of cross-observation. Panel data can establish a wide range of cross-sectional correlation. If the omitted common factor is related to regressors, the two standard homogeneous estimates (FE or RE) of panel data are inconstant (Henningsen & Henningsen, 2019). Therefore, Pesaran (2006) suggested to use the regression variables and cross-sectional average values of regression variables to estimate common factors that were not observed. The Pesaran CD test may be utilized to evaluate the cross-section dependence in the model. The hypotheses of the cross-section dependence test are as below:

Hypothesis	H_0= Residuals are no cross-sectional dependence H_1= Residuals are cross-sectional dependence

The decision rule is reject null hypothesis if the p value is smaller than 0.05 significant level. Thus, the residuals are cross-sectional dependence. Otherwise, do not reject the null hypothesis if the p value is greater than 0.05 significant level. Thus, the residuals are no cross-sectional dependence.

3.10.4 Multicollinearity

The formula for calculating the variance inflation factor (VIF) is as follows:

$$VIF_i = \frac{1}{1 - R_i^2}$$

High correlation among independent variables is considered a problem of multicollinearity. The reason of the multicollinearity may be the model specification wrongly, overdetermined model or the sample size is too large. Therefore, the individual effect of each variable on the dependent variable is hard to identify. Multicollinearity can cause unreliable parameter estimates, inflated standard errors, and difficulties in interpreter the results of the regression analysis. The VIF and TOL can be used to identify multicollinearity problems. The hypotheses of the multicollinearity test are as below:

Hypothesis	H_0= Independent variables do not have multicollinearity H_1= Independent variables have multicollinearity

Decision rule: If the VIF is larger than 5, reject the null hypothesis. the independent variables have multicollinearity. If VIF is greater than 10, the multicollinearity is serious. Otherwise, if VIF is smaller than 5, do not the null hypothesis and the independent variables do not have multicollinearity.

3.10.5 Normality

In a normal distribution, the data presents a symmetrical bell-shaped curve, the mean value is located in the centre of the curve, and the standard deviation determines the width of the curve. The normality test can ensure the validity of the model because it ensures that the model follows a conventional normal distribution. The normality test may be performed using the residuals histogram and the Jarque-Bera test. If residual histogram shows a slightly symmetrical bell-shaped distribution, it is possible that the residual will follow the normal distribution. Jarque-Bera test evaluates whether a given data set follows a normal distribution according to its skewness and kurtosis. Below are the hypotheses of the normality test.

Hypothesis	H_0= Residuals are normally distributed. H_1= Residuals are not normally distributed.

Decision rule: reject the null hypothesis if the p value associated with the Jarque-Bera test is less than 0.05 significant level. It can conclude that residuals are not normally distributed. Conversely, do not reject the null hypothesis if the p value is greater than the 0.05 significant level. Thus, the residuals follow a normal distribution.

3.11 Conclusion

This chapter involved the research methods, such as the design of the research, data collection approaches, data sources, research instruments, data processing, and model evaluation. All data are gathered from WDI and EIA. Then, Chapter 4 will further analysis the results and output of this study.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter uses the research model mentioned in Chapter 3 to process the data. The panel model analysis results are derived from annual data of 150 observations from 1990 to 2020. Before determining the best model, this chapter implements the panel unit root and cointegration tests to evaluate the stationarity and cointegration of the data. The Hausman test is then conducted to choose the best model from the fixed effect and random effect models. Meanwhile, this section also includes the output of diagnostic tests for the final model. These tests aim to ensure that the model is unbiased and accurate.

4.1 Data Estimation

4.1.1 Descriptive Statistics

Table 4.1 Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
lnCO2	0.0102	0.0092	0.1469	-0.1186	0.0441	150
lnEC	0.0119	0.0115	0.1509	-0.0919	0.0381	150
lnGDP	0.0298	0.0266	0.1278	-0.1580	0.0454	150
lnPOP	-0.0028	-0.0257	3.8344	-4.0071	0.7160	150
lnREC	0.0028	0.0009	0.2315	-0.2386	0.0643	150

Source: Developed for the research

The descriptive data from the top five emitter nations from 1990 to 2020 are shown in Table 4.1. The dependent variable, CO2, has a mean of 0.0102 and a median value of 0.0092. The minimum value is -0.1186, while 0.1469 is the maximum value. The standard deviation for CO2 is 0.0441. Next, the mean value of energy consumption is 0.0119, while the median is 0.0115. The maximum, minimum and the standard deviation value are 0.1509, -0.0919, 0.0381 respectively.

The mean of the GDP per capita is 0.0298, and the median is 0.0266. The maximum and minimum values for per capita GDP are 0.1278 and -0.1580 respectively. The standard deviation is 0.0454. Moreover, the average of population growth is -0.0028. The median, maximum and minimum values for population growth are -0.0257, 3.8344 and -4.0071 respectively. The standard deviation equal to 0.7160. The average value of renewable energy consumption is 0.0028, while the median value equals 0.0009. The maximum and minimum values for REC are 0.2315 and -0.2386, respectively. The standard deviation equals to 0.0643.

