Financial Policy and Socio-economic Dimension on CO2 Emissions: Revisiting the G20 Countries

A Thesis

Submitted to the Master's Study Program of Economics at the Faculty of Economics and Business in partial fulfillment of the requirements for the degree of

Master of Arts (M.A.)

by:

Andi Dzulfahmi Imran Hamzah

03212210012

UNIVERSITAS ISLAM INTERNASIONAL INDONESIA

DEPOK

2024

Financial Policy and Socio-economic Dimension on CO2 Emissions: Revisiting the G20 Countries

A Thesis

Submitted to the Master's Study Program of Economics at the Faculty of Economics and Business in partial fulfillment of the requirements for the degree of

Master of Arts (M.A.)

by:

Andi Dzulfahmi Imran Hamzah

03212210012

UNIVERSITAS ISLAM INTERNASIONAL INDONESIA

DEPOK

2024

ABSTRACT

Andi Dzulfahmi Imran Hamzah
03212210012
Master of Art (MA) in Economics
Universitas Islam Internasional Indonesia (UIII)

The issue of climate change, driven by high concentrations of CO2 emissions in the atmosphere, has garnered global attention. Consequently, the Paris Agreement represents a commitment by nations worldwide to address climate change by agreeing to limit the rise in global surface temperature to below 2°C, and ideally below 1.5°C, by 2050. This necessitates a transition to a greener economy, which is hindered by significant funding challenges, particularly for renewable energy financing and the transfer of environmentally friendly technology. Additionally, socio-economic factors must be considered, as population growth and urbanization increase demand in the energy and infrastructure sectors. This study aims to examine the effects of climate-related financial policy through climate-related financial policy index (CRFPI) and socio-economic factors on CO2 emissions in G20 countries from 2000 to 2020. Utilizing a panel regression random effects model, the impact of exogenous variables on CO2 emissions is found to be varied. CRFPI significantly reduces CO2 emissions, as does financial development. The Environmental Kuznets Curve (EKC) hypothesis is validated, showing that in the early stages, GDP positively affects CO2 emissions; however, as GDP growth reaches a turning point, economic growth negatively impacts CO2 emissions in the long term, indicating that G20 countries are predominantly characterized by progressive economic growth. Empirical evidence, particularly regarding socio-economic factors, presents diverse results. Renewable energy consumption leads to the most substantial reduction in CO2 emissions, while the response of CO2 emissions to FDI inflows shows a positive trend, suggesting that investment flows need better alignment with environmental sustainability goals. Finally, trade openness, urbanization, population, and technology patents do not show significant impacts. Despite the dynamic nature of empirical evidence, CRFPI, through various instruments such as green prudential policy, green financial principles, green investment and credit allocation, green bonds, and other disclosure requirements, can serve as alternative financing mechanisms to achieve net-zero emissions targets.

Keywords: *Climate change, G20, CRFPI, Financial policy, Socio-economic factors, CO2 emissions.*

ACKNOWLEDGEMENTS

I would like to express my heartfelt gratitude to everyone who supported, informed, and guided the work presented in this MA thesis.

First and foremost, I extend my deepest appreciation and thanks to my primary supervisor, Teguh Yudo Wicaksono, Ph.D., for his unwavering support, patience, and encouragement throughout the long journey of my Master's research. Without his guidance and constant feedback, this Master's thesis would not have been possible. I am also very grateful to my second supervisor, Aimatul Yumna, Ph.D., for her valuable comments.

I would like to express my special thanks to UIII (Universitas Islam Internasional Indonesia) for granting me the scholarship funds to pursue my Master’s degree. I am also deeply thankful to the University of Dundee, particularly Professor Bill Russel and Dr. Piotr Jaworski, for their extensive support and encouragement during my short study period in Dundee, which greatly contributed to the completion of this thesis.

My heartfelt thanks also go to my friends at UoD—Jody, Didi, and Yulva—who have provided invaluable support throughout my studies. I extend my gratitude to the administrative and secretarial staff of the Economics Studies department, particularly Professor Dian Masyita, Dean of the Faculty of Economics and Business (FEB) at UIII, for her consistent support in fostering the growth of all students.

A special thanks to my best friends, Aldi, Fahri, Nadif, and Algi—you have been like brothers to me. Thank you for your support and inspiration, especially during the challenging times at UIII. Our great discussions on economics, politics, life, and even women have been a tremendous help in navigating the tough moments of my studies.

My heartfelt thanks extend to my beloved extended family, the Karaeng Hamzah family. I am deeply grateful to God for blessing me with such a wonderful and kind-hearted family. Your warmth and love have always been my greatest source of strength.

My deepest thanks go to my beloved parents, Norhayati S.Ag and Andi Ali Imran Hamzah, M.Si. Words cannot express how grateful I am for your boundless love, prayers, patience, and encouragement throughout my studies, especially during the lowest points of my life. I humbly dedicate this MA degree to you. I also want to extend my special thanks to my siblings, Fuad, Muya, Farid, Bunga, and Furqon.

Finally, I thank Allah S.W.T. Thank you, Lord.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

LIST of APPENDIX

ABBREVIATION DIRECTORY

G20 : *Governments of Twenty*
CO2 : *Carbon*
GHG : *Green House Gas*
IPCC : *Intergovernmental Panel on Climate Change*
IEA : *International Energy Agency*
UNFCCC : *United Nations Framework Convention on Climate Change*
NDC : *Nationally Determined Contributions*
OECD : *Organisation for Economic Co-operation and Development*
COP : *Conference of Parties*
CRFPs : *Climate-related Financial Policies*
CRFPI : *Climate-related Financial Policy Index*
GDP : *Gross Domestic Product*
FDI : *Foreign Direct Investment*
UNEP : *United Nations Environment Programme*
UNCTAD : *United Nations Conference on Trade and Development*
ICC : *International Chamber of Commerce*
GGGI : *Global Green Growth Institute*
EEA : *European Environment Agency*
EU27 : *European Union 27 Countries*
US : *United States*
UK : *United Kingdom*
IFC : *International Finance Corporation*
FiT : *Feed-in-Tariffs*
NDBs : *National Development Banks*
KfW : *Kreditanstalt für Wiederaufbau*
GPP : *Green Prudential Policy*
GFG : *Green Financial Guidelines*
OGD : *Other Green Disclosure*
GB : *Green Bonds*
GCA : *Green Credit Allocation*
CAR : *Capital Adequacy Ratio*
GSF/BPF : *Green Supporting Factor / Brown Penalizing Factor*
CCyB : *Countercyclical Capital Buffer*
PRA : *Prudential Regulatory Authority*
CB : *Central Bank*
GOVT : *Government*
LCR : *Liquidity Coverage Ratio*
NSFR : *Net Stable Funding Ratio*
ICAAP : *Internal Capital Adequacy Assessment Process*
BA : *Banking Authority*
CRSTs : *Climate-related Stress Tests*
NGFS : *Network for Greening the Financial System*
TCFD : *Task Force on Climate-related Financial Disclosures*

ESG	*: Environmental, Social, and Governance*
EKC	*: Environmental Kuznets Curve*
STIRPAT	*: Stochastic Impacts by Regression on Population, Affluence, and Technology*
GCC	*: Gulf Cooperation Council*
RCEP	*: Regional Comprehensive Economic Partnership*
G7	*: Governments Seven*
MENA	*: Middle East and North Africa*
WDI	*: World Development Indicator*
IMF	*: International Monetary Fund*
EDGAR	*: Emissions Database for Global Atmospheric Research*
Mt	*: Million Tons*
OLS	*: Ordinary Least Squares*
PLS	*: Pooled Least Squares*
FEM	*: Fixed Effect Model*
REM	*: Random Effect Model*
GRM	*: Governance and Risk Management*
BaFin	*: Bundesanstalt für Finanzdienstleistungsaufsicht*
UNEP FI	*: United Nations Environment Programme Finance Initiative*
KEITI	*: Korea Environmental Industry & Technology Institute*

CHAPTER I

INTRODUCTION

1.1 Background of study

Considering the role of the financial sector and socio-economic factors in achieving low CO2 emissions, transformation is of paramount importance. Climate-related financial policies serve as a current and comprehensive source of information concerning policies addressing climate risks and promoting sustainable financing. They also provide the latest information regarding the adoption, bindingness, and responsible stakeholders in the implementation of climate-related financial policies. This information is pivotal in assessing the genuine commitments of nations towards the issue of climate change. Furthermore, socio-economic indicators are inseparable from efforts to combat climate change. Meticulous monitoring and analysis are imperative to attain the net-zero emission target, ensuring that the Earth's temperature remains below 2°C by the year 2050.

Global warming has become a widely discussed and controversial issue due to its detrimental consequences on the environment, humanity, and the global economic system. Global CO2 emissions are estimated to have reached an unprecedented peak, marking the highest levels in history with severe human impacts (Nagelkerken and Connell 2015). Human activities are the primary contributors to greenhouse gas emissions, with carbon dioxide (CO2) being the main output driving global warming. The vast and uncontrolled accumulation of CO2 emissions in the atmosphere will lead to severe negative impacts, posing significant challenges for future mitigation efforts.

Commencing with the groundbreaking research of Nobel Laureate William Nordhaus in the 1970s, scholars have delved into the intricate connections between climate change and the economy. The pivotal role of fossil fuels as a crucial input in production means that economic growth contributes to the escalation of greenhouse gas emissions. These emissions, in turn, instigate climate change, which holds the potential for significant adverse feedback effects on upcoming economic activities (Carney, 2015).

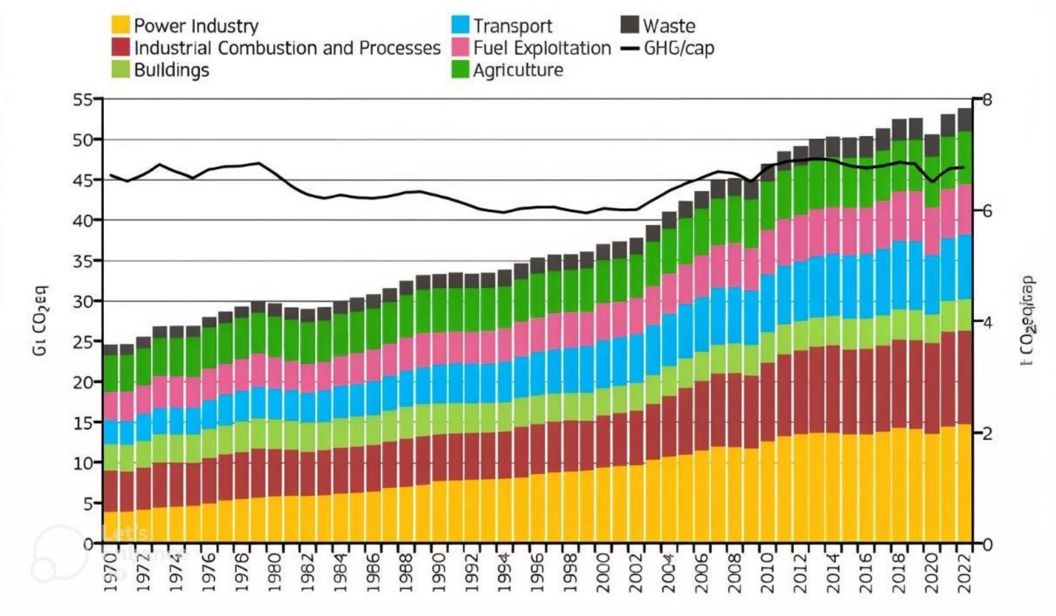


Figure 1.1 Global GHG (Green House Gass) emissions by sector, 1970-2022 (in Gt CO2eq).
Source: Joint Research Centre (JRC), (2023).

Figure 1.1 illustrates the global greenhouse gas (GHG) emissions trend from 1970 to 2022, including sectors like power generation, industry, transportation, buildings, agriculture, waste management, and fuel extraction. The COVID-19 pandemic caused a 3.7% drop in emissions in 2020 compared to 2019, interrupting a decade-long increase. Post-pandemic emissions rebounded, reaching 53.8 Gt CO2eq in 2022, a 2.3% rise from 2019 and 1.4% from 2021. Transport saw a notable -14.1% decline in 2020, but by 2022, it experienced the highest increase at 4.7%. Construction industry emissions slightly dropped by 0.4% in 2022 compared to a 4.6% rise in 2021. Meanwhile, global per capita emissions in 2022 increased by 0.4%, reaching 6.76 t CO2eq/cap, still 0.8% lower than 2019. In general, it can be observed that global CO2 emissions continue to increase, indicating the necessity for an efficient approach to reducing global CO2 emissions.

The primary focus of human activity has been identified as the main cause of global warming, garnering significant attention across various sectors since the mid-20th century. Additionally, the rise in the Earth's surface temperature by 1°C has been conspicuously observed between 1880 and 2012. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), it is noted that 20-40% of global regions have experienced regional warming exceeding 1.5°C in at least one season (IPCC, 2014). The 2021 IPCC report highlights that the consequences of temperature rise are causing significant disruptions to both human societal systems and the environment. This is evidenced by the heightened occurrences of droughts, floods, and other extreme weather events, as well as the deterioration of biodiversity and rising sea levels. Consequently, these disasters are poised to impact vulnerable populations and groups profoundly.

In recent decades, CO2 emissions have significantly driven climate change. Interestingly, disparate patterns have emerged between developed and developing nations. The International Energy Agency (IEA) reported in 2020 that global energy-related CO2 emissions plateaued 2019 after two years of growth. The analysis attributes this stagnation mainly to a marked reduction in CO2 emissions from the power sector in advanced economies. This reduction was facilitated by the increasing utilization of renewable energy sources (notably wind and solar PV), transitioning from coal to natural gas, decreased industrial activity, improved energy efficiency, and elevated nuclear power output (Newell et al., 2020). Furthermore, CO2 emissions in the European Union have decreased by nearly 20% since 1990, with a 10% reduction in the United States during the same timeframe. Conversely, developing nations have seen a substantial rise in CO2 emissions driven by rapid industrialization, unchecked population growth, and urbanization. China has become the leading global CO2 emitter, with significant increases observed in India, Indonesia, and other Southeast Asian countries. Increasingly, countries acknowledge the critical need for emission reductions, with nations such as China and India establishing targets for renewable energy integration and emission cuts (Hussain et al., 2023).

On an international scale, numerous efforts have been undertaken to alleviate the detrimental impacts of climate change by curbing CO2 emissions. The United Nations Framework Convention on Climate Change (UNFCCC) established Paris Agreement as the objective of maintaining global warming well below 2°C, intending to limit the increase to 1.5°C above pre-industrial levels as expeditiously as possible. To attain this goal, countries must drastically cut emissions to achieve a net-zero emission pathway by 2050. Nevertheless, a special report by the IPCC (2018) concerning global temperature targets reveals that the disparity between current trends and the emission reduction goals stipulated by countries through nationally determined contributions (NDC) is expanding, potentially leading to a temperature rise of 3°C to 4°C (den Elzen et al., 2019). Consequently, this indicates that greenhouse gas emissions have escalated and diverged from the agreed-upon targets. According to Le Quéré et al. (2019), to constrain global warming to below 2°C by 2100, greenhouse gas emissions must decrease by one to two billion tons annually.

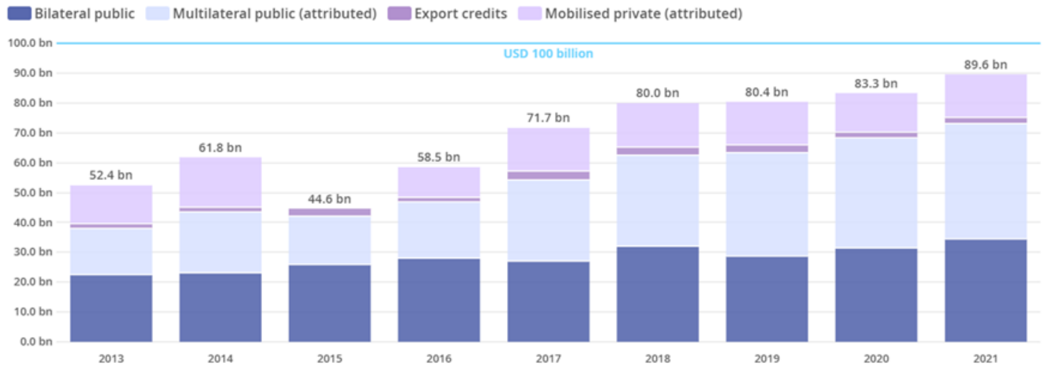


Figure 1.2 Climate Fund for Energy Transition.
Source: Organisation for Economic Co-operation and Development (OECD), (2023).

A tangible display of dedication to curbing CO2 emissions is evident at the 2021 Conference of Parties (COP), specifically, the 26th United Nations Climate Change Conference (COP 26), which is crucial in influencing financial and climate-related policies. This importance arises from the anticipation that, for the first time since the Paris Agreement, governments will likely concur on definitive commitments and elevated ambitions to restrict the global temperature rise to 1.5°C. The COP 26 President-designate, Alok Sharma, has highlighted that securing $100 billion in climate finance is the pivotal factor that will dictate the event's success or failure (OECD, 2023). Nevertheless, a perpetual dependence on international funding is unsustainable for nations. Concrete actions from governments and financial stakeholders are essential to develop domestic policies to mitigate climate change risks and enhance adaptation efforts.

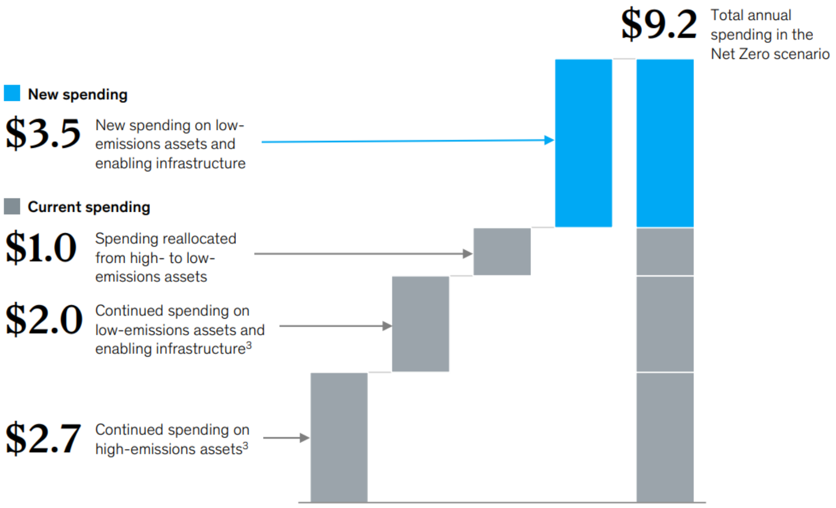


Figure 1.3 Financial Projection to achieve net zero emissions pathway
Source: Krishnan et al., (2022).

The magnitude of the necessary economic overhaul would be substantial. Specifically, Krishnan et al. (2022) projected that the total capital expenditure on tangible assets for achieving net-zero emissions between 2021 and 2050 would amount to approximately $275 trillion. This entails a transition from current spending levels of around $5.7 trillion to an annual average of $9.2 trillion by 2050, constituting a $3.5 trillion increment. Accounting for anticipated expenditure escalations due to economic growth, population expansion, and existing transition policies, the required spending hike would be mitigated but still amount to roughly $1 trillion. Thus, financial policy interventions are crucial for achieving the net zero emissions pathway of 1.5°C by 2050.

Carbon finance is a pivotal driver for promoting green economic development in this context. It is crucial to fund renewable and green energy initiatives to curb CO2 emissions and mitigate their adverse health effects. Additionally, it contributes to developing climate-resilient urban infrastructure and fosters environmental sustainability (Taghizadeh-Hesary & Yoshino, 2019). Given that the financial sector constitutes the nucleus of the contemporary economy, shaping the allocation of production resources and the flow of social capital, green finance is instrumental. This approach can mobilize significant capital, meeting the financial requirements for CO2 emissions reduction in high-carbon industries and facilitating the expansion of production in low-carbon sectors (Madaleno et al., 2022).

The relationship between financial stability and energy consumption has been explored in previous research (Nasreen et al., 2017), while a comprehensive body of literature, as evidenced in a recent review by G¨ok (2020), has delved into the impact of financial development. This latter aspect gains particular significance due to the pivotal roles played by capital markets and the financial sector in facilitating essential investments for adopting low-carbon technologies, thereby fostering green structural change (Zabediuk, 2022).

The implementation of adaptation and mitigation strategies is closely tied to the development of green technologies, which face various barriers such as costs, lack of competencies and knowledge, market structure, and lack of financial resources. Eco-innovation, particularly in green finance, requires long-term financial capital, which is riskier and more expensive than standard non-green innovation (Cheng et al., 2014). Despite positive trends in green finance development, financial resources remain insufficient to close the "green finance gap." This inadequacy in green finance volumes hinders the achievement of the 2°C scenario called for by the IPCC. It makes it challenging to achieve a green structural change (Arranz et al., 2020). The insufficiency of financial resources is influenced by a wide array of internal and external factors, as well as the characteristics of eco-innovations (Río et al., 2015). Furthermore, the impact of green finance on the transformation of energy consumption structure has been studied, with suggestions for improving energy consumption structure through developing green finance and formulating differentiated green finance development strategies (Gu et al., 2023).

In the context of China, it has been proposed to actively promote green investment, green credit, and the construction of a regional green financial system to enhance the development level of green finance (Wang et al., 2023). These findings underscore the significance of addressing financial barriers and enhancing green finance to facilitate the transition towards a more sustainable and eco-innovative economy. In light of recent literature, it is imperative to incorporate climate-related financial policies (CRFPs) to address the challenges of climate change. These policies, advocated primarily by central banks and financial regulators, serve two primary purposes: scaling up green finance and mitigating physical and transition risks for the financial sector (D'Orazio & Dirks, 2021).

The Governments of Twenty (G20) occupies a pivotal position in global deliberations on emission reductions, given its representation of a substantial fraction of the world's economy, trade, and energy-related CO2 emissions (Tian et al., 2021). Contributing over 70 percent to global emissions, G20 countries possess substantial influence over international climate change mitigation efforts. However, disparities in development levels among G20 countries present a formidable challenge to fully realizing the collective potential for emission reductions. Despite this, the G20 has the potential to lead initiatives like the Paris Climate Change Agreement, provided all member nations are fully committed to reducing CO2 emissions and collaborating towards shared environmental goals (Sadorsky, 2020).

Beyond financial considerations, global CO2 emissions growth must also be scrutinized through a socio-economic lens. Extensive research has established that human activity, particularly the combustion of fossil fuels, is the principal driver of rising temperatures, contributing significantly to global warming and accelerating changes in the climate system (Darwish et al., 2023; Sungwon & Bumsoo, 2020; Chen et al., 2023). This reinforces the understanding that climate change is primarily an anthropogenic issue rooted in human activities.

The burning of fossil fuels, especially in the context of economic development in urban areas, is widely acknowledged as the predominant source of global CO2 emissions (IPCC, 2007). Current evaluations indicate that urban regions account for more than 67% of global energy consumption and over 70% of CO2 emissions (IEA, 2012). Additionally, with over half of the global population residing in urban centers, a figure that continues to grow, a consequent rapid urban sprawl encroaching on agricultural lands and natural habitats (Fang et al., 2015). This urban expansion, coupled with significant demographic changes, has led to increased use of motorized vehicles and machinery, further entrenching cities as primary contributors to CO2 emissions (Ru et al., 2011; Wang et al., 2015).

Moreover, the rationale behind this research is that specific policies can directly stimulate the allocation of financial capital to sustainable, green, and non-polluting activities, thereby fostering a low-carbon transition. On the other hand, various policy types can create favorable conditions for green and sustainable investments by encouraging actions like financial institutions disclosing their exposure to "brown/polluting" assets or adopting a clear taxonomy of economic activities (i.e., sustainable, unsustainable, neutral), thus contributing to the progressive decarbonization of the economy and the low-carbon transition (Zhang et al., 2022). Additionally, from the author's perspective, adopting climate resilience testing or climate-aligned financial risk management actions can also play a role in mitigating CO_2 emissions when there is an indication of the relevance of climate risks to the financial sector. That will gradually prompt financial institutions to reduce their exposure to "climate-sensitive" assets, reducing the potential losses from extreme climate events resulting from global warming.

Building upon the context above, this study will undertake an empirical investigation to quantitatively assess the influence of the climate-related financial policy index (CRFPI) and financial development on total CO2 emissions and CO2 emissions generated by various sectors such as buildings, industries, land use, and forestry, fuel combustion, transportation, manufacturing and construction, electricity and heat. Additionally, a set of control variables, which represent socio-economic indicators, will be included in the analysis. These variables consist of total gross domestic product (GDP), which stands for economic growth; foreign direct investment (FDI) and trade openness, reflecting macro-level economic activities; urbanization and population representing social changes; patent in technology and renewable energy represent innovation. All these independent variables will be utilized to assess the overall CO2 emissions. The research will employ cross-sectional data, specifically focusing on G20 member countries and time series data from 2000 to 2020. Furthermore, the data will be subjected to panel regression analysis using R Studio, Phyton, and Stata.

The originality of this study is grounded in its incorporation of the climate-related financial policy index (CRFPI), financial development, total GDP, foreign direct investment (FDI), trade openness, urbanization, population, patent in technology, and renewable energy consumption, into a specific econometric framework for the analysis of 18 countries of G20 members. This research can enrich comprehension and evaluation of the effectiveness of financial measures in tackling climate change and mitigating CO2 emissions. The discoveries generated by this investigation hold importance in practical applications and academic spheres alike, providing deeper insights into the intricate relationship between climate-related financial policies and their repercussions on environmental deterioration, as exemplified by CO2 emissions.

1.2 Research objectives

The critical role of financial policies in reducing CO2 emissions cannot be overstated. This study, therefore, aims to analyze the impact of climate-related financial policies on global CO2 emissions. Additionally, the study recognizes the importance of socio-economic factors, as uncontrolled human activities contribute significantly to environmental degradation. As such, it also examines the relationship between socio-economic indicators and global CO2 emissions.

In particular, the research utilizes the Climate-Related Financial Policy Index (CRFPI) to measure a nation's dedication to green financial policymaking. It further considers socio-economic indicators, including total GDP, financial development, population, technological advancement, urbanization, population, foreign direct investment (FDI), trade openness, and renewable energy consumption, to assess their impact on total CO2 emissions within G20 countries. The analysis delves deeper by disaggregating CO2 emissions across various sectors, such as buildings, industries, land use, forestry, fuel combustion, transportation, manufacturing, construction, electricity, and heat, to comprehensively understand sector-specific impacts.

1.3 Problem statement

Still, an ongoing discourse surrounding the optimal pathways for transitioning to a low-carbon economy, the significance of financial policy instruments in supporting "green structural change" remains relatively underexplored. Furthermore, the ongoing pursuit of climate objectives grapples with the prevalent "green finance gap." Therefore, it is crucial to investigate climate-related financial policies through the climate-related financial policy index (CRFPI) to facilitate the attainment of net-zero emissions targets. Hence, it is critical to explore climate-oriented financial policies using the climate-related financial policy index (CRFPI) to aid in achieving net-zero emissions targets. This research will assess the impact of various socioeconomic determinants.

1.4 Research question

Based on the Problem stated above, the following research questions arise:

1. What is the impact of the Climate-Related Financial Policy Index (CRFPI) in the G20 countries on CO2 emissions?
2. What are the impacts of socio-economic factors such as total GDP, GDP2, Renewable energy, Financial Development, Population, Technological progress, Urbanization, Foreign Direct Investment (FDI), Trade Openness, and Urbanization on CO2 emissions in G20 countries?
3. What are the impacts of CRFPI and Socioeconomic factors on CO2 emissions by different sectors across G20 Countries?

1.5 Research significant

1.5.1 Theoretically

This research holds significant value in advancing understanding of the interplay between financial policies, socioeconomic factors, and CO2 emissions within the G20 countries. This research contributes to theoretical frameworks in environmental economics, policy studies, and sustainability science by investigating the effects of climate-related financial policies alongside socioeconomic indicators. It enhances comprehension of how policy interventions and socioeconomic dynamics influence CO2 emissions, enriching theoretical discussions on sustainable development, climate governance, and green finance.

1.5.2 Practically

This research offers crucial insights that can inform policy formulation, decision-making processes, and strategic interventions to mitigate CO2 emissions and foster sustainable development within the G20 countries. By identifying the impacts of financial policies and socioeconomic factors on CO2 emissions, the findings can guide policymakers, financial institutions, and stakeholders in designing more effective climate mitigation strategies, allocating resources efficiently, and promoting environmentally sustainable practices. This study is practical in guiding policy interventions and fostering collective action toward addressing climate change globally.

CHAPTER II

LITERATURE REVIEW

2.1 The theory of green economy

Several institutions have defined the green economy. These include the UNEP (United Nations Environment Programme), OECD (Organisation for Economic Co-operation and Development), UNCTAD (United Nations Conference on Trade and Development), World Bank, Green Economy Coalition, International Chamber of Commerce (ICC), Danish 92 Group, and the Global Green Growth Institute (Global Green Growth Institute).

The theory of Green Economy encompasses various concepts and perspectives, including sustainability, circular economy, and sustainable development. The vision of sustainability within the green economy is influenced by two economic theories: weak sustainability and strong sustainability (Loiseau et al., 2016). Stakeholder and institutional theories are also relevant in understanding the influence of stakeholders on the adoption of circular economy principles and green legitimacy (Baah et al., 2021). Moreover, the goal of the green economy is to alleviate environmental risks and ecological scarcities, which differs from traditional economic theory (Kang et al., 2022). Additionally, the theory emphasizes the contribution of ecologically responsible entrepreneurship to sustainable development and financial risk management prospects (Osipov et al., 2022).

Although there is a need for more consensus about precisely how the green economy should be defined, it is generally agreed that it should improve human well-being and reduce inequality while reducing human environmental impacts (Newton & Cantarello, 2014; Pieroni et al., 2019). The three leading proponents of green growth at the international level (UNEP, OECD, World Bank) agree on the method for achieving green growth. This is principally through technological change and substitution to improve the ecological efficiency of the economy and the role of the governments in accelerating this transition through regulations and incentives. However, definitions differ in the clarity of their claims (Hickel and Kallis, 2020). European Environment Agency (EEA), in 2014, reported that the scope of green economy definitions by various institutions is broadly characterized by three objectives: improving resource efficiency, ensuring ecosystem resilience, and enhancing social equity. One of the most widely quoted definitions of a green economy was proposed by the United Nations Environment Programme (UNEP) (Adamowicz, 2022):

> *“The green economy improves human well-being and social equity while significantly reducing environmental risks and ecological scarcities. In its simplest expression, a green economy can be thought of as one that is low-carbon, resource-efficient, and socially inclusive. In a green economy, growth in income and employment should be driven by public and private investments that reduce CO2 emissions and pollution, enhance energy and resource efficiency, and prevent the loss of biodiversity and ecosystem services* (UNEP, 2011).”

This definition perceives the green economy as a development approach to achieve economic growth, social equality, and environmental sustainability. This model includes a reduction of CO2 emissions, an increase in energy and resource efficiency, a rebuilding of natural capital, and a creation of green jobs. Also, the private and public sectors have roles to play in delivering this green transition. Accordingly, the UNEP emphasizes the complete separation of growth from environmental impact. This definition is aligned with ecological economics and strong sustainability (Zaatari, 2022).

The 'Green Swan' concept delineates a scenario wherein a corporation, prompted by exposure to an extreme physical event, adopts policies to mitigate climate change. Paradoxically, implementing these mitigation measures leads to economic losses for the corporation, consequently shifting risk to the financial sector, characterized by defaults and decreased market capitalization. On a significant scale, the enduring decline in asset prices contributes to systemic financial crises and triggers socio-economic deterioration (Carney, 2015). Diaz et al. (2020) contend that climate change poses a collective challenge for the world, particularly regarding health and well-being. Furthermore, climate change substantially risks the economy and the broader financial system. As a result, financial instruments devised to assess and manage the repercussions of future risks can aid society in comprehensively evaluating and responding to the risks associated with climate change.

2.2 CO2 emissions and GHG (Green House Gas)

The precise identification of rising global greenhouse gas (GHG) emissions from the early 21st century until 2019, paralleled with rapid economic growth in China and other developing nations, stands as a primary driver of global GHG emission increases (Rogelj et al., 2016; Krych et al., 2021). The rise in average global surface temperature is a consequence of increased emissions of CO2 and other trace gases, known as the "greenhouse effect." Notably, notable impacts were observed during the Little Ice Age despite a marginal 1°C cooling, especially in polar regions. It is widely anticipated that the retention of CO2 in the atmosphere will lead to noticeable warming, with considerable impacts at polar regions and minimal effects near the equator (Aubrecht, 1998; Crippa et al., 2023).

CO2 emissions have emerged as the predominant metric in scholarly research due to their significant impact on climate change. CO2 emissions are preferable due to their resilience compared to biases and simpler offered metrics, as well as their interconnectedness with various risks, making them a sensible proxy for climate change. The most expansive risk category related to environmental behavior is often termed "environmental risk." Within this classification, a more precise subset is recognized as "carbon risk" or "climate risk," representing any corporate risk stemming from climate change or dependence on fossil fuels (Hoffmann & Busch, 2008).

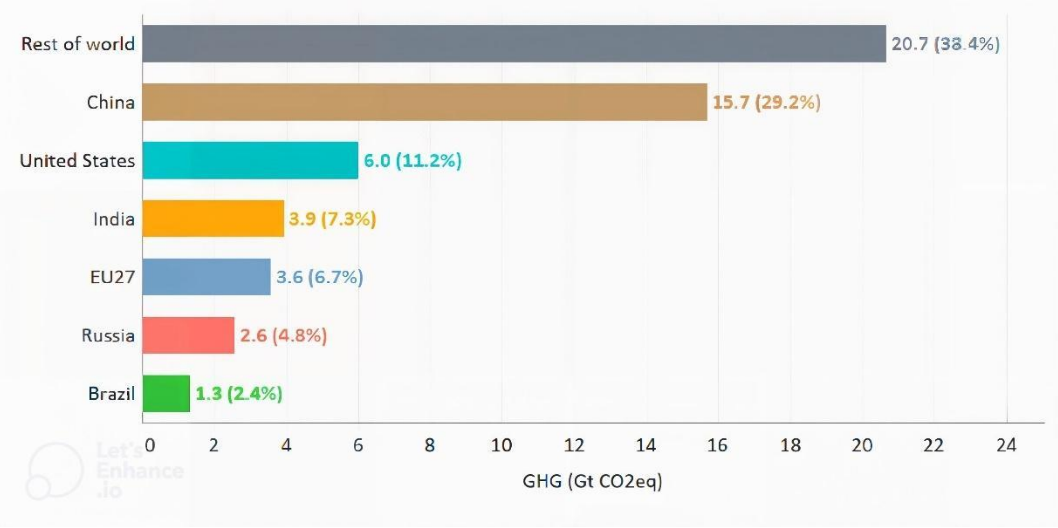
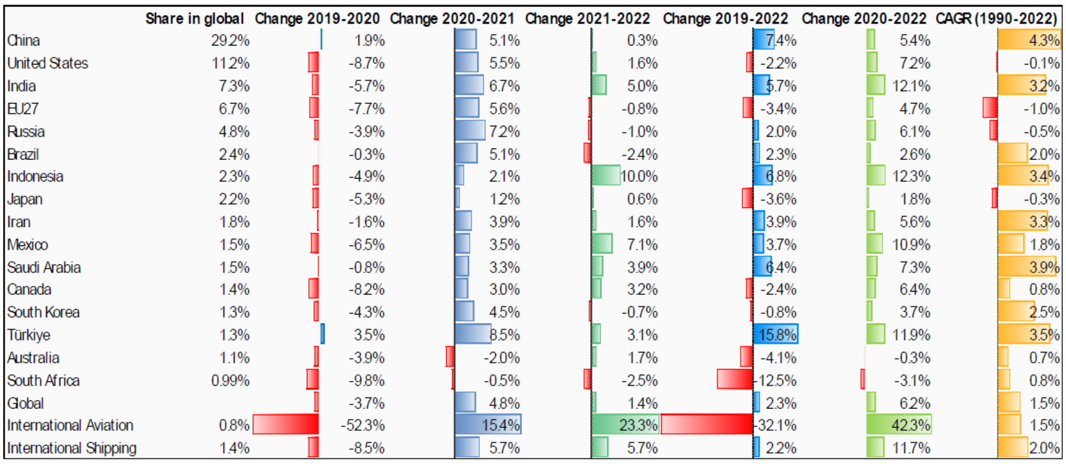


Figure 2.1 GHG emissions (in Gt CO2eq) by major economies and the rest of the world 2022
Source: JRC, (2023).

Among global emitters, China leads in CO2 emissions, followed by the US, India, the EU27, Russia, and Brazil (**Figure 2.1**). These six nations are the largest historical contributors to CO2 emissions, comprising 50.1% of the world's population, 61.2% of global gross domestic product (Crippa et al., 2023), 63.4% of global fossil fuel consumption, and 61.6% of global greenhouse gas emissions.



	Share in global	Change 2019-2020	Change 2020-2021	Change 2021-2022	Change 2019-2022	Change 2020-2022	CAGR (1990-2022)
China	29.2%	1.9%	5.1%	0.3%	7.4%	5.4%	4.3%
United States	11.2%	-8.7%	5.5%	1.6%	-2.2%	7.2%	-0.1%
India	7.3%	-5.7%	6.7%	5.0%	5.7%	12.1%	3.2%
EU27	6.7%	-7.7%	5.6%	-0.8%	-3.4%	4.7%	-1.0%
Russia	4.8%	-3.9%	7.2%	-1.0%	2.0%	6.1%	-0.5%
Brazil	2.4%	-0.3%	5.1%	-2.4%	2.3%	2.6%	2.0%
Indonesia	2.3%	-4.9%	2.1%	10.0%	6.8%	12.3%	3.4%
Japan	2.2%	-5.3%	1.2%	0.6%	-3.6%	1.8%	-0.3%
Iran	1.8%	-1.6%	3.9%	1.6%	3.9%	5.6%	3.3%
Mexico	1.5%	-6.5%	3.5%	7.1%	3.7%	10.9%	1.8%
Saudi Arabia	1.5%	-0.8%	3.3%	3.9%	6.4%	7.3%	3.9%
Canada	1.4%	-8.2%	3.0%	3.2%	-2.4%	6.4%	0.8%
South Korea	1.3%	-4.3%	4.5%	-0.7%	-0.8%	3.7%	2.5%
Türkiye	1.3%	3.5%	8.5%	3.1%	15.8%	11.9%	3.5%
Australia	1.1%	-3.9%	-2.0%	1.7%	-4.1%	-0.3%	0.7%
South Africa	0.99%	-9.8%	-0.5%	-2.5%	-12.5%	-3.1%	0.8%
Global		-3.7%	4.8%	1.4%	2.3%	6.2%	1.5%
International Aviation	0.8%	-52.3%	15.4%	23.3%	-32.1%	42.3%	1.5%
International Shipping	1.4%	-8.5%	5.7%	5.7%	2.2%	11.7%	2.0%

Figure 2.2 Shares in 2022 global emissions, yearly GHG emission relative changes over the period 2019-2022.
Source: JRC, (2023).

In 2022, CO2 emissions rose in the US, India, and China compared to 2021, with India experiencing the highest increase at 5%. The EU27's greenhouse gas emissions 2022 were 27.0%, lower than in 1990 at 3.59 Gt CO2eq and 0.8% lower than in 2021, accounting for 6.7% of global emissions. Among nations accounting for over 1% of global greenhouse gas emissions (refer to **Figure 2.2**), Australia achieved emission reductions of 1.9% in 2021 and 0.3% in 2022 relative to 2020. Moreover, Australia's emission intensity has steadily declined over the past decade, notwithstanding its per capita emissions surpassing those of the US and Russia. Conversely, Indonesia witnessed a substantial 10% surge in GHG emissions in 2022 compared to 2021.

2.3 CO2 emissions on G20 countries

G20 countries play a significant role in global CO2 emissions due to their impact on the global economy and energy-related CO2 emissions. These economies collectively represent a substantial portion of the world's economy, trade, and energy-related CO2 emissions (Tian et al., 2021). As a result, the G20 countries have a considerable influence on global CO2 emissions and are key players in international efforts to address climate change. The unbalanced development among G20 countries has been identified as a challenge that hinders the full potential of the G20 in global CO2 emissions reduction governance (Li et al., 2018). Despite this, the G20 has the potential to lead in meeting international climate agreements such as the Paris Climate Change Agreement, provided that all member countries are fully committed to reducing carbon dioxide emissions and collaborating towards shared environmental goals (Sadorsky, 2020).

Additionally, The G20 countries cover a wide range of areas and are representative of the global economy. G20 members account for approximately 78% of GHG emissions (IPCC 2019) and 90% of the global economy, including 80% of the global trade volume (Burck et al. 2015). Thus, if the G20 members do not act, any impact on the emissions gap is likely to be very limited.

Given the imperative of addressing carbon dioxide emissions as a key aspect of climate change research, numerous nations are actively crafting tailored energy policies. The G20 leaders have reiterated their pledge to diligently execute the United Nations Framework Convention on Climate Change and the Paris Agreement (Erdogan et al., 2020).

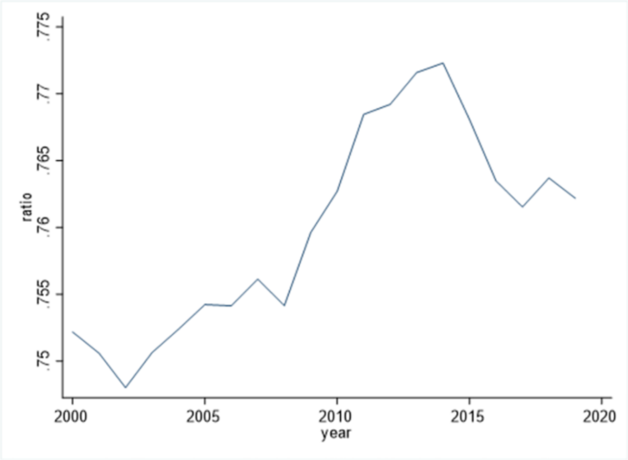


Figure 2.3 The Share of CO2 Emissions of G20 Countries from Total Global Emissions
Source: Wen et al., (2022)

The inclusion of the G20 group, comprising the most advanced economies and emerging market nations, significantly contributes to greenhouse gas emissions due to their industrial activities, energy consumption patterns, and economic development trajectories (Wen et al., 2022). Between 2002 and 2014, the fluctuating rise of this ratio culminated in 2014 at 0.772, indicating a substantial share of global CO2 emissions attributable to G20 countries, establishing them as primary global emitters.

The variance in CO2 emission focal points stems from fundamental disparities in economic advancement between developing and developed nations. Analysis of CO2 emissions by industry sector among G20 countries in 2014 World Bank, (2021) highlights pronounced discrepancies. Notably, developing nations' primary and secondary sectors accounted for higher CO2 emissions (2.64% and 67.41%) than their counterparts in developed nations (1.68% and 56.70%). In contrast, the tertiary sector contributed 41.61%

of CO2 emissions in developed countries, whereas this figure stood at approximately 30% in developing nations. Consequently, divergent sectoral CO2 emission distributions delineate varying pathways for environmental CO2 mitigation strategies between developing and developed nations within the G20.

Table 2.4 CO2 emissions by industry sector for G20 countries in 2014.

G20 Countries	**Primary Sector**	**Secondary Sector**	**Tertiary Sector**		
	Other Sectors Including Agriculture (%)	**Electricity and Heat Production (%)**	**Manufacturing Industries and Construction (%)**	**Transport (%)**	**Residential Buildings and Commercial and Public Services (0/0)**
Developing countries in the G20					
Argentina	6.47%	38.04%	16.87%	24.17%	14.46%
Brazil	4.05%	26.31%	20.60%	44.75%	4.29%
China	2.07%	52.25%	31.72%	8.60%	5.36%
Indonesia	3.02%	53.61%	26.41%	11.48%	5.49%
India	1.43%	44.25%	18.40%	30.81%	5.11%
Mexico	2.07%	44.07%	13.45%	35.09%	5.32%
Russia	1.15%	61.11%	12.32%	16.24%	9.17%
Saudi Arabia	0.00%	49.16%	24.10%	25.92%	0.82%
Turkey	3.71%	46.69%	14.62%	19.83%	15.16%
South Africa	2.42%	67.48%	12.58%	12.05%	5.47%
Average	2.64%	48.30%	19.11%	22.89%	7.07%
Developed countries in the G20					
Australia	1.69%	58.36%	11.49%	24.74%	3.72%
Canada	2.91%	38.73%	12.04%	31.79%	14.52%
Germany	0.05%	48.47%	12.44%	21.37%	17.67%
France	4.70%	13.80%	15.70%	42.41%	23.40%
UK	0.96%	41.93%	9.60%	28.45%	19.06%
Italy	2.23%	35.56%	11.19%	32.95%	18.07%
Japan	0.21%	53.10%	19.18%	17.54%	10%
South Korea	1.45%	60.49%	13.66%	16.28%	8.13%
USA	0.94%	45.99%	8.66%	33.40%	11.01%
Average	1.68%	44.05%	12.66%	27.66%	13.95%

Source: Yan et al., 2022.

a) CO2 Emissions in primary sector

In many developing countries, a significant portion of the workforce and income is concentrated in agriculture, raw materials, livestock, fishing, and forestry, which form the primary sector. Agriculture, which involves the cultivation of plants and animals, is fundamental to national economic development. For instance, in Nigeria, India, Indonesia, China, Northern Cyprus, and other developing nations, agriculture has consistently driven economic growth (Odetola and Etumnu 2013; Oluwole et al. 2021; Mahadevan 2003; Orhan et al. 2021; Adebayo et al. 2021).

