A COMPREHENSIVE INVESTIGATION INTO THE INTERPLAY OF ECONOMIC FINANCIAL FACTORS AND ENERGY ON CO_2 EMISSIONS IN G20 NATIONS

by

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Abstract

This comprehensive study delves into the intricate connections between economic and financial factors and carbon dioxide (CO_2) emissions across G20 nations (excluding the European Union) spanning 1994 to 2021. our investigation, utilizing a multiple linear regression model, meticulously examines diverse energy consumption types, financial institutions, life insurance premiums, economic factors, and the aftermath of the 2008 financial crisis. Our preliminary findings reveal robust links between various energy sources, financial institutions, life insurance volumes, and CO_2 emissions. Notably, the Financial Institutions Index and Life Insurance Premium Volume unveil novel insights that can add new visions to conventional perspectives. Recognizing the influential role of the G20 on a global scale, our research aspires to inform and guide sustainable policy decisions. Methodologically, after a comparative evaluation of various data transformation methods, we employ a cube root transformation to enhance analytical precision. Also, Principal Component Analysis (PCA) reveals underlying patterns in the data. Granger causality tests shed light on temporal relationships, complementing the robust quantification of each variable's impact on CO_2 emissions derived from the linear regression model. Rigorous validation, including Durbin-Watson, Breusch-Pagan, Shapiro-Wilk, RESET, Bonferroni Outlier test, and ADF stationarity tests, ensures the reliability of our results. Our linear model enhances interpretability and provides clear insights into the determinants of CO_2 emissions. This research significantly contributes to the field by extending our knowledge of the complex factors influencing CO_2 emissions. It unveils unexpected relationships, underscores the pivotal role of financial institutions, explores the repercussions of economic crises, and provides practical policy implications. Methodologically, our study stands out for its advanced statistical analyses. This research yields a valuable understanding of the sustainability framework, presenting a nuanced view for policymakers, researchers, and

practitioners alike. This study enhances the academic speech by thoroughly addressing the factors influencing CO_2 emissions and delivering a foundation for informed decision-making in pursuing a more sustainable future.

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List of Abbreviations

AC	After crisis - Dummy variable (1 for years after the 2009 crisis, zero otherwise)
ARDL	Autoregressive
AS	Agriculture Share
BRIC	Brazil, Russia, India, China
CAC	Capital Account Convertibility
CCPC	Coal consumption per capita - Energy per capita (e.g., kWh/person)
CD	Cobb–Douglas
CEFC	Central and Eastern European Countries
CO_2	CO_2 emissions (metric tons per capita)
CS	Capital Stock
DMBATGDP	Deposit Money Bank Assets to GDP
EC	Energy Consumption
EMP	Employment
EXP	Export
FA	Forest area (% of land area) - Percentage (%)
FDIAP/GDP	Foreign Direct Investment Inflows as a Percent of GDP
FFC	Fossil Fuel Consumption
FII	Financial Institutions Index - Index score (dimensionless)
FL	Financial Liberalization
FO	Financial Openness
FSDTGDP	Financial System Deposits to GDP

FT	Foreign Trade
GC	Granger Causality
GCC	Gulf Cooperation Council
GCT	Granger Causality Test
GDERD/GDP	Gross Domestic Expenditure in Research and Development as a Percentage of GDP
GDP	Gross Domestic Product
GDPP	Gross Domestic Product Per Capita
GDPPC	GDP per Capita
GDPPE	GDP per person employed (constant 2017 PPP $) - Constant 2017 PPP Dollars ($)
GECP	Gas energy consumption per capita - Energy per capita (e.g., MJ/person)
GF	Green Finance
GFCF	Gross Fixed Capital Formation
GGFCEGDP	General government final consumption expenditure (% of GDP) - Percentage (% of GDP)
GS	Genuine Saving
IAA	Index of Atmospheric Purity
IS	Industrial Share
ISMVA	Indicates Stock Market Value Added
JJ	Johansen-Juselius
LAB	Labor
LEC	Low Energy Consumption
LFI/GDP	Ratio of Loans in Financial Intermediation to GDP

LIPVGDP	Life insurance premium volume to GDP (%) - Percentage (% of GDP)
LL/GDP	Ratio of Liquid Liabilities from GDP
LLTGDP	Liquid Liabilities to GDP
MEGDP	Military expenditure (% of GDP) - Percentage (% of GDP)
NARDL	Nonlinear Autoregressive Distributed Lag
NECP	Nuclear energy consumption per capita - Energy per capita (e.g., kWh/person)
NREC	Non-Renewable Energy Consumption
NREC	
OECP	Oil energy consumption per capita - Energy per capita (e.g., kWh/person)
OLS	Ordinary Least Squares
OP	Oil Price
PCBDTGDP	Private Credit by Deposit Money Banks to GDP
PCI	Per Capita Income
PD	Panel Data
PDA	Panel Data Analysis
PDPSKLA	Population density - People per square kilometer (people/km^2)
POP	Population
PSL/NGDP	Private Sector Loans to Nominal GDP
QQR	Quantile Regression
REC	Renewable Energy Consumption
RECFEC	Renewable energy consumption (% of total final energy consumption) - Percentage (% of total energy consumption)

RPTP	Rural population (% of total population) - Percentage (%)
SLTEFFPEISI/GDP	Ratio of the Sum of Loans to Township Enterprises, Enterprises with Foreign Funds and Private Enterprises, and Self-Employed Individuals to GDP
SMCTGDP	Stock Market Cap to GDP
SMT	Stock Market Turnover
SMVTGDP	Stock Market Value Traded to GDP
SRM	Standard Reduced-Form Modeling Approach Form
SSA	Sub-Saharan Africa
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
TISGDP	Trade in services (% of GDP) - Percentage (% of GDP)
TO	Trade Openness
TR	Trade Ratio
UAE	United Arab Emirates
UP	Urban Population
UPD	Unbalanced Panel Data
USA	United States of America
VAR	Vector Autoregression
VECM	Vector Error Correction Model
WECP	Wind energy consumption per capita - Energy per capita (e.g., kWh/person)
ZA	Divot–Andrews

Glossary

ADF Test (Augmented Dickey-Fuller): Statistical test to determine if a time series is stationary.

Adjusted R-squared: -Definition: A modified version of the R-squared statistic that adjusts for the number of predictors in a regression model.

Adjusted R-squared-Significance: Provides insights into the model's goodness of fit, with higher values indicating a better fit.

AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion): -Definition: Information criteria used for model selection, balancing goodness of fit and model complexity.

ANOVA (Analysis of Variance): Statistical technique assessing differences between group means.

Autoregressive (ARDL): A modeling technique used in time series analysis.

Breusch-Pagan Test: Ensures the assumption of constant variance in linear regression models.

Breusch-Pagan Test: A statistical test used to assess heteroscedasticity, i.e., the variability of errors across levels of independent variables.

BRIC (Brazil, Russia, India, China): An acronym referring to major emerging national economies.

CCPC (Coal Consumption per Capita): Energy consumption per Person from coal sources.

Central and Eastern European Countries (CEFC): European countries typically transition from communism to market-oriented economies.

Cobb–Douglas (CD): A production function representing the economic relationship between inputs and outputs.

Coefficients: Values showing the strength and direction of the connection between variables.

Correlation Coefficient: An evaluation of the power and tendency of a linear relationship between two variables.

Cube Roots Transformation-Definition: A mathematical process applied to each data point involves calculating the value's cube root.

Cube Roots Transformation -Purpose: Used as a data transformation technique to meet assumptions of linear regression models, address skewness and kurtosis, and ensure normality.

Cumulative Explained Variance: The total variance in the data is explained by a set of principal components.

Data Quality Assessment-Definition: Evaluation of collected data's reliability, accuracy, and completeness.

Data Quality Assessment-Significance: Important for ensuring the validity and credibility of research findings.

Definition-Durbin-Watson Test: A statistical test applied to identify autocorrelation in the residuals of a regression study.

Descriptive Statistics-Definition: Statistical measures used to describe and summarize the primary features of a dataset.

Descriptive Statistics- Purpose: Provides a snapshot of the dataset's distribution, central tendency, and variability of variables.

Effect Size (KS D): Measure the deviation's magnitude from a normal distribution.

F-statistic: A statistical test assessing the overall significance of the regression model.

Functional Form Misspecification-Definition: The situation where the chosen functional form of the model does not accurately represent the actual relationship in the data.

Functional Form Misspecification-Significance: Assessed through tests like the RESET Test to ensure the adequacy of the model.

G20 Countries: A group of major economies that meet to discuss and coordinate economic policies.

GDP (Gross Domestic Product): The monetary worth of all goods and services produced within a country's borders in a specific time.

GDP per Person Employed (constant 2017 PPP $): Gross Domestic Product per Person employed, adjusted for purchasing power parity (PPP) and constant 2017 dollars.

Granger Causality Test- Definition: A statistical hypothesis test to decide whether one time series can anticipate another.

Granger Causality Test-Significance: Applied to identify causal relationships between economic indicators and CO_2 emissions.

Green Property Finance (GPF): Financing related to environmentally sustainable and energy-efficient properties.

Gulf Cooperation Council (GCC): A regional international diplomatic and commercial union of Arab states.

Homoscedasticity- Definition: The assumption that the variance of errors is steady throughout all levels of independent variables.

Homoscedasticity- Significance: Ensures the efficiency of estimates in statistical analyses; assessed through tests like the Breusch-Pagan Test.

Hypotheses: Assumptions or predictions formulated for evaluating the relationships between different variables.

Imputation-Definition: The process of replacing missing or incomplete data with estimated values.

Imputation-Significance: Ensures completeness of the dataset and avoids biases in analyses due to missing values.

Index of Atmospheric Purity (IAA): An index measuring the cleanliness and purity of the atmosphere.

Interpretation of Coefficients: Understanding the effect of independent variables on the dependent variable.

Johansen-Juselius (JJ): A statistical technique for analyzing multivariate time series data.

Loading Values: The weights assigned to each variable in a principal component, indicating the contribution of each variable to that component.

Mesokurtic Shape: Normal-like tails in the distribution.

Multiple Linear Regression Analysis: A statistical procedure applied to model the association linking dependent variables (CO_2 emissions) and multiple independent variables (energy consumption, financial indices, and so on).

Multiple R-squared: A measurement of how well the independent variables define the variation in the dependent variable.

Nonlinear Autoregressive Distributed Lag (NARDL): A modeling approach for analyzing the long-term relationships between variables.

Normality- Definition: The property of having a normal distribution; in the context of statistical tests, it refers to the statement that the data supports a normal distribution.

One-Sided Causality: Denotes a directional impact from one variable to another; one variable influences the other.

Ordinary Least Squares (OLS): A approach for reckoning the parameters in a linear regression model.

Outlier Data: Unusual or extreme values in economic data.

Panel Data Analysis (PDA): Analysis of data gathered over time on a group of entities.

PCA Analysis: Principal Component Analysis is a statistical method that simplifies data by reducing its dimensionality while retaining trends and patterns.

Quantile Quantile Regression (QQR): A statistical technique for assessing the conditional quantiles of a response variable.

R Square and Adjusted R Square: Measure how well the model explains variability in the dependent variable.

Regression Analysis: This is applied to understand the effect of independent variables on the dependent variable, such as CO_2 emissions, in this study.

Regression Analysis-Definition: A statistical method to explore the connection between a dependent variable and one or more independent variables.

Residual Regression: The difference between observed and predicted values in regression analysis.

Residual Standard Error-Definition: The standard deviation of the residuals in a regression model.

Residual Standard Error-Significance: Indicates the average deviation of observed values from the predicted values.

Robust Correlation: Strong and reliable relationship between variables.

Scree Plot: A graphical representation showing the distribution of explained variance across principal components.

Shapiro-Wilk Test-Definition: A statistical test used to assess the normality of a distribution.

Shapiro-Wilk Test-Significance: Employed to validate normal distribution assumptions in the context of residuals in regression analysis.

Significance Level (α): Threshold for accepting or rejecting the null hypothesis.

Significance-Durbin-Watson Test: Assesses the assumption of independence among residuals.

Skewness: A measure of the asymmetry of a distribution.

Standard Reduced-Form Modeling Approach Form (SRM): A modeling approach used to analyze economic systems.

Stationarity: Property of time series data with constant characteristics over time.

Statistical Significance-Definition: The likelihood that an observed result or relationship in data is not due to random chance.

Statistical Significance-Significance: Important in determining the practical importance of variables in regression models.

Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT): A model used to analyze the environmental impact of human activities.

Trade in Services: The exchange of services between countries, often expressed as a percentage of GDP.

Two-Sided Causality: Indicates mutual influence between variables; both variables influence each other.

Unbalanced Panel Data (UPD): Data collected over time on a group of entities where the number of observations for each entity may vary.

Unit Root Test: Evaluates whether a time series exhibits a unit root (nonstationary).

Vector Autoregression (VAR): A statistical model for analyzing the dynamic relationships among multiple time series variables.

Vector Error Correction Model (VECM): A model that analyzes the relationship between multiple time series variables.

Zivot–Andrews (ZA): A statistical test for identifying structural breaks or changes in time series data.

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Chapter One: Introduction

1.1 Introduction

The rapid carbon dioxide (CO_2) surge remains a critical global climate change crisis driver. Understanding the intricate connections between financial institutions, economic factors, and environmental impact is paramount. From 1994 to 2021, this thesis meticulously explores these interdependencies, specifically their nuanced effects on CO_2 emissions across G20 countries (excluding the European Union).

The harmful consequences of CO_2 emissions on our environment and human health underscore the urgency of addressing this issue. Climate change faces significant threats due to the escalating greenhouse gas levels, primarily CO_2. Therefore, a thorough analysis of the correlations between CO_2 emissions and economic and financial variables becomes essential.

The G20 nations, commanding around 80% of global economic output, 75% of international trade, and home to 60% of the world's population, exert considerable influence over international CO_2 emissions. A meticulous understanding of the factors influencing emissions in these nations promises invaluable insights into global trends, facilitating well-informed policy decisions. The G20 nations also spearhead global investments in energy infrastructure and technology, rendering them pivotal in the battle against climate change. Scrutinizing their emissions policies and measures becomes crucial in informing international strategies for emissions reduction.

Through their lending and investment practices, financial institutions wield influence over the behaviors of businesses and households, impacting the environment. Engaging environmentally, social and governance (ESG) principles into the strategic frameworks of these institutions serve to mitigate risks, uncover opportunities, and bolster their standing, consequently augmenting their financial performance (Atlason, 2023). In recognition of their societal responsibilities, financial institutions align their agendas with financial returns (BNP Paribas, 2020). As the sector rapidly expands its knowledge of climate risk, it simultaneously seizes opportunities to transition to a more inclusive and sustainable economy (BNP Paribas, 2020).

Research indicates that various economic and demographic factors significantly influence CO_2 emissions. Population size and GDP per capita, indicative of resource consumption and economic activity, positively correlate with emissions. Energy consumption, primarily from fossil fuel combustion, drives CO_2 emissions. Urbanization contributes to higher emissions due to increased energy consumption and waste production in urban areas. Moreover, the age structure of a population influences per-capita emissions, emphasizing the need for policies addressing these factors to mitigate climate change effectively. The Financial Institutions Index, a novel variable, sheds light on the intricate relationship between financial development and environmental sustainability. Studies reveal both positive and negative impacts of financial development on ecological sustainability (Musah et al., 2022; Ruza et al., 2022; Shehzad et al., 2023; Li et al., 2015; Khan et al., 2022).

By incorporating ESG principles, finance institutions can play a transformative role in transitioning to a carbon-neutral economy. Life Insurance Premium Volume is another innovative variable, elucidating insurance's role in climate change mitigation and adaptation. Well-designed insurance policies can enhance communities' resilience to climate change impacts (Grantham Institute). The sector can also promote greenhouse gas reduction through renewable energy infrastructure (Ward et al., 2008). However, challenges in profitability and affordability necessitate adjustments to existing business models (Fantini et al., 2023; McKinsey & Company, 2023).

Various variables, including energy consumption per capita, government final consumption, population density, and military expenditures, are analyzed to determine the relationship between CO_2 emissions and these variables. Two innovative variables, Life Insurance Premium Volume, and the Financial Institutions Index, offer unprecedented perspectives on financial institutions' impact on CO_2 emissions. This study unravels the role of financial and economic variables in shaping CO_2 emissions and fostering sustainable development. Throughout the project, we aim to provide policymakers globally with academically stimulating and relevant insights into the G20, pivotal players in the international economy, and significant contributors to global warming.

By delving into the intricate relationship between financial and economic variables and CO_2 emissions, the study's results help different users, such as governments, policymakers, and environmentalists, better understand the financial and economic practical variable relation of and decide how to reduce CO_2 emissions and promote sustainable development.

Regarding the 2008 financial crisis, this analysis research posits that economic downturns could particularly impact CO_2 emissions. Energy consumption and CO_2 emissions are nearly intertwined with economic activities, and disruptions like the 2008 financial crisis could have far-reaching consequences on the global economy.

In pursuing a sustainable future, this research aspires to transcend environmental economics by unraveling how financial institutions and economic dynamics shape CO_2 emissions. Evidence-based recommendations for policymakers, researchers, and practitioners will be formulated, with an analysis of the 2008 financial crisis offering insights into CO_2 emissions factors.

1.2 Statement of the Problem

In addition to its functional and societal importance, the study has theoretical, methodological, and practical significance. The study contributes to comprehending how diverse economic and financial factors influence CO_2 emissions in a way that provides appropriate insights for future research.

This article provides an innovative application of a multiple linear regression model to variable transformation using cube roots. The study's results may also be an excellent starting point for similar investigations. The study has many practical implications for policy and sustainable development. This will help policymakers identify factors influencing CO_2 emissions and devise strategies to decrease them.

Considering the urgency associated with climate change prevention efforts, the research is relevant from a social perspective. Its contribution to understanding the factors behind carbon dioxide emissions might support global initiatives to curb climate change.

G20 countries control a significant share of global GDP, and a large share of global carbon emissions is also controlled, as examined in this paper. Due to the critical changes in CO_2 emissions during the 2008 financial crisis, this investigation suggests understanding the association between economic downturns and environmental outcomes.

1.3 The Study's Importance

The study's importance is diverse, including academic, methodological, experimental, and societal aspects. Theoretically, it contributes to the understanding that CO_2 emissions can be affected by different economic and financial characteristics. The research shows how these factors interact to provide relevant insights for future studies.

In terms of research methods, we innovatively applied a multiple linear regression model to demonstrate the transformation of variables using cube roots. This approach also facilitated a comparative analysis of different transformation methods.

The study has significant policy and sustainable development implications, including its practical implications. The research findings will help policymakers reveal what influences CO_2 emissions so that they can devise effective strategies to reduce emission levels and promote sustainability.

Societally speaking, the research is significant due to the urgency attached to climate change prevention efforts. The study's contribution towards comprehending the factors behind carbon dioxide emissions might support global initiatives to curb climate change and reduce its impact on societies.

CO_2 emissions in G20 countries are closely correlated with economic and financial factors, as examined in this paper. In addition to controlling a significant share of global economic output, G20 countries are responsible for a considerable share of global carbon emissions. Based on the significant shifts in CO_2 emissions tracking the 2008 financial crisis, this study sheds light on how financial downturns affect environmental consequences.

