Toward a Sustainable Post-Pandemic Growth

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Abstract

Following the COVID-19 pandemic, environmental issues have become an important concern on the government's agenda because of the need for long-term economic recovery. The need for green recovery measures is growing as countries work to both restore their economies and preserve their long-term viability. Therefore, we look into how economic policies affect CO2 emissions to pinpoint routes toward greater environmental resilience. The study sample consisted of five Southeast Asian countries: Indonesia, Malaysia, Singapore, Thailand, and Vietnam. The study's author employed World Bank Data Indicator data, which comprised some data from 2000 to 2023. The cointegration regression model by Paramati et al. (2021) was used. Each country experienced various results.

Keywords: carbon emissions, R&D, sustainable development, sustainability

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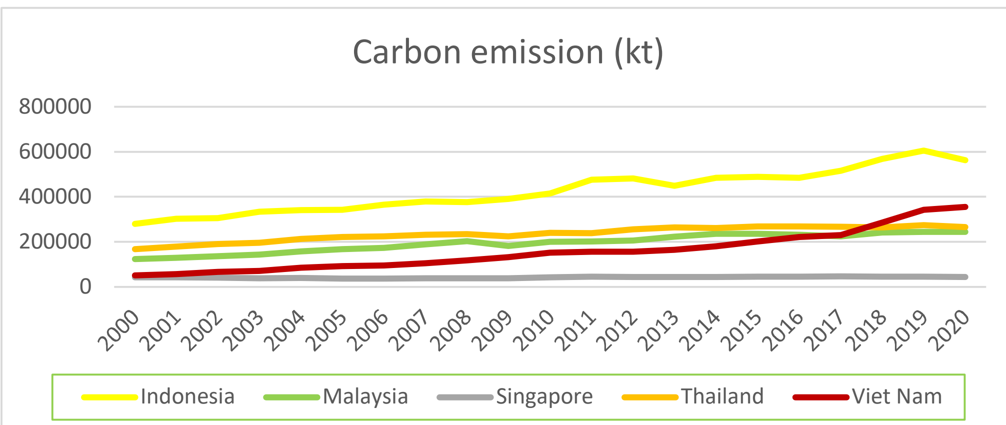
Introduction

The urgent need for sustainable economic recovery in the wake of the COVID-19 pandemic has brought environmental concerns to the forefront of policy discussions. As nations grapple with economic revival, there is growing recognition that green recovery strategies are essential for long-term growth. In this context, our study investigates the impact of economic policies on CO2 emissions, aiming to identify pathways toward a more environmentally resilient future.

We delve into the intricate relationship between policy measures and their effects on carbon emissions. By analyzing diverse policy approaches ranging from investment incentives and regulatory framework we seek to inform policymakers, researchers, and practitioners about effective strategies for achieving a green economic recovery. Our comparative analysis some countries sheds light on the nuanced interplay between economic growth and environmental sustainability.

In the wake of the global health crisis brought about by COVID-19, nations worldwide are facing with the dual challenges of economic recovery and environmental conservation. This juncture presents an opportune moment for reevaluating traditional economic paradigms and steering towards a greener, more resilient economic model that prioritizes carbon emission reduction and climate change mitigation.



Source: World bank development indicators

By examining the impact of diverse economic policies on CO2 emissions, the researchers aim to furnish policymakers with actionable insights to craft and implement strategies that facilitate a sustainable and eco-friendly recovery. This nuanced analysis of the efficacy of economic interventions in curbing carbon emissions holds significant implications for fostering environmentally responsible economic growth post-COVID-19.

Through empirical research and data-driven analysis, this study contributes substantively to the discourse on climate change economics, offering a robust foundation for evidence-based policy formulation and decision-making. The research outcomes have the potential to inform and shape national and international policy agendas, steering the global community towards a more sustainable and environmentally conscious economic trajectory in the aftermath of the pandemic.