However, a technology gap exists in agricultural practices between developed and developing countries, particularly in output per hectare and per worker. Developed countries achieve higher productivity and yields due to advanced technologies (Ruttan 2002; Mohsin et al. 2021). In the US, productivity growth is a key driver of economic growth in agriculture (Ball et al. 2016). Technological advancements can enhance labor productivity, supporting urban growth (Huffman and Orazem 2007). Additionally, advanced technologies can optimize energy use in agriculture, with potential savings of 10% to 40% through methods like reduced soil tillage, efficient fertilizer use, improved irrigation, and enhanced solar drying. Moreover, replacing fossil fuels with biomass in agriculture can reduce CO2 emissions, potentially substituting 0.25 to 1 Gt of fossil fuel carbon annually with biofuels (Sauerbeck 2001).

b) CO2 Emissions in secondary sector

The secondary sector includes middle-income countries that primarily generate their income through industrial production and construction activities such as mining, manufacturing, construction, and energy and water supply. The significance of the manufacturing industry for economic development is well-established; countries with a more robust manufacturing sector tend to develop a competitive service economy (Guerrieri & Meliciani, 2005; Wu et al., 2021). However, industrial activities significantly impact CO2 emissions in both developing and developed nations (Tunç et al., 2007; Parikh et al., 2009; Ali, 2015; Muangthai et al., 2016; Yuan et al., 2017; Abbasi et al., 2021). Developing economies typically have labor-intensive manufacturing, whereas developed countries have more technology-intensive industries (Liu et al., 2021; Shen et al., 2022).

These structural differences affect their CO2 emission sensitivity. Energy is crucial for economic activities but also the primary source of greenhouse gases. Since the mid-18th century, the global annual CO2 concentration has increased by over 48%, largely due to the extensive use of biomass and fossil fuels (Aziz et al., 2013; Shafiei & Salim, 2014;

Manuel et al., 2016; Crafts & Mills, 2017). Approximately 80% of global energy and 66% of electricity are derived from non-renewable fossil fuels (IPCC, 2019). Consequently, while recognizing the positive relationship between energy consumption and economic growth, researchers advocate for stronger energy policies, as reducing energy consumption could negatively impact GDP in the long term (Ghosh, 2002; Lee & Chang, 2008; Zhang & Cheng, 2009; Abbasi et al., 2021b; Khan et al., 2021).

The development of CO2 emissions in G20 countries is a multifaceted issue influenced by various factors such as economic growth, renewable energy, governance, and institutional quality. Understanding these dynamics is crucial for formulating effective policies to mitigate CO2 emissions and address climate change challenges.

2.4 CO2 emissions and global events.

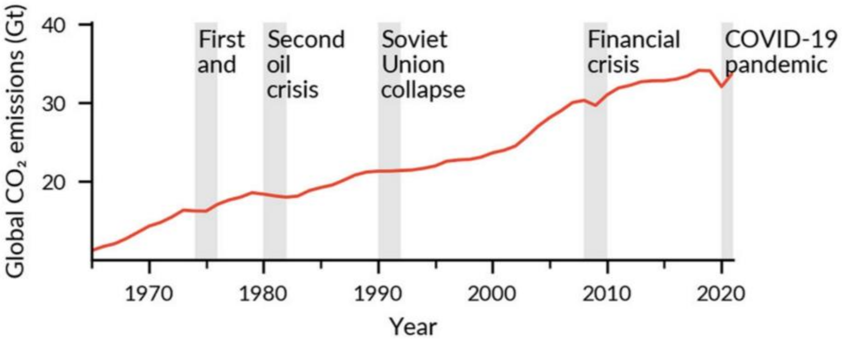


Figure 2.5 CO2 emissions and global events

Over the past 50 years, global CO2 emissions have steadily increased, with minor declines during major economic crises. Events like the oil crises (1973–75 and 1979–81), the collapse of the Soviet Union (1989–1991), and the Global Financial Crisis (GFC) (2007–09) caused only brief reductions in emissions, indicating that economic crises have a limited impact on global CO2 levels. This limited impact is due to the uneven effects on different countries, with some experiencing severe recessions while others continue to grow. For instance, the GFC led to recessions in 100 countries in 2008–09, but most quickly returned to growth. Similarly, the COVID-19 crisis caused a recession in 142 countries and a 3.2% reduction in global GDP in 2020, leading to a 5.9% decrease in CO2 emissions, which rebounded by 5.6% in 2021 (Bersalli et al., 2023).

2.4.1 Rapid growth of urbanization and industrialization in China.

As the world's largest CO2 emitter, understanding the dynamics of industrialization and urbanization in China from 2000 to 2020 is crucial. During this period, China's scope emissions saw a significant rise, averaging a 9.3% annual growth rate from 2000 to 2013 and peaking at 9.53 Gt before declining (Guan et al., 2021). This increase is largely due to rapid industrialization and urbanization, which spurred higher energy consumption and CO2 emissions.

China's industrialization was driven by economic reforms beginning in the 1980s and continuing into the 1990s. These reforms led to substantial growth in industrial productivity, capital accumulation, and rural-to-urban migration, significantly expanding the manufacturing sector (Acemoğlu et al., 2016). Firm-level data indicated an annual total factor productivity (TFP) growth of about 8% in manufacturing from 1998 to 2007, with aggregate TFP growth at 13.4% per year (Caliendo et al., 2019). The National Bureau of Statistics reported a 6.6% increase in manufacturing value added in 2020, significantly contributing to China's GDP.

The expansion of urban areas in China, particularly in coastal zones, has been rapid, driving industrial development and economic growth (Du et al., 2022). This urbanization and industrialization have significantly impacted CO2 emissions, with anthropogenic heat flux rising from 0.924 W/m² to 1.783 W/m² between 2000 and 2020 (Huang, 2024). Urbanization and ecological restoration have also reduced arable land by 54,996 square kilometers over the past two decades (Zhang, 2024).

China's rapid urbanization and industrialization boosted GDP from 10 trillion yuan in 2000 to 82 trillion yuan in 2017 (Meng & Zhou, 2021), but this economic growth has come at the cost of environmental degradation. Balancing industrial growth with environmental sustainability is essential for China's future development.

2.4.2 The implementation of Kyoto Protocol (2005)

The Kyoto Protocol, effective from February 2005, was crucial in global climate change efforts, requiring industrialized countries to limit and reduce greenhouse gas emissions (Ito et al., 2021). Despite the US not ratifying it, the Protocol aimed to cap emissions and imposed binding commitments on wealthier nations (Babiker et al., 2000). It served as the foundational framework for global climate policy until 2012 (Aldy et al., 2003) and introduced mechanisms for progress monitoring like the Forcing Equivalence Index (Wigley, 1998).

Studies show the Kyoto Protocol led to measurable CO2 reductions (Grunewald & Martínez-Zarzoso, 2015), but debates persist about its effectiveness (Almer & Winkler, 2017). The agreement mandated emissions monitoring and reporting, promoting transparency (Aichele, 2013), but also increased carbon imports in participating countries, causing emission leakage (Aichele & Felbermayr, 2013).

For G20 countries, the Protocol's enforcement in 2005 had significant implications, promoting international cooperation but its effectiveness remains debated (Zahran et al., 2007). It influenced global climate policy and future agreements (Mermod & Dömbekci, 2011), laying the foundation for future climate efforts and highlighting the importance of collective action.

2.4.3 Global Financial Crisis (2007-2009)

The 2008-2009 global financial crisis significantly impacted CO2 emissions in G20 countries. Post-crisis, CO2 emissions surged due to large government investments and increased consumption in emerging countries, highlighting the link between economic recovery and higher emissions (Peters et al., 2011; Jiang & Guan, 2017).

China, one of the major economies affected, saw lower changes in CO2 emissions, carbon intensity, and energy intensity post-crisis compared to pre-crisis levels, showing the crisis's impact on its carbon emissions trajectory (Sadorsky, 2020). This underscores the importance of balancing economic growth with environmental sustainability.

While financial crises can temporarily reduce CO2 emissions, the rebound effect often leads to increased emissions. Monitoring emissions trends and adopting sustainable practices like green finance and eco-innovation can mitigate the environmental impact of financial crises (Yusuf & Lytras, 2023; Khokhar, 2024). Understanding these dynamics is essential for developing strategies that balance economic growth and environmental conservation.

2.4.4 Paris Agreement (2015)

The Paris Agreement, adopted in 2015 by 196 countries, aims to limit global temperature rise to below 2°C and strive for a 1.5°C increase (Maslin et al., 2022). It requires countries to make nationally determined contributions (NDCs) to reduce greenhouse gas emissions and enhance climate resilience, aiming to peak emissions soon and balance anthropogenic emissions and removals by the second half of the century (Höhne et al., 2021).

The impact of the Paris Agreement on G20 countries' CO2 emissions has been notable. India aims to reduce emissions intensity by 30-35% by 2030, and Azerbaijan has pledged a 35% cut in greenhouse gas emissions by 2030 (Kumar et al., 2020; Gurbanov, 2021). The G20's role is crucial, but all nations must commit to reducing carbon emissions for the agreement's success (Sadorsky, 2020; Yang et al., 2020).

Forests and land use are vital, potentially becoming a net carbon sink by 2030, aiding emission reduction efforts (Grassi et al., 2017). The agreement also relies on reducing coal-based energy in industrializing countries (Meng et al., 2018). Achieving the Paris Agreement's targets requires reducing emissions, enhancing carbon sinks, and promoting sustainable practices (Rogelj et al., 2016). G20 countries must align their efforts to ensure a sustainable and climate-resilient future.

2.4.5 Implementation of renewable energy

Understanding renewable energy implementation in G20 nations requires examining various studies. One study notes that G20 countries hold about 80% of global renewable energy infrastructure, contributing 87% of its output (Sijabat, 2024). However, the renewable share has decreased since 1990, when it was 92.8%, mainly from hydroelectric sources (Sokulski et al., 2022). These findings indicate a shifting landscape in renewable energy adoption, necessitating ongoing monitoring of trends.

Research highlights the need to increase renewable energy’s share to reduce pollution and enhance sustainability in G20 nations (Ajide & Mesagan, 2022). Transitioning to renewable sources can lower carbon emissions without stifling economic growth (Pancasari, 2023), and renewable energy can improve productivity and environmental quality (Neffati, 2023; Kumari et al., 2021).

Additionally, three G20 countries significantly influence global energy dynamics, holding a large share of fossil fuel-based electricity capacity and renewable deployment potential (Saygin et al., 2019). As the world seeks sustainable energy transitions, understanding the relationship between economic growth, energy consumption, and environmental quality in the G20 is crucial (Bhat et al., 2022). These insights highlight the importance of research, policy initiatives, and international cooperation in advancing a sustainable energy future in G20 nations.

2.4.6 Pandemic covid 19

The COVID-19 pandemic significantly impacted emissions across G20 countries, causing a 5.9% drop in carbon emissions in 2020, the largest decline since World War II (IEA). This was followed by a 5.6% rebound in emissions in 2021 as the global economy recovered. Lockdowns temporarily reduced daily global CO2 emissions due to decreased industrial activity, transportation, and energy production (Quéré et al., 2020), highlighting the link between human activities and greenhouse gas emissions.

The pandemic also led to a notable decrease in power sector CO2 emissions, driven by reduced energy demand in G20 countries (Luke et al., 2021). This reduction resulted from a decline in industrial and commercial activities, emphasizing the connection between economic activity and carbon emissions.

Moreover, the pandemic influenced market forces and power demand, contributing to significant CO2 emission reductions in G20 nations (Bertram et al., 2021). These changes demonstrated the complex relationship between global events, economic activities, and environmental outcomes, underscoring the need for sustainable practices to mitigate emissions during unforeseen disruptions. The pandemic provided insights into how shifts in human behavior can impact emissions, offering valuable lessons for future strategies in G20 countries.

2.5 Climate finance

2.5.1 Theory of climate finance

Climate finance, as stipulated by the United Nations Framework Convention on Climate Change (UNFCCC), encompasses funding at local, national, or transnational levels from public, private, and alternative sources to bolster efforts in mitigating and adapting to climate change impacts (Bracking & Leffel, 2021). The management of climate finance extends across multiple tiers, encompassing international, transnational, national, and subnational levels, and entails interactions among public, private, third-sector, and non-state entities. Climate finance is pivotal in fostering connections among diverse actors, enhancing capabilities, and mitigating risks across sectors like agriculture (Odhong et al., 2019).

Moreover, it's crucial to recognize that climate finance extends beyond monetary transactions, encompassing governance structures and their influence on risk assessment and involvement in local adaptation efforts (Hussain & Ahmad, 2019). The OECD delineates four key facets of climate finance originating from developed nations: bilateral public climate finance, multilateral public climate finance, climate-linked officially supported export credits, and private finance catalyzed by public climate finance.

The UNFCCC instituted a financial mechanism accentuating the significance of climate finance to enhance accountability and transparency within this domain (Alexandraki, 2016). However, the rise of worldwide climate finance encourages strategies for urban climate adaptation, underscoring the pivotal role of climate finance on a global scale (Chu, 2018).

2.5.2 Climate financial policy: financial development and green finance

The magnitude of the necessary economic overhaul would be substantial. Specifically, Krishnan et al. (2022) projected that the total capital expenditure on tangible assets for achieving net-zero emissions between 2021 and 2050 would amount to approximately $275 trillion. This entails a transition from current spending levels of around $5.7 trillion to an annual average of $9.2 trillion by 2050, constituting a $3.5 trillion increment. Accounting for anticipated expenditure escalations due to economic growth, population expansion, and existing transition policies, the required spending hike would be mitigated but still amount to roughly $1 trillion. Thus, financial policy interventions are crucial for achieving the net zero emissions pathway of 1.5 C by 2050.

Sharma et al. (2022) proposed a novel concept of green finance, merging sustainable business with economic advancement, aiming to enhance societal green inclusivity, foster environmental stewardship, and mitigate climate change (Noh, 2019). Additionally, it facilitates funding for green energy initiatives, catalyzing industry growth (Pata et al., 2022).

Climate finance policies encompass strategies designed to procure funding for initiatives related to climate objectives, such as reducing greenhouse gases, adapting to climate change impacts, and enhancing resilience to climate disruptions. These policies, categorized as demand-side, supply-side, or linkage policies, target various market intervention points (Bhandary et al., 2021).

Finance is pivotal in facilitating the shift to a low-carbon, climate-resilient economy as outlined in the Paris Agreement. However, studies show a significant financial shortfall in achieving these objectives (Buchner et al., 2019; IPCC, 2018; UNCTAD, 2014). Rectifying this requires more efficient mobilization and direction of public and private funds toward climate-related initiatives.

Certainly, mitigating the adverse effects of human endeavors on the climate necessitates a shift in both private and public financial allocations, transitioning investments from carbon-intensive industries to low-carbon ones (HLEG-Sust-Fin, 2017).

Table 2.6 The Climate Financial Policy Instruments.

Policy Instrument	**Policy Definition**	**Country Experience**
Targeted lending	Requiring banks to lend a certain portion of their credit or deposits towards certain policy priorities, such as agriculture or clean energy.	India, China.
Green bonds	Bonds are earmarked for projects with environmental and climate benefits.	China, Indonesia, India, US.
Loan guarantees	Governments commit to cover the borrower's debt obligation if the borrower defaults on climate change projects.	US, International Finance Corporation (IFC).
Weather indexed insurance	Index-based insurance provides payouts based on a measurable condition related to agricultural production loss, such as drought.	India, Mongolia, and Ethiopia.
Tax credits	Permit taxpayers to subtract, dollar for dollar, from taxes they owe in return for new investments in climate-friendly projects.	US, Netherlands, Japan.
Feed-in-Tariffs (FiT)	Providing either a fixed total electricity price per kWh or a fixed Spain, Germany, or China premium on top of the wholesale electricity rates for fixed periods for low-carbon electricity providers.	Spain, Germany, China.
National development banks (NDBs)	Government-backed, sponsored, or supported financial institutions that have a specific public policy mandate to promote low-carbon development in a specific country. The NDBS in this study does not include those at multi-lateral, regional, or local levels.	KfW is in Germany, China Development Bank, and India.
National climate fund	Funding vehicles designed by governments to mobilize, access, and channel climate finance.	Brazil, Ethiopia, Bangladesh, Indonesia.
Disclosure	Requiring companies to report climate change information	The US.

Source: Bhandary et al. (2020)

Bhandary et al. (2020) devised a classification of climate finance measures, focusing on nine types detailed in **Table 2.4** Among these, FiT and NDBs are widely regarded as more effective in mobilizing climate mitigation funds than others. However, it's important to note that while FiT may not necessarily be the optimal tool for maximizing renewable electricity capacity, it remains extensively researched, particularly in the electric power sector (Couture & Gagnon, 2010). Surveys indicate that most investors, including institutional investors and venture capitalists, favor FiT, especially for emerging technologies. A minor climate policy change affecting the banking sector could trigger significant economic repercussions, potentially yielding substantial gains or losses for banks and impacting the real economy, especially if the policy is introduced abruptly and belatedly (Stolbova et al., 2018).

2.6 Climate-Related Financial Policy Index

D'Ozario & Thole (2022) delineate various strategies, termed Climate-Related Financial Policies (CRFPs), aimed at expanding green finance and mitigating climate risks to facilitate decarbonization and shifting towards a low-carbon economy. These strategies fall into four groups: climate-related prudential regulations, promotional credit measures, green financial principles promoting green financial markets, and additional climate-related disclosure requirements for non-financial institutions, insurance companies, and pension funds.

D'Ozario and Thole (2022) begin their study by elaborating on the definition of financial policy outlined by the International Monetary Fund (IMF) in 2000. The IMF defines financial policies as regulations, supervision, and oversight of financial and payment systems covering markets and institutions. These policies promote financial stability, improve market efficiency, and safeguard client assets and consumer interests. Considering previous research by Krogstrup and Oman (2019), D'Orazio (2021), and D'Orazio (2022), along with discussions on climate risks in the financial system, CRFPI examines policies targeting the financial sector to address:

i. Identifying and mitigating climate-induced financial threats falls under Green Prudential Regulations (GPP).
ii. Promoting environmentally-conscious financial markets is termed Green Financial Principles (GFG).
iii. Disclosure of climate-related financial risks is mandatory under Other Disclosure Requirements (OGD), including obligations for non-financial entities like insurers and pension funds.
iv. Progressing green lending via green bonds is under the Green Bonds Taxonomy and Issuing (GB).
v. Enabling green lending and investments through mechanisms like credit allocation and limits is known as Green Credit Allocation Policies (GCA).

Table 2.7 CRFPI (Climate-Related Financial Policy Index) Framework

Financial Policy Area	Description		Category	Instrument	Objective	Countries that adopted (Responsible authority for promotion and implementation)
Policy Area I	**Green Prudential Regulation**: Promoting the development of green macroprudential frameworks	**Capital**	Quality and Level of Capital	CAR with GSF/BPF	Mitigate and prevent excessive credit growth and leverage	
				CCyB		
				Sectoral Leverage Ratios		
				Sectoral Capital Requirements		
			Risk management and supervision	Governance and risk management		**Australia (PRA), China (CB, PRA, GOVT), France (PRA, GOVT), Indonesia (GOVT), Mexico (CB), UK (PRA).**
				Climate-related stress test (macro)	Evaluate the effect of economic or financial shocks on the financial system.	**Canada (CB), China (PRA), France (PRA), UK (PRA).**
				Green Asset Ratio	Assess exposure of banks' portfolios to carbon-intensive assets.	
				ICAAP	Internal Process of Capital Adequacy Assessment: Include social and environmental risks when assessing their capital needs	**Brazil (CB)**
			Enhanced risk disclosure and market discipline	Climate-related disclosure requirements	Inform about the concentration of carbon-intensive	**China (PRA), Indonesia (CB), Mexico (BA), Turkey (BA)**
		Liquidity	Liquidity	LCR	Mitigate and prevent market liquidity and maturity mismatch	
				NSFR		
		Large exposures	Lending limits	Large exposure limit	Mitigate systemic risk by limiting the concentration of certain exposures	

Policy Area II	**Green Financial Principles**: to create a green financial market		**All G20 Countries (Except Saudi Arabia)**
Policy Area III	**Other disclosure requirements**: to promote the public disclosure of climate risks (Including non-financial institutions)		**All G20 Countries (Except Argentina, Mexico, Saudi Arabia, and Turkey)**
Policy Area IV	**Green bonds taxonomy and issuing**: to promote green financial securities		**Indonesia (Other)**
Policy Area V	**Green Credit Allocation Policies**: to directly promote green credit measures and investments		**Japan (GOVT), South Korea (GOVT)**

Policy Area (I) focuses on regulating capital, governance, risk management, climate-related stress tests (CRSTs), and disclosures of climate-related risks in the banking sector, aligning with Basel III objectives for the Paris Agreement. Despite theoretical debates, the survey suggests that proposed measures, such as leverage ratios and Green Supporting Factors (GSF), haven't been adopted, likely due to disagreements among supervisors and regulators over their potential market impacts and risk weightings for different sectors (BoE-PRA, 2021; Restoy, 2022).

Additional measures falling under "Pillar 2 - Risk Management and Supervision," such as the Internal Capital Adequacy Assessment (ICAAP) and climate-related stress tests, are aimed at assessing the financial system's resilience to climate shocks. These evaluations consider potential impacts on individual financial institutions and the overall financial system (NGFS, 2019), providing policymakers with crucial insights into climate-related risks. Such insights aid in the calibration and assessment of green macroprudential tools. Furthermore, disclosure requirements concerning physical, liability, and transition risks associated with climate change are vital for establishing a credible green financial system and preventing "greenwashing" (TCFD, 2018).

In Policy Area (II), central banks can enact credit measures to directly foster green investments. Examples include initiatives like green lending quotas and concessional loans targeting priority and eco-friendly sectors, with notable instances observed in Indonesia, South Korea, and Japan.

Policy Area (III) nurtures "green financial markets" through initiatives such as green finance principles and taxonomies. These policies are widespread, with sustainability reporting and compliance practices increasingly considered essential alongside risk management to tackle concerns about climate change's adverse impacts. Policy Area (IV) deals with reporting regulations and environmental, social, and governance (ESG) criteria applicable to pension funds, insurance companies, and other non-financial institutions (Della Croce et al., 2011; Boermans and Galema, 2019; Krueger et al., 2020).

Policy Area (V) concerns green bonds, which are bonds dedicated solely to funding or refinancing eligible environmentally sustainable projects. Green bonds have gained considerable traction over the past decade, acknowledged by scholars and policymakers for their pivotal role in financing initiatives that promote environmental sustainability.

2.6.1 The Construction of CRFPI

The creation of CRFPI went through a fairly comprehensive stage. This aims to address the final result to be in accordance with the orientation and more specific on the object to be measured, in this case financial policies that lead to climate change mitigation. climate change mitigation. The stages of index creation can be seen in **Figure 2.8**.

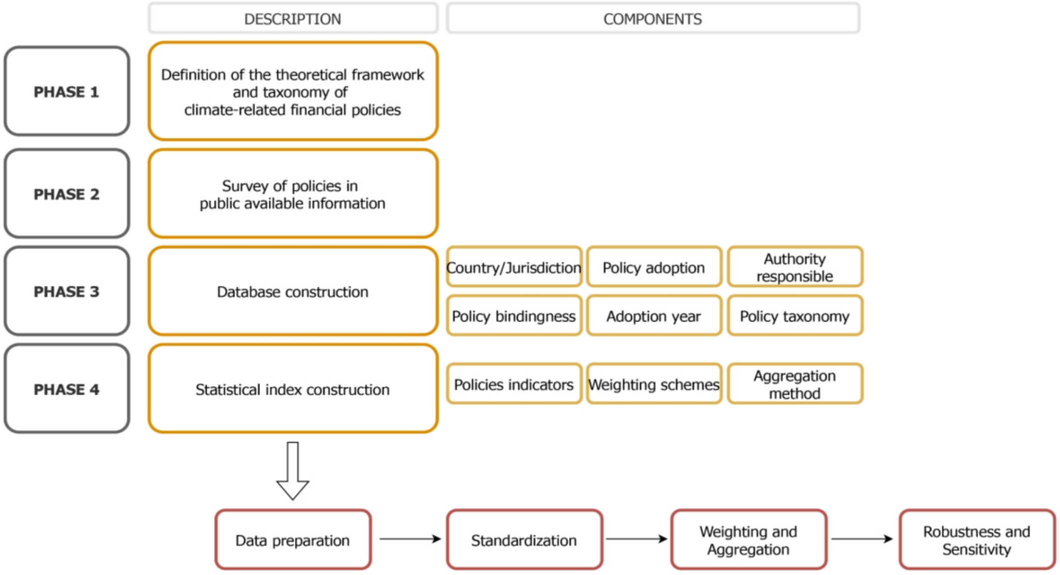


Figure 2.8 The flow of CRFPI Creation.
Source: D'Orazio & Thole (2022).

In four steps, D'Orazio & Thole (2022) developed the proposed CRFP index using the statistical methodological approach used to construct composite indices (OECD, 2008; Dobbie and Dail, 2013; Greco et al., 2019). Selecting measuring indicators is the initial step. Data normalization, which standardizes indicators, is the second phase. In the third stage, indicators are weighted by importance. Finally, the five components are aggregated into one composite index. In **Figure 2.7**, the index's design is explained.

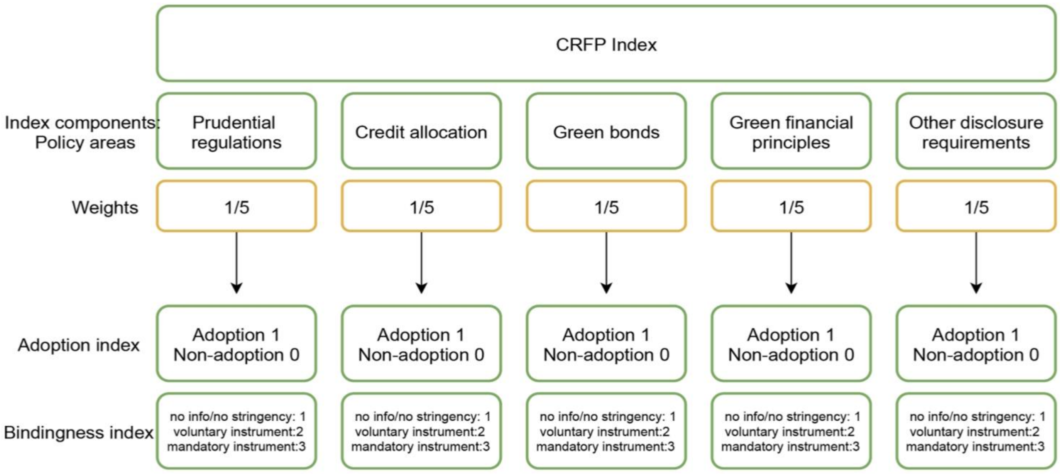


Figure 2.9 CRFPI Calculation Flow

I. Bindingness of the policy instrument

D'Orazio & Thole (2022) define a policy indicator I_{ijt} for each country (*i*) and policy area (*j*). Equation below shows that this indicator consists of P_{ijt} defining the policy P at the time (t) for the country (i) and is multiplied by the binding strength indicator $Bijt$ observed for each policy for the country (i) at the time (t). This step is crucial to account for potential differences.

$$I_{ijt} = P_{ijt} \times B_{ijt}$$

II. Re-scaling by normalization

This method uses the min-max method to rescale data into different intervals depending on minimum and maximum values to provide policy indicators with identical ranges. Normalized scores are calculated:

$$SC = \frac{I_t - I_{min,t}}{I_{max,t} - I_{min,t}} \times 100$$

Panel analysis of index performance requires rescaling to include upper and lower boundaries within the same period.

III. Aggregation and weighting

Rescaled indicators are aggregated into a single index, CRFPIt, for each country and period:

$$CRFPI_t = \sum_{j=0}^{p} \omega \, SC_{j,t}$$

According to the literature, where ω is the weight assigned to each rescaled policy indicator, the weight assigned to an indicator (e.g., policy area) reflects its importance or contribution to the index (OECD, 2008). Still, Becker et al. (2017) note that such weights do not necessarily reflect how much they affect the index score. Simple additive weighting (SAW) aggregation was used in this analysis, with fixed and exogenous weights.

IV. Analysis of alternate environments' uncertainty

Using the same weighting scheme, the benchmark setting assigns ω a value of 1/5 for all five policy indicators. Consider alternative weighting and aggregation strategies. The three extra settings test different weighting assumptions and show how sensitive the proposed index is to construction processes. The first method is preferred for financial policy research that seeks broad results.

2.7 Socio-economic dimensions

2.7.1 Economic growth towards CO2 emissions

The relationship between economic growth and environmental degradation has been extensively researched. The Environmental Kuznets Curve (EKC) theory suggests an inverted U-shaped relationship between economic growth and environmental degradation, indicating that environmental quality worsens initially with economic development but improves beyond a certain income level (Pastén, 2012; Aye, 2017; Khan et al., 2022; Lestari et al., 2020; Prasetyanto & Sari, 2021). This theory has been applied in studies investigating the impact of economic growth on CO2 emissions and other forms of environmental degradation in various countries (Khan & Rehan, 2020; Abdul-Mumuni et al., 2022; Juliansyah, 2019).

Likewise, Barua and Khataniar (2016) conclude that economies must shift from weak to strong sustainability to achieve strong and sustainable economic growth. They find that middle-income economies follow the path of weak sustainability. In contrast, high-income economies gradually move from weak to strong sustainability through various policy interventions to reduce CO2 emissions. This means that during their development stages, economies follow the argument of ‘grow now, clean up later.’ In the early stage of development, countries exploit possible and available resources to achieve economic growth.

However, after a certain level of development, economies gradually become more respectful towards the environment. This result agrees with the Environmental Kuznets Curve (EKC) in the environmental economics literature. The theory holds that GHG emissions per person initially increase with rising income per capita due to industrialization, then peak and decline after a GDP threshold as countries become more energy efficient, more technologically sophisticated, and more inclined and able to reduce their GHG emissions (Mir and Storm, 2016). The theory assumes an inverted U-shaped relationship between pollution and growth (Özcan and Öztürk, 2019).

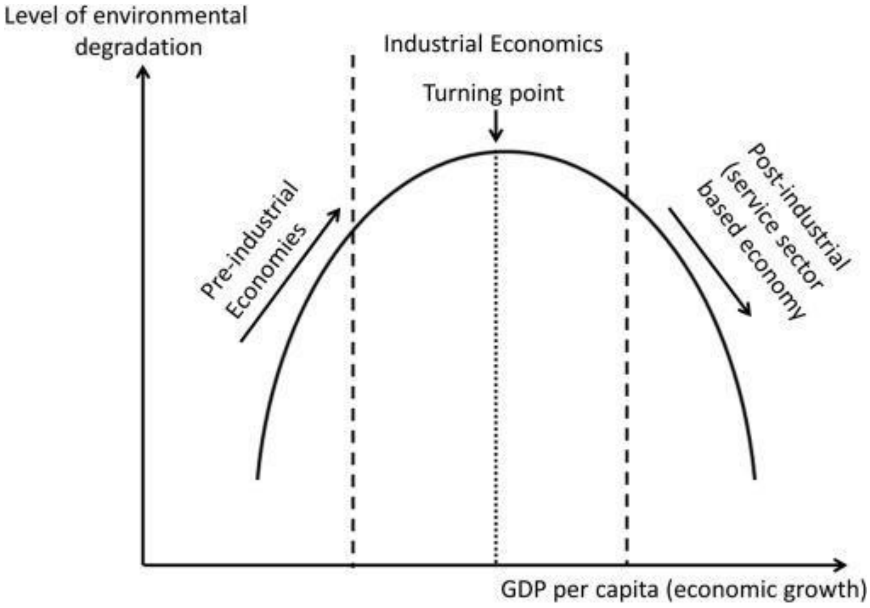


Figure 2.10 EKC (Environmental Kuznets Curve).
Source: Prasad, M. N. V. (2024).

Through various examinations conducted by scholars, distinctions in responses to environmental degradation have been identified. Certain studies have successfully demonstrated a diminishing trend in the relationship between economic growth and environmental degradation over specific periods. Conversely, other research has yielded findings asserting that the Environmental Kuznets Curve (EKC) hypothesis remains unsubstantiated.

Tachega et al. (2021) investigated the relationship between GDP, agriculture, energy, and CO2 emissions in 54 African economies, categorizing them into income groups. They supported the Environmental Kuznets Curve (EKC) hypothesis in low to upper-middle-income countries but not high-income nations. Similar trends were observed in the BCIM-EC member countries and 11 OECD nations. Despite some alignment with the EKC hypothesis in certain countries, Finland was the only one where the EKC turning point was identified, suggesting limited empirical evidence for the hypothesis (Iwata et al., 2011; Rahman et al., 2020).

Wang & Lv's (2022) study shows a contrary discovery: their Environmental Kuznets Curve (EKC) model indicates a rising inverted U-shaped relationship, revealing that economic growth in Henan Province's agricultural sector over the last two decades correlates with increased carbon dioxide (CO2) emissions from agriculture. This highlights the notion that agricultural economic progress came with a significant environmental toll, particularly in heightened CO2 emissions during the studied period.

Aung et al. (2019) found a positive correlation between CO2 emissions and GDP in Myanmar from 1970 to 2014, contradicting the Environmental Kuznets Curve (EKC) hypothesis for CO2. However, they observed EKC patterns for methane and nitrous oxide. Conversely, trade and financial openness were linked to lower CO2 emissions. Diverse studies challenge the EKC hypothesis, suggesting alternative relationships like U-shaped, N-shaped, and inverted N-shaped. Discrepancies in findings and turning point estimates, such as Grossman and Kruger's ($8,000 income per capita), arise from variable selection, temporal scope, econometric methods, and economic contexts (Aslan et al., 2019; Zaatari, 2022).

2.7.2 STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) Model

The STIRPAT model, a refinement of the IPAT model, aims to grasp the complex dynamics of environmental degradation. Introduced by Ehrlich and Holdren (1971), the IPAT framework examines how population (P), affluence (A), and technology (T) interplay to impact the environment. Hence, the IPAT model's constraints on non-propositional and non-monotonic variations in P, A, and T restrict its applicability, prompting Dietz and Rosa (1994) to devise the STIRPAT model as a solution, which is a stochastic adaptation of the IPAT framework.

The STIRPAT model, a sophisticated analytical tool, elucidates the determinants of environmental impacts by examining factors like population, technology, and economic growth (York et al., 2003; Ngong et al., 2022; Nasir et al., 2021). It offers a systematic approach to understanding the intricate relationship between human actions and their environmental effects.

The STIRPAT model is widely utilized across disciplines to analyze factors such as CO2 emissions, energy efficiency, air quality, and urbanization (An et al., 2022; Jiang et al., 2023; Dietz et al., 2007). It quantitatively assesses how various variables affect environmental outcomes, shedding light on the complex relationship between human activities and environmental changes (Lin et al., 2009; Jia et al., 2021; Sun et al., 2023).

Additionally, the model helps examine the impact of financial development, globalization, energy consumption, and technological advancements on environmental degradation (Yuan et al., 2022; Zhang & Xu, 2017; Liévanos, 2018). It identifies key drivers of environmental impacts and evaluates the effectiveness of policy interventions for sustainability and reducing ecological footprints (Lieu & Ngoc, 2023; Zhang & Luo, 2016; Li et al., 2018).

Furthermore, the STIRPAT model integrates spatial analysis, econometrics, and economic complexity measures to enhance its applicability across different research contexts (Tang et al., 2011; Zehr, 2014; Arbulú et al., 2016). This comprehensive approach aids in understanding the relationship between human activities and environmental outcomes, facilitating the development of effective environmental management strategies and policies (Han et al., 2021; Zhang et al., 2020; Olasehinde-Williams, 2022).

2.8 Previous Study

2.8.1 Financial policy and financial development on CO2 emissions

Table 2.11 Matrix of Financial Policy and Financial Development on CO2 emissions

	Financial Policy	
	Increase	Decrease
CO2 emissions	Financial Liberalization, (24 Transition economies). Tamazian & Rao, (2010).	Financial Development, (GCC) Countries, Salahuddin et al., (2015).
		Financial Development, (China). Chu et al., (2022); Xing et al., (2017).
	Economic Policy Uncertainty, (10 Resource rich countries). Adams et al. (2020).	Digital Finance, (China). Zhao et al. (2021)
		Financial Development, (172 Countries). Huang & Guo (2022).
	Financial Development, (Malaysia). Maji et al. (2017).	Green Finance, (Bibliometric). Xue et al. (2022).
	Fnancial Development, (46 sub-Saharan Africa Countries). Acheampong (2019).	Green Credit, (China). Qin et al., (2023).
		Green Finance (green credit, green securities, green investment, and green insurance), (China). Chen & Chen (2021).
	Digital Financial Inclussion, (Egypt). Salman et al., (2023).	Carbon Tax, (Swedia). Andersson (2019).

		Carbon Intensity Portofolio Standard*Carbon Taxes Recyle to Renewable Energies. Gerlagh & van der Zwaan, (2006).

Source: Synthetized by author.

The literature reveals a complex relationship between financial policies and CO2 emissions reduction. D'Orazio & Dirks (2021) suggest that financial policies, especially climate change-related ones, can promote investments in modern technologies to reduce CO2 emissions. Zhou et al. (2019) highlight the role of financial development in influencing CO2 emissions, particularly the size of financial intermediaries. Salman & Ismael (2023) indicate that digital financial inclusion can positively impact the green economy by investing in renewable energy projects, leading to significant reductions in CO2 emissions. These findings underscore the critical role of financial policies in shaping environmental outcomes and mitigating CO2 emissions.

Further research is needed to understand how financial development, digital finance, and green financial policies affect CO2 emissions. This understanding is crucial for designing effective climate change mitigation strategies. Coordinated actions involving governments, industries, the public, and academia are essential to address the challenges of climate change (Chen & Wang, 2016). Continued research in this area is imperative to guide the development of robust financial policies for reducing CO2 emissions and promoting sustainability.

The nexus between financial policy and CO2 emissions yields nuanced outcomes, as evidenced by scholarly inquiry. Xing et al. (2017) and Yao & Zhang (2021) assert that financial development correlates with CO2 emissions reduction, particularly notable in regions such as China. Conversely, Singh et al. (2022) found no substantial linkage between financial development and CO2 emissions. In contrast, Mensah & Abdul-Mumuni (2022) underscore the potential of financial development in curbing CO2 emissions over immediate and prolonged periods.

Moreover, D'Orazio & Dirks (2021) scrutinized the impact of climate-oriented financial policies on CO2 emissions within G20 countries, elucidating the pivotal roles of financial development, economic growth, and climate-specific financial measures. Tang et al. (2022) demonstrated the efficacy of green financial policies in enhancing carbon efficiency across Chinese urban landscapes. Furthermore, Yao & Zhang (2021) advocate for targeted financial reforms to incentivize reductions in CO2 emissions.

Diverse investigations have delved into the intersection of financial policy and CO2 emissions across varied contexts, encompassing sub-Saharan Africa (Mensah & Abdul-Mumuni, 2022), G20 economies (D'Orazio & Dirks, 2021), and China (Tang et al., 2022). These studies underscore the exigency of bespoke financial strategies to efficaciously mitigate environmental repercussions. The intricate interplay between financial policy and CO2 emissions, influenced by multifaceted determinants, accentuates the imperative of purposeful and sustainable financial interventions in fostering environmental sustainability.

Table 2.12 Matrix of Socio-economics Determinants on CO2 emissions.

	Socio-economic Factor	
	Increase	**Decrease**
CO2 emissions	**Economic Growth**	
	Per-Capita GDP, (RCEP Economies). Hassan et al., (2021).	Per Capita GDP, (Asean-5). Zhu et al., 2016.
	Per-Capita GDP, (France). Can & Gözgör, (2017).	Squared Per-Capita GDP, (France). Can & Gözgör, (2017).
	Real GDP, (Indonesia). Prasetyanto & Sari (2021).	Real GDP, (Iran). Rastegaripour, et al., (2019).
	Economic Growth (Per-Capita Income), (Pakistan). Khan & Rehan, (2020).	Real GDP, (18 Top Travel Countries). Khan et al., (2022).
	Economic Growth, (31 sub-Saharan Africa). Abdul-Mumuni et al., (2022).	Squared Real GDP, (Asian Emerging Markets). Lestari et al., (2020).
	Per-Capita GDP, (40 Countries). Mir & Storm (2016).	Squared Real GDP, (Indonesia). Prasetyanto & Sari (2021).
	Per-Capita GDP, (54- African Economies). Tachega et al., (2021).	Per-Capita GDP, (54- African Economies "Low, Lower, and Upper-middle Income"). Tachega et al., (2021).
	GDP Growth, (Indonesia). Juliansyah, (2019).	Economic Growth, (24 Transition economies). Tamazian & Rao, (2010)
	Agricultural Economic Growth, (China). Wang & Lv, (2022).	
	Real GDP, (Myanmar). Aung et al., (2017).	
	Population	
	Population, (31 Developing Countries). Aye, G. (2017).	
	Population, (Indonesia). Juliansyah, (2019).	

	Population, (Cross-Country), Liddle (2013).	
	Population, (Beijing). Fan & lei, et al., (2016).	
	Population, (G7 Countries). Chien et al., (2023).	
	Urbanization	
	Urbanization, (Yangtze River Economic Belt). Wu & Zhang, (2021).	Urbanization, (Province of Jiangsu). Zhong et al., (2022).
	Urbanization, (Provinces of China-30). Huo et al., (2021).	Urbanization, (Huaihe River Eco-Economic Zone). Pang et al., (2021).
		Urbanization, (China). li et al., (2018).
	Technology	
		Green Technology Innovation, (30-Provinces of China). Gao et al., (2022).
		Patents, (58-Countries). Dunyo et al., (2024).
		Total Patents, (Algeria). Bergougui, (2024).
		Patent Aplication, (G7). Khan et al., (2024).
		Technological Innovation, (South Africa). Iyke-Ofoedu et al., (2024).
	Foreign Direct Investment	
	FDI, (Asian Emerging Markets). Lestari et al., (2020).	FDI, (Aean-5). Zhu et al., (2016).
	FDI, (21 Asian Countries). Qamri et al., (2021).	FDI, (24 Transition economies). Tamazian & Rao, (2010)
	FDI, (Trantition Economies). Wencong et al., (2023).	FDI, (French). Shahbaz et al., (2018).
	FDI, (South Africa). Iyke-Ofoedu et al., (2024).	FDI, (China). Xia, & Gallagher, (2022).
	FDI, (5-Asean Countries). Nasir et al., (2019).	FDI, (182 countries). Boateng et al., (2024).
	FDI, (36-OCED Members). De Pascale et al., (2020).	FDI, (22 sub-Saharan African Countries). Opoku et al., (2021).
	FDI, (MENA Countries). Gorus & Aslan, (2019).	FDI, (Pakistan). Bakhsh et al., (2017)
	FDI, (31 sub-Saharan Africa). Abdul-Mumuni et al., (2022).	FDI, (Chinese Povinces-29). Bao et al., (2011).

	FDI, (G20). Viglioni et al., (2024).	FDI, (Central and South of American Countries-22). Jebli et al., (2019).
	FDI, (29 sub-Saharan Africa). Mantey & Adams, (2023).	FDI, (Mena Countries-12). Kahia et al., (2019).
		FDI, (164 Countries of the World). Kim & Adilov, (2012)
		FDI, (G7 Countries). Chien et al., (2023).
	Trade Openness	
	Trade Openness, (105 Countries divided by income level). Shahbaz et al., (2017).	Trade Openness, (182 Countries). Wang & Zhang, (2021).
	Trade Openness, (24 Trantition economies). Tamazian & Rao, (2010)	Trade Openness, (India). Kaur et al., (2023).
	Trade Openness, (Tanzania). Byaro et al., (2022).	Trade Openness, (Developed & Developing Countries). Khan et al., (2021).
	Trade Openness, (City of China). Yi-Ping et al., (2022).	Trade Openness (Composite Trade Intensity), (Myanmar). Aung et al., (2017).
	Trade Openness, (5-Asean Member). Perwithosuci et al., (2023).	Trade Openness*Institutional Quality, (24 Transition economies). Tamazian & Rao, (2010).
		Trade, (G7 Countries). Chien et al., (2023).
	Renewable Energy	
		Renewable Energy Consumption, (Ghana). Justice et al., (2024).
		Renewable Energy Generation, (China). Lian et al., (2024).
		Renewable Energy, (RCEP Economies). Hassan et al., (2021).
		Renewable Energy Consumption, (31 sub-Saharan Africa). Abdul-Mumuni et al., (2022).
		Renewable Energy, (54- African Economies). Tachega et al., (2021).
		Renewable energy, (29 sub-Saharan Africa). Mantey & Adams, (2023).
		Renewable energy, (Trantition Economies). Wencong et al., (2023).
	Energy Consumption	

	Energy Consumption, (Aean-5). Zhu et al., (2016).	
	Energy Consumption, (France). Can & Gözgör, (2017).	
	Energy Consumption, (Australia). Salahuddin & Khan (2013).	
	Energy Consumption, (31 Developing Countries). Aye, G. (2017).	
	Energy Consumption, (18 Tot Travel Countries). Khan et al., (2022).	
	Primary Energy Consumption, (Indonesia). Prasetyanto & Sari (2021).	
	Energy Consumption, (31 sub-Saharan Africa). Abdul-Mumuni et al., (2022).	

Source: Synthetized by author.

2.8.2 Economic growth on CO2 emissions

The correlation between economic advancement and CO2 emissions constitutes a multifaceted phenomenon that has garnered substantial attention within environmental scholarship. Investigations, such as those conducted by Tian & Zhang (2022) and Huang & Chen (2022), have delved into the dynamic evolution and determinants of CO2 emissions concerning economic growth, shedding light on the intricate interplay between economic development and CO2 emissions. These inquiries underscore the imperative of efficacious strategies to curb CO2 emissions while fostering sustainable economic progress. Their findings posit that economic growth frequently precipitates a surge in CO2 emissions, thereby accentuating the necessity of embracing sustainable methodologies to alleviate environmental repercussions.

Furthermore, scholarly inquiries by Zhang et al. (2023) and Khalfaoui et al. (2021) have scrutinized the ramifications of delineating economic growth objectives on urban CO2 emissions performance and the interconnection between economic advancement and carbon dioxide emissions across G7 nations. These analyses provide insights into the quandaries and prospects of harmonizing economic growth ambitions with environmental sustainability imperatives. Their outcomes intimate that economic growth targets and fiscal vulnerabilities wield sway over CO2 emissions, underscoring the imperative of devising sustainable development frameworks conducive to achieving a symbiotic equilibrium between economic prosperity and environmental preservation.

Moreover, studies by Zhu et al. (2021) and Byaro et al. (2021) have delved into the nexus between energy-related CO2 emissions and economic growth, alongside the repercussions of industrialization, commerce, and urban development on ecological integrity. These examinations unveil the nuanced correlation between economic advancement and CO2 emissions, suggesting that economic progress may instigate heightened CO2 emissions, notably within energy-intensive sectors. The findings accentuate the necessity of enacting efficacious policies and initiatives to mitigate CO2 emissions while nurturing economic advancement.