1.4 The Purpose of the Study

This study investigates the intricate connection between different per capita energy consumption forms and financial institutions' influence on CO_2 emissions across G20 countries. Our investigation encompasses specific energy sources (coal, gas, nuclear, renewable, wind, and oil) and broader economic indicators (Financial Institutions and life insurance premium volume). Understanding the potential impact of the 2008 financial crisis on CO_2 emissions is a key focus. We have formulated hypotheses that predict outcomes based on coal consumption, financial institutions' strength, life insurance premiums, and the historical financial crisis.

1.5 Research Questions

As part of this research, we aim to clarify how energy use impacts carbon dioxide (CO_2) emissions in G20 countries. To accomplish this, we need to address the following vital questions:

1. How are distinct types of energy consumption (coal, gas, nuclear, renewable, wind, oil) related to CO_2 emissions in G20 countries?
2. How do financial institutions, as the Financial Institutions Index indicates, impact CO_2 emissions?
3. What is the relationship between life insurance premium volume and CO_2 emissions?
4. How did the 2008 financial crisis impact CO_2 emissions?

1.6 Research Hypotheses

Our study proposes the following hypotheses based on these research questions:

Hypothesis 1: Distinct types of energy consumption (coal, gas, nuclear, renewable, wind, oil) have varying impacts on CO2 emissions in G20 countries. Specifically, coal, gas, and oil energy consumption are positively correlated with CO2 emissions, while nuclear, renewable, and wind energy consumption are negatively correlated with CO2 emissions.

Hypothesis 2: The performance of financial institutions, as indicated by the Financial Institutions Index, has a significant negative impact on CO2 emissions.

Hypothesis 3: A positive correlation exists between life insurance premium volume and CO2 emissions.

Chapter Two: Literature Review

2.1 Introduction

Investigating the intricate connection between financial and economic variables and carbon dioxide (CO_2) emissions is essential, especially considering climate change concerns. This literature study covers 1994 to 2021, focuses on the G20 countries, and explores the intricate interactions between many factors that affect environmental indicators.

The haste of handling climate change, driven by escalating greenhouse gas attention, underscores the significance of understanding the role played by economic and financial factors. From earnings and industrialization to urbanization, these elements contribute to CO_2 emissions and necessitate a comprehensive investigation.

Crucial understandings from diverse investigations are synthesized, protecting various issues such as financial inclusion, green finance, and the influence of Foreign Direct Investment (FDI) on CO_2 emissions. Studies from Le et al. (2020), Meo and Abd Karim (2022), Ashraf et al. (2022), and others contribute valuable perspectives on the complex interplay between economic variables and environmental indicators.

A vital aspect explored in the literature is the impact of economic crises on CO2 emissions. Various studies have indicated that economic downturns can lead to significant changes in CO2 emissions due to shifts in industrial production and energy consumption patterns.

The literature review identifies gaps in existing research, including the need for a comprehensive analysis of the G20 nations, exploration of diverse economic and financial factors, and the application of a multiple linear regression model. These gaps set the stage for the research's objectives, aiming to contribute to a more comprehensive understanding of the connection between economic and financial factors and CO_2 emissions, guiding sustainable policy decisions.

This chapter serves as a gateway to unraveling this relationship's complexities, thoroughly examining existing research. The global context, specifically focusing on G20 nations, sets the stage for an in-depth exploration of how economic variables shape environmental outcomes. The objective is to distill crucial insights from a diverse array of studies, unveiling patterns, trends, and research gaps that will inform the subsequent analysis in this study.

2.2 Background

Climate change, driven by the growth in concentrations of greenhouse gases (GHGs) in the air, is one of our most significant environmental issues. Greenhouse gas gains are due to emissions from human actions, such as the practice of fossil fuels and agriculture. The changing climate effects circumstances, human health, and thrift (Environment and Climate Change Canada, 2023).

Economic and financial factors are crucial in carbon dioxide (CO_2) emission, a primary GHG. Research has shown that incomes, resource utilization, industrialization, urbanization, foreign direct investment, and banking organizations have all influenced rising CO_2 emissions. However, greater economic access has reduced greenhouse gas emissions (Molico, 2019; Liu et al., 2022).

Technological progress, foreign investment, and energy consumption are certain factors of CO_2 emissions. Technological progress can decrease CO_2 emissions by studying and using green energy. Foreign investment reflects the pollution haven hypothesis, which includes tax environmental regulation, good market access to high-income countries, and corruption opportunities. Energy consumption determines the quantity of CO_2 emissions (Li et al., 2021).

Financial institutions and life insurance volumes have been found to have substantial links with CO_2 emissions relative to GDP. The Financial Institutions Index and Life Insurance Premium Volume offer novel insights into this relationship (Molico, 2019).

Understanding the macroeconomic and financial system effects of climate transformation and the shift to a low-carbon economy is a priority for many countries. This understanding is crucial for promoting countries' economic and financial welfare and understanding the potentially meaningful structural transformation impacting the economy and financial system due to climate change (Molico, 2019).

In conclusion, the intricate nexus between economic and financial factors and CO_2 emissions is a complex and critical area of study. This background provides the necessary context for understanding the importance of this research and its potential implications for policy decisions and financial stability.

2.3 Review of Literature

However, much literature has examined the intricate link between economic and financial factors and carbon dioxide (CO_2) emissions despite the urgency of addressing climate change globally. Focusing on G20 countries from 1994 to 2021, this review synthesizes critical studies contributing to our understanding of this complex interplay. Le, Le, and Taghizadeh-Hesary's (2020) exploration of financial inclusion across 31 Asian countries reveals a nuanced relationship, emphasizing the need for policymakers to align financial strategies with environmental goals. Meo and Abd Karim's (2022) innovative quantile-on-quantile regression approach offers insights into the asymmetric impact of green finance on CO_2 emissions in the top ten economies supporting green finance.

Notably, these studies extend beyond traditional economic indicators, highlighting the influence of financial institutions and green finance on environmental sustainability. Examining regional dynamics, Ashraf et al. (2022) delve into the unique challenges of Gulf Cooperation Council (GCC) economies, emphasizing the importance of sustainable practices and diversifying foreign direct investment. As we navigate the complex web of economic variables, this literature review aims to distill the key findings that inform our investigation into the G20 countries' CO_2 emissions landscape.

According to the study by Le, Le, and Taghizadeh-Hesary (2020), financial inclusion significantly impacts CO_2 emissions across 31 Asian countries. They looked at factors such as income, energy consumption, urbanization, industrialization, foreign direct investment, trade openness, and financial inclusion using the STIRPAT model. As a result, CO_2 emissions tend to increase due to these factors, including financial inclusion. Notably, higher trade openness was associated with lower emissions. The study highlights the need for policymakers to align financial inclusion efforts with environmental goals. It also touches on the potential positive and negative effects of financial inclusion on climate change, emphasizing the importance of integrating financial strategies into climate change adaptation plans for the vulnerable Asian region. The conclusion advocates for expanded access to climate finance to empower individuals and businesses in mitigating CO_2 emissions locally.

In their 2022 study, Ashraf et al. delve into the asymmetric connection between Foreign Direct Investment (FDI), oil prices, and carbon emissions contained by the Gulf Cooperation Council (GCC) economies. The research addresses a critical gap in comprehending how these elements contribute to environmental pollution, highlighting the unique challenges of oil dependent GCC economies.

In exploring the complex interplay between economic, financial, and energy factors on CO2 emissions, we found the study by Fu (2021) particularly enlightening. Fu's research, titled "Time-Varying Risk and the Relation between Idiosyncratic Risk and Stock Return," comprehensively analyzes the historical time-varying risk dynamics for individual stocks in the U.S. market. Fu's work, which decomposes the total risk of an individual stock into systematic and idiosyncratic components, offers valuable insights into the risk-return tradeoff. These insights have significantly informed our study's understanding of the dangers associated with energy sources and financial institutions.

The researchers employ a robust econometric framework, specifically the panel Nonlinear Autoregressive Distributed Lag (NARDL) analysis, which allows for a more in-depth examination of nonlinear relationships. The study offers nuanced insights into these asymmetric relationships, providing valuable guidance for policymakers and investors. It emphasizes the need for sustainable practices and diversifying FDI away from polluting industries. Findings may not apply to other global contexts. The study could be enhanced by considering temporal changes and exploring other factors influencing carbon emissions. Despite these limitations, the research offers valuable implications for sustainable development and is a crucial resource for stakeholders interested in environmental economics.

The 2022 study by Meo and Abd Karim discovers the association between green finance and CO_2 emissions in the leading ten economies supporting green finance. Using the quantile-on-quantile regression (QQR) approach, the authors verify the negative impact of green finance on CO_2 emissions, with variations across different quantiles due to market conditions and country-specific factors. The study's creative methodology and global applicability supply valuable understandings and practical substances for sustainable development, highlighting the position of fiscal policies and the need for improving green financial systems.

However, the study's area is limited to the top ten economies, potentially limiting the generalizability of its results. Despite offering an extension to investigate the co-movement between green finance and other financial markets, this area is not explored in the present study. Nevertheless, the study donates to the current literature on sustainable finance, offering a fresh perspective on the dynamics of green finance and its impact on CO_2 emissions.

In light of economic crises and their subsequent impact on CO2 emissions, the findings of a study exploring the effects of political uncertainty on firms' climate risk premium are particularly noteworthy. This global study, led by Xu et al. (2022), offers invaluable insights into how political dynamics can shape environmental outcomes, potentially influencing CO2 emissions. The result of the research underscores the intricate interplay between economic, political, and ecological factors in the context of climate change.

The 2022 study by Meo and Abd Karim provides an in-depth analysis of the connection among green finance and CO_2 (carbon dioxide) emissions in the top ten countries that promote green finance. Using a novel econometric approach, the authors use quantile-on-quantile regression (QQR) to analyze the association between green finance and CO_2 emissions. This innovative methodology allows for a nuanced understanding of the relationship, capturing its heterogeneity and asymmetry.

Studies show that green finance reduces CO_2 emissions. However, this impact varies across different quantiles, reflecting the influence of market conditions and country-specific factors. These findings are particularly relevant given the significant role of the building sector in global CO_2 emissions, contributing to 38% of the total.

The research has several strengths. Firstly, the innovative QQR methodology offers a fresh perspective in the field, allowing for a more nuanced analysis of the connection linking green finance and CO_2 emissions. Secondly, the study's focus on the top ten economies supporting green finance provides practical insights that can serve as benchmarks for other nations aspiring to adopt similar strategies. Lastly, the study's policy implications are valuable, emphasizing the role of fiscal policies in improving green financial systems and promoting green finance.

In understanding the impact of economic crises on CO2 emissions, it is pertinent to consider the results of a study led by Liu, X et al. (2022). This research investigated the effect of the oil price drop in 2014-2015 on labor investment in Chinese firms. The study provides valuable insights into how fluctuations in global commodity prices, such as oil, can have wide-ranging impacts on various sectors of the economy. More importantly, these economic shifts can influence CO2 emissions, a critical aspect of our investigation into the interplay of economic and financial factors on CO2 emissions across G20 nations. This reference underscores the intricate connections between economic phenomena and environmental outcomes, enriching our understanding of the factors influencing CO2 emissions.

When considering financial strategies to mitigate environmental impact, one cannot overlook the significant findings of an in-depth study on China's Green Credit Guidelines. This research, spearheaded by Li et al. (2022), offers a detailed empirical analysis that explores the convergence of green policies and corporate social responsibility. The insights gleaned from this study are particularly relevant to our investigation, which examines the complex interplay between economic and financial factors and their subsequent influence on CO2 emissions across G20 nations.

In addition, a study conducted by Gong et al. (2023) provides a comprehensive international analysis of climate risk's impact on fossil fuel companies' stock performance. This research highlights the far-reaching implications of environmental factors, such as climate risk, on various economic sectors, potentially influencing CO2 emissions. The study underscores the importance of incorporating environmental considerations into financial strategies.

Jamel and Maktouf's (2017) research provide valuable insights into the complex relationships among economic growth, financial development, trade openness, and environmental consequences in European countries. An affirmative aspect of the study lies in its comprehensive examination of bidirectional causal linkages, shedding light on the dynamics between key economic variables and CO_2 emissions. The utilization of the Cobb–Douglas production function and a panel dataset spanning three decades enhances the robustness of the findings. However, a potential limitation is the absence of consideration for regional variations or specific country characteristics that might influence the observed relationships. Additionally, while the study identifies bidirectional connections, it does not delve deeply into the mechanisms or policy implications that could guide effective interventions for sustainable development. Nevertheless, the research contributes significantly to the ongoing discourse on the intricate interplay between economic factors and environmental degradation in the European context. Zhang's 2011 research delves into the complex connection involving financial development and CO_2 output in China. The study employs various econometric techniques, including co-integration theory, the Granger causality test, and variance decay. The conclusions reveal that China's financial advance, particularly the scale of financial intermediation, is a significant driver for the increase in carbon emissions. The research underscores the need for policymakers to consider financial development alongside income levels when projecting demand for carbon emissions.

The study also highlights the influence of the financial intermediation scale on carbon emissions compared to other financial development indicators. It further investigates the distinct roles of China’s stock market scale and efficiency in influencing carbon emissions. The stock market scale is found to have an enormous impact, suggesting the need for efforts to improve standardization and trading liquidity in China’s stock markets. In contrast, foreign direct investment (FDI) is identified as having the most negligible influence on carbon emissions among the financial development indicators studied.

In the context of economic crises and their impact on CO2 emissions, the findings of a study that investigated the effects of temperature changes on stock returns in China are worth noting. This study, conducted by (Yan et al.,2022), provides valuable insights into how environmental factors (like temperature changes) can have wide-ranging impacts on various sectors of the economy, potentially influencing CO2 emissions. These insights align with our investigation into the interplay of economic and financial factors and their influence on CO2 emissions across G20 nations.

Despite its valuable insights, Zhang’s study has some limitations. It primarily focuses on national-level analysis, allowing further investigation into regional variations. Given China’s rapidly changing financial landscape and environmental policies, a more recent analysis could provide a more accurate picture of the current situation. The study does not extensively explore external factors, such as international economic conditions or global environmental policies, which could influence the connection linking financial growth and carbon emissions. Despite these limitations, the research provides valuable policy implications for China’s efforts to reduce the intensity of carbon emissions and anticipates the evolution of China's financial system. It suggests that economic reforms could be crucial, including integrating banks and capital markets.

2.4 Summary

The table compiles vital information from numerous studies that consider the associations relating economic variables and environmental values in different countries and periods. The authors, representing diverse research perspectives, explore the intricate connections between variables such as GDP, CO_2 emissions, trade openness, foreign direct investment, and energy consumption. The periods under consideration span several decades, providing a historical dimension to the analysis. The table outlines the specific variables studied, the countries involved, the methodologies employed (including the linear model, auto-regressive distributed lag, Granger causality, and others), and the primary results or findings from each study. This amalgamation of study efforts weaves a rich tapestry of understandings, unraveling the intricate interplay between financial development and environmental outcomes spanning various regions and temporal measurements. The ensuing literature review will delve deeper into the nuances of these findings, synthesizing the collective knowledge and identifying patterns, trends, and gaps in the existing research landscape.

Table 1- Summary of Research Studies

Authors	Period	Variables	Country	Methodology	Results
Warr & Ayres	1946–2000	GDP, CS, LAB, EC	USA	GC VEC, JJ	EC → GDP
Bowden & Payne	1949–2006	GDP, REC, NREC, GFCF, EMP	USA	TYGC	REC ↔ GDP NREC ↔ GDP
Lee & Chang	1953–2003	GDP, CS, LAB, EXP, EC	Taiwan	LM	EC has a positive effect on GDP
Jalil & Feridun	1953–2006	CO_2, EC, GDP, LL/GDP, TR, PSL/NGDP	China	GC ARDL	GDP → CO_2FDI negative CO_2
Halicioglu	1960–2005	CO_2, EC, PCI, FT	Turkey	GC ARDL	CO_2 ↔ GDP EC ≠ GDP FT ≠ CO_2
Menyah & Rufael	1960–2007	CO_2, REC, NEC, GDP	USA	MGC VEC	EC → CO_2 REC ≠ CO_2 NEC → CO_2
Zhang & Cheng	1960–2007	GDP, GFCF, EC, CO_2, UP	China	GC; VEC;	GDP → EC → CO_2, EC no→ GDP,
Yoo	1968–2002	OC, GDP	South Korea	GC VEC	GDP ↔ OCON
Shahbaz et al.	1975–2011	Yt, Et, Ft, TRt, Ct	Indonesia	ZA, ARDL, VECM	REC ↔ GDP, NREC ↔ GDP, CO_2 ↔ GDP, EC ≠ GDP, FT ≠ CO_2, GDP → CO_2,
Sbia et al.	1980–2010	CO_2, GDP, TO, FDI, EC	UAE	ARDL	LGDP → LEC
You	1980–2003	GDPPC, FFC, REC, GS	China	AVD, GIRF	FCON increases GDPP; REC increases GS
Kebede et al.	1980–2004	GDP, POP, EC, OP, IS, AS	SSA	TPM	EC has a “+” effect on GDP & GDPP
Zhang	1980–2005	CO_2, GDPPC, LFI/GDP, SLTEFFPEISI/GDP, SMCTGDP, SMTGDP, FDIAP/GDP	China	VEC GC, JJ	GDP & FDI (lnp CO_2) FDI → CO_2
Al-mulali and Lee	1980–2009	FD, EC, GDP, URB, TR	GCC	PD, GC	LEC ↔LGDP
Jamel & Maktouf, S.	1985–2014	GDP, CO_2, FD, TO, EC, FDI, INF, K, U	40 European economies	OLS, CD, PDA, GCT,	GDP ↔ CO_2, GDP ↔ FD, GDP ↔ TO, FD ↔ TO, TO ↔ CO_2: GDP → CO_2,
Tamazian et al.	1992–2004	CO_2, GDPP, GDERD/GDP, ISMVA, FDI, DMBATGDP, CAC, FL FO, OC, EC	BRIC	SRM	FDI & EDI have a negative effect on CO_2
Sadorsky	1996–2006	GDPPC, EC, OP, DMBATGDP, FSDTGDP, LLTGDP, PCBDTGDP, SMCTGDP, SMVTGDP, SMT	CEFC	GMMR	FDI has a + effect on EC
Sadorsky	1996–2006	EC, GDPP, IR, BDTGDP, SMCTGDP, SMVTGDP, SMT	EME	GMMR	Increases in stock market variables ↑ , energy demand
Ashraf, & Umar	1999–2016	FDI, OP, CO_2	GCC	NARDL	FDI → CO2, oil prices → CO_2
Le et al.	2004–2014	GHG (CO_2), INC, ENE, FDI, TRADE, URB, IND, FI (FII)	31 Asian countries	STIRPAT	Factors Leading to Higher CO_2 Emissions: INC →CO_2, ENE → CO_2, URB → CO_2, IND → CO_2, FDI → CO_2, FI → CO_2, Factor
Meo & Abd Karim	2008–2019	GF, CO_2	Ten countries	QQR, GC	CO_2 ↔ GF, GF ≠ CO_2 Quantiles
Gholipour et al.	2012–2018	GPF, CO_2	Ninety-eight CR	UPD	GPF ↔ CO_2 Emissions

Note OF Table 1: → represents unidirectional causality; ↔ implies bilateral causality, and no causality is represented by 2. VECM is the vector error correction model, and ECM is the error correction model.