4.1.2 Correlation Analysis

Table 4.2 Correlation Results

	lnCO2	lnEC	lnGDP	lnPOP	lnREC
lnCO2	1.0000	0.8613	0.7079	-0.0153	-0.5551
lnEC	0.8613	1.0000	0.7544	-0.1873	-0.4460
lnGDP	0.7079	0.7544	1.0000	-0.0336	-0.3115
lnPOP	-0.0153	-0.1873	-0.0336	1.0000	-0.0164
lnREC	-0.5551	-0.4460	-0.3115	-0.0164	1.0000

Source: Developed for the research

Table 4.2 shows the correlation output between the variables The findings reveal that CO2 emissions increase with the rise in energy consumption and GDP per capita, but decrease along with the rise of population growth and renewable energy consumption. The energy consumption has correlation value of 0.8613 with the Co2 emission, the relationship is positive. Then, there is positive relationship between Co2 emission and per capita GDP, the value is 0.7079. Moreover, correlation value between the population growth and Co2 emission is -0.1747. Therefore, the population growth is negatively correlated with Co2 emission. Next, the renewable energy consumption has correlation value of -0.5551 with the Co2 emission. Thus, the renewable energy consumption is negatively correlated with Co2 emission.

4.1.3 Panel Model Unit Root Test

A unit root exists in time series data when the mean and variance change randomly over time. The Levin, Lin, and Chu tests will be employed to determine the presence of unit roots in the panel model. I(0) indicates that the data is stationary at level. Then, I(1) and I(2) indicate that the data is stationary in the first difference and the second difference respectively. Below are the unit root test hypotheses:

Hypothesis	H_0= The time series data is nonstationary H_1= The time series data is stationary

Table 4.3 Unit Root Test Results

	Levin, Lin & Chu		
Variable	I(0)	I(1)	I(2)
lnCO2	-0.7624	-2.7416 ***	-10.5205 ***
lnEC	-0.8249	-2.2502 **	-9.4000 ***
lnGDP	-3.2726 ***	-1.1171 **	-8.9938
lnPOP	2.6474	-5.6348 ***	-6.8234 ***
lnREC	-0.5737	-2.4252 ***	-12.2398 ***

Notes: The symbols *, **, *** denote statistical significance at 10%, 5% and 1% level respectively.

Source: Developed for the research

According to the result shown in Table 4.3, only the per capita GDP do not have unit root (stationary) at level. Next, all variables are stationary at the first level. At the second difference level, Co2, EC, POP and REC are stationary, except for per capita GDP. Since all variables are stationary at the first different level, so we can proceed with the panel cointegration test.

4.1.4 Panel Cointegration Test

Panel cointegration tests is used to check whether a group of non-stationary time series variables in a panel data set are cointegration, which means that they have long-term relations that can be described as a linear combination. In this section, Kao Test Kao test will be utilized to test the panel cointegration.

Hypothesis	H_0= The variables are not cointegrated H_1= The variables are cointegrated

Table 4.4 Kao Panel Cointegration Test Results

	t-Statistic	Prob.
ADF	-7.3469	0.0000
Residual variance	0.0008	
HAC variance	0.0001	

Source: Developed for the research

The table illustrates the results of panel cointegration test. Kao test result reveal that the p value is 0.0000 and less than 0.01 level. Therefore, the null hypothesis can be rejected at α 0.01 level. As a result, there is sufficient evidence to show that the variables are cointegrated and have a long run relationship.

4.2 Model Selection

Table 4.5 Result of Panel Regression: POLS, FEM and REM

Variables	POLS	FEM	REM
lnEC	0.8153 [11.2803***]	0.8040 [10.7031***]	0.8153 [10.7031***]
lnGDP	0.1141 [2.0443**]	0.1426 [2.3520**]	0.1141 [2.0380***]
lnPOP	0.0072 [3.0379***]	0.0071 [2.9600***]	0.0072 [3.0286***]
lnREC	-0.1389 [-4.8436**]	-0.1427 [-4.8656***]	-0.1389 [-4.8287***]
C	-0.0025	-0.0032	-0.0025
R2	0.8004	0.8047	0.8004
Adjusted R2	0.7949	0.7936	0.7949

Notes: The symbols *, **, *** denote statistical significance at 10%, 5% and 1% level respectively.
Source: Developed for the research

The Hausman test is performed to decide which model is appropriate for this study. The hypotheses of Hausman Test are:

Hypothesis	H_0= Random Effects Model is preferred H_1= Fixed Effects Model is preferred

Table 4.6 Result of Hausman Test

Test Summary	Chi-Sq. Statistic	Prob.
Hausman Test	3.111722	0.5393

Source: Developed for the research.

The decision rule is If p-value is less than 0.05, reject the H_0. Otherwise, if the p-value greater than 0.05, do not reject the H_0 . Table 4.6 reveals the outcome of the Hausman test. The findings show a p-value of 0.5393, which is larger than the α value of 0.05. Therefore, the null hypothesis should not be rejected. Thus, the REM is preferred.

Therefore, the Random effects model is the preferred model for this research. The equation of the random effect panel model is shown as below:

$$lnCO2_{it-1} = -0.0025+0.8153lnEC_{it-1} + 0.1141lnGDP_{it-1}+0.0072lnPOP_{it-1}$$

[11.2457***] [2.0380***] [3.0286***]

$$-0.1389lnREC_{it-1} \tag{4.1}$$

[-4.8287***]

$R^2 = 0.8004$ $Adjusted\ R^2 = 0.7949$

Notes: The symbols *, **, *** denote statistical significance at 10%, 5% and 1% level respectively.
Source: Developed for the research

Equation 4.1 reveals the random effect model for the Co2 emission per capita model. R^2 is equal to 0.8004 indicate that the explanatory variables explained 80% of the variation in the model. According to the equation, the model's most significant variables are energy consumption, GDP per capita, population growth, and renewable energy consumption. All the explanatory variables are statistically significance at 0.05 level in the model.