Additionally, research endeavors by Du & Chuai (2022) and Xiao-Chun et al. (2022) have probed into the nonlinear impact of economic growth on CO2 emissions, spotlighting the inverted "U" and inverted "n" shaped curves that typify this relationship. These inquiries furnish invaluable insights into the intricacies characterizing the nexus between economic growth and CO2 emissions, accentuating the exigency of tailored interventions to advance sustainable development objectives and mitigate CO2 emissions. Cumulatively, the scholarly corpus posits that grappling with the challenges engendered by economic growth vis-à-vis CO2 emissions necessitates a holistic comprehension of the underlying determinants alongside the implementation of targeted measures to realize environmental sustainability objectives.

2.8.3 FDI (Foreign Direct Investment) on CO2 emissions

The intricate interplay between foreign direct investment (FDI) and CO2 emissions has garnered considerable attention in academic discourse. Research endeavors such as those undertaken by Qamri et al. (2021) and Abdul-Mumuni et al. (2022) have delved into the ramifications of FDI on environmental degradation, elucidating that FDI influxes may engender heightened environmental pollution. Conversely, studies by Matezo et al. (2021) and Widarni & Bawono (2021) have underscored the beneficial facets of FDI on economic advancement and progress, positing that FDI inflows catalyze economic vibrancy across diverse sectors.

Furthermore, scholars like Xia et al. (2022) and Xia & Gallagher (2022) have examined the impact of FDI on CO2 emissions within the framework of economic growth and technological dissemination. Their analyses delineate how FDI can mitigate climate risks and foster technological innovations, potentially curbing overall climate risks while advancing technological capabilities. Additionally, the catalytic role of FDI in stimulating economic growth and fostering trade openness has been scrutinized by Mustafa (2023), among others, revealing FDI's potential to propel economic growth and trade dynamics, with consequential implications for CO2 emissions.

Moreover, the nexus between FDI, energy infrastructure, and manufacturing output has been expounded upon by Onabote et al. (2021), accentuating how FDI injections can bolster infrastructure development and productivity across various industrial domains. Furthermore, the nexus between FDI, governance, and environmental policies has been probed by Missios et al. (2021), elucidating the pivotal role of FDI in shaping environmental regulatory frameworks and policy agendas. Collectively, these scholarly inquiries contribute to a nuanced comprehension of the intricate dynamics governing the relationship between FDI and CO2 emissions, illuminating the multifaceted impacts of FDI on economic, environmental, and developmental trajectories.

2.8.4 Trade openness on CO2 emissions

Trade openness substantially influences CO2 emissions, as elucidated by many scholarly investigations. Byaro et al. (2021) have underscored a notable correlation between trade openness and the release of carbon dioxide, accentuating the ramifications of industrialization on heightened greenhouse gas emissions. Similarly, Yi-ping et al. (2022) have uncovered an adverse effect of trade openness on environmental well-being, thereby unveiling a convoluted interplay between trade policies and environmental consequences. Moreover, Wang & Zhang (2021) have substantiated a reciprocal association between trade openness and CO2 emissions.

Furthermore, the facilitation of energy-efficient technology importation by trade openness has been demonstrated to yield a reduction in CO2 emissions (Kaur et al., 2023). Khan et al. (2021) have delved into the intricate nexus between elevated levels of trade openness and CO2 emissions. Chen et al. (2021) have likewise posited an inverse correlation between trade openness and CO2 emissions.

The impact of trade openness on CO2 emissions is further enigmatic due to regional disparities and structural transformations. Perwithosuci et al. (2023) have delineated a protracted linkage between trade openness, financial advancement, urbanization, energy consumption, and CO2 emissions. Similarly, Thuy (2022) has scrutinized the ramifications of trade openness on carbon productivity in burgeoning economies, accentuating the imperatives of contextual nuances and regional dynamics. Cumulatively, these studies contribute significantly to an enhanced comprehension of how trade openness shapes CO2 emissions and environmental sustainability, thereby underscoring the exigency for tailored policies to foster eco-friendly trade practices and alleviate environmental repercussions.

2.8.5 Urbanization on CO2 emissions

The nexus between urbanization and CO2 emissions has been extensively scrutinized within scholarly discourse. Scholars such as Li et al. (2022) and Wu & Zhang (2021) have investigated the ramifications of urbanization on CO2 emissions, underlining the imperative for comprehensive investigations across diverse regional and municipal contexts to augment the comprehension of this intricate relationship. Zhong et al. (2022) have observed a decrement in CO2 emissions at a particular threshold of urbanization owing to technological advancements and talent scalability. Nonetheless, Li et al. (2022) have underscored the inconsistent conclusions in extant empirical literature concerning the association between urbanization and carbon dioxide emissions.

Scholarly endeavors by researchers like Armstrong et al. (2022) and Huo et al. (2021) have delved into the nonlinear dynamics and spatial-temporal heterogeneity of urbanization's impact on CO2 emissions. Zhang et al. (2021) have investigated the repercussions of urban sprawl on CO2 emissions, accentuating the necessity of evaluating the influences of urbanization on CO2 emissions emanating from the construction sector. Furthermore, Armstrong et al. (2022) have identified disciplinary disparities in framing the environmental ramifications of urbanization, thereby showcasing divergent viewpoints in ecological and urban planning literature.

Furthermore, the nonlinear influence of urbanization on CO2 emissions, as elucidated by Huo et al. (2021), suggests a multifaceted relationship contingent upon diverse urban settings. Delgado-Baquerizo et al. (2021) have scrutinized the spatial and temporal dimensions of urbanization's sway on CO2 emissions, highlighting the importance of urban affluence, managerial practices, and climatic conditions in shaping urban soil ecosystems. These scholarly inquiries collectively contribute to a nuanced comprehension of how urbanization impacts CO2 emissions, underscoring the necessity for bespoke strategies to foster sustainable urban development and efficaciously mitigate environmental repercussions.

2.8.6 Population on CO2 emissions

Population dynamics significantly influence CO2 emissions. Research by Zheng et al. (2019) shows that while economic growth is the main driver of energy-related CO2 emissions in China, population growth has also led to a 6-fold increase in emissions. The study highlights the strong link between energy-related CO2 emissions and population growth, stressing the importance of considering population dynamics in CO2 emissions reduction strategies. Zhao et al. (2021) also examine the factors influencing CO2 emissions from the perspective of population development, revealing the complex relationship between population factors and CO2 emissions.

Zhang et al. (2021) found that an increase in total population generally boosts CO2 emissions. They also note that changes in population structure can help inhibit CO2 emissions, highlighting the nuanced interplay between population dynamics and CO2 emissions and the need for targeted interventions to manage and reduce emissions effectively.

Wu et al. (2021) provide insights into how population flow impacts regional CO2 emissions in China. Their study using panel data reveals that China's population flow can reduce the growth of CO2 emissions in both the short and long term. This suggests that understanding population movements and their effects on CO2 emissions is crucial for developing comprehensive strategies to curb emissions. These studies underscore the complex relationship between population dynamics and CO2 emissions, emphasizing the need for policies considering population factors to mitigate emissions effectively.

2.8.7 Patent in technology on CO2 emissions

Technological innovation, particularly environmental technology patents, is crucial in reducing CO2 emissions. Research has shown that these patents positively impact energy efficiency, decreasing CO2 emissions (Cheng et al., 2019). Studies have also indicated that patents for renewable energy and environmental technologies significantly influence the reduction of CO2 emissions (Alnafisah, 2024). The relationship between technological innovation, economic growth, and CO2 emissions has been explored, with findings suggesting that technology patents contribute to CO2 emissions reduction and carbon neutralization (Zhang, 2021).

The impact of patents on low-carbon innovation has been studied in the context of environmental policies like the European Carbon Market. Research has shown that policies like the EU Emissions Trading System have stimulated low-carbon innovation among regulated firms without displacing patenting for other technologies (Calel &

Dechezleprêtre, 2016). Green patents have been found to reduce CO2 emissions intensity in the short term, though they may pose a barrier in the long term (Wang et al., 2022). This highlights the intricate interplay between technological innovation through patents and its long-term implications for reducing CO2 emissions.

Various studies emphasize the significant role that technology patents play in influencing CO2 emissions. Technological innovation, as reflected in patents, can lead to short-term reductions in CO2 emissions per capita, and its long-term impact is more substantial in contributing to overall efforts to reduce CO2 emissions (Zhang et al., 2020). Policies incentivizing green technology patents and promoting low-carbon innovation are essential in global efforts to mitigate CO2 emissions and address climate change.

2.8.8 Renewable energy consumption on CO2 emissions

Renewable energy consumption significantly influences carbon dioxide (CO2) emissions. Numerous studies have explored the link between renewable energy use and CO2 emissions in various regions. Khan & Rehan (2020) discovered that fossil and solid fuel use typically raises CO2 emissions, while renewable energy consumption helps reduce them. Shafiei & Salim (2014) reported a positive relationship between non-renewable energy use and CO2 emissions, indicating that non-renewable energy leads to higher CO2 emissions. Abdel-Sadeq (2023) examined sub-Saharan Africa and found a short-run two-way causal relationship between renewable energy consumption and CO2 emissions, with long-term reductions in emissions due to renewable energy use.

The impact of renewable energy consumption on CO2 emissions differs across regions. Fuinhas et al. (2017) studied Latin America and confirmed that renewable energy policies help mitigate carbon dioxide emissions in the long run. Farhani & Shahbaz (2014) suggested that while nuclear energy might reduce CO2 emissions, renewable energy alone may not significantly lower emissions in the MENA region. Alharthi et al. (2021) found that renewable energy consumption significantly reduces emissions, especially at higher consumption levels.

The relationship between renewable energy use and CO2 emissions is complex and varies by context. While renewable energy generally reduces CO2 emissions in the long run, the impact depends on the region, energy sources, and consumption levels. Policymakers must consider these factors when developing strategies to transition to sustainable energy and reduce CO2 emissions.

2.9 Gap of the study

After reviewing previous studies, it is evident that many utilize the nominal amount of money allocated for green financing, such as green bonds issued to represent financial variables, or other proxies like ESG scores. However, these approaches primarily operate at the micro level, particularly within companies, rather than at the national level. The integration of green financial policies into quantitative models remains rare, as these policies are inherently interpretative. Additionally, many prior studies have focused predominantly on economic indicators, whereas the issue of climate change cannot be addressed through a single discipline but requires in-depth analysis, particularly from a social perspective.

Therefore, this study aims to address this research gap highlighted in previous works by introducing a climate-related financial policy index. This study brings a new perspective by examining how the strength of climate-related financial policies influences carbon emissions. Furthermore, socioeconomic dimensions must also be considered, as changes in social structures indirectly affect the behavior of economic agents regarding CO2 emissions.

This study employs two primary proxies to assess the financial sector's interventions on CO2 emissions: the climate-related financial policy index (CRFPI) and financial development. Additionally, the author includes supplementary variables such as GDP along with control variables representing socioeconomic dimensions, including population, urbanization, foreign direct investment (FDI), trade openness, renewable energy, and technology patents.

While previous studies have primarily focused on changes in total carbon emissions, this study seeks to provide more robust information by disaggregating carbon emissions into various sectors, such as manufacturing and construction, agriculture, heat, and electricity. Moreover, the study employs important indicators such as GDP, trade openness, and technology patents to assess their impact on CO2 emissions. Following the EKC theory, this study includes both GDP and its square. Unlike other studies that focus on renewable energy generation, this research examines the share of renewable energy in primary energy consumption to avoid biases from total energy consumption.

In this context, this study aims to fill several research gaps in the empirical literature, particularly concerning G20 economies. In alignment with the pollution haven or pollution halo hypothesis, this study also incorporates foreign direct investment as a crucial factor influencing CO2 emissions. Additionally, population and urbanization have been included, as they significantly affect CO2 emissions.

2.10 Conceptual framework

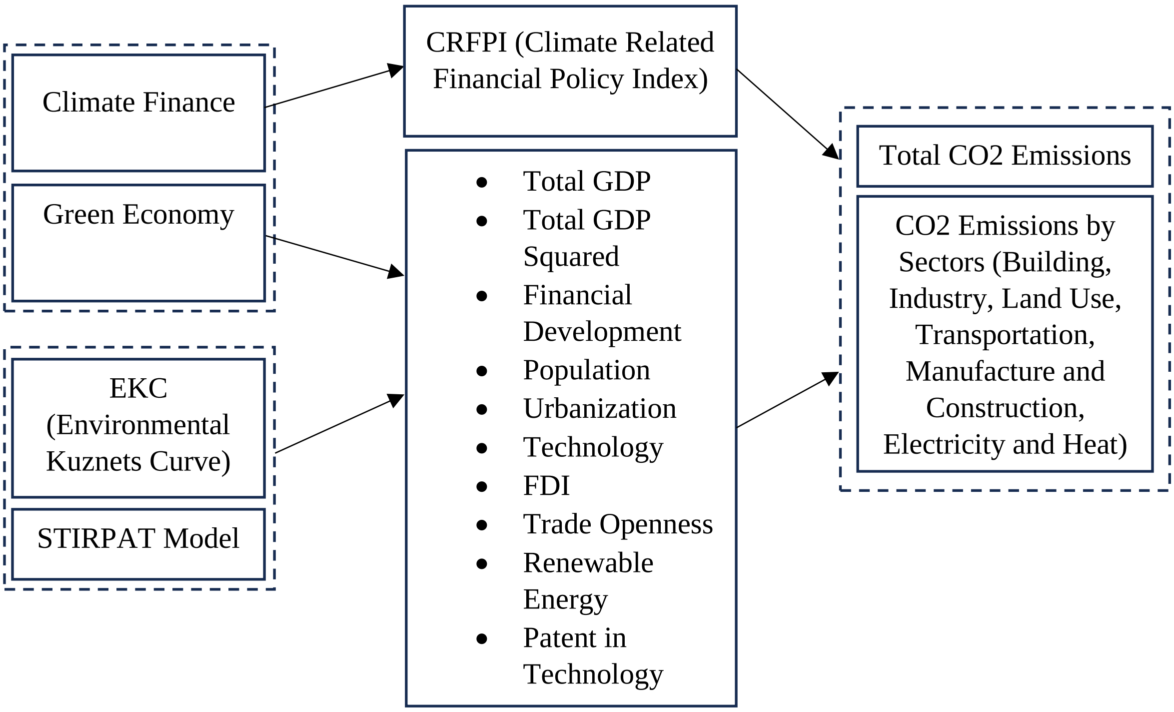


Figure 2.13 Conceptual framework
Source: Author

Figure 2.13 depicts that this study aims to elucidate the impact of financial policy, represented by the CRFPI (Climate-Related Financial Policy Index), on CO2 emissions, encompassing both total CO2 emissions and emissions from various sectors in G20 countries outside the European Union (EU) and Saudi Arabia such as Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Turkey, United Kingdom (UK), United States (US). The CRFPI, developed by D'Orazio (2023), maps financial policies adopted by 74 countries worldwide into an index spanning from 2000 to 2020. This index provides insight into the bindingness of climate-related financial policies, making it a suitable proxy for the financial policy variable. Additionally, the author incorporates socio-economic determinants adapted from the STIRPAT model, further modified by including several other control variables outlined in **Table 3.1**.

2.11 Research hypothesis

Based on the findings of previous research analysis, several key research positions were obtained as elucidated in the following table:

Table 2.14 Hypothesis

Null Hypothesis	Alternative Hypothesis	Expected Sign
There is no significant impact between the Climate-Related Financial Policy Index (CRFPI) on Carbon Emissions.	There exists a significant relationship between the Climate-Related Financial Policy Index (CRFPI) on Carbon Emissions.	-
There is no significant impact between Financial development on Carbon Emissions.	There exists a significant relationship between Financial development on Carbon Emissions.	±
There is no significant impact between GDP on Carbon Emissions.	There exists a significant relationship between GDP on Carbon Emissions.	+
There is no significant impact between GDP squared on Carbon Emissions.	There exists a significant relationship between GDP squared on Carbon Emissions.	-
There is no significant impact between Population Carbon Emissions.	There exists a significant relationship between Population on Carbon Emissions.	+
There is no significant impact Urbanization Carbon Emissions.	There exists a significant relationship between Urbanization on Carbon Emissions.	±
There is no significant impact between Technology and Carbon Emissions.	There exists a significant relationship between the Technology on Carbon Emissions.	-
There is no significant impact between the FDI on Carbon Emissions.	There exists a significant relationship between FDI on Carbon Emissions.	±
There is no significant impact between Trade Openness on Carbon Emissions.	There exists a significant relationship between Trade Openness on Carbon Emissions.	±
There is no significant impact between Renewable Energy on Carbon Emissions.	There exists a significant relationship between Renewable Energy on Carbon Emissions.	-

The hypotheses presented in the table above are grounded in previous research findings as outlined in the literature review. Financial policies related to climate exhibit varied impacts on carbon emissions. Policies such as financial development, financial inclusion, financial liberalization, and digital financial inclusion have been found to increase carbon emissions (Tamazian & Rao, 2010; Adams et al., 2020; Maji et al., 2017; Acheampong, 2019; Salman et al., 2023). Conversely, other studies have revealed that policy interventions in the financial sector have a negative impact on carbon emissions, particularly in policies such as financial development, digital finance, green finance, green credit, and carbon tax (Salahuddin et al., 2015; Chu et al., 2022; Xing et al., 2017; Huang & Guo, 2022; Xue et al., 2022; Qin et al., 2023; Chen & Chen, 2021; Andersson, 2019).

Economic growth, as indicated by GDP per capita, in various countries such as RCEP Economies, France, Indonesia, 31 sub-Saharan African nations, and 54-African countries, exhibits a positive relationship with carbon emissions, exacerbating environmental conditions (Hassan et al., 2021; Can & Gözgör, 2017; Prasetyanto & Sari, 2021; Abdul-Mumuni et al., 2022). However, some studies reveal a non-linear relationship between economic growth, denoted by squared GDP, and carbon emissions, confirming the validity of the Environmental Kuznets Curve (EKC) hypothesis, whereby at certain points, an increase in GDP is accompanied by a decrease in carbon emissions (Can & Gözgör, 2017; Lestari et al., 2020; Prasetyanto & Sari, 2021).

Additionally, population, a key socio-economic factor, demonstrates a positive correlation with carbon emissions in several countries and economic cooperation initiatives, such as 31 developing countries, cross-country partnerships, Beijing, and the G7 (Aye, 2017; Juliansyah, 2019; Liddle et al., 2011; Fan & Lei, 2016; Chien et al., 2023). In contrast, urbanization, Foreign Direct Investment (FDI), and Trade Openness yield more varied outcomes. Numerous studies suggest that urbanization tends to increase carbon emissions, but under specific circumstances, it may also decrease them (Wu & Zhang, 2021; Huo et al., 2021; Zhong et al., 2022; Pang et al., 2021; Gao et al., 2022; Dunyo et al., 2024; Bergougui, 2024; Qamri et al., 2021; Wencong et al., 2023; Zhu et al., 2016; Tamazian & Rao, 2010; Shahbaz et al., 2017; Kaur et al., 2023). Factors commonly associated with a decrease in carbon emissions include the adoption of renewable energy sources and technological advancements (Justice et al., 2024; Mantey & Adams, 2023).

CHAPTER III

METHODOLOGY

3.1 Research design

This study adopts a quantitative research design, which is a widely recognized approach in the social sciences, particularly economics. Linder et al. (2022) elucidated that quantitative research involves systematic empirical investigation through statistical, mathematical, or computational methods to quantify relationships between variables, test hypotheses, and develop or validate theories. This approach is distinguished by its emphasis on objectivity, replicability, and the generalizability of findings, making it a valuable method across disciplines such as psychology, sociology, economics, and business (Saha, 2022). By utilizing structured data collection, statistical analysis, and hypothesis testing, quantitative research provides a rigorous framework for understanding complex relationships and making evidence-based decisions (Janiszewski & Osselaer, 2022).

This study employs secondary open-source data and data from reputable academic papers. These data are meticulously extracted, compiled, and organized into Excel files before being processed using statistical software applications such as Stata and R Studio. The processed data is then subjected to panel regression analysis to investigate the relationships between the variables of interest. This method ensures a robust analysis, identifying significant patterns and relationships, and supports the development of well-founded conclusions and recommendations based on empirical evidence.

3.2 Data resource and collection method

The data collection technique represents a pivotal step in the research process. The selection of data sources based on their formation process and the specific information they endeavor to convey is paramount in addressing the research question and the research problem.

The initial data collection technique is library research, which holds significant importance given its widespread utilization in academic contexts, particularly in research endeavors spanning diverse disciplines. This method entails procuring data by thoroughly exploring and comprehending information closely linked to the research problem from a variety of sources, including books, theories, notes, documents, scientific reports papers, and policy briefs sourced from platforms such as Google Scholar, JSTOR, Emerald, Elsevier, among others, as well as internet-based information.

The second technique involves the extraction of requisite secondary data from diverse, reputable sources, particularly those commonly utilized in the academic field of economics, such as the WDI (World Development Indicator), Our World in Data, IMF (International Monetary Fund), EDGAR (Emissions Database for Global Atmospheric Research), OECDStat and data resources referenced in scholarly papers (see **Table 3.1**). Subsequently, extracted data is meticulously organized and managed within Microsoft Excel to suit specific requirements, including sample size determination and temporal parameters.

Table 3.1 Data Resources.

Variable	Definition	Source
Climate-Related Financial Policy Index (CRFPI), (Index 0-100)	The index tracking a nation's climate-related financial policies, including their binding nature, informs policy interventions.	D'Orazio & Thole, (2022)
Financial Development (Index 0-1)	Financial development is an indexed measurement across countries that evaluates the depth, access, and efficiency of their financial institutions and financial markets.	IMF
Total CO2 Emissions, Mt (Million Ton)	Carbon dioxide emissions arise from fossil fuel use (combustion, flaring), industrial processes (cement, steel, chemicals, and urea), and product use.	EDGAR
CO2 Emissions by Sectors (Tons)	Most primary sources and reservoirs emit the six major greenhouse gases, with non-CO_2 emissions standardized into CO_2 equivalents.	Our World in Data
Total GDP (Million USD 2015, constant)	The sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products.	WDI
Population (Million People)	The total population is determined by the de facto definition, encompassing all residents irrespective of legal status or citizenship, with values presented as midyear estimates.	WDI
Urbanization (% of the total. population)	The urban population comprises individuals residing in urban locales delineated by national statistical authorities, with data aggregation and refinement overseen by the United Nations Population Division.	WDI
Foreign Direct Investment (FDI) (Million Current USD)	Direct investment equity inflows encompass equity capital, earnings reinvestment, and other capital, representing cross-border investments where a resident in one economy exercises control or significant influence over managing an enterprise in another.	WDI

Trade Openness (%)	Trade, quantified as the ratio of exports plus imports to gross domestic product, embodies the essence of economic exchange.	WDI
Renewable Energy Consumption, (%)	Measured as a percentage of primary energy using the substitution method. Renewables include hydropower, solar, wind, geothermal, bioenergy, wave, and tidal, but not traditional biofuels, which can be a key energy source,	Our World in Data
Patent in Technology (Number)	The total patent count reflects the number of patents per country in areas such as ICT, AI, Biotechnology, Nanotechnology, environment-related technologies, and Health.	OECD

3.3 Panel data regression analysis

Panel data analysis, also known as longitudinal data analysis, is a robust econometric technique extensively discussed by Gujarati (2009) and Woolbridge (2013), serving as a significant subfield within econometrics (Utami et al., 2021). This approach facilitates the examination of datasets comprising both cross-sectional and time-series dimensions, enhancing the comprehension of economic phenomena. By accommodating individual-specific effects and time-specific trends, panel data analysis permits researchers to manage unobserved heterogeneity across entities and periods, enhancing the accuracy and reliability of variable relationships. Therefore, panel data regression is apt for this study, given several countries' cross-sections with equally lengthy time-series data for each nation (balanced panel data).

As delineated by Baltagi (1995), the ensuing advantages are conferred through the utilization of panel data regression analysis in empirical investigations:

a. Panel data, encompassing various entities like individuals, firms, and countries over time, inherently exhibits heterogeneity among these units. Panel data estimation techniques explicitly accommodate this heterogeneity by incorporating subject-specific variables, as the author will demonstrate shortly.
b. Panel data, which combines time series and cross-sectional observations, offers richer data, reduced collinearity among variables, increased degrees of freedom, and enhanced efficiency.
c. Panel data, through repeated cross-sectional observations, is more adept at analyzing the dynamics of change, particularly in phenomena like unemployment spells, job turnover, and labor mobility.

d. Panel data excels in identifying and quantifying effects beyond the scope of pure cross-sectional or time series data analysis.

The initial model (pooled OLS) of the panel is expressed below:

$$\gamma_{it} = \alpha_0 + \beta_1 X1_{it} + \cdots + \beta_N XN_{it} + \varepsilon_{it} \qquad (3.3.1)$$

$$\gamma_{it} = \alpha_0 + \beta_1 X1_{it} + \cdots + \beta_N XN_{it} + \mu_t + \omega_i + \varepsilon_{it} \qquad (3.3.2)$$

$$\gamma_{it} = \alpha_0 + \beta_1 X1_{it} + \cdots + \beta_N XN_{it} + \mu_t + \omega_i + \varepsilon_{it} \qquad (3.3.3)$$

Final model:

$$\gamma_{it} = \alpha_0 + \beta_1 X1_{it} + \cdots + \beta_N XN_{it} + \mu_t + v_{it} \qquad (3.3.4)$$

$$v_{it} = \omega_i + \varepsilon_{it} \qquad (3.3.5)$$

In this model, the dependent variable γ_{it} varies across different units (i) over time (t). It is influenced by the intercept α_0 and the slope coefficient β_1, which measures the impact of the independent variable $X1_{it}$ for each unit over time. The model incorporates several error terms: μ_{it} for unobserved time-dependent factors like economic changes, ω_i for country-specific factors such as political structures, and ε_{it} for random variations. This framework spans multiple countries (I = 1,..., N) and periods (T = 1,..., T), comprehensively analyzing the factors affecting the dependent variable.

The ultimate model equation delineated above will undergo scrutiny through three distinct estimation methodologies: pooled ordinary least squares (OLS), fixed effects, and random effects. Should the number of units be substantial, a re-evaluation of the inclusion of dummy variables is warranted.

Main Equation

$$Tot\_CO2_{it} = \alpha_0 + \beta_1 CRFPI_{it} + \beta_2 Financial\_Development_{it} + \beta_3 Total\_GDP_{it} + \beta_4 Total\_GDP2_{it} + \beta_5 Trade\_Openness_{it} + \beta_6 FDI\_Inflow_{it} + \beta_7 Urbanization_{it} + \beta_8 Population_{it} + \beta_9 Patent\_Tech_{it} + \beta_{10} Renewable\_Energy_{it} + \varepsilon_{it} \qquad (3.3.6)$$

This model examines the factors influencing total CO2 emissions Tot_CO2_{it}, starting with a baseline constant α_0. Key variables include the Climate-Related Financial Policy Index $CRFPI_{it}$, $Financial\_Development_{it}$, total GDP $Total\_GDP_{it}$ and its square $Total\_GDP2_{it}$, trade openness $Trade\_Openness_{it}$, and foreign direct investment inflow FDI_Inflow_{it}. Demographic influences are captured through urbanization $Urbanization_{it}$ and population size $Population_{it}$, while technological progress is indicated by patents in technology $Patent\_Tech_{it}$. The use of renewable energy

$Renewable\_Energy_{it}$ and an idiosyncratic error term ε_{it} are also included to account for random variations. The slope of parameters is denoted as $\beta_1, \beta_{2,} \dots \dots, N$.

2. C02 Emissions by sectors

$$CO2\_Build_{it} = \alpha_0 + \beta_1 CRFPI_{it} + \beta_2 Financial\_Development_{it} + \beta_3 Total\_GDP_{it} + \beta_4 Total\_GDP2_{it} + \beta_5 Trade\_Openness_{it} + \beta_6 FDI\_Inflow_{it} + \beta_7 Urbanization_{it} + \beta_8 Population_{it} + \beta_9 Patent\_Tech_{it} + \beta_{10} Renewable\_Energy_{it} + \varepsilon_{it} \quad (3.3.7)$$

$$CO2\_Indust_{it} = \alpha_0 + \beta_1 CRFPI_{it} + \beta_2 Financial\_Development_{it} + \beta_3 Total\_GDP_{it} + \beta_4 Total\_GDP2_{it} + \beta_5 Trade\_Openness_{it} + \beta_6 FDI\_Inflow_{it} + \beta_7 Urbanization_{it} + \beta_8 Population_{it} + \beta_9 Patent\_Tech_{it} + \beta_{10} Renewable\_Energy_{it} + \varepsilon_{it} \quad (3.3.8)$$

$$CO2\_L\_use_{it} = \alpha_0 + \beta_1 CRFPI_{it} + \beta_2 Financial\_Development_{it} + \beta_3 Total\_GDP_{it} + \beta_4 Total\_GDP2_{it} + \beta_5 Trade\_Openness_{it} + \beta_6 FDI\_Inflow_{it} + \beta_7 Urbanization_{it} + \beta_8 Population_{it} + \beta_9 Patent\_Tech_{it} + \beta_{10} Renewable\_Energy_{it} + \varepsilon_{it} \quad (3.3.9)$$

$$CO2\_Trans_{it} = \alpha_0 + \beta_1 CRFPI_{it} + \beta_2 Financial\_Development_{it} + \beta_3 Total\_GDP_{it} + \beta_4 Total\_GDP2_{it} + \beta_5 Trade\_Openness_{it} + \beta_6 FDI\_Inflow_{it} + \beta_7 Urbanization_{it} + \beta_8 Population_{it} + \beta_9 Patent\_Tech_{it} + \beta_{10} Renewable\_Energy_{it} + \varepsilon_{it} \quad (3.3.10)$$

$$CO2\_ManCon_{it} = \alpha_0 + \beta_1 CRFPI_{it} + \beta_2 Financial\_Development_{it} + \beta_3 Total\_GDP_{it} + \beta_4 Total\_GDP2_{it} + \beta_5 Trade\_Openness_{it} + \beta_6 FDI\_Inflow_{it} + \beta_7 Urbanization_{it} + \beta_8 Population_{it} + \beta_9 Patent\_Tech_{it} + \beta_{10} Renewable\_Energy_{it} + \varepsilon_{it} \quad (3.3.11)$$

$$CO2\_Elec\_Heat_{it} = \alpha_0 + \beta_1 CRFPI_{it} + \beta_2 Financial\_Development_{it} + \beta_3 Total\_GDP_{it} + \beta_4 Total\_GDP2_{it} + \beta_5 Trade\_Openness_{it} + \beta_6 FDI\_Inflow_{it} + \beta_7 Urbanization_{it} + \beta_8 Population_{it} + \beta_9 Patent\_Tech_{it} + \beta_{10} Renewable\_Energy_{it} + \varepsilon_{it} \quad (3.3.12)$$

The endeavor to model emissions dynamics across sectors serves the purpose of garnering enhanced insights and a comprehensive grasp of the nuanced impact of climate change financial policies on emissions, spanning not merely aggregate emissions but also delineating variations across diverse sectors, including but not limited to building, industrial, land use, transportation, manufacturing, and construction.

3.3.1 Pooled least square (PLS)

The conventional effect model within regression analysis, commonly referred to as the Pooled Least Square Model or Pooled Regression (Wijaya, 2022), entails the amalgamation of all data points to estimate a comprehensive regression model, thereby disregarding the inherent cross-sectional and time series characteristics of the dataset. Consequently, the Common Effect Model estimates a singular true effect magnitude across all studies or observations (Spinelli & Pandis, 2020). It presupposes the existence of a solitary common effect magnitude that is uniformly applicable to all entities or individuals under investigation. Moreover, the intercept value for each variable and the slope coefficient remains constant across all units of analysis, encompassing both cross-sectional units and time-series observations. The formulation of the Common Effect Model can be articulated as follows:

$$\gamma_{it} = \alpha_0 + \beta_1 X1_{it} + \cdots + \beta_N XN_{it} + v_{it} \qquad (3.3.1.1)$$

$$v_{it} = \omega_i + \varepsilon_{it} \qquad (3.3.1.2)$$

In the context of the equation above, it is posited that the coefficients of all regressors, including the intercept and slopes about each variable, are uniformly consistent across all firms. Additionally, an assumption is made regarding the non-stochastic nature of the regressors, implying that the error term remains uncorrelated with the explanatory variables.

$$\text{Cov}\ (v_{it}, X1_{it}) = 0 \qquad (3.3.1.3)$$

The last assumption that must be passed is the error term, $vit \sim iid(0, \sigma_v^2)$, identically and independently distributed about the mean of zero, and the constant variance condition is homoscedasticity or the error term should be white noise. However, there's rarely evidence that the error term or the specific heterogeneity effect doesn't correlate with the regressor. Therefore, the fixed or random effect methods account for the heterogeneity across units.

The final assumption necessitates scrutiny of the error term, which is assumed to be identically and independently distributed *(iid)* with a mean of zero and a constant variance, denoted by $v_{it} \sim iid(0, \sigma_v^2)$. This condition, termed homoscedasticity, posits that the error term should exhibit no systematic pattern in its variance. However, empirical evidence seldom supports the assumption that the error term, or the specific heterogeneity effect it encapsulates, is uncorrelated with the regressor. Consequently, researchers commonly employ fixed or random effect methodologies to accommodate the heterogeneity across units. The fixed effect model (FEM) emerges as a viable analytical approach within this context.

3.3.2 Fixed effect model (FEM)

The Fixed Effect Model constitutes a pivotal statistical framework employed in analyzing panel data, particularly adept at addressing datasets wherein observations are recurrently gathered from identical entities across multiple temporal intervals. Esteemed scholars underscore its preference in scenarios marked by apprehensions regarding latent heterogeneity, which could introduce bias into outcomes (Lee et al., 2018). Furthermore, fixed effect panel regression emerges as an indispensable tool in addressing concerns related to endogeneity and serial correlation of the error term inherent in the analysis (Othmani, 2022). Within the realm of fixed effect panel regression, emphasis is placed on accommodating entity-specific effects that remain invariant across time, thereby facilitating the management of unobserved heterogeneity across entities (Harshana & Wanniarachchige, 2022). By incorporating fixed effects tailored to each entity under scrutiny, this model effectively counters the perils of omitted variable bias while effectively controlling for the time-invariant attributes characterizing the entities under investigation (Bepari & Mollik, 2015). The formal representation of the

The fixed Effect Model is articulated as follows:

$$\gamma_{it} = \beta_0 + \beta_1 X_{it} + v_t + \alpha_i + \mu_{it}$$

In this equation, γ_{it} represents the dependent variable for individual *(i)* at time *(t)*. The term β_0 is the overall intercept, while β_1 is the coefficient of the explanatory variable X_{it}. The term v_t captures time-specific effects, α_i captures individual-specific effects, and μ_{it} is the idiosyncratic error term. Below is the complete matrix form of the model:

$$\begin{pmatrix} \gamma_{11} \\ \gamma_{12} \\ \vdots \\ \gamma_{it} \\ \vdots \\ \gamma_{NT} \end{pmatrix} = \beta_0 \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ \vdots \\ 1 \end{pmatrix} + \beta_1 \begin{pmatrix} X_{11} \\ X_{12} \\ \vdots \\ X_{it} \\ \vdots \\ X_{NT} \end{pmatrix} + \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_t \\ \vdots \\ v_T \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_i \\ \vdots \\ \alpha_N \end{pmatrix} + \begin{pmatrix} \mu_{11} \\ \mu_{12} \\ \vdots \\ \mu_{it} \\ \vdots \\ \mu_{NT} \end{pmatrix}$$

To estimate this model, it needs to eliminate the individual-specific effects α_i that could potentially bias the results. This is achieved through the "within transformation," which involves demeaning the data. The first is calculating the individual averages for the dependent and explanatory variables. This step is crucial as it allows us to isolate the within-individual variation:

$$\bar{\gamma}_i = \frac{1}{T}\sum_{t=1}^{T}\gamma_{it} \quad \bar{X}_i = \frac{1}{T}\sum_{t=1}^{T}X_{it} \quad \bar{v}_i = \frac{1}{T}\sum_{t=1}^{T}v_{it} \quad \bar{\mu}_i = \frac{1}{T}\sum_{t=1}^{T}\mu_{it}$$

Next, the original variables are transformed by subtracting these individual averages. This results in the demeaned variables:

$$\gamma_{it} - \bar{\gamma}_i = (\beta_0 + \beta_1 X_{it} + v_t + \alpha_i + \mu_{it}) - (\beta_0 + \beta_1 \bar{X}_i + \bar{v}_i + \alpha_i + \bar{\mu}_i)$$

Simplification of the equation:

$$\gamma_{it} - \bar{\gamma}_i = \beta_1 (X_{it} - \bar{X}_i) + (v_t - \bar{v}_i) + (\mu_{it} - \bar{\mu}_i)$$

Final fixed effect model:

$$\tilde{\gamma}_{it} = \beta_1 \tilde{X}_{it} + \tilde{v}_t + \tilde{\mu}_{it}$$

At this stage, both the overall intercept β_0 and the individual-specific effects α_i are removed, allowing us to estimate the fixed effects estimator β_1 by regressing the demeaned dependent variable on the demeaned explanatory variable.

The fixed effect model provides a robust framework for analyzing panel data by effectively controlling for individual and time-specific effects. By transforming the data to remove individual-specific traits α_i and including dummy variables to account for time-specific variations v_t, the model ensures that the estimates of β_1 reflect the true relationship between the explanatory variable X_{it} and the dependent variable γ_{it} within the same individual over time. This approach enhances the accuracy and reliability of the estimates by focusing on within-individual variations and addressing potential biases from unobserved heterogeneity and external time factors. The result is a clearer understanding of how changes in X_{it} impact γ_{it}, providing valuable insights while necessitating diagnostic checks for model validity.

3.3.3 Random effect model (REM)

The Random Effects Model, employed in panel data analysis, accommodates unobserved variations among entities within the panel by assuming that individual-specific effects are random and unrelated to the regressors, offering greater flexibility than fixed effect models (Tasnia et al., 2020). This model addresses the possibility that the regression model overlooks important explanatory variables that may remain constant over time, suggesting that including dummy variables masks a lack of understanding.

Advocates for the random effect model propose incorporating a disturbance term to acknowledge this uncertainty, as it more accurately represents the model's limitations. This approach aligns with Error Component Models (ECM) or Random Effects Models (REM). The equation of the Random Effects Model can be expressed as follows:

$$\gamma_{it} = \alpha_{0i} + \beta_1 X1_{it} + \cdots + \beta_N XN_{it} + \mu_{it} \qquad (3.3.3.1)$$

Instead of considering α_{0i} as constant (fixed), it accounts as a stochastic (random) variable with a mean value, α_0 (without subscript i), where ω_i represents a random error term with a mean of zero and variance σ_ε^2. The individual unit intercept can thus be formulated as such.

$$\alpha_{0i} = \alpha_0 + \omega_i \ (3.3.3.2)$$

The fundamental tenet of the common effect model lies in representing 18 sampled countries as a subset of the global landscape, ensuring each sample shares a common mean intercept α_0, in contrast, variations in individual intercept values are encapsulated within the error term ω_i.

$$\gamma_{it} = \alpha_0 + \beta_1 X1_{it} + \cdots + \beta_N XN_{it} + \omega_i + \mu_{it} \qquad (3.3.3.3)$$

$$\gamma_{it} = \alpha_0 + \beta_1 X1_{it} + \cdots + \beta_N XN_{it} + v_{it} \qquad (3.3.3.4)$$

$$v_{it} = \omega_i + \mu_{it} \qquad (3.3.3.5)$$

The composite error term v_{it} comprises two elements: ω_i, representing the individual-specific error, and μ_{it}, denoting the combined time series and cross-section error, often referred to as the idiosyncratic term due to its variability across both subjects and time.

The disparity between Fixed Effects Models (FEM) and Error Component Models (ECM) or CEM lies in their treatment of intercepts. Within FEM, each cross-sectional entity is endowed with its distinct intercept, thereby yielding N fixed intercept values for N cross-sectional units. Conversely, ECM adopts a contrasting approach where the intercept serves as the aggregate mean value of all cross-sectional intercepts. At the same time, the error component ω_i encapsulates the stochastic deviation of individual intercepts from this mean. However, it's crucial to note that ω_i remains concealed from direct observation, constituting an unobservable or latent variable within the model framework.

3.4 Selection of panel data regression model

Among the array of panel regression methodologies elucidated, rigorous testing procedures are necessitated to ascertain the optimal form of panel regression congruent with the research model. In the realm of panel data regression analysis, the Chow test, Hausman test, and Lagrange Multiplier test constitute integral components of a tripartite model estimation framework aimed at discerning the most suitable regression model among the Common Effect Model, Fixed Effect Model, or Random Effect. These tests serve as diagnostic tools for researchers to discern potential structural disruptions within the data, thereby influencing the selection of the appropriate regression model.

3.4.1 Chow test

Chow test, also known as the breakpoint test, is a statistical method commonly used in panel data regression analysis to assess structural changes or differences in coefficients within a regression model across two or more subgroups of data. This test is particularly valuable in identifying breakpoints or shifts in the relationships captured by the regression model, indicating changes in the data-generating process over time or across distinct entities (Chow, 1960).

The test involves dividing the data into subintervals and conducting separate regressions for each subinterval to compare the coefficients and assess if they are statistically different. By examining the significance of these differences, researchers can determine whether there are structural breaks in the data and whether the coefficients vary significantly between the subgroups. This information is crucial for understanding the data dynamics and selecting the most appropriate regression model for these changes (Chow, 1960). The Chow test statistic is then calculated to compare the fit of the two models and determine if there is a significant difference in the coefficients.

$$F = \frac{\frac{SSR\_CEM - SSR\_FEM}{q}}{\frac{SSR\_FEM}{N-K-2q}} \quad (3.4.1.1)$$

In an advanced economic framework, SSR_CEM represents the total squared residuals in the restricted (common effect model) model. At the same time, SSR_FEM stands for the total squared residuals in the unrestricted (fixed effect model) model. With q denoting the imposed restrictions in the restricted model, n representing the total observations, and k indicating the number of independent variables, the Chow test statistic conforms to an F-distribution with degrees of freedom equal to q and N – K – 2q (Gujarati & Porter, 2009).

The author compares the calculated F-statistic with the critical value from the F-distribution table at a given significance level (e.g., 0.05) to interpret the results. Suppose the calculated F-statistic is greater than the critical value. In that case, it rejects the null hypothesis, indicating a significant structural break, and the regression parameters are significantly different across the groups. If the F-statistic is less than the critical value, it doesn’t reject the null hypothesis, implying no significant difference in the regression parameters between the groups.

In the context of panel data analysis, the Chow test plays a vital role in detecting relationship shifts, identifying periods of change, and evaluating coefficients' stability across different data segments. This test provides researchers with valuable insights into the evolution of relationships over time or under varying conditions, enabling them to make informed decisions about model specification and interpretation in panel data regression analysis (Chow, 1960).

Overall, the Chow test is a powerful tool for detecting structural changes and assessing differences in coefficients within regression models, offering researchers a systematic approach to understanding the data dynamics and selecting appropriate modeling strategies in panel data analysis.

3.4.2 Hausman test

The Hausman test is a statistical test commonly used in econometrics to determine whether the coefficients in a regression model are consistent and unbiased. Specifically, the test helps researchers choose between fixed effects and random effects models in panel data analysis by evaluating the efficiency of estimates. The underlying principle of the Hausman test is to compare the coefficients obtained from two estimators, one of which is consistent and efficient but not necessarily unbiased (random effects). At the same time, the other is consistent, less efficient, but unbiased (fixed effects) (Ahn & Low, 1996).

The formula for the Hausman test statistic is based on comparing the two sets of estimates obtained from the fixed effects and random effects models. The test statistic is calculated as the difference between the coefficients estimated by the two models, multiplied by the inverse of the covariance matrix of the coefficients, and then further multiplied by the same coefficient difference. This test statistic follows a chi-squared distribution with degrees of freedom equal to the difference in the number of parameters estimated in the two models (Yin & Moffatt, 2019). The Hausman test statistic is calculated as follows:

$$H = (\beta_1 REM - \beta_0 FEM)' \, \Sigma\_\beta_0 FEM\hat{}(-1) \; (\beta_1 REM - \beta_0 FEM) \qquad (3.4.2.1)$$

Where $\beta_1 REM$ Coefficients are estimated from the Random Effects Mode, $\beta_0 FEM$ is Coefficients estimated from the Fixed Effects Model, Σ_FEM: Covariance matrix of the residuals from the Fixed Effects Model. It is imperative to delve into the nuanced significance of the terminology's consistency and efficiency to elucidate the outcomes of the static Hausman test.

1) In econometric analysis, the concept of **consistent estimation** denotes a scenario wherein the coefficients within the model progressively converge toward their genuine parameter values with the augmentation of the sample size.
2) **Efficient estimation** pertains to a state where the coefficients exhibit minimal variance relative to those derived from alternative estimators. This implies that errors are minimized in instances of efficient estimates compared to alternative estimation approaches.

Steps that need to be done in the test Hausman are as follows:

1) H0: Both estimates are consistent, but Random Effect estimates are efficient.
2) H1: Fixed Effects estimates are consistent, but Random Effects estimates are not.

The Hausman test statistic conforms to a chi-square distribution with degrees of freedom determined by the disparity in the number of estimated coefficients between the compared models. The significance of the test statistic suggests a preference for the fixed effects model, attributable to its consistency while indicating bias in the coefficients of the random effects model due to the interplay between fixed effects and independent variables.

3.4.3 Lagrange multiplier (LM) test

The Lagrange Multiplier (LM) test, a staple in econometrics, gauges structural breaks or changes in regression models. It discerns significant relationship shifts within the model, indicating alterations in the data generation process over time or across segments. Particularly adept at detecting breaks and assessing coefficient stability, it enhances understanding of data dynamics (Lee & Strazicich, 2003).

The LM test assesses the significance of coefficient differences in a model, detecting structural breaks that might affect variable relationships. By employing this test, researchers can identify data shifts and evaluate coefficient variations across periods or subgroups, offering insights into data dynamics and aiding model selection (Lee & Strazicich, 2003).