Variables: GPF (Green Property Finance), CO_2 (Carbon Dioxide Emissions), GHG (Greenhouse Gas Emissions), INC (Income), ENE (Energy Intensity), FDI (Foreign Direct Investment), TRADE (Trade Openness), URB (Urbanization), IND (Industrialization), FI (Financial Inclusion), FII (Financial Inclusion Index), Yt (Economic Growth), Et (Energy Consumption), Ft (Financial Development), TRt (Trade Openness), Ct (CO_2 Emissions), REC (Renewable Energy Consumption), NREC (Non-Renewable Energy Consumption), GDPP (Gross Domestic Product Per Capita), LEC (Low Energy Consumption), GDP (Gross Domestic Product), TO (Trade Openness), EC (Energy Consumption), REC (Renewable Energy Consumption), NREC (Non-Renewable Energy Consumption), GFCF (Gross Fixed Capital Formation), EMP (Employment), PCI (Per Capita Income), FT (Foreign Trade), LL/GDP (Ratio of Liquid Liabilities from GDP), TR (Trade Ratio), PSL/NGDP (Private Sector Loans to Nominal GDP), POP (Population), OP (Oil Price), IS (Industrial Share), AS (Agriculture Share), CS (Capital Stock), LAB (Labor), EXP (Export), GDPPC (GDP per Capita), DMBATGDP (Deposit Money Bank Assets to GDP), FSDTGDP (Financial System Deposits to GDP), LLTGDP (Liquid Liabilities to GDP), PCBDTGDP (Private Credit by Deposit Money Banks to GDP), SMCTGDP (Stock Market Cap to GDP), SMVTGDP (Stock Market Value Traded to GDP), SMT (Stock Market Turnover), GDERD/GDP (Gross Domestic Expenditure in Research and Development as a Percentage of GDP), ISMVA (Indicates Stock Market Value Added), DMBATGDP (Ratio of Deposit Money Bank Assets to GDP), CAC (Capital Account Convertibility), FL (Financial Liberalization), FO (Financial Openness), OC (Oil Consumption), OCON (Oil Consumption), FFC (Fossil Fuel Consumption), GS (Genuine Saving), LFI/GDP (Ratio of Loans in Financial Intermediation to GDP), SLTEFFPEISI/GDP (Ratio of the Sum of Loans to Township Enterprises, Enterprises with Foreign Funds and Private Enterprises and Self-Employed Individuals to GDP), FDIAP/GDP (Foreign Direct Investment Inflows as a Percent of GDP), GFCF (Gross Fixed Capital Formation), UP (Urban Population), GF (Green Finance).

Methodologies: UPD (Unbalanced Panel Data), STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology), ZA (Zivot–Andrews), ARDL (Autoregressive), VECM (Vector Error Correction Model), OLS (Ordinary Least Squares), CD (Cobb–Douglas), PDA (Panel Data Analysis), GCT (Granger Causality Test), IAA (Index of Atmospheric Purity), PD (Panel Data), GC (Granger Causality), SRM (Standard Reduced-Form Modeling Approach Form), JJ (Johansen-Juselius), NARDL (Nonlinear Autoregressive Distributed Lag), QQR (Quantile Quantile- Regression), VAR (Vector Autoregression).

Kind of Countries: UAE (United Arab Emirates), USA (United States of America), Turkey, China, SSA (Sub-Saharan Africa), Taiwan, CEFC (Central and Eastern European Countries), BRIC (Brazil, Russia, India, China), South Korea, GCC (Gulf Cooperation Council), Top ten economies that support green finance (10 countries), 98 high-income and developing economies, 31 Asian countries, Indonesia, 40 European economies.

2.5 Research Gap

The existing literature has contributed to our knowledge of the connection between financial and economic issues and CO_2 emissions. Still, this study points to several areas that need more investigation.

Many studies have primarily focused on individual countries or specific regions, resulting in a gap in our understanding of this relationship in a global context. This study seeks to bridge this gap by exploring the G20 nations (excluding the European Union) from 1994 to 2021.

Previous research has considered various economic and financial factors, but the impact of certain variables, such as the Financial Institutions Index and Life Insurance Premium Volume on CO_2 emissions, remains underexplored. This research intends to delve deeper into these aspects.

While separate models have been used to assess the relations connecting economic variables and CO_2 emissions, more literature is needed to employ a multiple linear regression model. This model allows for scrutinizing various energy consumption types, financial institutions, life insurance premiums, and the aftermath of the 2008 monetary crisis. This research aims to fill this gap.

The aftermath of the 2008 financial situation and its impact on CO_2 emissions is another area that requires further investigation. This research will shed light on this aspect by including a variable that captures the post-crisis period.

By addressing these gaps, this research aims to improve the current understanding and supply a more exhaustive understanding of the complex interplay between economic and financial factors and CO_2 emissions. The findings could potentially guide sustainable policy decisions and promote economic and financial welfare in the face of climate change.

2.6 Conclusion

A comprehensive overview of the most recent studies on the connection between financial and economic variables and CO_2 emissions can be found in the literature review. The impact of several factors, including life insurance premiums, financial institutions, energy consumption types, and the aftermath of the 2008 financial crisis, on CO_2 emissions has been emphasized. It has also drawn attention to several gaps in the research, chief among them being the requirement for a thorough examination of the G20 countries that considers a variety of financial and economic variables and uses a multiple linear regression model.

The research question of this study, "What is the intricate nexus between economic and financial factors and CO_2 emissions across G20 nations from 1994 to 2021?" is directly informed by the conclusions from the literature review. This research aims to provide a more comprehensive understanding of this complex relationship by addressing the identified gaps in the literature. The insights gained from this study could potentially guide sustainable policy decisions and promote countries' economic and financial welfare in the face of climate change.

Chapter 3: Methodology

3.1 Introduction to Methodology

This research uses multiple linear regression analysis to investigate the complex link between CO_2 emissions and other economic and financial elements among G20 countries. Thanks to this quantitative technique, we can measure the effect of each independent variable on CO_2 emissions while accounting for the impacts of all other factors. Considering how interrelated the variables affecting CO_2 emissions are, this is vital.

To improve the robustness and validity of our study, we use a cube root transformation for all variables. This transformation addresses issues of skewed data, stabilizes variance, and mitigates the influence of outliers, aligning with the fundamental assumptions of linear regression models.

Our approach also includes rigorous validation methods to increase the reliability of our regression findings. These consist of several statistical tests, including the Shapiro-Wilk test for normality, the Breusch-Pagan test for heteroscedasticity, and the Durbin-Watson test for autocorrelation. While these tests cannot guarantee the accuracy of our findings, they are critical steps in validating our regression model's assumptions and enhancing our results' reliability.

We want to give significant insights into the factors influencing CO_2 emissions through this systematic and rigorous methodology, helping to guide policy choices and advance sustainable development. Every stage of the process, from data transformation and collection to analysis and validation, will be covered in depth in this chapter.

3.2 Variables

After Crisis (AC): The 2008 financial crisis led to economic downturns worldwide, which could have affected CO_2 emissions due to industrial production and energy consumption changes.

Coal Consumption per Capita (CCPC): Burning coal for energy produces considerable CO_2 emissions. As a result, nations that consume more coal per person will emit more CO_2.

Financial Institutions Index (FII): Financial institutions can influence CO_2 emissions through investment decisions. Organizations that prioritize sustainable approaches might help decrease CO_2 emissions.

Forest Area (% of Land Area) (FA): Forests absorb CO_2 from the atmosphere, so countries with larger forest areas might have lower CO_2 emissions.

Gas Energy Consumption per Capita (GECP): Burning natural gas still releases CO_2, even if it is cleaner than coal. Therefore, increasing gas energy use per person may increase CO_2 emissions.

GDP per Person Employed (Constant 2017 PPP $) (GDPPE): This could reflect the economy's energy efficiency. Economies that produce more GDP per person employed might be more energy-efficient and have lower CO_2 emissions.

General Government Final Consumption Expenditure (% of GDP) (GGFCEGDP): This could reflect the government's spending on environmental protection measures, which might help reduce CO_2 emissions.

Life Insurance Premium Volume to GDP (%) (LIPVGDP): Countries with a higher ratio might have more resources to invest in green technologies, which could help reduce CO_2 emissions.

Military Expenditure (% of GDP) (MEGDP): Military activities can contribute to CO2 emissions, so countries with higher military expenditures might have higher CO2 emissions.

Nuclear Energy Consumption per Capita (NECP): Nuclear energy does not deliver CO2 emissions. However, the processes used in uranium mining and refinement, nuclear waste disposal, and factory dismantling generate CO2.

Oil Energy Consumption per Capita (OECP): Oil is a fossil fuel that generates CO2 when burned, so countries with higher per capita oil energy consumption are likely to have higher CO2 emissions.

Population Density (People per Sq. Km of Land Area) (PDPSKLA): Densely populated areas might have higher CO2 emissions due to greater energy consumption and waste production.

Renewable Energy Consumption (% of Total Final Energy Consumption) (RECFEC): Renewable energy sources like wind, solar, and hydro typically produce less CO2 emissions than fossil fuels. As a result, nations that use more renewable energy sources may emit less CO2.

Rural Population (% of Total Population) (RPTP): Rural populations might have different energy consumption patterns than urban populations, which could affect CO2 emissions.

Trade in Services (% of GDP) (TISGDP): The service sector is less energy-intensive than the industrial sector, so countries with a more extensive service sector might have lower CO2 emissions.

Wind Energy Consumption per Capita (WECP): Wind energy is a renewable energy resource that has the potential to influence CO2 emissions in both directions. On one hand, the operation of wind turbines does not produce CO2 emissions, unlike fossil fuel-based power sources. On the other hand, wind turbines' production, installation, and maintenance involve activities that generate CO2 emissions, such as using petroleum-based chemicals to produce composite materials and lubricate components.

3.3 Model Specification

This research utilizes a multiple linear regression analysis to study the intricate relationship between CO_2 emissions and economic and financial factors within G20 countries. The model facilitates the quantification of each independent variable's impact on CO_2 emissions while considering the interconnected nature of these factors.

To bolster the robustness and validity of our analysis, we applied a cube root transformation to all variables. This transformation offers several advantages, including addressing skewed data, stabilizing variance, and mitigating the influence of outliers. These adjustments align with the fundamental assumptions of linear regression models. The regression equation takes the form: $CO2^{1/3} = \beta_0 + \beta_1 \cdot AC^{\frac{1}{3}} + \beta_2 \cdot CCPC^{\frac{1}{3}} + \beta_3 \cdot FA^{\frac{1}{3}} + \beta_4 FII^{\frac{1}{3}}R + \beta_5 \cdot GDPPE^{\frac{1}{3}} + \beta_6 \cdot GECP^{\frac{1}{3}} + \beta_7 \cdot GGFCEGDP^{\frac{1}{3}} + \beta_8 \cdot LIPVGDP^{\frac{1}{3}} + \beta_9 \cdot MEGDP^{\frac{1}{3}} + \beta_{10} \cdot NECP^{\frac{1}{3}} + \beta_{11} \cdot OECP^{\frac{1}{3}} + \beta_{12} \cdot PDPSKLA^{\frac{1}{3}} + \beta_{13}. ECFEC^{\frac{1}{3}} + \beta_{14} \cdot RPTP^{\frac{1}{3}} + \beta_{15}. TISGDP^{1/3} + \beta_{16} \cdot WECP^{\frac{1}{3}} + \epsilon$

Where:

CO_2 is the dependent variable representing CO_2 emissions (metric tons per capita).

Independent Variables:

- AC (After crisis): Dummy variable (1 for years after the 2009 crisis, zero otherwise)
- CCPC (Coal consumption per capita): Energy per capita (e.g., kWh per person)

- FA (Forest area (% of land area)): Percentage (%) model's coefficients
- FII (Financial Institutions Index): Index score (dimensionless)
- GDPPE (GDP per person employed (constant 2017 PPP $)): Constant 2017 PPP
- GECP (Gas energy consumption per capita): Energy per capita (e.g., MJ per person)
- GGFCEGDP (General government final consumption expenditure (% of GDP)): Percentage (% of GDP)
- LIPVGDP (Life insurance premium volume to GDP (%)): Percentage (% of GDP)
- MEGDP (Military expenditure (% of GDP)): Percentage (% of GDP)
- NECP (Nuclear energy consumption per capita): Energy per capita (e.g., kWh per person)
- OECP (Oil energy consumption per capita): Energy per capita (e.g., kWh per person)
- PDPSKLA (Population density): People per square kilometer (people/km^2)
- RECFEC (Renewable energy consumption (% of total final energy consumption)): Percentage (% of total energy consumption)
- RPTP (Rural population (% of total population)): Percentage (%)
- TISGDP (Trade in services (% of GDP)): Percentage (% of GDP)
- WECP (Wind energy consumption per capita): Energy per capita (e.g., kWh per person)

- $Beta0$, \ $\beta1$, …, \ $\beta16$}) are the coefficients of the model.
- ϵ (epsilon) is the error term.
- All variables are transformed using the formula ($x^{\frac{1}{3}}$) which is cube root transformation

Employing a multiple linear regression analysis, we examined the association between CO_2 emissions and economic and financial factors in G-20 countries. The study model permits us to quantify the impact of each independent variable on CO_2 emissions while managing the effects of all other variables, which is critical given the complementary nature of the factors affecting CO_2 emissions. It stabilizes the variance of variables, addressing the assumption of homoscedasticity in linear regression.

However, it is essential to note that this transformation changes the interpretation of our coefficients. Now, the coefficients represent the change in the cube root of CO_2 emissions for a one-unit increase in the cube root of the corresponding independent variable, holding all other variables constant. Via this strict approach, we aim to provide a complete understanding of how financial institutions and economic dynamics shape CO_2 emissions, informing policy decisions and promoting sustainable development.

3.4 Data Collection and Research Scope

The research utilized several databases, including the World Bank Open Data, Our World in Data Energy dataset, the International Monetary Fund (IMF), and the Global Financial Development Database. The used databases offer a wealth of reliable and complete data on various financial and environmental indicators.

The scope of this research focuses on the G20 nations, excluding the European Union. The G-20 nations, comprising nineteen countries and the European Union, mean the world's major economies. g-20 group includes Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia Federation, Saudi Arabia, South Africa, South Korea, Turkey, the United Kingdom, and the United States.

The study spans three decades, from 1994 to 2021 and offers a thorough analysis of a model of CO_2 emissions and the analysis of several economic and financial variables on CO_2 emission.

Data collection involved extracting relevant data for each variable from the databases for all G20 nations over the specified period. The steps of gathering data included

CO_2 emissions, distinct types of energy consumption, the financial institution's index, life insurance premium volume, and the aftermath of the 2008 financial crisis.

The collected data was meticulously compiled and organized in a structured format suitable for further analysis. To guarantee the accuracy and completeness of the data, a strict imputation process was used where appropriate, and any missing values were replaced.

We have done a thorough and perceptive examination of the intricate link between CO_2 emissions and economic and financial issues inside the G20 countries because of this systematic data-gathering procedure that produced a robust dataset.

3.5 Data Transformation

Our research underwent a meticulous data transformation to ensure the most accurate analysis possible. After evaluating various transformation methods, we identified the Cube Roots transformation as the most effective for our requirements. This choice was substantiated by the results of comprehensive model validation statistical tests that scrutinized various aspects of linear regression assumptions, as detailed in Table 4.

Furthermore, the Granger causality test results, presented in Table 13, affirmed that the relationships between independent variables and CO2 emissions remained consistent when comparing the cube root transformation with no transformation. This consistency is pivotal as it ensures the transformation maintains the inherent relationships in the data, thereby bolstering the study's analytical precision.

To guarantee the reliability and validity of our model, we implemented a series of rigorous statistical tests. These included the Shapiro-Wilk Test to confirm the normality of our data, the Durbin-Watson Test to verify the independence of residuals, the Breusch-Pagan Test to check for homoscedasticity, the RESET Test to ensure correct model specification, and the Bonferroni Outlier Test for outlier detection. A higher p-value from these tests suggests better model assumptions, fewer outliers, and improved precision.

Finally, we assessed the model fit using AIC and BIC. Lower values from these tests indicate a better model fit and, hence, better precision. These rigorous tests collectively ensured the robustness and reliability of our model.

Our study employed the Cube Roots transformation for linear regression models, which proved exceptionally effective in mitigating skewness and kurtosis in our dataset. This transformation not only amplified the precision of our analysis but also significantly bolstered the robustness of our findings. We devoted considerable effort to scrutinizing various data transformation techniques before selecting the Cube Roots method. The primary objective was to delve into the cause-and-effect relationships between economic indicators and CO2 emissions, thereby reinforcing the resilience and validity of our dataset's analysis. These efforts and findings strongly support the cube root transformation as the best option for our data, playing a significant role in the robustness and reliability of our study's findings.

3.6 Data

Variable Information and Data Quality Assessment The research is compiled in Table 2, taken from authoritative databases spanning 1994 through 2021. This tableau encapsulates various variables, including energy consumption patterns, economic indicators, and environmental metrics. An extensive explanation of each variable is provided, revealing its unit of measurement, temporal range, data quality assessment, and classification as dependent or independent. Further, missing values are duly acknowledged, and a rigorous imputation methodology is detailed where applicable. Our World in Data, World Bank Open Data, International Monetary Fund (IMF), and Global Financial

Development Database provide the provenance of data. As an internal repository and scholarly asset, this tabular exposition facilitates transparency, reproducibility, and potential utilization by colleagues working in cognate areas.

Our study used linear regression imputation and other techniques leveraging historical data to address missing data. This method preserves the relationships between variables by using a statistical model to predict missing values based on other known data. It also retains the original distribution of the imputed variable, unlike more straightforward imputation methods like mean imputation. By incorporating relationships and preserving distributions, linear regression imputation helps reduce bias in the imputed values. Furthermore, we ensured there were less than 5% missing values in any row or column of our data. Statistically, having less than 5% missing data does not compromise the quality and reliability of the dataset. Therefore, our approach to handling missing data contributes to the robustness of our findings.

Table 2 - Variable Information and Data

Variable Description with Unit of Measurement (1994-2021)	Kind of Variable	Imputation Method	References	Aspects
CO2 emissions (metric tons per capita)	DV	LR (2021)	World Bank Open Data	Environmental
Rural population (% of total population)	IV	-	World Bank Open Data	Demographic
GDP per person employed (constant 2017 PPP $)	IV	-	World Bank Open Data	Economic-Finance
General government final consumption expenditure (% of GDP)	IV	-	World Bank Open Data	Economic-Finance
Military expenditure (% of GDP)	IV	-	World Bank Open Data	Economic-Finance
Trade in services (% of GDP)	IV	-	World Bank Open Data	Economic-Finance
Financial Institutions Index	IV	-	IMF	Economic-Finance
Life insurance premium volume to GDP (%)	IV	LR (Part of 2020,2021)	Global Financial Development Database	Economic-Finance
After Crisis	IV	-	-	-
Renewable energy consumption	IV	LR (2021)	World Bank Open Data	Energy
Coal consumption per capita	IV	-	Our World in Data Energy dataset	Energy
Gas energy consumption per capita	IV	-	Our World in Data Energy dataset	Energy
Nuclear energy consumption per capita	IV	-	Our World in Data Energy dataset	Energy
Oil energy consumption per capita	IV	-	Our World in Data Energy dataset	Energy
Wind energy consumption per capita	IV	-	Our World in Data Energy dataset	Energy
Forest area (% of land area)	IV	-	World Bank Open Data	Geographical
Population density (people per sq. km)	IV	-	World Bank Open Data	Geographical

Note: The information presented in Table 2 is a vital reference for understanding the variables, data quality assessments, and critical attributes associated with the dataset. It is crucial to note that the data quality across the variables is high, providing a reliable foundation for analysis. Additionally, imputation methods were employed to address missing values for certain variables, enhancing the completeness of the dataset. The diverse sources, including the World Bank Open Data, Our World in Data Energy dataset, International Monetary Fund (IMF), and the Global Financial Development Database, contribute to the robustness and comprehensiveness of the information. Researchers are encouraged to consider the specific details provided in the table, such as the unit of measurement, period covered, and references, to ensure an accurate interpretation of the data in subsequent analyses and discussions.