Therefore, 1 unit increase in the energy consumption, on average, has the positive relationship effect of increasing Co2 emission per capita by 0.8153 unit with statistically significance at the α 0.01 level. There is a positive relationship between energy consumption and Co2 emission per capita. Meanwhile, GDP per capita has a positive relationship and significant effect on CO2 emissions at α 0.01 level. The result reveals that a unit increases in GDP per capita will cause the Co2 emission per capita to increase by 0.1141 units. Besides, a 1 unit increase in the population growth, on average, has the positive relationship effect of increasing Co2 emission per capita by 0.0072 unit with statistically significance at the α 0.01 level. The result demonstrates that population growth and Co2 emission per capita have a positive relationship in the model. Lastly, a 1 unit increase in the renewable energy consumption, on average, has negative relationship effect of decreasing Co2 emission per capita by 0.1389 unit with statistically significance at the α 0.01 level. Therefore, the use of renewable energy and CO2 emissions have an adverse relationship.

4.3 Diagnostic Checking

4.3.1 Heteroskedasticity

The random effect model used generalized least squares (GLS) estimation, which has controlled the heteroscedasticity. GLS is one of a method to eliminate the heteroscedasticity. GLS weights explanatory variables to ensure that the residual variance of the weighted regression equation is constant. Therefore, we can get unbiased and consistent parameter estimates under GLS method. Since the estimation of the random effect model has solved the heteroskedasticity issue, so the heteroskedasticity test is not applicable in the diagnostic test (Law, 2018).

4.3.2 Autocorrelation

Autocorrelation occurs when the current variable value is similar to its own lagged version. The Durbin-Watson d test is used to estimate the autocorrelation problem. The hypotheses of the autocorrelation are as below:

Hypothesis	H_0= Residuals have no autocorrelation H_1= Residuals have autocorrelation

Table 4.7 Durbin-Watson d Test

Test Summary	**d Stat**
Durbin- Watson d Test	2.1110

First, if the d statistic is around 2, do not reject the null hypothesis. Thus, the residuals have no autocorrelation. If the d statistic is less than d_L or more than $4 - d_L$, null hypothesis can be rejected. Therefore, residuals have autocorrelation. Positive autocorrelation occurs when the d statistic is below d_L while negative autocorrelation occurs when d statistic above $4 - d_L$. Above table shows that the d statistic is 2.1110, which is close to 2. So, the null hypothesis cannot be rejected. The result indicates that the regression does not have an autocorrelation problem.

4.3.3 Cross-Sectional Dependence Test

The influence of cross-sectional dependence on estimation naturally depends on various factors, such as the size and nature of cross-sectional correlation (De Hoyos et al., 2006). The existence of cross-sectional correlation implies that it may be created by several measurements. Thus, the Breusch-Pagan LM, Pesaran scaled LM, and Pesaran CD will be employed to assess if the model has cross-sectional dependency. The hypotheses of the cross-section dependence test are as below:

Hypothesis	H_0= Residuals are no cross-sectional dependence H_1= Residuals are cross-sectional dependence

Table 4.8 Result of Cross-Section Dependence Test

Test	Statistic	Prob.
Breusch-Pagan LM	8.0794	0.6211
Pesaran scaled LM	-0.4295	0.6676
Pesaran CD	0.1266	0.8993

Source: Developed for the research

From Table 4.8, the outputs reveal that the statistic value of Breusch-Pagan LM, Pesaran scaled LM and Pesaran CD are 8.0794, -0.4295 and 0.1266 respectively. Since the p value of the result is greater than α 0.05 significant level, so do not reject the null hypothesis. Therefore, there is no strong indication that there is obvious dependence between the residuals.

4.3.4 Multicollinearity

Furthermore, the multicollinearity test was done below to determine the degree of linear correlation between the independent variables. The hypotheses of the multicollinearity are:

Hypothesis	H_0= Independent variables do not have multicollinearity H_1= Independent variables have multicollinearity

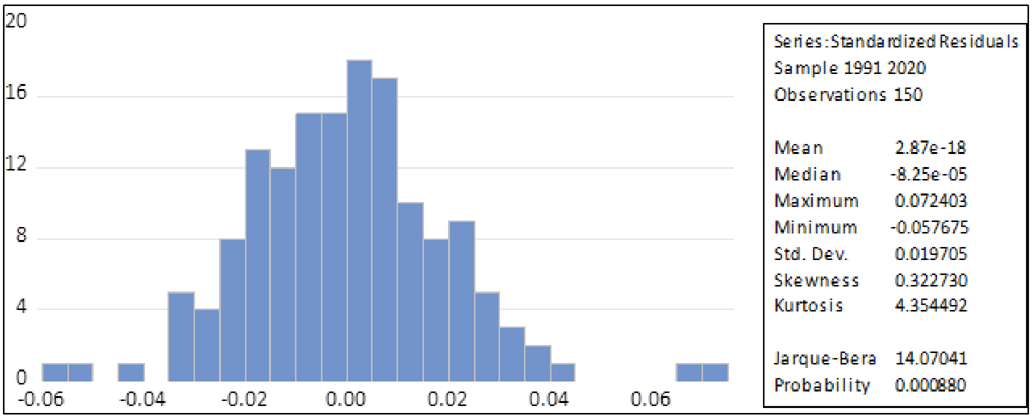
Table 4.9 Result of multicollinearity

Variable	VIF	TOL
lnEC	2.83	0.3532
lnGDP	2.40	0.4172
lnPOP	1.08	0.9239
lnREC	1.27	0.7876
Mean VIF	1.90	

Based on the decision rule, if the VIF is greater than 5, reject the null hypothesis and the independent variables have high multicollinearity. Otherwise, if the VIF is lesser than 5, do not reject the null hypothesis. Based on Table 4.9, the VIF values of EC, GDP, POP and REC are 2.83,2.40 ,1.08 and 1.27 respectively. The mean VIF is 1.90 which is less than 5. Since all of the independent variable value of VIF is less than 5, so do not the null hypothesis, there is no serious multicollinearity problem.

