DOES THE EXISTENCE OF INCOME INEQUALITY CONTRIBUTE TO THE VOLUME OF CARBON DIOXIDE EMISSION? AN ANALYSIS ON SELECTED SOUTHEAST ASIA COUNTRIES.

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DECLARATION

We hereby declare that:

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

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

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

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LIST OF ABBREVIATIONS

ADB	Asian Development Bank
ASEAN	Association of Southeast Asian Nations
BP-LM	Breusch-Pagan Lagrange Multiplier
CD	Cross-section Dependence
CNLRM	Classical Normal Linear Regression Model
CO_2	Carbon Dioxide
DWH	Durbin-Wu-Hausman
EKC	Environmental Kuznets Curve
EPF	Employees Provident Fund
FDI	Foreign Direct Investment
FEM	Fixed Effect Model
GDP	Gross Domestic Product
GHG	Green House Gas
GI	Gini Index
IMF	International Monetary Fund
LLC	Levin, Lin, and Chu
LM	Lagrange Multiplier
LR	Likelihood Ratio
POLS	Pooled Ordinary Least Square
REM	Random Effect Model
UNESCAP	United Nations Economic and Social Commission for Asia and the Pacific
UPOP	Urban population
VIF	Variance Inflation Factors

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ABSTRACT

With an increasing in carbon emission, factors in Southeast Asia's economic development that will influence the increase in carbon emissions needs to be studied more thoroughly in order to address the issue of rising carbon emissions. This study's primary goal is to look into the factors that have influenced carbon emissions in six Southeast Asia nations from 1981 to 2020. The data used in this research is secondary data with a total number of observations of 240. For analysis, we applied panel data techniques such as pooled least squares, fixed effects, random effects. The Environmental Kuznets Curve (EKC) hypothesis is supported by our models' findings in the Southeast Asia countries, where GDP per capita and its square term have positive and negative coefficients. In this research, the result illustrates that foreign direct investment (FDI), GDP per capita, urbanization positively contribute to environmental degradation in Southeast Asia countries' economies. This study's findings add to the body of knowledge on environmental degradation and give policymakers in Southeast Asia countries' economies a better understanding of environmental degradation. By examining all the independent variables that this study found to be associated with an increase in carbon emissions, policymakers can think about how to manage these variables going forward in order to lower carbon emissions.

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

The chapter introduced the background and relevant issues of CO_2 emissions and income inequality. Other than that, the chapter also covers the research problem, research question, research objectives, research significance, and organization of the study. The research is chosen to study the factors from the aspects of finance, economy, and society on the CO_2 emissions in Indonesia, Malaysia, Vietnam, Thailand, Myanmar, and Philippines. This research also aims to determine how income inequality plays a vital role in affecting Southeast Asia countries' CO_2 emissions.

1.1 Research Background

According to Gougoulias et al. (2014), the main greenhouse gas that is produced by human activity is carbon dioxide (CO_2). The CO_2 is present naturally in the carbon cycle in the earth's atmosphere. Human activities are increasing the amount of CO_2 in the atmosphere and affecting the capability of forests and soils to absorb and store CO_2, which led to the increasing amount of CO_2 in the earth's atmosphere. Ever since the start of the industrial revolution, humans have been the main cause of the increased amount of CO_2 in the atmosphere even though the emissions come from several natural sources (United States Environmental Protection Agency, 2022).

The United States Environmental Protection Agency (2022) stated the main driver of the emission of CO_2 is the combustion of fossil fuels. This may come from coal to biofuels, fuel consumption for transportation, industrial production, household use, and the generation of heat and power (Quadrelli & Peterson, 2007). In the early nineteenth century, it was found that the burning of fossil fuels releases carbon dioxide into the atmosphere which has been linked to an increase in the atmospheric carbon dioxide levels and a change in the Earth's thermal balance. There is solid evidence supporting the addition of CO_2 to the atmosphere linked to human activity (Sawyer, 1972). Another human activity that leads to the emission of CO_2 is the changes in land use and land cover. A significant component of the Global Carbon Budget (GCB) is the annual flux of CO_2 to the atmosphere brought on by this human-driven activity. After the burning of fossil fuels, it is one of the two historical anthropogenic sources of CO_2, and when combined with the land carbon sink, it results in the net land-to-atmosphere carbon exchange (Gasser et al., 2020). Deforestation, urbanization, and shifts in vegetation patterns are examples of changes in land use and land cover done by human activities (CLEAN, 2021).

One of the most significantly impacted regions on climate change are the Southeast Asia compared to other regions of the world as confirmed by the International Monetary Fund (Prakash, 2018). It could potentially be the main cause of global warming in the future and even in the current state. In recent years statistics have shown that Southeast Asia's CO_2 emission is in more rapid growth than other regions of the world. The ASEAN countries are the fastest-growing economies in the world in the recent decade which contain policies such as subsidizing the use of fossil fuels which encourage more burning of fossil fuels and eventually increase the level of CO_2 emissions in the near decades coupled with the region's high current level of emissions (Raitzer et al., 2015).

According to Iwata and Okada (2014), the high emissions of CO_2 in the atmosphere led to the introduction of the Kyoto Protocol which was proposed in 1997 by the United Nations Framework Convention on Climate Change. This protocol restricts and cuts down the emissions of greenhouse gases in the world. Each country, especially the developing countries, was given a specific target to limit their gas emissions. The participating countries were made responsible for the significant level of gas emissions in the atmosphere. The ASEAN leaders from Brunei, Indonesia, Malaysia, Thailand, Vietnam, Cambodia, Laos, Myanmar, Singapore, and the Philippines made a statement regarding the Kyoto Protocol in 2021 and admitted that the Southeast Asian region is exposed to the danger possessed by climate change which will affect their livelihood and restrict their development effort towards poverty and other development efforts. Therefore, the Southeast Asian countries acknowledged the importance of conserving and managing forests to reduce the emissions of CO_2 and other greenhouse gasses which might lead to climate change. The statement also underlined the urgency to ensure it will not interfere with the Earth’s atmosphere caused by humans proving their strong support for the Kyoto Protocol (Association of Southeast Asian Nations, 2021).

Among the Southeast Asia countries, we have chosen Indonesia, Malaysia, Vietnam, Thailand, Myanmar, and Philippines as the selected Southeast Asia countries in our study. It was statistically proven by the Association of Southeast Asian Nations that these six countries are among the top Southeast Asia countries with the highest income inequality issue as reported in the ASEAN Key Figures 2021 by the Association of Southeast Asian Nations (2022). On the other hand, according to Kameke (2022), for the past ten years, Indonesia, Malaysia, Vietnam, Thailand, Myanmar, Philippines had been the highest emitters of CO_2 which are suitable for this study

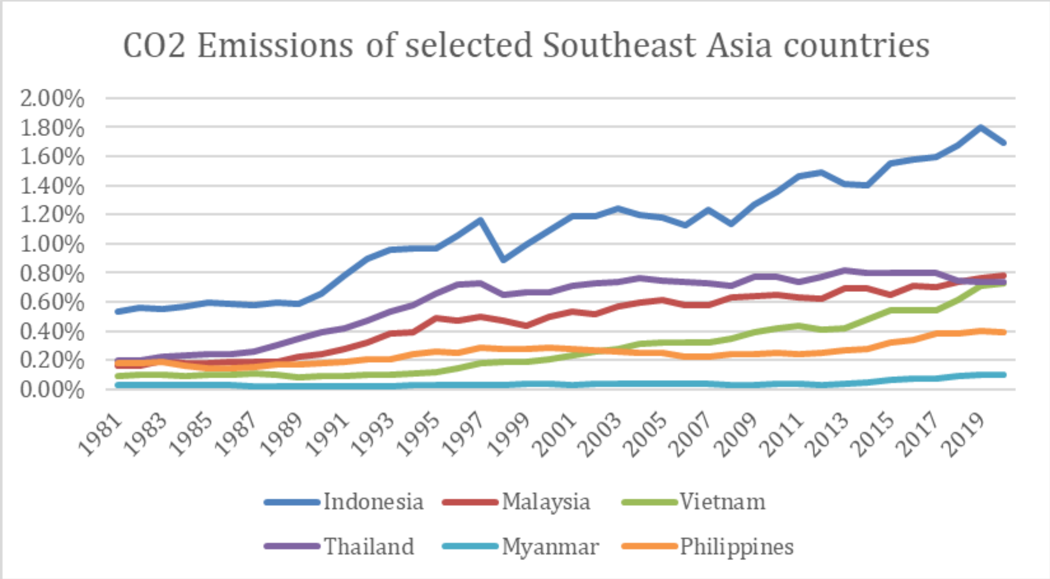

Figure 1.1. CO_2 emissions of selected Southeast Asia countries.

Source: Our World in Data (Ritchie et al., 2020)

As observed in figure 1.1, Indonesia's contribution to the world's CO_2 emissions is showing an increasing trend being the highest contributor of CO_2 among the six selected Southeast Asia countries from the year 1981 to 2020. Thailand had an increasing trend from 1981 to 1997 and then remained almost constant trendline contributing almost 0.8%. Malaysia's contribution to CO_2 emissions had a slight increase trendline from an estimated from 1981 to 2020. Vietnam had an obvious increase in trendline in contributing CO_2 emissions to the world while the Philippines had a fluctuation trend. Lastly, Myanmar had a constant trend with very little increase from 1995 until 2020.

According to Dabla-Norris et al. (2015), growing income inequality among emerging markets and developing nations is a topic that has drawn a lot of attention. Former United States President, Barack Obama labelled income inequality as the most concerning issue in these times. More than 60% of people globally said that the gap between the rich and the poor is a key concern in a Pew Research Center study. When there is a tenacious disadvantage for certain groups in society, inequality can be a symptom that there is a lack of opportunity and income mobility.

Widening income inequality is receiving more attention and has become some of the most contentious topics among researchers and policymakers.

Based on the report from United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP) cited by The Asean Post (2018), the Southeast Asia region may be one of the most rapidly growing economies than other regions in the past decade, but also its inequalities are increasing most, and they performed poorly in improving the inequalities including income inequality. Thailand Foreign Affairs Minister, Don Pramudwinai said in a press conference that the widening gaps in income distribution are one of the most concerning issues in the Southeast Asia region (Tongwaranan, 2018). Furthermore, the Thai Foreign Affairs Minister further stated that although the economic growth had reduced the poverty rate, it did not solve the issue of income inequality in the region. Instead, the worsened income inequality could potentially threaten to slowdown economic growth, higher poverty, and cause social cohesion. According to the IMF data cited by Tongwaranan, the rich benefited from the economic growth and became even richer but the poor were less unfortunate not only did they enjoy the benefit least but continue to be poorer.

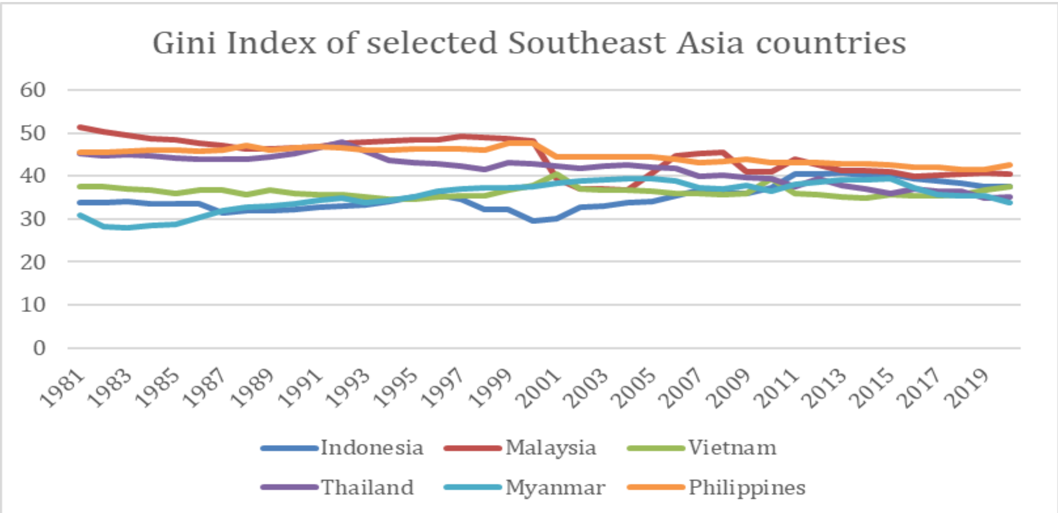

Figure 1.2. Gini Index of selected Southeast Asia countries

Source: World Bank Data

As observed in figure 1.2, among the six selected ASEAN countries, Malaysia recorded a fluctuation trend from 1981 to 2020 but remained one of the countries with the highest income inequality. Indonesia and Vietnam's Gini index showed a fluctuating trend but at different levels. Eventually, both Indonesia and Vietnam's Gini index meet up in 2019 and 2020. Thailand was showing a decreasing trend but at a much slower rate until 2020. Myanmar is showing an increasing trend in its Gini index from 1981 to 2020. As for the Philippines, it showed an almost stable trend from 1981 until 2020, remaining at a value below 50.

Comparing Figure 1.1 and Figure 1.2, it can be seen that the trend in CO_2 contribution and Gini index movements. For instance, Malaysia's Gini index is in a fluctuation trend while its CO_2 contribution had slightly increased. As for both Indonesia and Vietnam, they had a fluctuation form in the Gini index and then an increasing trend in CO_2 contributions. The decreasing trend at a slow rate in Thailand's Gini index can be observed, while its CO_2 contribution is showing an increasing trend at first then remain constant thereafter. Myanmar had an increasing trend in the Gini index while its CO_2 contributions remained almost constant. Lastly, Philippines showed a stable form in the Gini index while its contributions in CO_2 are in fluctuation form.

1.2 Issues in Southeast Asia Countries

According to a survey conducted by the World Bank Group (2015), Indonesia has been developing its economy rapidly but only the richest 20% are able to enjoy the development whereas the remaining 80% suffer from income disparity. Children who come from low income and low-status families lead them to poor and underserved start of their life as they do not receive many opportunities. As Indonesia is being more developed, the salary of the high skilled labourers kept on increasing but the low skilled labourers were stuck in inconsistent jobs with low productivity and salary. Consequently, those who did not get the opportunity to enjoy the benefit of the development in Indonesia failed to endow in education and health and limited their income earnings.

Based on the recent news by The Sun Daily (2022), income inequality in Malaysia has been driving a larger proportion of people from lower income levels to withdraw money from their Employees Provident Fund (EPF) savings. It was reported by the EPF that over seven million EPF members withdrew a sum of RM101 billion in these two years after the government adjusted the ruling allowing them to withdraw from the EPF multiple times. As a result, of the seven million members, 6.1 million of them were reported to have less than RM10,000 in their EPF savings. Consequently, this led to the savings glut where the need for funds is lesser than the supply of savings to generate economic activities. Income inequality would eventually widen as the higher income have more savings in their EPF increasing their financial and non-financial assets' value. The higher income increases their wealth with lesser economic activities and causes higher unemployment for those who fall in the lower income levels.

In Vietnam, widened income inequality was associated with unequal opportunities and discrimination (Brunori et al., 2013). According to Nguyen Tran (2017), the lower income levels tend to be excluded from enjoying the benefits of the policy design of the government and discrimination against their rights and voices from being heard. This resulted in a wider gap in social mobility, opportunity, and social exclusion. The political leaders tend to be associated with those with higher incomes and more political power which causes disadvantages to many parties. For instance, the poor ethnic minority youth suffered from various stigmas compared to the wealthy families of the Kinh youth. Research by Oxfam cited by Branden (2019) found out that children in Vietnam will be better off if the parent's income increases but this also shows that the poor will continue to be poor due to income inequality.

According to the China Daily (2021), income inequality in Thailand has caused issues in social services spending and social mobility of the people. The Thai government is focusing on further developing the country's economy by increasing investment flow. Therefore, the government is targeting the rich to help with investing. The government also wanted to attract foreigners into Thailand by providing them with free foreign income tax, permits to work automatically, and charging the same rate of tax income as Thai people. However, these are only applied to the rich. With more benefits being given to the rich compared to the poor, the rich are able to increase purchasing power more than the poor.

According to Mainzland (2022), Myanmar suffered from high income inequality due to the long history of political conflicts in the country as they were ruled by the military for many years. One of the few main contributions of income inequality in Myanmar is that their resources are fully controlled by the military forces and firms which are closely associated with the military. This caused an imbalance in distribution of wealth to the people of Myanmar as only certain people can get access to resources such as jade and rubies. The political instability in Myanmar had caused them to lose out on foreign investments as several foreign investors decided not to invest in Myanmar which led them to limited access to cash. According to Woods (2019), Myanmar had a major ethnic conflict which led to the government gaining control over the natural resources and the minority ethnic of Myanmar do not have sufficient access to Myanmar's wealth.

In the case of the Philippines, the economy was dominated by an oligarchy system. An oligarchy economy means the most powerful man and the richest family dominate and take control over the economy which benefited mostly themselves (Brennan, 2016). According to an article by Philstar (2020), these individuals, also referred to as oligarchs, took advantage through political connections with the governments to gain more wealth by taking part in unethical activities. The oligarchs also restricted the economic opportunities in the Philippines which made businesses in the country to be unable to compete and grow. As a result, unemployment tends to increase, and the income inequality issue emerges as the Filipinos are unable to earn an income whereas the oligarchs are able to earn them.

In 2015, Indonesia was grouped among the top ten countries in the world and the biggest CO_2 emitter in Southeast Asia by the United Nations (Dunne, 2019). According to Climate Transparency (2017), Indonesia is one of the participating countries in the G20 which is an intergovernmental forum consisting of 20 countries solving major global economic issues. It was reported that Indonesia has been excessively using fuels such as oil and coal compared to other developing countries which led to an increase in the annual average CO_2 emissions from 2012 to 2017. This prevents them from achieving the goal of reducing carbon emissions in the Paris Agreement. The most concerning issue to this day is that, if this trend continues to grow, the life of humans and nature and thousands of islands in Indonesia will be at risk triggered by global warming and climate change due to the emissions of CO_2 by Indonesia themselves (Lean & Smyth, 2010).

According to Saxena (2009), in Southeast Asia, Malaysia is considered to be the second-largest emitter of CO_2. Malaysia's increasing rate of CO_2 is a major concern despite the country's small role in global Greenhouse Gas (GHG) emissions. Malaysia as a developing country failed to reduce its emission level compared to other developed countries that have controlled their CO_2 emissions level, instead, Malaysia emitted more CO_2 as the country is developing (Olivier et al., 2014). Consequently, Malaysia is pressured domestically and internationally to contain the emissions. Solaymani (2022) reported that the most significant contributor to the emissions of CO_2 in Malaysia is the motor vehicle, as transportation tends to be the country's most fundamental infrastructure for development. Malaysia has over 32 million vehicles registered in the country and is expected to increase in the coming years along with the CO_2 emissions.

Moreover, the Vietnam's CO_2 emissions were recorded as an increase to 2.9 tons per capita in 2019 and in terms of million tons, Vietnam emitted 282 million tons of CO_2 which became the second-highest emitter of CO_2 just behind Indonesia among the ASEAN countries. It is expected that this trend will lead to another 7% increase in the total GHG emissions in this decade. This is because it was also expected that half of Vietnam's generation of electricity by 2030 will be the burning of fossil fuels. Due to the current and expected future level of emissions, Vietnam is highly incapable of achieving the goal of the Paris Agreement to reduce the CO_2 global emissions to net-zero emissions (Thang, 2021).

Meanwhile, the Thailand's CO_2 emissions are majorly caused by the energy consumption of transportation and contributed to the total domestic energy consumption of 35.8% (Ratanavaraha & Jomnonkwao, 2015). The increase in CO_2 emissions caused several respiratory illnesses among the people of Thailand especially those who live in the populated areas. Besides, the Thai marine ecosystem was significantly affected as well causing death to the marine animals due to the rise of temperature from the CO_2 emissions. In 2011, Thailand was hit by a flood crisis damaging areas close to Chao Phraya and the Mekong River. It was reported that the country's damage was estimated at 1.4 trillion Thai Baht. Such a disaster was caused by the rise in temperature and rainfalls due to CO_2 emissions (Impact Forecasting, 2012).

According to Cowan (2021), Myanmar has been overexploiting natural resources for several decades by deforestation and wildfire. This led to the excessive emission of carbon dioxide into the atmosphere. The Myanmar community made an effort to protect and preserve their old-growth forests but to no avail, since the military forces and the companies under them are exploiting more resources in the land of Myanmar by destroying these forests (Cowan, 2022). The author also reported that Myanmar fuelled its military activities through logging, mining, and extraction of gas and oil which contributed to the carbon dioxide emission and directly impacted environmental degradation

The oligarchs who ruled over the Philippine's economy tends to be one of the main causes of CO2 emission. According to Holden (2018), due to the oligarchy system, there are policies failure in the country on tackling environmental degradation. This is because the oligarchs have a large interest in the business of fuel, coal, and oil. This led to the mismanagement of natural resources which led to the emission of CO_2 which does not concern them as long as they profit from these activities.

In this case, there is a relation between income inequality affecting CO_2 emissions. According to the World Bank Group (2015), before the occurrence of the pandemic, Indonesia was experiencing a high rate of income inequality approximately 40% starting from 2011 which led to the rich to continue becoming richer. According to Nihayah et al. (2022), at the same time Indonesia emerged to become one of the world's rapidly developing economies contributed the most CO_2 emissions in Southeast Asia and Indonesia reached the highest level of CO_2 emission during their economic growth. The researchers further explained that statistics by the World Development Indicator showed that the economy expanded by approximately 0.1% to 0.3% in addition to a decrease of 10% in the air quality in Indonesia. It was also said the rich living in the urban areas further expand the economy by using more resources and potentially contributing to the high CO_2 emissions.

In the case of Malaysia, because of income inequality, some will have more EPF savings able to satisfy their wants and increase their purchasing power by purchasing their private vehicles. This is associated with the increased demand and spending on energy resources such as fossil fuels (Chik et al., 2013). The increasing attraction towards more modern facilities causes people who can afford to further purchase their private vehicles which increases CO_2 emissions.

As for the case of Vietnam, Branden (2019) highlighted that children are becoming worse off when their parents are not so wealthy and only the rich enjoy the benefits indicating income inequality issues in the country in addition to the growing economy in Vietnam. According to The World Bank (2021), the emissions of CO_2

of the country was because the economic growth in the country caused high demand and consumption of energy.