3.7 Data Analysis Techniques

Several methodologies were employed in the data analysis for this study project to provide a thorough and reliable investigation of the correlation between CO_2 emissions and different economic and financial parameters.

- **Multiple Linear Regression Analysis:** The primary technique used was multiple linear regression analysis. Employing linear regression statistical technique, we measured each independent variable's effect on CO_2 emissions while accounting for the impacts of all other factors.
- **Cube Root Transformation:** To address issues of skewed data, stabilize variance, and mitigate the influence of outliers, a cube root transformation was applied to all variables. This transformation aligns with the fundamental assumptions of linear regression models.
- **Principal Component Analysis (PCA):** PCA unveiled underlying patterns in the dataset. By reducing the dimensionality of the data, this method facilitates the identification of essential patterns and linkages.
- **Granger Causality Tests:** These tests were used to illuminate temporal relationships between the variables. They complement the linear regression model's robust quantification of each variable's impact on CO_2 emissions.
- **Statistical Tests for Model Validation:** Various statistical tests were used to validate the regression model's assumptions and ensure the reliability of the results. Statistical Tests for reliability performed in the research are the Durbin-Watson test for autocorrelation, the Breusch-Pagan examination for heteroscedasticity, the Shapiro-Wilk assessment for normality, the RESET test for model specification, and the ADF stationarity test.
- **Variance Inflation Factor (VIF):** VIF was used to check for multicollinearity among the independent variables. A high VIF indicates that the variable is highly correlated with the

other variables, which can affect the stability and interpretability of the regression coefficients.

- **Correlation Analysis:** Correlation analysis examined the pairwise relationships between the variables. This provides insights into the strength and direction of the relationships between variables.
- **Software:** The data analysis was conducted using R program statistical software. R program provides various tools and functions for conducting statistical analyses, including multiple linear regression, PCA, and statistical tests.

Via these rigid data analysis techniques, we provided meaningful insights into the determinants of CO_2 emissions, informing policy decisions and promoting sustainable development.

3.8 Validation

Assuring the reliability and validity of the outcomes is crucial to this research. The study assumptions supply a foundation for precise forecasts and meaningful interpretations. Let us delve into each assumption and how we aimed to validate them via statistical tests. We assumed a linear relationship relating CO_2 emissions and the independent variables. The accuracy of our estimates depends on the assumptions. We utilized methods such as scatter plots and diagnostic plots to inspect the relationship's nature to consider linearity visually.

We assumed the residuals (errors) are independent, implying no systematic pattern or correlation between them. The violation of this assumption can contribute to biased estimates. The Durbin-Watson test assessed autocorrelation, providing insights into whether the residuals exhibit any systematic patterns over time. Homoscedasticity assumes a constant variance of errors across all levels of independent variables. Heteroscedasticity could lead to inefficient estimates. Breusch-Pagan statistical tests, including the Breusch-Pagan test, were utilized to examine and validate the constancy of variance. We presumed that the residuals followed a normal distribution. Departures from normality may affect hypothesis testing and confidence intervals. Normality was assessed through statistical tests like the Shapiro-Wilk test and visual examinations using histograms and Q-Q plots.

We aimed to verify that variance inflation factors (VIFs) and correlation matrices did not present problematic multicollinearity, making it difficult to determine individual effects when independent variables are highly correlated. In the ADF stationarity test, we determine whether the variables' mean, and variance remained constant over time based on the assumption that the variables' statistical properties do not change. The tests were accomplished systematically to confirm the robustness of our model and the goodness of our conclusions. If any assumptions were violated, appropriate adjustments or transformations were applied, and the model was re-evaluated to ensure the reliability of our regression results. Granger Causality was used to determine whether a one-time series helps forecast another. In the context of this research, Granger Causality Tests were used to examine the historical connections involving CO_2 emissions and different economic and financial factors. This test can help determine if changes in a particular variable (like energy consumption or GDP) cause changes in CO_2 emissions. It is crucial to mention that Granger causality does not indicate true causality. Instead, it suggests a predictive relationship, where one variable's past values help predict another's future values.

3.9 Ethical Considerations

Throughout the study process, we followed several ethical guidelines to guarantee the authenticity and reliability of our findings:

We ensured that no private or personal information was used using data from databases made available to the public. To maintain its privacy, all data was managed and kept safely. We transparently took our study method. We made our methods, data sources, and analytical strategies very transparent so that others could duplicate and validate our findings. No adverse procedures or treatments were used in our research. We examined the available data to comprehend the connection between the financial and economic aspects of CO_2 emissions.

Our research does not include CO_2 emissions and the factors that influence them, which are essential for sustainable development and policymaking. Our efforts are in line with the broader society.

We conducted our research with integrity. We reported all findings as they were, without any manipulation or misrepresentation. We openly acknowledged any limitations or potential biases in our study.

By adhering to these ethical considerations, we ensured our research met the highest academic integrity standards and positively contributed to the body of knowledge on this topic.

3.10 Data Limitations

Our study relies on data collected from various authoritative databases, and the accuracy of our findings is contingent upon the reliability of these sources. Inaccuracies or limitations within the databases may introduce biases or uncertainties in our results.

Though a powerful analytical tool, the multiple linear regression model is built on selected assumptions. Assumptions such as linearity, independence of errors, and normality of residuals may only be kept in real-world situations, potentially adopting the robustness of our conclusions.

Our research focuses on the period from 1994 to 2021, providing a comprehensive overview of three decades. However, this temporal scope may not capture short-term fluctuations or recent developments that could impact the relationship between economic factors and CO_2 emissions.

The findings derived from G20 countries may only apply to some nations or regions. Variations in economic structures, policy frameworks, and environmental regulations across different countries could limit the generalizability of our results.

While our research explores associations between variables, establishing causality is inherently challenging. The Granger causality tests provide insights into temporal relationships but do not establish definitive causal links between economic factors and CO_2 emissions.

Despite our efforts to include a comprehensive set of variables, there is always the possibility of omitted variable bias. Unaccounted factors that influence CO_2 emissions might exist, leading to incomplete insights into the determinants of environmental outcomes.

The complexity of our multiple linear regression model, while allowing for a nuanced analysis, might pose challenges in interpretation. Balancing model complexity with interpretability is an ongoing consideration, and simplifying the model may be necessary for more precise insights.

The assumption of stationarity in the time series data, evaluated through the Augmented Dickey-Fuller (ADF) test, is critical. However, the stationarity assumption might only hold perfectly for some variables, potentially affecting the reliability of our regression results.

External factors such as geopolitical events, technological advancements, or global economic trends could influence CO_2 emissions independently of the variables considered in our model. These external factors are challenging to control and may introduce unaccounted variability.

Also, it is crucial to note that imputing missing data presents another layer of complexity. Although imputations were performed, the number of imputations, less than 0.01% of the entire dataset, raises questions about the representativeness of the imputed values and their potential impact on the overall analysis.

Acknowledging these limitations provides a nuanced perspective on the scope and applicability of our methodology. As we interpret our findings in Chapter 4, these limitations will guide the cautious and informed discussion of the implications and contribute to the ongoing dialogue within the academic community.

3.11 Conclusion

At the end of Chapter 3, the methodology chapter, we described the plan that directs our research into the complex interplay between CO_2 emissions and other financial and economic variables across the G20 nations. Ensuring the trustworthiness of the insights we seek to give is contingent upon the robustness and validity of our study approach.

The methodology introduction underscored this chapter's significance as the foundation for our research endeavor. By employing a multiple linear regression analysis, we quantify the impact of independent variables on CO_2 emissions, acknowledging the interconnected nature of the factors influencing this critical environmental indicator.

Our approach incorporates a cube root transformation applied to all variables, a deliberate choice aimed at addressing skewed data, stabilizing variance, and mitigating the influence of outliers. This transformation aligns seamlessly with the fundamental assumptions of linear regression models, bolstering the robustness and validity of our analysis.

The validation procedures integrated into our methodology are paramount in ensuring the credibility of our regression results. Rigorous statistical tests, involving the Durbin-Watson test for autocorrelation, the Breusch-Pagan examination for heteroscedasticity, and the Shapiro-Wilk test for normality, contribute to the comprehensive validation of our model.

Moving to the research design, we elucidated the rationale behind choosing multiple linear regression analysis, emphasizing its suitability for unraveling the complex relationship under investigation. Each independent variable, from CO_2 emissions to the aftermath of the 2008 financial crisis, was introduced, and its significance in our research was elucidated.

The model specification section presented a detailed regression equation, encapsulating the essence of our quantitative analysis. The cube root transformation was explicitly integrated into the model, and each variable's role was elucidated, accompanied by a thorough discussion of assumptions and validation methods.

Data collection, a pivotal step in ensuring the richness and relevance of our dataset, was detailed with a focus on authoritative databases such as the World Bank, Our World in Data, IMF, and the Global Financial Development Database. The G20 nations, excluding the European Union, formed the core of our study, spanning from 1994 to 2021.

Variables, the building blocks of our analysis, were comprehensively detailed, each playing a distinctive role in unraveling the multifaceted determinants of CO_2 emissions. Each variable contributes to a holistic understanding of the interconnected dynamics, from energy consumption metrics to economic indices and post-crisis indicators.

Model specification unveiled the intricacies of our multiple linear regression model, providing a transparent and comprehensive representation of the relationships between variables. The cube root transformation, applied uniformly to all variables, enhances the model's interpretability, and aligns with linear regression analysis assumptions.

Data analysis techniques were employed to extract meaningful insights from our dataset, ranging from multiple linear regression analysis to principal component analysis, Granger causality tests, and various statistical tests for model validation. These techniques form the analytical backbone, empowering us to uncover patterns, relationships, and temporal dynamics.

The validation section underscored our commitment to methodological rigor. By subjecting our model to a battery of tests, we ensured that assumptions were met, laying a robust foundation for the subsequent interpretation of results. Ethical considerations permeated every facet of our methodology, from data privacy and transparency to social responsibility and academic integrity.

Chapter 3, the methodology chapter, is the scaffolding for our research. With meticulous diligence, we have crafted a comprehensive and systematic plan, ensuring that our investigation into the determinants of CO_2 emissions within G20 countries adheres to the highest standards of scholarly inquiry. As we transition to the data analysis phase in Chapter 4, we carry forward the methodological rigor established here, confident in the reliability and validity of our approach.

Chapter 4: Results

4.1 Introduction

In this pivotal chapter, we delve into the heart of our research findings, thoroughly exploring the data analysis and interpretation of results. The primary objective is to unfold the intricate relationships between CO_2 emissions and various independent variables, shedding light on the nuanced dynamics that govern these connections. As we guide through the layers of statistical analyses, we seek to provide a thorough understanding of the critical factors affecting CO_2 emissions within the context of G20 countries. This chapter serves as a crucial point in solving the implications of our research questions and contributes significantly to the broader discourse on the intersection of economic and environmental factors.

4.2 Descriptive statistic

Table 3 presents a comprehensive overview of critical variables in the dataset. It involves measures of central tendency, variability, and distribution. For instance, the mean CO_2 emissions are 1.9 metric tons per capita, and the mean coal consumption per capita is 17.1. Other notable figures include the Financial Institutions Index (0.8), forest area as a percentage of land area (3.0), gas energy consumption per capita (19.3), and GDP per person employed (constant 2017 PPP $) (38.8). The table also provides information on the standard error, median, mode, standard deviation, kurtosis, skewness, range, minimum, maximum, sum, and count for each variable. These statistics provide a comprehensive picture of the distributional characteristics, potential outliers, and overall profile of each variable in the dataset. They form the basis for further analysis and interpretation in the research.

Table 3 - Descriptive statistic

Descriptive statistic	CO2 emissions	Coal energy	Financial Institutions	Forest area	Gas energy	GDP	government expenditure	Life insurance	Military expenditure	Nuclear energy	Oil energy	Population density	Renewable energy	Rural population	Trade in services	Wind energy
Mean	1.9	17.1	0.8	3.0	19.3	38.8	2.5	1.3	1.2	9.5	23.5	4.4	2.2	2.9	2.1	4.3
Standard Error	0.0	0.3	0.0	0.0	0.3	0.4	0.0	0.0	0.0	0.4	0.3	0.1	0.0	0.0	0.0	0.2
Median	2.0	18.0	0.9	3.1	20.3	41.1	2.6	1.4	1.2	7.9	23.5	4.5	2.1	2.8	2.1	3.2
Mode		0.1		0.8						0.1		7.0	0.2	2.6		0.1
Standard Deviation	0.5	7.5	0.1	0.8	7.6	8.5	0.2	0.6	0.3	8.2	6.8	2.0	0.8	0.5	0.3	4.0
Sample Variance	0.2	56.0	0.0	0.6	58.0	72.1	0.1	0.3	0.1	66.6	46.2	3.9	0.7	0.3	0.1	15.9
Kurtosis	-0.9	-0.8	-1.0	1.7	-1.0	-0.4	-0.1	-0.9	2.2	-1.1	-0.7	-1.2	0.1	0.1	-0.4	-0.2
Skewness	-0.2	-0.2	-0.4	-1.1	-0.2	-0.7	-0.6	-0.1	1.2	0.4	0.1	0.2	-0.2	0.7	0.2	0.9
Range	1.8	31.7	0.6	3.3	26.7	37.1	1.3	2.4	1.8	27.3	30.4	6.8	3.6	2.2	1.7	16.0
Minimum	0.9	0.1	0.4	0.8	5.3	15.8	1.8	0.2	0.7	0.1	9.5	1.3	0.2	2.0	1.3	0.1
Maximum	2.7	31.8	1.0	4.1	32.0	52.9	3.1	2.6	2.4	27.4	39.9	8.1	3.8	4.2	2.9	16.1
Sum	1011	9112	438	1617	10291	20660	1351	696	660	5077	12521	2336	1149	1559	1110	2267
Count	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532.0
Largest (1)	2.7	31.8	1.0	4.1	32.0	52.9	3.1	2.6	2.4	27.4	39.9	8.1	3.8	4.2	2.9	16.1
Smallest (1)	0.9	0.1	0.4	0.8	5.3	15.8	1.8	0.2	0.7	0.1	9.5	1.3	0.2	2.0	1.3	0.1
Sample size	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Note: *Table 3 presents descriptive statistics for various key variables, offering insights into the central tendencies and dispersion of the data. The mean CO_2 emissions (metric tons per capita) from 1994 to 2021 is 1.9, with a standard error of 0.0 and a median of 2.0. The table further provides information on sample variance, standard deviation, kurtosis, skewness, range, minimum, maximum, sum, and count, offering a comprehensive overview of the dataset's characteristics. Researchers can utilize these statistics to understand better the distribution and variability of the selected variables for informed analyses and interpretations.*

4.3 Comparative Evaluation of Transformation Methods in Regression Analysis

Table 4 comprehensively compares various transformation methods and their corresponding statistical test results for model evaluation. The transformation methods explored include Logarithmic, Natural Logarithm, Z-Score, Square Root, Min-Max, Standardize, No Transformation, and Cube Roots.

Each transformation method is evaluated using several statistical tests. These include the Shapiro-Wilk Test, which checks for the normality of residuals; the Durbin-Watson Test, which detects the presence of autocorrelation in the residuals; the Breusch-Pagan Test, which tests for heteroscedasticity in the residuals; the RESET Test, which checks for functional form misspecification; and the Bonferroni Outlier Test, which is used for outlier detection.

The p-values resulting from these tests range from 0 to 0.9998. Here, a p-value of 0 should be understood as a value extremely close to zero; notably, p-values above 0.05 suggest that we fail to reject the null hypothesis, indicating that the transformation method does not significantly affect the model's performance. These are desirable results as they suggest that the transformation method improves the model's fit to the data.

In particular, the cube root transformation method shows promising results with high p-values in all statistical tests, indicating that the regression model's assumptions are not violated. Moreover, it has the second lowest AIC and BIC values among all transformation methods, suggesting a good model fit.

The values are presented without units as they are statistical test results, typically dimensionless or in the form of p-values, AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion) scores. The AIC and BIC are relative measures of model fit, with lower values indicating a better fit to the data.

Each transformation method is briefly defined, elucidating the mathematical functions involved. These insights underscore the cube root transformation as the optimal choice for our data, significantly contributing to the robustness and reliability of our study's conclusions. The transformation method facilitated a more accurate analysis and maintained the integrity of the data's relational structure.

Table 5 presents the distinctive results of a multiple linear regression model across different transformation methods. The table compares data transformation methods, including Logarithmic, Natural Logarithm, Z-Score, Square Root, Min-Max, Standardize, No Transformation, and Cube Roots. Each transformation method is evaluated using several statistical tests, such as Adjusted R-squared, Residual Standard Error, Number of Non-Significant Variables, Multiple R-squared, F-statistic, and p-value of the model.

The p-values resulting from these tests range from approximately 0 to 0.9998. Here, a p-value of 0 should be understood as close to zero, indicating strong evidence against the null hypothesis. Notably, p-values above 0.05 suggest that we failed to reject the null hypothesis, indicating that the transformation method does not significantly affect the model's performance. These are desirable results as they suggest that the transformation method improves the model's fit to the data.

To address the concern of overfitting, which is indicated by an adjusted R-squared of 0.9944 in Table 5, we can refer to the results of the statistical tests in Table 4.

The presentation of this tabulated information substantiates a compelling rationale for selecting the Cube Roots transformation method. For a more exhaustive comprehension, it is judicious to accompany this table with supplementary contextualization elucidating the significance of each test, its contextual relevance in the realm of linear regression, and how the confluence of results cohesively supports the rationale underpinning the adoption of the Cube Roots transformation method.

Table 4 - Comparison of Transformation Methods: Statistical Test Results and Model Evaluation

Tests	Logarithmic	Natural Logarithm	Z-Score	Square Root	Min-Max	Standardize	No Transformation	Cube Roots
Shapiro-Wilk Test (p-value)	0	0	0	0.0196	0	0	0	0.5411
Durbin-Watson Test (p-value)	0.9998	0.9998	0.6138	0.0929	0.6138	0.6138	0.6138	0.6318
Breusch-Pagan Test (p-value)	0.0002	0.0002	0	0.618	0	0	0	0.3569
RESET Test (p-value)	0	0	0	0.9111	0	0	0	0.2188
Bonferroni Outlier (p-value)	-	-	-	-	-	-	-	0.20635
AIC (dimensionless)	-1042.943	-155.5321	-1232.57	-1382.823	-2655.966	-1232.57	517.7957	-1902.904
BIC (dimensionless)	-965.9631	-78.55256	-1155.59	-1305.844	-2578.986	-1155.59	594.7753	-1825.925

Note: *Table 4 comprehensively compares various transformation methods and their corresponding statistical test results for model evaluation. The transformation methods explored include Logarithmic, Natural Logarithm, Z-Score, Square Root, Min-Max, Standardize, No Transformation, and Cube Roots. Each transformation method is evaluated using several statistical tests. These include the Shapiro-Wilk Test, which checks for the normality of residuals; the Durbin-Watson Test, which detects the presence of autocorrelation in the residuals; the Breusch-Pagan Test, which tests for heteroscedasticity in the residuals; the RESET Test, which checks for functional form misspecification; and the Bonferroni Outlier Test, which is used for outlier detection.*
The p-values resulting from these tests range from 0 to 0.9998. Here, a p-value of 0 should be understood as a value extremely close to zero; notably, p-values above 0.05 suggest that we fail to reject the null hypothesis, indicating that the transformation method does not significantly affect the model's performance. These are desirable results as they suggest that the transformation method improves the model's fit to the data.
In particular, the cube root transformation method shows promising results with high p-values in all statistical tests, indicating that the regression model's assumptions are not violated. Moreover, it has the second lowest AIC and BIC values among all transformation methods, suggesting a good model fit.
The values are presented without units as they are statistical test results, typically dimensionless or in the form of p-values, AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion) scores. The AIC and BIC are relative measures of model fit, with lower values indicating a better fit to the data.