In the pages that follow, we explore how targeted policies can mitigate CO2 emissions while fostering economic prosperity. By aligning our efforts with global climate goals, we aspire to contribute to a resilient and equitable post-pandemic era one where economic progress harmonizes with ecological stewardship.

Literature review

The research conducted by Huang, Wenji, et.al. (2022) delves into the intricate relationship between economic policies and CO2 emissions, with a specific focus on charting a path towards achieving a green economic recovery in the aftermath of the COVID-19 pandemic. Published in the esteemed journal Climate Change Economics in 2022, this study sheds light on the critical intersection of economic decision-making and environmental sustainability in the post-pandemic era. Studies conducted by Huang, Wenji, et. al. (2022) had shown that regional efforts in the European Union (EU) aimed at reducing pollution levels have been contrasting with individual member countries' unique policies to achieve a 10% reduction per country. The research contributes to the existing literature by developing a novel framework that investigates the link between macroeconomic policies, energy usage patterns, and CO2 emissions levels in EU countries from 1990 to 2016. The utilization of the second-generation cross-sectional-autoregressive-distributed lag (CS-ARDL) panel data method in this study has enabled the identification of relationships between monetary policies and CO2 emissions, highlighting the impact of growth monetary policy (GMP), tightening monetary policy (TMP), environmental tax, carbon capture tax on environmental factors. Findings from the research indicate that GMP exacerbates the adverse effects of CO2 emissions, whereas TMP helps in reducing the harmful implications of CO2 emissions levels. Moreover, The Granger casualty analysis authenticated our findings by confirming the one-way connection to CMP and EMP on carbon emissions, emphasizing the connectedness of economic policies and environmental concerns. In addition, Environmental Taxes have a negative and statistically significant relationship with CO2 emissions across all models. This suggests that higher environmental taxes are associated with lower CO2 emissions. The magnitude of the effect varies across models. Carbon Capture Taxes have a positive but statistically significant relationship with CO2 emissions in the OLS and DOLS models. This is counterintuitive, as we'd expect carbon capture taxes to reduce emissions. It could indicate a rebound effect (increased emissions due to other factors) or model misspecification. However, the effect is not significant in the FMOLS and PMG models. The studies instigate on the dual policy instruments (GMP and TMP) and their relationship with ecological factors provides a unique contribution to empirical analyses, shedding light on the importance of integrating environmental considerations into monetary policy decisions for achieving sustainable and green economic recovery in the aftermath of the COVID-19 pandemic.

In their study, Petrović and Lobanov (2019) explore the impact of research and development (R&D) expenditures on CO2 emissions across sixteen OECD countries. Their findings reveal a negative association between R&D spending and environmental degradation. Specifically, higher R&D expenditures tend to mitigate carbon emissions. However, several countries had different result. This study highlights the impact of R&D investments on CO2 emissions in 16 OECD countries between 1981 and 2014. While the expected average effect appears negative, the long-run impact can be positive in a significant percentage of cases. Interestingly, about 40% of countries do not follow this trend. Additionally, short-term analyses reveal varying effects—positive, negative, or neutral—over several years. These findings emphasize the need for empirical estimation rather than assuming a universally negative impact of R&D investments on emissions. Policymakers should focus on R&D activities that specifically reduce CO2 emissions or enable their capture, storage, and utilization. Furthermore, the study considers other relevant factors, such as gross domestic product (GDP), which exhibits a positive long-term impact and aligns with the scale effect in the relationship between CO_2 emissions and GDP.

The paper by Fernández Fernández et al., (2017) investigates the relationship between innovation, specifically research and development spending, and CO_2 emissions. The authors analyze data from the European Union, the United States, and China between 1990 and 2013 to determine if increased investment in innovation leads to a reduction in CO_2 emissions. The study finds that R&D spending has a positive impact on reducing CO_2 emissions in developed countries. This suggests that technological advancements and innovation can contribute to a more sustainable and environmentally friendly economy. The European Union demonstrates a more significant corrective effect compared to the United States, indicating regional differences in the effectiveness of innovation for emissions reduction. Furthermore, the paper highlights the role of energy consumption in CO_2 emissions. As expected, increased energy consumption is linked to higher emissions. However, the European Union again shows a lower impact, suggesting that its energy consumption is less polluting compared to the United States and China. The authors conclude that promoting R&D expenditure is crucial for combating climate change and achieving sustainable development.