According to the China Daily (2021), in Thailand, due to the rich benefiting a lot from the government, they are able to increase their spending on luxury items such as vehicles, televisions, or other kinds of technologies that require power generation from the burning of fossil fuels or natural gas. This indeed will increase the emission of CO_2 into the atmosphere.

According to Mainzland (2022), the way the emission of CO_2 by Myanmar can be linked to income inequality issues in Myanmar. Since the foreign investment flow into Myanmar is being pulled over by the investors, insufficient cash leads to Myanmar being fully controlled over its resources. The limited access to resources by Myanmar's people is what led to income inequality between the people and the military forces. As a result of insufficient funds, the Myanmar military effectively funds their activities through the natural gas revenue which allows companies from the United States, United Kingdom, and Canada to extract them (Cowan, 2021). This is how it led to the increase of CO_2 emission due to the overexploitation of natural resources.

Lastly, the oligarchy economy in the Philippines increased the gap of income inequality as they missed many economic opportunities for the countries. According to Holden (2018), he described the terrible inequalities of the Philippines as the total income combined for the 73,808,000 lowest income levels in the Philippines are equivalent to the top 25 income levels of the country. Thus, the oligarchs truly dominate certain sectors of the economy such as the natural resources which led to the high emissions of CO_2. Overall, based on the four selected Southeast Asia countries, it can be seen that there is a linkage between how income inequality affects CO_2 emission.

1.3 Research Problem

CO_2 emission which is known as carbon dioxide pollution has been increasing steadily over the past few years. According to the surveys from IEA (2021), CO_2 emission has caused global climate change due to human activity and natural sources, for instance fossil fuels burning, gas emission from transportation and others.

Income inequality refers to the uneven income distributed in a population, in which the gap of wage paid to the people who do the same jobs is different. According to NASA (2014), since 1750, industrial activities have raised the world carbon dioxide levels by nearly 50%. With the development of urban areas, income inequality happened. The researcher finds out a shocking result that shows that the richest 10% of the world's population accounts for about 50% of global emission. It is because they eat more meat, create more waste, and produce more carbon dioxide (González et al., 2020). It shows that income inequality will affect CO_2 emission. In an investigation of 50 years of economic data, it is found that in countries with a large income inequality, the people who are poor are getting poorer while people who are rich are getting richer (Kopp, 2021). Unfortunately, Southeast Asia countries are having income inequality problems. Philippines and Thailand have the worst income inequality; however, Malaysia and Vietnam have successfully put in effort to reduce the income inequality (Erik, 2016). Researcher Golley and Meng (2012) found that direct and indirect of CO_2 emissions for high-income population is much higher than that the low-income population. However, other researcher found out that there is mixed relationship exist between income inequality and CO_2 emissions. Lower or higher income inequality in a country may cause both positive and negative impact to the CO_2 emissions (Hao et al, 2016).

As the income inequality of a country reduce, the income for middle and high-income population increases. It showed that the low-income population are getting lesser, and the scale of middle-income population is expanded. When the gap is getting smaller, the demand for energy and carbon-intensive products will increase, since the population that able to consume the energy increased. Thus, the CO_2 emission will increase. On the other hand, higher income inequality may cause negative impact on CO_2 emission. Since in the high-income inequality country, the richer are distribute with more wealth and political right. With the improvement in education and technology, the demand of resource products in high income population will change. Compared with low-income groups, their awareness and action to protect the environment will be higher. They are also more capable of keeping up with the pace of science and technology and using more renewable energy rather than non-renewable energy in their daily life. For example, solar panel and electric car which release less CO_2. In this case, as the gap getting larger, the CO_2 emission will decrease (Yang et al., 2022).

In cities, people's economic conditions are much better than those who live in rural areas. People in the cities have more ability to buy transportations, which will lead to traffic congestion, thus increasing CO_2 emission. In Southeast Asia countries, most of the transportation uses fossil fuels like gasoline and diesel to generate the energy. The more the transportation used, the more the CO_2 emission. One of the Southeast Asia countries, which is Vietnam, shows that private motorcycles are the main transportation used in major urban areas. However, the high density of motorcycles in urban areas has caused the increase of CO_2 emission. It is because the private vehicles are powered by fossil fuels, the more the number of private vehicles used, the greater the CO_2 emission. Traffic congestion has also caused the increase of CO_2 emission as the vehicles stuck in the traffic; the more fossil fuel will be used. Thus, greater inequality would increase the CO2 emission (Huu & Ngoc, 2021).

The Gini index is a measure of the income distribution across a population, which determines the income inequality of a country. The higher the Gini index, the greater the income inequality. Each country has a rural-urban area, urban area can be characterized by development level and higher population compared to rural area.

Lesser population in rural areas is because the development in the cities is lesser due to less investors that are willing to invest in the cities. Thus, the opportunities, industries, transport, and others will be lesser than urban areas. This has caused the income inequality in a country to increase as the people living in rural areas have lesser income and people living in urban areas have higher income due to the development and high salary paid in the cities. Income inequality will affect the energy consumption in the cities. High populations in urban areas will have larger purchasing power, demand and usage of energy such as fossil fuels much more compared to rural areas. With the high population and high purchasing power in urban areas, demand for food increased. The production of foods, transportation, and management of foods will increase the CO_2 emission (Buzby, 2022). As a result, lesser energy used for transportation and manufactures in the rural area will have lesser CO_2 emission compared to urban areas (Zhou, et al., 2020). According to the research, in 2017, the Gini index for Malaysia, 40.3, the CO_2 emission in Malaysia in 2017 is 7.32 metric tons per capita. In 2018, the Gini index for Malaysia is 40.5, while the CO_2 emission is 7.75 metric tons per capita (The World Bank, 2022). The result shows that when the Gini index increases, the income inequality increases, and it will lead the CO_2 emission to increase. As the urban area develops rapidly and rural areas develop slowly, it causes the Gini index to increase. The industry and manufacturing development in urban areas will increase the release of CO_2 due to the use of fossil fuel to generate energy to produce more products. Other than that, more and more high-income populations will accumulate in urban areas. The research of Golley and Meng (2012) found that direct and indirect of CO_2 emissions for the high-income population is much higher than that of the low-income population. The income inequality can affect CO_2 emissions through the consumption possibility curve (Huo & Chen, 2022). Therefore, the studies are to explore how the Gini index affects CO_2 emissions.

Foreign direct investment (FDI) inflow is an essential indicator influencing the country’s rapid economic growth. Commonly, foreign are mostly invested in the manufacturing sector of Southeast Asia countries. According to the research, in 2019, Southeast Asia countries had received FDI inflow of about 56.24 billion U.S. dollars (Leander, 2021). FDI will bring environmental pollution to the host country as the usage and demand of fossil fuels required for industrial development increases. The purpose of FDI is to maximize the amount of profit, cleaner technologies which will help host countries to improve environmental quality require more funds. In this case, foreign investors may choose to invest in countries who are not strict in environmental policy (Li & Tanna, 2019).

In Southeast Asia countries, the primary energy demand is fossil fuel. Industries and manufacturers tend to use fossil fuels to generate the energy to produce the products. Still, human activities such as burning fossil fuel is one of the main reasons that cause the CO_2 emission. According to the Asian Development Bank (ADB), Southeast Asia had excessive reliance on fossil fuel, and it showed the fastest growth of CO_2 emission in the world between 1990 until 2010 (Alexander, 2020). Thailand and Malaysia had received FDI in electronics manufacturing, while Indonesia received the FDI in chemicals and paper manufacturing (Department of Statistics Malaysia Official Portal, 2022; OECD, 2020; Statista Research Department, 2022). Manufacturing sectors of electronic, paper, and chemicals will increase the CO_2 emission, as the manufacturing requires the combustion of fossil fuels in order to generate heat and continue the production progress (Polly, 2018). In 2018, FDI inflow of Indonesia is 1.814 % of GDP; the CO_2 emission is 2.156 metric tons per capita. In the next year, the FDI inflow increased to 2.233 % of GDP, the CO_2 emission followed the step to increase to 2.290 metric tons per capita (World Development Indicators, 2022). It shows that when the FDI inflow increases, the CO_2 emission will increase as well. Thus, investigating the relationship between CO_2 emission and FDI are important to detect how FDI affects the CO_2 emission.

Urbanizations refers to the total number of citizens living in urban areas to the total population. According to research, the increase in urbanization will cause the high population accumulation and the demand of fossil fuels like oil and coal, housing, land usage, and food will increase as well (Zhang et al., 2017). To expand urbanization, countries will choose to destroy forests to get enough space for development. However, more than 1.5 billion tons of CO_2 are estimated to have been released to the atmosphere due to deforestation (Carrington, 2021). Expanded urbanization in Malaysia and Thailand shows an expansion in financial results per capita in these economies. These nations are giving higher consideration to counter the adverse consequences of urbanization which they are accomplishing by bringing down emanations and more use of sustainable power. At similar time, more elevated levels of urbanization genuinely affect CO_2 outflows in these nations having serious ramifications for in general populace wellbeing (Anwar et.al., 2020). The reason for the high expansion in urbanizations is because Malaysia and Thailand have developed rapidly in the non-agriculture industry in recent decades, these phenomena make the ratio of urbanization grow in a flash. Both countries have achieved a high level of urbanizations where most of their citizens live in urban areas. According to Anwar et. al. (2020), the proportion of urbanization of Malaysia and Thailand was reached at 75.44% and 49.2% correspondingly. The high growth of urbanizations has caused the CO_2 emission to rise up to a high level, since the expansion process in urbanization will be the source of increasing CO_2 emission.

A historical study pointed out that in Indonesia, yearly energy-related CO_2 outflows have expanded extensively from 25 Mt (Megatonne) in 1971 to 455 Mt in 2016. This has basically been driven by populace development, rising pay levels, furthermore, developing dependence on petroleum derivatives for energy utilization. Additionally, fuel blend remains one of the really contributing variables to outflows development in Indonesia, notwithstanding a consistent decrease in its commitment from 34% during 1990-2009, and 32% during 2010-2016 (Sandu, 2019). For the situation to concentrate on in light of Ho Chi Minh city, Vietnam, because of the quick urbanization and advancement, the discharge rate from the business and transportation prompts the expansion in how much carbon dioxide which has been demolishing the environmental change (Nguyen et. al., 2021). Consequently, we expect that the higher convergence of urbanizations will build the outflows of CO_2 discharge.

In addition, the changes in GDP per capita will significantly influence the CO_2 emissions of Southeast Asia countries. GDP per capita is a commonly used economic indicator that measures the average economic output per person in a given country or region. It is calculated by dividing the total Gross Domestic Product (GDP) of a country by its population. GDP per capita provides a general idea of the economic well-being of a country's citizens, as it takes into account both the overall size of the economy and the size of the population. It can be used to compare the economic performance of different countries or to track changes in the economic growth of a particular country over time (WHO, 2019). According to ASEAN Secretariat (2021), the economies of Southeast Asia countries expanded gradually from 2000 to 2019 with an average annual growth of 5.7%. While looking into the GDP per capita of Southeast Asia countries in 2020, the impact of Covid-19 was negatively influenced the Southeast Asia countries' share of world nominal GDP to 3.5% in 2020 which is slightly lower with comparing to the previous year at 3.6%. Meanwhile, the selected Southeast Asia countries' economy was mostly contracted in the second quarter of 2020 as the GDP of Malaysia and Thailand by about -17.1% and -12.2% respectively then followed by Indonesia which recorded a reduction in GDP of around -5.3%. Only Viet Nam had shown a positive GDP growth rate of 0.4% (ASEAN Secretariat, 2022).

After that, the relationship between GDP per capita and CO_2 emissions remains substantial and it has been typically explained by the EKC hypothesis. As the GDP per capita increases, the CO_2 emission increases as the energy demand and usage increases (Bersalli et al., 2023). Rapid economic growth in a country such as Singapore depends on the utilization of fossil fuels. The increase of using fossil fuels lead a rise in CO_2 emission in Singapore (Raihan & Tuspekova, 2022). For most of the emerging and developing economies, CO_2 emissions are rising due to the transformation of industrialization and are mostly caused by non-renewable consumption such as coal, gas, and oil which are the primary source to support the transportation, manufacturing activities, consumption of goods and service which have the significant contribution in GDP growth (Alam, 2014). According to ASEAN Secretariat (2022), the services sector was the leading contributor to Southeast Asia countries' economies, and its share of the region's GDP improved to 50.6% in 2020 from 46.6% in 2005. However, Hamdan et al. (2018) pointed out that the expansion of economic growth can impose continuous stress on the environment as economic activities would require intensive energy consumption to meet the increasing demand for energy to run the manufacturing operation and production. It can be ensured that human needs would be met through intense consumption but there would be serious pollution and additional pressure on environmental resources (Qazi et al., 2013). Therefore, increased in the volume of CO_2 emission will increase as GDP per capita increased in Southeast Asia countries.

1.4 Research Questions

I. How would income inequality affect the volume of CO_2 emission?
II. How would FDI net inflow affect the volume of CO_2 emission?
III. How would urbanization affect the volume of CO_2 emission?
IV. How would GDP per capita affect the volume of CO_2 emission?

1.5 Research Objectives

1.5.1 General Objective

The general objective of this study is to examine the factors of CO_2 emission in the selected Southeast Asia countries and the significance of income inequality on CO_2 emission.

1.5.2 Specific Objectives

I. To examine the effect of income inequality on the CO_2 emission in selected Southeast Asia countries.
II. To examine the effect of FDI inflow on the CO_2 emission.
III. To examine the effect of urbanization on the CO_2 emission.
IV. To examine the effect of GDP per capita on the CO_2 emission

1.6 Research Significance

The primary focus of this study is the income inequality and CO_2 emissions in the selected Southeast Asia countries which are Myanmar, Philippines, Thailand, Vietnam, Malaysia, and Indonesia from year 1981 to 2020. From the growing evidence in the research on the connection between income inequality and CO_2 emissions since the 1990s, the economist had found that the countries with a greater gap between rich and poor would contribute a negative impact on the environmental quality (Dorling, 2017). Income inequality has been the main concern among Southeast Asia countries as they experienced booming economic expansion and development in the last two decades accompanied by the aid of technological advancements and strategic planning for a long-term sustainable economy (Tongwaranan, 2018). According to recent news and articles, it had revealed that the increase in the number of poor in Southeast Asia countries has placed one of the most unequal regions in the world as the lack of equitable access to employment, resources, and social development had further increased the imbalance of living standard among different groups in the region (Agarwal, 2020).

Apart from that, Rasiah et al. (2016) argued that income inequalities have a reciprocal relationship with environmental deterioration through air pollution and resource depletion. In their influential study into the unexpected impact of income inequality on the environment, Haupt (2012) concluded that severe income inequality in the country could result in wasteful resource usage by the wealthy, whose relative purchasing power excessively affects the demand for the resource and further worsens the environment, which leads to unsustainable resource consumption in the end. For example, Moran et al. (2008) discussed that CO_2 emissions and energy consumption are continuing to rise above sustainable levels from their findings. In addition, the higher inequality of the wealth allocation provides the advantaged position to certain societal groups to deny any modifications and distribution of economic incentives (De Schutter, 2016). Therefore, it indicates that the equality of income distribution could be the significant determinant of the CO_2 emissions that causes environmental degradation instead of the average levels of income (Jun et al., 2011).

Besides that, the CO_2 emissions of Southeast Asia countries have become one of the key contributors to worsening the environmental quality and eventually leading to serious environmental issues. As in the emerging economy, most people live in vulnerable conditions and face the challenge to achieve sustainable development goals for reducing environmental pollution (Khan et al., 2022). In general, the higher energy consumption of fossil fuels to encourage economic development would stimulate economic growth and reduce poverty as well as other types of inequality in Southeast Asia countries. However, the degradation of the environment of Southeast countries would place an irreversible effect and make most of the developing economies extremely vulnerable and less able to offset the negative impact of environmental issues (Papakonstantinidis, 2017).

From this research, a few variables will be chosen to study the relationship with CO_2 emissions. Then, we will focus on the CO_2 emissions and determine the effect of FDI net inflow, urbanization, and GDP per capita on environmental pollution. To reveal the effect of wealth distribution among the region, income inequality would be the gap variable as there is limited literature available to support the significance of the particular variable. The related theory to the selected variables would be the EKC hypothesis and urban sustainability which will be explained in Chapter 2. Thus, the variables are chosen based on the aspect of finance, economy, and society, which are playing the role as major components in achieving environmental sustainability. Therefore, the first contribution of the study is to provide insight into the influencing factors of CO_2 emissions in Southeast Asia countries and study how income inequality causes a direct or indirect effect that influences CO_2 emissions in Southeast Asia countries.

Other than that, the second contribution of the research is to use income inequality as an economic variable to determine the relationship on CO_2 emissions as there are limited literature reviews in the previous studies. The reason to introduce income inequality in the research is that it would place affect CO_2 emissions as the more marginalized citizens from unequal societies are more likely to adapt to higher levels of environmental pollution (Das & Basu, 2022). Hence, the purchasing power of the citizens and CO_2 emissions seem to be correlated as the consumption of the rich and poor causes environmental inequalities in the region. The poor could only live somewhere have higher air pollution location while the rich can afford the air conditioning and obtain benefits from the transportation that cause the air pollution (Boyce, 2018). Therefore, the connection between income inequality and CO_2 emission had led to increasing recognition and it should be rebalanced to achieve the sustainable development goal in the selected Southeast Asia countries.

In short, the CO_2 emissions would be discovered through the aspect of financial, economic, and social in this research. Additionally, the researcher that wishes to study in the same field could explore the relationship between income inequality and CO_2 emissions and have a deeper understanding of the current condition of the social and environmental issues. Moreover, the research will bring benefit to the region's policymakers in adjusting the policy measure to control economic inequality and environmental issues based on different perspectives. Other than that, the research will provide the suggested policy for improving the environmental quality to achieve a sustainable environment in Southeast Asia countries.

1.7 Organization of study

The first chapter of the study focuses on providing an outline of the CO_2 emissions and income inequality in Southeast Asian countries. Besides that, it also emphasizes the research problem that arises, the objective of the study, the significance of the research variables, and the organization of the study. The background of the study, the theoretical and empirical review of the relevant dependent and independent variables, the theoretical framework, and the hypothesis development of the research are all covered in the second chapter. The third chapter of the study includes the research design, data collection method, sampling design, research instrument, proposed methodologies, model selection, and diagnostic test. In the fourth chapter of the study, we will discover and analyze the results of the proposed methodologies. Lastly, the fifth chapter will discuss and summarise the results of the proposed methods, evaluate the study's limitations, and provide recommendations for future research on the relevant topic.

1.8 Conclusion

CO_2 emissions have become the crucial factor that contributes to the negative environmental impact, and it is more difficult to control, especially in the ASEAN developing countries. In this research, the objectives focus on determining the relationship between the volume of CO_2 emissions and income inequality as measured by the Gini Index, FDI net inflow, GDP per capita, and urbanization in the selected Southeast Asia countries, including Indonesia, Malaysia, Vietnam, Thailand, Myanmar and Philippines.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Previous research studies have determined the economic factors related to CO_2 emissions that support and contribute to our research on the development of the framework. In this chapter, the discussion will focus on the detail of the factors that affecting CO_2 emissions. The influential factors of CO_2 emissions are included income inequality, FDI net inflow, urbanization, and GDP per capita.

2.1 Theories review

2.1.1 Environmental Kuznets Curve (EKC) Hypothesis

Environmental Kuznets Curve (EKC) Hypothesis was proposed by Grossman and Krueger in year 1991 (Zhang et al., 2017). In EKC hypothesis, it stated that with increased economic growth, environmental degradation would show an increasing trend then start falling at a certain level of economic growth, which can be shown by an inverted U-shaped curve in graphical style.

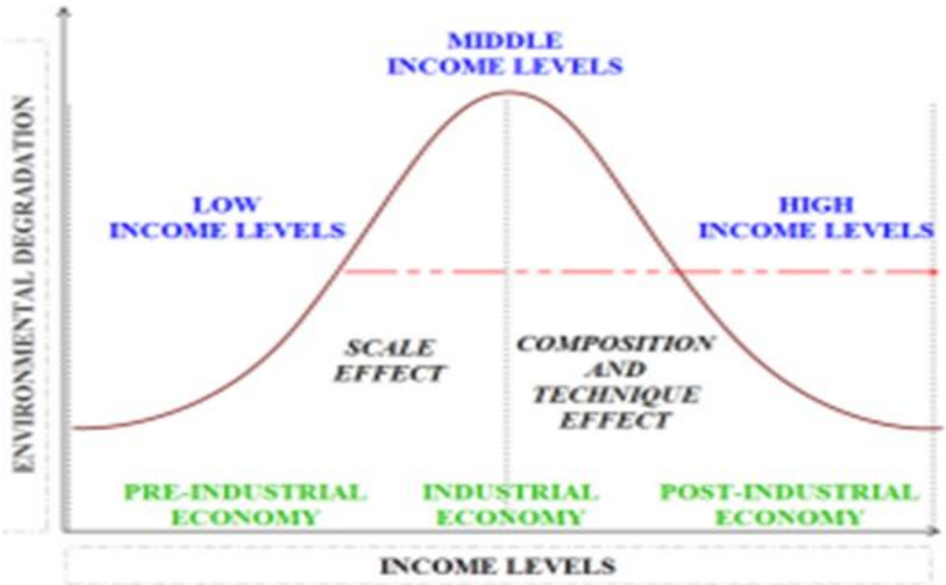

Figure 2.1: Environmental Kurnetz Curve from Sarkodie & Strezov (2019)

The EKC Hypothesis stated that in order to boost the economy, people would allocate more resources to produce more energy in order to accelerate development without regard for the environment. As a consequence, the pollution is likely to worsen caused by development activities like deforestation to increase available land. However, the environment will begin to degrade when it reaches its maximum level. When a country reaches a high level of development, it will recognize the value of a clean environment and will begin to deal with pollution by spending income to minimize or slow down pollution (Dogan and Inglesi-Lotz ,2020).