Table 5 - Comparative Evaluation of Transformation Methods on Linear Regression Model

Tests	Logarithmic	Natural Logarithm	Z-Score	Square Root	Min-Max	Standardize	No Transformation	Cube Roots
Adjusted R-squared	0.9336	0.9336	0.9944	0.9953	0.9944	0.9944	0.9944	0.9927
Residual Standard Error	0.0892	0.2054	0.0747	0.0648	0.0196	0.0747	0.3868	0.0398
Number of Non-Significant Variables	4	4	3	1	3	3	3	0
Multiple R-squared	0.9356	0.9356	0.9946	0.9955	0.9946	0.9946	0.9946	0.9929
F-statistic	467.9	467.9	5924	7080	5924	5924	5924	4524
p-value of Model	0	0	0	0	0	0	0	0

Note: Table 5 presents the distinctive results of a multiple linear regression model across different transformation methods. The table compares data transformation methods, including Logarithmic, Natural Logarithm, Z-Score, Square Root, Min-Max, Standardize, No Transformation, and Cube Roots. Each transformation method is evaluated using several statistical tests, such as Adjusted R-squared, Residual Standard Error, Number of Non-Significant Variables, Multiple R-squared, F-statistic, and p-value of Model.
The p-values resulting from these tests range from approximately 0 to 0.9998. Here, a p-value of 0 should be understood as close to zero, indicating robust evidence against the null hypothesis. Notably, p-values above 0.05 suggest that we failed to reject the null hypothesis, indicating that the transformation method does not significantly affect the model's performance. These are desirable results as they suggest that the transformation method improves the model's fit to the data.
To address the concern of overfitting, which is indicated by an adjusted R-squared of 0.9944, we can refer to the results of the statistical tests in Table 4.

4.4 Bivariate Analysis

In the Bivariate Analysis section (4.4), the research examines the bivariate relationships between CO_2 emissions and each independent variable, shown in Figure 1. Visual aids such as scatter plots or correlation matrices illustrate these relationships. This examination allows a better understanding of the effect of individual variables on CO_2 emissions, delivering a more complicated view of their relations. However, a detailed analysis cannot be provided without the scatter plots or correlation matrices.

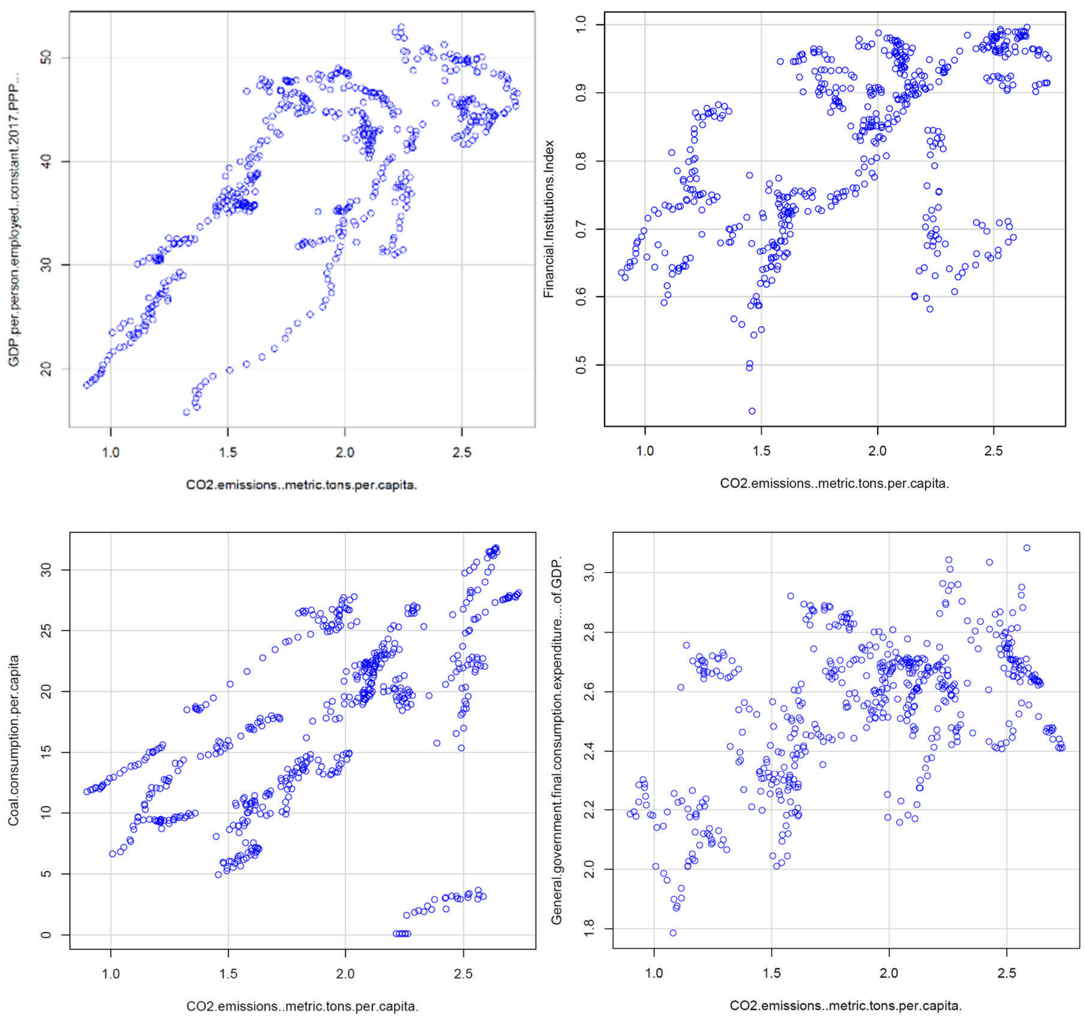

Figure 1 (continued)

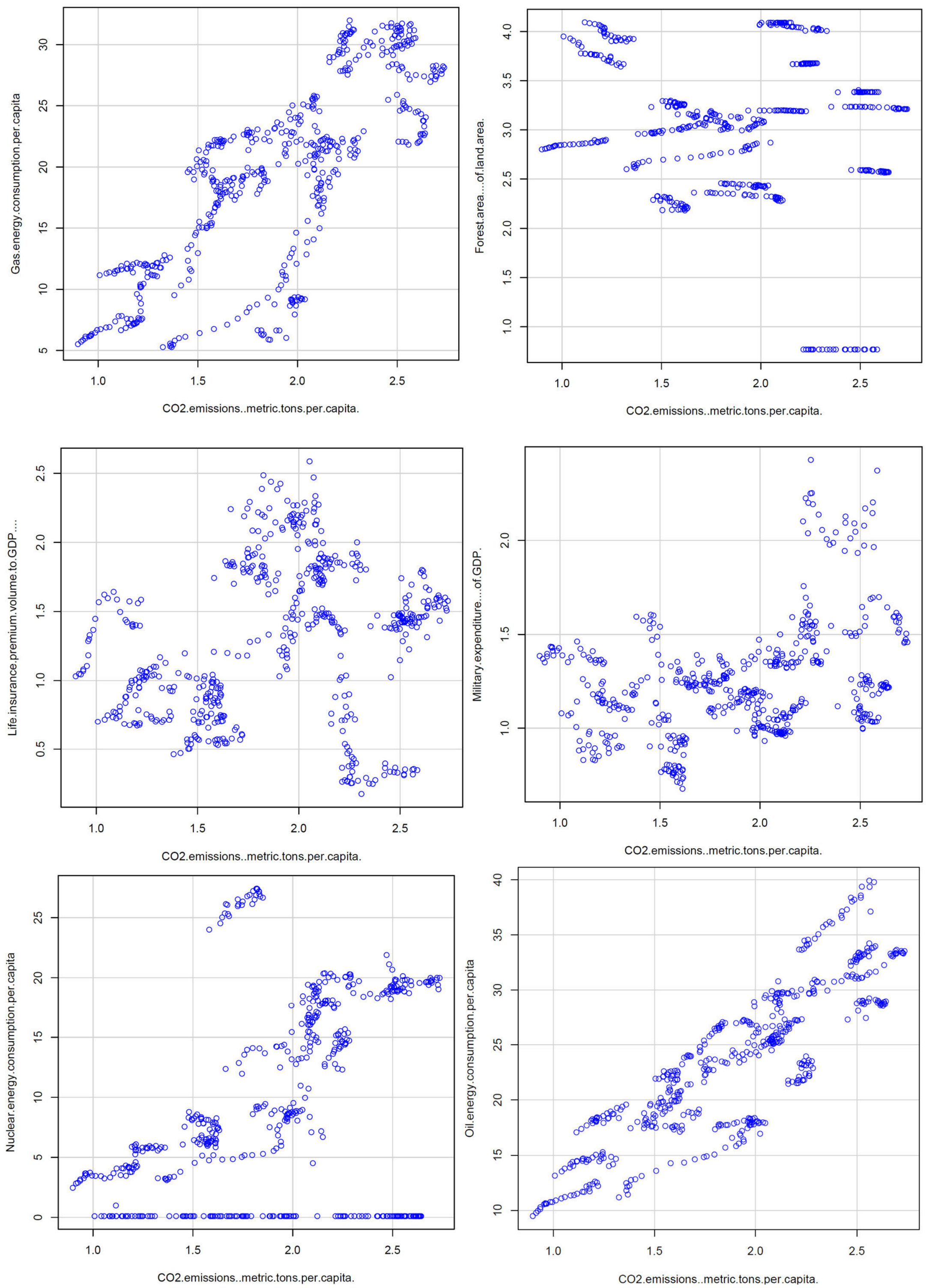

Figure 1 (continued)

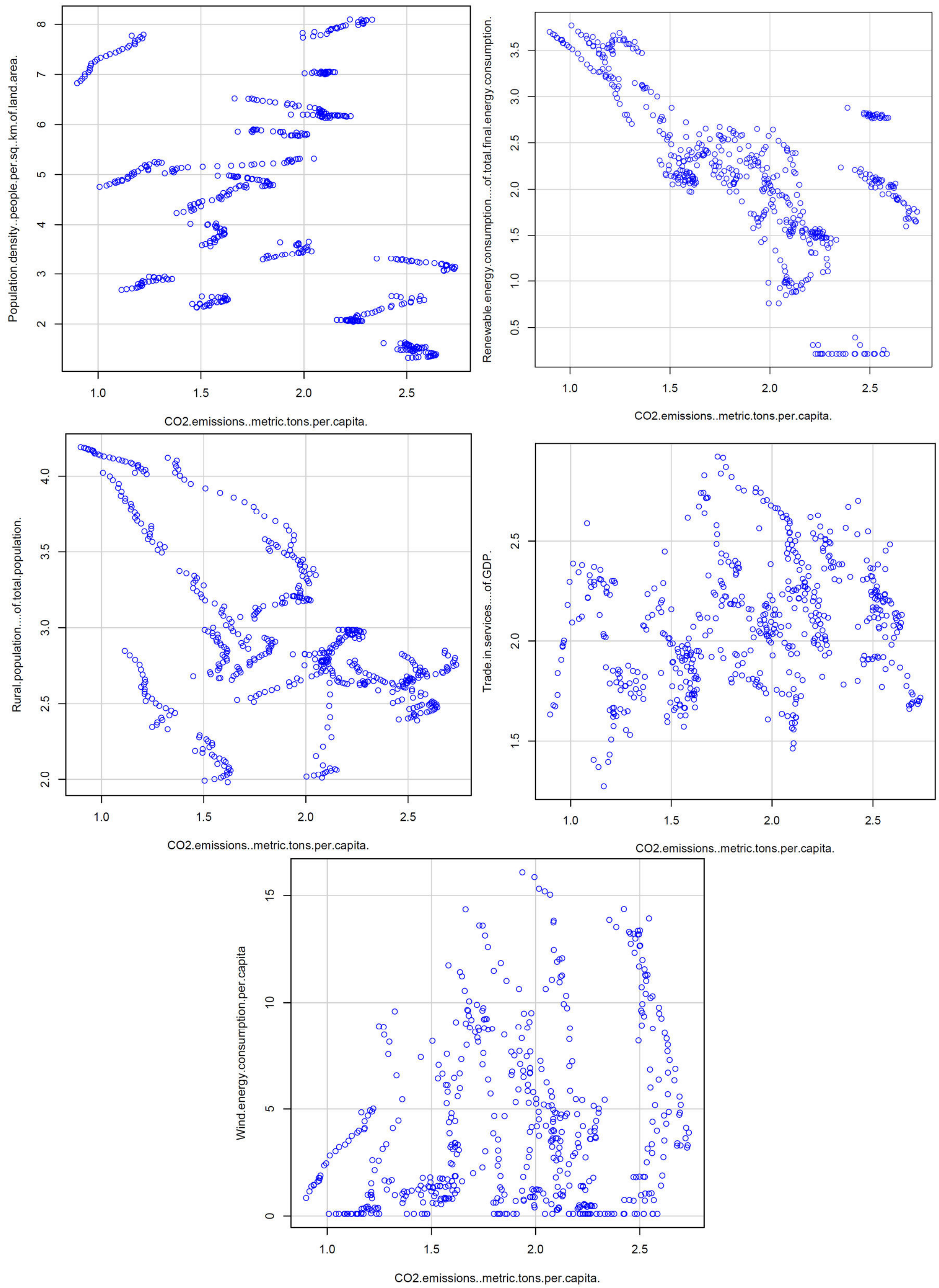

Figure 1 - Scatter plots of variables

Note: Figure *1 shows a string of scatter plots displaying the relationships between various economic, financial, and economic factors. Each plot represents a different model or dataset, with the x-axis representing CO2 emissions per capita and the y-axis representing the IV variables. The blue dots represent individual data points, and the lines connecting some of the dots indicate specific patterns or trends. This figure visually represents the complex interplay between these factors and their impact on CO2 emissions.*

4.5 Statistical Analysis - Correlation and VIF

Table 5 delivers a correlation matrix indicating the Pearson correlation coefficients- their corresponding p-values between pairs of variables.

The correlation Coefficient in Table 6 measures the linear relationship between two variables. It ranges from -1 to 1. A weight close to 1 shows a robust positive relationship, a value close to -1 shows a strong negative connection and a value close to 0 means no connection. For example, the correlation coefficient 0.54 between CO_2 and CCPC indicates a moderate positive relationship.

The p-value from the test determines whether to defect the null hypothesis in favor of the alternative hypothesis. If the p-value is less than a chosen significance level (0.05), we reject the null hypothesis and suppose there is proof of a correlation. If the p-value exceeds the significance level, we fail to desert the null hypothesis and conclude there is inadequate evidence to suggest a correlation.

Table 6 - Correlation Matrix

Correlation/ p-values	CO2	CCPC	GECP	NECP	RECFEC	GGFCEGDP	WECP	PDPSKLA	MEGDP	AC	TISGDP	RPTP	OECP	FII	GDPPE	LIPVGDP
CCPC	0.54 (<.0001)															
GECP	0.78 (<.0001)	0.05 (0.28)														
NECP	0.39 (<.0001)	0.33 (<.0001)	0.33 (<.0001)													
RECFEC	-0.67 (<.0001)	-0.08 (0.08)	-0.61 (<.0001)	-0.21 (<.0001)												
GGFCEGDP	0.53 (<.0001)	0.08 (0.07)	0.49 (<.0001)	0.3 (<.0001)	-0.37 (<.0001)											
WECP	0.26 (<.0001)	0.26 (<.0001)	0.27 (<.0001)	0.24 (<.0001)	0.11 (<.0001)	0.33 (<.0001)										
PDPSKLA	-0.32 (<.0001)	0.09 (<.0001)	-0.39 (<.0001)	0.15 (<.0001)	0.01 (0.81)	-0.27 (<.0001)	0.08 (0.07)									
MEGDP	0.35 (<.0001)	-0.12 (<.0001)	0.37 (<.0001)	-0.03 (0.51)	-0.51 (<.0001)	0.34 (<.0001)	-0.15 (<.0001)	-0.14 (<.0001)								
AC	0.04 (0.36)	0 (0.92)	0.12 (<.0001)	-0.03 (0.45)	0.04 (0.33)	0.17 (<.0001)	0.56 (<.0001)	0.04 (0.35)	-0.07 (0.13)							
TISGDP	0.21 (<.0001)	-0.04 (0.38)	0.31 (<.0001)	0.21 (<.0001)	-0.29 (<.0001)	0.32 (<.0001)	0.31 (<.0001)	0.23 (<.0001)	0.35 (<.0001)	0.14 (<.0001)						
RPTP	-0.5 (<.0001)	0.02 (0.6)	-0.62 (<.0001)	-0.31 (<.0001)	0.45 (<.0001)	-0.49 (<.0001)	-0.27 (<.0001)	0.33 (<.0001)	0 (0.94)	-0.17 (<.0001)	0 (0.96)					
OECP	0.87 (<.0001)	0.16 (<.0001)	0.81 (<.0001)	0.41 (<.0001)	-0.69 (<.0001)	0.54 (<.0001)	0.18 (<.0001)	-0.25 (<.0001)	0.4 (<.0001)	-0.02 (0.72)	0.27 (<.0001)	-0.64 (<.0001)				
FII	0.57 (<.0001)	0.57 (<.0001)	0.37 (<.0001)	0.54 (<.0001)	-0.17 (<.0001)	0.5 (<.0001)	0.58 (<.0001)	0.13 (<.0001)	-0.11 (<.0001)	0.23 (<.0001)	0.19 (<.0001)	-0.43 (<.0001)	0.52 (<.0001)			
GDPPE	0.72 (<.0001)	0.09 (<.0001)	0.78 (<.0001)	0.34 (<.0001)	-0.61 (<.0001)	0.64 (<.0001)	0.44 (<.0001)	-0.16 (<.0001)	0.28 (<.0001)	0.15 (<.0001)	0.38 (<.0001)	-0.67 (<.0001)	0.84 (<.0001)	0.56 (<.0001)		
LIPVGDP	0.23 (<.0001)	0.58 (<.0001)	-0.1 (<.0001)	0.48 (<.0001)	-0.05 (0.29)	0.18 (<.0001)	0.33 (<.0001)	0.44 (<.0001)	-0.27 (<.0001)	0.03 (0.49)	0.26 (<.0001)	-0.02 (0.59)	0.11 (<.0001)	0.69 (<.0001)	0.19 (<.0001)	
FA	-0.17 (<.0001)	0.3 (<.0001)	-0.18 (<.0001)	0.33 (<.0001)	0.41 (<.0001)	-0.3 (<.0001)	0.05 (0.22)	0.31 (<.0001)	-0.5 (<.0001)	0 (0.93)	-0.31 (<.0001)	0.03 (0.56)	-0.18 (<.0001)	0.28 (<.0001)	-0.24 (<.0001)	0.19 (<.0001)

Note: *Table 6 represents the correlation coefficient (p-value) table presents the statistical relationships between CO2 emissions and various independent variables. Each cell in the table represents the correlation coefficient and its corresponding p-value, indicating the strength and significance of the relationship between the pair of variables.*

VIF, on the other hand, gauges multicollinearity, the experience where independent variables in a regression model are connected. High VIF values (typically above 5 or 10) may indicate problematic multicollinearity, leading to imprecise coefficient estimates and reduced model interpretability. The VIF (Table 7) table, in which Table 10 shows these thresholds, shows acceptable independence among variables. However, elevated VIF values for variables like OECP suggest potential issues, urging a closer examination of their impact on the regression model.