The study conducted by Muhammad Shahbaz, et. al. (2020), sheds light on the interplay between economic growth, financial development, R&D expenditures, and carbon dioxide (CO_2) emissions. The study situates itself within the context of two significant trends: the 4th industrial revolution and global decarbonization. The 4th industrial revolution, characterized by technological advancements like AI, IoT, and machine learning, has the potential to transform economies and societies. Importantly, if harnessed effectively, it could contribute to a cleaner environment. The authors explore how these trends intersect with the UK's commitment to achieving net-zero emissions by 2050. Methodologically, the researchers employ a bootstrapping bound testing approach to analyze short- and long-run relationships. Their dataset spans historical data from 1870 to 2017, allowing them to explore the dynamics over time.

The results indicate the existence of cointegration between CO_2 emissions and their determinants, suggesting that these variables are interconnected. Both financial development and energy consumption contribute to environmental degradation. Interestingly, R&D expenditures help reduce CO_2 emissions, aligning with the idea that innovation and research can drive sustainable practices. The relationship between economic growth and environmental effects follows an EKC pattern. Initially, as economies grow, emissions rise, but beyond a certain point, they decline due to improved technologies and policies. Financial development exhibits a U-shaped relationship with CO_2 emissions, implying that its impact is nonlinear. The study suggests using financial development and R&D expenditures as key tools to meet emissions targets in the fight against climate change. In summary, this research underscores the importance of innovation, sustainable finance, and strategic policy measures in achieving a net-zero carbon future for the UK.

The paper conducted by Han Sol Lee, et.al (2021) empirically analyzes sustainable relations between inward FDI (IFDI), outward FDI (OFDI), the R&D expenditure ratio and CO_2 emissions based on balanced panel data from the BRICS (namely, Brazil, Russia, India, China and South Africa) countries for the period 2003–2017. Commonly, the results confirm a negative effect of IFDI and a positive effect of OFDI on the R&D expenditure ratio, both with statistical significance. Further examination of the IFDI, OFDI and R&D impacts on CO_2 emissions was based on an assumption that innovation development mitigates environmental pollution. The research outcome revealed positive associations between IFDI and the R&D expenditure ratio with CO_2 emissions, showing the connection of investment growth-focused national economic strategies positive connections to CO_2

emissions. Based on these outcomes, they commend some strategies: the drafting of New Development Bank specific environment-friendly investment programs aimed at innovation activities and looking into further easing the green technologies from developed countries.

The study conducted by Paramati, et. al. (2021) examines the long-run relationship between R&D investment and environmental sustainability in a panel of 25 European Union (EU) member countries over a period of 17 years (1998–2014). They use robust and reliable econometric methods to capture the interactions between R&D investment on renewable energy consumption and CO2 emissions. The findings confirm that the growth of R&D expenditures promotes renewable energy consumption and plays a significant role in reducing CO2 emissions in the sample countries. Furthermore, the findings suggest that increasing the share of renewable energy consumption in the total energy mix also reduces CO2 emissions. Given these results, they suggest that the EU policymakers provide more financial and regulatory assistance to the R&D activities, specifically in the energy sector, to ensure promoting low carbon economies in this region. The empirical findings of their study confirm the presence of a significant long-run association among the variables: R&D, REC and CO2 emissions. The results also show that the growth of the R&D expenditures positively contributes to more renewable energy production and consumption and helps reduce CO2 emissions in the EU economies. The findings also assert that increasing the consumption of renewable energy mitigates CO2 emissions. Given these findings, they strongly suggest that by increasing the R&D activities, the EU countries not only promote renewable energy technologies and production but also help mitigate CO2 emissions by improving the access to emission-controlling technologies. The major policy implications of the study are as follows. (i) since the findings on long-run elasticities indicate that the growth of R&D activities increases REC and reduces CO2 emissions, thereby they argue that the policymakers of the EU countries should increase the funding allocated to the R&D activities so that they can bring more innovations to new and existing sources of energy, particularly renewable energy, and introduce more emission-controlling technologies such as catalytic converters to reduce CO2 emissions at source (of the automobile exhausts). These new innovations in the energy sector will greatly assist EU countries to further promote the generation and use of renewable energy and combat the growth of CO2 emissions. (ii) The results also show that the consumption of renewable energy also decreases CO2 emissions.