The LM test statistic is derived from these residuals. The formula for the test statistic is:

$$LM = \frac{N(T-1)}{2}\left(\frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{u}_{it}^{2} - T\sum_{i=1}^{N}\bar{\hat{u}}_{i}^{2}}{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{u}_{it}^{2}}\right) \quad (3.4.3.1)$$

In this analysis, N denotes the number of countries, T refers to the number of periods, $\hat{u}_{it}$ represents the residuals from the pooled OLS regression, and $\bar{\hat{u}}_{it}$ signifies the average residual for country i. One must compare the calculated LM statistic to a critical value from the chi-squared distribution with one degree of freedom to determine the significance of individual-specific effects. If the LM statistic exceeds this critical value, it suggests that the null hypothesis, which states that individual-specific effects are zero, should be rejected.

Interpreting these results is crucial for selecting the appropriate model. If the null hypothesis is not rejected, it indicates no significant country-specific effects; thus, the simpler PLS model is sufficient for the analysis. Conversely, if the null hypothesis is rejected, it implies that country-specific effects are significant. In this case, the RE model is more appropriate as it accounts for the unique characteristics of each country, leading to a more accurate and insightful analysis.

If the LM test statistic shows significance, it implies that added variables or transformations greatly affect model fit, hinting at omitted variables or functional form errors. In such instances, it's advisable to incorporate pertinent variables or refine the model's functional form for enhanced accuracy.

The LM test is crucial in econometric analysis, pinpointing model misspecifications and bolstering the reliability of regression findings. Its implementation enables researchers to detect and rectify issues like omitted variables or incorrect functional forms, ensuring more precise and resilient regression analysis. Consequently, this fosters more insightful interpretations and dependable policy implications drawn from estimated coefficients.

3.5 Violation diagnostic

3.5.1 Normality test

The concept of normally distributed residuals pertains to the presumption that the errors or residuals within a statistical model adhere to a Gaussian distribution. This assumption is significant across various statistical analyses, particularly within linear regression and other parametric models. Its significance lies in facilitating the utilization of inferential statistical tests reliant on the normality assumption to yield precise outcomes (Pain et al., 2018; Dallaire et al., 2015; Rocha & Simas, 2017).

Nevertheless, the mean and variance sufficiently describe the series when data adhere strictly to a normal distribution. Given that most data samples do not conform to this distribution, accounting for additional statistical descriptors, known as higher moments, is imperative to comprehensively characterize them. The mean and variance represent the first and second moments of a distribution, while the third and fourth moments, termed skewness and kurtosis, provide further insights into the distribution's asymmetry and peak (Evans, 2023).

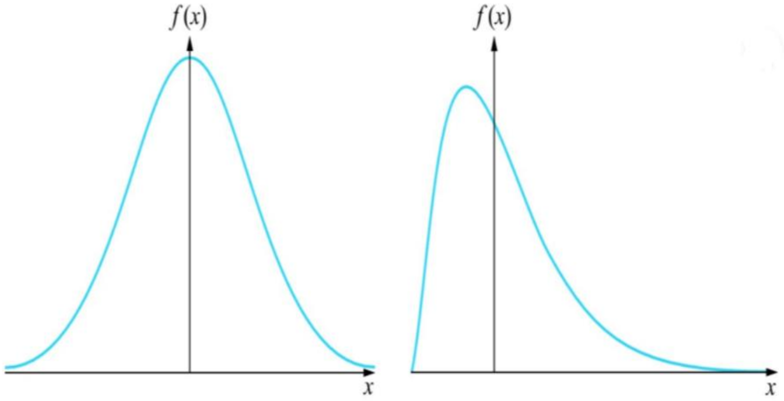


Figure 3.2 Skewness curves

Skewness characterizes the asymmetry of a distribution around its mean and quantifies the degree to which the distribution deviates from symmetry. The left panel of the graph below illustrates a symmetrical distribution, resulting in a skewness value of zero, where the mean and median coincide. Conversely, the right panel depicts a distribution with positive skewness, indicated by a significant peak on the left side and an extended tail on the right.

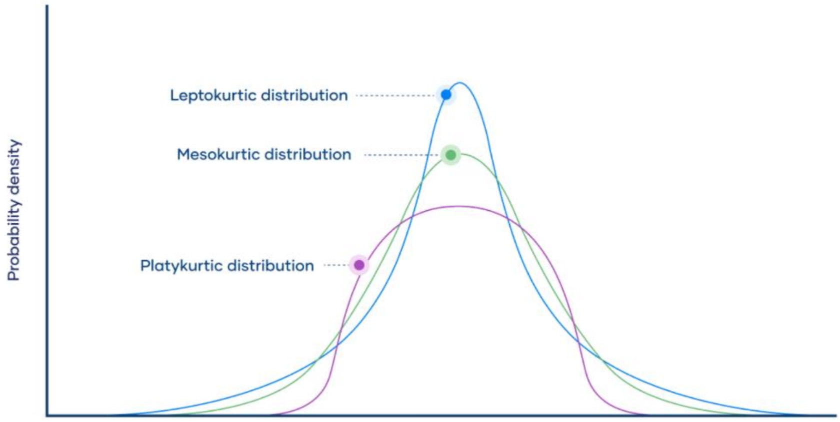


Figure 3.3 Kurtosis curves

Kurtosis quantifies the thickness of the tails of a distribution and the sharpness of its peak around the mean. A normal distribution, termed mesokurtic (green curve), has a kurtosis of 3. When a distribution's kurtosis exceeds 3, it is classified as leptokurtic (blue curve), indicating it has fatter tails and a sharper peak at the mean compared to a normal distribution. Conversely, a distribution with kurtosis less than 3 is considered platykurtic (platykurtic), featuring thinner tails and a less pronounced peak at the mean relative to the normal distribution.

When residuals conform to a normal distribution, the model's errors in forecasting the outcome variable occur randomly and adhere to a symmetrical bell-shaped curve. Departures from this normative distribution in the residuals may indicate potential deficiencies in the model's ability to capture all underlying data patterns, consequently predisposing the estimation of biased or inefficient parameters (Dallaire et al., 2015; Rocha & Simas, 2017).

Researchers commonly evaluate the normality of residuals through diagnostic plots, statistical tests such as the Kolmogorov-Smirnov test, or by scrutinizing residual distributions vis-a-vis a theoretical normal distribution. Significant deviations from normality in residuals may signal violations of model assumptions, prompting the exploration of alternative modeling methodologies or data transformations (Evans, 2023).

3.5.2 Heteroscedasticity

Heteroscedasticity, a fundamental concept in statistical analysis, denotes a scenario wherein the variance of residuals within a regression framework exhibits non-constant behavior across the spectrum of independent variables. Put, it indicates unequal error variability across the range of independent variable values, deviating from the premise of homoscedasticity, where error variance remains constant. This deviation harms the statistical test validity and model prediction reliability (Xiong & Tian, 2014; Ilori & Tanimowo, 2022).

Detecting heteroscedasticity is paramount in statistical inquiry because it can potentially induce biased parameter estimations, inaccurate standard errors, and spurious hypothesis testing outcomes. Heteroscedasticity undermines estimator efficiency, compromising goodness-of-fit evaluations and overall model precision (Xiong & Tian, 2014). Consequently, identifying and rectifying heteroscedasticity is imperative before undertaking further analysis to uphold the integrity of statistical findings.

The consequence of using OLS estimation with heteroscedasticity still gives unbiased (and consistent) coefficient estimates. Still, they are no longer BLUE because they no longer have the minimum variance among the class of unbiased estimators. This implies that the standard errors could be inappropriate when using OLS in the presence of heteroscedasticity. Hence, any statistical inference (t-test, F-test, and confidence intervals) could be misleading. Whether the standard errors calculated using the usual formulas are too big or too small will depend upon the form of the heteroscedasticity.

Researchers have devised various methods to identify and address heteroscedasticity in statistical models, with White's test being a commonly employed approach. Nevertheless, it is advisable to utilize multiple tests to detect such issues. Suggestions for mitigating heteroscedasticity include employing estimation methods such as generalized least squares (GLS), transforming variables into logarithms, or utilizing White's heteroscedasticity consistent standard error estimates. Properly addressing heteroscedasticity can enhance the precision and dependability of statistical analyses (Zhang et al., 2013). The White statistical test can be represented as follows:

$$\text{White test} = N^*R^2 \sim \chi^2(k) \qquad (3.5.2.1)$$

Obtain R squared from the auxiliary regression and multiply it by the number of observations, N. Where *k* is the number of regressors in the auxiliary regression excluding the constant term, if the test statistic result is greater than the corresponding value from the statistical table, then reject the null hypothesis that the disturbances are homoscedastic.

In summary, heteroscedasticity complicates statistical analysis by breaching the assumption of constant error variance. Detecting and rectifying heteroscedasticity is crucial to uphold the integrity of statistical inferences and the resilience of regression models.

3.5.3 Multicollinearity

Multicollinearity, a statistical phenomenon, arises when independent variables within a model exhibit significant intercorrelations, impacting the reliability of statistical inferences (Amoroso et al., 2019; Shrestha, 2020). This can destabilize parameter estimates in regression models, leading to fluctuations even with minor sample changes. Moreover, it complicates model interpretation and diminishes predictive accuracy (Lipovetsky & Conklin, 2004; K.P. & U.P., 2023).

The OLS method assumes independence among variables, implying that changes in one variable won't affect the coefficients of others. Though perfect independence is rare, low correlation maintains precision. Multicollinearity arises when variables are highly correlated, categorized as perfect or near multicollinearity.

The coefficient correlation test offers a straightforward yet effective approach to diagnosing multicollinearity. This test involves calculating the pairwise correlation coefficients between explanatory variables, providing insight into their degree of linear association. The correlation coefficient, denoted as r, quantifies this relationship on a scale from -1 to 1:

- (r = 1) signifies a perfect positive linear relationship.
- (r = -1) signifies a perfect negative linear relationship.
- (r = 0) signifies no linear relationship.

The absolute value of r indicates the strength of the linear relationship, with values closer to 1 or -1 suggesting stronger correlations (Wooldridge, 2013).

$$r_{XY} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

(3.2.3.1)

The coefficient correlation test quantifies the degree of linear association between two variables using the correlation coefficient, denoted as r. This coefficient ranges from -1 to 1, with values closer to 1 or -1 indicating stronger linear relationships. Calculating the correlation coefficient involves comparing the variables' covariance to the product of their standard deviations. When the absolute value of r exceeds certain thresholds (e.g., $|r| > 0.8$ or $|r| > 0.9$), it signals potential multicollinearity, prompting further scrutiny of the variables involved. Moderate correlations ($0.5 < |r| < 0.8$) also warrant attention, especially if multiple variables exhibit these correlations (Kennedy, 2008).

3.5.4 Autocorrelation

Autocorrelation contravenes one of the fundamental assumptions of classical linear regression, which posits that the error terms are not interrelated. When autocorrelation is present, the estimated coefficients may remain unbiased; however, the standard errors and hypothesis tests can become invalid, leading to erroneous inferences about the significance of the coefficients and potentially misleading conclusions regarding the relationships between variables (Kennedy, 2008).

Autocorrelation, also termed serial correlation, refers to the relationship between a regression model's error terms or residuals at various time points or observations. This phenomenon arises when the errors in a time series or panel data display a systematic correlation pattern.

The Wooldridge test for autocorrelation operates on the principle that the residuals from a regression model will exhibit a systematic pattern over time rather than being random (Wooldridge, 2002). The process begins with specifying a simple panel data model:

$$Y_{it} = \alpha + \beta_1 X_{it} + \mu_{it} \quad (3.5.4.1)$$

Here, Y_{it} is the dependent variable, X_{it} is the independent variable, α and β are parameters to be estimated, and μ_{it} is the error term. Once the model is specified, it is estimated using ordinary least squares (OLS) to obtain the residuals $\widehat{\mu_{it}}$.

Following the estimation, an auxiliary regression is formulated to detect autocorrelation. This involves regressing the obtained residuals $\widehat{\mu_{it}}$ on their lagged values $\widehat{\mu_{it-1}}$ along with a new error term v_{it}. The regression equation is structured as follows:

$$\widehat{\mu_{it}} = \rho\widehat{\mu_{it-1}} + \beta_1 X_{it} + v_{it} \qquad (3.5.4.2)$$

In this formula, $\widehat{\mu_{it-1}}$ represents the lagged residuals, and ρ is the coefficient that indicates the degree of autocorrelation. If ρ is significantly different from zero, it suggests that the residuals are correlated over time, indicating the presence of autocorrelation.

CHAPTER IV

RESULT AND DISCUSSION

4.1 Data description

4.1.1 Statistical description of the data

The dataset provides an extensive overview of various economic, demographic, and technological factors affecting total CO2 emissions, measured in million tons. Analyzing the descriptive statistics for these variables helps us comprehend their distributions and potential impacts on CO2 emissions. Data obtained from related official websites, presented in an annual period (2000-2020) with a total of 18 countries that are members of G20 (China, United States, Argentina, Australia, Brazil, Canada, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, South Africa, South Korea, Turkiye, and United Kingdom). The data set obtained has different units of account (**See Table 3.2**).

Table 4.1 Statistical description.

Variable	**Obs.**	**Mean**	**Std. deviation**	**Min**	**Max**
Total CO2 (Mt)	378	1369.132	2209.357	125.8877	11948.12
CRFPI (index 1-100)	378	22.08113	22.8816	0	86.66667
Financial Development (index (0-1)	378	.6361362	.2135967	.2653349	.9744189
Total GDP (USD)	378	2.81e+12	3.94e+12	2.22e+11	1.99e+13
GDP2 (USD)	378	2.34e+25	6.89e+25	2.22e+11	1.99e+13
Trade Openness (%)	378	50.45323	16.79292	19.5596	105.5663
FDI Inflow (USD)	378	5.37e+10	7.86e+10	-2.51e+10	5.11e+11
Urbanization (%)	378	72.79334	15.50118	27.667	92.111
Population (People)	378	2.36e+08	3.81e+08	1.90e+07	1.41e+09
Patent in Technology (Number of patent)	378	10242.26	16520.77	7.2667	68392.12
Renewable Energy (%)	378	10.32071	10.16957	.3121983	48.69333

Source: Author's calculation in Stata.

The dependent variable, Total CO2 Emissions, comprises 378 observations with an average value of 1.369,132 Mt and a standard deviation of 2.209,357, spanning 125,8877 to a maximum of 11.948,12. This significant variability suggests that CO2 emissions are influenced by diverse factors such as economic activities, policy implementations, and technological advancements.

The Climate-Related Financial Policy Index (CRFPI) scores, which represent climate-related financial policies, exhibit considerable variability with a mean score of 22,08113 and a standard deviation of 22,8816 These scores range from 0 to 86,67, indicating diverse policy implementations across different entities. Higher CRFPI scores may reflect more robust regulatory frameworks to reduce CO2 emissions, while lower scores might suggest less stringent or absent climate policies. This variability underscores the differing levels of commitment and effectiveness in climate-related financial policies among various countries.

Financial Development, measured as a percentage, displays a mean of 0.64 and a standard deviation of 0.21, with values ranging from 0.27 to 0.97. This metric reflects the level of financial sector development across entities, where higher financial development is generally linked to better access to capital. Enhanced financial development can facilitate investments in green technologies and infrastructure, potentially reducing CO2 emissions. Total GDP, expressed in USD, also shows significant variability with a mean of 2.81 trillion and a standard deviation of 3.94 trillion, ranging from 222 billion to 19.9 trillion USD. The large values and standard deviations in GDP highlight substantial economic disparities, which likely contribute to differing levels of CO2 emissions based on economic activity. Similarly, GDP Squared (GDP2) follows the same pattern due to its derivation from GDP values.

Trade Openness, another percentage-based metric, has a mean of 50,4% and a standard deviation of 16,8%, with values ranging from 19,5% to 105%. This indicates the extent of engagement in international trade, where higher trade openness might lead to increased CO2 emissions due to heightened industrial and transportation activities. Foreign Direct Investment (FDI) Inflow, measured in USD, shows substantial variability with a mean of 53,7 billion USD and a standard deviation of 78,6 billion USD, ranging from -25,1 to 511 billion USD. This variability reflects positive and negative inflows, which impact CO2 emissions depending on whether the investments are directed toward high-emission industries or greener technologies. Urbanization expressed as a percentage, has a mean value of 72,8% and a standard deviation of 15,5%, with rates varying from 27.7 to 92,1%. Higher urbanization typically correlates with increased energy consumption and CO2 emissions due to concentrated industrial and residential activities.

Population, measured by the number of people, shows a mean of 236 million and a substantial standard deviation of 381 million, ranging from 19 million to 1.410 billion people. This widespread population size across entities suggests that larger populations can increase CO2 emissions due to greater energy and resource demands. Patent in Technology, indicating the number of patents, has a mean of 10.242,26 and a high standard deviation of 16.520,77, ranging from 7.2667 to 68.392,12. Significant differences in technological innovation levels are evident, where more patents typically reflect greater innovation, potentially leading to more efficient technologies and lower CO2 emissions. Renewable Energy Consumption, as a percentage, has a mean of 10.,3%, and a standard deviation of 10,1%, with values ranging from 0,31 to 48,7%. This indicates varying degrees of reliance on renewable energy sources, where higher percentages of renewable energy consumption are expected to reduce CO2 emissions by replacing fossil fuel-based energy sources.

The descriptive statistics reveal considerable variability across all variables, highlighting the dataset's diverse economic, demographic, and technological contexts. Understanding these differences is crucial for analyzing their impact on CO2 emissions. The high variability in CO2 emissions, economic activities, policy indices, and technological innovation points to the complex interplay of these factors. Effective policymaking to reduce CO2 emissions must consider this complexity, promoting financial development, technological innovation, and increased renewable energy consumption while managing economic growth and urbanization impacts.

4.1.2 An Overview of the climate-related financial policy index (CRFPI)

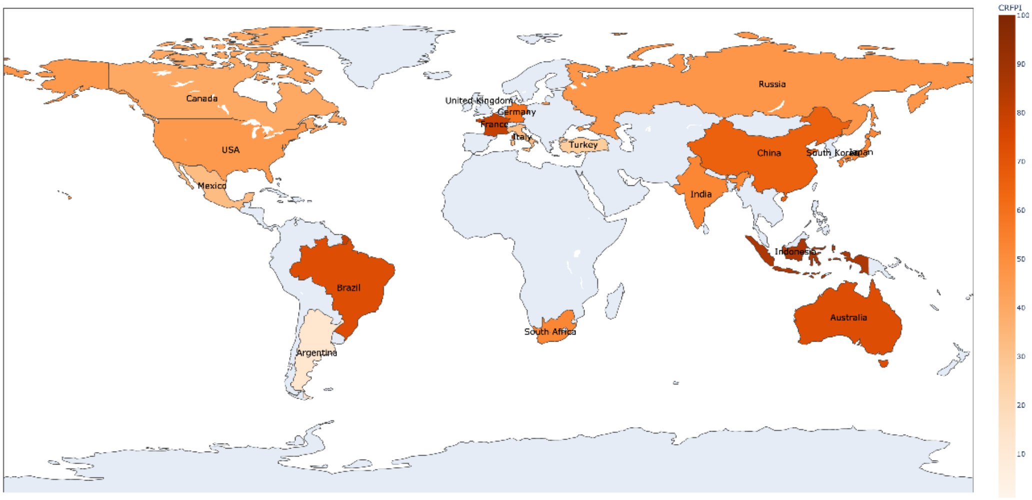


Figure 4.2 Distribution Map for CFRPI across G20 Countries.
Source: Author's calculation in Phyton.

Figure 4.2 presents the findings using the benchmark method while analyzing the distribution of the index for 2020.

Initially, it is evident that only a handful of countries exhibit a high CRFPI; these nations include Australia, Brazil, China, France, Indonesia, and South Korea, as indicated in dark brown in **Figure 4.2**. The index identifies the countries with the lowest CRFPI and poor performances, such as Argentina, Turkiye, Italy, and Mexico, highlighted in faded brown. In contrast, other countries, such as the United States, Canada, Russia, Germany, Russia, and India, are considered at a moderate level.

Furthermore, a location or bandwagon effect is observed, predominantly in South and East Asia and the Pacific. A similar trend is noticeable in Europe, where France, followed by Germany and the UK. Conversely, Brazil is the leading nation in Latin America, with other countries showing significantly lower index values. In North America, the highest index is noted in the USA; however, its green financial policymaking needs to stand out compared to global standards. Only a few instances are observed in Africa, with South Africa recording the highest CRFPI.

The outcomes for countries like Indonesia, Australia, China, and Brazil, among others, are particularly intriguing and underscore the potential of the proposed index. For these nations, the CRFPI reflects a strong commitment to financial policymaking, which does not align with national climate objectives. Specifically, the scores for these countries appear inconsistent with their economic and energy policies—for instance, Australia being the world's largest coal exporter (Crowley, 2021; Hudson, 2019; Edwards, 2019), the high pollution levels reported in China (Shao et al., 2006; Wong, 2013; Guan et al., 2014), and the Bolsonaro administration's stance against environmental sustainability in recent years (Araújo, 2020; Pereira and Viola, 2019; Brito et al., 2019). This observed inconsistency can be explained in two ways. Firstly, the independence of central banks and financial supervisors from political influence may allow them to pursue climate-related objectives regardless of the national government's commitment to climate policy. Secondly, it might indicate a misalignment or lack of coordination among policy actors, highlighting the need for closer collaboration to achieve significant sustainability and climate mitigation goals. Thus, the index is instrumental in revealing that significant engagement in climate-related financial policymaking does not always result in environmentally sustainable policy outcomes.

Figure 4.3 presents the distribution of sub-indices, representing various policy areas, from 2000 to 2020. The temporal variations across various policy indicators can be discerned by categorizing the sample into three income brackets based on the World Bank's classification. Since the early 2000s, developed countries have been the most proactive across the entire policy spectrum. Throughout the 21 years covered in the analysis, the largest proportion is attributed to other green disclosure requirements (represented by the green area in the graphs), with green financial principles following closely behind.

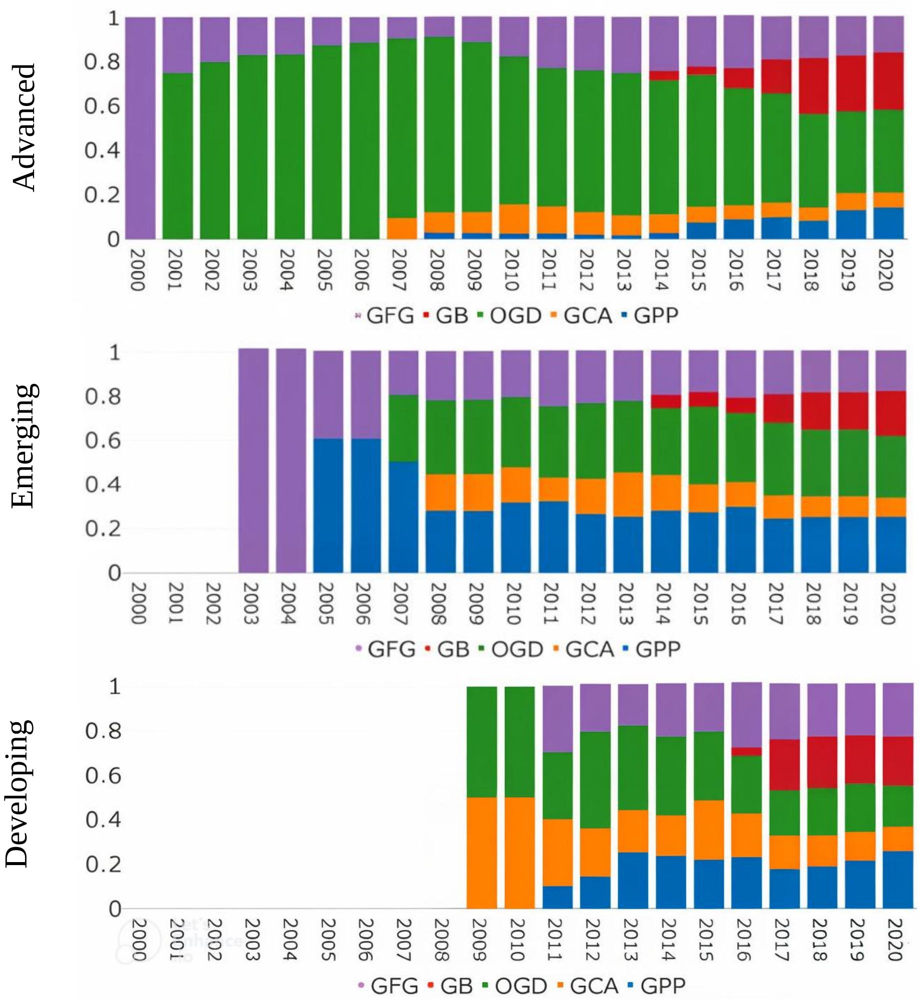


Figure 4.3 The temporal variation in the implementation of policies across different income groups. Annotations: GPP (Green Prudential Policy), OGD (Other Green Disclosure Requirements), GFG (Green Financial Guidelines), GB (Green Bond), GCA (Green Capital Allocation).

Source: D'Orazio & Thole (2022).

Recently, green bonds have gained significance due to heightened investor interest in environmental investments. Similarly, green prudential regulations are becoming more prevalent, largely owing to the introduction of climate-related stress tests in several regions, such as the UK and France. Regarding emerging economies, no policies were recorded until 2003. In general, the distribution of policies in these economies differs from that in advanced economies, with green prudential policies (blue area in the graphs) playing a more significant role, followed by credit allocation measures (orange area). In the case of developing economies, climate-related financial policies have been adopted later compared to the other two income groups. The distribution of policy areas resembles that seen in emerging economies in recent years. Nonetheless, since 2015, there has been a slightly higher proportion of green prudential and credit allocation policies.

4.2 Interaction between CRFPI and CO2 emissions

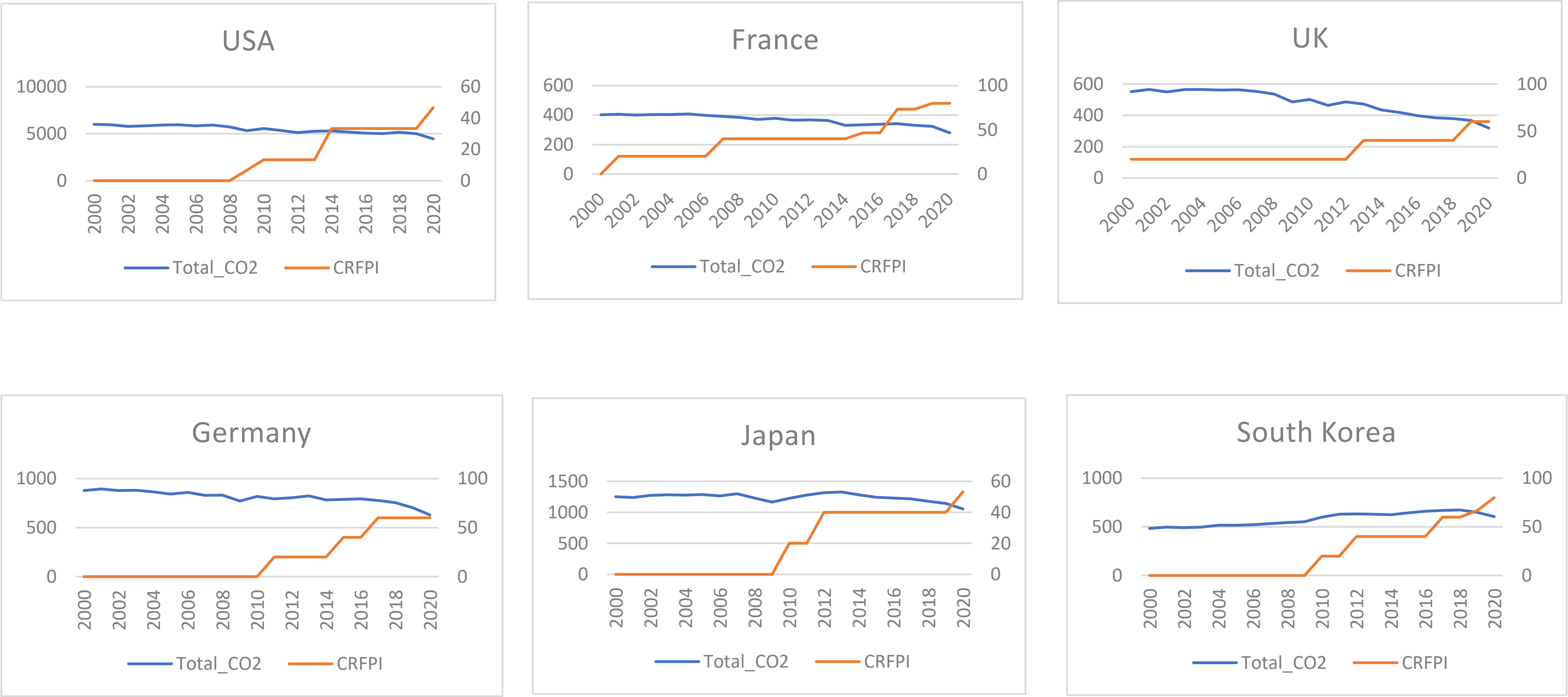


Figure 4.4 The interaction between CO2 emissions and CRFPI by Countries.

Table 4.5 Types of financial policy adopted by countries

Country	**Policy (**D'orazio & Thole 2022; D'Orazio & Dirks 2022)					**Discussions**
	Green prudential regulation	**Green financial principle**	**Other disclosures requirements**	**Green bond taxonomy**	**Green credit and investment**	
USA	√	√	√	√		**Green prudential regulation**: governance and risk management (GRM). Morover, the United States, California issued 300 million USD green bonds.
France	√	√	√	√	√	The concept of **green prudential regulation**, exemplified by CrST (Climate-related stress tests), evaluates the resilience of the financial system to climate-related risks. Since 2007, the green **credit allocation policy** mandates banks to allocate a portion of funds from specific savings accounts to domestic energy conservation loans. Additionally, **climate-related disclosure requirements** primarily target non-financial institutions, pension funds, and insurance companies. In 2017, France became the first country to issue a **sovereign green bond**; however, it lacks a comprehensive sustainable finance taxonomy.
UK	√	√	√	√		In 2019, the Prudential Regulation Authority (PRA) in the UK issued a Supervisory Statement outlining expectations for firms to consider climate risk. The statement focused on four key areas: **governance arrangements, risk management, stress testing and scenario analysis, and disclosure.**
Germany		√	√	√		Germany's financial regulatory agency, BaFin, is considering the implementation of sustainability risk management and ESG (Environmental, Social, and Governance) **disclosure requirements**.

Japan		√	√	√	√	In the realm of **green credit and investment**, measures such as quotas and concessional loans are being allocated to priority and environmentally friendly sectors, with initiatives including a minimum credit floor and subsidized liquidity for environmentally friendly projects. In Japan, the Development Bank introduced the Environmental Rating Loan program in 2004, which integrates environmental ratings into preferential interest rates based on companies' environmental management. This was followed in 2007 by a project subsidizing interest payments on these loans. Additionally, the "Principal Terms and Conditions for the Fund-Provisioning Measure to Support Strengthening the Foundations for Economic Growth," signed on June 15, 2010, outlines sectors and requirements for liquidity support under the Loan Support Program.
South Korea		√	√	√	√	The establishment of the First Climate Change Response Master Plan in Korea is dated December 2016. In April 2017, Shinhan Bank launched its ‘Green Management Firm Loan Program’ with the South Korean Ministry of Environment and KEITI, a UNEP FI Supporting Institution. The program allocates US$87 million for Eco-friendly Small and Medium Enterprises, and loans are characterized by interest rates of up to 1.3% lower than existing programmes.

4.2.1 United States of America (USA)

CO2 emissions remained relatively stable from 2000 to 2008, but experienced a noticeable decline between 2008 and 2012, likely due to the economic recession. Emissions then stabilized post-2012, with a significant drop in 2020 attributed to the COVID-19 pandemic. In contrast, the CRFPI showed minimal activity until 2009, followed by a gradual increase. A substantial rise between 2012 and 2014 aligns with the stabilization of CO2 emissions, suggesting that financial policies contributed to reducing emissions. The CRFPI's sharp increase in 2020 indicates an intensified focus on climate policies.

Overall, there are five key financial actions oriented towards climate in the USA: (1) Increased levels of sustainable and responsible investing; (2) A heightened focus from the largest US banks and other financial institutions on sustainability, risk management, lending practices, and related opportunities; (3) Development and evolution of sustainability risk frameworks by US insurance companies and related regulators; (4) Acceleration of the ongoing US low carbon energy transition through federal and state policies; (5) Financial innovation driving meaningful change in many investment sectors, alongside social innovation and cultural development.

Climate-related financial policies in the US are largely driven by the private sector through green investments and loans, such as sustainable investment, banking, and lending practices. This is evident from the rise of Environmental, Social, and Governance (ESG) issues in the US, with one study showing ESG factors reflected in assets worth $6.57 trillion managed in the US as of 2014, a growth of 76% since 2012. Additionally, Bank of America has allocated $125 billion to low carbon business commitments. The private sector's contributions are further exemplified by Goldman Sachs' increased commitment to clean energy investments to $150 billion by 2025 and large green bond issuances by Morgan Stanley and Bank of America Merrill Lynch (UNEP, 2016).

4.2.2 France

Over this period, total CO2 emissions, depicted by the blue line, show a general downward trend, with fluctuations between 2000 and 2006, followed by a notable decline from 2006 onwards. This decrease in emissions becomes more pronounced around 2008-2009 and 2013-2014, with a particularly sharp drop observed around 2018 continuing through 2020. Conversely, the CRFPI, represented by the orange line, starts at zero in 2000 and rises significantly from 2007, with steep increments from 2013 to 2016, eventually stabilizing around the 80 after 2016. This index measures the robustness and comprehensiveness of climate-related financial policies, indicating increased regulatory activity and policy implementation focused on climate change mitigation.

The interaction between CO2 emissions and the CRFPI suggests a direct correlation between the strengthening of climate-related financial policies and the reduction in CO2 emissions. The rise in CRFPI coincides with significant decreases in CO2 emissions, particularly notable during periods of steep policy enhancements, such as between 2013 and 2016. This correlation underscores the effectiveness of France's climate policies in driving down emissions. The introduction and enforcement of these policies, as reflected in the rising CRFPI, appear to have compelled industries and sectors to adopt greener practices and technologies, contributing to the overall reduction in emissions. The steepest declines in CO2 emissions align with the periods when CRFPI experienced its most significant increases, highlighting the pivotal role of policy-driven approaches in achieving environmental objectives.

Supporting this analysis, France's legislative framework, particularly Article 173 of the law on energy transition and green growth, has been instrumental in driving these changes. This legislation mandates comprehensive climate risk reporting and the incorporation of ESG (Environmental, Social, and Governance) criteria into investment strategies by companies and financial institutions. By requiring detailed disclosures of climate-related financial risks and alignment with the national strategy for energy and ecological transition, Article 173 has likely contributed to the observed rise in CRFPI. This regulatory environment incentivized companies to reduce their carbon footprints and prioritize sustainable investments, aligning financial practices with climate goals. Consequently, the implementation of these rigorous financial policies, as indicated by the CRFPI, correlates with the observed reduction in CO2 emissions, demonstrating the impact of France's proactive climate policy framework (D’orazio & Popyan, 2018).

4.2.3 United Kingdom (UK)

Data from 2000 to 2008 indicate that CO2 emissions were relatively high and stable, coinciding with a flat CRFPI, which suggests minimal policy activity concerning climate-related financial regulations during this period. However, a marked increase in CRFPI from 2013 onward corresponds with the introduction of more stringent financial policies designed to combat climate change. This rise in CRFPI aligns with a notable decrease in CO2 emissions, indicating that these newly implemented policies effectively contributed to reducing emissions. The subsequent rise and stabilization of CRFPI around 2018 further coincide with ongoing reductions in emissions, highlighting the role of these policies in fostering sustainable practices and lowering carbon footprints.

According to a report by the Bank of England (2017), the disclosure of climate-related risks is an effective policy solution for guiding the financial sector towards sustainability-oriented business practices. The disclosure of climate-related financial risks has become a critical component of financial reporting worldwide, with various initiatives and frameworks aimed at improving transparency and understanding of these risks. In the UK, the Financial Stability Board's Task Force on Climate-related Financial Disclosures (TCFD) plays a crucial role in standardizing the reporting of financial flows that reflect climate uncertainty as financial risk (Farbotko, 2019). This standardization is essential for stakeholders to understand and assess the climate-related risks and opportunities faced by organizations, including those listed on the UK's FTSE 100 (Borghei, 2023).

The significance of climate-related financial disclosures extends to pension funds and insurance companies in the UK, where regulatory bodies such as the Prudential Regulation Authority have provided guidance on managing financial risks associated with climate change (Klumpes et al., 2019). Additionally, the UK government has mandated climate risk disclosures, reflecting a global trend where countries like the US, France, Hong Kong, and New Zealand are also implementing government-mandated disclosure initiatives (Lin et al., 2023).

4.2.4 Germany

The blue line represents total CO2 emissions, showing a general decline over the two decades, with a notable drop after 2017. The orange line represents the CRFPI, indicating the adoption and strengthening of climate-related financial policies. From 2000 to 2012, the CRFPI remains flat, suggesting minimal policy activity. Starting in 2013, the CRFPI increases sharply, reaching significant levels by 2017, after which it stabilizes. This trend indicates a period of intensified policy implementation aimed at addressing climate change.

The interaction between CO2 emissions and the CRFPI in Germany highlights a strong correlation between policy activity and emissions reduction. The period from 2000 to 2012, with a stable CRFPI, shows relatively high CO2 emissions with minor fluctuations. However, the sharp rise in CRFPI from 2013 aligns with a subsequent decrease in CO2 emissions. The most pronounced drop in emissions occurs around 2017, coinciding with the peak and stabilization of the CRFPI. This correlation suggests that the introduction of more rigorous financial policies and initiatives in Germany, reflected by the rising CRFPI, has been effective in driving down CO2 emissions. These policies likely encouraged industries and sectors to adopt greener practices and technologies, contributing to the overall reduction in emissions.

Germany's proactive stance in the green bond market and recent financial regulations underscores its commitment to sustainable finance, despite the absence of comprehensive green financial regulation and sustainable finance guidelines. Notable initiatives include the Deutsche Börse's launch of the Sustainable Finance Initiative in 2017, the Federal State of Berlin's introduction of a sustainability index for pension fund investments, and the Federal State of Hesse's plans to make Frankfurt a green finance hub. Additionally, the Federal Ministry of Finance's commissioned research report on the potential impact of climate change on financial market stability reflects a growing awareness and action towards integrating climate considerations into financial practices. These efforts have likely contributed to the rise in CRFPI and the subsequent reduction in CO2 emissions, demonstrating the impact of policy-driven approaches in addressing climate change (D'orazio & Popyan, 2018).

4.2.5 Japan

The period from 2000 to 2008, characterized by a stable CRFPI, shows relatively high and stable CO2 emissions. However, from 2008 onwards, as the CRFPI begins to rise, there is a noticeable decline in CO2 emissions, particularly after 2013. This suggests that the implementation of more rigorous financial policies and measures has effectively contributed to reducing emissions. The steepest rise in CRFPI, particularly between 2013 and 2016, aligns with a significant drop in CO2 emissions, highlighting the impact of these policies on driving down emissions and promoting environmental sustainability.

Supporting these findings, Japan's strategic initiatives in environmental finance have played a crucial role. The Development Bank of Japan's introduction of the Environmental Rating Loan program in 2004, which provided preferential interest rates based on a company's environmental performance, marked an early effort to integrate environmental considerations into financial practices. This initiative was further strengthened in 2007 with the subsidization of interest payments on environmental-rating loans. Additionally, the 2010 "Principal Terms and Conditions for the Fund-Provisioning Measure to Support Strengthening the Foundations for Economic Growth" provided liquidity support to sectors and projects aimed at economic growth with an environmental focus. These measures likely contributed to the rise in CRFPI, reflecting a growing emphasis on climate-related financial policies. The corresponding decline in CO2 emissions underscores the effectiveness of these financial initiatives in encouraging companies to adopt greener practices and technologies, thus reducing their carbon footprint (D'orazio & Popyan, 2018).

4.2.6 South Korea

Total CO2 emissions, shows an overall increasing trend with a few fluctuations, especially a notable rise around 2012-2014, followed by a slight dip post-2018. The orange line, representing the CRFPI, remains flat until around 2008, after which it begins a sharp ascent, particularly from 2010 onwards, reflecting the implementation and intensification of climate-related financial policies.

Examining the interaction between CO2 emissions and the CRFPI, it is evident that there is a strong correlation between policy implementation and emissions trends. Until 2008, CO2 emissions remained relatively stable, but as the CRFPI began to rise sharply from 2010 onwards, indicating increased regulatory activities, emissions initially increased, peaking around 2013-2014. However, the consistent rise in CRFPI, particularly post-2013, aligns with a stabilization and subsequent slight reduction in CO2 emissions, particularly noticeable after 2018. This trend suggests that the policies encapsulated by the CRFPI have started to exert their influence, gradually curbing the previously rising emissions.

Supporting this analysis, South Korea's extensive green finance and policy initiatives have been instrumental. The full launch of its green finance scheme in 2009, the environmental information disclosure system in 2013, and the emissions trading scheme in 2015 marked significant steps towards integrating environmental considerations into financial and industrial practices. These measures are reflected in the rising CRFPI. Additionally, the $313 billion green financing plan announced to slash greenhouse gas emissions by 40% from 2018 levels by 2030, and the establishment of the First Climate Change Response Master Plan in 2016, underscore the country's commitment. The launch of Shinhan Bank's 'Green Management Firm Loan Program' in 2017, which offers substantial financial support to eco-friendly SMEs at lower interest rates, further highlights efforts to incentivize greener business practices. These comprehensive financial policies and initiatives, as indicated by the CRFPI, have played a crucial role in moderating CO2 emissions, showcasing the effectiveness of South Korea's policy-driven approach in addressing climate change (D'orazio & Popyan, 2018).

4.2.7 Indonesia

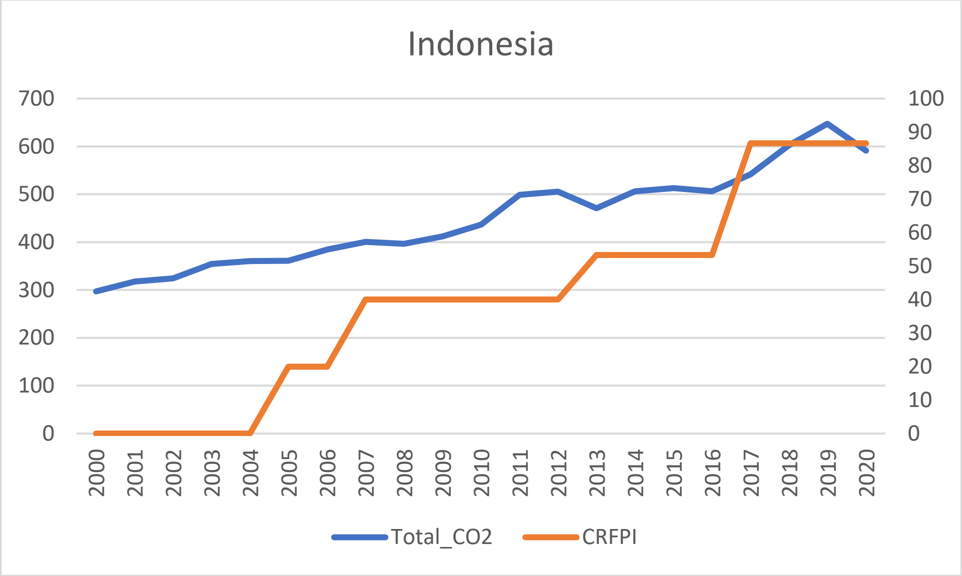


Figure 4.6 Indonesia’s CRFPI and CO2 emissions

The chart above illustrates the movement of carbon emissions in Indonesia from 2000 to 2020, showing a significant growth in CO2 emissions over this period. Notably, despite this increase, Indonesia stands out as the country with the highest climate-related financial policy index globally. This paradox between rising emissions and strong climate-related financial policies warrants closer examination.

A key development in Indonesia's approach to sustainable finance was the launch of the Sustainable Finance Roadmap by the Indonesia Financial Services Authority (Otoritas Jasa Keuangan, OJK) in December 2014. This initiative marked the beginning of a systematic effort to embed sustainability principles into the nation's financial system. In a further step to reinforce these efforts, OJK introduced the Sustainable Finance Umbrella Policy on July 12, 2017. This policy aimed to provide a cohesive framework for the financial sector in Indonesia, including banking, capital markets, and non-bank financial services, by setting out clear guidelines and unified standards for implementing sustainable finance.

The Umbrella Policy established a common understanding of sustainable finance within the financial industry and introduced key principles that financial institutions must follow to align their operations with broader sustainability objectives. Importantly, it also included an action plan detailing specific steps for different sectors within the financial system to adopt and implement sustainable finance practices effectively. Under the regulations mandated by OJK, financial institutions are now required to submit annual plans outlining how they will integrate sustainable finance practices into their operations. These plans must cover the development of green financing products and services, along with strategies to expand their green portfolios. This requirement ensures that financial institutions contribute to environmental sustainability by directing more funds towards green projects and initiatives. Moreover, institutions must make organizational adjustments, such as revising risk management frameworks, corporate governance practices, and standard operating procedures (SOPs) to incorporate sustainability principles.

The Sustainable Finance Roadmap and the Umbrella Policy also underscore the need for regulatory support and incentives to encourage the growth of sustainable financing. OJK aims to increase the availability of sustainable finance in the market by promoting the development of green financing products and offering targeted loans and guarantee schemes. Additionally, the introduction of green lending models, green bonds, and a green index further supports Indonesia's transition to a more sustainable financial system. These measures are not only intended to advance sustainability but also to build a more resilient financial sector capable of adapting to changing economic and environmental conditions.

However, when juxtaposing Indonesia's climate-related financial policies with its rising CO2 emissions, a clear paradox emerges, where policy efforts appear misaligned with the country’s commitment to reducing carbon emissions. To understand the underlying causes of Indonesia's high carbon emissions, it is essential to consider several factors highlighted in the literature. One major contributor is Indonesia's heavy reliance on fossil fuels for energy production and transportation (Idroes, 2023). A significant portion of Indonesia's electricity is generated from coal (59.9%), gas (22.3%), and oil (6%), with renewable sources accounting for only 11.8% (Idroes, 2023). This dependence on fossil fuels, particularly coal, a major greenhouse gas emitter, plays a significant role in the country's high carbon emissions.