Table 7 - VIF Matrix

VIF	CO_2	CCPC	GECP	NECP	RECFEC	GGFCEGDP	WECP	PDPSKLA	MEGDP	AC	TISGDP	RPTP	OECP	FII	GDPPE	LIPVGDP
CO_2																
CCPC	1.4															
GECP	2.6	1.0														
NECP	1.2	1.1	1.1													
RECFEC	1.8	1.0	1.6	1.0												
GGFCEGDP	1.4	1.0	1.3	1.1	1.2											
WECP	1.1	1.1	1.1	1.1	1.0	1.1										
PDPSKLA	1.1	1.0	1.2	1.0	1.0	1.1	1.0									
MEGDP	1.1	1.0	1.2	1.0	1.4	1.1	1.0	1.0								
AC	1.0	1.0	1.0	1.0	1.0	1.0	1.5	1.0	1.0							
TISGDP	1.0	1.0	1.1	1.0	1.1	1.1	1.1	1.1	1.1	1.0						
RPTP	1.3	1.0	1.6	1.1	1.3	1.3	1.1	1.1	1.0	1.0	1.0					
OECP	4.0	1.0	2.9	1.2	1.9	1.4	1.0	1.1	1.2	1.0	1.1	1.7				
FII	1.5	1.5	1.2	1.4	1.0	1.3	1.5	1.0	1.0	1.1	1.0	1.2	1.4			
GDPPE	2.1	1.0	2.5	1.1	1.6	1.7	1.2	1.0	1.1	1.0	1.2	1.8	3.4	1.4		
LIPVGDP	1.1	1.5	1.0	1.3	1.0	1.0	1.1	1.2	1.1	1.0	1.1	1.0	1.0	1.9	1.0	
FA	1.0	1.1	1.0	1.1	1.2	1.1	1.0	1.1	1.3	1.0	1.1	1.0	1.0	1.1	1.1	1.0

Note: *Table 7 provides the Variance Inflation Factor (VIF) matrix, a diagnostic tool used to assess multicollinearity among independent variables in regression analysis. The VIF methods show how much the variance of an expected regression coefficient grows when the predictors are connected. A VIF value 1 implies no multicollinearity, while values beyond 5 or 10 are often considered concerning.*

In this matrix, each diagonal element represents the VIF for the corresponding variable, with values close to 1 indicating low multicollinearity. Larger VIF values suggest an increased correlation with other variables. Researchers can use this matrix to identify potential multicollinearity issues and make informed decisions about variable selection and model refinement in subsequent analyses.

4.6 Multivariate Analysis - Unveiling the Dynamics of CO_2 Emissions

In this pivotal section of our study, we delve into the intricacies of multiple linear regression analysis, a cornerstone for unraveling the complex relationships governing CO_2 emissions within the context of G20 countries. Our analytical lens focuses on presenting a comprehensive overview of the regression results, unveiling the coefficients, standard errors, p-values, and R-squared values derived from the model. These statistical measures serve as the foundation for evaluating the influence of diverse independent variables on CO_2 emissions, paving the way for nuanced discussions on the significance and implications of each predictor.

Model Insights: Coefficients and Standard Errors The coefficients extracted from the regression model offer quantitative insights into the magnitude and direction of each independent variable's influence on CO_2 emissions. These coefficients are accompanied by their corresponding standard errors, measuring the precision and reliability of the estimated effects. A meticulous examination of these values allows us to discern the statistical significance of each predictor and the relative strength of their impact.

P-values and Significance Testing P-values play a fundamental role in establishing the significance of each variable in explaining the variance in CO_2 emissions. By scrutinizing these p-values, we discern whether a particular predictor holds substantial explanatory power. A lower p-value signifies greater statistical significance, underscoring the relevance of the variable in the regression model. This significance testing aids in identifying key drivers of CO_2 emissions within the G20 nations.

R-squared Values: Gauging Model Fit The R-squared values derived from the multiple linear regression model provide a holistic measure of how well the selected independent variables collectively explain the observed variation in CO_2 emissions. A higher R-squared value means a more suitable fit, signifying the model's ability to capture a more significant proportion of the variability in CO_2 emissions. This metric is a crucial benchmark for evaluating the regression model's effectiveness and explanatory power.

Discussion on Variable Significance and Impact Following the presentation of regression results, an in-depth discussion ensues to unravel the significance of each variable and its specific impact on CO_2 emissions. Variables with notable coefficients and low p-values emerge as influential contributors to the model. Through a synthesis of statistical evidence and contextual understanding, we delineate the practical implications of these findings, providing stakeholders and policymakers with valuable insights for informed decision-making and targeted interventions. This comprehensive multivariate analysis is a cornerstone for raising our understanding of the complex interplay between economic factors and environmental sustainability within the G20 nations.

4.7 Multivariate Analysis

The initial findings from the regression analysis provide substantial insights into the determinants of CO_2 emissions among G20 countries, summarized in Tables 8 and 9. The multiple R of 0.9964 signifies a robust correlation between the selected independent variables and CO_2 emissions.

Table 8 - Summary of Regression Analysis

Regression Statistics	
Multiple R	0.996
R Square	0.993
Adjusted R Square	0.993
Standard Error	0.040
Observations	532

Note: *Table 8 supplies an overview of the regression analysis. The key statistics involve Multiple R, R Square, Adjusted R Square, Standard Error, and the amount of observation. These metrics collectively deliver an overview of the model's implementation, indicating a strong positive correlation and a good fit for the model. Further diagnostic tests and validation are necessary to ensure the model's robustness and reliability.*

The ANOVA results (table 9) yield a highly significant F-statistic of 4524.10 with a corresponding p-value of 0, reinforcing the statistical significance of the overall regression model. These results support rejecting the null hypothesis, suggesting a significant connection connecting` the independent variables and CO_2 emissions in the G20 countries. This analysis forms a solid foundation for understanding the complex interplay between economic and financial factors and CO_2 emissions.

Table 9 - Analysis of Variance (ANOVA) for Regression

	df	SS	MS	F	Significance F
Regression	16	114.4	7.2	4524.1	0
Residual	515	0.8	0.0		
Total	531	115.2			

Note: Table 9 is an ANOVA table for the regression model. It indicates that the model is statistically important with a high F statistic and a p-value of 0, indicating that at least one predictor significantly contributes to predicting the outcome variable. The total variability in the data is 115.2, with the model explaining a significant portion (SS of 114.4) and leaving a small residual (SS of 0.8).

Upon examining the coefficients, several vital variables emerge. These include coal consumption, gas, nuclear energy consumption, energy consumption, renewable energy consumption, general government final consumption expenditure, wind energy consumption per capita, population density, military expenditure, post-2008 financial crisis, trade in services, rural population, oil energy consumption per capita, Financial Institutions Index, GDP, life insurance premium volume to GDP, and forest area. All these variables show statistically significant relationships with CO_2 emissions.

The Financial Institutions Index coefficient of -0.2492 suggests a significant negative association, indicating that countries with higher Financial Institutions Index values tend to have lower CO_2 emissions. The results support the hypothesis that the robust Financial Institutions Index is associated with reduced CO_2 emissions, reflecting sustainable methods in financial institutions.

Moreover, the coefficient for life insurance premium volume to GDP (%) is 0.0376, indicating a positive relationship. The results align with the hypothesis that an increase in life insurance premium volume relative to GDP is associated with decreased CO_2 emissions, potentially indicating more excellent resources for green technologies.

The analysis also uncovers a significant impact of the 2008 financial crisis on CO_2 emissions, as suggested by the coefficient for the variable "after crisis" being 0.0223. The model implies a noticeable increase in CO_2 emissions following the crisis, providing insights into the intersection of economic downturns and environmental outcomes.

These initial results deliver a promising insight into the intricate relationships between financial institutions, economic variables, and CO_2 emissions in G20 countries. The subsequent exhaustive analysis and performance will offer a comprehensive understanding of these dynamics, assisting policymakers and researchers in devising effective strategies for sustainable development and climate change mitigation. The model explains 99.29% of the variance in CO_2 emissions across the G20 countries, suggesting a solid fit of the model. Diverse types of energy consumption per capita have varying degrees of influence on CO_2 emissions. Notably, coal consumption per capita shows a positive relationship with CO_2 emissions, suggesting that countries with higher coal consumption tend to have higher CO_2 emissions. The Financial Institutions Index shows a negative relationship with CO_2 emissions, suggesting that countries with more developed financial institutions promoting sustainable practices tend to have lower CO_2 emissions. The life insurance premium volume to GDP (%) also negatively impacts CO_2 emissions, suggesting that countries with a higher ratio might have more resources for green technologies.

Table 10 - Regression Coefficients and Statistics

SUMMARY OUTPUT	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.548	0.039	13.956	9E-38 ***	0.47	0.63
Financial Institutions Index	-0.249	0.04	-6.28	7E-10 ***	-0.33	-0.17
Renewable energy	-0.112	0.005	- 20.939	7E-71 ***	-0.12	-0.1
Trade in services	-0.068	0.008	-8.087	4E-15 ***	-0.08	-0.05
Military expenditure	-0.039	0.009	-4.141	4E-05 ***	-0.06	-0.02
Population density	-0.033	0.002	- 18.799	2E-60 ***	-0.04	-0.03
Forest area (% of land area)	-0.027	0.005	-5.927	6E-09 ***	-0.04	-0.02
GDP per person employed	-0.005	0.001	-9.436	1E-19 ***	-0.01	0
Nuclear energy	-0.002	0	-5.708	2E-08 ***	0.0	0.0
Wind energy	0.009	0.001	9.814	6E-21 ***	0.01	0.01
Gas energy	0.016	0.001	28.273	7E-107 ***	0.01	0.02
after crisis	0.022	0.005	4.857	2E-06 ***	0.01	0.03
Coal energy	0.028	0	68.452	9E-261 ***	0.03	0.03
Oil energy	0.038	0.001	54.412	1E-215 ***	0.04	0.04
Life insurance premium volume to GDP (%)	0.038	0.008	4.988	8E-07 ***	0.02	0.05
Rural population	0.091	0.006	14.209	7E-39 ***	0.08	0.1
government expenditure	0.157	0.012	12.675	3E-32 ***	0.13	0.18

Note: Table 10 summarizes the regression coefficients and their statistics. Each row describes a predictor variable in the model, and the columns show the estimated coefficient, standard error, t-statistic, p-value, and 95% confidence interval for each predictor. The p-value allows for determining the significance of each predictor, with a smaller p-value indicating a more significant predictor. The confidence intervals provide a range of values within which the proper population parameter lies with 95% confidence. *** denotes a p-value less than 0.001 in this table, indicating a highly significant result.

4.8 Analysis of Energy Consumption and Financial Factors Impacting CO_2 Emissions

The regression model coefficients provide insights into each variable's importance.

Energy Consumption Types: The coefficients for distinct types of energy consumption, such as coal, gas, nuclear, renewable and wind energy, indicate their relative impact on CO_2 emissions. For instance, the positive coefficient for coal consumption per capita suggests that increased coal consumption is associated with increased CO_2 emissions. On the other hand, the negative coefficient for renewable energy consumption indicates that an increase in renewable energy consumption is associated with decreased CO_2 emissions.

Financial Institutions and Life Insurance Premiums: The Financial Institutions Index and Life Insurance Premium Volume also emerge as significant factors. The negative coefficient for the Financial Institutions Index suggests that improvements in financial institutions are associated with decreased CO_2 emissions. Similarly, the positive coefficient for Life Insurance Premium Volume indicates that increasing life insurance premiums is related to rising CO_2 emissions.

The aftermath of the 2008 Financial Crisis: The variable 'after the crisis' captures the impact of the 2008 financial crisis on CO_2 emissions. Its positive coefficient suggests that the aftermath of the crisis has been associated with an increase in CO_2 emissions.

These findings emphasize the importance of considering several economic and financial factors to reduce CO_2 emissions. Policymakers, researchers, and practitioners can leverage these insights to guide sustainable policy decisions and contribute to a more sustainable future.

4.9 Variable Importance

The coefficients, standard errors, p-values, and R-squared values provide a comprehensive lens through which we discern the relative importance, as shown in Figure 2, of each variable and its impact on shaping environmental outcomes.

Examining the regression coefficients, several variables emerge as pivotal contributors to CO_2 emissions. Coal consumption per capita, gas energy consumption per capita, nuclear energy consumption per capita, renewable energy consumption (% of total final energy consumption), general government final consumption expenditure (% of GDP), wind energy consumption per capita, population density, military expenditure (% of GDP), post-2008 financial crisis, trade in services (% of GDP), rural population (% of total population), oil energy consumption per capita, Financial Institutions Index, GDP per person employed (constant 2017 PPP $), life insurance premium volume to GDP (%), and forest area (% of land area) all exhibit statistically significant relationships with CO_2 emissions.

Amidst the statistical significance, unexpected findings may arise, challenging conventional wisdom. For instance, the negative coefficient of the Financial Institutions Index (-0.2492) signifies a counterintuitive negative association. Unraveling such anomalies becomes crucial for a nuanced interpretation of the data.

The negative association between CO_2 emissions and the Financial Institutions Index could indicate that countries with more robust and sustainable financial institutions contribute less to carbon emissions. This unexpected finding underscores the need for further investigation into the mechanisms through which financial institutions impact environmental outcomes.

Beyond statistical metrics, the discussion contextualizes the influential variables within the broader socio-economic and environmental landscape. The results entail a deeper exploration of how variables like life insurance premium volume to GDP (%) might reflect a country's capacity for green technologies.

As we unravel the importance of variables, the discussion extends to practical implications for policymakers and researchers. For instance, understanding the positive impact of life insurance premium volume on reducing CO_2 emissions could guide policies encouraging investment in sustainable practices.

This exploration of variable importance is a critical foundation for informed decision-making and policy formulation, guiding stakeholders in navigating the complex terrain of economic factors influencing environmental outcomes.

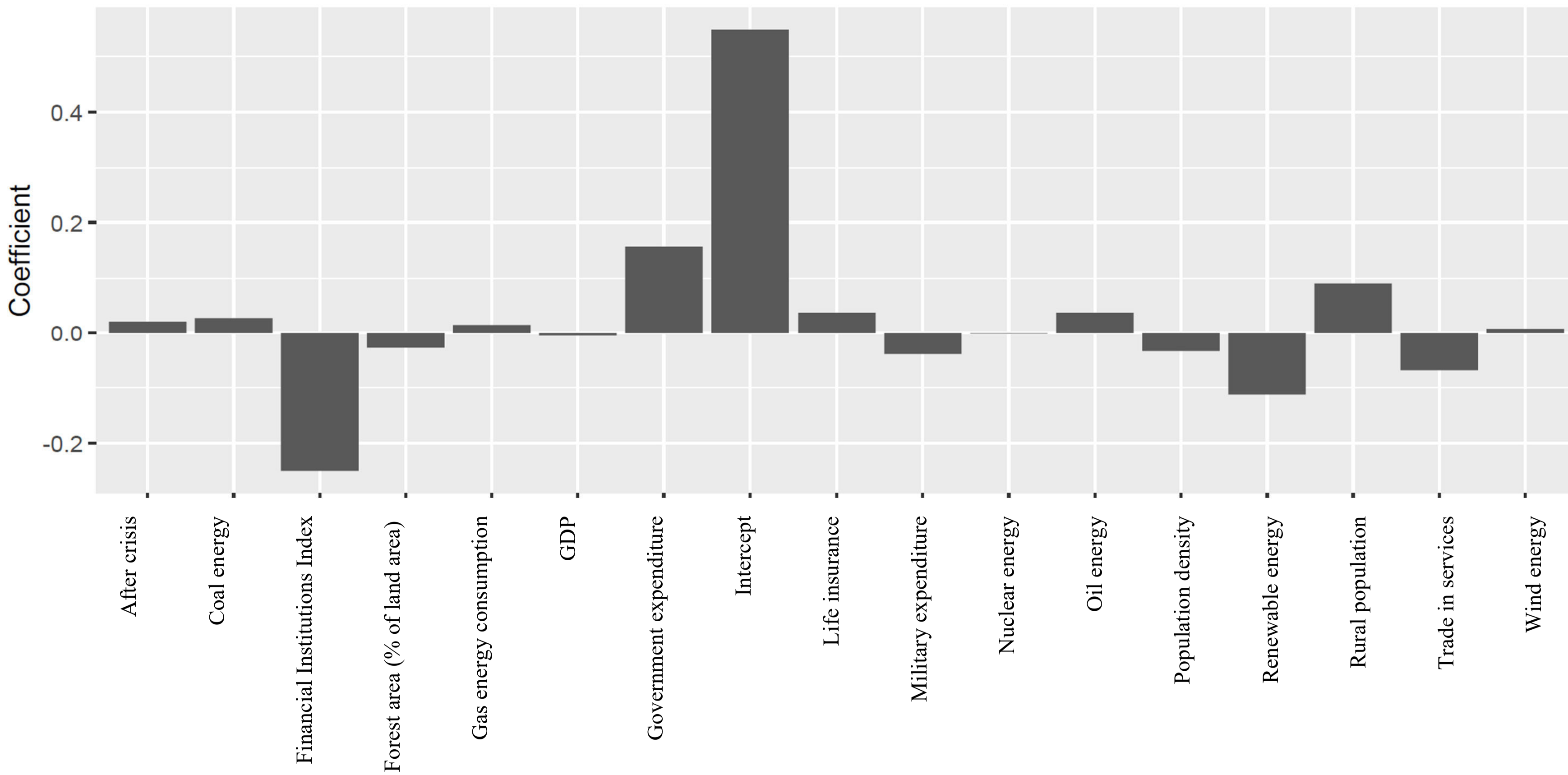

Figure 2 - Importance of coefficients of the model

***Note:** (Figure 2) visually represents the importance of various economic and environmental variables in influencing CO_2 emissions. The variables are displayed on the x-axis, and the height of the bars on the y-axis represents their coefficients. A higher bar indicates a stronger positive relationship with CO_2 emissions, while a lower bar indicates a negative relationship. The diagram provides a comprehensive view of the comparable significance of each variable and its effect on shaping environmental outcomes. It reveals several pivotal contributors to CO_2 emissions, including coal consumption per capita, gas consumption per capita, nuclear energy consumption per capita, and others.*

4.10 Principal Component Analysis

We identified the essential components for more exploration by looking at the highest loading values for each element in the research question or hypothesis. The details with the highest loadings are the ones that explain the most variance in the data and are, therefore, the most relevant to the research.

The PCA results that are shown in Table 11 suggest that Component 1, which has strong positive loadings for CO_2.emissions.metric.tons.per.capita., Oil energy consumption and Financial Institutions. The index might be the most relevant to our research. This component captures the effects of energy consumption and financial institutions on CO_2 emissions.