This hypothesis is further explained in detail by saying that the EKC hypothesis might face limitations when examining poor or undeveloped countries. It is because these nations did not meet the maximum point where the environmental degradation shows a decreasing trend with increased economic growth. Henceforth, it is difficult when researchers try to suspect the impact of economic growth factor toward the environment (Al-mulali et al., 2015).

In terms of the validation of the theory proposed in the EKC Hypothesis, there were many conducted studies that showed that their result is aligned with the EKC Hypothesis. For illustrations, Saboori and Sulaiman (2013) analyze energy consumption and economic growth in ASEAN countries; Danish et. al. (2021) study in nuclear energy and pollution in India; Tenaw and Beyene (2021) investigate in 20 sub-Saharan African (SSA) countries; Leal and Marques (2020) revealed the relationship between economic growth and environmental degradation for the 20 highest CO_2 emitters among OECD countries; and the finding by Balsalobre-Lorente et al. (2021) about connection between carbon emission and economic growth of five European Union (EU-5) countries. These past studies all support the idea that the EKC hypothesis does hold as they all found the economic growth factor has an inverted U-shaped curve relationship with environmental pollution.

To capture the existence of EKC hypothesis in the study, the key variables should be included is the GDP per capita as it is considered the primary driver of environmental degradation in the early stages of economic growth, but it may also enable the adoption of cleaner technologies and the implementation of environmental regulations as economic development continues. By adding the GDP per capita squared, the turning point would be reflected as the quadratic variable and illustrated followed by a decline in emissions as GDP per capita continues to rise. Therefore, the GDP per capita squared will be negative and resulting in a peak turning point from which the curve thereafter declines.

2.1.2 Urban sustainability

The importance of urban cities for achieving sustainability has been recognized to strengthen the quality of the ecosystem and remain the natural resources for future generations (Brundtland, 1987). In 1992, the concept of urban sustainability had further emphasized and promoted in the Rio Declaration on Environment and Development (UN, 1992). The theory of urban sustainability refers to the urban revitalization and transformation should aim to promote on minimize the contribution of negative impact on the environment while maximizing the economic and social co-benefits (Patnaik, 2021). Besides that, the concept pointed out that the urban area should be able to be self-sufficient in energy requirements and distribution of essential resources (Caprotti et al, 2017). Urban sustainability builds along with the three main pillars of sustainability including Environmental Sustainability, Economical Sustainability, and Social Sustainability which focus on the environment, economic and social to guarantee sustainable resources.

While the increasing environmental pollution has been a global concern, it has led to the growth of awareness of sustainable development. In June 1972, the first world conference by United Nation stated that environmental pollution had become one of the key challenges in the world, emphasizing the importance of essential action to improve the human environment and protect the natural habitats (UN, 1972). Following the 1992 Rio Summit, the UN established the Commission of Sustainable Development (CSD) to offer guidelines and keep track of the efficiency of the implementation of Agenda 21 and the Rio Declaration 1992 (UN, 1995). Meanwhile, the global community is expected to achieve eight millennium development goals (MDGs) by 2015, in parallel with the CSD (UN, 2001). Each MDGs has its own specific targets and date for achieving the targets and the goal related to the environment is Goal 7 which was called 'ensure environment sustainability. The targets of the particular goal are focused to ensure efficient management and conservation in order to stop the depletion of natural resources and greatly prevent the loss of biodiversity (UN, 2008).

However, it is increasingly argued that urban cities are mainly responsible for negative environmental impacts due to daily actions, innovations, and business expansion. Not only that, the urban population is now surpassed the rural population for the first time in history as more than half of the world's population lives in the cities (Seto et al, 2010). As a result of the increasing urbanization trend, urban cities would have a greater demand for energy, essential consumption, waste management, and transportation service. According to Madlener and Sunak (2011), cities account for nearly 75% of global resource consumption and GHG emissions worldwide. Besides, the cities are also responsible for 70% of energy-related GHG emissions to the environment (Grimm et al, 2008). Due to the problem of satisfying the growth of demand, the cities have a larger proportion of environmental impact through the unnecessary by-product of existing unsustainable socio-technological systems. Therefore, the urban sustainability problems can be found in cities where the origin location for most of the unsustainability systems.

Although the cities can focus on their own people and resources, which may contribute to their internal sustainability, it may be unrealistic to expect cities to be entirely sustained by resources produced within their administrative boundaries. Ultimately, all of the resources that support the urban population are come from other places on earth, mostly outside the cities and the country in which the city located (Ferrão, 2016). While the multiple cities are dependent on the resources supply from the same region, urban sustainability cannot be achieved as the cities' sustainability cannot be isolated from the limited resources from earth especially considering the cumulative effect of all cities on resource and energy consumption (Seto et al, 2012). Without paying attention to limited resources, urban sustainability may become increasingly difficult to achieve in the 21st century continues, depending on the availability and cost of major natural resources and energy (McDonnell & MacGregor-Fors, 2016; Ramaswami et al., 2016). To achieve the goals of urban sustainability, the effort to promote sustainable development strategies requires a higher level of interaction between different systems and their boundaries, as the effects of urban-based consumption and pollution affect global resource management (McGranahan & Satterthwaite, 2003). In fact, urban sustainability would require unprecedented system boundary extensions to resolve the interconnections and impacts on the earth.

Lastly, urban cities are different from islands as they are having urban systems that involve complex networks of interdependent subsystems to support the urban population. Urban sustainability requires the involvement of citizens, private entities, and government authorities to ensure that all resources are mobilized and working towards a clear set of articulated goals. It is particularly significant as the regions experience different degrees of urbanization that bring the effect of redrawing borders and spheres of economic effect (Wilbanks et al., 2012). Indeed, sustainable solutions should be customized to each stage of urban development while balancing local constraints and opportunities. Besides that, all cities should then seek to articulate a multiscale and multidimensional vision for improving human well-being (Bai, 2007). For example, climate change caused by GHG emissions has been highlighted as it primarily occurs on a regional to global scale and its impacts and policy responses tend to be locally determined (Wilbanks & Kates, 1999).

2.2 Review of the literature

2.2.1 Income inequality and CO_2 emissions

Empirical studies made by past researchers had researched the relation between income inequality and CO_2 emissions. Yang et al. (2022) supported that there is a positive relationship between income inequality and carbon dioxide. They explained that as the rich become richer, they are able to increase purchasing power and afford modern facilities such as vehicles to satisfy their needs and wants which lead to increase in CO_2 emissions. Besides, it is explained that the poor are more likely to exploit natural resources and engage in rude production to earn more income, harming the environment, while the rich may not always increase investment for the better environment when the inequality between those who are wealthy and those who are poor broadens and the quality of the economy is poor. Kang (2022) also further supported the positive relationship between income inequality and CO_2 emissions. The authors concluded that the gap in income inequality caused more CO_2 emissions as the gap is widened. The U-shaped relationship is formed when relate to the income inequality per capita and carbon emissions per capita. The authors also pointed out that the average income inequality does not reach the turning point. This suggests that although economic growth has already set the foundation for improvements in environmental quality, rising income inequality contributes to environmental degradation within the examined countries.

In contrast, there are further studies where the researchers refuted the positive relationship by suggesting that income inequality and CO_2 emissions have a negative relationship. For instance, Hao et al. (2016) who used panel data analysis concluded that the different income levels can make an impact on the emissions of CO_2. They also noted that the wealthy would prefer to live in areas with greater environmental quality and can afford to do so, whereas the poor normally stay in more polluted areas. The income inequality, which in turn affects the quality of the environment, may be further impacted by an inequality in living conditions. Hence, lower income inequality will increase the CO_2 emissions and higher income inequality will reduce the CO_2 emissions. Moreover, Kusumawardani and Dewi (2020) who observed on the Indonesia data and the analysis revealed their empirical studies mentioned that the widening income inequality caused further CO_2 emissions in the atmosphere which suggested a negative relationship between the two variables. They claim that efforts to enhance income equality through raising the income levels of low-income families in an effort to bring those levels closer to those of higher-income households will result in greater usage of energy and CO_2 emissions.

On the other hand, an analysis by Jorgenson et al. (2017), resulted in no significant relationship for income inequality and CO_2 emissions as they obtained a result where the Gini coefficient have no significant impact on the emissions of CO_2. Mader (2018) who researched the nexus of social inequality and CO_2 emissions defied the occurrence of the relationship between the two variables. The deep and thorough investigation by Mader (2018) found that income inequality and CO_2 emissions do not prove any relationship exists between them as there is no solid pragmatic evidence. According to the author, this is due to the difference in confounding variables, estimating methods, and indices picked.

2.2.2 FDI net inflow and CO_2 emissions

According to the research from Tang and Tan (2015), there is a positive impact between FDI inflow and CO_2 emission. It means that an increase in FDI inflow would lead to an increased emission of CO_2. The assumption is backed by the pollution haven hypothesis. It assumes that as the trade and investment barriers between countries are removed, the companies that produce pollutant production will be willing to escape from their own country's costly laws and are projected to shift to countries with relatively poor environmental policies. In this case, FDI inflow will cause an increase in CO_2 emission (Copeland, 2008). Another researcher uses a panel smooth transition regression model (PSTR) version with non-linear and dynamic characteristics to test the relationship between FDI and CO_2 emission. This test proved that FDI has a positive effect on CO_2 emission. FDI inflows could lead to more host country to increase CO_2 emissions, especially for countries in dire need of economic development and the poor environmental regulations which had attracted foreign investment (Xie et al., 2019).

Furthermore, Azam and Raza (2022) report the relationship between foreign capital flows and the environment as measured by trade-adjusted consumption-based CO_2 emissions. Results of system GMM analyses show that FDI is significantly positively associated with emissions in Asia and Africa, whereas in Latin America, the Caribbean, and Europe regions, the association between these two variables is not insignificant. Thus, FDI and CO_2 emission has significant positive relationship in developing countries.

In the previous studies, researchers disputed a negative connection when it comes to FDI inflow and CO_2 emission. In theory, Pollution Halo Hypothesis is used to test the relationship between FDI and CO_2 emission, and it suggests that reduction in level of CO_2 emission is due to increasing FDI (Demena & Afesorgbor, 2019). The halo effect is supported by the assumption that the foreign firms are more energy efficient than domestic firms. It assumes that the foreign firms can spread the clean technology, which is less harmful to the environment to domestic firms, leading to overall reductions in CO_2 emission. FDI is said to have potential to transfer clean technologies and practices to developing countries. Thus, reduce the CO_2 emission. This is the evidence that FDI inflows are more protective of the environment compared to domestic firms. In addition, Zhu et al. (2016) also argue that the foreign firms are more sensitive to the environment as they have advanced technology to operate the cleaning process. This hypothesis is empirically supported by many studies. For example, Eskeland and Harrison (2003) found that US investors that invest in developing countries are more energy efficient and use more clean energy than domestic investors.

Besides, by using panel data, Alshubiri and Elheddad (2019) argued that there is a non-linear relationship between FDI inflow and CO_2 emission. Left side inflection point shows that FDI inflows positively impact the CO_2 emission. However, the right side inflection point shows that FDI inflows negatively impact the CO_2 emission. In addition, some researchers stated that FDI does not independently affect CO_2 emission. There are other factors that would affect the CO_2 emission, such as economic development and pollution emission.

2.2.3 Urbanization and CO_2 emissions

Refer to the research paper examined by Wang et al. (2016), the positive relationship between urbanization and carbon emission was found by using the panel fully modified ordinary least squares model with panel data from ASEAN countries during the period year 1980 to 2009. Based on the study carried out by Wang and Li (2021), with the selected 154 countries in the period sample of year 1992 until 2016, they used an individual time double fixed effect model to try to find the relationship between urbanizations and CO_2 emission per capita. They found that urbanization positively affects carbon dioxide emissions, which means that with the growth of urbanizations, the carbon emission will rise also. While this study is aligned with the result from Ali et al. (2019). They use the ARDL (Auto Regressive Distributed Lag) model with the time series data from year 1972 to 2014 in Pakistan, they have concluded their finding by saying that urbanization will significantly affect carbon emission in the long run. Another past study also concluded a similar result; it examined the selected ten Asian nations from year 1995 to 2018 with a cross sectional ARDL model. The result indicates that urbanization has a positive association with carbon emission (Chien et al., 2022). This is consistent with the outcome inferred by Sufyanullah et al. (2022), they also test on the impact of urbanization on carbon emission in Pakistan by using ARDL approach, and their result shows that developing on urbanization will increase the CO_2 emission. Besides, empirical research proposed by Wang and Wang (2021), they include 137 nations and classifies the sample into four types of income group. Their finding implies that urbanization and carbon emission are positively correlated in low-income, lower-middle, and upper-middle income groups while the high-income group shows non-linear relationship of inverted U-shaped curve.

Moreover, a few past studies point out the inverted U-shaped relationship between urbanization and carbon emission. As mentioned in the research done by Zi et al. (2016), they performed their result by using threshold model, and it shows that urbanization and CO_2 emission have an inverted U-shaped relationship with specified sample, China from year 1979 to 2013. This is steady with results indicated by He et al. (2017), also studied in China, but with specified 29 states from 1995 until 2013. They have stated the similar conclusion by applying the STIRPAT model. Furthermore, a research about China and Japan proposed by Ouyang and Lin (2017) found the similar result also by using cointegration model.

In different circumstances, some scholars have found that urbanization will negatively influence carbon emission. A finding specific in 30 of China's provinces, by developing the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model with panel data from 2000 until 2015, it determines urban population has a negative influence towards the carbon emission in the urban building sector (Huo et al., 2020). Another exploration about 20 countries in the MENA region, by constructing a semi-parametric panel fixed effect model, the conclusion indicates that if the urbanization process continues, carbon emission per capita will show decreasing trend (Abdallh & Abugamos, 2017). Based on the analysis completed by Wang et al. (2022), they analyze the impact of urbanization towards the CIWB (Carbon intensity of human well-being) of 125 nations in the year 1990 until 2017. By using a two-way fixed effect approach, they reveal that reduction in carbon emission is due to the urbanization increased in countries with low and medium urbanizations concentrations. In addition, they propose that the effect of urbanization will become lower over time in high urbanisation concentration countries.

2.2.4 GDP per capita and CO_2 emissions

A great number of past studies had established a causal relationship between CO_2 emissions and GDP per capita, especially in OECD countries, G7 countries, Asian countries, and developed and developing countries (Zakarya et al., 2015). Other than that, the study discovered that economic growth has the Granger causal impact on CO_2 emissions in the long run but the CO_2 emissions contribute to output growth (Sharma, 2010). According to Niu et al. (2011), the previous research used panel data approaches to examine the long-run relationship between GDP per capita and CO_2 emissions for eight Asia-Pacific countries, including four developing nations, namely India, Thailand, Indonesia, and China. The result of the study concludes that emerging nations would see greater carbon emissions as a result of modernization, and economic expansion will continue to be the primary objective. These nations must identify the challenging alternative, which calls for smart energy policy design to address the nexus between economic and GHG emissions reduction. The study also discovered that there was a positive relationship between GDP per capita and CO_2 emissions in the short run as the rapid production increases could be achieved through more intense energy usage by existing technologies, which boosts capacity and CO_2 emissions (Kasperowicz, 2015).

Moreover, Jacques (2010) explored the relationship between CO_2 emissions and economic growth in seven African countries and concluded that economic growth positively affected CO_2 emissions. Besides that, the recent studies by Acheampong (2018) examined the causal relationship between GDP per capita and CO_2 emissions for 116 countries by using a panel VAR and System-GMM. One of its conclusions is that CO_2 emissions and economic growth have a positive correlation at a global level. Furthermore, Al-mulali et al. (2013) investigated the causal relationship between GDP per capita and CO_2 emissions in Latin American and Caribbean countries using Canonical Cointegration Regression (CCR) and discovered that 60% of the countries have a positive bidirectional long-run relationship between GDP per capita and CO_2 emissions while the other 40% showed the mixed results in the study.

Dogan and Aslan (2017) mentioned that the rising economic growth reduced CO_2 emissions in high-income countries, which were the United States, France, and Canada, which is also consistent with the negative relationship between GDP per capita and CO_2 emissions. The study conducted on 31 developing countries by Aye and Edoja (2017) aimed to assess the effect of GDP per capita on CO_2 emission by using the dynamic panel threshold framework. Apart from this, Olusanya and Musa (2018) concluded that the existence of a short-run negative relationship between GDP per capita and CO_2 emissions in Liberia, Malawi, Zimbabwe, and Senegal. The finding demonstrated a strong correlation between GDP per capita and CO_2 emissions, highlighting that GDP per capita had a negative relationship with CO_2 emissions in the regime of weak growth. The previous study also highlighted the presence of the long-term negative relationship between GDP per capita and CO_2 emissions due to the development of low-carbon technologies that enable higher GDP with lower CO_2 emissions in the long run (Pejović et al., 2021).

However, it had been experimentally demonstrated that GDP per capita has no causal effect on CO_2 emissions in Turkey from the Granger causality test (Soytas & Sari, 2009). Another previous study by Saboori et al. (2012) studied the long-term relationship between Malaysia's GDP per capita and CO_2 emissions from 1980 to 2009. Based on the empirical results of the Granger Causality test reveal that there is no relationship between the two variables in the short run. Not only that, the recent previous study indicated that the relationship between economic growth and CO_2 emissions is not the same for all countries, but the emissions of CO_2 of China, India, and South Africa from 1980 to 2011 are explained by their lag in a year with OLS method which concluded that there was no significant relationship appear in those countries (Azevedo et al., 2018).

2.3 Proposed Framework

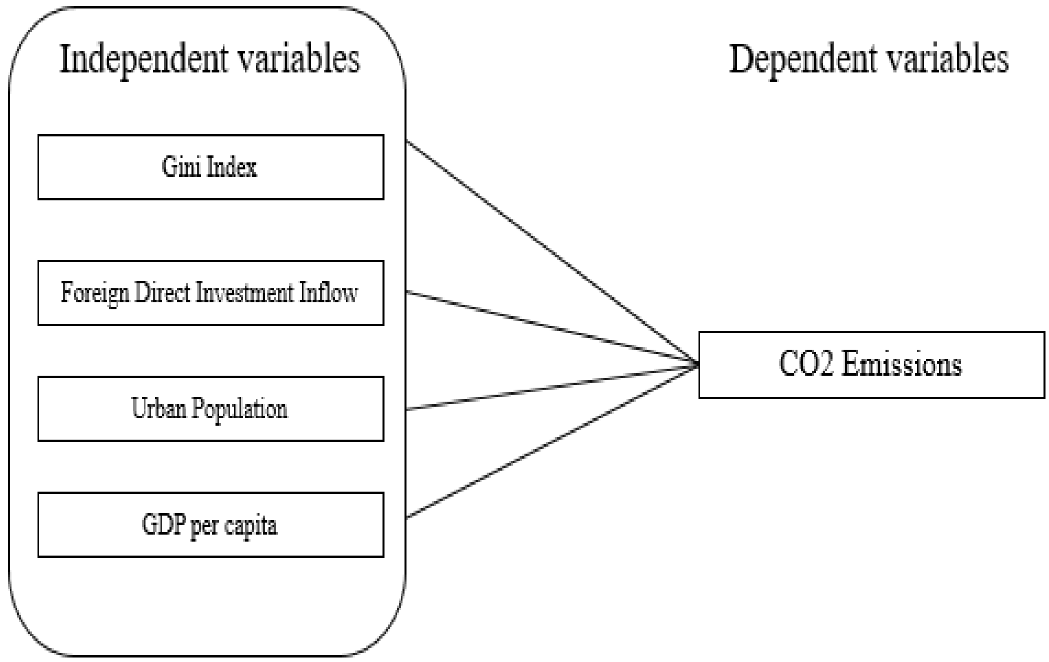

Figure 2.2 Proposed Research Framework

2.4 Conclusion

In chapter two, we mainly discussed the theories that exist to support our study. We have come out with the EKC hypothesis and urban sustainability theory in our study. The relationship between the variables such as income inequality, FDI net inflow, urbanization, and GDP per capita with CO_2 emissions which was concluded by past studies was being discussed as well. We found out that the gap of the literature review for this study is that there are fewer journals and articles discussed on the topic of income inequality and CO_2 emissions in these past 10 years. There is also less study and analysis of this topic in Southeast Asia countries.

CHAPTER 3: METHODOLOGY

3.0 Introduction

The research methodology is the set of processes for solving the research problem in the study. To achieve the research objective, this chapter will go through the primary research methodology used in this study. Besides that, the chapter will cover the data description, sources, and collection method of the selected variables. Moreover, the chapter will include the introduction of various methodologies for analyzing the statistical result and performing diagnostic checking for the data and model accuracy

3.1 Research design

This research focus on study the relationship between the CO_2 emission and net inflow of foreign direct investment (*FDI*), gross domestic product (*GDP*) per capita, GDP per capita squared, income inequality which measure by Gini index (*GI*) and urban population (*UPOP*) in Malaysia, Indonesia, Vietnam, Thailand, Philippines and Myanmar. The dependent variable in this research is CO_2 emission while the independent variables are of foreign direct investment (FDI), gross domestic product (GDP) per capita, GDP per capita squared, Gini index (*GI*) and urban population (*UPOP*). The reason CO_2 emission is chosen as dependent variable is because the CO_2 emission that drive the global climate change are a serious topic to individual. The emission of CO_2 resulting from human activities such as manufacturing and deforestation has been a matter of concern. Therefore, this study seeks to examine how these five independent variables impact CO_2 emissions. The data used in this study are annual figures obtained from the World Development Indicators.

3.1.1 Extension Model

$$CO_{2it} = \beta_0 + \beta_1(GDP)_{it} - \beta_2(GDP^2)_{it} + \beta_3(GI)_{it} + \beta_4(UPOP)_{it} + \beta_5(FDI)_{it} + \varepsilon_{it}$$

CO_{2it} = CO_2 emission (Metric tons per capita)

GDP_{it} = GDP per capita

$GDP^2{}_{it}$ = GDP per capita squared

GI_{it} = Gini Index

$UPOP_{it}$ = Urban Population (% of total population)

FDI_{it} = Foreign Direct Investment, Net inflow (% of GDP)

β_0 = Slope intercept

i = Malaysia, Indonesia, Vietnam, Thailand, Philippines, Myanmar

t = Year 1981, 1982, 1983,…, 2020

ε = Error term

The base model of this research is adopted from Dietz and Rosa(1997) as well as Kais and Sami (2016), which suggesting that the urban population and gross domestic product (GDP) per capita are the influence factor on CO_2 emissions. To develop the base model, we had included both income inequality and foreign direct investment to contribute for the current understanding of the issue on CO_2 emissions. Therefore, this model focuses the studies on the relationship between the CO_2 emission and gross domestic product (GDP) per capita, GDP per capita squared, Gini index (*GI*), urban population (*UPOP*) and foreign direct investment (*FDI*).