4.3.5 Normality

Figure 3Figure 4.1 Normality Test for Residuals



The normality test determines if the data sample follows the normal distribution. The normality test will ensure that the model is unbiased and consistent, and the minimum variance and residual are normal distribution (Gujarati & Porter, 2009). Below are the hypotheses of normality test.

Hypothesis	H_0= Residuals are normally distributed. H_1= Residuals are not normally distributed.

Figure 4.1 shows that the p value of the normality test is 0.0009, which is less than the 0.05 significant level, so we reject the null hypothesis. Hence, residuals do not follow a normal distribution. If the sample has hundreds of observations, we may ignore the data distribution (Altman and Bland, 1995). Ghasemi and Zahedia (2012) show that the violation of the normality assumption should not lead to serious problems if the sample size is sufficiently large (>30 or 40). Therefore, there are 150 observations in this research, so the violation of the normality assumption will not bring serious problems for the model.

4.4 Panel Model Analysis Hypothesis Test

Table 4.10 Hypotheses Testing for Panel Model

Alternative hypothesis	Decision	Result
H_{A1} : There is significant relationship between energy consumption and Co2 emissions	Sig-p-value < α 0.01	Supported Positive
H_{A2} : There is significant relationship between GDP per capita and Co2 emissions	Sig-p-value < α 0.01	Supported Positive
H_{A3} : There is significant relationship between population growth and Co2 emissions	Sig-p-value < α 0.01	Supported Positive
H_{A4} : There is significant relationship between renewable energy consumption and Co2 emissions.	Sig-p-value < α 0.01	Supported Negative

Firstly, H_{A1} is supported by Begum et al. (2015), Dogan and Aslan (2017). The findings indicate that per capita energy consumption and CO2 emissions have a positive relationship. Secondly, the H_{A2} is also supported. The alternative hypothesis between Co2 emission and GDP per capita in consistent with Karaaslan and Çamkaya (2022), Ahmad et al. (2018), and Begum et al. (2015). The results show that GDP has a positive relationship with Co2 emission.

Thirdly, H_{A3} is supported in the paper. Population growth and Co2 emissions have a significant relationship. The results line up with Dong et al. (2018). Dong et al. (2018) investigated imbalanced panel data sets in 28 countries and found a positive relationship between CO2 emissions and population growth. Lastly, H_{A4} has been supported. This finding is consistent with Li and Haneklausb (2022), who using ARDL approach found that there the Co2 emission has a negative relationship with renewable energy consumption in G7 countries.

4.5 Conclusion

In Chapter 4， the research results reveal that energy consumption, GDP per capita, population growth renewable energy consumption have significant relationship with Co2 emissions. The cointegration tests has proved the long run relationship between the variables. Furthermore, the diagnostic check performed in this chapter support the model's validity. Finally, the following chapter will summarize Chapter 4 statistical analysis and examine its major findings, implications for policy, study limitations, and recommendations for further research.

CHAPTER 5: DISCUSSION AND CONSLUSION

5.0 Introduction

The previous chapter presented the estimation results from the model. Chapter 5 will summarize the findings of the previous chapter and compare the expected relationship with the result. Besides, this chapter will also discuss the implication of this study on policy makers, society and individuals. Furthermore, it will discuss the limitations of the current study and offer recommendations for future researchers in this section.

5.1 Summary of Statistical Analysis

Model selection		
	Analysis	**Result**
FEM and REM	Hausman Test	REM is preferred
Diagnostic Testing		
Heteroskedasticity	Not applicable	GLS controlled the heteroscedasticity
Cross-Section Dependence	Breusch-Pagan LM Pesaran scaled LM Pesaran CD	Residuals are no cross sectional dependence
Multicollinearity	VIF	No serious multicollinearity
Normality	Jarque-Bera test	Residuals are not normally distributed but violation should not lead serious problems

The study examines the factors of CO2 emissions in the top five carbon generating nations (China, the United States, Japan, India, and Russia) between 1990 and 2020. A panel model was used to investigate the relationship between emissions of CO2 and four independent variables: energy consumption, GDP per capita, population growth, and renewable energy consumption. Besides, the unit root test revealed that the panel data is stationary at the first level, and the cointegration test confirmed the variables are cointegrated and have a long-term relationship.

Based on the Hausman test, the Random Effects Model was selected as the best model for the top five emitting countries. All variables are significant at the 0.01 significance level. The results show that GDP per capita, the use of energy, population growth, and renewable energy consumption are important factors affecting CO2 emissions. Moreover, the model does not have the multicollinearity, autocorrelation, and cross section dependence. Heteroskedasticity test is not applicable because heteroskedasticity has been effectively controlled by the GLS method. Although the residuals do not have a normal distribution but the sample size of 150 observations which is greater than 30. Therefore, it allows the model to disregard the violation of the normality assumption without causing serious problems for the model.

5.2 Discussion of Major Finding

According to the empirical results of the model for the top-5 emitters, there are significant positive relationships between energy consumption, GDP per capita, and population growth with CO2 emissions per capita, as well as a significant negative relationship between renewable energy consumption and CO2 emissions per capita.