Furthermore, Indonesia's economic structure, dominated by resource-intensive industries, is another key factor driving high carbon emissions (Iskandar, 2019). The focus on sectors such as mining and manufacturing, which have substantial energy demands and large carbon footprints, contributes to the country’s elevated emissions levels. Transitioning to a more service-oriented economy and promoting the adoption of renewable energy sources are strategies that have been proposed to mitigate environmental degradation and reduce carbon emissions (Iskandar, 2019).

Additionally, rapid urbanization and population growth in cities like Jakarta, which has one of the highest CO2 emission levels in Indonesia, have exacerbated the country's carbon emissions (Azaria et al., 2018). The increasing number of vehicles, industrial activities, and energy consumption associated with urban areas significantly contribute to Indonesia's overall carbon footprint. Addressing these drivers of high carbon emissions in Indonesia requires a multi-faceted approach that includes transitioning to cleaner energy sources, encouraging sustainable economic practices, and implementing policies to reduce emissions from urban centers and industrial activities.

4.3 Step of data estimation

Embarking on a journey to uncover insights through panel data regression analysis begins with the meticulous process of downloading and arranging data. This involves gathering data from reliable and relevant sources, ensuring it is organized into a structured format such as CSV or Excel for seamless import into statistical software like R, Stata, or Python. Once the data is loaded, the next crucial step is data preparation. This involves cleaning the dataset to handle amissing values or outliers and ensuring consistency.

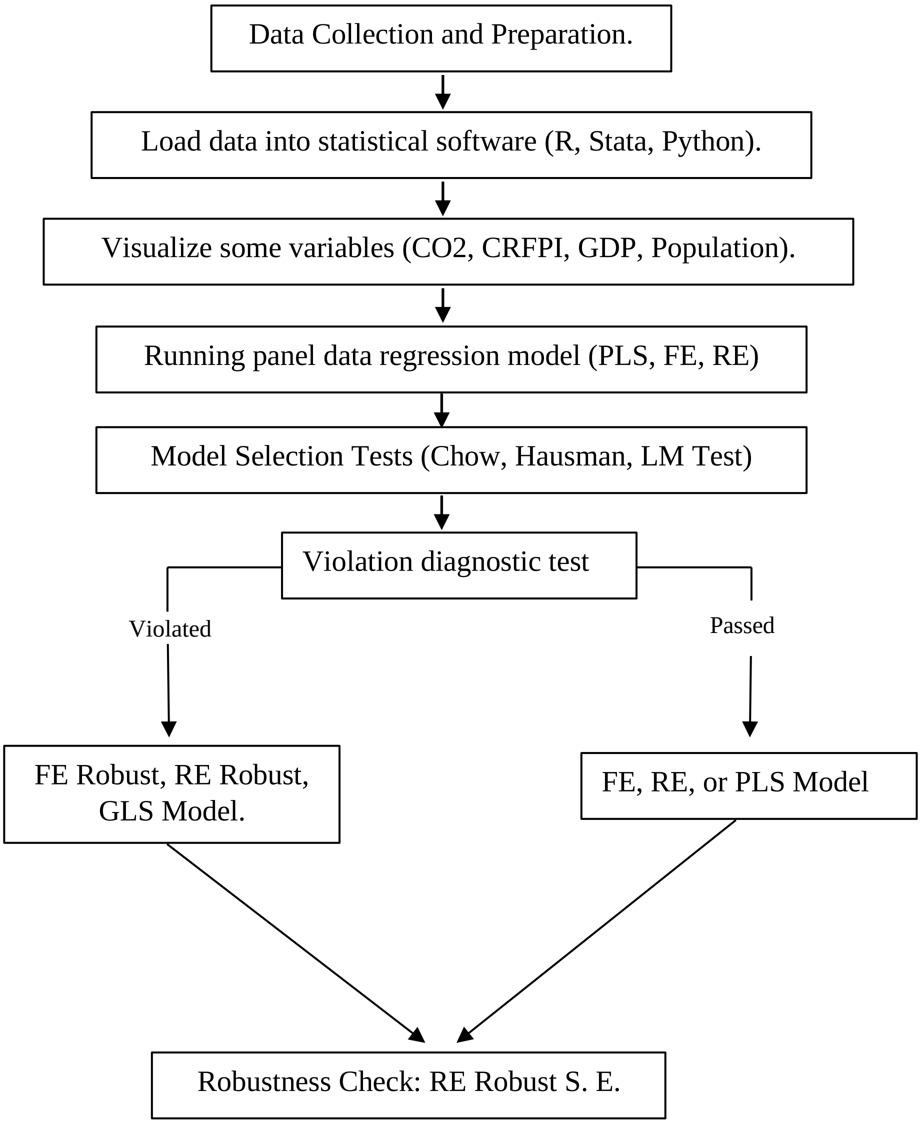


Figure 4.7 Flow of statistic estimation technique.
Source: Author creation.

With a well-prepared dataset, the focus shifts to understanding the data distribution through normality tests such as skewness and kurtosis. Visual tools like histograms and correlation plots play a pivotal role in this phase, offering a clear visual representation of data distribution. The core of the analysis lies in running various panel data regression models: Pooled Least Squares (PLS), Fixed Effects (FE), and Random Effects (RE). Each model offers unique insights, with PLS providing a baseline without individual effects, FE controlling for time-invariant characteristics, and RE assuming random variation across entities. The choice among these models is guided by rigorous selection tests, including the Chow, Hausman, and Lagrange Multiplier (LM) Test, each designed to pinpoint the most suitable model for the data.

The final phase of the analysis involves rigorous diagnostic tests to ensure the robustness of the selected model. Tests for multicollinearity using the correlation coefficient, heteroscedasticity via modified Wald-test, and autocorrelation through the Wooldridge test are essential to validate the assumptions of the regression models. Should any violations be detected, alternative models with robust standard errors, such as FE Robust RE Robust or GLS (Generalized Least Square), are employed to address these issues. A robustness check, including techniques like the Driscoll-Kraay standard errors, also ensures reliable findings and can withstand scrutiny. This comprehensive approach, from data collection to robustness checks, ensures that the insights derived from the panel data regression analysis are credible and actionable.

4.4 Violation diagnostic test

4.4.1 Normality

A normality test aims to evaluate whether a given dataset adheres to a normal distribution, a crucial assumption in various statistical analyses, including regression. Normality tests assess the symmetry of data points around the mean, with most observations concentrated near the center. Statistical methods for testing normality, such as the Jarque-Bera test, examine skewness and kurtosis to detect deviations from normality (Thadewald & Büning, 2007).

Table 4.8 Skewness and kurtosis normality test

Variable	**Obs**	**Skewness**	**kurtosis**	**Adj. chi Squared**	**Prob.**
Residuals	378	0.1712	0.0003	13.35	0.0013

Source: Author’s calculation in Stata.

The normality test results for the residuals show a skewness of 0.1712 and kurtosis of 0.0003, indicating leptokurtic distribution. The adjusted chi-squared statistic is 13.35 with a corresponding p-value of 0.0013. These values indicate a deviation from normality, as the low p-value (less than 0.05) suggests that the residuals are not normally distributed, rejecting the null hypothesis of normality.

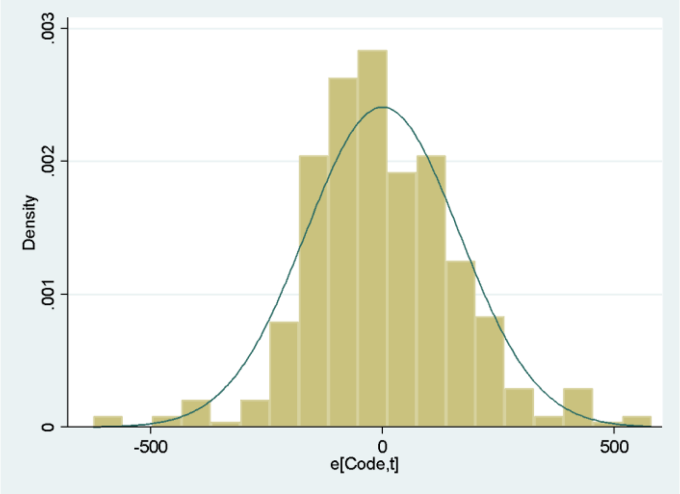


Figure 4.9 Normal distribution plot
Source: Author calculation in Stata.

The data do not pass normality tests, but it can still be effectively utilized in econometric analysis because many estimation techniques are robust against violations of the normality assumption. Techniques such as Generalized Least Squares (GLS) and robust standard errors are designed to address non-normality issues, providing consistent and efficient estimators. Wooldridge (2010) explains that these methods enable valid statistical inferences even when error terms deviate from a normal distribution, ensuring reliable results from panel data models despite non-normality.

4.4.2 Multicollinearity

The purpose of conducting a multicollinearity test using coefficient correlation is to evaluate the degree of correlation between independent variables in a regression model. Multicollinearity can result in inaccurate parameter estimates, reduced statistical power, and the exclusion of significant predictor variables during model creation (Graham, 2003).

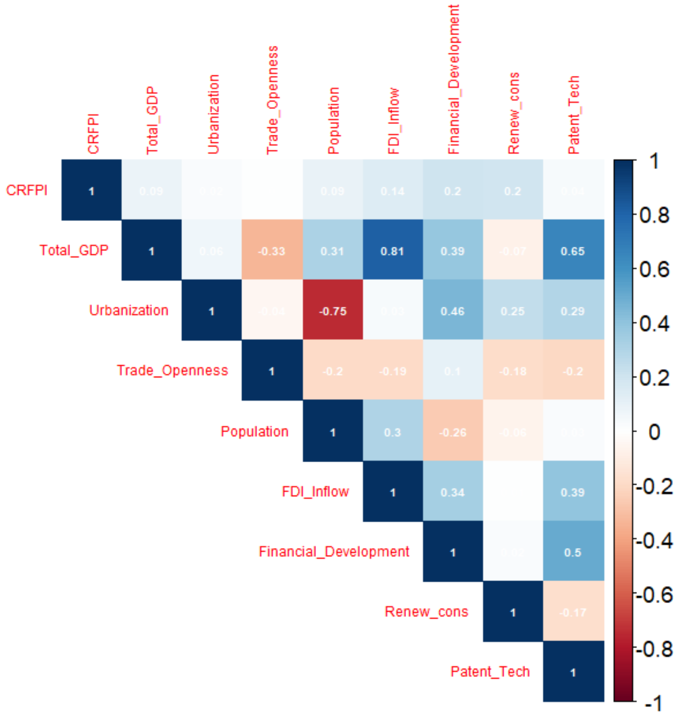


Figure 4.10 Correlation plot of independent variables
Source: Author's calculation in R.

Interpreting coefficient correlation in a multicollinearity test is crucial for understanding the relationships between independent variables in a regression model. The correlation coefficient between independent variables is a key indicator when assessing multicollinearity. While no strict threshold is universally agreed upon, some common guidelines exist in the literature.

One study suggests that a correlation coefficient above 0.7 may indicate the onset of severe distortion in model estimation and subsequent prediction due to collinearity (Dormann et al., 2012). Another research mentions that a correlation coefficient exceeding 0.9 may signal a multicollinearity problem, with potential issues even at coefficients above

0.8, while 0.6 is considered a baseline for an acceptable correlation coefficient (Sun et al., 2018).

It is essential to note that a higher correlation coefficient between two independent variables does not necessarily imply multicollinearity in the regression model. Multicollinearity arises from a high degree of linear dependence among multiple explanatory variables rather than just high pairwise correlations (Chen, 2023). Therefore, the context of the entire set of independent variables in the regression model should be considered when interpreting correlation coefficients.

4.4.3 Heteroscedasticity

Heteroscedasticity describes a condition in which the error variability or residuals in a regression model vary across different levels of the independent variables. Essentially, this means that the dispersion or spread of residuals changes with different predictor values. Such a condition breaches one of the core assumptions of classical linear regression, which presumes constant error variance, termed homoscedasticity. Detecting and addressing heteroscedasticity is crucial to maintaining the accuracy and dependability of regression analysis outcomes (Woolridge, 2010).

Table 4.11 Wald-test heteroscedasticity test

Chi^2	526.60
Prob > Chi^2	0.0000

Source: Author's calculation in Stata.

The Modified Wald test for groupwise heteroskedasticity in the fixed effect regression model evaluates if the error term variances are consistent across different groups. The null hypothesis posits that all groups' variances $\sigma i2$ are equal, indicating homoskedasticity. The test decisively rejects the null hypothesis at standard significance levels with a chi-squared statistic of 526.60 and a p-value of 0.0000. This outcome provides strong evidence of heteroskedasticity, suggesting that the variance of the error terms differs across groups in the model.

When regression results show heteroscedasticity, where error variance is inconsistent, Generalized Least Squares (GLS) effectively addresses this issue. GLS transforms the original model to stabilize the variance of error terms, yielding more efficient and unbiased parameter estimates than Ordinary Least Squares (OLS). As Greene

(2012) explains, GLS adjusts the estimation process to accommodate heteroscedasticity, enabling valid statistical inferences and enhancing the reliability of regression outcomes.

Additionally, an alternative approach is the use of random effects models in panel regression. These models are designed to consider unobserved individual-specific effects by assuming these effects are uncorrelated with the explanatory variables. This assumption enables random effects models to manage heteroscedasticity without requiring a separate heteroscedasticity test (Singla & Samanta, 2019). The random effects model inherently mitigates heteroscedasticity concerns by incorporating individual-specific effects that account for the variability associated with unobserved factors.

4.4.4 Autocorrelation

The Wooldridge test for autocorrelation in panel data tests the null hypothesis that there is no first-order autocorrelation in the data. In this case, the test statistic is an F-value of 50.999, and the corresponding p-value is 0.0000. Since the p-value is significantly less than the standard significance levels (e.g., 0.05 or 0.01), it rejects the null hypothesis. This result indicates strong evidence of first-order autocorrelation in the panel data, suggesting that the errors in the model are not independent across time for the same entity.

Table 4.12 Wooldridge autocorrelation test

F	50.999
Prob	0.0000

Source: Author’s calculation in Stata.

Generalized Least Squares (GLS) could effectively address autocorrelation in regression models by transforming the model to account for correlated errors, thereby providing more reliable parameter estimates. Ordinary Least Squares (OLS) estimates become inefficient in autocorrelation, resulting in biased standard errors and invalid statistical inferences. GLS corrects for autocorrelation by incorporating the error term's correlation structure into the estimation process, leading to more accurate and efficient estimates. Wooldridge (2010) highlighted that GLS is particularly beneficial in situations where errors exhibit serial correlation, enabling consistent and reliable inference.

4.4.5 Unit root test

Table 4.13 Panel unit root tests

Variable	CO2	GDP	CRFPI	Financial development	Population	Urbanization	Renewable energy	Patent in technology	FDI	Trade openness
Level										
Levin-lin-chu	-1.7559**	-4.0656***	3.4859	-3.0821***	-3.6137***	-26.1148***	10.8419	0.6866	-3.1543***	-2.6905***
First Difference										
Levin-lin-chu			-6.0319***				-1.9327**	12.8109		

*p < 0.10, ∗∗p < 0.05, ∗∗∗p < 0.01

In the next stage, the author assesses the stationary properties of all variables using the Levin-Lin-Chu test, the most commonly employed method for this analysis. **Table 4.12** shows the results of the panel unit root tests, revealing that the null hypothesis of a unit root cannot be rejected for CRFPI, renewable energy, and technology patent variables at the specified level. However, the null hypothesis for all variables at first differences can be nearly completely rejected at the 1% level. This suggests that the empirical analysis should utilize first-differenced variables to avoid potential bias in OLS estimates due to spurious relationships. While using first differences addresses this issue, it results in a loss of long-term relationships between variables. Moreover, regressing nonstationary data can produce spurious results. Therefore, the author employs various regression models, including fixed effects, random effects, PLS, and panel robust standard errors, to compare coefficients for significant deviations. If there are substantial differences, regression techniques can still provide consistent estimates despite the nonstationary data.

4.5 Empirical result of a regression model

4.5.1 PLS (Pooled-Least Square) regression

The Pooled Least Square (PLS) model is a statistical method used to analyze panel data, including multiple observations across time and entities. This approach aggregates the data, assuming individual differences across entities do not vary over time. The author applies the PLS model to investigate the relationship between total CO2 emissions and economic, technological, and demographic factors in this context.

Table 4.14 PLS regression result.

Total CO2	Coefficient	Std. error	t
CRFPI	-1.304203	1.817593	-0.72
Financial Development	-1769.298***	263.8329	-6.71
Total GDP	0.00102***	7.43e-11	13.78
GDP2	-3.23e-11***	3.33e-24	-9.71
Trade Openness	9.097796***	2.777996	3.27
FDI Inflow	-2.90e-10	9.57e-10	-0.30
Urbanization	32.27377***	5.235006	6.16
Population	2.899***	2.39e-07	12.10
Patent Tech	-.0338014***	.0044334	-7.62
Renewable Energy	-22.77184***	4.525441	-5.03
constant	-2492.843***	432.276	-5.77
R-squared		0.8850	
Adj. R squared		0.8819	

***(10%), **(5%), *(1%)

Source: Author’s calculation in Stata.

Our analysis focuses on Total CO2 Emissions, measured in Million tons, as the dependent variable. The author incorporated several independent variables in our model: CRFPI (Climate-Related Financial Policy Index) scores, financial development percentages, total GDP in million USD, trade openness percentages, FDI inflow in million USD, urbanization percentages, population size in Million, number of technology patents, and renewable energy consumption percentages. Additionally, the analysis includes the R-squared value to indicate the model's explanatory power. Starting with the CRFPI, it observes that an increase in this index correlates with a slight decrease in CO2 emissions, denoted by a coefficient of -1.30 million tons. However, this relationship lacks statistical significance, suggesting that variations in climate-related financial policies, as measured by this index, do not significantly impact CO2 emissions within the scope of our model.

Conversely, financial development is identified as a significant factor, with a coefficient of -1769.298, indicating that a 1% increase in financial development results in a notable reduction of CO2 emissions by approximately 1.769,3 Mt. This strong negative relationship emphasizes the potential of financial progress in mitigating environmental impacts. In contrast, total GDP exhibits a positive and significant effect on CO2 emissions, with a coefficient of 0.00102, suggesting a slight increase in emissions as the economy grows. Additionally, the quadratic term GDP2, with its negative coefficient, implies a non-linear relationship, indicating that at higher GDP levels, the rate of emission increases may decelerate. Trade openness, reflected as a percentage, also demonstrates a positive and significant impact on CO2 emissions, with a coefficient of 9.097796. This implies that a 1% increase in trade openness is linked to roughly 9.10 million tons in CO2 emissions, likely due to heightened industrial activity and transportation associated with more open trade.

Other factors in our model further elucidate the dynamics influencing CO2 emissions. Although showing a negative relationship with CO2 emissions, FDI inflow is not statistically significant, indicating that variations in foreign direct investments do not consistently impact emissions within our study's parameters. Urbanization presents a strong positive and significant correlation with CO2 emissions, where a 1% increase in urbanization leads to an increase of about 32.27 Mt in emissions, highlighting the environmental challenges of growing urban populations. Population growth also significantly affects CO2 emissions, with each additional 1 million population contributing approximately 2.899 Mt to emissions. While this figure appears minimal, it translates to a substantial rise in emissions considering large population increases. Technological advancements, represented by the number of technology patents, show a significant negative relationship with CO2 emissions, with each additional patent correlating to a reduction of about 0.0338 Mt in emissions. This underscores the role of innovation in reducing environmental impacts. Renewable energy consumption is another critical factor, with a coefficient of -22.77184, indicating that a 1% increase in renewable energy share significantly reduces CO2 emissions by approximately 22.77 Mt. Finally, the constant term of -2492.843, which is statistically significant, provides a baseline for CO2 emissions when all independent variables are zero.

The R-squared value of 0.8819 signifies that about 88.19% of the variability in CO2 emissions is explained by the independent variables in our model, suggesting a good fit. In summary, our Pooled Least Square model analysis reveals significant insights into the factors affecting CO2 emissions. Financial development and renewable energy consumption emerge as critical areas for policy intervention. Promoting financial development and increasing the share of renewable energy can substantially reduce CO2 emissions. Furthermore, urbanization and technological innovation play pivotal roles in shaping environmental outcomes, necessitating balanced and forward-looking policies to manage their impacts effectively.

4.5.2 Fixed effect model

The Fixed Effect (FE) panel regression model is a powerful statistical tool used to analyze data that spans multiple periods and entities, accounting for time-invariant characteristics unique to each entity. In this study, the author employs the FE model to investigate the impact of various economic, technological, and demographic factors on total CO2 emissions measured in Mt.

Table 4.15 FEM regression result.

Total_CO2	**Coefficient**	**Std. error**	**T**
CRFPI	-7.563537***	.6879052	-11.00
Financial_Development	-591.5837**	268.3841	-2.20
Total_GDP	0.00156***	3.87e-11	40.39
GDP2	-4.93e-11***	1.36e-24	-36.20
Trade_Openness	-3.851635	1.335223	-0.29
FDI_Inflow	0.000513**	2.31e-10	2.22
Urbanization	14.54366**	7.082442	2.05
Population	-1.217***	4.50e-07	-2.71
Patent_Tech	-.005187	.0038714	-1.34
Renewable_Energy	-27.79652***	4.496443	-6.18
constant	-1770.853***	409.9116	-4.32
R-squared (Overall)		0.5315	

***(1%), **(5%), *(1%)

Source: Author's calculation in Stata.

This study centers on Total CO2 Emissions as the dependent variable, exploring its relationship with several independent factors: the Climate-Related Financial Policy Index (CRFPI), financial development, total GDP, trade openness, FDI inflow, urbanization, population size, technology patents, and renewable energy consumption. The model achieves an R-squared value of 0.5315, indicating that these variables explain approximately 53.15% of the variance in CO2 emissions.

Analyzing the CRFPI, the first finding is a significant negative coefficient of -7.563537, suggesting that higher CRFPI scores correspond to substantial reductions in emissions. This underscores the efficacy of climate-related financial policies in mitigating environmental impacts, supported by its robust statistical significance at a 1% level. Similarly, financial development demonstrates a significant negative relationship by coefficient -591.5837, indicating that enhanced financial sector development correlates with lower CO2 emissions, likely due to increased investments in cleaner technologies.

Conversely, total GDP positively impacts CO2 emissions by 0.00156 Mt, illustrating that economic growth contributes to higher emissions. The quadratic term GDP2 further reveals a diminishing emission increase rate at higher GDP levels, reflecting a nuanced relationship between economic growth and environmental impact.

Exploring other factors, trade openness shows a negative yet insignificant association with emissions. At the same time, FDI inflow exhibits a positive and significant impact by 0.000513, indicating potential emissions rise from capital-intensive industries. Urbanization significantly increases emissions by 14.54366 Mt, highlighting urban growth’s environmental challenges, such as increased energy demand and industrial activities.

Despite a negative coefficient, population size significantly influences emissions within our model’s framework. Technological innovation, represented by patents, also demonstrates a non-significant effect on emissions, suggesting its potential but limited impact.

Finally, renewable energy consumption emerges as a potent factor, significantly reducing emissions of 27,8 Mt. This underscores its critical role in environmental mitigation efforts and its potential as a pivotal policy. At the same time, our model explains a substantial portion of CO2 emission variability; it acknowledges the complexity of factors influencing emissions. The findings emphasize the pivotal role of climate-related financial policies, renewable energy, and prudent economic strategies in achieving sustainable development goals, advocating for comprehensive policies that balance economic growth with environmental stewardship.

4.5.3 Random effect model

The random effects model used in this analysis of CO2 emissions provides insights into the impacts of various economic and policy-related factors across different entities. In this model, the dependent variable is Total CO2 emissions measured in Mt, and the independent variables include the Climate-Related Financial Policy Index (CRFPI), Financial Development, Total GDP, Trade Openness, FDI Inflows, Urbanization, Population, Patents in Technology, and Renewable Energy Consumption.

Table 4.16 REM regression result.

Total_CO2	**Coefficient**	**Std. error**	**Z**
CRFPI	-7.536545***	.7161377	-10.52
Financial Development	-562.0337**	273.2505	-2.06
Total GDP	0.001534***	4.01e-11	38.27
GDP2	-4.85e-11***	1.42e-24	-34.11
Trade Openness	-.7805893	1.389689	-0.56
FDI Inflow	0.000531**	2.42e-10	2.19
Urbanization	9.720904	6.806643	1.43
Population	-0.2825	3.96e-07	-0.71
Patent Tech	-0.0048507	.0039836	-1.22
Renewable Energy	-25.14766***	4.597808	-5.47
constant	-1606.628***	483.4946	-3.32
R-squared (Overall)		0.6384	

***(1%), **(5%), *(1%)

Source: Author's calculation in Stata.

The results indicate that the CRFPI significantly negatively affects CO2 emissions, with a one-unit increase in the CRFPI score leading to a decrease of approximately 7.54 Mt of CO2 emissions. This suggests that stronger climate-related financial policies are effective in reducing emissions. Similarly, Financial Development shows a significant negative relationship with CO2 emissions, where a one percentage point increase in financial development results in a reduction of about 562.03 Mt of emissions. These findings highlight the importance of financial structures in facilitating environmentally friendly practices.

Conversely, Total GDP has a significant positive effect on CO2 emissions. A 1 Million USD increase in Total GDP is associated with an increase of 0.00153 Mt of emissions, indicating that economic growth, while beneficial for prosperity, tends to increase environmental pollution. However, the squared term of GDP2 exhibits a significant negative effect, suggesting a non-linear relationship where the rate of increase in CO2 emissions diminishes as GDP grows. This could reflect economies of scale and improvements in efficiency as economies develop.

Despite having a negative coefficient, trade openness does not significantly affect CO2 emissions. This indicates that the degree of a country's integration into global trade markets does not substantially impact its CO2 emissions in this model. On the other hand, FDI Inflows significantly increase CO2 emissions, with a 1 Million USD increase in FDI inflows leading to an increase of 0.0005315 Mt of CO2 emissions. This suggests that foreign direct investments while fostering economic development, may also contribute to higher emissions due to increased industrial activity.

Although included in the model, urbanization, population, and patents in technology do not show statistically significant effects on CO2 emissions. This indicates that the direct impact of urbanization rates, population size, and technological patents on emissions needs to be clarified and may be influenced by other mediating factors not captured in this model.

Renewable Energy Consumption stands out as a significant factor in reducing CO2 emissions. A one percentage point increase in renewable energy consumption is associated with a reduction of approximately 25.15 Mt in CO2 emissions. This strong negative relationship underscores the crucial role of renewable energy sources in mitigating environmental pollution and promoting sustainable development.

The findings from the random effects model suggest that while economic growth and foreign investments drive up CO2 emissions, climate-related financial policies, financial development, and renewable energy consumption play significant roles in reducing emissions. Policymakers should consider these variables in designing strategies to balance economic development with environmental sustainability. The non-significant results for trade openness, urbanization, population, and patents in technology highlight the complexity of emissions determinants and the need for comprehensive approaches considering multiple interacting factors.

4.6 Selection model of regression.

4.6.1 Chow test

To determine the most suitable model for panel data analysis, adding a dummy variable allows for testing if different intercepts exist using the F statistic test. This test helps assess whether the Fixed Effect method's panel data regression technique is preferable to the panel data model regression without dummy variables, known as the Common Effect method.

The null hypothesis for this test posits that the intercepts are identical, implying that the Common Effect model is appropriate for panel data regression. The alternative hypothesis asserts that the intercepts differ, indicating that the Fixed Effect model is suitable for panel data regression.

The calculated F statistic adheres to the F distribution, with degrees of freedom determined by the number of restrictions (m) for the numerator and the number of observations minus the number of parameters (n – k) for the denominator. Here, "m" represents the number of restrictions in the model without dummy variables: the number of individuals minus one. The total number of observations (n) is the product of the number of individuals and periods. In contrast, the number of parameters in the Fixed Effect model (k) includes the number of variables plus the number of individuals. If the calculated F value exceeds the critical F value, the null hypothesis is rejected, indicating that the Fixed Effect model is appropriate for panel data regression. Conversely, if the calculated F value is less than the critical F value, the null hypothesis is accepted, favoring the Common Effect model for panel data regression (Iqbal, 2015).

Several tests need to be conducted to identify the best model for Total CO2 emissions. The first test is the Chow Test, which compares the Common Effect Model (CEM) and the Fixed Effect Model (FEM). According to **Appendix 7**, the Chow Test yields a probability (F-Count) of 0.000, less than the 0.005 threshold, indicating that the null hypothesis must be rejected. Thus, the appropriate model is the FEM.

4.6.2 Hausman test

The Hausman test is a crucial tool in panel data analysis. It allows researchers to determine the most appropriate model for their data: the fixed effects (FE) model or the random effects (RE) model. In this context, the author performed the Hausman test to analyze the relationship between various factors and total CO2 emissions.

Table 4.17 Hausman test result.

	Coefficients			
Variables	**(b) fixed**	**(B) random**	**(b-B) Difference**	**sqrt(diag(V_b-V_B)) Std.error**
CRFPI	-7.563537	-7.536545	-.0269919	.
Financial	-591.5837	-562.0337	-29.55002	.
Total_GDP	1.56e-09	1.53e-09	2.99e-11	.
GDP2	-4.93e-23	-4.85e-23	-8.11e-25	.
Trade_Open~s	-.3851635	-.7805893	.3954258	.
FDI_Inflow	5.13e-10	5.31e-10	-1.83e-11	.
Urbanization	14.54366	9.720904	4.822756	1.957188
Population	-1.22e-06	-2.83e-07	-9.34e-07	2.13e-07
Patent_Tech	-.005187	-.0048507	-.0003363	.
Renewable_~y	-27.79652	-25.14766	-2.648861	.

b = Consistent under H0 and Ha; obtained from xtreg.
B = Inconsistent under Ha, efficient under H0; obtained from xtreg.
Test of H0: Difference in coefficients not systematic
chi2 = 1.56
Prob > chi2 = 0.9062

Source: Author's calculation in Stata.

The Hausman test output presents the coefficients for both the fixed and random effects models, comparing how each model estimates the impact of variables. For instance, the Climate-Related Financial Policy Index (CRFPI) has a coefficient of -7.563537 under the fixed effects model and -7.536545 under the random effects model. These slight differences indicate minor discrepancies between the two models in estimating CRFPI's impact on CO2 emissions. The test also calculates the differences between these coefficients (b-B) and their standard errors, highlighting issues such as missing standard errors due to rank deficiencies in the variance matrix.

The chi-square test statistic from the Hausman test is 1.56, with a high p-value of 0.9062. This high p-value means the result fails to reject the null hypothesis, which posits that the differences in coefficients between the fixed and random effects models are not systematic. Consequently, this result suggests that the random effects model is appropriate for the data. The random effects model assumes that individual-specific effects are uncorrelated with the regressors, and the test confirms this assumption, indicating that the RE model is both consistent and efficient for estimating the impact of various factors on total CO2 emissions.

Choosing the random effects model offers several advantages, primarily its efficiency in using both within-group and between-group variations in the data, leading to more precise estimates. This is particularly beneficial for understanding the effects of financial development, total GDP, urbanization, and renewable energy consumption on CO2 emissions. The Hausman test thus provides clear guidance in selecting the appropriate model for panel data analysis, and the random effects model emerges as the preferred choice. This model will enable us to draw more efficient and consistent conclusions about the determinants of CO2 emissions, aiding in developing effective policies and strategies to reduce emissions and combat climate change.

4.6.3 Lagrange multiplier (LM) test

The Breusch and Pagan Lagrange Multiplier (LM) test is a fundamental statistical tool used in panel data analysis to decide whether to adopt a random effects model or stick with a simple ordinary least squares (OLS) regression. This decision is crucial as it determines how well the model can account for individual-specific variations in the data, which, in this case, involves the study of total CO2 emissions across different entities.

The LM test results provide detailed insights into the variances of different model components. The dependent variable under consideration is Total CO2 Emissions, and the model is structured as follows:

$$Total\_CO2 = Xb + \mu + e$$

In this equation, Xb represents the fixed part of the model, μ denotes the random effects specific to each entity (such as different countries), and e signifies the idiosyncratic error term.

The table presented in the output lists the variances and standard deviations of these components:

- Total_CO2 shows the overall variance of the dependent variable at 4881259, with a standard deviation of 2209.357.
- e, the idiosyncratic error term, has a variance of 29595.08 and a standard deviation of 172.032.
- μ, the random effects, shows a substantial variance of 1051697 with a standard deviation of 1025.523.

The critical aspect of the LM test involves the chi-square statistic and its corresponding p-value. In this case, the test statistic is chi2 = 2360.40. The LM test's null hypothesis (H0) posits that the variance of the random effects (Var(u)) is zero, implying that the OLS model is adequate because there are no significant individual-specific effects to consider. However, the p-value associated with this chi-square statistic is extremely low (Prob > chi2 = 0.0000), indicating strong evidence against the null hypothesis. Consequently, it rejects the null hypothesis, concluding that the variance of the random effects is significant. This result suggests that the random effects model is more appropriate than the OLS model for this data. Therefore, given the results of the LM test, it is evident that the random effects model is the better choice for analyzing the impact of various factors on total CO2 emissions.

Significant random effects in the data are evidenced by a high chi-square statistic and a very low p-value, indicating that unobserved heterogeneity factors across entities, such as different countries, significantly influence the dependent variable, Total CO2 Emissions. When random effects are significant, the random effects model is more efficient than the ordinary least squares (OLS) model. This efficiency arises because the random effects model captures both within-group and between-group variations, thus providing more precise and unbiased estimates by accounting for individual-specific variations. Incorporating random effects enhances the model's fit to the data, acknowledging that each entity may possess unique characteristics impacting the dependent variable. This improved fit is crucial for making valid inferences and reliable predictions.

The decision to use the random effects model stems directly from the empirical evidence from the LM test. The significant random effects detected by the test highlight the importance of accounting for individual-specific characteristics that remain constant over time but vary between entities. Ignoring these effects by using a simple OLS model would lead to biased and inconsistent estimates, undermining the reliability of the analysis.

The Breusch and Pagan Lagrangian Multiplier test strongly supports adopting the random effects model for this panel data analysis. This model effectively captures the individual-specific variations in total CO2 emissions, leading to more accurate and meaningful results. Consequently, the random effects model is the preferred choice for understanding the determinants of CO2 emissions across different entities, providing a robust framework for policy analysis and decision-making.

4.6.4 Regression comparative analysis

Table 4.10 presents the outcomes from fixed effect (FE), random effect (RE), and pooled least square (PLS) regressions. Analyzing these regression results necessitates a deep understanding of econometrics to compare the values of each coefficient and standard error, determining which are unbiased and which are more efficient. Standard error and coefficient estimation are vital elements in regression analysis, providing insights into the reliability and significance of the estimated coefficients. The standard error indicates the variability or uncertainty associated with the coefficient estimates; a smaller standard error implies a more precise or efficient estimate of the coefficient, while a larger standard error suggests greater uncertainty in the estimation (Arellano & Bond, 1991).

In regression analysis, coefficient estimates indicate the strength and direction of the relationship between independent and dependent variables. A highly significant coefficient denotes a strong relationship between the variables, whereas a non-significant coefficient implies that the variable may not significantly impact the outcome (Anandasayanan, 2018).

The unbiasedness of coefficient estimates is crucial to ensure that the estimated coefficients accurately reflect the true population parameters. Unbiased estimates do not systematically overestimate or underestimate the true values. Conversely, efficiency in coefficient estimation pertains to the precision of the estimates. More efficient estimators have smaller standard errors, yielding more reliable and precise coefficient estimates (Arellano & Bond, 1991).

Table 4.18 Comparative regression result.

Variable	FE	RE	PLS
CRFPI	-7.5635369*** (.6879052)	-7.536545*** (.7161377)	-1.3042034 (1.817593)
Financial Development	-591.58369** (268.3841)	-562.03367** (273.2505)	-1769.2978*** (263.8329)
Renewable Energy	-27.796524*** (4.496443)	-25.147664*** (4.597808)	-22.771843*** (4.525441)
Total GDP	1.565e-09*** (3.87e-11)	1.535e-09*** (4.01e-11)	1.024e-09*** (7.43e-11)
Total GDP2	-4.931e-23*** (1.36e-24)	-4.850e-23*** (1.42e-24)	-3.230e-23*** (3.33e-24)
Trade Openness	-.38516348 (1.335223)	-.78058932 (1.389689)	9.097796** (2.777996)
FDI Inflow	5.132e-10** (2.31e-10)	5.315e-10** (2.42e-10)	-2.897e-10 (9.57e-10)
Urbanization	14.543659** (7.082442)	9.7209037 (6.806643)	32.273766*** (5.235006)
Population	-1.217e-06*** (4.50e-07)	-2.826e-07 (3.96e-07)	2.893e-06*** (2.39e-07)
Patent Tech	-.00518701 (.0038714)	-.00485071 (.0039836)	-.03380139*** (.0044334)
Constant	-1770.8526*** (409.9116)	-1606.6283*** (483.4946)	-2492.8432*** (432.276)
Legend: * p<0.1;p<0.05**;p<001***;std.error()			

Source: Author's calculation in Stata.

When the Hausman test suggests using the Random Effects (RE) model, despite higher standard errors in the RE model compared to the Fixed Effects (FE) model, several considerations must be made to select the most appropriate model regarding unbiasedness and efficiency. In structural testing to choose the best model between random effect and fixed effect through the Hausman test, the random effect model is the preferred estimation when entity-specific effects are not correlated with the independent variables. In this scenario, the RE model is generally considered more efficient as it utilizes both within-group and between-group variation in the data. This efficiency implies that the model provides more accurate parameter estimates with smaller variance, resulting in more reliable outcomes.

4.7 Discussion of the empirical result

4.7.1 The effect of financial policy on CO2 emissions

Firstly, most of the regression outcomes indicate that adopting climate-focused financial policies significantly reduces CO2 emissions, suggesting that such policies enhance environmental quality within G20 countries. These findings underscore the crucial role of financial policies aligned with climate goals and the more immediate impact of climate mitigation strategies. In achieving green transformation, there remains a substantial constraint on environmentally friendly financial resources. Furthermore, green technology investments demand considerable and long-term funding, highlighting the necessity for green-oriented financial policies.

The empirical evidence of this research reveals that the Climate-Related Financial Policy Index (CRFPI), encompassing five key indicators such as green prudential regulation, green financial principles, other disclosure requirements, green bond taxonomy, and green credit allocation, exerts a significantly negative impact on the reduction of total CO2 emissions at 1% level of significance. Increasing one point in the CRFPI can reduce CO2 emissions by 7.53 Mt. This indicates that climate-focused financial policies can be crucial in mitigating the negative environmental impacts associated with economic growth.

It is commonly known that green prudential policies are relatively new policy instruments but are worth considering, especially since they usually fall within the scope of central banks. These policies involve regulatory measures encouraging environmentally friendly practices within the financial sector to tackle climate-related risks and promote sustainable development. Through such policies, central banks can advance green finance and incorporate sustainability goals into their policy frameworks to maintain macro-financial stability. By embedding climate-related risks into core policy implementation frameworks, central banks can significantly contribute to reducing the impacts of climate change (Dikau & Volz, 2021). Furthermore, reducing capital requirements on bank loans to green sectors through their Capital Cyclical Buffer (CCyB) can enhance efforts to mitigate climate change. However, broadly applying climate-friendly prudential policies may be less effective due to the varying carbon intensities across different activities (Krogstrup & Oman, 2019).

Green prudential policies, particularly the strategy of green quantitative easing (QE), leverage monetary policy tools to support environmentally friendly initiatives. Although green QE programs can help reduce global warming, they are insufficient to prevent severe climate change, highlighting the need for a comprehensive array of environmental policies and strategies (Bernal-Ramírez & Ocampo, 2020). To establish a credible green financial system and prevent "greenwashing" within the financial industry, integrating climate-related financial policies, such as disclosure requirements for climate risks and green investments, is essential (D'Orazio & Dirks, 2021).

By developing frameworks that include climate transparency disclosures, climate capital requirements, and stress tests related to climate risks, financial institutions can better manage the impacts of climate change on their operations (Nkwaira & Poll, 2023). Green prudential policies can significantly contribute to climate change mitigation by promoting sustainable practices within the financial sector, incorporating climate-related risks into regulatory frameworks, and supporting green investments. By aligning financial regulations with environmental objectives, central banks, and policymakers can play a crucial role in fostering a more sustainable economy.

Additionally, green financial principles as part of the instruments in CRFPI are essential in establishing a green financial market that can effectively aid in mitigating climate change. Financial regulators and institutions can steer the transition towards sustainable practices by utilizing green financial instruments like green bonds. Green bonds are specifically tailored to fund climate-friendly projects such as renewable energy, energy efficiency, pollution control, sustainable management, clean transportation, and eco-efficient products. These instruments offer investors a way to back environmentally friendly initiatives while anticipating measurable economic returns, thereby encouraging investments that help combat climate change (Fu & Ng, 2021).

Moreover, the disclosure of environmental, social, and governance (ESG) information by companies enhances transparency and accountability, compelling firms to take responsibility for the environmental impacts of their operations. Pressure from stakeholders such as investors and consumers to adhere to higher ESG standards drives the adoption of more eco-friendly practices, ultimately leading to a significant decrease in CO2 emissions. This transformation of financial systems not only supports sustainable development but also assists in bridging the climate financing gap by mobilizing substantial financial resources from both the public and private sectors.

Green bond taxonomy and green credit allocation also significantly reduce CO2 emissions. The green bond taxonomy provides clear classifications and standards, ensuring that funds raised are used for sustainable projects, thereby increasing investor confidence and the number of projects funded. By offering more favorable loans for environmentally friendly projects, green credit allocation motivates companies and individuals to invest in green technologies and sustainable practices. The findings of this study demonstrate that financial policies integrated with environmental goals can be effective tools in the global effort to reduce CO2 emissions and mitigate climate change, thereby supporting overall sustainable development.

Green bonds and green credit allocation play a crucial role in influencing CO2 emissions through various mechanisms. Research indicates that green credit, which encompasses environmental regulations and economic incentives, can significantly enhance total factor CO2 emissions performance (TFCEP) (Cao & Niu, 2022). Green bonds help reduce greenhouse gas emissions by funding projects that decrease energy consumption and support cleaner products, as well as by motivating companies to improve their environmental practices (Bukvić et al., 2023). The influence of green credit on corporate CO2 emissions intensity is considerable, with key channels including the optimization of energy consumption structures, upgrading of industrial structures, and suppression of investment carbon intensity (Li, 2023). Additionally, green credit has been shown to reduce carbon intensity by encouraging industrial upgrades, fostering technological innovation, and creating signaling effects, thus contributing to emission reduction targets (Hu & Zheng, 2021). These findings underscore the vital role of green bonds and green credit in promoting emissions reductions and facilitating a shift toward a more sustainable and environmentally friendly economic system.

Some empirical findings support that financial development can drive the adoption of energy-efficient technologies, leading to lower CO2 emissions (Boutabba, 2014). Specific policies, such as those promoting digital financial inclusion, have been shown to reduce emissions significantly (Zhao et al., 2021). Empirical evidence from China highlights that green financial policy, like green credit, effectively channel financial resources into environmentally friendly investments and innovations, thus reducing emissions (Qin, 2022). Similarly, the synergy between CO2 emissions trading and green financial instruments underscores the vital role of financial mechanisms in mitigating environmental impacts (Yu, 2024). Studies by Wang & Yi (2022) and Xing et al. further emphasize the potential of financial sector development to anchor CO2 emissions reductions by allocating resources towards eco-friendly technologies. Collectively, these findings illustrate that integrating financial strategies with environmental objectives is crucial for meaningful progress in combating climate change and promoting sustainable development.

4.7.2 The effect of financial development on CO2 emissions

The effect of our indicator for financial development on CO2 emissions is negative at a 5% significance level. This result confirms that an increase in financial development contributes to improving environmental quality, aligning with research indicating the positive role of financial development in decreasing environmental degradation.

The regression result indicating that a 0.01 increase in financial development significantly reduces CO2 emissions by 562 Mt highlights a crucial link between financial markets and environmental sustainability. This relationship can be explained through several mechanisms. Enhanced financial development typically leads to better access to capital for businesses and individuals, promoting investments in cleaner technologies and energy-efficient processes. Through their lending and investment policies, financial institutions can incentivize firms to adopt sustainable practices and transition towards greener operations.

Moreover, developed financial markets often have robust regulatory frameworks encouraging transparency and corporate social responsibility, pressuring companies to minimize their carbon footprint. This result suggests that policies aimed at strengthening financial systems support economic growth and play a vital role in environmental protection. It underscores the importance of integrating financial development strategies with environmental policies to achieve sustainable development goals. As financial markets evolve, their potential to drive significant reductions in CO2 emissions becomes an essential consideration for policymakers aiming to balance economic and environmental objectives.

This discovery is consistent with numerous studies exploring the link between financial development and CO2 emissions. Shahbaz et al. (2018) identified a detrimental influence of financial development on CO2 emissions, indicating that advancements in financial systems typically lead to a reduction in CO2 emissions. This conclusion is corroborated by Shobande & Ogbeifun (2021), who also observed a negative correlation between financial development and CO2 emissions in a study of 97 countries. Conversely, Yao & Zhang (2021) reported differing results, highlighting that although clean energy consumption mitigates CO2 emissions, the development of the financial sector in China exacerbates them.

The impact of financial development on CO2 emissions varies across regions and countries. Sun (2022) demonstrated that the effect of financial development on CO2 emissions is non-linear and dependent on economic development and foreign trade levels. Huang & Guo (2022) decomposed financial development into financial scale and structure, revealing a negative correlation between financial development and CO2 emissions. Ren-Zhong et al. (2022) found that the relationship between financial development and CO2 emissions in China follows an inverted U-shape in some regions.

The literature suggests that factors such as technological innovation and structural optimization influence the relationship between financial development and CO2 emissions. Liu & Liu (2021) highlighted that financial development reduces the intensity of CO2 emissions through technological innovation and structural optimization. This indicates that the mechanisms through which financial development affects CO2 emissions are multifaceted and involve the financial sector, technological advancements, and structural changes. Overall, the literature underscores the importance of considering various factors and regional contexts when examining the impact of financial development on CO2 emissions.