3.1.2 Linear Regression Analysis

$$ln(CO_2)_{it} = \beta_0 + \beta_1 ln(GDP)_{it} - \beta_2 (GDP^2)_{it} + \beta_2 ln(GI)_{it} + \beta_3 ln(UPOP)_{it} + \beta_4 ln(FDI)_{it} + \varepsilon_{it}$$

$ln(CO_2)_{it}$ = Natural logarithm of CO_2 emission (Metric tons per capita)

$ln(GDP)_{it}$ = Natural logarithm of GDP Per Capita

${GDP^2}_{it}$ = GDP per capita squared

$ln(GI)_{it}$ = Natural logarithm of Gini Index

$ln(UPOP)_{it}$ = Natural logarithm of Urban Population (% Of total population)

$ln(FDI)_{it}$ = Natural logarithm of Foreign Direct Investment, Net Inflow (% Of GDP)

β_0 = Slope intercept

i = Malaysia, Indonesia, Vietnam, Thailand, Philippines, Myanmar

t = Year 1981, 1982, 1983, …, 2020

ε = Error term

The linear regression model studies on the relationship between the CO_2 emission and GDP per capita, GDP per capita squared, income inequality which measure by Gini index and urban population. All the variables are converted into natural logarithm form except the GDP per capita squared. The variables used in the research is a highly skewed variables, to make it normalized, logarithmic transformation is needed. After converted all variables into logarithm form, the fitness of the model will improve, and the distribution will become more normally shaped bell curve. In this case, the error possible occur in the model will be smaller.

3.2 Data Collection Methods

In the research, secondary data is used to investigate the relationship between CO_2 emission and net inflow of FDI, GDP per capita, GDP per capita squared, income inequality which measure by Gini index and urban population. The data used is collected from World Development Indicators. The panel data analysis had included Malaysia, Indonesia, Vietnam, Thailand, Philippines and Myanmar from the period 1981 to 2020. Panel data is the combination of time series data and cross-sectional data. The chosen period for the study is from 1981 to 2020 with the intention of obtaining a sufficiently large dataset to conduct model estimation and to prevent potential data limitations.

Table 3.1: Description of variables

Variables	Definition	Unit Measurement
Carbon Dioxide Emissions	Carbon dioxide emissions is come from burning of fossil fuels, such as oil, coal, and gas for energy use. It also come from open burning of wood and waste, and manufacturing cement. These include carbon dioxide produced from liquid, solid and gaseous fuel used and gas flaring (World Bank, 2015).	Metric tons per capita

Foreign Direct Investment (FDI), Net Inflow	Net inflow of foreign direct investment is the amount of investment made by non-resident investors in a country, including lesser capital repatriations and loan repayments, reinvested earnings, and intra-company loans. Investment made by non-resident investors is consider as FDI when the voting right in the company operation is at least 10% (World Bank, 2015).	% Of GDP
Gross domestic product (GDP) per capita	Gross Domestic Product (GDP) per capita involves adding up the gross value added by all resident producers in the economy and any product taxes, while subtracting subsidies that are not included in the valuation of output. This total is then divided by the mid-year population to obtain the GDP per capita, which is a measure of the economic output per person in the country (World Bank, 2015). .	Current US$
Gini Index	The Gini index measures the distribution of income of individuals or households in a country, which determine the income inequality of a country. Gini index measure from 0 to 100, 0 represent perfect equality and 100 refers perfect inequality (World Bank, 2015).	-

Urban Population	Urban population refers to the population living in areas that are more densely populated than rural areas. It refers to people who live in cities (Donev, 2021).	% Of total population

3.3 Model estimation

3.3.1 Pooled Ordinary Least Squares model (POLS)

As the panel data is applied in this research, the POLS model would be adopted for the regression analysis. POLS model is the type of ordinary least squares (OLS) model that pools different data of variables to run the OLS regression model. To perform the POLS model, it should be assumed that all of the coefficients are constant which refers to the same intercepts as well as the same slope among the variables. Besides that, the model also assumes that the data are time-invariant which indicates that there is no cross-sectional and time effect over the period (Gujarati & Porter, 2009).

Furthermore, the POLS model would need to fulfill the condition that the independent variables should be non-stochastic and uncorrelated to the error term for avoiding bias. Not only that, the POLS would have a constant variance which means that the variation of the error term is consistent with the observed data and this condition is well-known as homoscedasticity (Knaub, 2007). The result of this model would show whether the selected independent variables are statistically significant in explaining the dependent variable using the panel data.

Even though the POLS model can be the most suitable regression model to explain the relationship among the panel data. However, there are drawbacks to using the POLS model as it could treat the effects of different observations as the same over the period, so it could not detect the variation of the effects that occurred in the observed data over time. Aside from that, another limitation of the POLS model is that it is incapable to measure heterogeneous observations; otherwise, the generated result would be biased, inconsistent, and inefficient (Currit, 2002). The following model shows the POLS regression model for the study.

$$Y_{it} = \beta_0 + \beta_1(X_{it,1}) + \beta_2(X_{it,2}) + \ldots + \beta_k(X_{it,k}) + \mu_{it}$$

Y_{it} = Dependent variable

$X_{it,k}$ = Independent variables; i = country; t = time period; k = 1, 2, 3, …

β_0 = Slope intercept of the model

β_k = Coefficient of independent variables

μ_{it} = Idiosyncratic error

3.3.2 Fixed Effect Model (FEM)

FEM is the regression model that has constant parameters and non-random characteristics. In panel data analysis, the term ‘fixed effects’ in the FEM also recognized as time-invariant refers to the intercepts’ effects that will not alter over time and are unrelated to the characteristics of other subjects, but intercepts that vary between individuals may do so (Bollen & Brand, 2010). To perform FEM in analysis, the model will need to fulfill the Classical Linear Regression Model (CLRM) assumption. Apart from that, to ensure the accuracy and appropriateness of the findings, the error terms cannot be related. However, the exogenous variables and individual effects should be correlated. FEM should be assumed to hold no common intercept and replace it with the unobserved time-invariant individual effect which cannot be directly controlled. The limitation of using FEM in panel data analysis is it will remove numerous degrees of freedom and lead to unreliable estimation (Hill et al., 2019). The following model shows the FEM formed for the study.

$$Y_{it} = \beta_1(X_{1it}) + \beta_2(X_{2it}) + \ldots + \beta_k(X_{kit}) + \alpha_i + \mu_{it}$$

Y_{it} = Dependent variable

X_{kit} = Time variant independent variables, k = 1, 2, 3, …

α_i = Unobserved time invariant individual effect

μ_{it} = Error term

3.3.3 Random Effect Model (REM)

REM is most commonly to be used in panel data analysis as the individual specific and cross-section effect are assumed to be random and not correlated with the independent variables. REM is considered the type of hierarchical linear model that assumes the observation are randomly drawn from different populations (Gardiner et al., 2009). The primary objective of using REM is to determine the characteristics of an individual which hold in the sample based on the random error term. Furthermore, REM also assumes that there is no correlation between individual unobserved heterogeneity and independent variables. Besides that, another assumption of REM is that all of the observed variables will not vary over time which is known as time-invariant. To conduct REM, the independent variables should be linearly independent and exogenous as well as the residual need to be independent and identically distributed (Dieleman & Templin, 2014). Therefore, the measurement of REM would be unbiased and efficient when all assumptions are fulfilled.

$$Y_{it} = \beta_0 + \beta_1(X_{1it}) + \beta_2(X_{2it}) + \ldots + \beta_k(X_{kit}) + \varepsilon_i + \mu_{it}$$

Y_{it} = Dependent variable

X_{kit} = Explanatory variables, k = 1, 2, 3, …

ε_i = Unobserved cross-sectional effect

μ_{it} = Idiosyncratic error

3.4 Model selection

We will involve the classic three test for panel data analysis in our research, which are Likelihood Ratio (LR) test, Hausman specification test, and Breusch-Pagan Lagrange Multiplier (BP-LM) Test

3.4.1 Likelihood Ratio (LR) test

LR test was a thought from Neyman and Pearson in 1933. As propose in the Neyman-Pearson lemma, they had shown that LR test is the most suitable approach to test between null hypothesis and alternate hypothesis (Neyman & Pearson, 1933). The purpose of LR test is likewise being utilized to make a contrast on the decency of fit of POLS model and FEM model based on their likelihood ratio. The null hypothesis of the LR testis that POLS being more superior than FEM whereas FEM being more superior than POLS would be the alternative hypothesis.

In LR test selection rule, dismissal of null hypothesis in the event that the p-value of the measured model is not exactly the significance level of 1%, 5% and 10%. Else, it will not be dismissed. Other than that, is the t-statistic is found being greater than the model's critical value. Consequently, the null hypothesis will not be rejected, and it is assumed that POLS is the best model.

3.4.2 Hausman specification test

Hausman Specification Test was planned by James Durbin, De-Min Wu, and Jerry A. Hausman. The Durbin-Wu-Hausman (DWH) test or the augmented regression test for endogeneity are other names for this test. The tests essentially look to see if there is a relationship between the unique errors and the regressors in the model. The null hypothesis states that no correlation exists between the two (Glen, 2020). Initially, it is utilized to look at the consistency of an assessor while making examination with a less proficient assessor which is now ended up being reliable. Likewise, capturing endogenous regressor in a regression model is also a function of this test. The OLS strategy proposes that there should not have any relationship between the endogenous regressor and error term. The t-statistic and p-value of a hypothesis testing will be inaccurate and misleading if endogenous regressors exist in a model which led to invalid result. By getting the idea of Hausman Specification Test, deciding the propriety of model among FEM and REM in this exploration will be applied (Hausman, 1978).

The null hypothesis in this test will be REM is ideal than FEM while the alternative hypothesis will be FEM is superior to REM (Frondel & Vance, 2010). Dismissal of invalid speculation if the p-value of the measured model is not exactly the importance level of 1%, 5% and 10% else there is no dismissal of null hypothesis.

3.4.3 Breusch-Pagan Lagrange Multiplier (BP-LM) Test

BP-LM test was first developed by Breusch and Pagan in year 1979, this test used to research theories about evaluators in a likelihood system (Breusch & Pagan, 1979). The hypothesis under this test is revealed as at least one requirement on the upsides of evaluators. To lead a LM test just assessment of the evaluators subject to the limitations is required. One of the most well-known LM test is BP-LM test and it will be taken on in this review.

This test empowers the scholar to decide if whether random effect model or ordinary least squares is desirable over do the accompanying hypothesis testing process. The variance across the factor is supposed to be zero under null hypothesis. In this test, the null hypothesis will be POLS is ideal than REM while the alternative hypothesis will be REM is superior to POLS. However, there is a study point out that LM test can only detect heteroscedasticity problem in linear functions, there will be an inconsistence result in non-linear function (Zaman, 2000).

3.5 Diagnostic checking

3.5.1 Panel unit root test

The parameters are considered as inefficient if the variables in the panel data are non-stationary unless they are cointegrated. When the data is independent from the changes of time period, the panel data is referring as stationary. Bhattarai (2019) highlighted that unit root is the major factor that lead the panel data into non-stationary and it could exhibit the systematic trend and become unpredictable. For the first generation of panel unit root tests, the null hypothesis typically assume that the panel data contain a unit root while alternative hypothesis assume that the panel data is stationary (Levin et al., 2002; Breitung, 2001).

The first generation of tests will help to analyze the properties of the panel unit root tests under the assumption that the data is independently and identically distributed across individuals. However, the main limit of using the these tests is that they are all built under the condition that the individual time series in the pane data set are cross-sectionally independently distributed; instead, large number of studies had showed the evidence of co-movements between the economic variables (Barbieri, 2009). The following model shows the univariate regression model to demonstrate the general form of panel unit root tests:

$$\Delta Y_{i,t} = z'_{it}\,\gamma + \rho_i Y_{it-1} + u_{it}$$

Where $\Delta Y_{it} = Y_{it} - Y_{it-1}$, for the individuals, i = 1, 2, 3, …, and t = 1, 2, ... is the observed time period, the z_{it} would represent as the deterministic components which can be zero or one and u_{it} would be the stationary process.

For this study, the Levin, Lin, and Chu (LLC) test would be the selected panel unit root test to determine the hypothesis on the stationarity of panel data. The LLC test generalizes Quah's model and allows for heterogeneity of individual deterministic effects as well as heterogeneous serial correlation structure of the error terms under the assumption of homogenous first-order autoregressive estimators (Levin et al., 2002). The test also assumes that both i and t would result in infinity but t would expand at a rapid rate. The process would use the pooled t-statistic of the estimator to determine the null hypothesis that the panel data set consists of unit root against that the data set is stationary as the alternative hypothesis. For the structure of the LLC test can be modelled as the following method:

$$\Delta Y_{it} = \rho_i Y_{it-1} + \alpha_{0i} + \alpha_{1i} t + u_{it}$$

Where the individual effects (α_i) and time trend ($\alpha_{1i}t$) are incorporated. It is also important to highlight that the deterministic components are the significant source of heterogeneity for the LLC model as the coefficient of the lagged dependent variables should not be homogeneous among all units in the panel data set. For the hypothesis testing, the null hypothesis would be $H_0 \ : \rho_i = \rho = 0$ for all individuals against the alternative hypothesis $H_1 \ : \rho_i = \rho < 0$ for all individuals.

Before we conduct the first generation of panel unit root tests, we will need to investigate cross-sectional dependence as the preliminary analysis. For the cross-sectional dependence test, we used several cross-sectional dependence tests that can detect the problem including Breush and Pagan (1980) LM test, Pesaran (2004) scaled LM test, and Pesaran (2004) CD test. Then, the null hypothesis for these tests is that "there is no cross-section dependence exists in the panel data".

At first, we may refer to the statistical result of the Breuch-Pagan LM test if the data is made up of panel observations from a small number of cross-section units. If the panel data sets are composed of a large number of cross-section units, Pesaran (2004) projected the standardized version of the scaled LM test which is applicable and appropriate for the panel data under large and cross-sectional settings. However, the number of cross-section units and time dimension is different in size, and the size distortion caused by the expected value of the correlation coefficients captured from unobserved individual-specific effects exacerbates the situation (Tugcu, 2018). To overcome the drawback of the scaled LM test, the Pesaran CD test has been developed as it has good properties for the panels with both small cross-sections and time dimensions.

Table 3.2: Cross-section dependence test

Test	Statistic	d.f	Probability
Pesaran CD	1.243036	15	0.2139

Upon examining Figure 3.1, the cross-section dependence test results indicate that we reject the null hypothesis at 5% significance level. This implies that there is no evidence of cross-sectional dependence in the residuals of the panel data. Therefore, the first generation unit root test is allow to be used for testing the stationarity of the data.

3.5.2 Multicollinearity

Ragnar Frisch was the first person to introduce the multicollinearity term when the found out a highly correlation of variables in his regression equation (Sastry, 1970). According to Jensen and Ramirez (2013), multicollinearity is an occurrence of high correlation among the independent variables in a regression model. Multicollinearity also called as the near-linear dependence. The independence variables are considered as orthogonal if there happened to be no linear relationship among them.

According to Vatcheva et al. (2016), multicollinearity problem could potentially lead to false independent variables significance interpretation as the standard error and p-value are uneven and biased. There are four types of symptoms associated to multicollinearity (Lafi & Kaneene, 1992). Firstly, the coefficients have a larger figure of standard error. Secondly, the effect of the independent variables on the dependent variable might be wrongly justified and differ from the theory. Thirdly, the independent and dependent variables are found to have a high correlation. Lastly, the R-squared is found to have a large figure.

According to Daoud (2017), variance inflation factors (VIF) is an indicator the detect multicollinearity. The variance of the independent variable's coefficients will be inflated if the standard error increase due to the correlation exist among the independent variables. In this case, VIF is used as an indicator to measure the inflated variance. If the VIF is equal to 1, it is interpreted as not correlated. If VIF is larger than 5, it is highly correlated. If VIF is between 1 and 5, it is moderately correlated. The formula to calculate VIF is:

$$VIF = \frac{1}{1 - R^2}$$

3.5.3 Normality Test

The Classical Normal Linear Regression Model (CNLRM) have a total of ten assumptions. According to Knief and Forstmeier (2021), it is essential not to violate the normality assumptions. Violating the normality assumptions will bring a non-reliable statistical hypothesis testing and affect the regression analysis (Mantalos, 2010). According to Lumley et al. (2002), the error term assumption is one of the most famous normality assumptions that it must be normally distributed in parametric statistics. The author underlies an essential assumption that when testing for the significance of statistics, the error term must be normally distributed. The most widely used of regression technique when testing the significance is the t-test and ANOVA test.

To test whether the error term is normally distributed, Bera and Jarque introduced the Jarque-Bera (JB) test (Bowman & Shenton, 1975). In econometrics, it is widely used to examine the normality of the sample distribution. JB statistic has always been distributed chi-square asymptotically and often have the degree freedom of two. In this case, this is further supported by Thadewald and Buning (2007), that the null hypothesis of this test must not be rejected if the JB statistic is lower than the chi-squared with degree of freedom of two (critical value).

To conduct the hypothesis testing, the null hypothesis is the error term is normally distributed whereas the alternative hypothesis is that the error term is not normally distributed. The decision rule for this test is that if the JB statistic is found greater than the critical value or the p-value is found to be lower than the significance value of 5%, then it means that the error term is not normally distributed.

H_0: The error term is normally distributed
H_A: The error term is not normally distributed

The formula to compute JB test is:

$$JB = n\left[\frac{skewness^2}{6} + \frac{(kurtosis - 3)^2}{24}\right]$$

3.5.4 Breusch-Godfrey Serial Correlation LM Test

According to Brooks (2019), the Breusch-Godfrey Serial Correlation LM Test proposed by Breusch, and Godfrey is used to test the autocorrelation problem. It is said to be more suitable to use the Breusch-Godfrey test rather than the Durbin-Watson test that will enable testing on second order autocorrelation and higher. In conducting the hypothesis testing, the null hypothesis will be there is no serial correlation problem whereas the alternative hypothesis will be there is serial correlation problem. In rejecting the null hypothesis, the p-value must be lower than the significance level of 5%, then it means the serial correlation problem does not exist otherwise if the p-value is found to be greater than the significance level we do not reject the null hypothesis and it means that the serial correlation problem exists.

H_0: There is no serial correlation problem

H_A: There is serial correlation problem

3.5.5 Breusch-Pagan-Godfrey Test

Breusch and Pagan (1979) stated that in general linear regression model, it is essential to question the existence of heteroscedasticity problem in the model. Negligence of testing the heteroscedasticity problem may lead to invalid inference. According to Downs and Rocke (1979), the estimated regression coefficient may have a large figure of standard errors if heteroscedasticity problem is detected. Hence, Breusch and Pagan proposed the Breuch-Pagan-Godfrey test to test on the heteroscedasticity problem in the model. In conducting the hypothesis testing, the null hypothesis will be there is no heteroscedasticity problem, and the alternative hypothesis will be there is heteroscedasticity problem. If the p-value is found to be lower than the significance level, then the null hypothesis must be rejected which indicates that heteroscedasticity problem exist. On the other hand, if p-value is found to be greater than the significance level, then it indicates that there is no heteroscedasticity since the null hypothesis is not rejected.

H_0: There is no heteroscedasticity

H_A: There is heteroscedasticity

3.6 Conclusion

In this chapter, we constructed the extension model and the linear regression model based on our dependent and independent variables. Then, we stated out the data collection method which is secondary data retrieved from the World Development Indicator and define each variable and its unit measurement. Next, we introduced the model estimation for our research in which we are using the Pooled Ordinary Least Squared (POLS) method, Fixed Effect Model (FEM), and Random Effect

Model (REM). Besides, for the model selection method, we have selected the Likelihood Ratio (LR) test to compare the goodness of fit of the POLS and FEM models. The Hausman Specification test to test for the existence of endogeneity in the regression model and decide if the REM or FEM model is better to be used. The Breusch-Pagan Lagrange Multiplier (BP-LM) test will be testing the better model between REM and POLS models. Lastly, it comes to the diagnostic checking we introduced the Panel unit root test to test the stationarity of the panel data. The multicollinearity test is also introduced to test the high correlation among the independent variables in the regression model. The Normality test by using the JB test will be testing whether the error term is normally distributed. Lastly, we introduced the Breusch-Godfrey Serial Correlation LM Test and the Breusch-Pagan-Godfrey Test to test the autocorrelation and heteroscedasticity problems, respectively.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter aims to present the outcomes of our empirical research, alongside the interpretation of the data collected, as we outlined in the previous chapter of methodology. We conducted model estimation, model selection and diagnostic checks with using the software, Eviews to analyze our panel data, and the results obtained from this analysis will be presented herein.

4.1 Descriptive Analysis

4.1.1 Extension model estimation

Table 4.1.1: Extension model estimation

Variables	Extension model			
	Coefficient	Standard Error	T-Statistic	Probability
C	-1.429474	0.0377078	-3.790924	0.0002***
FDI	0.083371	0.021430	3.890310	0.0001***
GDP	0.000634	7.00E-05	9.053973	0.0000***
GDP^2	-5.85E-09	6.06E-09	-0.965575	0.3353
GI	0.019364	0.010721	1.806222	0.0722*
UPOP	0.024334	0.006822	3.566893	0.0004***
R-squared	0.856602			
Adjusted R-squared	0.853525			

Table 4.1.1 shows the proposed extension model estimation have the R-squared value of 0.8566, indicating that 85.66% of the changes in CO_2

emission can be accounted by the independent variables' changes. The independent variables such as FDI, GDP per capita and urban population have the p-value of 0.0000 which indicate that the particular variables have significant positive relationship with CO_2 emission and statistically significant at 1%. Furthermore, the Gini index and GDP per capita squared are recorded at the p-value with 0.0722 and 0.3353 respectively, indicating that both Gini index and GDP per capita squared are insignificant to affect the CO_2 emissions in the extension model.