5.2.1 Energy Consumption

Firstly, the use of energy has a positive relationship and significant influence on Co2 emissions, and this impact is cointegration in the long run. The result is align with Begum et al. (2015), Zhou (2023), Kanjilal and Ghosh (2013). There may be several reasons for the positive relationship between energy use and emissions of carbon dioxide. One of the reasons is reliance on fossil fuels. The majority of energy usage comes from fossil fuels which includes natural gas, coal, and petroleum. Because fossil fuels account for a significant portion of the world's energy system. When these energy sources are consumed for power production, transportation, and industrial activities, they emit a huge amount of CO2 into the environment. As a result, this procedure will cause an increase in carbon dioxide emissions.

Second, the economic activities of the countries need a lot of energy to support. Therefore, economic growth and industrialization progress will come with the increase in energy consumption and carbon dioxide emissions. The research of Souza Mendon ça et al. (2020) confirmed that China and India still rely mainly on high-carbon energy sources, such as coal. Although the carbon-free energy policy in the United States has achieved certain results, energy consumption continues to rise because of the continued reliance on traditional sources of energy. These findings suggest that there is a positive link between energy usage and CO2 emissions.

5.2.2 GDP per capita

The findings show that GDP per capita has a significant positive relationship with CO2 emissions per capita in top five emitting countries. The relationship between GDP per capita and CO2 emissions per capita is statistically significant at the 1% level. The results are in line with the finding from Ahmad et al. (2018), Begum et al. (2015), Karaaslan and Çamkaya (2022). As the main economies in the world, the top five emitting countries have a huge industrial base. The industrial activities include energy-intensive products such as cars and electrical appliances. The production and use of those products require a lot of energy, resulting in a rise in the release of carbon dioxide. Economic growth is usually accompanied by the urbanization and the increase in traffic demand, which leads to more construction activities, car use and other energy-intensive activities, thus increasing Co2 emissions.

According to Ortega-Ruiz et al. (2022), China's rapid economic growth since 2002, especially after the reform of the national constitution and economic policy in 2004, led to a significant increase in its Co2 emissions. As a result of large-scale infrastructure construction and higher-intensity energy use, Co2 emissions increased significantly during that period in China. Second, a rise in GDP per capita usually related to an improvement in living standards. People will pursue a higher quality and more convenient lifestyle, such as a high car usage and the popularity of air conditioners. As the economy grows, industry continues to hold a significant position in these five countries. The fast expansion of industry drives a rise in energy use and carbon emissions. This highlights the necessity of combining renewable energy and energy efficiency into sustainable growth strategies to reduce the negative environmental impacts.

5.2.3 Population Growth

Population growth and Co2 emission per capita have a significant positive relationship in this research. The result is consistent with Souza Mendonça (2020), Dong et al. (2018), Alam et al. (2016). The reason is that a growth in population will be accompanied by increased energy consumption, which leads to an increase in the release of CO2. Population dynamics have a significant impact on energy consumption patterns and the release of CO2 emissions (Souza Mendonça et al., 2020). The demand for a large number of construction activities has increased with the increase of population. the expansion of the transportation system and higher energy demand have resulted in more emissions. In nations with high population growth, CO2 emissions tend to rise from increased energy consumption and the usage of fossil fuels.

According to Dong et al. (2018), the population has a positive and significant relationship on the Co2 emissions at global and regional levels. The growth of populations also caused changes in consumption patterns, such as increasing demand for high-energy products and services, which are often harmful to environmental sustainability. The agricultural expansion and deforestation need more agricultural land to meet the food needs of the growing population, but this action will increase carbon dioxide emissions. Therefore, the population growth can be a key variable to explain carbon dioxide emissions and the greenhouse effect, which helps to evaluate the role of population policies in comprehensive emission reduction strategies and formulate comprehensive policies.

5.2.4 Renewable Energy Consumption

The negative relationship between renewable energy consumption and carbon dioxide emissions has been proven in this study. The majority of research agrees that utilization of renewable energy has an adverse effect on CO2 emissions (Karaaslan and Çamkaya, 2022; Dong et al., 2018; Bilgili et al., 2016). According to Karaaslan and Çamkaya's (2022) research, green energy could boost economic growth and create a cleaner environment. Renewable energy has gradually become a feasible choice to replace traditional fossil fuels with the technological innovation. This substitution reduces the dependence on high-carbon energy sources such as oil and coal, thus reducing carbon dioxide emissions. Globally, solar photovoltaic accounts for three-quarters of the new renewable energy production capacity in the world, while China accounts for almost 60% of the expected increase in the new renewable energy production capacity in the world, and it is expected to be put into operation before 2028 (IEA, 2024).

According to Liand Haneklaus (2022), the consumption of clean energy has effectively alleviated environmental deterioration. Low-cost renewable energy provides an effective way to replace high-emission fossil fuel. This is because the emissions of carbon dioxide produced by the consumption of renewable energy are far lower than those produced by fossil fuels. For example, solar energy and wind energy hardly produce carbon dioxide emissions during power generation, and their cost are lower than the fossil fuels. Therefore, increase the portion of renewable energy in the energy structure can significantly reduce the overall Co2 emission and achieve zero or low emissions.

At the same time, the supportive policy environment and the increasing economic attraction of solar photovoltaic power generation and onshore wind energy have increased the consumption demand for renewable energy. It is estimated that the growth of solar pv power generation and onshore wind energy in the United States and India will more than double by 2028 (IEA, 2024). In conclusion, the inverse relationship between emissions of CO2 and renewable energy consumption is a result of renewable energy become an effective replacement of fossil fuels, which successfully reduces CO2 emissions. This inverse relationship is expected to grow even stronger as technology advances and supportive regulations are implemented.