Research has consistently explored how financial development correlates with CO2 emissions, with Shahbaz et al. (2018) observing a decrease in emissions as financial systems mature. This was echoed by Shobande & Ogbeifun (2021) in their study of 97 countries. Yet, Yao & Zhang (2021) found that while clean energy use lowers emissions, financial sector growth in China raises them. This suggests regional and national variations in this dynamic, as Sun (2022) noted, the non-linear relationship between financial development and emissions, influenced by economic development and foreign trade. Huang & Guo (2022) further dissected financial development into scale and structure, finding a negative correlation with emissions. Ren-Zhong et al. (2022) identified an inverted U-shape relationship in some Chinese regions. The complexity deepens when considering factors like technological innovation and structural optimization, as Liu & Liu (2021) highlighted the reduction of emissions intensity through these avenues. These studies collectively emphasize the importance of a multifaceted and context-specific approach to understanding the impact of financial development on CO2 emissions.

4.7.3 The effect of total GDP and GDP2 on CO2 emissions

The squared term—introduced to capture the non-linear effects of economic growth on CO2 emissions—is negative, proving the EKC's existence, as discussed in the "Literature review" section. The regression results show the impact of GDP and GDP squared (GDP2) on CO2 emissions, providing insights into the Environmental Kuznets Curve (EKC) hypothesis. The coefficient for GDP is 0.00000000156, or it can be simplified where an increase by 1 million USD of GDP, aligning with increase in CO2 emissions by 1.53 Mt, while the coefficient for GDP2 is -4.85e-23 (-4.85e-15/GDP in million USD), This finding indicate strong evidence that GDP and GDP2 have significant impacts on CO2 emissions.

The positive coefficient for GDP suggests that, initially, CO2 emissions also increase as GDP increases. This aligns with the first phase of the EKC theory, where economic growth leads to higher pollution levels due to increased industrial activity and energy consumption. However, the negative coefficient for GDP2 implies that as GDP grows, the increase in CO2 emissions slows down and eventually becomes negative. This reflects the second phase of the EKC theory, where further economic growth reduces pollution levels. This phase occurs because higher income levels typically result in greater demand for cleaner technologies, stricter environmental regulations, and more investments in sustainable practices.

The turning point of the EKC, where CO2 emissions start to decline as GDP increases, can be estimated from these coefficients. This turning point occurs when the marginal effect of GDP on CO2 emissions equals zero, which happens when GDP reaches a level where the negative effect of GDP2 exactly offsets the positive effect of GDP. The regression coefficients support the EKC hypothesis, indicating that economic growth initially exacerbates environmental degradation but eventually contributes to environmental improvements once a certain income level is achieved.

Various studies explore the complex relationship between GDP and CO2 emissions, focusing on the quadratic effect of GDP. The Environmental Kuznets Curve theory suggests an inverted U-shaped relationship, indicating that initial economic growth leads to increased emissions, but further growth may reduce them. Wu (2023) supports this with findings of a positive correlation between GDP and CO2 emissions, suggesting that higher GDP can mitigate emissions. Dhillon & Kaur (2023) emphasize the need to include GDP squared to understand both linear and non-linear impacts on emissions, addressing multicollinearity. Naseem et al. (2021) also proposed a long-term negative link between GDP and emissions, driven by advancements in low-carbon technologies, highlighting the potential for sustainable growth decoupled from emissions. These findings underscore the necessity for nuanced policies balancing economic development with environmental sustainability.

The results suggest that policymakers should promote sustainable economic growth that facilitates the transition to cleaner technologies and stronger environmental regulations. This dual approach can help countries move along the EKC trajectory, achieving economic development and environmental sustainability.

4.7.4 The effect of trade openness on CO2 emissions

Trade openness, defined as the degree to which a country participates in international trade, is frequently quantified by the ratio of the sum of exports and imports to GDP. This metric is pivotal in understanding trade policies' broader economic and environmental implications. Empirical analysis reveals insignificance relationship between trade openness and CO2 emissions.

The lack of a significant impact of trade openness on CO2 emissions in G20 countries may be attributed to several factors. Firstly, the G20 countries exhibit considerable diversity in their levels of industrialization, energy sources, and environmental policies. This variation implies that while some nations might implement strict regulations that reduce emissions, others may rely heavily on fossil fuels, thereby offsetting the potential benefits of increased trade openness. Furthermore, the extent of environmental technology transfer and the promotion of cleaner production practices through trade can differ greatly among these countries. As a result, aggregated data might obscure the more nuanced effects observed within individual nations.

This outcome suggests that merely increasing trade openness is unlikely to lead to substantial changes in CO2 emissions across the G20. It indicates that policy measures must be customized to fit specific national contexts. For example, countries with weaker environmental regulations may require more robust frameworks to leverage trade for environmental benefits effectively. Additionally, international cooperation aimed at sustainable trade practices and technology transfer is essential to ensure that trade openness has a positive impact on environmental outcomes. This finding emphasizes the complexity of the trade-environment relationship and the need for targeted policies and collaborative efforts.

However, in other studies, the impact of trade openness on CO2 emissions varies across different economic contexts. For instance, Wang and Zhang (2021) observed that trade openness led to reduced CO2 emissions in high-income and upper-middle-income countries but did not significantly affect lower-middle-income countries and increased emissions in low-income countries. This heterogeneity suggests that a country's economic status influences the effects of trade openness on CO2 emissions. Similarly, Mignamissi (2023) reported a positive correlation between trade openness and CO2 emissions, suggesting that increased trade could lead to higher CO2 emissions in certain contexts.

Conversely, other studies highlight the potential for trade openness to reduce CO2 emissions. Khan et al. (2021) noted that while trade openness directly increased emissions, it indirectly reduced them through its positive effect on per capita income, negatively impacting CO2 emissions. Safdar et al. (2020) also found that trade openness significantly decreased carbon dioxide emissions, supporting the argument that trade liberalization may help mitigate environmental degradation. The contrasting findings, such as Ye et al. (2021), which show differing impacts in developed countries and China, respectively, underscore the complexity of this relationship. These discrepancies highlight the importance of considering specific economic and policy contexts when assessing the environmental implications of trade openness.

4.7.5 The effect of foreign direct investment (FDI) on CO2 emissions

This study delves into the intricate relationship between Foreign Direct Investment (FDI) and CO2 emissions within G20 countries. The regression analysis indicates a positive correlation, with FDI contributing to an increase in CO2 emissions quantified at 5.31e-10 Mt per USD. A significant portion of FDI targets capital-intensive sectors such as manufacturing, energy, and mining—industries notorious for their substantial carbon footprints. These investments boost production capacities, which in turn elevate emissions. Additionally, FDI frequently funds large-scale infrastructure projects, which, while critical for economic growth, are resource-intensive and emit considerable amounts of carbon dioxide during construction and operational phases. These sectors, combined with the transfer of technology—often outdated and less environmentally friendly due to weaker regulations in host countries—compound the environmental impact of FDI. This mixed impact highlights the necessity for stringent environmental standards to effectively manage these investments' influx.

Higher FDI inflows spur economic growth, increasing energy consumption and CO2 emissions. As G20 countries develop, their demand for energy-intensive goods and services escalates. FDI promotes urbanization, leading to more construction activities and heightened energy demands in urban centers. These changes collectively contribute to the rising CO2 emissions associated with increased FDI. Furthermore, the regulatory environment plays a crucial role in this dynamic. The stringency of environmental regulations varies significantly across G20 countries, and nations with less stringent standards may attract more FDI at the cost of higher CO2 emissions as firms exploit weaker regulatory frameworks to reduce operational costs. Thus, there is a critical need for robust environmental regulations to mitigate these adverse effects and ensure that economic development does not come at the expense of environmental health.

Several studies provide evidence supporting the notion that Foreign Direct Investment (FDI) can have varying impacts on CO2 emissions. For instance, Abdul-Mumuni et al. (2022) found that FDI significantly positively affects CO2 emissions in sub-Saharan Africa, indicating that increased FDI leads to higher CO2 emissions (Huang et al., 2022). Similarly, Opoku et al. explored the effects of FDI inflows on CO2 emissions in sub-Saharan African countries. They concluded that FDI flows robustly impact CO2 emissions reductions, aligning with the pollution halo hypothesis. Additionally, it studied the effects of FDI on CO2 emissions in ASEAN-5 countries. It found that FDI can help mitigate CO2 emissions in high-emission countries, supporting the idea that FDI may act as a pollution control mechanism in certain regions (Tang et al., 2022). Moreover, it validated the Pollution Haven Hypothesis (PHH) by showing that increasing CO2 emissions can attract FDI due to relatively low regulatory standards, potentially increasing overall CO2 emissions (Terzi & Pata, 2020). This indicates that the relationship between FDI and CO2 emissions is complex and can vary depending on regulatory standards and regional contexts. Overall, the literature reviewed provides insights into the multifaceted impacts of FDI on CO2 emissions, emphasizing the importance of considering various factors when assessing the environmental consequences of foreign investments.

Given these findings, policymakers must take decisive action to address the environmental impacts of FDI. Strengthening environmental regulations and implementing stricter emissions standards are essential steps. Governments should also provide incentives for green investments, encouraging foreign investors to adopt environmentally sustainable practices. Aligning FDI with Sustainable Development Goals (SDGs), particularly those related to climate action (Goal 13) and sustainable industrialization (Goal 9), is vital for ensuring that economic progress is sustainable. International collaboration is equally important; harmonizing environmental standards through international agreements and frameworks can prevent a "race to the bottom" in environmental practices. Continuous monitoring and research are necessary to understand the evolving dynamics between FDI and CO2 emissions, facilitating the development of data-driven policies. By enforcing stringent environmental regulations, promoting green technologies, and enhancing international cooperation, G20 countries can attract FDI while minimizing their carbon footprint and fostering sustainable economic growth that benefits both the economy and the environment.

4.7.6 The effect of urbanization, population and patent in technology on CO2 emissions

In the analysis of CO2 emissions across G20 countries, the regression results revealed unexpected outcomes. Contrary to common beliefs, urbanization, population growth, and technology patents showed minimal significant effects on CO2 emissions. This surprising result highlights the need for a more nuanced investigation into the complex environmental dynamics present in these economically diverse nations.

CO2 emissions are influenced by a web of interconnected factors. While urbanization and population growth are often viewed as major contributors to environmental degradation, their direct effects may be overshadowed by other crucial elements. Factors such as industrial composition, energy consumption patterns, governmental policies, and the level of economic development all play significant roles in shaping emissions. The complexity of these interactions can dilute the apparent influence of urbanization and population growth, rendering their effects statistically insignificant in the regression model.

Technological progress, as indicated by patents, presents a more intricate picture. Although patents signify technological advancement, they do not always translate into immediate or widespread adoption of environmentally friendly practices. Many patents remain theoretical or are not effectively commercialized, and those that are may not directly address emissions reduction. Additionally, patents cover a broad range of fields, including those unrelated to CO2 emissions, such as medical innovations or software, which further diminishes their measurable impact on environmental outcomes.

The environmental impact of urbanization is highly context-dependent. Well-planned urban areas can benefit from efficient public transportation systems and lower per capita energy consumption, potentially reducing emissions. Conversely, poorly managed urbanization can exacerbate issues like traffic congestion and inefficient energy use. Consequently, the overall impact of urbanization on CO2 emissions can be ambiguous, which may explain its lack of significance in the regression results.

Population growth does not consistently lead to increased CO2 emissions. Its effects can be moderated by factors such as consumption patterns, energy efficiency, and economic structure. In more developed G20 countries, higher population levels often coincide with stringent environmental regulations and advanced technologies that mitigate emissions. This interaction can neutralize the expected direct relationship between population growth and CO2 emissions.

Given the high variance and complexity among G20 countries, the fixed effect regression results must also be considered when analyzing the impact of urbanization and population growth on CO2 emissions. The Fixed Effects Model (FEM) indicates that a one percent increase in urbanization is associated with an increase in CO2 emissions by 14.54 Mt, underscoring a significant environmental impact. This finding supports economic theories of urbanization, which propose that as urban areas grow, there is an escalation in economic activities, industrial production, and vehicular traffic. These activities, driven by the demand for energy, transportation, and goods, are major contributors to CO2 emissions. Consequently, urban areas, while being centers of economic development and innovation, also become focal points of environmental stress due to this increased demand. Supporting this, various studies have demonstrated the significant impact of urbanization on CO2 emissions. For example, Li et al. (2016) and Chang et al. (2022) both find a correlation between higher urbanization levels and increased greenhouse gas emissions, while Yang et al. (2023) show a positive relationship between urban density and CO2 emissions. These findings align with our regression results, highlighting that as urbanization increases, so does the environmental burden from higher emissions.

Additionally, urban transport is identified as a major contributor to cities' greenhouse gas emissions, as Ni’Am et al. (2021) noted. This emphasizes the interconnectedness of urbanization and CO2 emissions, where the transportation systems within urban areas play a vital role in contributing to the overall carbon footprint. Urban areas are recognized as major sources of greenhouse gas emissions (Kennedy et al., 2009; Kosovac, 2023), further emphasizing the importance of understanding the relationship between urbanization and CO2 emissions. This relationship highlights the necessity for sustainable urban planning to mitigate the impact of urbanization on CO2 emissions. Strategies such as incorporating green spaces and promoting compact, transit-oriented development (Guerra, 2011) are essential for counterbalancing the CO2 emissions associated with urbanization. In conclusion, the regression analysis and supporting literature collectively highlight the significant environmental impact of urbanization on CO2 emissions, underscoring the urgent need for integrated urban planning strategies that prioritize sustainability to address the increasing carbon footprint of growing urban areas in G20 countries.

Urbanization typically leads to higher energy consumption as cities grow and infrastructure expands. The construction of buildings, roads, and other facilities requires significant energy and resources, resulting in higher carbon outputs. Additionally, urban areas tend to have higher concentrations of industries and services, which, while boosting economic productivity, also elevate pollution levels. The transportation sector in urbanized regions, characterized by dense traffic and extensive use of fossil fuels, further exacerbates CO2 emissions. This suggests that urban growth in G20 countries could only continue to have substantial environmental repercussions with effective policies and technologies to reduce the carbon footprint.

The implications of this result are multifaceted. Economically, it highlights a critical challenge for policymakers balancing urban growth with environmental sustainability. The positive relationship between urbanization and CO2 emissions calls for integrated urban planning strategies prioritizing green infrastructure, renewable energy sources, and sustainable public transportation systems. It also emphasizes the need for international cooperation among G20 countries to develop and implement best practices for reducing urban carbon footprints. As these nations are among the world's largest economies and emitters, their policies and actions can significantly influence global CO2 emissions. Thus, the research findings serve as a crucial reminder of the environmental costs of urbanization and the urgent need for sustainable urban development practices.

The FEM model also shows significant results regarding the impact of population growth on CO2 emissions. The finding that a one-person increase in population results in a decrease in CO2 emissions by 1.217e-06 Mt within G20 countries is both intriguing and counterintuitive. Typically, larger populations are linked with higher CO2 emissions due to greater resource demand, energy use, and economic activity. However, the negative coefficient in these results indicates a more complex dynamic specific to G20 countries. This result challenges traditional assumptions and suggests that advanced technologies, stringent regulations, and efficiency improvements in these countries may effectively counterbalance the environmental impact of population growth. This underscores the intricate relationship between population size and CO2 emissions, highlighting the necessity for detailed analyses that factor in demographic changes and environmental policies.

Research on the impact of population size on CO2 emissions reveals a multifaceted relationship influenced by various factors. Wu et al. (2021) highlight that population movement in China can potentially reduce CO2 emissions growth, indicating the role of migration patterns and demographic shifts in shaping emissions trajectories. Conversely, studies by Rao et al. (2023) and Wen & Zhang (2020) suggest that larger populations generally increase CO2 emissions, aligning with the conventional understanding that larger populations drive higher demands for resources and energy.

Furthermore, the influence of population structure, including age demographics and changes in population composition, further complicates this relationship. Chai (2024) suggests an aging population might decrease emissions due to reduced economic activity and energy consumption among older demographics. In contrast, Tong et al. (2018) and Liddle & Lung (2010) link overall population growth to higher energy consumption and emissions, underscoring the environmental challenges associated with demographic shifts. Moreover, the role of population dynamics in urbanization and economic development significantly impacts CO2 emissions. Studies by Sun (2018) and Zhao et al. (2021) emphasize how population growth drives urban expansion and economic activities, contributing to elevated CO2 emissions. These findings collectively highlight the importance of adopting nuanced approaches in addressing the environmental impacts of population dynamics and integrating demographic trends with effective environmental policies to achieve sustainable development goals.

One possible explanation for this unexpected result could lie in the advanced technological and policy measures adopted by G20 countries. These nations are often at the forefront of implementing stringent environmental regulations, promoting renewable energy, and enhancing energy efficiency. As populations grow, these measures may become more effective per capita. For instance, larger populations could lead to more concentrated urban areas where public transportation and efficient waste management systems are more viable, reducing per capita carbon footprint. Additionally, increased population density can spur innovation and economies of scale in green technologies, further mitigating the impact of population growth on emissions.

Moreover, this result could imply that the G20 countries are experiencing a decoupling of economic growth and CO2 emissions, a phenomenon where economic development continues without a corresponding increase in environmental degradation. As these countries invest in sustainable infrastructure and shift towards service-oriented economies, the relationship between population growth and CO2 emissions might follow different patterns observed in less developed regions. This suggests that the G20 countries are on a path towards sustainable development, where economic activities and population growth do not necessarily lead to higher CO2 emissions but contribute to a more efficient and environmentally conscious economy.

These findings have important implications for policymakers and researchers. Policymakers should acknowledge the complexity of CO2 emissions and avoid oversimplified solutions. Effective policies should integrate energy efficiency, sustainable industrial practices, and comprehensive environmental regulations. Future research should explore additional variables and interactions to better understand CO2 emissions determinants, including energy mix, effectiveness of environmental regulations, and socio-economic factors.

Furthermore, the practical deployment and scaling of eco-friendly technologies must be emphasized. Governments and industries need to work together to ensure that technological innovations are not only patented but also successfully implemented to reduce emissions. Urban planning should aim at developing smart cities with efficient public transportation, green spaces, and energy-efficient buildings to minimize the environmental impact of urbanization.

4.7.7 The impact of renewable energy consumption on CO2 emissions

The findings from this study reveal a significant inverse relationship between renewable energy consumption and CO2 emissions across G20 countries. Specifically, each percentage point increase in the share of renewable energy in primary energy consumption is associated with a reduction of approximately 25 Mt of CO2 emissions. This underscores the critical role of renewable energy sources in combating climate change by reducing reliance on fossil fuels, the primary contributors to greenhouse gas emissions.

The evidence synthesized from multiple studies underscores the significant role of renewable energy consumption in reducing CO2 emissions. Research by Sinha & Shahbaz (2018), Liu et al. (2022), and Koengkan & Fuinhas (2018) consistently demonstrates that integrating renewable energy sources substantially decreases CO2 emissions. Moreover, Erdoğan et al. (2023) emphasized that renewable energy diminishes CO2 emissions and supports the transition towards carbon neutrality goals. Shen et al. (2023) further highlight that renewable energy adoption effectively curbs the growth of CO2 emissions intensity in specific regions. These findings underscore the critical importance of promoting renewable energy initiatives as a cornerstone in advancing sustainable environmental practices and combating climate change.

From an economic standpoint, this relationship can be explained by both the substitution effect and technological advancements. As nations transition towards renewable sources such as wind, solar, and hydroelectric power, they diminish their dependence on coal, oil, and natural gas. Renewable technologies are increasingly cost-competitive due to advancements and economies of scale, offering lower marginal costs once infrastructure is established. This economic shift mitigates external costs linked to CO2 emissions, such as health impacts and environmental degradation, and fosters new industries and job opportunities, promoting sustainable economic growth.

These findings have significant implications for policymakers in G20 countries. The substantial reduction in CO2 emissions associated with increased renewable energy consumption underscores the urgency of investing in renewable energy infrastructure and supporting policies that facilitate the transition from fossil fuels. Such measures could encompass subsidies for renewable projects, carbon pricing mechanisms, and regulations promoting energy efficiency. Moreover, given the substantial global carbon footprint of G20 countries, their leadership in adopting and promoting renewable energy can set a precedent for global climate change mitigation efforts. In summary, this research provides compelling evidence that expanding renewable energy consumption is feasible and an effective strategy for achieving substantial reductions in CO2 emissions, thereby advancing global sustainability objectives.

4.8 The existence of pandemic covid-19 on empirical result

Table 4.19 Regression result of dummy variable of pandemic covid-19

Total_CO2	Coefficient	Std. err.	z	P-value
D2020	87.0917	51.63804	1.69	0.092
CRFPI	-7.696195	.7202336	-10.69	0.000
Financial_Development	-615.1661	274.3102	-2.24	0.025
GDP	.001535	.00004	38.39	0.000
GDP2	-4.87e-11	1.42e-12	-34.26	0.000
Trade_Openness	-.505656	1.39498	-0.36	0.717
FDI	.0005688	.0002426	2.34	0.019
Urbanization	9.407369	6.792678	1.38	0.166
PopulationM	-.3095588	.3954615	-0.78	0.434
Patent_Tech	-.0028863	.0041391	-0.70	0.486
Renewable_Energy	-27.16161	4.735495	-5.74	0.000
_cons	-1556.455	483.6482	-3.22	0.001

In the regression model used, the D2020 variable serves as a dummy variable to capture the specific impact of the year 2020, marked by the COVID-19 pandemic, on total CO2 emissions. The year 2020 was an exceptionally unique period in global economic history, as the pandemic caused significant disruptions across various sectors, including industry, transportation, and energy. Governments worldwide implemented lockdowns, travel restrictions, and temporary shutdowns of many economic activities in an effort to curb the spread of the virus.

Theoretically, these measures should have led to a substantial reduction in CO2 emissions due to the decreased industrial activity and human mobility, which are major contributors to carbon emissions. With factory closures, reduced production capacity, and a sharp decline in transportation use, initial expectations might have pointed towards a significant drop in CO2 emissions during 2020. However, the regression results indicate a different outcome.

The positive coefficient for D2020, amounting to 87.091, suggests that despite the pandemic and the associated economic downturn, there was an increase in predicted total CO2 emissions by 87.091 units in 2020 compared to previous years. This finding indicates that although most economic activities declined, other factors contributed to the rise in carbon emissions during this period.

Several factors may explain this outcome, including increased household energy consumption due to remote work, the use of more energy-intensive household appliances, or higher emissions from sectors that did not experience significant reductions in activity. Additionally, the pandemic may have forced some countries to delay or cancel their green initiatives, such as the transition to renewable energy, ultimately increasing reliance on fossil fuel-based energy sources.

Overall, these results underscore the complexity of the COVID-19 pandemic’s impact on CO2 emissions. While the pandemic was generally expected to lower emissions due to reduced economic activity, the reality shows that indirect factors and anomalies in energy consumption patterns can lead to unexpected outcomes. Therefore, further analysis is crucial to identify the specific factors driving the increase in carbon emissions during 2020. This understanding is essential to fully grasp the pandemic's environmental impact and to formulate more effective policies in the future.

4.9 The effect of CRFPI on CO2 emissions by sectors

To provide a comprehensive understanding of the relationship between financial polcy represents by CRFPI and CO2 emissions, this study analyzes the influence of CRFPI and socioeconomic factors across five primary sectors: buildings, industries, land use and forestry, fuel combustion, transportation, manufacturing and construction, and electricity and heat. The findings reveal that the CRFPI exerts a significant negative impact on CO2 emissions in all sectors, indicating that improvements in managing carbon risks, as reflected by higher CRFPI values, are associated with substantial reductions in emissions.

The electricity and heat sector demonstrates the most considerable reduction in emissions, with a decrease of 4.7 Mtnes (Mt) for each one-point increase in the CRFPI. This significant impact can be attributed to the sector's reliance on fossil fuels and its substantial potential for efficiency improvements and renewable energy adoption. Policies promoting investment in clean energy technologies and stricter emission regulations further enhance the effectiveness of the CRFPI in this sector.

In the manufacturing and construction sector, notable emission reductions are observed. This sector's responsiveness can be linked to advancements in energy efficiency, cleaner production processes, and sustainable construction practices. Economic incentives and regulatory pressures associated with the CRFPI encourage firms to innovate and reduce their carbon footprint.

The land use and forestry sector also experiences significant emission reductions, reflecting the importance of sustainable land management practices. Initiatives such as reforestation, sustainable agriculture, and habitat protection contribute to the positive response to higher CRFPI values. These practices not only reduce emissions but also enhance carbon sequestration, providing dual benefits for the environment.

The industrial sector shows a moderate yet significant reduction in emissions with increasing CRFPI. This can be attributed to improvements in industrial processes, energy efficiency measures, and the adoption of low-carbon technologies. The economic implications of the CRFPI motivate industries to invest in cleaner technologies and practices, thereby reducing their carbon footprint.

While the transportation sector shows a reduction in emissions, it is to a lesser extent compared to the previously mentioned sectors. The sector's high dependence on fossil fuels and slower adoption of electric vehicles and alternative fuels contribute to the relatively smaller impact. However, improvements in fuel efficiency, public transportation systems, and urban planning still contribute to the overall emission reductions in this sector.

The buildings sector, encompassing residential and commercial buildings, also benefits from increased CRFPI values. Energy-efficient building designs, retrofitting existing structures, and the use of renewable energy sources such as solar panels contribute to emission reductions in this sector. Economic incentives linked to the CRFPI encourage homeowners and businesses to adopt sustainable practices.

Lastly, the fuel combustion sector shows the least reduction in emissions, indicating the challenges associated with decarbonizing this sector. The inherent reliance on fossil fuels for energy generation poses significant hurdles. However, advancements in carbon capture and storage (CCS) technologies and shifts towards cleaner fuels can gradually enhance the sector's response to higher CRFPI values.

Overall, this analysis underscores the varying impacts of the CRFPI on different sectors and highlights the importance of tailored policies and measures to maximize CO2 emissions reductions. By incentivizing financial performance in managing carbon risks, the CRFPI plays a crucial role in driving sustainable practices and reducing the overall carbon footprint across sectors. Continued innovation, regulatory support, and investment in clean technologies are essential to achieve comprehensive and sustained reductions in CO2 emissions.

Table 4.20 FEM regression result in various emissions sectors.

	Building	**Industry**	**Land forestation**	**Fuel combustion**	**Transportation**	**Manufacture & Construction**	**Electricity & heat**
Independent Variable	**Coefficient**						
CRFPI	-0.487***	-0.609***	-1.789***	-0.132***	-0.509***	-2.262***	-4.700***
Financial Development	24.741	-19.217	-972.096***	16.7299**	48.201	-209.930*	7.302943
Total GDP	0.000052***	0.0001022***	-0.00014***	0.0000174***	0.0001105***	0.0004317***	0.0007135***
GDP2	-1.79***	-2.88e-18***	4.66e-12***	-5.76e-13***	-3.51e-12***	-1.36e-11***	-2.39e-11***
Trade Openness	-0.362***	-0.127	0.2917	0.118***	-1061015***	0.706907	-2.135102***
FDI Inflow	-0.0000406**	0.0000397**	-0.0001251	0.000023***	0.0000477	.0004838***	0.0000864
Urbanization	-0.732	0.562	27.0446***	-0.296	-1.073444	1.03262	4.116455
Population	0.0278	-0.1016***	0.5047*	0.03796***	0.3139***	-0.4489**	-0.2561129
Patent in Technology	-0.000283	-0.0009185***	0.00160	-000513***	0.00186***	-0.00826***	0.00789***
Renewable Energy	0.0489634	-3.53e-09	1.67e-07	1.29e-08	8.193-09	3.10e-07	-1.34e-07
constant	67.18995**	-145.1681***	-1181.42***	-9.008461	30.46355	195.2682**	-956.013***

4.9.1 Research contribution

A framework: The role of central bank and financial supervisory board in mitigating green financial risk

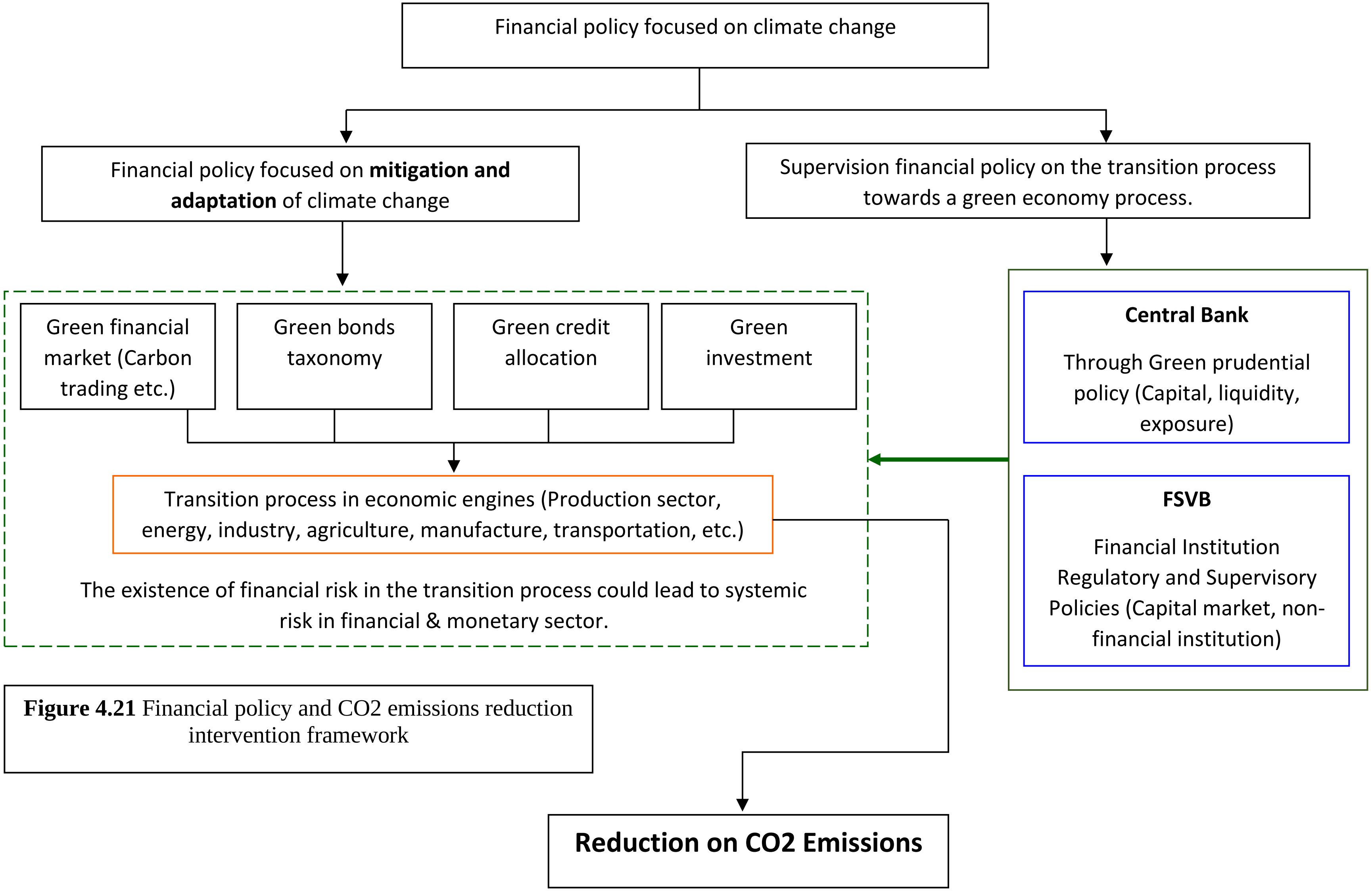


Figure 4.21 Financial policy and CO2 emissions reduction intervention framework

The above framework illustrates how financial policy indirectly impacts the reduction of CO2 emissions. Based on the comprehensive discussion in this study, the author concludes that empirical results show financial policies generally have a negative and significant effect on reducing CO2 emissions. Therefore, financial policies need to be considered for their indirect impacts as well.

Through the framework above, the author aims to provide a different perspective on the types of policies that should be implemented to address climate change risks. The first type is financial policies that are active and aligned with climate change mitigation and adaptation missions. The second type is financial policies that focus on monitoring and preventing crisis risks in the financial sector caused by the transition from brown to greener business models.

For instance, Indonesia is quite active in generating climate-related financial policies, such as through the Financial Service Authority (OJK) with green bonds, sustainability bonds, and sustainability-linked bonds as regulated in POJK No.18/2023 on the Issuance and Requirements for Debt Securities and Sukuk Based on Sustainability. This policy aims to mitigate the impact of climate change by directing development projects towards more environmentally friendly and sustainability-oriented sectors, such as renewable energy. Additionally, other policies, such as OJK Regulation Number 14 of 2023 (POJK No.14/2023) on Carbon Trading through Carbon Trade (POJK Carbon Trade), also encourage markets and companies to transition and adjust their operational activities to align with sustainability principles. The final policy example is POJK No.17/2023 on Governance Implementation for Commercial Banks (POJK Governance), where governance is fundamental in managing a bank's business activities to develop healthily and sustainably. One of the instruments used is conducting stress testing on capital adequacy through detailed and forward-looking carbon footprint calculations.

These policies not only drive the economic sector to transform but also, through banking risk management via climate stress tests, push the business sector to transition and require capital, whether through investment or loans. Alongside this, there is an inherent risk, namely the risk of default when an industry fails in the transition process, which could have repercussions on the financial sector. If this escalates to a systemic risk level, it could potentially lead to the worst-case scenario of a social crisis.

The author recommends expanding financial policies under the central bank and the Financial Supervisory Board to oversee the transition process involving financial capital. These two types of financial policies complement each other to ensure the economic transition not only proceeds smoothly and meets CO2 reduction targets but also does not create new financial risks, which could be more detrimental.

4.9.2 Robustness Check

Table 4.22 Robustness check

	I	**II**	**III**
Independent Variable		**Coefficient**	
CRFPI	-9.231491***	-9.161377***	-7.545048***
Financial Development	-122.8104	-147.2491	-566.3636
Total GDP	1.54e-09***	1.52e-09***	1.52e-09***
GDP2	-4.89e-23***	-4.88e-23***	-4.82e-23***
Trade Openness		-3.036343	-1.070154
FDI Inflow		6.85e-10	5.62e-10
Urbanization			9.008557
Population			-2.26e-07
Renewable energy			-24.17648**
constant	-1520.091***	-1348.91***	-1565.622*

To gain further insight into this research question, the author run three additional specifications of the model and check the robustness of the empirical research findings. Specification I is a more restricted model and does not consider socioeconomic dimensions such as trade openness, FDI inflow, urbanization, population and renewable energy. Specification II also considers socioeconomic variables (trade openness & FDI inflow) and III is a more flexible model by including three important factors namely urbanization, population, and renewable energy. The results are reported in **table 4.18**.

Based on the robustness check results, the author notes that the results regarding the role of climate-related financial policy have not changed. The coefficient shows a negative sign with a significance level of 1%. However, the author notes that in this case, the coefficient is higher for specifications I and II compared to the baseline results described in the "Empirical Results and Discussion" section.

CHAPTER V

CONCLUSION AND IMPLICATION

5.1 Conclusion.

Financial and socio-economic policies significantly affect G20 CO2 emissions, as this study shows. This study is based on the IPCC consensus at COP 26 and the Paris Agreement, which aim to limit global temperature rise to below 2°C and to 1.5°C above pre-industrial levels by 2050. Since the G20, which includes 19 countries and the EU, represents 85% of global GDP, 75% of international trade, and two-thirds of the world's population, the conversations are crucial. Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Turkey, the UK, and the US are G20 members. The European Commission and European Central Bank represent the European Union.

Investing heavily in the energy sector to transition from a brown economy to a green economy is necessary to achieve this goal. This study examines how climate change-related financial policies affect CO2 emissions reduction and control variables like Total GDP, Foreign Direct Investment (FDI), Trade Openness, Urbanization, Population, Patents in Technology, and Renewable Energy Consumption.

This study used panel random effects regression model estimation to examine 2000–2020 data from 18 G20 countries. Environmentally friendly financial policies such as green prudential, financial principles, disclosure regulations, bond taxonomy, and credit allocation rules significantly reduce CO2 emissions in all models. The results strongly suggest that well-structured financial policies reduce CO2 emissions and improve environmental quality. Buildings, industry, land use, transportation, manufacturing and construction, and power and heat are high-emission sectors. Therefore, robustness strengthens this conclusion.

The study found that total GDP increases CO2 emissions by 1.53e-09 Mt, demonstrating that economic growth naturally increases emissions. In the quadratic GDP term, emissions increase less at greater GDP levels, suggesting that economic maturity may encourage more sustainable practices. Given the industry's emissions-intensive nature, FDI inflows contribute 5.315e-10 Mt to emissions while trade openness, urbanization, population, and technology patents do not show significant impacts. Specifically, renewable energy consumption reduced emissions by 25.14 Mt, demonstrating the transformative potential of clean energy adoption.

The G20 determines global economic policy and addresses financial stability, international commerce, sustainable development, and climate change. The G20 helps maintain a stable, resilient, and sustainable global economy by promoting cooperation among major economies. Securing a brighter future requires the G20's collaborative actions and policies on CO2 emissions. G20 policies are crucial to global climate change and environmental sustainability due to their significant GDP and emission shares.

The study highlights that strategic finance policies with socio-economic elements are essential to global CO2 emissions reduction and green economy transition. G20 countries' large GDP and emission shares are crucial to this transformation. Their initiatives are crucial to meeting the Paris Agreement's climate targets and creating a more stable and resilient global environment. With this research, governments may create and implement effective financial and socio-economic solutions to mitigate climate change. This study proves that climate-related finance policies work and that socio-economic elements are crucial to CO2 emissions reduction measures. Results show that global sustainable development and environmental conservation require sustained international cooperation and policy innovation.

5.2 Suggestion and policy recommendation.

5.2.1 Shifting to a green economy.

Transitioning from a brown to a green economy requires massive energy sector investment. Governments should emphasize renewable energy investment with subsidies, tax incentives, and grants to expedite the switch from fossil fuels to renewable energy sources like solar, wind, and hydropower. Supporting green technology R&D improves efficiency and lowers prices, making renewable energy more affordable. Removing fossil fuel subsidies and shifting cash to renewable energy efforts can accelerate this transition.

5.2.2 Implementing climate-related financial policies.

Climate-related financial policy broadly encompasses five key policy components: green prudential policy, green financial principles, green bonds, other disclosure requirements, and green credit allocation. The institutions responsible for issuing these policies, such as central banks, governments, and financial supervisory boards, vary across countries. Each policy also possesses its own distinct instruments. For instance, climate stress tests (CRSTs) assess the resilience of financial institutions to climate-related risks; lending limits impose restrictions on the amount that banks can lend to carbon-intensive industries; green bonds are debt securities issued to finance environmentally sustainable projects; and disclosure requirements mandate that both financial and non-financial institutions (e.g., pension funds and insurance companies) provide transparency on their climate-related exposures and activities. These policies can serve as alternatives for policymakers aiming to fulfill funding targets in their climate change mitigation and adaptation efforts. Furthermore, such policies can facilitate the growth and penetration of the renewable energy sector and green technology.

5.2.3 Addressing socio-economic dimensions that affect CO2 emissions.

Several control variables significantly impact CO2 emissions and require targeted strategies for effective management. Total GDP growth can be steered towards sustainability by encouraging industries to adopt energy-efficient and low-carbon technologies. Implementing a carbon tax or cap-and-trade system can further motivate industries to reduce their CO2 emissions. Similarly, attracting Foreign Direct Investment (FDI) with green technology incentives ensures that incoming capital supports environmentally responsible projects. Requiring comprehensive environmental studies for FDI projects helps minimize their carbon footprint.

Trade openness also plays a crucial role in CO2 emissions, necessitating the integration of environmental protection measures and green technology exchanges into trade strategies. Implementing carbon border adjustments can prevent carbon leakage and promote emission reductions among trading partners. Urban carbon footprints can be significantly reduced through public transit, green buildings, and smart city technologies, while urban green spaces mitigate the environmental impact of urbanization. Furthermore, promoting energy-efficient appliances, public transportation, and waste reduction in densely populated areas can lower per capita emissions, with educational initiatives fostering sustainable living practices.

5.2.4 Sector-specific policies for high-emitting sectors.

Carbon reduction initiatives must target high-emitting sectors. Energy efficiency criteria for new buildings and energy-efficient technology upgrades for existing structures are crucial in the building sector. Enforcing rules and promoting clean technologies can lower industrial emissions. Afforestation and sustainable agriculture boost land use carbon sequestration. Public transportation, electric car infrastructure, and transportation emissions reduction regulations are crucial. Encourage green materials and sustainable construction to reduce production and construction emissions. Coal and other fossil fuels must be replaced with renewable energy for power and heating.

5.2.5 Enhancing G20 collaboration on climate action.

Effective climate action requires G20 cooperation. The Paris Agreement is strengthened by strengthening international accords and ensuring G20 countries meet emissions reduction targets. A platform for G20 countries to share best practices, technologies, and carbon reduction plans enables technology and knowledge sharing. Through co-financing, increase financial support for climate change programs in underdeveloped and vulnerable nations.

5.2.6 Sustainable international cooperation and policy innovation.

Global CO2 emissions reductions require sustained international cooperation and policy innovation. Establish or expand a global climate fund to fund mitigation and adaptation measures. Create global innovation centers for green technology development. Review and update climate policies with new scientific and technological insights to ensure sustainability. G20 countries may reduce global CO2 emissions, promote sustainable development, and meet Paris Agreement commitments by implementing these policies.

5.2.7 Limitation of research.

I. The lack of specific data within each policy area that constitutes the CRFPI presents a challenge in assessing the specific effects of each type of policy on CO2 emissions. Consequently, the policy recommendations provided are general in nature.

II. Data scope and period: Only 18 of the 20 G20 countries were studied from 2000 to 2020. Due to frequent technology and policy changes, this narrow scope may reflect a partial influence of financial and socio-economic policies on CO2 emissions.

III. Variable Selection and Measurement: This study considers Total GDP, FDI, Trade Openness, Urbanization, Population, Patents in Technology, and Renewable Energy Consumption, but not political stability, regulatory enforcement, cultural factors, or public awareness. Additionally, these variables may be measured and accurate differently between countries, affecting results reliability.

IV. Sectoral and Regional Heterogeneity: This study includes high-emitting emissions from buildings, industries, land use, transportation, manufacturing, and thermal power. The influence of financial policy on CO2 emissions in these industries and across G20 regions is not differentiated. Further sectoral and regional studies may reveal the efficacy of these policies.

These constraints indicate opportunities for additional research on financial policy and CO2 emissions reductions.

REFERENCES

Abbasi, K. R., Shahbaz, M., Jiao, Z., & Tufail, M. (2021). How energy consumption, industrial growth, urbanization, and CO2 emissions affect economic growth in Pakistan? A novel dynamic ARDL simulations approach. Energy, 221, 119793.

Abdel-Sadeq, S. (2023). A review study on the effects of using renewable energy on carbon dioxide emissions in china. Zagazig Journal of Agricultural Research, 50(4), 505-513.

Abdul-Mumuni, A., Mensah, B., & Fosu, R. (2022). Asymmetric effect of renewable energy consumption and economic growth on environmental degradation in sub-saharan africa. International Journal of Energy Sector Management, 17(5), 1013-1033.

Acemoğlu, D., Autor, D., Dorn, D., Hanson, G., & Price, B. (2016). Import competition and the great us employment sag of the 2000s. Journal of Labor Economics, 34(S1), S141-S198.

Acheampong, A. O. (2019). Modelling for insight: does financial development improve environmental quality?. *Energy Economics, 83*, 156-179.

Adamowicz, M. (2022). A green concept of economic growth and development. Economic and Regional Studies / Studia Ekonomiczne I Regionalne, 15(2), 158-180.

Adams, S., Adedoyin, F., Olaniran, E., & Bekun, F. (2020). Energy consumption, economic policy uncertainty and CO2 emissions; causality evidence from resource rich economies. Economic Analysis and Policy, 68, 179-190.

Adebayo, T. S., Akinsola, G. D., Kirikkaleli, D., Bekun, F. V., Umarbeyli, S., & Osemeahon, O. S. (2021). Economic performance of Indonesia amidst CO2 emissions and agriculture: A time series analysis. Environmental Science and Pollution Research, 28, 47942–47956.

Adjei-Mantey, K., & Adams, S. (2023). Renewable energy, foreign direct investment and carbon dioxide emissions: do sectoral value additions and policy uncertainty matter?. *Energy Nexus*, *10*, 100193.

Ahn, S. C., & Low, S. (1996). A reformulation of the Hausman test for regression models with pooled cross-section-time-series data. *Journal of Econometrics*, *71*(1-2), 309-319.

Aichele, R. (2013). The effect of the kyoto protocol on carbon emissions. Journal of Policy Analysis and Management, 32(4), 731-757.

Ajide, K. and Mesagan, E. (2022). Heterogeneous analysis of pollution abatement via renewable and non-renewable energy: lessons from investment in g20 nations. Environmental Science and Pollution Research, 29(24), 36533-36546.

Aldy, J., Barrett, S., & Stavins, R. (2003). Thirteen plus one: a comparison of global climate policy architectures. SSRN Electronic Journal.

Alexandraki, C. (2016). Strengthening accountability in climate finance: an agenda for change. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2836848

Alharthi, M., Doğan, E., & Taşkın, D. (2021). Analysis of co2 emissions and energy consumption by sources in mena countries: evidence from quantile regressions. Environmental Science and Pollution Research, 28(29), 38901-38908.

Ali, Y. (2015). Measuring CO2 emission linkages with the hypothetical extraction method (HEM). Ecological Indicators, 54, 171–183.

Almer, C. and Winkler, R. (2017). Analyzing the effectiveness of international environmental policies: the case of the kyoto protocol. Journal of Environmental Economics and Management, 82, 125-151.

Alnafisah, N. (2024). Assessing the impacts of technological innovation on CO2 emissions in mena countries: application of the innovation curve theory. Energies, 17(4), 904.

An, B., Liu, W., Tsering-Xiao, B., Li, C., & Xiao, Y. (2022). Energy and air? the impact of energy efficiency improvement on air quality in china.

Anandasayanan, S. (2018). Stock return predictability with financial ratios: an empirical study of listed manufacturing companies in sri lanka. International Journal of Accounting and Financial Reporting, 8(4), 471.

Andersson, JJ (2019). Pajak Karbon dan Emisi CO_2: Swedia sebagai Studi Kasus. *Jurnal Ekonomi Amerika: Kebijakan Ekonomi*, *11*(4), 1–30.

Arbulú, I., Lozano, J., & Rey-Maquieira, J. (2016). Waste generation flows and tourism growth: a stirpat model for mallorca. Journal of Industrial Ecology, 21(2), 272-281.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: monte carlo evidence and an application to employment equations. The Review of Economic Studies, 58(2), 277.