4.1.2 Panel Unit Root Test (Levin, Lin and Chu Test)

Table 4.1.2: Panel Unit Root Test

	Individual Effect	Individual Effect, Individual Linear Trends	Individual Effect	Individual Effect, Individual Linear Trends
	Level Form		First Difference	
CO_2	-1.77460** (0.0380)	3.42469 (0.9997)	-3.30797*** (0.0005)	-1.76890** (0.0385)
FDI	-3.21349*** (0.0007)	-2.74870*** (0.0030)	-10.8703*** (0.0000)	-7.90936*** (0.0000)
GDP	4.59645 (1.0000)	-1.65438*** (0.0490)	5.30071*** (0.0000)	-3.05862*** (0.0011)
GDP^2	3.93051 (1.0000)	2.00536 (0.9775)	-4.29854*** (0.0000)	-3.50253*** (0.0002)
GI	-2.34625*** (0.0095)	-2.35964*** (0.0091)	-8.49289*** (0.0000)	-7.88858*** (0.0000)
UPOP	-8.12454*** (0.0000)	-2.58005*** (0.0049)	-4.16003*** (0.0000)	-2.08533** (0.0185)

*Note that the use of asterisks, namely *, **, and ***, signifies the rejection of the null hypothesis at the 10%, 5%, and 1% level of significance, respectively. The value in parenthesis is the P-value.*

To test for the panel unit root, the Levin, Lin, and Chu (LLC) test is used to test the stationarity of the panel data. The null hypothesis for this test is that the panel data has unit root whereas the alternative hypothesis is that the panel data is stationary. Referring to Table 4.1.2 is the outcome of the LLC Test generated using the EViews. At level form, only FDI, Gini Index, and urban population are stationary at 10%, 5%, and 1% at individual effect and individual effect, individual linear trends. Carbon dioxide emission is only stationary at 5% significance level at individual effect but is not stationary at individual effect, individual linear trends. GDP per capita is only stationary at individual effect, individual linear trends. GDP per capita squared are not stationary at both individual effect and individual effect, individual linear trends. On top of that, all the variables are stationary at least at 5% significance level in individual effect and individual effect, individual linear trends.

4.2 Panel Data Model Estimation

4.2.1 Pooled OLS estimation

Table 4.2.1: Pooled OLS

Variables	Pooled OLS			
	Coefficient	Standard Error	T-Statistic	Probability
C	-5.798504	0.998337	-5.808161	0.0000***
LN(FDI)	0.045347	0.022147	2.047569	0.0417**
LN(GDP)	0.636316	0.188190	3.381245	0.0008***
LN(GDP^2)	0.008283	0.014905	0.555748	0.5789
LN(GI)	0.013759	0.279688	0.049195	0.9608
LN (UPOP)	0.246454	0.160741	1.533242	0.1266

R-squared	0.856221
Adjusted R-squared	0.853136

*Note that the use of asterisks, namely *, **, and ***, signifies the rejection of the null hypothesis at the 10%, 5%, and 1% level of significance, respectively. Additionally, the standard error is reported in parentheses.*

$$ln(CO_2)_{it} = -5.798504 + 0.045347\ln(FDI)_{it} + 0.636316\ln(GDP)_{it} + 0.008283\ln(\mathrm{GDP}^2)_{it} + 0.013759\ln(GI)_{it} + 0.246454 ln(\mathrm{UPOP})_{it} + \varepsilon_{it}$$

Table 4.2.1 presents the results of the POLS model estimation. As can be seen from the table, it exhibits an R-squared value of 0.8562, indicating 85.62% of the CO_2 changes can be accounted for by the independent variables' changes. The result indicates that both FDI inflow and urban population are statistically significant at the 5% of significance level. The GDP per capita squared, Gini index and urban population are the insignificant variables in POLS model as the P-value is more than significance level of 5%.

The Pooled OLS results reveal that in the absence of other independent variables, the average CO_2 emissions of the selected southeast countries is -5.798504% in metrics ton per capita. However, with every increase of 1% in foreign direct investment, there is an average increase in CO_2 emissions per capita by 0.045347% metric tons. Besides, with every increase of 1% in GDP per capita, there is an average increase in CO_2 emissions per capita by 0.636316% metric tons. Moreover, with every increase of 1% in GDP per capita after turning point, it would cause the average increase in CO_2 emissions per capita by 0.008283% metric tons. Other than that, with every increase of 1% in Gini index, the CO_2 emissions per capita increases by 0.013759% metric tons. Furthermore, the data also shows that with every increase of 1% in urban population, the CO_2 emissions per capita increases by 0.246454% metrics ton. In summary, the findings suggest that all variables have a positive correlation with CO_2 emissions but only FDI and GDP per capita are significantly positive correlated with CO_2 emissions.

4.2.2 Fixed Effect Model Estimation

Table 4.2.2: Fixed Effect Model

Variables	Fixed Effect Model			
	Coefficient	Standard Error	T-Statistic	Probability
C	-5.564318	1.004277	-5.540623	0.0000***
LN(FDI)	0.064468	0.012909	4.994179	0.0000***
LN(GDP)	0.961171	0.137828	6.973716	0.0000***
LN(GDP^2)	-0.048954	0.011330	-4.320877	0.0000***
LN(GI)	-0.809352	0.239949	-3.373011	0.0009***
LN (UPOP)	1.195193	0.162999	7.332493	0.0000***
R-squared	0.963348			
Adjusted R-squared	0.961740			

*Note that the use of asterisks, namely *, **, and ***, signifies the rejection of the null hypothesis at the 10%, 5%, and 1% level of significance, respectively. Additionally, the standard error is reported in parentheses.*

$$ln(CO_2)_{it} = -5.564318 + 0.064468\, ln(FDI)_{it} + 0.961171\, ln(GDP)_{it} - 0.048954 \ln(GDP^2)_{it} - 0.809352\, ln(GI)_{it} + 1.195193 ln(UPOP)_{it} + \varepsilon_{it}$$

According to the results of the fixed effect model estimation presented in Table 4.2.2, the R-squared value is 0.9633 which indicates that 96.33% of the changes in CO_2 emission can be accounted for by the independent variables' changes. The result shows that all variables are statistically significant at the 5% of significance level.

The results of the fixed effect model analysis indicate that without considering other independent variables, the average CO_2 emissions for the selected southeast countries is -5.5643% in metric tons per capita. For every

1% increase in foreign direct investment, there is an average increase in CO_2 emissions per capita by 0.064468% metric tons. Similarly, for every 1% increase in GDP per capita, there is an average increase in CO_2 emissions per capita by 0.9612% metric tons. Conversely, with every increase of 1% in GDP per capita after turning point, there is an average decrease in CO_2 emissions per capita by 0.04895% metric tons. For every increase 1% in Gini index, the CO_2 emissions per capita will decrease by 0.8094% in metric tons. While for every 1% increase in urban population, the CO_2 emissions per capita increase by 1.1952% in metric tons. Overall, the results suggest that FDI, GDP per capita and urban population have a significant positive relationship with CO_2 emissions, while the Gini index and GDP per capita squared have a significant negative relationship with CO_2 emissions.

4.2.3 Random Effect Model Estimation

Table 4.2.3: Random Effect Model

Variables	Random Effect Model			
	Coefficient	Standard Error	T-Statistic	Probability
C	-5.798504	0.509554	-11.37957	0.0000***
LN(FDI)	0.045347	0.011304	4.011678	0.0001***
LN(GDP)	0.636316	0.096052	6.624667	0.0000***
LN(GDP^2)	0.008283	0.007607	1.088844	0.2773
LN(GI)	0.013759	0.142753	0.096385	0.9233
LN (UPOP)	0.246454	0.082042	3.003987	0.0030***
R-squared	0.856221			
Adjusted R-squared	0.853136			

*Note that the use of asterisks, namely *, **, and ***, signifies the rejection of the null hypothesis at the 10%, 5%, and 1% level of significance, respectively. Additionally, the standard error is reported in parentheses.*

$$\begin{aligned} ln(CO_2)_{it} = {} & -5.798504 + 0.045347\, ln(FDI)_{it} + 0.636316\, ln(GDP)_{it} \\ & + 0.008283 \ln(GDP^2)_{it} + 0.013759\, ln(GI)_{it} \\ & + 0.246454 ln(UPOP)_{it} + \varepsilon_{it} \end{aligned}$$

Based on the random effect model estimation results presented in Table 4.2, the R-squared value is 0.8562 which indicates that 85.62% of the changes in CO_2 emission can be accounted for by the independent variables' changes. The result further suggest that all the independent variables are statistically significant at the 5% of significance level except the variables of Gini index and GDP per capita squared.

The results of the random effect model analysis indicate that without considering other independent variables, the average CO_2 emissions for the selected southeast countries is -5.7985% in metric tons per capita. However, for every 1% increase in foreign direct investment, there is an average increase in CO_2 emissions per capita by 0.04535% in metric tons. Similarly, for every 1% increase in GDP per capita, there is an average increase in CO_2 emissions per capita by 0.636316% in metric tons. Besides that, every increase of 1% in GDP per capita after the turning point, there is an average increase of in CO_2 emissions per capita by 0.008283% metric tons. For every 1% increase in Gini index, the CO_2 emissions per capita increases by 0.01376% in metric tons, and for every 1% increase in urban population, the CO_2 emissions per capita increase by 0.2465% in metric tons. Overall, the results suggest that all variables are having significant positive correlation with CO_2 emissions except GDP per capita squared and Gini index.

4.3 Panel Data Model Estimation

4.3.1 Likelihood Ratio Test

Table 4.3.1:Likelihood Ratio Test

Test summary	Chi-sq. Statistic	Chi-sq. d. f.	Probability
Cross-section Chi-square	326.6664	5	0.0000***

H_0: Endorsement of POLS is more favourable.

H_1: Endorsement of FEM is more favourable.

Decision Rule: H_0 is rejected when p-value is less than α. Otherwise, we do not reject H_0.

Decision Making: H_0 will be rejected due to the p-value (0.0000) is lower as compared to α at 1% of significance level.

Conclusion: Endorsement of FEM is more favourable.

4.3.2 Breusch Pagan-Lagrange Multiplier (BP-LM) test

Table 4.3.2:Breusch Pagan-Lagrange Multiplier (BP-LM) test

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	736.7443 (0.0000)	25.07165 (0.0000)	761.8159 (0.0000)

H_0: Endorsement of POLS is more favourable.

H_1: Endorsement of REM is more favourable.

Decision Rule: H_0 is rejected when p-value is less than α. Otherwise, we do not reject H_0.

Decision Making: H_0 will be rejected due to the p-value (0.0000) is lower as compared to α at 1% of significance level.

Conclusion: Endorsement of REM is more favourable.

4.3.3 Hausman Test

Table 4.3.3 Hausman Test

Test summary	Chi-sq. Statistic	Chi-sq. d. f.	Probability
Cross-section random	666.3978	5	0.0000***

H_0: Endorsement of REM is more favourable.

H_1: Endorsement of FEM is more favourable.

Decision Rule: H_0 is rejected when p-value is less than α. Otherwise, we do not reject H_0.

Decision Making: H_0 will be rejected due to the p-value (0.0000) is lower as compared to α at 1% of significance level.

Conclusion: Endorsement of FEM is more favourable.

4.4 Diagnostic Checking

4.4.1 Multicollinearity

Table 4.4.1: Variance Inflation Factor (VIF)

Variables	Variance Inflation Factor	Result
FDI	1.04	Moderately correlated
GDP	13.1005	Highly correlated

GDP^2	8.9240	Highly correlated
GI	1.3845	Moderately correlated
UPOP	4.0779	Moderately correlated

Factors that could potentially lead to multicollinearity issues are the coefficients have a larger figure of standard error, high correlation between the independent and dependent variables, and the R-squared is found to have a large figure (Lafi & Kaneene, 1992). Hence, in this study, multicollinearity will be tested using the variance inflation factor (VIF). The result of the VIF can be judged if it is equal to 1, it is not correlated. If VIF is larger than 5, it is highly correlated. If VIF is between 1 and 5, it is moderately correlated. Table 4.4.1 shows the result of VIF generated by using EViews. According to the table, the VIF value of FDI, Gini Index, and urban population are between 1 and 5 which means they are moderately correlated. Only GDP per capita and GDP per capita squared VIF value are greater than 5 which means they are highly correlated. This shows that our model has multicollinearity issues. Multicollinearity issues will highly likely occur when GDP per capita and squared GDP are used as the explanatory variables in the same model. This is due to the parabolic relationship in the EKC hypothesis (Alkan & Bulut, 2022; Alsaedi et al, 2022).

4.4.2 Normality test

Table 4.4.2: Normality test

Jarque-Bera	Probability
2.651003	0.2657

Table 4.4.2 shows the summary result of the normality test. For the normality test, Jarque-Bera test is selected to test whether the error term of the model is normally distributed. The error term is normally distributed being the null hypothesis, and the error term is not normally distributed being the alternative hypothesis. According to Table 4.4.2, the Jarque-Bera statistic shows a value of 2.651003 and P-value of 0.2657. Since, the P-value is greater than 5% significance level, we do not reject the null hypothesis. Hence, we have sufficient evidence to conclude that the error term is normally distributed at 5% significance level.

4.4.3 Breusch-Godfrey Serial Correlation LM Test

Table 4.4.3: Breusch-Godfrey Serial Correlation LM Test

F-statistic	Obs*R-squared	Prob.F	Prob. Chi-square
1.514079	35.53749	0.0653	0.0608

The Breusch-Godfrey Serial Correlation LM Test is selected to detect the serial correlation of the model. The null hypothesis of this test is that there is no serial correlation problem, and the alternative hypothesis is there is serial correlation problem. To overcome the autocorrelation in the OLS regression, Keele and Kelly (2006) highlighted that the inclusion of a lagged dependent variable often eliminates the any residual serial correlation. Therefore, we included the lagged CO_2 emissions in the Breusch-Godfrey Serial Correlation LM Test as the corrective procedure. According to Table 4.4.3 the P-value is greater than 5% significance level and that concludes that the null hypothesis will not be rejected. Hence, there is sufficient evidence to prove that the model does not have the serial correlation problem.

4.4.4 Breusch-Pagan-Godfrey Test

Table 4.4.4: Breusch-Pagan-Godfrey Test

F-statistic	Obs*R-squared	Prob.F	Prob. Chi-square
1.537127	13.61572	0.1359	0.1367

The Breusch-Pagan-Godfrey Test is used to test the heteroscedasticity problem in the model. The null hypothesis for this test is there is no heteroscedasticity problem whereas the alternative hypothesis is there is heteroscedasticity problem in the model. According to Table 4.4.4, the P-value obtained is greater than 5% significance level which indicates that we do not reject the null hypothesis. Hence, we have sufficient evidence to conclude that the model does not have heteroscedasticity problems and the model is homoscedasticity.

4.5 Conclusion

Based on our research, the FEM is the most appropriate model for our analysis. We have determined that FDI inflow, GDP per capita, income inequality, and urbanization have a significant impact on CO_2 emissions in Southeast Asian countries between 1981 and 2020. We have conducted a LLC unit root test and determined that our variables are stationary at the first difference form. However, we have identified a problem with multicollinearity between GDP per capita and GDP per capita squared due to the parabolic relationship in the Environmental Kuznets Curve (EKC) hypothesis. Furthermore, the data has undergone tests for normality, heteroscedasticity, and autocorrelation, and the results indicate that it is normally distributed. Additionally, we have determined that the model is not affected by heteroscedasticity or autocorrelation issues.

CHAPTER 5: CONCLUSION

5.0 Introduction

The focus of this research is to explore the connection between CO_2 emissions and four independent variables: FDI, GDP per capita, gini index, and urban population in selected Southeast Asian countries. The main aim is to determine whether income inequality has any impact on the changes in CO_2 emissions. In this chapter, each independent variable's relationship with the dependent variable is examined, taking into account the statistical information and findings from Chapter 4. Based on the results, the study's implications are discussed, highlighting areas that require changes or improvements in the future. Additionally, the study's limitations are outlined, and recommendations are made to enhance research in the future.

5.1 Discussion of Major Findings

Table 5.1: Summarized Model Estimation Result

	POLS	FEM	REM
C	-5.798504** (0.998337)	-5.564318*** (1.004277)	-5.798504*** (0.509554)
LN(FDI)	0.045347** (0.022147)	0.064468*** (0.012909)	0.045347*** (0.011304)
LN(GDP)	0.636316*** (0.188190)	0.961171*** (0.137828)	0.636316*** (0.096052)
LN(GDP^2)	0.008283 (0.014905)	-0.048954*** (0.011330)	0.008283 (0.007607)

LN(GI)	0.013759 (0.279688)	-0.809352*** (0.239949)	0.013759 (0.142753)
LN(UPOP)	0.246454 (0.160741)	1.195193*** (0.162999)	0.246454*** (0.082042)
R-Squared Adjusted R-Squared	0.856221 0.853136	0.963348 0.961740	0.856531 0.853452

Table 5.2: Summarized Model Selection Result

	Likelihood-Ratio (LR) Test	Breusch Pagan-Lagrange Multiplier (BP-LM) test	Hausman Test
P-value	0.0000***	0.0000***	0.0000***
Decision Making	We will reject the null hypothesis	We will reject the null hypothesis	We will reject the null hypothesis
Conclusion	FEM is more favourable than POLS	REM is more favourable than POLS	FEM is more favourable than REM

*Note that the use of asterisks, namely *, **, and ***, signifies the rejection of the null hypothesis at the 10%, 5%, and 1% level of significance, respectively.*

According to the outcomes of the Likelihood-Ratio (LR) test, FEM is preferred to POLS because the p-value (0.0000) is lesser than all significance levels at 1%. The null hypothesis that POLS is better is thus rejected as a result of this. The Breusch Pagan-Lagrange Multiplier (BP-LM) test was then used to determine whether POLS or REM was the better option. According to the p-value of the BP-LM test, it is found to be lesser than the significant level of 1%. As a result, REM is more appropriate than POLS. Additionally, by examining FEM and REM using the Hausman Test it resulted in FEM being more preferable than REM. FEM is more preferable to REM, as shown by the Hausman test, whose p-value (0.0000) is lower than significance levels of 1%. FEM is therefore the most suitable model out of the three models. It indicates that each country included in the data has unique characteristics, which will be taken into consideration in this study.

Since FEM is the most suitable model, a comparison between the real and expected indicators of FEM results was performed. In this study, a positive relationship between FDI and CO_2 emissions are anticipated. The result shown by FEM is consistent with the anticipation of the study. A significant positive relationship was shown by the output result on FDI and CO_2 emissions. This result is consistent with empirical results by Tang and Tan (2015). The findings show that FDI has positive impact on CO_2 emissions and stated that the positive coefficient of FDI is supported by the pollution haven hypothesis. Besides that, the result is consistent with the studies by Copeland (2008), which highlighted that the FDI inflow will cause the increase in CO_2 emissions. Meanwhile, the findings are also consistent with the research by Xie et al (2019), as the FDI inflows could often come with increased industrialization which can lead to greater energy use and emissions in the developing countries with weak environmental regulation. Therefore, the FDI inflow is significantly achieve the research objective which shows that there is positive relationship between FDI inflow and CO_2 emissions.

For GDP per capita and CO_2 emissions, it has a positive and significant relationship in the selected Southeast Asia countries. This result is consistent with the expectation that economic growth drives energy consumption, leading to increased emissions. The finding is also supported by research conducted by Munir et al. (2020), which showed that GDP per capita and emissions have a positive linear relationship in all ASEAN-5 countries. The positive relationship between GDP per capita and CO_2 emissions can be attributed to the fact that economic growth is typically accompanied by an increase in energy consumption. As ASEAN countries are growing, they are requiring more energy to power their industries, transportation, and households. In developing economies, where energy consumption is low, economic growth often leads to an increase in energy demand and emissions. This trend is particularly evident in ASEAN countries, where the energy sector is a crucial driver of economic development. For countries like the Philippines, which rely heavily on energy, energy consumption is a significant driver of economic growth. As the country continues to develop, it will require more energy to sustain its growth, which will lead to increased carbon emissions. This trend is consistent with the "energy transition" theory, which suggests that countries will continue to rely on fossil fuels until they have reached a certain level of economic development, after which they will begin to transition to cleaner sources of energy (Drewello, 2022). Furthermore, the GDP per capita squared has the negative relationship which indicates that there is valid existence of the EKC theory in the selected Southeast Asia countries as the result shows the inverted U-shaped relationship between the GDP per capita and CO_2 emissions.

Moreover, urban population impact on CO_2 emission has a positive relationship, which the result is aligned with anticipation mentioned. The analysis contributed by Wang et al. (2016) regarding the linking between urbanizations and emissions in ASEAN countries, it stated that urbanizations have a positive impact towards emissions, but the effect varies depending on the particular country’s development phases and also income level. The effect is very clearly shown in the country with middle- and high-income levels. It indicates that highly developed urbanizations will increase the usage of resources and therefore increase the overall CO_2 emissions. Apart from that, the result of FEM is consistent with the research by Chien et al. (2022) which had mentioned that the urbanization would have the positive association with carbon emission, primarily due to increased energy use associated with urban living. As people move into cities, they tend to consume more energy for transportation, heating, cooling, and other daily activities which can lead to increased CO_2 emissions. The concentration of industries and businesses in urban areas can also contribute to higher carbon emissions. For example, cities may have more power plants, factories, and transportation hubs that emit greenhouse gases and eventually contribute negative impact to the environment.

Last but not least, the income inequality, which is measured by the Gini index, was expected to have a positive relationship with CO_2 emissions. However, the result is inconsistent with the initial expectations as it shows the negative relationship between income inequality and CO_2 emissions. With observing the result, the findings are consistent with the research by Kusumawardani and Dewi (2020) which the researchers concluded that the negative relationship pattern between income inequality and CO_2 emissions is depends on the GDP per capita level. On the other hand, Hao et al. (2016) observed that there is a negative association between income inequality and CO_2 emissions. This is because individuals with higher income levels are more likely to prioritize environmental sustainability and opt to purchase products made from materials that have lower pollution levels (Ravallion, 2000; Scruggs, 1998). Therefore, the result of FEM had showed the significantly negative relationship between income inequality and CO_2 emissions that able to demonstrate the contribution of our study.