5.3 Implications of Study

This study investigated the influence of consumption of energy, GDP, growth in population, and renewable energy consumption on the release of CO2 in top five carbon-emitting countries. The empirical evidence indicates that energy consumption, GDP, population growth, and renewable energy consumption have a major impact on CO2 emissions. Therefore, governments should implement supportive policies to foster energy efficiency and encourage investment in green energy technology.

The widespread use of fossil fuels in these five countries has led to the possibility that replacing fossil fuels with renewable energy in already stable energy structures may be considered risky and unworthy. The sector with the highest CO2 emissions in these countries is the electricity and heat producers. Therefore, policymakers can implement strict emission standards and regulatory policies to boost energy efficiency and the portion of renewables in the energy mix (Dogan and Aslan, 2017). For example, China has established regulations for the electricity spot market. Although this policy still being gradually established and improved, other countries could consider adopting similar policies to enhance energy efficiency and optimize resource allocation. Market mechanisms can prioritize the dispatch of low-carbon power sources to reduce the dependence on fossil fuel power generation. This policy can allow inefficient and high-emission old power facilities to be gradually replaced by cleaner new technologies, effectively reduce the overall carbon emissions and promote technological innovation and green investment development.

Since the GDP growth is associated with increased Co2 emissions, governments can focus on economy transformation. Economic transformation include changing the fundamental structure of the economy, enhancing value-added activities, or reducing dependence on carbon-intensive sectors. Governments can support sectors like information technology, services, and green manufacturing with funding, as these typically emit less compared to traditional industrial sectors. Pao, Yu and Yang (2011) suggested that the Russian government will need to exert more effort to enhance the energy efficiency of energy equipment and devices to reduce emissions and avoid negative impacts on economic growth. Therefore, energy conservation is expected to improve the efficiency of energy use, promote the economic growth and environmental quality. In the context of globalization, countries can strengthen international cooperation to achieve carbon reduction goals. For example, the United States, China, and Japan can provide some financial and technology support with countries like India and Russia, where energy efficiency is low. The reason is not all countries have the capacity to implement economic transformation and develop new technologies. The countries that provide the support can also gain economic opportunities to open up new markets for green technology firms. This measure will help the nations work together to reduce greenhouse gas emissions.

Meanwhile, the finding showed that the population growth is positively affect the CO_2 emissions. This phenomenon is often influenced by people's preference for traditional energy sources and a lack of awareness about clean energy. In India, traditional fuels are still widely used, while the adoption rate of renewable energy remains low. The lack of information leads to people's lack of understanding of the impact of Co_2 emissions and the importance of sustainable development. This problem increases the challenge of adopting environmentally friendly energy alternatives. In view of the difficulty in controlling population growth, it is necessary for the government to raise public awareness of environmental problems through education, publicity and policy support. Education about the climate change, environmental pollution and global sustainable development are closely related to every country. The education system should strengthen the promotion and dissemination of renewable energy. Additionally, governments can introduce policies such as replace the public transport with low-emission electric vehicles or provide the incentives for electric car purchases to reduce per capita CO_2 emissions. At the same time, society can advocate for environmentally friendly behaviours by encourage individuals and businesses to take proactive environmental measures to collectively address the challenges posed by CO_2 emissions.

Lastly, the findings indicate that renewable energy can lower CO2 emissions. Thus, governments can implement effective policies to promote the usage of renewable energy. However, green energy necessitates the use of specialized materials and technology, that has become a key problem for developed nations. The slow growth of this energy is driven by a shortage of financial assistance and renewable energy facilities (Souza Mendonça, 2020). Renewable energy is used minimally in these five nations compared to other energy sources. The governments and the private sector can promote investment in renewable energies through various incentives such as financial subsidies, tax benefits, and low-interest loans. This type of economic support not only helps to promote the research and development of new technologies but also expands the production scale of renewable energies, thereby their competitiveness in the market can be enhance while reducing costs. Besides, the government also can support the innovation and commercialization of renewable energy technologies. For example, the government can invest in research and development of new solar technologies or efficient hydroelectric power technologies. The advancement in such technologies can not only improve energy conversion efficiency but also can reduce environmental pollution and greenhouse gas emissions.

In summary, the measures mentioned in this section are helpful for countries to promote the green economic transformation, strengthen national energy security and reduce dependence on high emission energy. The combined use of economic incentives and policy support will help accelerate the dissemination and application of renewable energy technologies and lay a solid foundation for achieving low-carbon development goals.

5.4 Limitations of Study

This study has some limitations. First, the limitations of data range. The data of the dependent variable and independent variables in accessible databases extends only up to year 2020. This restriction makes it very difficult to obtain data after 2020, which may capture major trends, such as the changes brought about by the Covid-19. Moreover, this study may not widely consider external factors such as geopolitical events or changes in trade policy. These factors may indirectly influence the energy sector and emissions statistics. In addition, this study comprehensively investigated the top five carbon emitting countries but did not make a detailed country analysis. This method ignores some unique national conditions, policies and interventions measures, which may have a major impact on carbon dioxide emission patterns.

5.5 Recommendations for Future Research

The limitations provide opportunities and suggestions for future researchers in this field. This section provides some suggestions to resolve these limitations. First, the future studies can expand the data range after 2020 to capture the main economic and environmental trends that may affect energy consumption patterns and Co2 emissions after the andemic. Additionally, the researchers should also consider including more variables, such as geopolitical dynamics, international trade indicators and economic indicators to have a more comprehensive understanding of the factors affect the Co2 emissions.