Armstrong, J. H., Nisi, A. C., & Millard-Ball, A. (2022). A disciplinary divide in the framing of urbanization’s environmental impacts. *Conservation Science and Practice*, *4*(3), e624.

Arranz, N., Arroyabe, M., Li, J., & Arróyabe, J. (2020). Innovation as a driver of eco-innovation in the firm: an approach from the dynamic capabilities theory. Business Strategy and the Environment, 29(3), 1494-1503.

ASLAN, A., DOGAN, E. and ALTINOZ, B., 2019. Single-Country Versus MultipleCountry Studies. In: Özcan, B. and Öztürk, I. eds. Environmental Kuznets curve (EKC): a manual. Academic Press, pp.25-36.

Aubrecht, G. (1988). Trace gases, co2, climate, and the greenhouse effect. the Physics Teacher, 26(3), 145-152.

Aung, T., Saboori, B., & Rasoulinezhad, E. (2017). Economic growth and environmental pollution in myanmar: an analysis of environmental kuznets curve. Environmental Science and Pollution Research, 24(25), 20487-20501.

Aye, G. (2017). Effect of economic growth on co2 emission in developing countries: evidence from a dynamic panel threshold model. Cogent Economics & Finance, 5(1), 1379239.

Azaria, L., Wibowo, A., & Shidiq, I. (2018). Carbon sequestration capability analysis of urban green space using geospatial data. E3s Web of Conferences, 73, 03009.

Aziz, A. A., Mustapha, N. H. N., & Ismail, R. (2013). Factors affecting energy demand in developing countries: A dynamic panel analysis. International Journal of Energy Economics and Policy, 3, 1–6.

Baah, C., Afum, E., Agyabeng-Mensah, Y., & Agyeman, D. (2021). Stakeholder influence on adoption of circular economy principles: measuring implications for satisfaction and green legitimacy. Circular Economy and Sustainability, 2(1), 91-111.

Babiker, M., Reilly, J., & Jacoby, H. (2000). The kyoto protocol and developing countries. Energy Policy, 28(8), 525-536.

Bakhsh, K., Rose, S., Ali, M. F., Ahmad, N., & Shahbaz, M. (2017). Economic growth, CO2 emissions, renewable waste and FDI relation in Pakistan: New evidences from 3SLS. *Journal of environmental management*, *196*, 627-632.

Ball, E. V., Wang, S. L., Nehring, R., & Mosheim, R. (2016). Productivity and economic growth in U.S. agriculture: A new look. *Applied Economic Perspectives and Policy*, 38(1), 30–49. https://doi.org/10.1093/aepp/ppv031

Baltagi, B. H. (1995). Editors Introduction Panel Data.

Bank of England – Prudential Regulation Authority (BoE-PRA). (2021). Climate-related financial risk management and the role of capital requirements. _Climate Change Adaptation Report 2021_ – October 2021. Technical report.

Bao, Q., Chen, Y., & Song, L. (2011). Foreign direct investment and environmental pollution in China: a simultaneous equations estimation. *Environment and Development Economics*, *16*(1), 71-92.

Barua, A., & Khataniar, B. (2016). Strong or weak sustainability: A case study of emerging Asia. *Asia-Pacific Development Journal*, *22*(1), 1-31.

based on nighttime lighting data. Polish Journal of Environmental Studies, 33(3), 3183-3192.

Becker, W., Saisana, M., Paruolo, P., & Vandecasteele, I. (2017). Weights and importance in composite indicators: Closing the gap. *Ecological Indicators, 80*, 12–22.

Ben Jebli, M., Ben Youssef, S., & Apergis, N. (2019). The dynamic linkage between renewable energy, tourism, CO2 emissions, economic growth, foreign direct investment, and trade. *Latin American Economic Review*, *28*(1), 1-19.

Bepari, K. and Mollik, A. (2015). Effect of audit quality and accounting and finance backgrounds of audit committee members on firms' compliance with ifrs for goodwill impairment testing. Journal of Applied Accounting Research, 16(2), 196-220.

Bergougui, B. (2024). Moving toward environmental mitigation in Algeria: Asymmetric impact of fossil fuel energy, renewable energy and technological innovation on CO2 emissions. *Energy Strategy Reviews*, *51*, 101281.

Bernal-Ramírez, J. and Ocampo, J. (2020). Climate change: policies to manage its macroeconomic and financial effects.

Bersalli, G., Tröndle, T., & Lilliestam, J. (2023). Most industrialised countries have peaked carbon dioxide emissions during economic crises through strengthened structural change. Communications earth & environment, 4(1), 44.

Bertram, C., Luderer, G., Creutzig, F., Bauer, N., Ueckerdt, F., Malik, A., … & Edenhofer, O. (2021). Covid-19-induced low power demand and market forces starkly reduce co2 emissions. Nature Climate Change, 11(3), 193-196.

Bhandary, R. R., Gallagher, K. S., & Fang, Z. (2021). Climate finance policy in practice: a review of the evidence. Climate Policy, 21(4), 529-545.

Bhat, M., Sofi, A., & Sajith, S. (2022). Domino-effect of energy consumption and economic growth on environmental quality: role of green energy in g20 countries. Management of Environmental Quality an International Journal, 33(3), 756-775.

Boateng, E., Annor, C. B., Amponsah, M., & Ayibor, R. E. (2024). Does FDI mitigate CO2 emissions intensity? Not when institutional quality is weak. *Journal of Environmental Management*, *354*, 120386.

Boermans, M. A., & Galema, R. (2019). Are pension funds actively decarbonizing their portfolios?. Ecological Economics, 161, 50–60.

Boutabba, M. A. (2014). The impact of financial development, income, energy and trade on CO2 emissions: evidence from the indian economy. Economic Modelling, 40, 33-41.

Bracking, S. and Leffel, B. (2021). Climate finance governance: fit for purpose?. Wiley Interdisciplinary Reviews Climate Change, 12(4). https://doi.org/10.1002/wcc.709

Buchner, B., Clark, A., Falconer, A., Macquarie, R., Meattle, C., Tolentino, R., & Cooper, W. (2019). Global landscape of climate finance2019. Climate Policy Initiative.

Bukvić, I., Pekanov, D., & Crnković, B. (2023). Green bonds and CO2 emissions. Ekonomski Vjesnik, 36(1), 113-123. https://doi.org/10.51680/ev.36.1.9

Burck, J., Marten, F., & Bals, C. (2015). The Climate Change Performance Index: Results 2016. Germanwatch.

Byaro, M., Mafwolo, G., & Mayaya, H. (2021). Keeping an eye on environmental quality in tanzania as trade, industrialization, income and urbanization continue to grow..

Calel, R., & Dechezleprêtre, A. (2016). Environmental policy and directed technological change: Evidence from the European carbon market. Review of Economics and Statistics, 98(1), 173-191.

Caliendo, L., Dvorkin, M., & Parro, F. (2019). Trade and labor market dynamics: general equilibrium analysis of the china trade shock. Econometrica, 87(3), 741-835.

Can, M. and Gözgör, G. (2017). The impact of economic complexity on CO2 emissions: evidence from france. Environmental Science and Pollution Research, 24(19), 16364-16370.

Cao, L. and Niu, H. (2022). Green credit and total factor CO2 emissions performance—evidence from moderation-based mediating effect test. International Journal of Environmental Research and Public Health, 19(11), 6821. https://doi.org/10.3390/ijerph19116821

Carney M (2015) Breaking the tragedy of the horizon - climate change and financial stability (speech). Bank of England, Speech

Chai, S. (2024). Impact of household population ageing on CO2 emissions: micro-scale evidence from china. Frontiers in Environmental Science, 12.

Chang, J., Sun, P., & Wei, G. (2022). Spatial driven effects of multi-dimensional urbanization on CO2 emissions: a case study in Chengdu-Chongqing urban agglomeration. *Land*, *11*(10), 1858.

Chen, C., Qin, Y., & Gao, Y. (2023). Does new urbanization affect CO2 emissions in China: a spatial econometric analysis. Sustainable Cities and Society, 96, 104687.

Chen, H., Guo, R., Hung, C., Lin, Z., & Wu, M. (2023). Behavioral intentions of bank employees to implement green finance. Sustainability, 15(15), 11717.

Chen, J., Jia, J., Liu, C., & Mao, D. (2021). Decoupling analysis of the CO2 emissions' change and the economic growth in jiangxi's agricultural sector. E3s Web of Conferences, 228, 01005.

Chen, X. and Chen, Z. (2021). Can green finance development reduce CO2 emissions? empirical evidence from 30 chinese provinces. Sustainability, 13(21), 12137.

Chen, X. and Wang, X. (2016). Effects of CO2 emissions reduction policies on transportation mode selections with stochastic demand. Transportation Research Part E Logistics and Transportation Review, 90, 196-205.

Cheng, C., Ren, X., Wang, Z., & Yan, C. (2019). Heterogeneous impacts of renewable energy and environmental patents on CO2 emission-Evidence from the BRIICS. *Science of the total environment*, *668*, 1328-1338.

Cheng, C., Yang, C., & Sheu, C. (2014). The link between eco-innovation and business performance: a taiwanese industry context. Journal of Cleaner Production, 64, 81-90.

Chien, F., Hsu, C. C., Zhang, Y., & Sadiq, M. (2023). Sustainable assessment and analysis of energy consumption impact on CO2 emissions in G7 economies: mediating role of foreign direct investment. *Sustainable Energy Technologies and Assessments*, *57*, 103111.

Chow, Gregory C. (1960). Tests of Equality Between Sets of Coefficients in Two Linear Regressions". *Econometrica*. **28** (3): 591–605.

Chu, E. (2018). Transnational support for urban climate adaptation: emerging forms of agency and dependency. Global Environmental Politics, 18(3), 25-46.

Chu, S., Zhang, Y., Pan, Y., Fan, B., Wang, R., & Gu, J. (2022). Research on the impact of financial development on CO2 emissions: does industrial structure upgrading matter?., 1597-1606.

Couture, T., & Gagnon, Y. (2010). An analysis of feed-in tariff remuneration models: Implications for renewable energy investment.Energy Policy, 38(2), 955–965.

Crafts, N., & Mills, T. C. (2017). Six centuries of British economic growth: A time-series perspective. European Review of Economic History, 21(2), 141–158.

Crippa, M., Guizzardi, D., Pagani, F., Banja, M., Muntean, M., Schaaf E., Becker, W., Monforti-Ferrario, F., Quadrelli, R., Risquez Martin, A., Taghavi-Moharamli, P., Köykkä, J., Grassi, G., Rossi, S., Brandao De Melo, J., Oom, D., Branco, A., San-Miguel, J., Vignati, E. (2023). GHG emissions of all world countries, Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/953332, JRC134504.

D'Orazio Paola (2021) Climate-related financial policymaking in the G20: a panel dataset. FigShare.

D'Orazio, P. and Dirks, M. (2021). Exploring the effects of climate-related financial policies on CO2 emissions in g20 countries: a panel quantile regression approach. Environmental Science and Pollution Research, 29(5), 7678-7702.

D'Orazio, P., & Thole, S. (2022). Climate-related financial policy index: a composite index to compare the engagement in green financial policymaking at the global level. *Ecological Indicators*, *141*, 109065.

Dallaire, D., Zeman, J., & Thrash, T. (2015). Differential effects of type of children's contact with their jailed mothers and children's behavior problems. *Children's contact with incarcerated parents: Implications for policy and intervention*, 23-38.

Darwish, A.M., Zagow, M., & Elkafoury, A. (2023). Impact of land use, travel behavior, and socio-economic characteristics on CO2 emissions in cool-climate cities, USA. Environmental Science and Pollution Research, 30(2023), 91108–91124.

De Pascale, G., Sardaro, R., Faccilongo, N., & Contò, F. (2020). What is the influence of FDI and international people flows on environment and growth in OECD countries? A panel study. *Environmental Impact Assessment Review*, *84*, 106434.

Delgado-Baquerizo, M., Eldridge, D., Liu, Y., Sokoya, B., Wang, J., Hu, H., … & Fierer, N. (2021). Global homogenization of the structure and function in the soil microbiome of urban greenspaces. Science Advances, 7(28).

Della Croce, R., Kaminker, C., & Stewart, F. (2011). The role of pension funds in financing green growth initiatives.

den Elzen M, Kuramochi T, H¨ohne N, Cantzler J, Esmeijer K, Fekete H, Fransen T, Keramidas K, Roelfsema M, Sha F et al (2019) Are the G20 economies making enough progress to meet their NDC targets? Energy Policy 126:238–250.

Dhillon, D. and Kaur, K. (2023). A nexus between sustainability, energy utilisation and economic growth at aggregate and disaggregate level: a case of india. International Journal of Energy Sector Management, 18(3), 433-456.

Díaz, S., Zafra-Calvo, N., Purvis, A., Verburg, P. H., Obura, D., Leadley, P., ... & Zanne, A. E. (2020). Set ambitious goals for biodiversity and sustainability. *Science*, *370*(6515), 411-413.

Dietz, T., & Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence and technology. *Human ecology review*, *1*(2), 277-300.

Dietz, T., Rosa, E., & York, R. (2007). Driving the human ecological footprint. Frontiers in Ecology and the Environment, 5(1), 13-18.

Dikau, S., & Volz, U. (2021). Central bank mandates, sustainability objectives and the promotion of green finance. *Ecological Economics*, *184*, 107022.

Dobbie, M. J., & Dail, D. (2013). Robustness and sensitivity of weighting and aggregation in constructing composite indices. Ecological Indicators, 29, 270–277.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C. M., Carl, G., Carré, G., … & Lautenbach, S. (2012). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography, 36(1), 27-46.

Du, L. and Chuai, X. (2022). Research progress on the relationship between CO2 emissions and socio-economic growth in china. Frontiers in Humanities and Social Sciences, 2(8), 5-11.

Du, P., Hou, X., & Xu, H. (2022). Dynamic expansion of urban land in china's coastal zone since 2000. Remote Sensing, 14(4), 916.

Dunyo, S. K., Odei, S. A., & Chaiwet, W. (2024). Relationship between CO2 emissions, technological innovation, and energy intensity: Moderating effects of economic and political uncertainty. *Journal of Cleaner Production*, *440*, 140904.

Ehrlich, P. R., & Holdren, J. P. (1971). Impact of population growth. Science, 171*, 1212-1217.

Erdogan, S., Pata, U. K., & Solarin, S. A. (2023). Towards carbon-neutral world: The effect of renewable energy investments and technologies in G7 countries. *Renewable and Sustainable Energy Reviews*, *186*, 113683.

Erdoğan, S., Yıldırım, S., Yıldırım, D. Ç., & Gedikli, A. (2020). The effects of innovation on sectoral CO2 emissions: Evidence from G20 countries. *Journal of environmental management*, *267*, 110637.

Evans, R. (2023). Verifying model assumptions and testing normality. Veterinary Surgery, 53(1), 17-17. https://doi.org/10.1111/vsu.14034

Fan, F. and Lei, Y. (2016). Decomposition analysis of energy-related CO2 emissions from the transportation sector in beijing. Transportation Research Part D Transport and Environment, 42, 135-145.

Fang, C.L., Wang, S.J., & Li, G.D. (2015). Changing urban forms and carbon dioxide emissions in China: A case study of 30 provincial capital cities. Applied Energy, 158, 519–531.

Farhani, S. and Shahbaz, M. (2014). What role of renewable and non-renewable electricity consumption and output is needed to initially mitigate co2 emissions in mena region?. Renewable and Sustainable Energy Reviews, 40, 80-90.

Farooq, F. (2023). Economic policy uncertainty, renewable energy consumption and environmental sustainability in china. Pakistan Journal of Humanities and Social Sciences, 11(2).

Fu, J. and Ng, A. W. (2021). Scaling up renewable energy assets: issuing green bond via structured public-private collaboration for managing risk in an emerging economy. Energies, 14(11), 3076.

Fuinhas, J., Marques, A., & Koengkan, M. (2017). Are renewable energy policies upsetting carbon dioxide emissions? the case of latin america countries. Environmental Science and Pollution Research, 24(17), 15044-15054.

Gao, P., Wang, Y., Zeng, Y., Su, X., Che, X., & Yang, X. (2022). Green technology innovation and CO2 emissions nexus in china: does industrial structure upgrading matter?. Frontiers in Psychology, 13.

Gerlagh, R., & van der Zwaan, B. (2006). Options and Instruments for a Deep Cut in CO_2 Emissions: Carbon Dioxide Capture or Renewables, Taxes or Subsidies? *The Energy Journal*, *27*(3), 25–48.

Ghosh, S. (2002). Electricity consumption and economic growth in India. *Energy Policy*, 30(2), 125–129.

Gök A (2020) The role of financial development on CO2 emissions: a meta regression analysis. Environ Sci Pollut Res:1–19.

Gorus, M. S., & Aslan, M. (2019). Impacts of economic indicators on environmental degradation: evidence from MENA countries. *Renewable and Sustainable Energy Reviews*, *103*, 259-268.

Graham, M. H. (2003). Confronting multicollinearity in ecological multiple regression. Ecology, 84(11), 2809-2815.

Grassi, G., House, J., Dentener, F., Federici, S., Elzen, M., & Penman, J. (2017). The key role of forests in meeting climate targets requires science for credible mitigation. Nature Climate Change, 7(3), 220-226.

Grassi, G., Rossi, S., Brandao De Melo, J., Oom, D., Branco, A., San-Miguel, J., Vignati, E., GHG emissions of all world countries, Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/953322, JRC134504.

Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. Social Indicators Research, 141(1), 61–94.

Greene, W. H. (2012). Econometric Analysis (7th ed.). Pearson.

Grunewald, N. and Martínez-Zarzoso, I. (2015). Did the kyoto protocol fail? an evaluation of the effect of the kyoto protocol on co2 emissions.

Gu, X., Qin, L., & Zhang, M. (2023). The impact of green finance on the transformation of energy consumption structure: evidence based on china. Frontiers in Earth Science, 10.

Guan, Y., Shan, Y., Huang, Q., Chen, H., Wang, D., & Hubacek, K. (2021). Assessment to china's recent emission pattern shifts. Earth S Future, 9(11).

Guerra, E. (2011). Too much riding on climate change?. Berkeley Planning Journal, 23(1).

Guerrieri, P., & Meliciani, V. (2005). Technology and international competitiveness: The interdependence between manufacturing and producer services. Structural Change and Economic Dynamics, 16(4), 489–502.

Gujarati, D.N. and Porter, D.C. (2009) Basic Econometrics. 5th Edition, McGraw Hill Inc., New York.

Gurbanov, S. (2021). Role of natural gas consumption in the reduction of co2 emissions: case of azerbaijan. Energies, 14(22), 7695. https://doi.org/10.3390/en14227695

Han, C., Gu, Z., & Yang, H. (2021). Ekc test of the relationship between nitrogen dioxide pollution and economic growth—a spatial econometric analysis based on chinese city data. International Journal of Environmental Research and Public Health, 18(18), 9697.

Harshana, K. and Wanniarachchige, M. (2022). Effect of covid -19 pandemic on the performance of sri lankan banks. International Journal of Accounting and Business Finance, 8(2), 135.

Hassan, T., Song, H., & Kırıkkaleli, D. (2021). International trade and consumption-based CO2 emissions: evaluating the role of composite risk for rcep economies. Environmental Science and Pollution Research, 29(3), 3417-3437.

Hickel, J., & Kallis, G. (2019). Is Green Growth Possible? *New Political Economy*, *25*(4), 469–486.

HLEG (2017) Final report on financing a sustainable European economy. Interim Report - High-Level Expert Group on Sustainable Finance.

Hoffmann, V. H., & Busch, T. (2008). Corporate carbon performance indicators: Carbon intensity, dependency, exposure, and risk. *Journal of Industrial Ecology*, *12*(4), 505-520.

Höhne, N., Gidden, M., Elzen, M., Hans, F., Fyson, C., Geiges, A., … & Rogelj, J. (2021). Wave of net zero emission targets opens window to meeting the paris agreement. Nature Climate Change, 11(10), 820-822.

Hu, Y. and Zheng, J. (2021). Is green credit a good tool to achieve "double carbon" goal? based on coupling coordination model and pvar model. Sustainability, 13(24), 14074. https://doi.org/10.3390/su132414074

Huang, J. (2024). Spatiotemporal variation characteristics analysis of anthropogenic heat fluxes based on nighttime lighting data. Polish Journal of Environmental Studies, 33(3), 3183-3192.

Huang, J. and Guo, L. (2022). Research on the impact of financial development in different regions on the decoupling of CO2 emissions from economic growth. Energy & Environment, 34(6), 2007-2030.

Huang, X. and Chen, M. (2022). Analysis on the nonlinear impact of financial risks on co2 emissions: designing a sustainable development goal framework for asian economies. Journal of Environmental and Public Health, 2022, 1-10.

Huffman, W. E., & Orazem, P. F. (2007). Agriculture and human capital in economic growth: Farmers, schooling and nutrition. In R. Evenson & P. Pingali (Eds.), Handbook of Agricultural Economics (Vol. 3, pp. 2281–2341). Elsevier.

Huo, T., Cao, R., Du, H., Zhang, J., Cai, W., & Liu, B. (2021). Nonlinear influence of urbanization on china's urban residential building CO2 emissions: new evidence from panel threshold model. The Science of the Total Environment, 772, 145058.

Hussain, F. A., & Ahmad, M. M. (2019). Effects of climate finance on risk appraisal: A study in the southwestern coast of Bangladesh. *Advances in Meteorology*, *2019*, 1-16.

Hussain, S., Akbar, M., Gul, R., Shahzad, S. J. H., & Naifar, N. (2023). Relationship between financial inclusion and CO2 emissions: International evidence. *Heliyon*, *9*(6).

Idroes, G. (2023). Unveiling the carbon footprint: biomass vs. geothermal energy in indonesia. Ekonomikalia Journal of Economics, 1(1), 10-18.

IEA. (2012). World energy outlook 2012. Paris: International Energy Agency (IEA), 700.

ILORI, O. and TANIMOWO, F. (2022). Heteroscedasticity detection in cross-sectional diabetes pedigree function: a comparison of breusch-pagan-godfrey, harvey and glejser tests. International Journal of Scientific and Management Research, 05(12), 150-163.

Intergovernmental Panel on Climate Change (IPCC). (2007). Climate change 2007: The fourth assessment report of the Intergovernmental Panel on Climate Change. England: Cambridge University Press.

International Monetary Fund (IMF). (2000). Code of good practices on transparency in monetary and financial policies, part 1 - introduction. (Approved by the IMF Executive Board on July 24, 2000).

IPCC (2014) Climate change 2014: synthesis report. In: Technical report. Climate Change, Inter-governmental Panel on Climate Change.

IPCC (2018) Global warming of 1.5 degrees: summary for policymakers. Technical report, intergovernmental panel on climate change.

IPCC. (2019). *United Nations Environment Programme (UNEP) Emissions Gap Report*. Retrieved from https://www.unenvironment.org/resources/emissions-gap-report-2019

Iskandar, A. (2019). Economic growth and co2 emissions in indonesia : investigating the environmental kuznets curve hypothesis existence. Jurnal BPPK Badan Pendidikan Dan Pelatihan Keuangan, 12(1), 42-52.

Ito, T., Iwata, K., McKenzie, C., & Urata, S. (2021). Energy and the environment: editors' overview. Asian Economic Policy Review, 16(1), 1-21.

Iwata, H., Okada, K., & Samreth, S. (2012). Empirical study on the determinants of co2emissions: evidence from oecd countries. Applied Economics, 44(27), 3513-3519.

Iyke-Ofoedu, M. I., Takon, S. M., Ugwunta, D. O., Ezeaku, H. C., Nsofor, E. S., & Egbo, O. P. (2024). Impact of CO2 emissions embodied in the agricultural sector on carbon sequestration in South Africa: The role of environmental taxes and technological innovation. *Journal of Cleaner Production*, 141210.

Janiszewski, C., & Van Osselaer, S. M. (2022). Abductive theory construction. *Journal of consumer psychology*, *32*(1), 175-193.

Jia, J., Rong, Y., Chen, C., Xie, D., & Yang, Y. (2021). Contribution of renewable energy consumption to co2 emissions mitigation: a comparative analysis from the income levels' perspective in the belt and road initiative (bri) region. International Journal of Climate Change Strategies and Management, 13(3), 266-285.

Jiang, X. and Guan, D. (2017). The global co2 emissions growth after international crisis and the role of international trade. Energy Policy, 109, 734-746.

Juliansyah, R. (2019). The influence of economic growth, population, and industrial sectors on environmental degradation in indonesia. Sriwijaya International Journal of Dynamic Economics and Business, 93-106.

Justice, G., Nyantakyi, G., & Isaac, S. H. (2024). The effect of renewable energy on CO2 emissions through globalization. *Heliyon*.

K.P., E. and U.P., O. (2023). A comparative approach on bridge and elastic net regressions. African Journal of Mathematics and Statistics Studies, 6(1), 103-115.

Kahia, M., Ben Jebli, M., & Belloumi, M. (2019). Analysis of the impact of renewable energy consumption and economic growth on carbon dioxide emissions in 12 MENA countries. *Clean Technologies and Environmental Policy*, *21*, 871-885.

Kang, D., Zhai, X., Chen, F., Wang, W., & Jia, L. (2022). How to promote the development of a green economy: talent or technology?—evidence from china's high-speed rail. Frontiers in Psychology, 13.

Kaur, J., Singh, K., Chaudhary, R., & Vashishtha, S. (2023). How economic growth, sustainable energy and CO2 emissions impact each other? new insights from india using ardl approach. Opec Energy Review, 47(3), 216-238.

Kennedy, C., Steinberger, J., Gasson, B., Hansen, Y., Hillman, T., Havranek, M., … Mendez, G. (2009). Greenhouse gas emissions from global cities. Environmental Science & Technology, 43(19), 7297-7302.

Kennedy, P. (2008). A Guide to Econometrics (6th ed.). Wiley-Blackwell.

Khalfaoui, R., Tiwari, A., Khalid, U., & Shahbaz, M. (2021). Nexus between carbon dioxide emissions and economic growth in g7 countries: fresh insights via wavelet coherence analysis. Journal of Environmental Planning and Management, 66(1), 31-66.

Khan, A., Basit, A., Khan, U., & Khan, M. (2022). The progressive correlation between CO2 emissions, economic growth, energy use, and oil consumption by the most prominent contributors to travel and tourism gdps. Frontiers in Environmental Science, 10.

Khan, H., Weili, L., Khan, I., & Khamphengxay, S. (2021). Renewable energy consumption, trade openness, and environmental degradation: a panel data analysis of developing and developed countries. Mathematical Problems in Engineering, 2021, 1-13.

Khan, I., Hou, F., Zakari, A., & Tawiah, V. K. (2021). The dynamic links among energy transitions, energy consumption, and sustainable economic growth: A novel framework for IEA countries. Energy, 222, 119935.

Khan, M. and Rehan, M. (2020). The relationship between energy consumption, economic growth and carbon dioxide emissions in pakistan. Financial Innovation, 6(1).

Khan, S., Yuan, H., Yahong, W., & Xu, Q. (2024). Pathways to carbon neutrality in G7 economies: The role of technology-innovation and R&D in reducing CO2 emissions. *Gondwana Research*, *128*, 55-68.

Khokhar, Z. (2024). The impact of green finance, and eco-innovation on co2 emissions: the pool mean group evidence from asean countries in the context of sdgs. ABGMCE, 4(1).

Kim, M.H. and N. Adilov (2012), The lesser of two evils: an empirical investigation of foreign direct investment-pollution tradeoff, Applied Economics, 44(20), pp.2597-2606

Koengkan, M., Fuinhas, J. A., & Marques, A. C. (2018). Does financial openness increase environmental degradation? Fresh evidence from MERCOSUR countries. *Environmental Science and Pollution Research*, *25*(30), 30508-30516.

Kosovac, M. (2023). Urban areas as major sources of greenhouse gas emissions: A global perspective. Journal of Urban Environmental Studies, 12*(2), 45-56. Retrieved from https://www.journalurbanenvironmentalstudies.com/issues/volume12/issue2/kosovac.

Krishnan, M., Samandari, H., Woetzel, J., Smit, S., Pacthod, D., Pinner, D., ... & Imperato, D. (2022). The net-zero transition: what it would cost, what it could bring.

Krogstrup, S. and Oman, W. (2019). Macroeconomic and financial policies for climate change mitigation. Imf Working Paper, 19(185).

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. Review of Financial Studies, 33(3), 1067–1111.

Krych, K., Heeren, N., & Hertwich, E. G. (2021). Factors influencing the life-cycle ghg emissions of brazilian office buildings. Buildings and Cities, 2(1), 856-873.

Kumar, S., Managi, S., & Jain, R. (2020). Co2 mitigation policy for indian thermal power sector: potential gains from emission trading. Energy Economics, 86, 104653.

Kumari, N., Kumar, P., & Sahu, N. (2021). Do energy consumption and environmental quality enhance subjective wellbeing in g20 countries?. Environmental Science and Pollution Research, 28(42), 60246-60267.

Le Qúeŕe C, Korsbakken JI, Wilson C, Tosun J, Andrew R, An-dres RJ, Canadell JG, Jordan A, Peters GP, van Vuuren DP. (2019). Drivers of declining co 2 emissions in 18 developed economies. Nat Clim Chang 9(3):213–217

Lee, C. C., & Chang, C. P. (2008). Energy consumption and economic growth in Asian economies: A more comprehensive analysis using panel data. Resource and Energy Economics, 30(1), 50–65.

Lee, J., & Strazicich, M. C. (2003). Minimum Lagrange multiplier unit root test with two structural breaks. *Review of economics and statistics*, *85*(4), 1082-1089.

Lee, J., Cho, Y., Koo, Y., & Park, C. (2018). Effects of market reform on facility investment in electric power industry: panel data analysis of 27 countries. Sustainability, 10(9), 3235.

Lestari, I., Effendi, N., & Priyono, A. (2020). Financial development, economic growth, and environmental degradation nexus in asian emerging markets. Jurnal Ekonomi Pembangunan, 18(2), 177-189.

Li, A., Li, X., Li, Y., Wang, H., & Zhang, H. (2022). The impact of urbanization on CO2 emissions and spatial–temporal differentiation based on meta-analysis in china. Sustainability, 14(22), 14840.

Li, C. (2023). Guided by the goal of "double carbon", what is the CO2 emissions reduction effect of the promotion and application of green technology in china?.

Li, J. (2023). Network evolutionary game analysis of green credit: a perspective of CO2 emissions trading. Managerial and Decision Economics, 45(3), 1343-1362. https://doi.org/10.1002/mde.4064

Li, J., Chen, Y., Li, B., & Liu, Z. (2018). Quantitative analysis of the impact factors of conventional energy CO2 emissions in kazakhstan based on lmdi decomposition and stirpat model. Journal of Geographical Sciences, 28(7), 1001-1019.

Li, Q., Wei, Y. N., & Dong, Y. (2016). Coupling analysis of China's urbanization and CO2 emissions: example from Hubei Province. *Natural Hazards*, *81*, 1333-1348.

Li, W., Elheddad, M., & Doytch, N. (2021). The impact of innovation on environmental quality: Evidence for the non-linear relationship of patents and CO2 emissions in China. *Journal of Environmental Management*, *292*, 112781.

Lian, W., Sun, X., Wang, Y., Duan, H., Gao, T., & Yan, Q. (2024). The mechanism of China's renewable energy utilization impact on CO2 emissions intensity: Evidence from the perspective of intermediary transmission. *Journal of Environmental Management*, *350*, 119652.

Liddle, B. (2013). Impact of population, age structure, and urbanization on CO2 emissions/energy consumption: evidence from macro-level, cross-country analyses. Population and Environment, 35(3), 286-304.

Liddle, B. and Lung, S. (2010). Age-structure, urbanization, and climate change in developed countries: revisiting stirpat for disaggregated population and consumption-related environmental impacts. Population and Environment, 31(5), 317-343.

Lieu, P. and Ngoc, B. (2023). The relationship between economic diversification and CO2 emissions in developing countries. International Journal of Applied Economics Finance and Accounting, 15(1), 21-28.

Liévanos, R. (2018). Retooling calenviroscreen: cumulative pollution burden and race-based environmental health vulnerabilities in california. International Journal of Environmental Research and Public Health, 15(4), 762.

Lin, S., Zhao, D., & Marinová, D. (2009). Analysis of the environmental impact of china based on stirpat model. Environmental Impact Assessment Review, 29(6), 341-347.

Lipovetsky, S. and Conklin, W. (2004). Decision making by variable contribution in discriminant, logit, and regression analyses. International Journal of Information Technology & Decision Making, 03(02), 265-279.

Liu, J., Liu, L., Qian, Y., & Song, S. (2021). The effect of artificial intelligence on carbon intensity: Evidence from China's industrial sector. Socio-Economic Planning Sciences, 83, 101002.

Liu, X. and Liu, X. (2021). Can financial development curb CO2 emissions? empirical test based on spatial perspective. Sustainability, 13(21), 11912.

Liu, Y. (2024). Green technology advancement, energy input share and CO2 emissions trend studies. Scientific Reports, 14(1).

Liu, Z., Lan, J., Chien, F., Sadiq, M., & Nawaz, M. A. (2022). Role of tourism development in environmental degradation: A step towards emission reduction. *Journal of environmental management*, *303*, 114078.

Loiseau, E., Saikku, L., Antikainen, R., Droste, N., Hansjürgens, B., Pitkänen, K., … & Thomsen, M. (2016). Green economy and related concepts: an overview. Journal of Cleaner Production, 139, 361-371. https://doi.org/10.1016/j.jclepro.2016.08.024

Lu, Q. (2023). Spatiotemporal variation and development stage of co2 emissions of urban agglomerations in the yangtze river economic belt, china. Land, 12(9), 1678.

Luke, M., Somani, P., Cotterman, T., Suri, D., & Lee, S. (2021). No covid-19 climate silver lining in the us power sector. Nature Communications, 12(1).

Madaleno, M., Doğan, E., & Taşkın, D. (2022). A step forward on sustainability: the nexus of environmental responsibility, green technology, clean energy and green finance. Energy Economics, 109, 105945.

Mahadevan, R. (2003). Productivity growth in Indian agriculture: The role of globalization and economic reform. Asia-Pacific Development Journal, 10(2), 57–72.

Mahmood, T., Shireen, S., & Mumtaz, M. (2021). Testing the role of financial development and urbanization in the conventional ekc: evidence from china and india. International Journal of Sustainable Development and Planning, 16(3), 445-455.

Maji, I. K., Habibullah, M. S., & Saari, M. Y. (2017). Financial development and sectoral CO 2 emissions in Malaysia. *Environmental Science and Pollution Research*, *24*, 7160-7176.

Manuel, A. Z. M., Valverde B. I., Aguilar B. J., & Mendoza J. M. (2016). Relationship between economic growth and environmental degradation: Is there an environmental evidence of Kuznets curve for Brazil? International Journal of Energy Economics and Policy, 6(2), 208–216.

Maslin, M., Lang, J., & Harvey, F. (2022). A short history of the successes and failures of the international climate change negotiations.

Matezo, E., Makengo, B., & Muhole, A. (2021). The influence of export diversification on economic growth: a case of southern african development community (sadc). American Journal of Industrial and Business Management, 11(07), 829-845.

Meng, J., Mi, Z., Guan, D., Li, J., Tao, S., Li, Y., … & Davis, S. (2018). The rise of south–south trade and its effect on global co2 emissions. Nature Communications, 9(1).

Meng, M. and Zhou, J. (2021). Threshold effect of urbanization level on household energy consumption in beijing-tianjin-hebei region. Polish Journal of Environmental Studies, 30(5), 4069-4083.

Mensah, B. and Abdul-Mumuni, A. (2022). Asymmetric effect of remittances and financial development on CO2 emissions in sub-saharan africa: an application of panel nardl approach. International Journal of Energy Sector Management, 17(5), 865-886.

Mermod, A. and Dömbekci, B. (2011). Emission trading applications in the european union and the case of turkey as an emerging market. International Journal of Energy Sector Management, 5(3), 345-360.

MIGNAMISSI, D. (2023). Does trade openness increase co2 emissions in africa? a revaluation using the composite index of squalli and wilson.

Milindi, C.B., & Inglesi-Lotz, R. (2022). The impact of technological progress on emissions levels: Evidence and lessons from different income-group countries. Energy Reports. Available at: The impact of technological progress on emissions levels.

Mir, G. U. R., & Storm, S. (2016). CO2 emissions and economic growth: production-based versus consumption-based evidence on decoupling. *Institute for new Economic Thinking working paper series*, (41).

Missios, P., Yildiz, H., & Ferrara, I. (2021). Foreign direct investment and the choice of environmental policy.

Mohsin, M., Taghizadeh-Hesary, F., Panthamit, N., Anwar, S., Abbas, Q., & Vo, X. V. (2021). Developing low carbon finance index: Evidence from developed and developing economies. Finance Research Letters, 43, 101520.

Mustafa, G. (2023). The dynamic relationship between financial development, economic growth, foreign direct investment and trade openness: evidence from south asian countries. Millennial Asia, 14(3), 406-433.

Nagelkerken, I., & Connell, S. D. (2015). Global alteration of ocean ecosystem functioning due to increasing human CO2 emissions. *Proceedings of the National Academy of Sciences*, *112*(43), 13272-13277.

Naseem, S., Hui, W., Sarfraz, M., & Mohsin, M. (2021). Repercussions of sustainable agricultural productivity, foreign direct investment, renewable energy, and environmental decay: recent evidence from latin america and the caribbean. Frontiers in Environmental Science, 9.

Nasir, M. A., Huynh, T. L. D., & Tram, H. T. X. (2019). Role of financial development, economic growth & foreign direct investment in driving climate change: A case of emerging ASEAN. *Journal of environmental management*, *242*, 131-141.

Nasir, M., Nguyen, C., & Le, T. (2021). Environmental degradation & role of financialisation, economic development, industrialisation and trade liberalisation. Journal of Environmental Management, 277, 111471.

Neffati, M. (2023). Renewable and non-renewable energy consumption and total factor productivity growth: the case of g20 countries. Energy Economics Letters, 10(1), 78-89.

Network for Greening the Financial System (NGFS). (2019). A call for action – climate change as a source of financial risk, first comprehensive report.

Newell, R., Raimi, D., Villanueva, S., & Prest, B. (2020). Global Energy Outlook 2020: energy transition or energy addition. *Resources for the Future*.

Newton, A., Cantarello, E., Shiel, C., & Hodder, K. (2014). Lessons learned from developing a new distance-learning masters course in the green economy. Sustainability, 6(4), 2118-2132.

Ngong, C., Bih, D., Onyejiaku, C., & Onwumere, J. (2022). Urbanization and carbon dioxide (co2) emission nexus in the cemac countries. Management of Environmental Quality an International Journal, 33(3), 657-673.

Ni'Am, M.F., Yulianto, A., & Pramitasari, G. (2021). Urban transport and its contribution to greenhouse gas emissions in cities. *Environmental Science and Pollution Research, 28*(30), 39871-39883.

Nkwaira, C. and Poll, H. (2023). Anticipating the unforeseen and expecting the unexpected: effectiveness of macro-prudential policies in curbing the impact of stranded assets in the banking sector. Risks, 11(5), 87.

Noh, Y. (2019). The effects of corporate green efforts for sustainability: An event study approach. *Sustainability*, *11*(15), 4073.

Odetola, T., & Etumnu, C. (2013, July 22–23). Contribution of agriculture to economic growth in Nigeria [Paper presentation]. 18th Annual Conference of the African Econometric Society (AES) Accra, Ghana, at the Session organized by the Association for the Advancement of African Women Economists (AAAWE), Accra, Ghana.

Odhong, C., Wilkes, A., Dijk, S., Vorlaufer, M., Ndonga, S., Sing'ora, B., … & Kenyanito, L. (2019). Financing large-scale mitigation by smallholder farmers: what roles for public climate finance?. Frontiers in Sustainable Food Systems, 3.

OECD (2023), Climate Finance Provided and Mobilised by Developed Countries in 2013-2021: Aggregate Trends and Opportunities for Scaling Up Adaptation and Mobilised Private Finance, Climate Finance and the USD 100 Billion Goal, OECD Publishing, Paris.

OECD, (2008). Handbook on constructing composite indicators: methodology and user guide. Joint Research Centre, European Commission and others – OECD publishing.

Olasehinde-Williams, G. (2022). Does economic complexity influence environmental performance? empirical evidence from oecd countries. International Journal of Finance & Economics, 29(1), 356-382. https://doi.org/10.1002/ijfe.2689

Oluwole, I. O., Attama, P. I., Onuigbo, F. N., & Atabo, I. (2021). Agriculture: A panacea to economic growth and development in Nigeria. *Journal of Economics and Allied Research*, 6(2), 134–146.

Onabote, A., Abuh, O., Emmanuel, O., Eseyin, O., & Okafor, V. (2021). Foreign direct investment, energy infrastructure and manufacturing output in nigeria. International Journal of Energy Economics and Policy, 11(3), 163-269.

Opoku, E. E. O., Adams, S., & Aluko, O. A. (2021). The foreign direct investment-environment nexus: does emission disaggregation matter?. *Energy Reports*, *7*, 778-787.

Orhan, A., Adebayo, T. S., Genç, S. Y., & Kirikkaleli, D. (2021). Investigating the linkage between economic growth and environmental sustainability in India: Do agriculture and trade openness matter? Sustainability, 13(9), 4753.

Osipov, V., Krupnov, Y., Semenova, G., & Tkacheva, M. (2022). Ecologically responsible entrepreneurship and its contribution to the green economy’s sustainable development: financial risk management prospects. Risks, 10(2), 44.

Othmani, H. (2022). Foreign institutional ownership and bank performance: evidence from tunisia. African Development Review, 34(1), 42-53. https://doi.org/10.1111/1467-8268.12625

Otoritas Jasa Keuangan (OJK). (2024). Climate Risk Management dan Skenario Analisis Perbankan 2024. Retrieved from: https://ojk.go.id/id/berita-dan-kegiatan/info-terkini/Documents/Pages/Climate-Risk-Management-and-Scenario-Analysis-CRMS/Buku%201_Panduan%20Umum%20CRMS%20OJK%202024.pdf

Özcan, B., & Öztürk, I. (Eds.). (2019). *Environmental Kuznets curve (EKC): a manual*. Academic Press.

Pain, O., Dudbridge, F., & Ronald, A. (2018). Are your covariates under control? how normalization can re-introduce covariate effects. European Journal of Human Genetics, 26(8), 1194-1201.

Pancasari, D. (2023). Systematic literature review: the dynamic impacts of carbon emissions and investment in the g20 forum. Jurnal Ilmiah Ekonomi Dan Bisnis, 20(2), 128-135.

Pang, Q., Zhou, W., Zhao, T., & Zhang, L. (2021). Impact of urbanization and industrial structure on CO2 emissions: evidence from huaihe river eco-economic zone. Land, 10(11), 1130.

Pappas, D., Chalvatzis, K., Guan, D., & Ioannidis, A. (2018). Energy and carbon intensity: a study on the cross-country industrial shift from china to india and se asia. Applied Energy, 225, 183-194.

Parikh, J., Panda, M., Ganesh-Kumar, A., & Singh, V. (2009). CO2 emissions structure of Indian economy. Energy, 34(8), 1024–1031.

Parry, I., Mylonas, V., & Vernon, N. (2018). Mitigation policies for the paris agreement: an assessment for g20 countries. SSRN Electronic Journal.

Pastén, R. (2012). The environmental kuznets curve: a survey of the theoretical literature. International Review of Environmental and Resource Economics, 6(3), 195-224.

Pata, U. K., Yilanci, V., Zhang, Q., & Shah, S. A. R. (2022). Does financial development promote renewable energy consumption in the USA? Evidence from the Fourier-wavelet quantile causality test. *Renewable Energy*, *196*, 432-443.

Perwithosuci, W., Hadibasyir, H., & Arif, M. (2023). CO2 emissions and urbanization in asean-5 countries. Optimum Jurnal Ekonomi Dan Pembangunan, 12(2), 203-212.

Peters, G., Marland, G., Quéré, C., Boden, T., Canadell, J., & Raupach, M. (2011). Rapid growth in co2 emissions after the 2008–2009 global financial crisis. Nature Climate Change, 2(1), 2-4.

Pieroni, M. P. P., McAlloone, T. C., Pigosso, D. C. A. (2019). Business model innovation for circular economy and sustainability: a review of approaches. Journal of Cleaner Production, Vol. 215, p. 198–216.

Prasad, M. N. V. (2024). Bioremediation, bioeconomy, circular economy, and circular bioeconomy—Strategies for sustainability. In Bioremediation and Bioeconomy (pp. 3-32). Elsevier.

Prasetyanto, P. and Sari, F. (2021). Environmental kuznets curve: economic growth with environmental degradation in indonesia. International Journal of Energy Economics and Policy, 11(5), 622-628.

Qamri, G., Bing, S., Khan, R., & Hanim, W. (2021). Unleashing the indirect influence of fdi in environmental degradation via financial development and economic growth. new evidence from asian countries.

Qin, J. (2022). CO2 emissions reduction effects of green credit policies: empirical evidence from china. Frontiers in Environmental Science, 10.

Qin, L., Liu, S., Hou, Y., Zhang, Y., Wu, D., & Yan, D. (2023). The spatial spillover effect and mediating effect of green credit on agricultural CO2 emissions: evidence from china. Frontiers in Earth Science, 10.

Qin, L., Liu, S., Hou, Y., Zhang, Y., Wu, D., & Yan, D. (2023). The spatial spillover effect and mediating effect of green credit on agricultural CO2 emissions: evidence from china. Frontiers in Earth Science, 10.

Quéré, C., Jackson, R., Jones, M., Smith, A., Abernethy, S., Andrew, R., … & Peters, G. (2020). Temporary reduction in daily global co2 emissions during the covid-19 forced confinement. Nature Climate Change, 10(7), 647-653.

R., C., & Restoy, F. (2022). The regulatory response to climate risks: Some challenges. _FSI Brief_ (No. 16), 17 February 2022. Technical report, Financial Stability Institute – Bank for International Settlements.

Rahman, A., Murad, S., Ahmad, F., & Wang, X. (2020). Evaluating the ekc hypothesis for the bcim-ec member countries under the belt and road initiative. Sustainability, 12(4), 1478.

Rao, C., Huang, Q., Chen, L., Goh, M., & Hu, Z. (2023). Forecasting the CO2 emissions in hubei province under the background of carbon neutrality: a novel stirpat extended model with ridge regression and scenario analysis. Environmental Science and Pollution Research, 30(20), 57460-57480.