As the summary of the major findings, the study has identified several significant factors that affect CO_2 emissions in the selected Southeast Asian countries, including FDI inflow, GDP per capita, GDP per capita squared, urban population, and income inequality. These findings support the research question that aimed to explore the relationship between independent variables and CO_2 emissions. Specifically, the study found that FDI inflow has a positive impact on CO_2 emissions, which indicates that foreign investment may contribute to increased pollution in the region. GDP per capita and urban population also show a positive correlation with CO_2 emissions, suggesting that economic development and urbanization may lead to higher carbon emissions. Additionally, income inequality has a negative correlation with CO_2 emissions, which implies that countries with more equal income distribution tend to have lower levels of pollution.

Overall, these findings provide insights into the complex relationships between various factors and their impact on environmental sustainability in the Southeast Asian region. The results of this study could inform policy decisions aimed at reducing carbon emissions and promoting sustainable development in the region.

5.2 Implication of Study

The research has found that certain variables, including foreign direct investment (FDI), GDP per capita, income inequality, and urbanization, have a significant impact on CO_2 emissions. From these major findings, we can conclude that these variables play a crucial role in influencing the level of carbon emissions. Consequently, policymakers can draw important implications from these conclusions in their efforts to mitigate the effects of climate change. These findings highlight the importance of implementing policies that encourage sustainable economic growth, reduce income inequality, and promote the use of clean energy to reduce the carbon footprint. By addressing these factors, policymakers can work towards creating a more sustainable and eco-friendly future.

The concept of eco-economic decoupling is a crucial element of the European Green Deal, which seeks to achieve economic growth while preserving a healthy environment. The EU's objective is to increase GDP while simultaneously reducing carbon emissions to net-zero levels. To this end, the EU has set a target to reduce carbon emissions by 50% to 55% by 2030 (BBC News, 2021). However, despite these efforts, global temperatures are still projected to rise by 3.2 degrees Celsius by the end of the century. To achieve the ambitious goal of net-zero carbon emissions by 2050, unprecedented and significant cuts in CO_2 emissions will be required. This highlights the urgent need for aggressive action and the implementation of policies that promote sustainable economic growth while simultaneously reducing carbon emissions. By achieving this balance, we can work towards creating a more sustainable and eco-friendly future for generations to come.

For instance, the European Union has taken bold steps to reduce carbon emissions through the implementation of a carbon tax policy. The policy aims to control and reduce CO_2 emissions and is part of the EU's commitment to achieving net-zero carbon dioxide emissions by 2050. As one of the world's largest carbon taxes, it targets carbon-intensive industries within the EU and sets strict emission standards for these enterprises (Figures et al., 2021). The policy seeks to ensure that these industries are not weakened by competitors from countries with weaker environmental regulations. The EU has adopted a gradual approach to implementing the policy, starting with the goods that are most likely to release higher amounts of carbon dioxide, such as iron, steel, aluminum, and electricity production. This initiative is an important step towards achieving the EU's ambitious carbon reduction goals and promoting sustainable economic growth while protecting the environment. By implementing these policies, the EU is setting an example for other countries to follow in the fight against climate change. The government will set a price per ton of greenhouse gas emission the emitters need to pay. The more greenhouse gas emission by an industry or company, the more tax they need to pay. To minimize the amount of carbon tax that businesses must pay, they will need to adopt new technologies that reduce their carbon emissions. One example of this is Sweden, which set a carbon tax rate of SEK1222/tCO2 in 2022 (Åkerfeldt, 2022). By implementing new technologies that reduce their carbon footprint, businesses can lower their carbon tax burden while also helping to reduce overall carbon emissions. This creates an incentive for companies to invest in clean energy technologies and promote sustainable economic growth. Therefore, the Southeast Asia countries should adopt these innovative solutions and encourage businesses operation to a cleaner and healthier environment while also remaining competitive in the global marketplace.

One policy that governments in Southeast Asia can adopt to promote sustainability is to improve their procurement policies. By implementing sustainable procurement policies, these governments can ensure that the products and services they purchase are produced in an environmentally and socially responsible manner. According to the United Nations (2020), sustainable procurement means businesses minimize the environmental degradation impact through a more sustainable way in their supply chain. The procurement touches on the activities of purchasing goods and services with the lowest environmental negative impact possible. The strategies of the procurement policy vary from using sustainability evaluation factors in the organization's procurement processes, evaluating and monitoring businesses' compliance to the sustainable supply chain, and stimulating, integrating, promoting and enhancing sustainable procurement in businesses. Another policy that can decoupling the economic growth from environmental degradation for these countries to promote green innovation. According to Giunipero et al. (2012), innovation in technology is an efficient way for sustainable procurement to reduce environmental concerns. The technological innovation used can produce goods and services which create a new market for sustainable products and services with the lowest impact on the environment (Ghadge et al., 2019).

The government can also adopt the Circular Economy practice. Circular Economy prescribes that industrial production minimizes waste while also reusing it in industrial processes (Hartley et al., 2020). In this case, the governments should take more attention primarily to waste management, recycling, and reuse in industrial production. Consideration of waste treatment in the production process has a high potential in eliminating environmental degradation (Saavedra et al., 2018). A Circular Economy encourages the production of goods that minimize waste and resources used are long-lasting. For instance, products that can be reused, recycle, and repaired or reduce packaging and use renewable sources to replace non-renewable sources (Klein et al., 2020). Businesses can reduce costs and boost their bottom line by using resources smartly to increase productivity. This can increase GDP while reducing environmental effects for instance the release of carbon dioxide into the atmosphere.

Next, Southeast Asia countries are recommended to prioritize the acceleration of regional power interconnectivity to promote renewable energy (RE) for reducing CO_2 emission in the region. The deployment of RE sources through regional power interconnectivity can reduce the reliance on fossil fuels and promote the transition to a low-carbon energy system (Shadrina, 2019). Fossil fuels are a major contributor to carbon emissions and climate change, and their continued use is not sustainable in the long term (Nunez, 2019). In contrast, RE sources such as solar, wind, hydro, and geothermal are clean and renewable, and their use can significantly reduce carbon emissions. Power interconnectivity can facilitate the deployment of RE sources by enabling the sharing of electricity generated from renewable sources across borders, thereby reducing the need for individual countries on carbon consumption (UN, 2020). Besides that, accelerating regional power interconnectivity can enhance energy security and resilience in Southeast Asia countries as the sharing of electricity across borders, power interconnectivity can help to ensure that countries have access to electricity in the event of disruptions or outages. This can further enhance the resilience of critical infrastructure such as hospitals and emergency services and help to mitigate the impacts of climate change (Wong & Lee, 2022).

To accelerate regional power interconnectivity and promote RE in the ASEAN region, policymakers can take a range of actions. Firstly, they can establish a policy framework that encourages cross-border cooperation on renewable energy development and facilitates the development of interconnection projects. This can include policies such as imposing feed-in tariffs (FIT) and providing subsidies to encourage the deployment of renewable energy sources (Chitedze et al., 2020). For example, policymakers can offer tax breaks and subsidies to companies that invest in renewable energy projects, which can help to lower the cost of renewable energy and make it more competitive with fossil fuels. These financial incentives can help to mobilize private sector resources and expertise, which can accelerate the deployment of renewable energy and interconnection projects in the Southeast Asia region.

In order to promote environmentally sustainable industries through FDI, policymakers have proposed adjusting the types of foreign investment allowed. This includes controlling the inflow of FDI into industrial sectors that are known to cause environmental degradation. By limiting FDI in these sectors, governments can encourage investment in more sustainable industries, such as renewable energy, sustainable agriculture, and eco-tourism. The advancement of manufacturing technical level and effective resource utilization should be funded by foreign capital (Ren et. al., 2014). Additionally, policymakers should promote the norms where different domestic regions should refrain from competing for foreign investment for the benefit of regional economic growth and only select high-quality investments. Local domestic firms are advised not to blindly accept the foreign direct investment which may possibly harm the environment. Besides, it is also advisable to strengthen industrial instruction for foreign investment and promote foreign investment into environmentally friendly sectors, such as ecological agriculture, the service sector, and so forth. In other words, the government must limit and forbid initiatives that result in significant pollution.

Moreover, the government may implement an optimal land use policy that imposes fees on new construction. This would result in greater taxes being placed in areas with higher carbon emissions. With this strategy, high-emission industries will attempt to reduce carbon emissions to pay less tax. Although many believe that land use regulations raise the cost of local development, they appear to be softer in areas with greater emissions (Glaeser et. al., 2010). Moreover, the government could enforce land use restrictions to protect certain areas like residential areas. It is possible that land use restrictions may very well be driving people from lower emission regions into areas with higher emissions. Therefore, it is crucial to reduce carbon emissions by bridging the gap between urban and rural regions through a more deliberate urbanization process (Wu et. al., 2016).

Although the income inequality was found to have the negative relationship with the CO_2 emissions, the policies that able to reduce the income inequality of a countries is still important and necessary for the Southeast Asia countries to adopt. The policymaker could implement the progressive taxation policy which the individuals with higher incomes are taxed at a higher rate than those with lower incomes. This is done with the goal of redistributing income and reducing income inequality within a country. The policy controls the income inequality by reduce the income of the higher earners to narrow the gap of the income inequality (Lynham

& OpenStax, 2018). For example, United State also the country that used progressive income tax (PIT) to control the income inequality. The tax brackets in 2013 indicate that the different income levels need to pay different tax rates, the range of the income taxes are from 10% to 37% (IEA, 2016). The extra revenue generated from this policy can be used by the government to provide public goods and services that benefit society as a whole, such as education, healthcare, and infrastructure.

As high-income individuals earn more money, they contribute a larger share of taxes to the government. This means that the government can collect more revenue and use it to provide public goods and services that are essential for a healthy and prosperous society. For example, the revenue generated from progressive taxation can be used to fund education programs that provide equal opportunities for all citizens, regardless of their income levels. It can also be used to support healthcare programs that ensure access to quality healthcare for all citizens, regardless of their income.

5.3 Limitation of study

Throughout our research study on this topic, we found many limitations which will influence our study result. One of the limitations are the present of missing values for secondary data. We collected the data for our research mainly from the World Bank. As our sample size data is 40 years data from year 1981 until year 2020 and the countries used for research are Philippines, Indonesia, Malaysia, Vietnam, Thailand, and Myanmar. Some countries do not update their data regularly in the World Bank. It causes the missing value in the data used for our research, for example, Gini index is one of the independent variables used for research which have missing value for few years in each country.

While our research objective was to examine the causes of the increase in CO_2 emissions, our study only focused on four independent variables: FDI inflows, GDP per capita, income inequality, and urban population. It is important to note that there are likely many other factors contributing to rising CO_2 emissions, and the limited use of independent variables in our study may impact the accuracy of our results. Additionally, our study only included six countries of Southeast Asia - Philippines, Indonesia, Malaysia, Vietnam, Thailand, and Myanmar and we did not include high-income countries such as Singapore and Brunei. This means that our findings may not represent the overall situation in Southeast Asia, and the accuracy of our results may be affected as a result.

5.4 Recommendation of study

To address the first limitation of missing value of secondary data, we suggest the researcher explore additional sources of data to supplement the World Bank data. This could involve looking at data collected by national statistics agencies or other international organizations such as the United Nations or the International Monetary Fund. As we have seen in our study, the lack of regularly updated data can significantly impact the accuracy and reliability of our findings. Therefore, these sources may have data that is more up-to-date and comprehensive than the World Bank data.

Regarding the issue of missing data points for the obtained data, we recommend the researchers use imputation techniques to estimate missing values. Imputation is a statistical method that involves filling in missing values using information from other variables or data points (Khan & Hoque, 2020). This can help us to estimate missing values and improve the completeness of our data set. Multiple imputation and mean imputation are two common imputation methods that could be used in our research. By employing these techniques, it can reduce the impact of missing data on the findings and improve the overall quality of our analysis. However, it is important to note that imputation methods have their own limitations and assumptions, which could affect the validity of the findings. Therefore, future researchers must exercise caution when using imputation techniques and carefully assess the reliability and accuracy of the imputed values.

Moreover, accuracy of results for our study due to the limitation of less variables and countries involved can be solved by adding additional meaningful variables and involving more Southeast Asia countries. For instance, energy consumption, technology progress, renewable energy investment and other variables that will cause the carbon dioxide to increase or decrease in a country. The inclusion of additional relevant variables can help to address omitted variable bias, which occurs when relevant variables are excluded from the analysis, leading to biased or inaccurate results (Clarke, 2005). Therefore, researchers should consider including other relevant independent variables to capture the full range of factors that impact CO_2 emissions accurately. For insufficient numbers of countries, researchers can include all Southeast Asia countries or various income stage's countries in our study for further study. Researchers can gain a deeper knowledge of the link between the variables and CO_2 emission by including various income stage's countries.

By addressing these limitations and implementing these recommendations, researchers can generate more accurate and reliable findings on CO_2 emissions. The research may be more valuable for policy makers to make the policy decisions and help to mitigate the adverse effects of excess CO_2 emissions while promoting sustainable practices in Southeast Asia countries. It is also crucial to raise awareness and promote individual and collective action to reduce carbon footprints and support policies and initiatives that prioritize the reduction of excess CO_2 emissions.

5.5 Conclusion

Our study has examined the factors that contribute to CO_2 emissions in selected Southeast Asian countries, and we have found that FDI, GDP per capita, income inequality, and urbanization have a significant impact on CO_2 emissions during the sample period from 1981 to 2020. Our research has also proposed several strategies to mitigate CO_2 emissions, including the implementation of a carbon tax, promoting sustainable FDI, advancing regional power interconnectivity, and developing green technology.

The implications of our research are crucial, as they can increase policymakers and society's awareness, attention, and motivation to address the pressing environmental issue. By recognizing the impact of key factors on CO_2 emissions, decision-makers can take necessary measures to curb the emission levels and promote sustainable economic growth. Additionally, our proposed solutions can serve as a roadmap for policymakers and stakeholders to create policies and initiatives that encourage sustainable practices and support the transition towards a greener and more sustainable future.

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Appendices

Appendix 3.1: Cross-sectional dependence test

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in weighted residuals
Equation: Untitled
Periods included: 40
Cross-sections included: 6
Total panel (unbalanced) observations: 239
Note: non-zero cross-section means detected in data
Test employs centered correlations computed from pairwise samples

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	29.26788	15	0.0149
Pesaran scaled LM	2.604947		0.0092
Pesaran CD	1.243036		0.2139

Appendix 4.1.1: Extension model estimation

Dependent Variable: CO2_EMISSIONS
Method: Panel Least Squares
Date: 03/27/23 Time: 22:59
Sample: 1981 2020
Periods included: 40
Cross-sections included: 6
Total panel (unbalanced) observations: 239

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FDI	0.083371	0.021430	3.890310	0.0001
GDP_PER_CAPITA	0.000634	7.00E-05	9.053973	0.0000
GDP_PER_CAPITA_SQUARED	-5.85E-09	6.06E-09	-0.965575	0.3353
GINI_INDEX	0.019364	0.010721	1.806222	0.0722
URBAN_POPULATION	0.024334	0.006822	3.566893	0.0004
C	-1.429474	0.377078	-3.790924	0.0002

R-squared	0.856602	Mean dependent var	1.869230
Adjusted R-squared	0.853525	S.D. dependent var	1.890055
S.E. of regression	0.723363	Akaike info criterion	2.214974
Sum squared resid	121.9183	Schwarz criterion	2.302249
Log likelihood	-258.6894	Hannan-Quinn criter.	2.250143
F-statistic	278.3696	Durbin-Watson stat	0.099438
Prob(F-statistic)	0.000000		

Appendix 4.1.2: LLC Test for CO2 at Level Form (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: CO2_EMISSIONS
Date: 03/28/23 Time: 15:28
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 196
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-1.77460	0.0380

** Probabilities are computed assuming asympotic normality

Intermediate results on CO2_EMISSIONS

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	0.10568	0.0008	0.0024	9	9	3.0	30
Philippines	-0.21771	0.0030	0.0054	2	9	2.0	37
Indonesia	-0.01662	0.0026	0.0013	9	9	25.0	30
Malaysia	-0.08397	0.0430	0.0785	8	9	0.0	30
Vietnam	0.05700	0.0104	0.0298	9	9	7.0	30
Thailand	-0.05454	0.0251	0.0284	0	9	1.0	39

	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-0.05911	-3.655	1.028	-0.544	0.880		196

Appendix 4.1.3: LLC Test for CO2 at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: CO2_EMISSIONS
Date: 03/28/23 Time: 15:44
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 8
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 209
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	3.42469	0.9997

** Probabilities are computed assuming asympotic normality

Intermediate results on CO2_EMISSIONS

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-1.33812	0.0007	0.0014	7	9	1.0	32
Philippines	-0.39115	0.0025	0.0053	2	9	2.0	37
Indonesia	-1.59616	0.0016	0.0005	8	9	38.0	31
Malaysia	-0.29086	0.0677	0.0784	0	9	0.0	38
Vietnam	0.22659	0.0086	0.0230	7	9	10.0	32
Thailand	-0.01888	0.0250	0.0230	0	9	2.0	39

	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-0.21863	-3.839	1.138	-0.657	0.915		209

Appendix 4.1.4: LLC Test for FDI at Level Form (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: FDI
Date: 03/28/23 Time: 15:50
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 6
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 227
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-3.21349	0.0007

** Probabilities are computed assuming asympotic normality

Intermediate results on FDI

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.60233	2.7927	0.7348	6	9	31.0	33
Philippines	-0.37880	0.4216	0.0288	0	9	38.0	39
Indonesia	-0.42370	0.4478	0.0527	0	9	22.0	39
Malaysia	-0.36872	2.1170	1.8002	0	9	2.0	39
Vietnam	-0.20422	2.2682	2.8649	1	9	1.0	38
Thailand	-0.49355	1.4325	1.9158	0	9	0.0	39

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.35796	-7.039	1.013	-0.539	0.860	227

Appendix 4.1.5: LLC Test for FDI at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: FDI
Date: 03/28/23 Time: 15:49
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 230
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-2.74870	0.0030

** Probabilities are computed assuming asympotic normality

Intermediate results on FDI

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.50351	3.1984	0.3255	4	9	25.0	35
Philippines	-0.52240	0.3874	0.0254	0	9	38.0	39
Indonesia	-0.62350	0.3977	0.0403	0	9	20.0	39
Malaysia	-0.39816	2.0672	1.7943	0	9	2.0	39
Vietnam	-0.18079	2.3190	2.8393	0	9	1.0	39
Thailand	-0.52909	1.4123	1.1420	0	9	1.0	39

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.40113	-7.342	1.021	-0.643	0.885	230

Appendix 4.1.6: LLC Test for GDP at Level Form (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: GDP_PER_CAPITA
Date: 03/29/23 Time: 00:11
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 5
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 226
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	4.59645	1.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on GDP_PER_CAPITA

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	0.07031	2398.6	11855.	5	9	4.0	34
Philippines	0.02733	15576.	28843.	0	9	4.0	39
Indonesia	-0.00278	44781.	67725.	1	9	2.0	38
Malaysia	-0.01139	409632	400805	0	9	2.0	39
Vietnam	0.03438	11062.	42548.	1	9	4.0	38
Thailand	-0.00892	93359.	101014	1	9	0.0	38

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	0.02279	2.134	1.016	-0.539	0.860	226

Appendix 4.1.7: LLC Test for GDP at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: GDP_PER_CAPITA
Date: 03/29/23 Time: 00:08
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 5
User-specified bandwidth: 63 and Bartlett kernel
Total number of observations: 227
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-1.65438	0.0490

** Probabilities are computed assuming asympotic normality

Intermediate results on GDP_PER_CAPITA

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.00731	2123.1	558.47	5	9	63.0	34
Philippines	-0.08677	13405.	1908.5	0	9	63.0	39
Indonesia	-0.11986	39228.	6011.0	1	9	63.0	38
Malaysia	-0.19450	365216	42713.	0	9	63.0	39
Vietnam	0.00098	10568.	1456.6	0	9	63.0	39
Thailand	-0.16721	80887.	8701.0	1	9	63.0	38

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.05148	-2.547	1.024	-0.647	0.892	227

Appendix 4.1.8: LLC Test for GDP[2] at Level Form (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: GDP_PER_CAPITA_SQUARED
Date: 03/28/23 Time: 23:34
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 211
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	3.93051	1.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on GDP_PER_CAPITA_SQUARED

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	6.06398	7.E+09	3.E+10	9	9	3.0	30
Philippines	0.03921	3.E+11	5.E+11	0	9	4.0	39
Indonesia	-0.01489	1.E+12	1.E+12	1	9	0.0	38
Malaysia	-0.01427	1.E+14	9.E+13	0	9	5.0	39
Vietnam	-0.30860	6.E+10	9.E+11	7	9	4.0	32
Thailand	-0.02790	7.E+12	1.E+13	6	9	4.0	33

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	0.00251	0.142	1.044	-0.541	0.867	211

Appendix 4.1.9: LLC Test for GDP2 at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: GDP_PER_CAPITA_SQUARED
Date: 03/28/23 Time: 23:56
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 203
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	2.00536	0.9775

** Probabilities are computed assuming asympotic normality

Intermediate results on GDP_PER_CAPITA_SQUARED

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	0.27297	7.E+09	2.E+10	8	9	2.0	31
Philippines	-0.04949	2.E+11	2.E+11	0	9	2.0	39
Indonesia	-0.11629	1.E+12	1.E+12	1	9	3.0	38
Malaysia	-0.36070	7.E+13	8.E+13	9	9	6.0	30
Vietnam	-0.27040	5.E+10	2.E+11	7	9	3.0	32
Thailand	-0.16341	6.E+12	2.E+12	6	9	19.0	33

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.08452	-2.797	1.041	-0.661	0.923	203

Appendix 4.1.10: LLC Test for Gini Index at Level Form (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: GINI_INDEX
Date: 03/28/23 Time: 16:10
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified maximum lags
Automatic lag length selection based on AIC: 0 to 1
User-specified bandwidth: 28 and Bartlett kernel
Total number of observations: 231
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-2.34625	0.0095