In addition, this paper suggests that future studies should explore the specific situation of each country. For example, the researchers can combine VECM model and panel data model to reveal the impact of various factors on the trend of Co2 emissions in each country. Finally, researchers can also broaden the global perspective of research by extending the scope of research to more countries. This would be helpful to analyse the trends and changes of Co2 emissions in the world, including developed and developing countries. These recommendations will help to expand the scope and depth of carbon emission research and strengthen the understanding of effective climate change strategies at the global and national levels

5.6 Conclusion

In summary, the research project explores the relationship between energy use, population growth, GDP per capita, renewable energy consumption, and CO2 emissions in the world's top five carbon-emitting countries. It successfully identifies the major factors affecting CO2 emissions. The findings indicate the important relationships between all the studied factors and CO2 emissions. Furthermore, GDP per capita, energy consumption and population growth have a significant influence on the emission of CO2, whereas renewable energy consumption has an essential role in reducing emissions. This chapter also emphasizes the stable long term cointegration among these variables, which is crucial for policymaker. Additionally, the chapter discusses the main findings and their underlying reasons. These results provide the key insights for policymakers and highlight the importance of enhancing renewable energy use to effectively reduce CO2 emissions. Future research could build on the limitations and recommendations identified in this study to further explore additional variables influencing CO2 emissions. Lastly, this study has completely addressed the research problems and objectives. Therefore, Chapter 5 not only summarizes the statistical findings but also discusses the broader implications of these results for national and global environmental strategies. It lays a foundation for policymakers to formulate more targeted and effective environmental regulations and provides a basis for future researchers to offer new insights into sustainable practices.

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APPENDICES

Appendix 1 Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
lnCO2	0.0102	0.0092	0.1469	-0.1186	0.0441	150
lnEC	0.0119	0.0115	0.1509	-0.0919	0.0381	150
lnGDP	0.0298	0.0266	0.1278	-0.1580	0.0454	150
lnPOP	-0.0028	-0.0257	3.8344	-4.0071	0.7160	150
lnREC	0.0028	0.0009	0.2315	-0.2386	0.0643	150

Appendix 2 Correlation Analysis

	lnCO2	lnEC	lnGDP	lnPOP	lnREC
lnCO2	1.0000	0.8613	0.7079	-0.0153	-0.5551
lnEC	0.8613	1.0000	0.7544	-0.1873	-0.4460
lnGDP	0.7079	0.7544	1.0000	-0.0336	-0.3115
lnPOP	-0.0153	-0.1873	-0.0336	1.0000	-0.0164
lnREC	-0.5551	-0.4460	-0.3115	-0.0164	1.0000

Appendix 3 Unit Root Test- Co2 emissions

Level Data

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.76235	0.2229	5	145
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.68088	0.7520	5	145
ADF - Fisher Chi-square	13.7619	0.1841	5	145
PP - Fisher Chi-square	9.30176	0.5037	5	150

1 st difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.74157	0.0031	5	144
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.06992	0.0000	5	144
ADF - Fisher Chi-square	34.7058	0.0001	5	144
PP - Fisher Chi-square	36.5135	0.0001	5	145

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

2 nd difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.5205	0.0000	5	137
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-13.0604	0.0000	5	137
ADF - Fisher Chi-square	122.135	0.0000	5	137
PP - Fisher Chi-square	139.080	0.0000	5	140

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4 Unit Root Test- Energy consumption

Level Data

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.82493	0.2047	5	148
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.49559	0.9326	5	148
ADF - Fisher Chi-square	8.44563	0.5854	5	148
PP - Fisher Chi-square	5.52569	0.8534	5	150

1 st difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.25015	0.0122	5	143
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.97613	0.0000	5	143
ADF - Fisher Chi-square	44.4162	0.0000	5	143
PP - Fisher Chi-square	43.9501	0.0000	5	145

2 nd difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-9.40001	0.0000	5	138
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-11.7798	0.0000	5	138
ADF - Fisher Chi-square	109.904	0.0000	5	138
PP - Fisher Chi-square	116.625	0.0000	5	140

Appendix 5 Unit Root Test- GDP per capita

Level Data

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.27260	0.0005	5	146
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.68864	0.2455	5	146
ADF - Fisher Chi-square	11.2884	0.3355	5	146
PP - Fisher Chi-square	7.84829	0.6437	5	150

1 st difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.11707	0.0241	5	145
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.17793	0.0007	5	145
ADF - Fisher Chi-square	30.9776	0.0006	5	145
PP - Fisher Chi-square	31.2129	0.0005	5	145

2 nd difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.99381	0.1320	5	139
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-10.8038	0.0000	5	139
ADF - Fisher Chi-square	99.0326	0.0000	5	139
PP - Fisher Chi-square	117.897	0.0000	5	140

Appendix 6 Unit Root Test- Population growth

Level Data

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	2.64741	0.9959	5	147
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.88281	0.9701	5	147
ADF - Fisher Chi-square	8.23227	0.6062	5	147
PP - Fisher Chi-square	14.2229	0.1631	5	150

1 st difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.63480	0.0000	5	144
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.51217	0.0000	5	144
ADF - Fisher Chi-square	68.6896	0.0000	5	144
PP - Fisher Chi-square	66.0711	0.0000	5	145

2 nd difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.82335	0.0000	5	137
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.65284	0.0000	5	137
ADF - Fisher Chi-square	88.7471	0.0000	5	137
PP - Fisher Chi-square	69.4667	0.0000	5	140