Table 11 - PCA Analysis

	Suggesting representing	AC	CO_2	CCPC	FII	FA	GECP	GGFCE GDP	GDPPE	LIPVGDP	MEGDP	NECP	OECP	PDPSKLA	RECFEC	RPTP	TISGDP	WECP	Proportion	Cumulative
1	Impacts of energy and financial institutions on CO_2	0.07	0.36	0.12	0.28	-0.08	0.34	0.37	0.29	0.12	0.15	0.20	0.37	-0.09	-0.28	-0.28	0.17	0.18	0.357	0.36
2	Economic Development vs. Environmental Preservation	0.11	-0.02	0.34	0.36	0.37	-0.16	-0.05	-0.05	0.43	-0.33	0.26	-0.10	0.29	0.21	0.04	-0.01	0.26	0.185	0.54
3	Trade-Off between Growth and Sustainability	0.25	-0.16	-0.15	-0.03	-0.33	-0.11	0.04	0.10	0.17	0.26	-0.09	-0.12	0.40	-0.06	0.28	0.58	0.23	0.097	0.64
4	Impact of the 2008 Financial Crisis	0.56	-0.14	-0.24	0.03	0.00	0.07	0.09	0.13	-0.23	-0.24	-0.20	-0.10	-0.26	0.29	-0.25	-0.08	0.45	0.096	0.73
5	Impact of Coal Consumption on CO_2	0.09	0.29	0.57	0.07	-0.31	-0.11	-0.15	0.11	0.09	0.16	-0.34	-0.11	-0.37	0.12	0.32	-0.12	0.12	0.059	0.79
6	Impact of the 2008 Crisis on Government E	0.46	0.19	0.22	-0.10	0.27	0.20	-0.04	-0.51	-0.27	0.17	-0.15	0.09	0.28	-0.30	0.08	-0.10	0.04	0.045	0.84
7	Impact of Renewable and Nuclear Energy on CO_2	0.07	-0.03	-0.02	0.06	-0.34	-0.24	0.14	-0.03	0.29	-0.33	-0.43	0.00	0.26	-0.39	-0.31	-0.30	-0.13	0.040	0.88
8	Impact of the 2008 Financial Crisis on Gas E	0.36	-0.10	-0.03	0.10	0.13	-0.25	-0.19	0.50	-0.04	0.44	0.23	-0.09	0.13	-0.11	-0.07	-0.38	-0.23	0.032	0.91
9	Contrast between Nuclear Energy and Financial INS	0.34	0.05	0.07	-0.29	-0.31	0.04	-0.26	-0.16	0.17	-0.26	0.54	-0.18	-0.28	-0.23	-0.09	0.12	-0.15	0.025	0.93
10	Trade-Off between Trade in Services and Nuclear E	0.20	0.03	0.09	0.07	0.37	0.07	-0.13	0.25	0.04	-0.20	-0.36	-0.02	-0.14	-0.02	-0.09	0.50	-0.53	0.018	0.95
11	Contrast between Rural Population and Coal	0.28	0.04	-0.39	0.28	-0.10	0.10	0.10	-0.21	0.32	0.00	0.01	0.37	-0.14	0.22	0.42	-0.18	-0.31	0.014	0.97
12	Contrast between Rural Population	0.01	0.13	-0.01	-0.18	0.01	0.18	0.16	0.43	-0.25	-0.48	0.07	-0.03	0.20	-0.18	0.55	-0.16	0.01	0.012	0.98
13	The contrast between GDP per Person Employed	0.13	0.10	0.15	-0.31	0.04	-0.66	0.32	-0.01	-0.17	-0.08	0.11	0.46	-0.04	0.16	-0.01	0.14	-0.05	0.008	0.99
14	The contrast between GDP and Oil	0.07	-0.18	0.11	-0.31	0.20	0.11	0.67	-0.04	0.31	0.19	-0.01	-0.40	-0.17	0.00	0.06	-0.09	-0.12	0.006	0.99
15	The contrast between Financial INS and Life I	0.00	-0.21	0.09	0.60	-0.12	-0.21	0.28	-0.18	-0.44	-0.07	0.15	-0.25	-0.17	-0.23	0.12	0.11	-0.15	0.004	1.00

Note: Table 11 presents the outcomes of the Principal Component Analysis (PCA), revealing the significant components and their loadings that illuminate the underlying patterns in the dataset. This table provides a comprehensive guide to understanding the key components and their associated loadings, shedding light on the relationships among the original variables. Notably, the first few components, particularly the initial component (Comp.1), play a pivotal role in elucidating a substantial portion of the dataset's variance.

In examining the Diagram 1-Scree Plot, which visually illustrates the distribution of explained variance across principal components (Comp.1 to Comp.15), crucial insights into the dataset's structural dynamics emerge. The scree plot shown in Figure 2, with the x-axis denoting components and the y-axis representing the proportion of variance explained, shows that the initial components carry substantial weight in elucidating the dataset's variance. Notably, the first component (Comp.1) explains around 35.7% of the total variance, underscoring its pivotal role. As we progress through the components, the cumulative explained variance reaches 73.3% by the fourth component (Comp.4), suggesting that subsequent components contribute progressively less to the overall variance. The pattern in the table and figure highlights the importance of the initial components in grabbing the dataset's nature.

Considering the interpretation of the principal components, each component shows a linear combination of the original variables, and discerning their meaning involves examining the loadings or coefficients of each variable. For example, Comp.1 encapsulates the overall impact of energy consumption and financial institutions on CO_2 emissions. In contrast, Comp.2 reflects the trade-off between economic development and environmental preservation, and Comp.3 indicates the repercussions of the 2008 financial crisis on various variables. The dot whisker plot and principal component performance collectively highlight the need for a more detailed investigation of loadings to understand the dataset's principal patterns and connections.

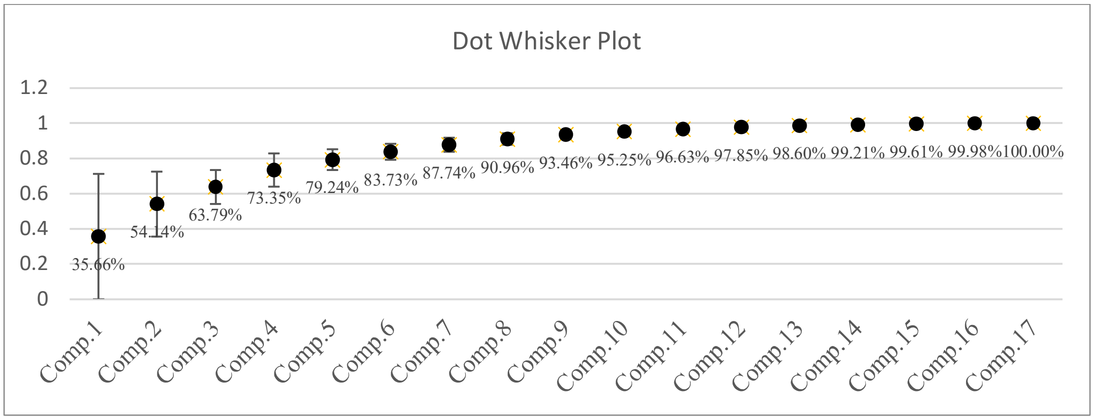

Figure 3 - Dot Whisker Plot

***Note**: The accompanying Dot Whisker Plot in Figure 3 visually reinforces these findings by depicting the estimated effects and their variability across the principal components. The x-axis represents individual components, while the y-axis illustrates the estimated effect size for each element. Notably, the first few components, particularly the initial component (Comp.1), play a pivotal role in elucidating a substantial portion of the dataset's variance. The dot represents the estimated effect, and the whiskers extend to the 95% confidence intervals, underscoring the precision of the estimates. The plot highlights the significant contributions of the initial components and the diminishing impact of subsequent components.*

In exploring the causal relationships between various economic indicators and CO_2 emissions, we employed Granger causality tests with Cube Root Transformation on the dataset. The results, detailed in Table 12 - Granger Causality Test Results for Various Transformations Predicting Dependent Variable from Independent Variables, uncover intricate causation patterns, shedding light on the directional influence and mutual interactions among the examined variables.

The Cube Root Transformation was implemented to the variables before the analysis. Our findings categorize the relationships into two main types: Two-Sided Causality, indicating mutual influence, and One-Sided Causality, denoting a directional impact from the causal variable to CO_2 emissions (CO_2PC). This nuanced understanding enhances our comprehension of how specific economic factors contribute to or are influenced by CO_2 emissions, offering valuable insights for policymakers and researchers alike.

Different transformation methods allow for a comprehensive analysis, such as natural logging, logarithmic, Minmax, cube root, square root, standardize, z-score and no transformation. Notably, the Cube Root Transformation emerges as a robust and meaningful choice, as highlighted in the results. These transformations unveil nuanced relationships between economic, environmental, and policy-related factors and carbon dioxide emissions.

Table 12 - Granger Causality Test Results for Various Transformations Predicting Dependent Variable from Independent Variable

Row Names	Column Names	Nat Log (p-value)	Log (p-value)	Minmax (p-value)	Cube Root (p-value)	Sqrt (p-value)	STD (p-value)	Z-Score (p-value)	No Trans (p-value)
CCPC	**CO_2PC**	0.0075*	0.0075*	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
FII	**CO_2PC**	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
FA	**CO_2PC**	0.0000***	0.0000***	0.0005*	0.0001**	0.0008**	0.0005*	0.0005*	0.0001**
GECC	**CO_2PC**	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
GDP/PE	**CO_2PC**	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
GGFCE	**CO_2PC**	0.0372*	0.0372*	0.0000***	0.0008***	0.0002***	0.0000***	0.0000***	0.0008***
LIPV	**CO_2PC**	0.0003**	0.0003**	0.0112**	0.0044***	0.0085***	0.0112**	0.0112**	0.0044***
ME	**CO_2PC**	0.0003*	0.0003**	0.464	0.0117***	0.0508	0.464	0.464	0.0117***
NECC	**CO_2PC**	0.0000***	0.0000***	0.0000***	0.0174**	0.0000***	0.0000***	0.0000***	0.0174**
OECC	**CO_2PC**	0.0000***	0.0000***	0.7624	0.0093***	0.0804	0.7624	0.7624	0.0093***
PD	**CO_2PC**	0.0000***	0.0000***	0.347	0.0001***	0.0256***	0.347	0.347	0.0001***
RECC	**CO_2PC**	0.0762	0.0762	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
RP	**CO_2PC**	0.654	0.654	0.0000***	0.0262***	0.0032***	0.0000***	0.0000***	0.0262***
TS	**CO_2PC**	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
WECC	**CO_2PC**	0.0034*	0.0034*	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***

Note: Table 12 illustrates the results of the Granger causality tests. These tests are used to determine if one time series can predict another. The p-values listed in the table represent the likelihood that the correlations observed in the data occurred by chance. A smaller p-value indicates more substantial evidence of causality. The dependent variable in this investigation is carbon dioxide emission (CO2PC), and the independent variables are listed in the row names. The relationships estimated can be either one-sided or two-sided. This table shows whether independent variables can predict the variable carbon dioxide trend according to the test. The data has been transformed using various methods indicated in the column headers. These transformations include Natural Logarithm (Nat Log), Logarithmic (Log), Min and Max Method (Minmax), Cube Roots (Cube Root), Square Root (Sqrt), Standardize (STD), Z-Score, and No Transformation (No Trans). The significance of the p-values is denoted with asterisks. A single asterisk (*) signifies a p-value less than 0.05, two asterisks (**) indicate a p-value less than 0.01, and three asterisks (***) signify a p-value less than 0.001

Table 13 - Granger Causality Test Results for Various Transformations Predicting Independent Variables from Dependent Variable presents the causality relationships from CO_2 emissions (CO_2PC) to the respective independent variables. The p-values associated with different transformations offer insights into the significance of these relationships. Variables like CCPC, GECC, GDP/PE, GGFCE, LIPV, NECC, OECC, PD, RECC, RP, and WECC exhibit a robust two-sided causality with CO_2PC, indicating a mutual and reciprocal influence.

Table 13 - Granger Causality Test Results for Various Transformations Predicting Independent Variables from Dependent Variable

Row names	Column names	Nat Log (p-value)	Log (p-value)	Min-max (p-value)	cube Root (p-value)	Sqrt (p-value)	Std (p-value)	Z-Score (p-value)	No Trans (p-value)
CO_2PC	**CCPC**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
CO_2PC	**FII**	0.019*	0.019*	0.046*	0.527	0.872	0.046*	0.046***	0.527
CO_2PC	**FA**	0.33	0.33	0.304	0.899	0.784	0.304	0.304	0.899
CO_2PC	**GECC**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
CO_2PC	**GDP/PE**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
CO_2PC	**GGFCE**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
CO_2PC	**LIPV**	0.000***	0.000***	0.494	0.000***	0.001***	0.494	0.494	0.000***
CO_2PC	**ME**	0.148	0.148	0.202	0.935	0.625	0.202	0.202	0.935
CO_2PC	**NECC**	0.082	0.082	0.438	0.011*	0.027*	0.438	0.438	0.011*
CO_2PC	**OECC**	0.000***	0.000***	0.009	0.000***	0.000***	0.009**	0.009**	0.000***
CO_2PC	**PD**	0.001***	0.001***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
CO_2PC	**RECC**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
CO_2PC	**RP**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
CO_2PC	**TS**	0.006**	0.006**	0.547	0.057	0.128	0.547	0.547	0.057
CO_2PC	**WECC**	0.001***	0.001***	0.004**	0.001***	0.001***	0.004**	0.004**	0.001***

Note: Table 13 illustrates the results of the Granger causality tests. These tests are used to determine if one time series can predict another. The p-values listed in the table represent the likelihood that the correlations observed in the data occurred by chance. A smaller p-value indicates more substantial evidence of causality. The dependent variable in this analysis is carbon dioxide emission (CO2PC), and the independent variables are listed in the row names. The relationships estimated can be either one-sided or two-sided.
This table shows whether the dependent variable, carbon dioxide, can predict the independent trend according to the test.
The data has been transformed using various methods indicated in the column headers. These transformations include Natural Logarithm (Nat Log), Logarithmic (Log), Min and Max Method (Minmax), Cube Roots (Cube Root), Square Root (Sqrt), Standardize (Std), Z-Score, and No Transformation (No Trans).
The significance of the p-values is denoted with asterisks. A single asterisk (*) signifies a p-value less than 0.05, two asterisks (**) indicate a p-value less than 0.01, and three asterisks (***) signify a p-value less than 0.001.

Additionally, Table 14 - Causal Relationship Types between Independent and Dependent Variables under Various Transformations categorizes the relationships into Two-Sided Causality or One-Sided Causality, providing a clear overview of the nature of influence between the variables. This thorough analysis, supported by statistical significance and p-values, yields valuable insights into the dynamics between critical economic factors and carbon emissions. These findings are essential for policymakers and researchers, guiding informed decision-making in environmental management and sustainable policy development.

The Granger causality assessments, operated with Cube Root Transformation, exposed intricate causation patterns between financial and economic indicators and CO_2 emissions. One-sided causality, indicating a directional impact from the variable to CO_2 emissions, was observed for the Financial Institutions Index (FII), Forest Area (FA), Military Expenditure (ME), and Trade in Services (TS). On the other hand, two-sided causality, indicating mutual influence, was found between CO_2 emissions and variables such as Coal Consumption per Capita (CCPC), General Government Final Consumption Expenditure (GGFCE), GDP per Employee (GDP/PE), Gas Energy Consumption per Capita (GECC), Life Insurance Premium Volume to GDP (%) (LIPV), Nuclear Energy Consumption Oil Energy Consumption Population Density, Renewable Energy Consumption per Capita (RECC), Rural Population (RP), and Wind Energy Consumption per Capita (WECC). The results supply a helpful understanding of the elements impacting CO_2 emissions and highlight the necessity for a multi-faceted strategy to address this issue. The research contributes to the more expansive discourse on the junction of economic and environmental factors and is a steppingstone for future research.

Table 14 - Causal Relationship Types between Independent and Dependent Variables under Various Transformation

Causality type (relationship)	Nat log	Log	Minimax	Cube root	Sqrt	Std	Z-score	No trans
CCPC →CO_2PC	two side	two side	two side	two side	two side	two side	two side	two side
FII → CO_2PC	two side	two side	two side	one side	one side	two side	two side	one side
FA → CO_2PC	one side	one side	one side	one side	one side	one side	one side	one side
GECC → CO_2PC	two side	two side	two side	two side	two side	two side	two side	two side
GDP/PE → CO_2PC	two side	two side	two side	two side	two side	two side	two side	two side
GGFCE → CO_2PC	two side	two side	two side	two side	two side	two side	two side	two side
LIPV → CO_2PC	two side	two side	one side	two side	two side	one side	one side	two side
ME → CO_2PC	one side	one side	-	one side	-	-	-	one side
NECC → CO_2PC	one side	one side	one side	two side	two side	one side	one side	two side
OECC → CO_2PC	two side	two side	-	two side	-	-	-	two side
PD → CO_2PC	two side	two side	-	two side	two side	-	-	two side
RECC → CO_2PC	-	-	two side	two side	two side	two side	two side	two side
RP → CO_2PC	-	-	two side	two side	two side	two side	two side	two side
TS → CO_2PC	two side	two side	one side	one side	one side	one side	one side	one side
WECC → CO_2PC	two side	two side	two side	two side	two side	two side	two side	two side

Note: Table 14 illustrates the causal connections between the independent and dependent variables underneath various transformations. The relationships are categorized as one-way or two-way causality.

IN a one-way causality, one variable is considered to have a causal effect on another. For instance, in Granger causality tests, if variable a has a one-way causal relationship with variable b, changes in a are believed to influence b, but not vice versa. In the context of this table, a one-way relationship implies that the independent variable can predict the dependent variable, carbon dioxide emission (co2pc).

On the other hand, a two-way causality suggests a mutual causal relationship between two variables, meaning both variables influence each other. In Granger causality tests, this would mean that past information from both variables contributes to predicting each other's future values. A two-way relationship in the table indicates that the dependent variable (co2) and the independent variable can predict each other.

The symbol "-" in the table denotes that neither the independent variable can anticipate the dependent variable, nor can the dependent variable predict the independent variable. This test suggests that no significant causal relationship was found between the variables under the corresponding transformation.

4.11 Normality test

When analyzing economic data, it is crucial to identify and manage outlier data to obtain accurate results. Although variables may deviate from a normal distribution, removing all outlier data may significantly reduce the available data and compromise the quality of the results. Therefore, it is essential to normalize the residual regression result carefully.

As shown in Table 15, the Shapiro-Wilk test assesses whether a given data set significantly deviates from a normal distribution. In our case, we applied this test to a sample of 532. The null hypothesis (H0) posits that the data follows a normal distribution. Since the p-value (0.5411) exceeds the significance level (α), we accept H0. Consequently, we assume that the data is normally distributed. However, it is essential to note that no significance does not prove H0 correct; it merely indicates that we cannot reject the null assumption. The test statistic (W) 0.9973 falls within the 95% acceptance region, supporting the normality assumption. The small effect size (KS - D = 0.03556) suggests minimal deviation between the sample and normal distributions.

Given the p-value of 0.5411, we conclude that the observed data is consistent with a normal distribution. This finding has implications for subsequent statistical analyses, as many parametric tests assume normality. Researchers can proceed confidently with methods relying on normal assumptions. However, further investigations may be necessary to explore potential outliers or other factors affecting the distribution. Overall, understanding the normality of the data enhances the validity of subsequent inferential analyses.