** Probabilities are computed assuming asympotic normality

Intermediate results on GINI_INDEX

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.10035	0.5532	1.2988	1	1	28.0	38
Philippines	-0.06619	0.4999	0.1353	0	1	28.0	39
Indonesia	-0.07885	1.1615	0.4506	1	1	28.0	38
Malaysia	-0.17466	3.2162	0.5948	1	1	28.0	38
Vietnam	-0.50090	1.0067	0.1803	0	1	28.0	39
Thailand	-0.00515	0.9125	0.2851	0	1	28.0	39

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.08906	-3.842	1.029	-0.539	0.857	231

Appendix 4.1.11: LLC Test for Gini Index at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: GINI_INDEX
Date: 03/28/23 Time: 16:24
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 4
User-specified bandwidth: 19 and Bartlett kernel
Total number of observations: 227
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-2.35964	0.0091

** Probabilities are computed assuming asympotic normality

Intermediate results on GINI_INDEX

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	0.00570	0.8556	0.5418	0	9	19.0	39
Philippines	-0.36809	0.4138	0.1260	1	9	19.0	38
Indonesia	-0.20101	1.0522	0.5415	1	9	19.0	38
Malaysia	-0.38015	2.7310	0.7481	1	9	19.0	38
Vietnam	-0.49657	1.0055	0.1580	0	9	19.0	39
Thailand	-0.41856	0.6637	0.1110	4	9	19.0	35

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.22065	-5.241	1.044	-0.647	0.892	227

Appendix 4.1.12: LLC Test for Urban Population at Level Form (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: URBAN_POPULATION
Date: 03/28/23 Time: 16:35
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified maximum lags
Automatic lag length selection based on AIC: 1 to 10
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 202
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-8.12454	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on URBAN_POPULATION

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	0.00950	5.E-06	0.0053	8	10	4.0	31
Philippines	-0.05266	0.0163	0.7925	1	10	5.0	38
Indonesia	-0.00294	0.0047	0.1505	1	10	5.0	38
Malaysia	-0.02269	0.0010	0.2567	10	10	5.0	29
Vietnam	-0.00482	5.E-05	0.2623	10	10	5.0	29
Thailand	0.00016	0.0198	0.9055	2	10	5.0	37

	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-0.00771	-8.419	1.321	-0.543	0.876		202

Appendix 4.1.13: LLC Test for Urban Population at Level Form (Individual Effects, and Individual Effect, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: URBAN_POPULATION
Date: 03/28/23 Time: 16:37
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
User-specified maximum lags
Automatic lag length selection based on AIC: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 228
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-2.58005	0.0049

** Probabilities are computed assuming asympotic normality

Intermediate results on URBAN_POPULATION

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	0.10338	0.0002	0.0019	1	1	3.0	38
Philippines	-0.06080	0.0150	0.5422	1	1	5.0	38
Indonesia	-0.02114	0.0045	0.0901	1	1	5.0	38
Malaysia	-0.02855	0.0068	0.2065	1	1	5.0	38
Vietnam	-0.02723	0.0011	0.0185	1	1	4.0	38
Thailand	-0.02854	0.0172	0.4510	1	1	5.0	38

	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-0.02639	-5.349	1.057	-0.643	0.885		228

Appendix 4.1.14: LLC Test for CO2 at 1st difference (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: D(CO2_EMISSIONS)
Date: 03/27/23 Time: 23:07
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 224
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-3.30797	0.0005

** Probabilities are computed assuming asympotic normality

Intermediate results on D(CO2_EMISSIONS)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.55135	0.0014	0.0008	1	1	5.0	37
Philippines	-0.67555	0.0038	0.0037	0	1	2.0	38
Indonesia	-1.50022	0.0052	0.0015	1	1	37.0	37
Malaysia	-1.23529	0.0760	0.1989	0	1	0.0	37
Vietnam	-2.43577	0.0412	0.0659	1	1	7.0	37
Thailand	-0.97399	0.0285	0.0102	0	1	10.0	38

	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-1.09758	-12.026	1.069	-0.539	0.860		224

Appendix 4.1.15 LLC Test for CO2 at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: D(CO2_EMISSIONS)
Date: 03/27/23 Time: 23:42
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
User-specified maximum lags
Automatic lag length selection based on AIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 224
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-1.76890	0.0385

** Probabilities are computed assuming asympotic normality

Intermediate results on D(CO2_EMISSIONS)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.69885	0.0013	0.0008	1	1	5.0	37
Philippines	-0.65498	0.0038	0.0035	0	1	2.0	38
Indonesia	-1.58273	0.0051	0.0007	1	1	37.0	37
Malaysia	-1.23669	0.0759	0.1988	0	1	0.0	37
Vietnam	-3.60709	0.0230	0.0626	1	1	7.0	37
Thailand	-1.06496	0.0249	0.0089	0	1	11.0	38

	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-1.25611	-12.555	1.142	-0.647	0.892		224

Appendix 4.1.16 LLC Test for FDI at 1st difference (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: D(FDI)
Date: 03/27/23 Time: 23:44
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 220
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-10.8703	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on D(FDI)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-2.16908	3.6444	0.7421	4	9	12.0	34
Philippines	-1.26665	0.4955	0.0569	0	9	18.0	38
Indonesia	-2.05661	0.4919	0.0792	2	9	15.0	36
Malaysia	-1.37485	2.5016	0.5556	1	9	7.0	37
Vietnam	-0.87909	2.5851	0.3374	0	9	15.0	38
Thailand	-1.75996	1.5881	0.6437	1	9	4.0	37
	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-1.29997	-13.874	1.040	-0.540	0.864		220

Appendix 4.1.17 LLC Test for FDI at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: D(FDI)
Date: 03/27/23 Time: 23:45
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 5
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 216
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-7.90936	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on D(FDI)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-2.27645	3.4960	0.7419	4	9	12.0	34
Philippines	-1.26679	0.4936	0.0549	0	9	18.0	38
Indonesia	-2.07933	0.4854	0.0789	2	9	15.0	36
Malaysia	-1.37567	2.4905	0.5411	1	9	7.0	37
Vietnam	-0.88344	2.5734	0.3041	0	9	16.0	38
Thailand	-3.89648	1.1926	0.6442	5	9	4.0	33
	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-1.29371	-12.826	1.064	-0.650	0.899		216

Appendix 4.1.18 LLC Test for GDP at 1st difference (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: D(GDP_PER_CAPITA)
Date: 03/27/23 Time: 23:46
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 6
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 221
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-5.30071	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on D(GDP_PER_CAPITA)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.32525	2566.9	2598.6	6	9	3.0	32
Philippines	-0.73721	15476.	6117.8	0	9	7.0	38
Indonesia	-0.70039	44792.	14003.	0	9	8.0	38
Malaysia	-0.92594	419218	52065.	0	9	37.0	38
Vietnam	-0.44483	12031.	1106.9	1	9	25.0	37
Thailand	-0.66782	93616.	38329.	0	9	12.0	38
	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-0.65135	-9.224	1.016	-0.540	0.864		221

Appendix 4.1.19 LLC Test for GDP at 1st difference (Individual Effects and Individual Effects, Individual Trend Effects)

Null Hypothesis: Unit root (common unit root process)
Series: D(GDP_PER_CAPITA)
Date: 03/27/23 Time: 23:46
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 206
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-3.05862	0.0011

** Probabilities are computed assuming asympotic normality

Intermediate results on D(GDP_PER_CAPITA)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-1.01880	2124.9	2583.8	4	9	3.0	34
Philippines	-2.70729	8785.2	5961.7	9	9	8.0	29
Indonesia	-0.75308	43755.	12682.	0	9	8.0	38
Malaysia	-3.59965	276884	29741.	9	9	37.0	29
Vietnam	-0.71748	9904.9	1125.4	0	9	25.0	38
Thailand	-0.70034	92949.	35678.	0	9	12.0	38
	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-0.86930	-9.522	1.066	-0.657	0.915		206

Appendix 4.1.20 LLC Test for GDP^2 at 1st difference (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: D(GDP_PER_CAPITA_SQUARED)
Date: 03/27/23 Time: 23:48
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified maximum lags
Automatic lag length selection based on AIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 227
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-4.29854	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on D(GDP_PER_CAPITA_SQUARED)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.48667	2.E+10	1.E+10	0	1	3.0	38
Philippines	-0.75404	3.E+11	2.E+11	0	1	8.0	38
Indonesia	-0.62850	1.E+12	5.E+11	0	1	6.0	38
Malaysia	-0.91490	1.E+14	2.E+13	0	1	37.0	38
Vietnam	-0.20934	1.E+11	8.E+09	0	1	37.0	38
Thailand	-0.92651	9.E+12	6.E+12	1	1	11.0	37

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.52611	-8.117	1.045	-0.539	0.860	227

Appendix 4.1.21 LLC Test for GDP^2 at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: D(GDP_PER_CAPITA_SQUARED)
Date: 03/27/23 Time: 23:49
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
User-specified maximum lags
Automatic lag length selection based on AIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 226
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-3.50253	0.0002

** Probabilities are computed assuming asympotic normality

Intermediate results on D(GDP_PER_CAPITA_SQUARED)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.63913	1.E+10	1.E+10	0	1	3.0	38
Philippines	-1.03953	2.E+11	1.E+11	0	1	8.0	38
Indonesia	-0.69105	1.E+12	5.E+11	0	1	6.0	38
Malaysia	-1.18791	1.E+14	1.E+13	1	1	37.0	37
Vietnam	-0.51009	8.E+10	7.E+09	0	1	37.0	38
Thailand	-1.17847	8.E+12	6.E+12	1	1	10.0	37

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.77008	-9.820	1.025	-0.647	0.892	226

Appendix 4.1.22 LLC Test for Gini Index at 1st difference (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: D(GINI_INDEX)
Date: 03/27/23 Time: 23:51
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 220
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-8.49289	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on D(GINI_INDEX)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.67234	0.6652	0.6251	0	9	2.0	38
Philippines	-1.57010	0.4433	0.1108	1	9	18.0	37
Indonesia	-0.80395	1.2171	0.2094	0	9	12.0	38
Malaysia	-1.26915	3.2220	2.7927	3	9	3.0	35
Vietnam	-1.24458	1.2992	0.4302	0	9	7.0	38
Thailand	-1.44353	0.7932	0.1126	4	9	12.0	34
	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-1.01514	-12.737	1.040	-0.540	0.864		220

Appendix 4.1.23 LLC Test for Gini Index at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: D(GINI_INDEX)
Date: 03/27/23 Time: 23:51
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 220
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-7.88858	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on D(GINI_INDEX)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.76411	0.5380	0.5413	0	9	3.0	38
Philippines	-1.64919	0.4250	0.0821	1	9	19.0	37
Indonesia	-0.80652	1.2150	0.2058	0	9	12.0	38
Malaysia	-1.27146	3.2180	2.7922	3	9	3.0	35
Vietnam	-1.25310	1.2795	0.4270	0	9	7.0	38
Thailand	-1.73586	0.7230	0.1119	4	9	12.0	34
	Coefficient	t-Stat	SE Reg	mu*	sig*		Obs
Pooled	-1.04778	-13.413	1.042	-0.650	0.899		220

Appendix 4.1.24 LLC Test for Urban Population at 1st difference (Individual Effects)

Null Hypothesis: Unit root (common unit root process)
Series: D(URBAN_POPULATION)
Date: 03/27/23 Time: 23:53
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified maximum lags
Automatic lag length selection based on AIC: 0 to 7
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 219
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-4.16003	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate results on D(URBAN_POPULATION)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.29788	0.0003	0.0006	1	7	2.0	37
Philippines	-0.10497	0.0213	0.0232	0	7	0.0	38
Indonesia	-0.07185	0.0054	0.0056	0	7	0.0	38
Malaysia	-0.05453	0.0082	0.0100	0	7	2.0	38
Vietnam	-0.27121	0.0006	0.0020	7	7	2.0	31
Thailand	-0.08659	0.0198	0.0308	1	7	2.0	37

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.16220	-6.845	1.040	-0.540	0.864	219

Appendix 4.1.25 LLC Test for Urban Population at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (common unit root process)
Series: D(URBAN_POPULATION)
Date: 03/27/23 Time: 23:55
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
User-specified maximum lags
Automatic lag length selection based on AIC: 0 to 9
Newey-West automatic bandwidth selection and Bartlett kernel
Total number of observations: 208
Cross-sections included: 6

Method	Statistic	Prob.**
Levin, Lin & Chu t*	-2.08533	0.0185

** Probabilities are computed assuming asympotic normality

Intermediate results on D(URBAN_POPULATION)

Cross section	2nd Stage Coefficient	Variance of Reg	HAC of Dep.	Lag	Max Lag	Band-width	Obs
Myanmar	-0.57762	0.0002	0.0006	1	9	2.0	37
Philippines	-0.08518	0.0211	0.0246	0	9	2.0	38
Indonesia	-0.15844	0.0048	0.0053	0	9	2.0	38
Malaysia	-0.79811	0.0011	0.0080	9	9	0.0	29
Vietnam	-0.12372	5.E-05	0.0013	9	9	5.0	29
Thailand	-0.13106	0.0194	0.0283	1	9	1.0	37

	Coefficient	t-Stat	SE Reg	mu*	sig*	Obs
Pooled	-0.27195	-8.227	1.210	-0.657	0.915	208

Appendix 4.1.26 IPS Test for CO2 at Level Form (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: CO2_EMISSIONS
Date: 03/29/23 Time: 05:59
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified maximum lags
Automatic lag length selection based on SIC: 0 to 17
Total number of observations: 182
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-1.51073	0.0654

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-2.1599	0.2252	-1.228	1.229	17	17	22
Philippines	-3.0133	0.0428	-1.471	0.841	2	17	37
Indonesia	-2.1454	0.2300	-1.217	1.221	15	17	24
Malaysia	-0.6393	0.8497	-1.524	0.774	0	17	38
Vietnam	-1.9256	0.3152	-1.228	1.229	17	17	22
Thailand	-2.0276	0.2743	-1.523	0.772	0	17	39
Average	-1.9852		-1.365	1.011			

Appendix 4.1.27 IPS Test for CO2 at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: CO2_EMISSIONS
Date: 03/29/23 Time: 05:57
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 8
Total number of observations: 208
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-0.40778	0.3417

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-3.8123	0.0293	-1.844	1.047	8	9	31
Philippines	-4.0466	0.0155	-2.113	0.718	2	9	37
Indonesia	-4.3062	0.0095	-1.844	1.047	8	9	31
Malaysia	-2.3521	0.3974	-2.173	0.662	0	9	38
Vietnam	1.7021	1.0000	-1.927	0.982	7	9	32
Thailand	-0.1800	0.9913	-2.173	0.659	0	9	39
Average	-2.1659		-2.012	0.852			

Appendix 4.1.28 IPS Test for FDI at Level Form (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: FDI
Date: 03/29/23 Time: 06:00
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 6
Total number of observations: 227
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-3.83470	0.0001

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-2.6058	0.1019	-1.346	0.999	6	9	33
Philippines	-3.0036	0.0433	-1.523	0.772	0	9	39
Indonesia	-3.2909	0.0222	-1.523	0.772	0	9	39
Malaysia	-2.7979	0.0678	-1.523	0.772	0	9	39
Vietnam	-2.2114	0.2057	-1.520	0.809	1	9	38
Thailand	-3.5331	0.0122	-1.523	0.772	0	9	39
Average	-2.9071		-1.493	0.816			

Appendix 4.1.29 IPS Test for FDI at Level Form (Individual Effects and Individual Effect, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: FDI
Date: 03/29/23 Time: 06:03
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 219
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-3.38022	0.0004

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-2.4681	0.3407	-1.945	0.910	6	9	33
Philippines	-3.5611	0.0467	-2.173	0.659	0	9	39
Indonesia	-4.0298	0.0157	-2.173	0.659	0	9	39
Malaysia	-4.2539	0.0110	-1.835	1.063	9	9	30
Vietnam	-1.8646	0.6535	-2.173	0.659	0	9	39
Thailand	-3.5489	0.0479	-2.173	0.659	0	9	39
Average	-3.2877		-2.079	0.768			

Appendix 4.1.30 IPS Test for GDP at Level Form (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: GDP_PER_CAPITA
Date: 03/29/23 Time: 06:10
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 5
Total number of observations: 226
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	6.03206	1.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	2.4615	1.0000	-1.399	0.953	5	9	34
Philippines	1.1580	0.9973	-1.523	0.772	0	9	39
Indonesia	-0.0926	0.9431	-1.520	0.809	1	9	38
Malaysia	-0.3481	0.9081	-1.523	0.772	0	9	39
Vietnam	1.5102	0.9990	-1.520	0.809	1	9	38
Thailand	-0.3107	0.9139	-1.520	0.809	1	9	38
Average	0.7297		-1.501	0.820			

Appendix 4.1.31 IPS Test for GDP at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: GDP_PER_CAPITA
Date: 03/29/23 Time: 06:17
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 5
Total number of observations: 227
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	2.32951	0.9901

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-0.1451	0.9918	-2.019	0.856	5	9	34
Philippines	-1.6622	0.7489	-2.173	0.659	0	9	39
Indonesia	-1.9807	0.5928	-2.176	0.696	1	9	38
Malaysia	-2.0925	0.5337	-2.173	0.659	0	9	39
Vietnam	0.0300	0.9953	-2.173	0.659	0	9	39
Thailand	-2.2517	0.4488	-2.176	0.696	1	9	38
Average	-1.3504		-2.148	0.704			

Appendix 4.1.32 IPS Test for GDP^2 at Level Form (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: GDP_PER_CAPITA_SQUARED
Date: 03/29/23 Time: 06:24
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 211
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	3.54506	0.9998

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	2.0047	0.9998	-1.266	1.105	9	9	30
Philippines	1.5803	0.9992	-1.523	0.772	0	9	39
Indonesia	-0.4084	0.8976	-1.520	0.809	1	9	38
Malaysia	-0.3478	0.9082	-1.523	0.772	0	9	39
Vietnam	-2.6444	0.0949	-1.329	1.043	7	9	32
Thailand	-0.3787	0.9016	-1.346	0.999	6	9	33
Average	-0.0324		-1.418	0.917			

Appendix 4.1.33 IPS Test for GDP^2 at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: GDP_PER_CAPITA_SQUARED
Date: 03/29/23 Time: 06:31
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 203
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	2.41049	0.9920

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	1.9338	1.0000	-1.844	1.047	8	9	31
Philippines	-1.0941	0.9172	-2.173	0.659	0	9	39
Indonesia	-1.9560	0.6058	-2.176	0.696	1	9	38
Malaysia	-1.2535	0.8802	-1.835	1.063	9	9	30
Vietnam	-2.3340	0.4049	-1.927	0.982	7	9	32
Thailand	-1.6169	0.7644	-1.945	0.910	6	9	33
Average	-1.0535		-1.983	0.893			

Appendix 4.1.34 IPS Test for Gini Index at Level Form (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: GINI_INDEX
Date: 03/29/23 Time: 08:56
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 2
Total number of observations: 229
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-0.37492	0.3539

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-2.6619	0.0900	-1.520	0.809	1	9	38
Philippines	-0.0497	0.9476	-1.471	0.841	2	9	37
Indonesia	-1.2951	0.6219	-1.520	0.809	1	9	38
Malaysia	-2.2589	0.1900	-1.520	0.809	1	9	38
Vietnam	-3.5280	0.0123	-1.523	0.772	0	9	39
Thailand	-0.1059	0.9417	-1.523	0.772	0	9	39
Average	-1.6499		-1.513	0.802			

Appendix 4.1.35 IPS Test for Gini Index at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: GINI_INDEX
Date: 03/29/23 Time: 08:55
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 4
Total number of observations: 227
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-0.86177	0.1944

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	0.0785	0.9959	-2.173	0.659	0	9	39
Philippines	-2.8870	0.1778	-2.176	0.696	1	9	38
Indonesia	-2.2930	0.4274	-2.176	0.696	1	9	38
Malaysia	-3.4393	0.0611	-2.176	0.696	1	9	38
Vietnam	-3.4156	0.0639	-2.173	0.659	0	9	39
Thailand	-2.7187	0.2357	-2.033	0.802	4	9	35
Average	-2.4459		-2.151	0.701			

Appendix 4.1.36 IPS Test for Urban Population at Level Form (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: URBAN_POPULATION
Date: 03/29/23 Time: 08:58
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified maximum lags
Automatic lag length selection based on AIC: 1 to 10
Total number of observations: 202
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-4.34819	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	1.8188	0.9996	-1.272	1.094	8	10	31
Philippines	-3.2774	0.0231	-1.520	0.809	1	10	38
Indonesia	-2.1876	0.2139	-1.520	0.809	1	10	38
Malaysia	-11.642	0.0000	-1.255	1.127	10	10	29
Vietnam	-3.5216	0.0145	-1.255	1.127	10	10	29
Thailand	0.0384	0.9562	-1.471	0.841	2	10	37
Average	-3.1285		-1.382	0.968			

Appendix 4.1.37 IPS Test for Urban Population at Level Form (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: URBAN_POPULATION
Date: 03/29/23 Time: 09:04
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 17
Total (balanced) observations: 132
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-2.45946	0.0070

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-0.8975	0.9384	-1.771	1.229	17	17	22
Philippines	-0.5820	0.9699	-1.771	1.229	17	17	22
Indonesia	-0.7178	0.9586	-1.771	1.229	17	17	22
Malaysia	-1.3816	0.8377	-1.771	1.229	17	17	22
Vietnam	-11.348	0.0000	-1.771	1.229	17	17	22
Thailand	-2.3786	0.3792	-1.771	1.229	17	17	22
Average	-2.8843		-1.771	1.229			

Appendix 4.1.38 IPS Test for CO2 at 1st difference (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: D(CO2_EMISSIONS)
Date: 03/29/23 Time: 09:07
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 199
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-5.32470	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-3.5224	0.0142	-1.266	1.105	8	9	30
Philippines	-3.1205	0.0341	-1.462	0.883	3	9	35
Indonesia	-2.8181	0.0681	-1.255	1.127	9	9	29
Malaysia	-7.5240	0.0000	-1.524	0.776	0	9	37
Vietnam	0.7260	0.9908	-1.266	1.105	8	9	30
Thailand	-4.8274	0.0004	-1.524	0.774	0	9	38
Average	-3.5144		-1.383	0.962			