Rastegaripour, F., Karbasi, A., & Pirmalek, F. (2019). RELATIONSHIP BETWEEN CO^2 EMISSIONS, ENERGY CONSUMPTION, AND ECONOMIC GROWTH IN IRAN. *The Journal of Energy and Development*, *45*(1/2), 197–212.

Ren-zhong, L., Du, J., & Wei, L. (2022). Financial development, heterogeneous technological progress, and CO2 emissions: an empirical analysis based on provincial panel data in china.

Río, P., Romero-Jordán, D., & Peñasco, C. (2015). Analysing firm-specific and type-specific determinants of eco-innovation. Technological and Economic Development of Economy, 23(2), 270-295.

Rocha, A. V., & Simas, A. B. (2017). Asymptotic adjustments of Pearson residuals in exponential family nonlinear models. *Journal of Statistical Computation and Simulation*, *87*(8), 1684-1700.

Rogelj, J., Elzen, M. d., Höhne, N., Fransen, T., Fekete, H., Winkler, H., … & Meinshausen, M. (2016). Paris agreement climate proposals need a boost to keep warming well below 2 °c. Nature, 534(7609), 631-639.

Rogelj, J., Elzen, M., Höhne, N., Fransen, T., Fekete, H., Winkler, H., … & Meinshausen, M. (2016). Paris agreement climate proposals need a boost to keep warming well below 2 °c. Nature, 534(7609), 631-639.

Ru, M.Y., Tao, S., Smith, K., & Shen, G.F. (2011). Direct energy consumption associated emissions by rural-to-urban migrants in Beijing. Environmental Science & Technology, 49(22), 13708–13715.

Ruttan, V. W. (2002). Productivity growth in world agriculture: Sources and constraints. Journal of Economic Perspectives, 16(4), 161–184.

Sadorsky, P. (2020). Energy related co2 emissions before and after the financial crisis. Sustainability, 12(9), 3867.

Sadorsky, P. (2020). Energy related CO2 emissions before and after the financial crisis. Sustainability, 12(9), 3867.

Safdar, N., Ghaffar, H., Farooq, F., & Liaquat, M. (2020). Trade liberalization, economic growth and environmental quality nexus: an empirical evidence from pakistan. Review of Education Administration and Law, 3(3).

Saha, R. (2022). Quantitative and Qualitative Approaches to Accounting Research. *International Journal of Multidisciplinary Research & Reviews*, *1*(2), 1-6.

Salahuddin, M., & Khan, S. (2013). EMPIRICAL LINK BETWEEN ECONOMIC GROWTH, ENERGY CONSUMPTION AND CO2 EMISSION IN AUSTRALIA. *The Journal of Developing Areas*, *47*(2), 81–92.

Salahuddin, M., Gow, J., & Öztürk, İ. (2015). Is the long-run relationship between economic growth, electricity consumption, carbon dioxide emissions and financial development in gulf cooperation council countries robust?. Renewable and Sustainable Energy Reviews, 51, 317-326.

Salman, D. and Ismael, D. (2023). The effect of digital financial inclusion on the green economy: the case of egypt. Journal of Economics and Development, 25(2), 120-133.

Sauerbeck, D. R. (2001). CO2 emissions and C sequestration by agriculture—Perspectives and limitations. Nutrient Cycling in Agroecosystems, 60, 253–266.

Saygin, D., Rigter, J., Caldecott, B., Wagner, N., & Gielen, D. (2019). Power sector asset stranding effects of climate policies. Energy Sources Part B Economics Planning and Policy, 14(4), 99-124.

Shafiei, S., & Salim, R. A. (2014). Non-renewable and renewable energy consumption and CO2 emissions in OECD countries: A comparative analysis. Energy Policy, 66, 547–556.

Shahbaz, M., Nasir, M., & Roubaud, D. (2018). Environmental degradation in france: the effects of fdi, financial development, and energy innovations. Energy Economics, 74, 843-857.

Shahbaz, M., Nasreen, S., Ahmed, K., & Hammoudeh, S. (2017). Trade openness–CO2 emissions nexus: the importance of turning points of trade openness for country panels. Energy economics, 61, 221-232.

Shan, Y., Wang, X., Wang, Z., Liang, L., Li, J., & Sun, J. (2020). The pattern and mechanism of air pollution in developed coastal areas of china: from the perspective of urban agglomeration. Plos One, 15(9), e0237863.

Sharma, G. D., Verma, M., Shahbaz, M., Gupta, M., & Chopra, R. (2022). Transitioning green finance from theory to practice for renewable energy development. *Renewable Energy*, *195*, 554-565.

Shen, F., Simayi, Z., Yang, S., Mamitimin, Y., Zhang, X., & Zhang, Y. (2023). A Bibliometric Review of Household Carbon Footprint during 2000–2022. *Sustainability*, *15*(7), 6138.

Shen, J. H., Long, Z., Lee, C. C., & Zhang, J. (2022). Comparative advantage, endowment structure, and trade imbalances. Structural Change and Economic Dynamics, 60, 365–375.

Shobande, O. and Ogbeifun, L. (2021). The criticality of financial development and energy consumption for environmental sustainability in oecd countries: evidence from dynamic panel analysis. International Journal of Sustainable Development & World Ecology, 29(2), 153-163.

Sijabat, R. (2024). The long-run relationship between renewable energy consumption, non-renewable energy consumption, population, and economic growth in g20 countries. International Journal of Sustainable Development and Planning, 19(4), 1599-1610.

Singh, A., Tandon, P., & Jasuja, D. (2022). Does financial inclusion spur CO2 emissions in india: an ardl approach. Management of Environmental Quality an International Journal, 34(2), 511-534.

Singla, H. K. and Samanta, P. K. (2019). Determinants of dividend payout of construction companies: a panel data analysis. Journal of Financial Management of Property and Construction, 24(1), 19-38.

Sinha, A., & Shahbaz, M. (2018). Estimation of Environmental Kuznets Curve for CO2 emission: Role of renewable energy generation in India. *Renewable Energy, 119*(C), 703-711.

Sokulski, C., Barros, M., Salvador, R., Broday, E., & Francisco, A. (2022). Trends in renewable electricity generation in the g20 countries: an analysis of the 1990–2020 period. Sustainability, 14(4), 2084.

Spineli, L. and Pandis, N. (2020). Fixed-effect versus random-effects model in meta-regression analysis. American Journal of Orthodontics and Dentofacial Orthopedics, 158(5), 770-772.

Stock, J. H., & Watson, M. W. (2015). Introduction to Econometrics (3rd ed.). Pearson.

Stolbova, V., Monasterolo, I., & Battiston, S. (2018). A financial macro-network approach to climate policy evaluation. *Ecological Economics*, *149*, 239-253.

Sun, J., Zhang, L., Sun, R., Jiang, Y., Chen, X., He, C., … & Wei, J. (2018). Exploring the influence of resiliency on physician trust in patients: an empirical study of chinese incidents. Plos One, 13(12), e0207394.

Sun, Y., Bao, Q., & Taghizadeh-Hesary, F. (2023). Green finance, renewable energy development, and climate change: evidence from regions of china. Humanities and Social Sciences Communications, 10(1).

Sungwon, L.E.E., & Bumsoo, L. (2020). Comparing the impacts of local land use and urban spatial structure on household VMT and GHG emissions. Journal of Transport Geography, 84, 102694.

Tachega, M., Yao, X., Liu, Y., Ahmed, D., Ackaah, W., Gabir, M., … & Gyimah, J. (2021). Income heterogeneity and the environmental kuznets curve turning points: evidence from africa. Sustainability, 13(10), 5634.

Taghizadeh–Hesary, F. and Yoshino, N. (2019). The way to induce private participation in green finance and investment. Finance Research Letters, 31, 98-103.

Tamazian, A. and Rao, B. (2010). Do economic, financial and institutional developments matter for environmental degradation? evidence from transitional economies. Energy Economics, 32(1), 137-145.

Tan, J. and Chen, L. (2023). Green finance, energy consumption, and carbon dioxide emissions: a gmm panel data analysis from china. Iop Conference Series Earth and Environmental Science, 1152(1), 012001.

Tang, K., Chen, Q., Tan, W., & Feng, Y. (2022). The impact of financial deepening on carbon reductions in china: evidence from city- and enterprise-level data. International Journal of Environmental Research and Public Health, 19(18), 11355.

Tang, W., Zhong, X., & Xu, D. (2011). Analysis of major driving forces of ecological footprint based on the stripat model and rr method: a case of sichuan province, southwest china. Journal of Mountain Science, 8(4), 611-618.

Task Force on Climate-related Financial Disclosures (TCFD). (2018). TCFD: 2018 status report.

Tasnia, Mashiyat & Alhabshi, Syed Musa & Rosman, Romzie. (2020). The impact of corporate social responsibility on stock price volatility of the US banks: a moderating role of tax. Journal of Financial Reporting and Accounting. ahead-of-print. 10.1108/JFRA-01-2020-0020.

Terzi, H. and Pata, U. (2020) Is the Pollution Haven Hypothesis (PHH) Valid for Turkey? Panoeconomicus, 67, 93-109.

Thadewald, T. and Büning, H. (2007). Jarque–bera test and its competitors for testing normality – a power comparison. Journal of Applied Statistics, 34(1), 87-105.

Thuy, D. (2022). Effects of trade openness on environmental quality: evidence from developing countries.

Tian, X. L., Bélaïd, F., & Ahmad, N. (2021). Exploring the nexus between tourism development and environmental quality: Role of Renewable energy consumption and Income. Structural Change and Economic Dynamics, 56, 53-63.

Tian, Y. and Zhang, Y. (2022). Study on the regional difference, dynamic evolution and influencing factors for china's CO2 emissions.. https://doi.org/10.21203/rs.3.rs-2141059/v1

Tong, X., Li, X., Lin, T., & Jiang, X. (2018). Spatial spillover and the influencing factors relating to provincial CO2 emissions in china based on the spatial panel data model. Sustainability, 10(12), 4739.

Tunç, G. I., Türüt-Aşik, S., & Akbostancı, E. (2007). CO2 emissions vs. CO2 responsibility: An input–output approach for the Turkish economy. Energy Policy, 35(2), 855–868.

un, Y. (2022). Financial development, foreign trade, regional economic development level and CO2 emissions. Frontiers in Environmental Science, 10.

UNCTAD (Ed.). (2014). Investing in the SDGs: An action plan. World Investment Report 2014. United Nations.van Rooijen, S. N. M., & van Wees, M. T. (2006). Green electricity policies in the Netherlands: An analysis of policy decisions. EnergyPolicy, 34(1), 60–71.

UNEP, (2011). Towards a Green Economy: Pathways to Sustainable Development and Poverty Eradication - A Synthesis for Policy Makers, www.unep.org/greeneconomy.

Utami, B. H. S., Irawan, A., Gumanti, M., & Primajati, G. (2021). Hausman and taylor estimator analysis on the linear data panel model. *Jurnal Varian*, *5*(1), 81-88.

Viglioni, M. T. D., Calegario, C. L. L., Viglioni, A. C. D., & Bruhn, N. C. P. (2024). Foreign direct investment and environmental degradation: Can intellectual property rights help G20 countries achieve carbon neutrality?. *Technology in Society*, 102501.

Wang, C., Gong, W., Wen, Y., & Liu, Y. (2023). The development level of green finance

Wang, H. and Zhang, X. (2021). Examining the driving factors of industrial co2 emissions in chinese cities using geographically weighted regression model. Clean Technologies and Environmental Policy, 23(6), 1873-1887.

Wang, H., Li, R., & Huang, Y. (2022). The dual role of green technology patents in CO2 emissions reduction: Evidence from China. Energy Policy, 160, 112610.

Wang, Q. and Zhang, F. (2021). The effects of trade openness on decoupling CO2 emissions from economic growth – evidence from 182 countries. Journal of Cleaner Production, 279, 123838.

Wang, S. and Yi, X. (2022). Can the financial industry 'anchor' CO2 emissions reductions?— the mediating and moderating effects of the technology market. Energy &Amp; Environment, 34(3), 533-559.

Wang, S.J., Fang, C.L., Wang, Y., Huang, Y.B., & Ma, H.T. (2015). Quantifying the relationship between urban development intensity and carbon dioxide emissions using a panel data analysis. Ecological Indicators, 49, 121–131.

Wang, Z. and Lv, D. (2022). Analysis of agricultural co2 emissions in henan province, china, based on ekc and decoupling. Sustainability, 14(3), 1931. https://doi.org/10.3390/su14031931

Wen, L., Zhang, Z. (2020). Probing Energy-Related CO_2 Emissions in the Beijing-Tianjin-Hebei Region Based on Ridge Regression Considering Population Factors. Polish Journal of Environmental Studies, 29(3), 2413-2427. https://doi.org/10.15244/pjoes/110515

Wen, Y., Song, P., Yang, D., & Gao, C. (2022). Does governance impact on the financial development-carbon dioxide emissions nexus in G20 countries. *Plos one*, *17*(8), e0273546.

Wencong, L., Kasimov, I., & Saydaliev, H. B. (2023). Foreign direct investment and renewable energy: Examining the environmental Kuznets curve in resource-rich transition economies. *Renewable Energy*, *208*, 301-310.

Widarni, E. and Bawono, S. (2021). The comparation of foreign financial investment and human investment effect on economic in indonesia base on macro economic point of view. Studies of Applied Economics, 39(12).

Wigley, T. (1998). The kyoto protocol: co2 ch4 and climate implications. Geophysical Research Letters, 25(13), 2285-2288.

Wijaya, T. (2022). Panel data regression analysis on factors affecting firm value in manufacturing companies. Journal of Applied Business Taxation and Economics Research, 2(1), 62-75.

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. MIT Press.

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data (2nd ed.). MIT Press.

Wooldridge, J. M. (2013). Introductory Econometrics: A Modern Approach (5th ed.). South-Western, Cengage Learning.

Wu, J. (2023). Measuring economic development and carbon dioxide emissions inefficiency. Sage Open, 13(1), 215824402311544.

Wu, S. and Zhang, K. (2021). Influence of urbanization and foreign direct investment on CO2 emissions efficiency: evidence from urban clusters in the yangtze river economic belt. Sustainability, 13(5), 2722.

Xia, L. and Gallagher, K. (2022). Assessing the climate change exposure of foreign direct investment. Nature Communications, 13(1).

Xiao-chun, Z., Jiang, M., & Zhang, W. (2022). Decoupling between economic development and CO2 emissions and its driving factors: evidence from china. International Journal of Environmental Research and Public Health, 19(5), 2893.

Xing, T., Jiang, Q., & Ma, X. (2017). To facilitate or curb? the role of financial development in china's CO2 emissions reduction process: a novel approach. International Journal of Environmental Research and Public Health, 14(10), 1222.

Xiong, W. and Tian, M. (2014). A novel robust and efficient tool for detecting heteroscedasticity. Journal of Mathematics and Statistics, 10(2), 169-185.

Xue, Q., Feng, S., Chen, K., & Li, M. (2022). Impact of digital finance on regional CO2 emissions: an empirical study of sustainable development in china. Sustainability, 14(14), 8340.

Yan, K., Gupta, R., & Wong, V. (2022). CO2 emissions in G20 nations through the three-sector model. Journal of Risk and Financial Management, 15(9), 394.

Yang, L., Zhang, H., Liao, X., Wang, H., Bian, Y., Liu, G., & Luo, W. (2023). The relationship between spatial characteristics of urban-rural settlements and CO2 emissions in Guangdong Province. *International Journal of Environmental Research and Public Health*, *20*(3), 2659.

Yang, P., Cui, C., Li, L., Chen, W., Shi, Y., Mi, Z., … & Guan, D. (2020). Carbon emissions in countries that failed to ratify the intended nationally determined contributions: a case study of kyrgyzstan. Journal of Environmental Management, 255, 109892.

Yao, S. and Zhang, S. (2021). Energy mix, financial development, and CO2 emissions in china: a directed technical change perspective. Environmental Science and Pollution Research, 28(44), 62959-62974.

Yao, S. and Zhang, S. (2021). Energy mix, financial development, and CO2 emissions in china: a directed technical change perspective. Environmental Science and Pollution Research, 28(44), 62959-62974.

Ye, H., Zhang, H., & Wei, L. (2021). Impact of trade openness on carbon productivity of emerging economies. American Journal of Industrial and Business Management, 11(01), 19-31.

Yin, Y., & Moffatt, P. G. (2019). Correcting the bias in the Practitioner Black-Scholes method. *Journal of Risk and Financial Management*, *12*(4), 157.

York, R., Rosa, E., & Dietz, T. (2003). Stirpat, ipat and impact: analytic tools for unpacking the driving forces of environmental impacts. Ecological Economics, 46(3), 351-365.

Yu, H. and Zhang, X. (2024). Are CO2 emissions trading and green financial instruments synergistic? -comprehensive quantitative research based on content analysis. Plos One, 19(3), e0298601.

Yuan, K., Feng, C., & Guo, L. (2022). Peaking global and g20 countries' co2 emissions under the shared socio-economic pathways. International Journal of Environmental Research and Public Health, 19(17), 11076.

Yuan, R., Behrens, P., & Rodrigues, J. F. D. (2017). The evolution of inter-sectoral linkages in China's energy-related CO2 emissions from 1997 to 2012. *Energy Economics*, 69, 404–417.

Yusuf, N. and Lytras, M. (2023). Competitive sustainability of saudi companies through digitalization and the circular carbon economy model: a bold contribution to the vision 2030 agenda in saudi arabia. Sustainability, 15(3), 2616.

Zaatari, R. (2022). *The green economy of Morocco* (Doctoral dissertation, University of Glasgow).

Zabediuk, M. (2022). Main aspects of forming the financial potential of ukrainian enterprises. Економічні Науки Серія Регіональна Економіка, (19(75)), 83-89.

Zahran, S., Kim, E., Chen, X., & Lubell, M. (2007). Ecological development and global climate change: a cross-national study of kyoto protocol ratification. Society & Natural Resources, 20(1), 37-55.

Zehr, S. (2014). The sociology of global climate change. Wiley Interdisciplinary Reviews Climate Change, 6(2), 129-150. https://doi.org/10.1002/wcc.328

Zeng, C., Wu, S., Zhang, H., & Cheng, M. (2022). The impact of urbanization growth patterns on carbon dioxide emissions: evidence from guizhou, west of china. Land, 11(8), 1211.

Zhang, D., Wang, Z., Li, S., & Zhang, H. (2021). Impact of land urbanization on CO2 emissions in urban agglomerations of the middle reaches of the yangtze river. International Journal of Environmental Research and Public Health, 18(4), 1403.

Zhang, H. and Luo, M. (2016). An empirical analysis of the impact on CO2 emissions of china's urbanization.

Zhang, R., Xu, P., Guo, L., Zhang, Y., Li, P., & Yao, D. (2013). Z-score linear discriminant analysis for eeg based brain-computer interfaces. Plos One, 8(9), e74433.

Zhang, S., Li, Z., Ning, X., & Li, L. (2021). Gauging the impacts of urbanization on co2 emissions from the construction industry: evidence from china. Journal of Environmental Management, 288, 112440.

Zhang, W. (2024). Spatiotemporal change of cultivated land in china during 2000–2020. Plos One, 19(1), e0293082.

Zhang, W. and Xu, H. (2017). Effects of land urbanization and land finance on CO2 emissions: a panel data analysis for chinese provinces. Land Use Policy, 63, 493-500.

Zhang, X. P., & Cheng, X. M. (2009). Energy consumption, carbon emissions, and economic growth in China. Ecological Economics, 68(10), 2706–2712.

Zhang, X., Zhao, X., & Lei, Y. (2020). The impact of technological innovation on CO2 emissions reduction: Evidence from patent data. Technological Forecasting and Social Change, 153, 119954.

Zhang, Y., Zhang, J., Xu, Z., Hu, X., Hu, D., & Yang, G. (2023). Does the setting of local government economic growth targets promote or hinder urban CO2 emissions performance?evidence from china.

Zhang, Z., Liu, Y., Han, Z., & Liao, X. (2022). Green finance and CO2 emissions reduction: a bibliometric analysis and systematic review. Frontiers in Environmental Science, 10.

Zhao, H., Yang, Y., Li, N., Liu, D., & Li, H. (2021). How does digital finance affect CO2 emissions? evidence from an emerging market. Sustainability, 13(21), 12303.

Zheng, J., Mi, Z., Coffman, D. M., Shan, Y., Guan, D., & Wang, S. (2019). The slowdown in China's CO2 emissions growth in the new phase of economic development. *One Earth*, *1*(2), 240-253.

Zhong, X., Li, X., & Li, Y. (2022). Urban expansion and CO2 emissions logistic curve hypothesis and its verification: a case study of jiangsu province. Land, 11(7), 1066.

Zhou, Y., Fang, Z., Li, N., Wu, X., Du, Y., & Liu, Z. (2019). How does financial development affect reductions in CO2 emissions in high-energy industries?—a perspective on technological progress. International Journal of Environmental Research and Public Health, 16(17), 3018.

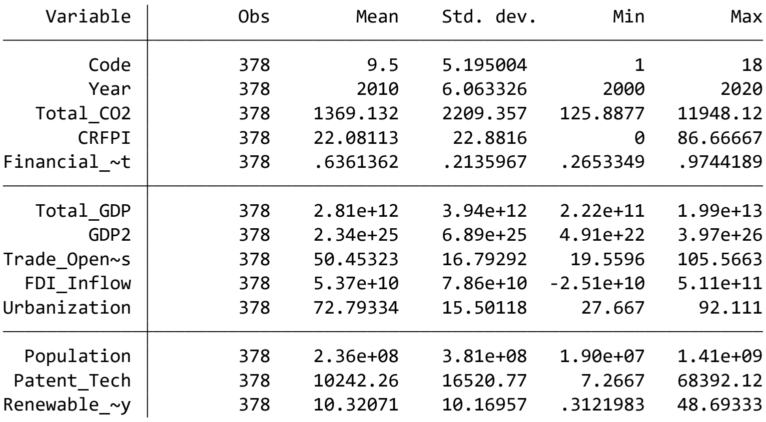
Zhu, H., Liu, D., Guo, Y., & Yu, K. (2016). The effects of fdi, economic growth and energy consumption on CO2 emissions in asean-5: evidence from panel quantile regression. economic Modelling, 58, 237-248.

Zhu, L., Zhou, X., Huang, Y., & Huang, W. (2021). An empirical study on the relationship between energy CO2 emissions and economic growth based on ekc—take yunnan province as an example.

APPENDIX

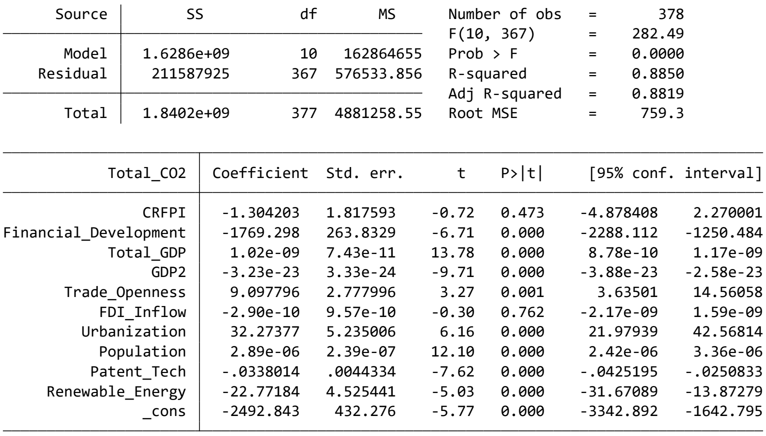
Appendix

1. Statistic descriptive



```
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
        Code |        378         9.5    5.195004          1         18
        Year |        378        2010    6.063326       2000       2020
   Total_CO2 |        378    1369.132    2209.357   125.8877   11948.12
       CRFPI |        378    22.08113     22.8816          0   86.66667
Financial_~t |        378    .6361362    .2135967   .2653349   .9744189
-------------+---------------------------------------------------------
   Total_GDP |        378    2.81e+12    3.94e+12   2.22e+11   1.99e+13
        GDP2 |        378    2.34e+25    6.89e+25   4.91e+22   3.97e+26
Trade_Open~s |        378    50.45323    16.79292    19.5596   105.5663
  FDI_Inflow |        378    5.37e+10    7.86e+10  -2.51e+10   5.11e+11
Urbanization |        378    72.79334    15.50118     27.667     92.111
-------------+---------------------------------------------------------
  Population |        378    2.36e+08    3.81e+08   1.90e+07   1.41e+09
 Patent_Tech |        378    10242.26    16520.77     7.2667   68392.12
Renewable_~y |        378    10.32071    10.16957   .3121983   48.69333
```

2. Pooled-least Square (PLS) Model



```
      Source |       SS           df       MS      Number of obs   =       378
-------------+----------------------------------   F(10, 367)      =    282.49
       Model |  1.6286e+09        10   162864655   Prob > F        =    0.0000
    Residual |   211587925       367  576533.856   R-squared       =    0.8850
-------------+----------------------------------   Adj R-squared   =    0.8819
       Total |  1.8402e+09       377  4881258.55   Root MSE        =     759.3

------------------------------------------------------------------------------------
         Total_CO2 | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------------+----------------------------------------------------------------
             CRFPI |  -1.304203   1.817593    -0.72   0.473    -4.878408    2.270001
Financial_Development |  -1769.298   263.8329    -6.71   0.000    -2288.112   -1250.484
         Total_GDP |   1.02e-09   7.43e-11    13.78   0.000     8.78e-10    1.17e-09
              GDP2 |  -3.23e-23   3.33e-24    -9.71   0.000    -3.88e-23   -2.58e-23
    Trade_Openness |   9.097796   2.777996     3.27   0.001      3.63501    14.56058
        FDI_Inflow |  -2.90e-10   9.57e-10    -0.30   0.762    -2.17e-09    1.59e-09
      Urbanization |   32.27377   5.235006     6.16   0.000     21.97939    42.56814
        Population |   2.89e-06   2.39e-07    12.10   0.000     2.42e-06    3.36e-06
       Patent_Tech |  -.0338014   .0044334    -7.62   0.000    -.0425195   -.0250833
  Renewable_Energy |  -22.77184   4.525441    -5.03   0.000    -31.67089   -13.87279
             _cons |  -2492.843    432.276    -5.77   0.000    -3342.892   -1642.795
------------------------------------------------------------------------------------
```

3. Fixed Effect (FE) Model

```
Fixed-effects (within) regression               Number of obs     =        378
Group variable: Code                            Number of groups  =         18

R-squared:                                      Obs per group:
     Within  = 0.9391                                         min =         21
     Between = 0.5086                                         avg =       21.0
     Overall = 0.5315                                         max =         21

                                                F(10,350)         =     540.14
corr(u_i, Xb) = -0.6286                         Prob > F          =     0.0000

----------------------------------------------------------------------------------------
             Total_CO2 | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-----------------------+----------------------------------------------------------------
                 CRFPI |  -7.563537   .6879052   -11.00   0.000    -8.916485   -6.210589
 Financial_Development |  -591.5837   268.3841    -2.20   0.028    -1119.432   -63.73526
             Total_GDP |   1.56e-09   3.87e-11    40.39   0.000     1.49e-09    1.64e-09
                  GDP2 |  -4.93e-23   1.36e-24   -36.20   0.000    -5.20e-23   -4.66e-23
        Trade_Openness |  -.3851635   1.335223    -0.29   0.773    -3.011233    2.240906
            FDI_Inflow |   5.13e-10   2.31e-10     2.22   0.027     5.92e-11    9.67e-10
          Urbanization |   14.54366   7.082442     2.05   0.041     .6141612    28.47316
            Population |  -1.22e-06   4.50e-07    -2.71   0.007    -2.10e-06   -3.32e-07
           Patent_Tech |   -.005187   .0038714    -1.34   0.181    -.0128011    .0024271
      Renewable_Energy |  -27.79652   4.496443    -6.18   0.000    -36.63997   -18.95308
                 _cons |  -1770.853   409.9116    -4.32   0.000    -2577.052   -964.6528
-----------------------+----------------------------------------------------------------
               sigma_u |   1986.096
               sigma_e |   172.0322
                   rho |  .99255315   (fraction of variance due to u_i)
----------------------------------------------------------------------------------------
F test that all u_i=0: F(17, 350) = 399.97                   Prob > F = 0.0000
```

4. Random Effect (RE) Model

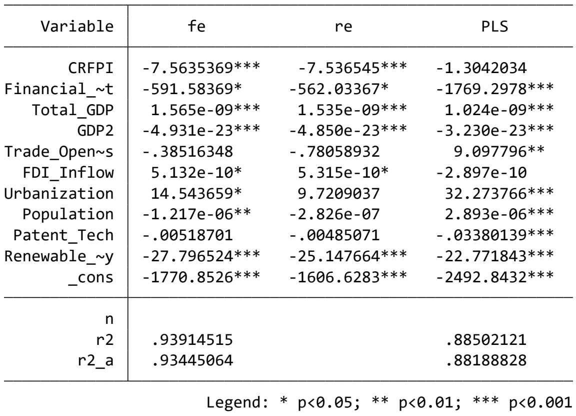
```
Random-effects GLS regression                   Number of obs     =        378
Group variable: Code                            Number of groups  =         18

R-squared:                                      Obs per group:
     Within  = 0.9383                                         min =         21
     Between = 0.6230                                         avg =       21.0
     Overall = 0.6384                                         max =         21

                                                Wald chi2(7)      =          .
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =          .
theta        = .96341829

----------------------------------------------------------------------------------------
             Total_CO2 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-----------------------+----------------------------------------------------------------
                 CRFPI |  -7.536545   .7161377   -10.52   0.000    -8.940149   -6.132941
 Financial_Development |  -562.0337   273.2505    -2.06   0.040    -1097.595   -26.47258
             Total_GDP |   1.53e-09   4.01e-11    38.27   0.000     1.46e-09    1.61e-09
                  GDP2 |  -4.85e-23   1.42e-24   -34.11   0.000    -5.13e-23   -4.57e-23
        Trade_Openness |  -.7805893   1.389689    -0.56   0.574    -3.504329    1.943151
            FDI_Inflow |   5.31e-10   2.42e-10     2.19   0.028     5.65e-11    1.01e-09
          Urbanization |   9.720904   6.806643     1.43   0.153    -3.619872    23.06168
            Population |  -2.83e-07   3.96e-07    -0.71   0.475    -1.06e-06    4.94e-07
           Patent_Tech |  -.0048507   .0039836    -1.22   0.223    -.0126585    .0029571
      Renewable_Energy |  -25.14766   4.597808    -5.47   0.000     -34.1592   -16.13613
                 _cons |  -1606.628   483.4946    -3.32   0.001     -2554.26   -658.9963
-----------------------+----------------------------------------------------------------
               sigma_u |  1025.5227
               sigma_e |   172.0322
                   rho |  .97262989   (fraction of variance due to u_i)
----------------------------------------------------------------------------------------
```

5. Comparative regression result



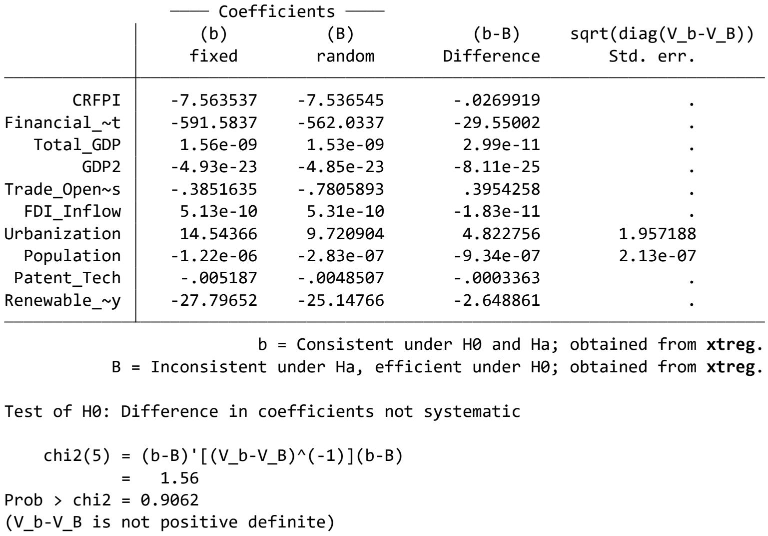
```
    Variable        fe                re                PLS

       CRFPI   -7.5635369***    -7.536545***    -1.3042034
 Financial_~t  -591.58369*      -562.03367*     -1769.2978***
    Total_GDP   1.565e-09***     1.535e-09***    1.024e-09***
         GDP2  -4.931e-23***    -4.850e-23***   -3.230e-23***
 Trade_Open~s  -.38516348       -.78058932       9.097796**
   FDI_Inflow   5.132e-10*       5.315e-10*     -2.897e-10
 Urbanization   14.543659*       9.7209037       32.273766***
   Population  -1.217e-06**     -2.826e-07       2.893e-06***
  Patent_Tech  -.00518701       -.00485071      -.03380139***
 Renewable_~y  -27.796524***    -25.147664***   -22.771843***
        _cons  -1770.8526***    -1606.6283***   -2492.8432***

            n
           r2   .93914515                        .88502121
         r2_a   .93445064                        .88188828

                       Legend: * p<0.05; ** p<0.01; *** p<0.001
```

6. Hausman test



```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference       Std. err.
-------------+----------------------------------------------------------------
       CRFPI |   -7.563537    -7.536545       -.0269919               .
 Financial_~t|   -591.5837    -562.0337       -29.55002               .
    Total_GDP|    1.56e-09     1.53e-09        2.99e-11               .
         GDP2|   -4.93e-23    -4.85e-23       -8.11e-25               .
 Trade_Open~s|   -.3851635    -.7805893        .3954258               .
   FDI_Inflow|    5.13e-10     5.31e-10       -1.83e-11               .
 Urbanization|    14.54366     9.720904        4.822756        1.957188
   Population|   -1.22e-06    -2.83e-07       -9.34e-07        2.13e-07
  Patent_Tech|    -.005187    -.0048507       -.0003363               .
 Renewable_~y|   -27.79652    -25.14766       -2.648861               .
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   1.56
Prob > chi2 = 0.9062
(V_b-V_B is not positive definite)
```

7. Chow test

```
. regress $ylist $xlist i. Code

      Source |       SS           df       MS      Number of obs   =       378
-------------+----------------------------------   F(27, 350)      =   2290.02
       Model |  1.8299e+09        27  67773192.4   Prob > F        =    0.0000
    Residual |  10358277.7       350  29595.0791   R-squared       =    0.9944
-------------+----------------------------------   Adj R-squared   =    0.9939
       Total |  1.8402e+09       377  4881258.55   Root MSE        =    172.03

------------------------------------------------------------------------------------
         Total_CO2 | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------------+----------------------------------------------------------------
             CRFPI |  -7.563537   .6879052   -11.00   0.000    -8.916485   -6.210589
Financial_Develo~t |  -591.5837   268.3841    -2.20   0.028    -1119.432   -63.73526
         Total_GDP |   1.56e-09   3.87e-11    40.39   0.000     1.49e-09    1.64e-09
              GDP2 |  -4.93e-23   1.36e-24   -36.20   0.000    -5.20e-23   -4.66e-23
    Trade_Openness |  -.3851635   1.335223    -0.29   0.773    -3.011233    2.240906
        FDI_Inflow |   5.13e-10   2.31e-10     2.22   0.027     5.92e-11    9.67e-10
      Urbanization |   14.54366   7.082442     2.05   0.041     .6141612    28.47316
        Population |  -1.22e-06   4.50e-07    -2.71   0.007    -2.10e-06   -3.32e-07
       Patent_Tech |   -.005187   .0038714    -1.34   0.181    -.0128011    .0024271
  Renewable_Energy |  -27.79652   4.496443    -6.18   0.000    -36.63997   -18.95308
                   |
              Code |
                2  |  -8232.461    530.069   -15.53   0.000    -9274.982    -7189.94
                3  |  -2945.571   695.5995    -4.23   0.000    -4313.652    -1577.49
                4  |  -3260.822   638.7501    -5.11   0.000    -4517.093   -2004.551
                5  |  -2714.748   567.3385    -4.79   0.000    -3830.569   -1598.926
                6  |  -2882.502   603.5372    -4.78   0.000    -4069.518   -1695.486
                7  |  -4637.266   600.3704    -7.72   0.000    -5818.053   -3456.478
                8  |  -5301.718   584.3642    -9.07   0.000    -6451.025   -4152.411
                9  |  -552.8918   120.1626    -4.60   0.000    -789.2233   -316.5602
               10  |  -1996.521    471.207    -4.24   0.000    -2923.275   -1069.768
               11  |  -3945.072   568.0983    -6.94   0.000    -5062.387   -2827.756
               12  |  -6165.239   599.4369   -10.29   0.000     -7344.19   -4986.287
               13  |  -3289.115   616.0614    -5.34   0.000    -4500.763   -2077.467
               14  |  -1997.162    573.333    -3.48   0.001    -3124.773   -869.5504
               15  |  -1997.287   574.8183    -3.47   0.001    -3127.819   -866.7541
               16  |   -3208.34   620.1951    -5.17   0.000    -4428.118   -1988.562
               17  |  -2526.641   585.6808    -4.31   0.000    -3678.538   -1374.745
               18  |   -5209.44   610.9819    -8.53   0.000    -6411.098   -4007.782
                   |
             _cons |   1610.414   549.1739     2.93   0.004     530.3178     2690.51
------------------------------------------------------------------------------------
 ( 1)  2.Code = 0
 ( 2)  3.Code = 0
 ( 3)  4.Code = 0
 ( 4)  5.Code = 0
 ( 5)  6.Code = 0
 ( 6)  7.Code = 0
 ( 7)  8.Code = 0
 ( 8)  9.Code = 0
 ( 9)  10.Code = 0
 (10)  11.Code = 0
 (11)  12.Code = 0
 (12)  13.Code = 0
 (13)  14.Code = 0
 (14)  15.Code = 0
 (15)  16.Code = 0
 (16)  17.Code = 0
 (17)  18.Code = 0

       F( 17,   350) =  399.97
            Prob > F =    0.0000
```

8. LM test

```
Breusch and Pagan Lagrangian multiplier test for random effects

        Total_CO2[Code,t] = Xb + u[Code] + e[Code,t]

        Estimated results:
                                 |       Var     SD = sqrt(Var)
                        ---------+-----------------------------
                       Total_CO2 |    4881259       2209.357
                               e |   29595.08       172.0322
                               u |    1051697       1025.523

        Test: Var(u) = 0
                                    chibar2(01) =  2360.40
                                 Prob > chibar2 =   0.0000
```

9. Normality test

```
Skewness and kurtosis tests for normality
                                                          ------ Joint test ------
    Variable |        Obs   Pr(skewness)   Pr(kurtosis)   Adj chi2(2)  Prob>chi2
-------------+----------------------------------------------------------------------
   residuals |        378         0.1712         0.0003         13.35     0.0013
```

10. Heteroscedasticity test

```
Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (18)  =      526.60
Prob>chi2 =      0.0000
```

11. Autocorrelation test

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      17) =     50.999
           Prob > F =      0.0000
```

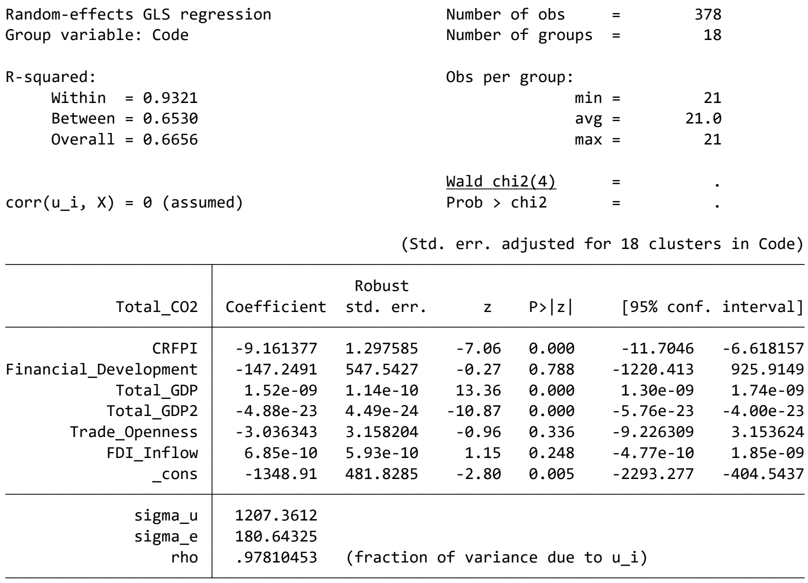
12. Robustness check by RE Robust standard error

```
Random-effects GLS regression                   Number of obs     =        378
Group variable: Code                            Number of groups  =         18

R-squared:                                      Obs per group:
     Within  = 0.9295                                         min =         21
     Between = 0.6507                                         avg =       21.0
     Overall = 0.6632                                         max =         21

                                                Wald chi2(2)      =          .
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =          .

                                   (Std. err. adjusted for 18 clusters in Code)
-------------------------------------------------------------------------------
                    |               Robust
          Total_CO2 | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
--------------------+----------------------------------------------------------------
              CRFPI |  -9.231491   1.343652    -6.87   0.000     -11.865   -6.597981
Financial_Development |  -122.8104    536.448    -0.23   0.819   -1174.229    928.6083
          Total_GDP |   1.54e-09   1.28e-10    11.95   0.000    1.28e-09    1.79e-09
         Total_GDP2 |  -4.89e-23   4.87e-24   -10.04   0.000   -5.84e-23   -3.93e-23
              _cons |  -1520.091   520.4503    -2.92   0.003   -2540.155   -500.0274
--------------------+----------------------------------------------------------------
            sigma_u |  1165.4028
            sigma_e |  183.46895
                rho |   .9758153   (fraction of variance due to u_i)
-------------------------------------------------------------------------------------
```

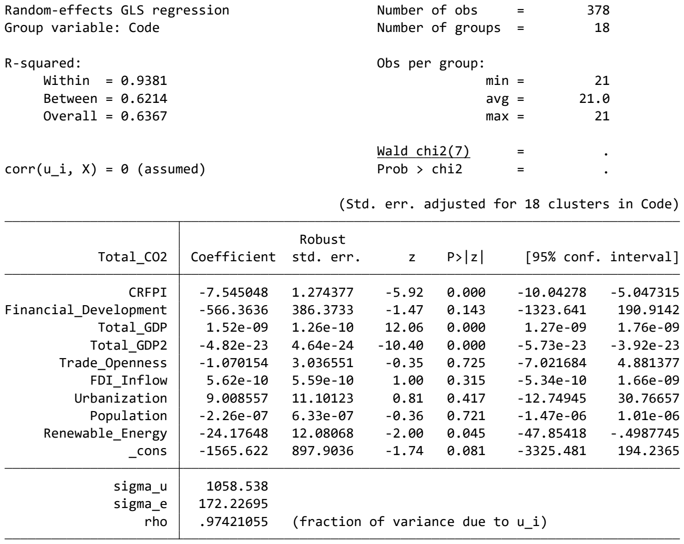


```
Random-effects GLS regression                   Number of obs     =        378
Group variable: Code                            Number of groups  =         18

R-squared:                                      Obs per group:
     Within  = 0.9321                                         min =         21
     Between = 0.6530                                         avg =       21.0
     Overall = 0.6656                                         max =         21

                                                Wald chi2(4)      =          .
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =          .

                                         (Std. err. adjusted for 18 clusters in Code)
─────────────────────────────────────────────────────────────────────────────────────
                      │               Robust
            Total_CO2 │ Coefficient  std. err.      z    P>|z|     [95% conf. interval]
──────────────────────┼──────────────────────────────────────────────────────────────
                CRFPI │  -9.161377   1.297585    -7.06   0.000     -11.7046   -6.618157
Financial_Development │  -147.2491   547.5427    -0.27   0.788    -1220.413    925.9149
            Total_GDP │   1.52e-09   1.14e-10    13.36   0.000     1.30e-09    1.74e-09
           Total_GDP2 │  -4.88e-23   4.49e-24   -10.87   0.000    -5.76e-23   -4.00e-23
       Trade_Openness │  -3.036343   3.158204    -0.96   0.336    -9.226309    3.153624
           FDI_Inflow │   6.85e-10   5.93e-10     1.15   0.248    -4.77e-10    1.85e-09
                _cons │   -1348.91   481.8285    -2.80   0.005    -2293.277   -404.5437
──────────────────────┼──────────────────────────────────────────────────────────────
              sigma_u │  1207.3612
              sigma_e │  180.64325
                  rho │  .97810453   (fraction of variance due to u_i)
─────────────────────────────────────────────────────────────────────────────────────
```



```
Random-effects GLS regression                   Number of obs     =        378
Group variable: Code                            Number of groups  =         18

R-squared:                                      Obs per group:
     Within  = 0.9381                                         min =         21
     Between = 0.6214                                         avg =       21.0
     Overall = 0.6367                                         max =         21

                                                Wald chi2(7)      =          .
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =          .

                                         (Std. err. adjusted for 18 clusters in Code)
─────────────────────────────────────────────────────────────────────────────────────
                      │               Robust
            Total_CO2 │ Coefficient  std. err.      z    P>|z|     [95% conf. interval]
──────────────────────┼──────────────────────────────────────────────────────────────
                CRFPI │  -7.545048   1.274377    -5.92   0.000    -10.04278   -5.047315
Financial_Development │  -566.3636   386.3733    -1.47   0.143    -1323.641    190.9142
            Total_GDP │   1.52e-09   1.26e-10    12.06   0.000     1.27e-09    1.76e-09
           Total_GDP2 │  -4.82e-23   4.64e-24   -10.40   0.000    -5.73e-23   -3.92e-23
       Trade_Openness │  -1.070154   3.036551    -0.35   0.725    -7.021684    4.881377
           FDI_Inflow │   5.62e-10   5.59e-10     1.00   0.315    -5.34e-10    1.66e-09
         Urbanization │   9.008557   11.10123     0.81   0.417    -12.74945    30.76657
           Population │  -2.26e-07   6.33e-07    -0.36   0.721    -1.47e-06    1.01e-06
     Renewable_Energy │  -24.17648   12.08068    -2.00   0.045    -47.85418   -.4987745
                _cons │  -1565.622   897.9036    -1.74   0.081    -3325.481    194.2365
──────────────────────┼──────────────────────────────────────────────────────────────
              sigma_u │   1058.538
              sigma_e │  172.22695
                  rho │  .97421055   (fraction of variance due to u_i)
─────────────────────────────────────────────────────────────────────────────────────
```