Table 15 - The Shapiro-Wilk test result

Parameter	Value
P-value	0.5411
W	0.9973
Sample size (n)	532
Average ($\bar{x}$)	1.88E-12
Median	0.02519
Sample Standard Deviation (S)	1
Sum of Squares	531
b	23.0124
Skewness	-0.04896
Skewness Shape	0.644
Excess kurtosis	0.1712
Kurtosis Shape	0.418

Note: Table 15 presents the results of the Shapiro-Wilk normality test applied to a sample of 532 observations. This test assesses whether a given data set significantly deviates from a normal distribution. The null hypothesis (H0) posits that the data follows a normal distribution. Given the p-value of 0.5411, which exceeds the significance level (α), we accept H0 and assume that the data is normally distributed. However, it is essential to note that this does not prove H0 correct; it merely indicates that we cannot reject the null assumption.

The test statistic (W) 0.9973 falls within the 95% acceptance region, supporting the normality assumption. The small effect size (KS - D = 0.03556) suggests minimal deviation between the sample and normal distributions.

The table also provides additional statistics such as the sample size (n), median, sample standard deviation (S), sum of squares, average ($\bar{x}$), skewness, and excess kurtosis. The skewness shape is symmetrical (p-value=0.644), and the kurtosis shape is mesokurtic, with normal-like tails (p-value=0.418).

Given the p-value of 0.5411, we conclude that the observed data is consistent with a normal distribution.

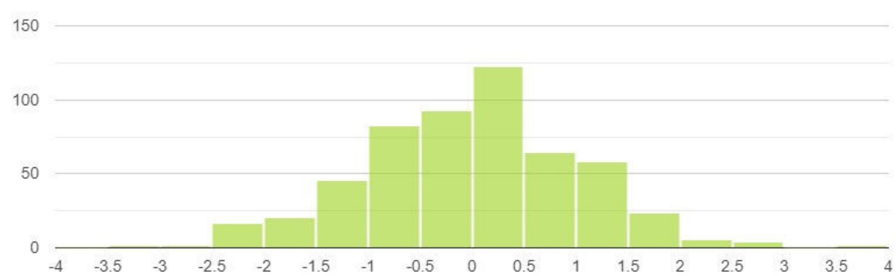

Figure 4 - Histogram of residual

Note: Figure 3 presents a histogram of residuals. The histogram is a visual indication that contains a group of data points in a specified range. In this case, the data points are residuals, the distinctions between observed and predicted values in a model. The x-axis is the value of residuals, and the y-axis indicates the occurrence of these quantities. The histogram figure can deliver an understanding of the statistical properties of the residuals, such as their distribution, central tendency, and dispersion.

Diagram 4 - Q-Q Plot: The Q-Q plot visually represents how well the data matches a normal distribution, supporting the findings from Table 14.

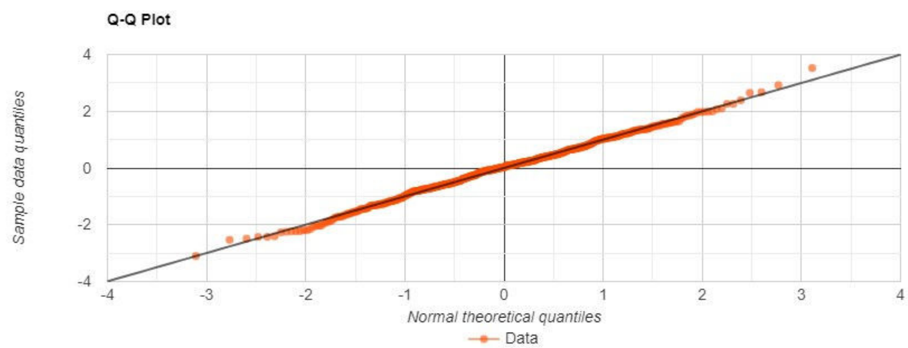

Figure 5 - Q-Q Plot

Note: Figure 5 displays a Q-Q plot, a graphic means used to evaluate if a dataset sees a normal distribution. The characterizes the theoretical quantiles of standard normal distribution, and the y stands for the model data's quantiles.
The orange line labeled “Data” represents the observed data points. The black reference line represents where the data points would lie if they observed a normal distribution perfectly.
The plot shows that the residuals closely follow the reference line but deviate slightly at both ends. This figure suggests that the sample data has lighter tails than a normal distribution, indicating potential outliers or skewness in the data.

4.12 Augmented Dickey-Fuller Test Results

Table 16 presents the results of an augmented Dickey-Fuller (ADF) test on many variables. The ADF statistic and its corresponding p-value are listed, and the conclusion is drawn based on a 0.05 significance level. Despite the p-value being less than the significance level in all cases, the uniform conclusion is “Reject.” As a result of the test results, the null hypothesis o

holding a unit root is rejected for each variable, indicating that the series is stationary.

Stationarity is crucial in time series analysis due to the natural temporal building of the data. While not required for standard linear regression, stationarity becomes essential when dealing with time-dependent data—the ADF test tests for a unit root, implying stationarity. Rejecting the null hypothesis in the ADF test suggests our time series is stationary, enhancing the reliability of subsequent linear regression analyses.

As stationary time series exhibit constant properties over time, they make analyzing them reliably and consistently easier. The ADF test serves as a crucial tool in assessing stationarity, essential for ensuring the robustness of subsequent time series analyses. The constant rejection of the null hypothesis across all variables reinforces the stationary nature of these time series, providing a solid foundation for further investigation and modeling. The results align with best time series modeling practices, as non-stationary data can lead to misleading regression results. Robust statistical techniques are needed when dealing with temporal dependencies.

Table 16 - Augmented Dickey-Fuller Test Results for Stationarity Assessment

Variable	ADF Statistic	P Value	Conclusion
CO_2	-11.1728	0.01	Reject
CCPC	-7.03342	0.01	Reject
GECC	-11.5026	0.01	Reject
NECC	-9.80022	0.01	Reject
RECC	-17.5712	0.01	Reject
GGFCE	-12.3101	0.01	Reject
WECC	-14.7761	0.01	Reject
PD	-10.928	0.01	Reject
ME	-9.81853	0.01	Reject
TS	-8.50034	0.01	Reject
RP	-10.7764	0.01	Reject
OECC	-10.7911	0.01	Reject
FII	-10.9043	0.01	Reject
GDP/PE	-11.0591	0.01	Reject
LIPV	-9.9623	0.01	Reject
FA	-8.72735	0.01	Reject

Note: The variable under consideration. : The Augmented Dickey-Fuller test statistic for the variable. : The p-value for the test statistic. : The decision is founded on the p-value (Reject if $p < 0.05$).In the table, all the variables have a p-value of 0.01, which is less than 0.05, and the conclusion for all the tests is “Reject,” suggesting that all these time series are stationary. The ADF test is used to determine whether a time series is stationary.

4.13 Discussion of Findings

The regression analysis results deliver a valuable understanding of the correlation relating CO_2 emissions and different economic and financial factors in G20 countries. Here is an investigation of the key results:

Coal consumption per capita (CCPC), Gas energy consumption per capita (GECP), Wind energy consumption per capita (WECP), and Oil energy consumption per capita (OECP) all have a positive effect on CO_2 emissions. The result means that as the per capita consumption of these sorts of energy rises, CO_2 emissions also increase.

Nuclear energy consumption per capita and Renewable energy consumption have a negative connection with CO_2 emissions. The outcome shows that increased nuclear and renewable energy consumption is associated with decreased CO_2 emissions.

The Financial Institutions Index (FII) has an opposing effect on CO_2 emissions. The result could suggest that a well-developed financial sector might promote investments in cleaner technologies or industries with lower CO_2 emissions.

Life insurance premium volume to GDP (%) (LIPVGDP) positively impacts CO_2 emissions. The consequence could be that a more meaningful life insurance sector might be associated with raised economic movement, leading to increased CO_2 emissions.

Chapter 5: Conclusion

5.1 Unveiling Connections: A Multivariate Analysis of CO_2 Emissions Among G20 Countries

5.1.1 Robust Correlation

The regression analysis, boasting a multiple R of 0.9964, underscores a robust correlation between selected independent variables and CO_2 emissions. The highly significant F-statistic of 4524.10 (P-value: near) from the ANOVA results solidifies the statistical significance of the general regression model.

Upon observing the coefficients, numerous variables emerge as pivotal contributors to CO_2 emissions, establishing statistically significant relationships. These include coal consumption, gas energy consumption, nuclear energy consumption, renewable energy consumption, general government final consumption expenditure, wind energy consumption per capita, population density, military expenditure, post-2008 financial crisis, trade in services, rural population, oil energy consumption per capita, Financial Institutions Index, GDP, life insurance premium volume to GDP, and forest area.

5.1.2 Financial Impact: The Role of Institutions in CO_2 Emissions

The Financial Institutions Index (FII) exhibits a notable coefficient of -0.2492, suggesting a significant negative association. Countries with higher FII values tend to demonstrate lower CO_2 emissions, challenging conventional expectations and highlighting the crucial role of sustainable financial institutions.

The positive relationship indicated by the coefficient (0.0376) for life insurance premium volume to GDP (%) implies that growth in this ratio is associated with decreased

CO_2 emissions. The result implies potential resources for green technologies, emphasizing the affirmative effect of financial strategies on environmental conclusions.

The analysis uncovers a substantial impact of the 2008 financial crisis on CO_2 emissions, as evidenced by the coefficient for the variable "after crisis" (0.0223). The finding signifies a noticeable increase in CO_2 emissions following the crisis, offering insights into the intersection of economic downturns and environmental outcomes.

5.1.3 Causation Patterns: Granger Causality Tests with Cube Root Transformation

Granger causality tests, employing Cube Root Transformation, unravel intricate causation patterns. The relationships are categorized into Two-Sided Causality, indicating mutual influence, and One-Sided Causality, signifying a directional impact. Notably, Cube Root Transformation emerges as a robust choice.

1. **One-Sided Causality (from the variable to CO_2 emissions):** FII, Forest Area (FA), Military Expenditure (ME), Trade in Services (TS)
2. **Two-sided Causality (mutual influence with CO_2 emissions):** CCPC, GGFCE, GDP/PE, GECC, LIPV, NECC, OECC, PD, RECC, RP, WECC

These findings completely understand the dynamic relationships between economic, financial, and environmental factors influencing CO_2 emissions. The results provide crucial insights for policymakers, researchers, and stakeholders involved in devising effective strategies for sustainable development and climate change mitigation. It is important to note that different transformations may yield varying results, and the significance of relationships is interpreted based on p-values.

5.2 contributions to knowledge

5.2.1 Holistic Approach: Comprehensive Examination of CO_2 Emissions

The analysis contributes to a holistic experience of CO_2 emissions by examining a broad set of variables, including various energy sources (coal, gas, nuclear, renewable, wind, and oil) and economic indicators (financial institutions, life insurance premiums, GDP, etc.). This comprehensive approach goes beyond singular factors, providing a nuanced view of the interplay among diverse elements.

5.2.2 Challenging Conventions: Unexpected Relationships in Financial Dynamics

Identifying unexpected relationships, such as the counterintuitive negative association between the Financial Institutions Index (FII) and CO_2 emissions, challenges conventional wisdom. These surprising findings prompt further investigation into the mechanisms through which financial institutions impact environmental outcomes, contributing new dimensions to the discourse.

5.2.3 Financial Strategies for Environmental Impact

The research highlights the crucial role of financial institutions in influencing CO_2 emissions. The negative association linking FII, and emissions implies that countries with robust and sustainable financial institutions contribute less to carbon emissions. This finding emphasizes the potential for financial strategies to drive sustainable practices and reduce environmental impact.

To broaden our understanding of financial strategies, we can draw upon the findings of a comprehensive study on the interconnections between climate change, decarbonization, and green finance. This study emphasizes the urgency of addressing climate change and its catastrophic consequences. It highlights green finance as a crucial tool in the global fight against environmental damage. Green finance involves providing investments, loans, or capital to support environmentally friendly activities, facilitating the transition to a more sustainable future. These insights resonate with our investigation into the complex interplay of economic and financial factors and their influence on CO2 emissions across G20 nations. (Fu et al.,2024)

The findings of a comprehensive study on green finance and sustainable development are worth noting. This study underscores the crucial role of substantial investments in green and low-carbon initiatives in effectively handling climate change and encouraging sustainable economic growth. Such insights align with our investigation into the interplay of economic and financial factors and their influence on CO2 emissions across G20 nations. (Fu et al.,2023)

When discussing financial strategies to reduce environmental impact, it is essential to highlight the results of a study that scrutinized the CSR disclosure of foreign firms compared to US firms, focusing on CSR's environmental and social aspects. This research, led by (Chowdhury et al., 2021), offers crucial insights into the role of corporate social responsibility in promoting environmental sustainability. These findings are particularly relevant to our investigation, which explores the complex relationship between economic and financial factors and their effect on CO2 emissions across G20 nations.

5.2.4 From Metrics to Action: Practical Implications

By revealing the practical effect of the 2008 fiscal crisis on CO_2 emissions, the analysis contributes to recognize the aftermath of economic declines on environmental outcomes. Understanding the impact is crucial for policymakers and researchers navigating the intersection of financial challenges and climate change mitigation.

The research extends beyond statistical metrics to offer practical implications for policymakers and researchers. For instance, recognizing the positive impact of life insurance premium volume on reducing CO_2 emissions suggests policies encouraging investment in sustainable practices. The insights derived from variable importance and causality tests provide a foundation for informed decision-making in environmental management and policy development.

5.2.5 Advancing Methodology: Granger Causality Tests with Cube Root Transformation

Applying Granger causality tests with Cube Root Transformation represents a methodological contribution. The nuanced analysis categorizes relationships into Two-Sided and One-Sided Causality, offering a refined understanding of the directional influences among variables. The choice of transformation methods, with emphasis on Cube Root, enhances the robustness of the analysis.

In summary, this research significantly advances knowledge in the field by offering a comprehensive understanding of the determinants of CO_2 emissions, unveiling unexpected relationships, emphasizing the role of financial institutions, exploring the aftermath of economic crises, providing practical policy implications, and contributing methodologically through advanced statistical analyses. These contributions enrich the academic discourse on the intricate relationships between economic factors and environmental outcomes, guiding future research and policy initiatives.

5.3 Limitations

- **Study Scope**: The study focused on G20 countries, excluding the European Union, from 1994 to 2021. Consequently, the effects may not be generalized to other countries or durations.
- **Data Reliability Concerns:** The study relied on available data for various economic indicators and CO_2 emissions. Any inaccuracies or inconsistencies in the data could affect the conclusions. The study might have included only some potential factors affecting CO_2 emissions due to data availability constraints.
- **Methodological Drawbacks**: While the study considered a range of variables, other relevant factors might not be included in the analysis that could influence CO_2 emissions.
  - The examination used a multiple linear regression model and Granger causality tests with Cube Root Transformation. These approaches have drawbacks, even if they present insightful information. For instance, they make the potentially erroneous assumption that variables always have a linear relationship.
  - The findings are based on statistical data analysis. However, real-world situations can be complex, and the relationships between variables might be influenced by factors not captured in the data.
- **Policy Implementation Challenges:** The study provides policy implications based on the findings. However, implementing these policies in the real world can be challenging due to various practical constraints.

5.4. Charting Future Paths: Suggestions for Future Studies

- **Extend the Coverage of Energy Sources:** This analysis concentrated on distinctive energy sources such as coal, gas, nuclear, renewable, wind, and oil. Prospective research could evaluate other occurring energy sources, such as hydrogen or bioenergy, to supply a wider knowledge of their impact on CO_2 emissions.

- **Incorporate More Economic Indicators:** While this study considered the role of financial institutions and life insurance premiums, many other economic indicators could influence CO_2 emissions. Future research could incorporate trade openness or technological innovation indicators.
- **Regarding Other Environmental Indicators:** This examination concentrated on CO_2 emissions, but economic and financial factors could impact other environmental indicators. Coming research could evaluate water usage, air quality, or biodiversity indicators.
- **Longitudinal Analysis:** This study provided a snapshot of the relationship between economic and financial factors and CO_2 emissions. Future research could conduct a longitudinal analysis to understand how these relationships evolve.
- **Policy Analysis:** This research highlighted the critical role of informed policy decisions. Future studies could delve deeper into the effectiveness of policies in reducing CO_2 emissions and promoting sustainable development.
- **Case Studies:** While this investigation furnished a broad outline of the G20 countries, future research could include in-depth case studies of specific nations to understand their unique challenges and opportunities in decreasing CO_2 emissions.
- **Impact of COVID-19:** The global pandemic has had significant economic and environmental effects. Future research could explore how COVID-19 has influenced CO_2 emissions and the role of economic and financial factors in this context.

5.5 Guiding Policies: Recommendations

5.5.1 Promoting Renewable Energy

Given the significant influence of different types of energy consumption on CO_2 emissions, policies should promote renewable energy sources and avoid the usage of fossil fuels such as coal and gas. Motivations could be provided for renewable energy, and restrictions could be enforced to limit energy sources donating significantly to CO_2 emissions.

5.5.2 Strengthening Financial Institutions

The research highlighted the role of financial institutions in influencing CO_2 emissions. Policies should strengthen these institutions and promote sustainable practices within them. The steps could include regulations requiring financial institutions to consider environmental elements in their decision-making developments.

5.5.3 Regulating Life Insurance Premiums

The study discovered a positive relationship between life insurance premium volume and CO_2 emissions. Policymakers could establish regulations to ensure that increasing life insurance premiums does not increase CO_2 emissions. The implementation of rules could include policies encouraging life insurance companies to invest in sustainable practices.

5.5.4 Considering Economic Crises

The research uncovered that the aftermath of the 2008 financial crisis significantly affected CO_2 emissions. Policymakers should consider the potential environmental impact of economic crises when developing economic recovery plans. The plans could include measures to promote sustainable practices during economic recovery.

5.5.5 Investing in Sustainable Energy Research and Development

Policymakers should promote research and development in sustainable energy. Developing the research could include allowance for new energy sources or technologies that can decrease CO_2 emissions.

5.5.6 Comprehensive Climate Policies

Given the complex interplay of various economic and financial factors influencing CO_2 emissions, policymakers should develop comprehensive climate policies that consider these factors. The steps could include policies that address energy consumption and other economic and financial aspects.

5.6 Conclusion

This research detailed the interplay between per capita energy consumption, financial institutions, and CO_2 emissions across G20 countries. The investigation contained a field of energy sources (coal, gas, nuclear, renewable, wind, and oil) and economic indicators (Financial Institutions and life insurance premium volume), offering a holistic understanding of their impact on CO_2 emissions.

The findings illuminated the substantial influence of different types of energy consumption and the role of financial institutions on CO_2 emissions. The study also highlighted the repercussions of the 2008 financial crisis on CO_2 emissions, delivering valuable insights into the interconnection of economic downturns and environmental outcomes.

The study questions posed at the outset have been thoroughly addressed, elucidating the relationships between distinct types of energy consumption, financial institutions' role, life insurance premiums' volume, and the aftermath of the 2008 financial crisis on CO_2 emissions in G20 countries.

The ideas in response to these research questions have experienced extensive testing, providing evidence for the relationships between different forms of energy consumption, financial institutions' influence, life insurance premiums' volume, and the effects of the 2008 financial crisis on CO_2 emissions in G20 nations.

This study contributes to the larger conversation of how economic and environmental issues interact. Considering the complex interactions between various economic and financial factors, the results underscore the need for an all-encompassing strategy to mitigate CO_2 emissions. This research emphasizes the essential role of well-informed strategy decisions in moving toward a more sustainable future as the globe grapples with the pressing issue of weather change. This study lays the groundwork for more research in this area, which might impact policy choices and support efforts for sustainable development in G20 nations and beyond. This study is critical because it emphasizes how urgent it is to manage CO_2 emissions and how vital financial and economic factors are in this global crisis.

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