Appendix 4.1.39 IPS Test for CO2 at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: D(CO2_EMISSIONS)
Date: 03/29/23 Time: 09:11
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 194
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-4.11027	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-3.7130	0.0369	-1.835	1.063	8	9	30
Philippines	-2.7805	0.2134	-2.104	0.772	3	9	35
Indonesia	-2.5364	0.3097	-1.820	1.092	9	9	29
Malaysia	-2.1922	0.4765	-1.912	1.009	7	8	30
Vietnam	-4.7729	0.0029	-1.937	0.922	6	9	32
Thailand	-5.4425	0.0004	-2.173	0.662	0	9	38
Average	-3.5729		-1.964	0.920			

Appendix 4.1.40 IPS Test for FDI at 1st difference (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: D(FDI)
Date: 03/29/23 Time: 09:12
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 4
Total number of observations: 220
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-11.5269	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-4.0519	0.0035	-1.408	0.922	4	9	34
Philippines	-7.8800	0.0000	-1.524	0.774	0	9	38
Indonesia	-5.5234	0.0001	-1.470	0.844	2	9	36
Malaysia	-5.4905	0.0001	-1.520	0.811	1	9	37
Vietnam	-5.3104	0.0001	-1.524	0.774	0	9	38
Thailand	-6.3178	0.0000	-1.520	0.811	1	9	37
Average	-5.7624		-1.494	0.823			

Appendix 4.1.41 IPS Test for FDI at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: D(FDI)
Date: 03/29/23 Time: 09:13
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 5
Total number of observations: 216
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-9.57526	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-4.1903	0.0116	-2.028	0.811	4	9	34
Philippines	-7.7853	0.0000	-2.173	0.662	0	9	38
Indonesia	-5.5094	0.0004	-2.110	0.724	2	9	36
Malaysia	-5.4242	0.0004	-2.176	0.701	1	9	37
Vietnam	-5.2629	0.0006	-2.173	0.662	0	9	38
Thailand	-4.6462	0.0039	-2.014	0.867	5	9	33
Average	-5.4697		-2.112	0.738			

Appendix 4.1.42 IPS Test for GDP at 1st difference (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: D(GDP_PER_CAPITA)
Date: 03/29/23 Time: 09:14
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 6
Total number of observations: 221
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-5.77718	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-1.2779	0.6275	-1.341	1.007	6	9	32
Philippines	-4.3345	0.0014	-1.524	0.774	0	9	38
Indonesia	-4.2526	0.0018	-1.524	0.774	0	9	38
Malaysia	-5.3164	0.0001	-1.524	0.774	0	9	38
Vietnam	-2.7294	0.0787	-1.520	0.811	1	9	37
Thailand	-3.8498	0.0054	-1.524	0.774	0	9	38
Average	-3.6268		-1.492	0.819			

Appendix 4.1.43 IPS Test for GDP at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: D(GDP_PER_CAPITA)
Date: 03/29/23 Time: 09:17
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 206
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-5.52477	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-4.4759	0.0058	-2.028	0.811	4	9	34
Philippines	-4.2077	0.0126	-1.820	1.092	9	9	29
Indonesia	-4.3050	0.0081	-2.173	0.662	0	9	38
Malaysia	-3.4301	0.0669	-1.820	1.092	9	9	29
Vietnam	-4.3512	0.0072	-2.173	0.662	0	9	38
Thailand	-3.7469	0.0310	-2.173	0.662	0	9	38
Average	-4.0861		-2.031	0.830			

Appendix 4.1.44 IPS Test for GDP^2 at 1^{st} difference (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: D(GDP_PER_CAPITA_SQUARED)
Date: 03/29/23 Time: 09:18
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 187
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-2.70666	0.0034

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-1.2720	0.6287	-1.255	1.127	9	9	29
Philippines	-3.7212	0.0090	-1.255	1.127	9	9	29
Indonesia	-3.7710	0.0067	-1.524	0.774	0	9	38
Malaysia	-2.7119	0.0842	-1.255	1.127	9	9	29
Vietnam	-1.9303	0.3145	-1.255	1.127	9	9	29
Thailand	-1.2960	0.6196	-1.395	0.960	5	9	33
Average	-2.4504		-1.323	1.041			

Appendix 4.1.45 IPS Test for GDP^2 at 1^{st} difference (Individual Effects and Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: D(GDP_PER_CAPITA_SQUARED)
Date: 03/29/23 Time: 09:19
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 183
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-3.54832	0.0002

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-1.9525	0.6017	-1.820	1.092	9	9	29
Philippines	-5.3533	0.0008	-1.820	1.092	9	9	29
Indonesia	-2.6178	0.2756	-1.820	1.092	9	9	29
Malaysia	-3.5180	0.0561	-1.820	1.092	9	9	29
Vietnam	-3.4709	0.0572	-2.173	0.662	0	9	38
Thailand	-3.1408	0.1161	-1.820	1.092	9	9	29
Average	-3.3422		-1.879	1.020			

Appendix 4.1.46 IPS Test for Gini Index at 1st difference (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: D(GINI_INDEX)
Date: 03/29/23 Time: 09:21
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 4
Total number of observations: 220
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-10.1615	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-4.6904	0.0005	-1.524	0.774	0	9	38
Philippines	-6.5361	0.0000	-1.520	0.811	1	9	37
Indonesia	-4.9192	0.0003	-1.524	0.774	0	9	38
Malaysia	-4.4295	0.0012	-1.462	0.883	3	9	35
Vietnam	-7.6367	0.0000	-1.524	0.774	0	9	38
Thailand	-3.3273	0.0213	-1.408	0.922	4	9	34
Average	-5.2565		-1.493	0.823			

Appendix 4.1.47 IPS Test for Gini Index at 1st difference (Individual Effects and Individual Effects, Individual Linear Trends)

Null Hypothesis: Unit root (individual unit root process)
Series: D(GINI_INDEX)
Date: 03/29/23 Time: 09:23
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 4
Total number of observations: 220
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-9.74445	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-5.6778	0.0002	-2.173	0.662	0	9	38
Philippines	-6.6560	0.0000	-2.176	0.701	1	9	37
Indonesia	-4.8609	0.0019	-2.173	0.662	0	9	38
Malaysia	-4.3618	0.0075	-2.104	0.772	3	9	35
Vietnam	-7.6205	0.0000	-2.173	0.662	0	9	38
Thailand	-3.7834	0.0299	-2.028	0.811	4	9	34
Average	-5.4934		-2.138	0.712			

Appendix 4.1.48 IPS Test for Urban Population at 1st difference (Individual Effects)

Null Hypothesis: Unit root (individual unit root process)
Series: D(URBAN_POPULATION)
Date: 03/29/23 Time: 09:26
Sample: 1981 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 217
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-2.98087	0.0014

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-3.3553	0.0193	-1.520	0.811	1	9	37
Philippines	-1.8158	0.3675	-1.524	0.774	0	9	38
Indonesia	-1.0396	0.7291	-1.524	0.774	0	9	38
Malaysia	-0.8341	0.7978	-1.524	0.774	0	9	38
Vietnam	-6.9917	0.0000	-1.255	1.127	9	9	29
Thailand	-1.5419	0.5016	-1.520	0.811	1	9	37
Average	-2.5964		-1.478	0.845			

Appendix 4.1.49 IPS Test for Urban Population at 1st difference (Individual Effects and Individual Effects, Individual Linear Trend)

Null Hypothesis: Unit root (individual unit root process)
Series: D(URBAN_POPULATION)
Date: 03/29/23 Time: 09:27
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 0 to 9
Total number of observations: 208
Cross-sections included: 6

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-4.12048	0.0000

** Probabilities are computed assuming asympotic normality

Intermediate ADF test results

Cross section	t-Stat	Prob.	E(t)	E(Var)	Lag	Max Lag	Obs
Myanmar	-5.2154	0.0007	-2.176	0.701	1	9	37
Philippines	-1.2097	0.8942	-2.173	0.662	0	9	38
Indonesia	-2.0177	0.5733	-2.173	0.662	0	9	38
Malaysia	-9.3540	0.0000	-1.820	1.092	9	9	29
Vietnam	-1.9584	0.5986	-1.820	1.092	9	9	29
Thailand	-1.7130	0.7253	-2.176	0.701	1	9	37
Average	-3.5780		-2.056	0.818			

Appendix 4.2.1: POLS model

Dependent Variable: LOG(CO2_EMISSIONS)
Method: Panel Least Squares
Date: 04/10/23 Time: 20:12
Sample: 1981 2020
Periods included: 40
Cross-sections included: 6
Total panel (unbalanced) observations: 239

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(FDI)	0.045347	0.022147	2.047569	0.0417
LOGGDP	0.636316	0.188190	3.381245	0.0008
LOGGDP2	0.008283	0.014905	0.555748	0.5789
LOG(GINI_INDEX)	0.013759	0.279688	0.049195	0.9608
LOG(URBAN_POPULATION)	0.246454	0.160741	1.533242	0.1266
C	-5.798504	0.998337	-5.808161	0.0000

R-squared	0.856221	Mean dependent var	0.060480
Adjusted R-squared	0.853136	S.D. dependent var	1.188425
S.E. of regression	0.455438	Akaike info criterion	1.289671
Sum squared resid	48.32979	Schwarz criterion	1.376946
Log likelihood	-148.1157	Hannan-Quinn criter.	1.324840
F-statistic	277.5092	Durbin-Watson stat	0.101154
Prob(F-statistic)	0.000000		

Appendix 4.2.2: Fixed Effect Model

Dependent Variable: LOG(CO2_EMISSIONS)
Method: Panel Least Squares
Date: 04/10/23 Time: 20:14
Sample: 1981 2020
Periods included: 40
Cross-sections included: 6
Total panel (unbalanced) observations: 239

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(FDI)	0.064468	0.012909	4.994179	0.0000
LOGGDP	0.961171	0.137828	6.973716	0.0000
LOGGDP2	-0.048954	0.011330	-4.320877	0.0000
LOG(GINI_INDEX)	-0.809352	0.239949	-3.373011	0.0009
LOG(URBAN_POPULATION)	1.195193	0.162999	7.332493	0.0000
C	-5.564318	1.004277	-5.540623	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.963348	Mean dependent var	0.060480
Adjusted R-squared	0.961740	S.D. dependent var	1.188425
S.E. of regression	0.232457	Akaike info criterion	-0.035293
Sum squared resid	12.32024	Schwarz criterion	0.124711
Log likelihood	15.21753	Hannan-Quinn criter.	0.029184
F-statistic	599.2657	Durbin-Watson stat	0.267250
Prob(F-statistic)	0.000000		

Appendix 4.2.3: Random Effect Model

Dependent Variable: LOG(CO2_EMISSIONS)
Method: Panel EGLS (Cross-section random effects)
Date: 04/10/23 Time: 20:14
Sample: 1981 2020
Periods included: 40
Cross-sections included: 6
Total panel (unbalanced) observations: 239
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(FDI)	0.045347	0.011304	4.011678	0.0001
LOGGDP	0.636316	0.096052	6.624667	0.0000
LOGGDP2	0.008283	0.007607	1.088844	0.2773
LOG(GINI_INDEX)	0.013759	0.142753	0.096385	0.9233
LOG(URBAN_POPULATION)	0.246454	0.082042	3.003987	0.0030
C	-5.798504	0.509554	-11.37957	0.0000

Effects Specification

	S.D.	Rho
Cross-section random	0.000000	0.0000
Idiosyncratic random	0.232457	1.0000

Weighted Statistics

R-squared	0.856221	Mean dependent var	0.060480
Adjusted R-squared	0.853136	S.D. dependent var	1.188425
S.E. of regression	0.455438	Sum squared resid	48.32979
F-statistic	277.5092	Durbin-Watson stat	0.101154
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.856221	Mean dependent var	0.060480
Sum squared resid	48.32979	Durbin-Watson stat	0.101154

Appendix 4.3.1: Likelihood Ratio Test

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	133.279578	(5,228)	0.0000
Cross-section Chi-square	326.666422	5	0.0000

Cross-section fixed effects test equation:
Dependent Variable: LOG(CO2_EMISSIONS)
Method: Panel Least Squares
Date: 04/10/23 Time: 20:16
Sample: 1981 2020
Periods included: 40
Cross-sections included: 6
Total panel (unbalanced) observations: 239

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(FDI)	0.045347	0.022147	2.047569	0.0417
LOGGDP	0.636316	0.188190	3.381245	0.0008
LOGGDP2	0.008283	0.014905	0.555748	0.5789
LOG(GINI_INDEX)	0.013759	0.279688	0.049195	0.9608
LOG(URBAN_POPULATION)	0.246454	0.160741	1.533242	0.1266
C	-5.798504	0.998337	-5.808161	0.0000

R-squared	0.856221	Mean dependent var	0.060480
Adjusted R-squared	0.853136	S.D. dependent var	1.188425
S.E. of regression	0.455438	Akaike info criterion	1.289671
Sum squared resid	48.32979	Schwarz criterion	1.376946
Log likelihood	-148.1157	Hannan-Quinn criter.	1.324840
F-statistic	277.5092	Durbin-Watson stat	0.101154
Prob(F-statistic)	0.000000		

Appendix 4.3.2: Hausman Test

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

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	666.397888	5	0.0000

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

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LOG(FDI)	0.064468	0.045347	0.000039	0.0022
LOGGDP	0.961171	0.636316	0.009770	0.0010
LOGGDP2	-0.048954	0.008283	0.000070	0.0000
LOG(GINI_INDEX)	-0.809352	0.013759	0.037197	0.0000
LOG(URBAN_POPULATION)	1.195193	0.246454	0.019838	0.0000

Cross-section random effects test equation:
Dependent Variable: LOG(CO2_EMISSIONS)
Method: Panel Least Squares
Date: 04/10/23 Time: 20:15
Sample: 1981 2020
Periods included: 40
Cross-sections included: 6
Total panel (unbalanced) observations: 239

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.564318	1.004277	-5.540623	0.0000
LOG(FDI)	0.064468	0.012909	4.994179	0.0000
LOGGDP	0.961171	0.137828	6.973716	0.0000
LOGGDP2	-0.048954	0.011330	-4.320877	0.0000
LOG(GINI_INDEX)	-0.809352	0.239949	-3.373011	0.0009
LOG(URBAN_POPULATION)	1.195193	0.162999	7.332493	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.963348	Mean dependent var	0.060480
Adjusted R-squared	0.961740	S.D. dependent var	1.188425
S.E. of regression	0.232457	Akaike info criterion	-0.035293
Sum squared resid	12.32024	Schwarz criterion	0.124711
Log likelihood	15.21753	Hannan-Quinn criter.	0.029184
F-statistic	599.2657	Durbin-Watson stat	0.267250
Prob(F-statistic)	0.000000		

Appendix 4.3.3: Breusch Pagan-Lagrange Multiplier (BP-LM) test

Lagrange Multiplier Tests for Random Effects
Null hypotheses: No effects
Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided
(all others) alternatives

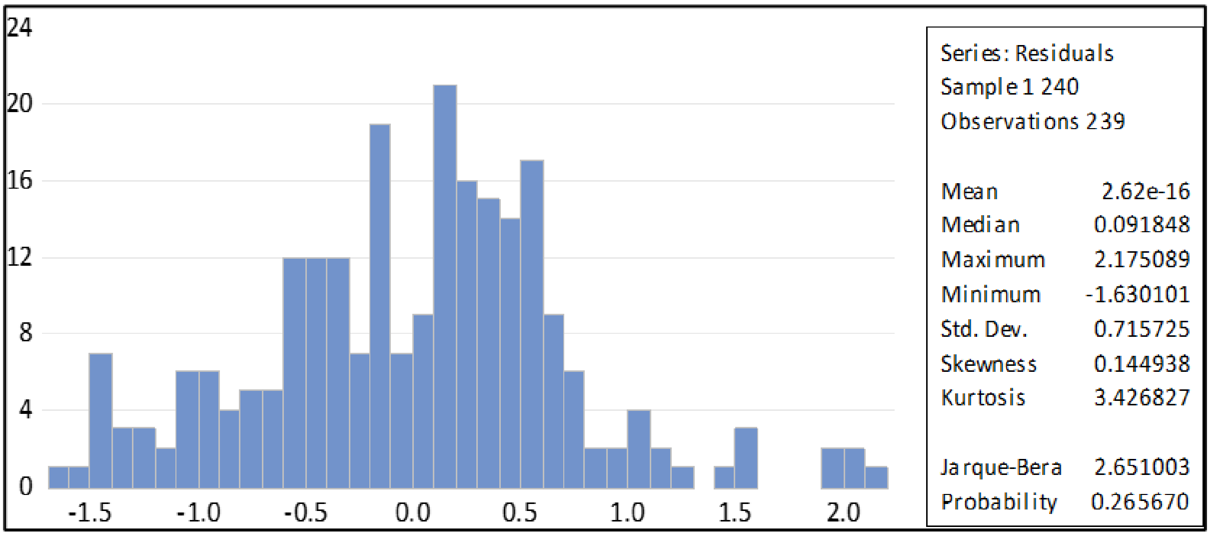
	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	736.7443	25.07165	761.8159
	(0.0000)	(0.0000)	(0.0000)
Honda	27.14303	5.007160	22.73362
	(0.0000)	(0.0000)	(0.0000)
King-Wu	27.14303	5.007160	27.24223
	(0.0000)	(0.0000)	(0.0000)
Standardized Honda	47.29240	5.202058	23.25709
	(0.0000)	(0.0000)	(0.0000)
Standardized King-Wu	47.29240	5.202058	38.57837
	(0.0000)	(0.0000)	(0.0000)
Gourieroux, et al.	--	--	761.8159
			(0.0000)

Appendix 4.4.1: Multicollinearity Test (Variance Inflation factor)

Variance Inflation Factors
Date: 03/29/23 Time: 09:50
Sample: 1 240
Included observations: 239

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
FDI	0.000459	2.709945	1.040000
GDP_PER_CAPITA	4.90E-09	24.08203	13.10053
GDP_PER_CAPITA_...	3.67E-17	10.86407	8.923994
GINI_INDEX	0.000115	83.76486	1.384517
URBAN_POPULATION	4.65E-05	36.85134	4.077936
C	0.142188	64.94523	NA

Appendix 4.4.2: Normality Test



Appendix 4.4.3: Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 24 lags

F-statistic	1.514079	Prob. F(24,206)	0.0653
Obs*R-squared	35.53749	Prob. Chi-Square(24)	0.0608

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 04/12/23 Time: 10:43
Sample: 2 240
Included observations: 237
Presample and interior missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FDI	0.003690	0.006300	0.585726	0.5587
GDP_PER_CAPITA	-1.29E-05	2.31E-05	-0.558379	0.5772
GDP_PER_CAPITA_SQUARED	-2.19E-10	1.74E-09	-0.125495	0.9003
GINI_INDEX	-0.003371	0.003525	-0.956384	0.3400
URBAN_POPULATION	0.000797	0.001967	0.405289	0.6857
CO2_EMISSIONS(-1)	0.028431	0.023762	1.196491	0.2329
C	0.074145	0.114204	0.649237	0.5169
RESID(-1)	0.177960	0.077031	2.310228	0.0219
RESID(-2)	-0.232226	0.078622	-2.953704	0.0035
RESID(-3)	-0.008634	0.081080	-0.106482	0.9153
RESID(-4)	-0.030449	0.078884	-0.385998	0.6999
RESID(-5)	-0.181639	0.079568	-2.282812	0.0235
RESID(-6)	0.072723	0.079526	0.914457	0.3615
RESID(-7)	-0.157555	0.079258	-1.987858	0.0482
RESID(-8)	0.107343	0.080294	1.336867	0.1827
RESID(-9)	-0.147308	0.080832	-1.822403	0.0698
RESID(-10)	-0.008079	0.083792	-0.096412	0.9233
RESID(-11)	0.014806	0.091512	0.161792	0.8716
RESID(-12)	-0.170002	0.088377	-1.923608	0.0558
RESID(-13)	-0.035442	0.083962	-0.422116	0.6734
RESID(-14)	-0.076399	0.081255	-0.940239	0.3482
RESID(-15)	-0.078989	0.080625	-0.979710	0.3284
RESID(-16)	-0.112292	0.079401	-1.414240	0.1588
RESID(-17)	0.119970	0.078381	1.530593	0.1274
RESID(-18)	-0.045779	0.078174	-0.585603	0.5588
RESID(-19)	0.042385	0.077327	0.548123	0.5842
RESID(-20)	-0.049808	0.076499	-0.651095	0.5157
RESID(-21)	-0.096445	0.076486	-1.260944	0.2088
RESID(-22)	0.092866	0.077140	1.203869	0.2300
RESID(-23)	-0.085098	0.076337	-1.114775	0.2662
RESID(-24)	-0.039293	0.074846	-0.524991	0.6002

R-squared	0.149947	Mean dependent var	2.80E-16
Adjusted R-squared	0.026153	S.D. dependent var	0.197208
S.E. of regression	0.194612	Akaike info criterion	-0.314199
Sum squared resid	7.802004	Schwarz criterion	0.139429
Log likelihood	68.23260	Hannan-Quinn criter.	-0.131358
F-statistic	1.211263	Durbin-Watson stat	1.984438
Prob(F-statistic)	0.218668		

Appendix 4.4.4: Heteroscedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.537127	Prob. F(9,229)	0.1359
Obs*R-squared	13.61572	Prob. Chi-Square(9)	0.1367
Scaled explained SS	17.09996	Prob. Chi-Square(9)	0.0472

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 04/11/23 Time: 23:08
Sample: 1 240
Included observations: 239

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.490941	0.579861	-0.846652	0.3981
LOGFDI	0.003841	0.012883	0.298178	0.7658
LOGGDP	0.349697	0.109642	3.189448	0.0016
LOGGDP2	-0.025284	0.008674	-2.914970	0.0039
LOGGI	-0.116455	0.162546	-0.716444	0.4744
LOGUPOP	-0.022504	0.093700	-0.240175	0.8104

R-squared	0.056970	Mean dependent var	0.161132
Adjusted R-squared	0.019907	S.D. dependent var	0.267084
S.E. of regression	0.264412	Akaike info criterion	0.218322
Sum squared resid	16.01021	Schwarz criterion	0.363781
Log likelihood	-16.08949	Hannan-Quinn criter.	0.276938
F-statistic	1.537127	Durbin-Watson stat	0.687134
Prob(F-statistic)	0.135881		