Appendix 7 Unit Root Test- Renewable energy consumption

Level Data

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.57372	0.2831	5	146
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	2.40587	0.9919	5	146
ADF - Fisher Chi-square	4.55787	0.9187	5	146
PP - Fisher Chi-square	5.32128	0.8687	5	150

1 st difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.42517	0.0077	5	142
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.16021	0.0000	5	142
ADF - Fisher Chi-square	51.6775	0.0000	5	142
PP - Fisher Chi-square	82.2080	0.0000	5	145

2 nd difference

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-12.2398	0.0000	5	137
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-13.8178	0.0000	5	137
ADF - Fisher Chi-square	126.039	0.0000	5	137
PP - Fisher Chi-square	111.776	0.0000	5	140

Appendix 8 Kao Panel Cointegration Test

Kao Residual Cointegration Test
Series: LNCO2A LNECA LNPGDPA LNPOPGA LNRECA
Date: 05/03/24 Time: 11:02
Sample: 1990 2020
Included observations: 155
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend
Automatic lag length selection based on AIC with a max lag of 1
Newey-West automatic bandwidth selection and Bartlett kernel

	t-Statistic	Prob.
ADF	-7.346935	0.0000
Residual variance	0.000806	
HAC variance	0.000149	

Appendix 9 Pooled Ordinary Least Squares Model (POLS)

Dependent Variable: LNCO2A
Method: Panel Least Squares
Date: 05/03/24 Time: 11:04
Sample (adjusted): 1991 2020
Periods included: 30
Cross-sections included: 5
Total panel (balanced) observations: 150

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNECA	0.815312	0.072277	11.28034	0.0000
LNPGDPA	0.114113	0.055820	2.044311	0.0427
LNPOPGA	0.007223	0.002378	3.037909	0.0028
LNRECA	-0.138874	0.028672	-4.843581	0.0000
C	-0.002488	0.002026	-1.228049	0.2214

Root MSE	0.019639	R-squared	0.800364
Mean dependent var	0.010212	Adjusted R-squared	0.794857
S.D. dependent var	0.044102	S.E. of regression	0.019975
Akaike info criterion	-4.955914	Sum squared resid	0.057855
Schwarz criterion	-4.855560	Log likelihood	376.6936
Hannan-Quinn criter.	-4.915143	F-statistic	145.3309
Durbin-Watson stat	2.110999	Prob(F-statistic)	0.000000

Appendix 10 Fixed Effect Model

Dependent Variable: LNCO2A
Method: Panel Least Squares
Date: 05/03/24 Time: 11:06
Sample (adjusted): 1991 2020
Periods included: 30
Cross-sections included: 5
Total panel (balanced) observations: 150

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNECA	0.803975	0.075116	10.70313	0.0000
LNPGDPA	0.142616	0.060636	2.351980	0.0201
LNPOPGA	0.007069	0.002388	2.960010	0.0036
LNRECA	-0.142692	0.029327	-4.865633	0.0000
C	-0.003192	0.002182	-1.462602	0.1458

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	0.019426	R-squared	0.804675
Mean dependent var	0.010212	Adjusted R-squared	0.793593
S.D. dependent var	0.044102	S.E. of regression	0.020036
Akaike info criterion	-4.924410	Sum squared resid	0.056605
Schwarz criterion	-4.743772	Log likelihood	378.3307
Hannan-Quinn criter.	-4.851022	F-statistic	72.60927
Durbin-Watson stat	2.158265	Prob(F-statistic)	0.000000

Appendix 11 Random Effect Model

Dependent Variable: LNCO2A
Method: Panel EGLS (Cross-section random effects)
Date: 05/03/24 Time: 11:07
Sample (adjusted): 1991 2020
Periods included: 30
Cross-sections included: 5
Total panel (balanced) observations: 150
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNECA	0.815312	0.072500	11.24574	0.0000
LNPGDPA	0.114113	0.055992	2.038039	0.0434
LNPOPGA	0.007223	0.002385	3.028589	0.0029
LNRECA	-0.138874	0.028760	-4.828722	0.0000
C	-0.002488	0.002032	-1.224281	0.2228

Effects Specification

	S.D.	Rho
Cross-section random	0.000000	0.0000
Idiosyncratic random	0.020036	1.0000

Weighted Statistics

Root MSE	0.019639	R-squared	0.800364
Mean dependent var	0.010212	Adjusted R-squared	0.794857
S.D. dependent var	0.044102	S.E. of regression	0.019975
Sum squared resid	0.057855	F-statistic	145.3309
Durbin-Watson stat	2.110999	Prob(F-statistic)	0.000000

Unweighted Statistics

R-squared	0.800364	Mean dependent var	0.010212
Sum squared resid	0.057855	Durbin-Watson stat	2.110999

Appendix 12 Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	3.111722	4	0.5393

** WARNING: estimated cross-section random effects variance is zero.

Appendix 12 Residual Cross-Section Dependence Test

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in residuals
Equation: Untitled
Periods included: 30
Cross-sections included: 5
Total panel observations: 150
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	8.079385	10	0.6211
Pesaran scaled LM	-0.429463		0.6676
Pesaran CD	0.126555		0.8993

Appendix 13 Multicollinearity- VIF and TOL

Variable	VIF	TOL
lnEC	2.83	0.3532
lnGDP	2.40	0.4172
lnPOP	1.08	0.9239
lnREC	1.27	0.7876
Mean VIF	1.90	

Appendix 13 Histogram- Normality