To achieve sustainable development, countries around the world are choosing advanced technological capabilities and implementing environment-related innovations, including renewable energy. This offers an interesting opportunity for researchers to explore unique determinants of carbon dioxide emissions. The N-11 economies is one of the main emitters of carbon dioxide and energy consumption. The study by Wang, R., et.al. (2020) analyses the dynamics of carbon emissions for N-11 countries from 1990 to 2017. They introduce some innovative factors such as financial development, human capital, renewable energy consumption, and gross domestic product as determinants of carbon dioxide (CO2) emissions. This study uses the second-generation panel cointegration method of N- 11 countries from 1990 to 2017 to assess the relationship between carbon emissions and country-specific variables. We found that in the long run, financial development and economic growth are positively related to CO2 emissions. On the contrary, renewable energy consumption, technological innovation, and human capital are negatively related to CO2 emissions in N-11 economies. These finding remained robust when multiple econometric specifications were used. These findings have important implications, and they recommend the promotion of technological innovation and the use of renewable energy consumption. This will help in achieving the goals set by COP21.

The paper by Erdyas, B.T., et. al. 2017 evaluates the long run and short run causality issues between fossil fuel consumption (oil, natural gas, and coal), CO2 emissions, and economic growth in Indonesia by using Vector Error Correction Model (VECM) Granger Causality for the period of 1965-2012. Empirical results suggest each type of fossil fuel has different causality direction both in the long run and short run. In the short-run there are unidirectional Granger causalities running from coal consumption to economic growth (growth hypothesis) and from economic growth to oil consumption (conservation hypothesis). Subsequent, in the long run the results suggest unidirectional Granger causality (growth hypothesis) only running from oil consumption to economic growth and carbon dioxide emissions while other variables have bidirectional Granger causality (feedback hypothesis). Thus, Indonesia should adopt different policies for each type of energies in order to maintain the economic growth while the effort of reducing fossil fuel consumption is in progress.

Data and Empirical Methodology

The current study makes use of the annual data for some Southeast Asia member countries (Indonesia, Malaysia, Singapore, Thailand, Vietnam) over the period 2000–2023 which is the common data among some countries when we embarked on this study. That is, the selection of the sample period and the ASEAN countries are based on the availability of data. The required data on CDE, FDI, PI, POP, FM and R&D are obtained from the World Development Indicators online database supplied by the World Bank.

This study developed adjusted model from Paramati, S.R. et.al. (2021) to investigate the impact of R&D expenditure and renewable energy on CO2 emissions, we make use of the environmental theoretical model (Ehrlich & Holdren, 1971 mentioned in Paramati, S.R. et.al. 2021) to determine the drivers of CO2 emissions. This theoretical model is built based on the association among the population, income, technology and the environmental impact. To account various other potential drivers of emissions, we base our empirical model in Paramati, S.R. et.al. (2021) as described below:

$$CDE_{it}=f(POP_{it},PI_{it},R\&D_{it},FDI_{it},FM_{it},v_{it})$$

This equation aims to identify the role of R&D in reducing CO2 emissions. where CDE, PI, R&D, FDI, and FM denote CO2 emissions, per capita income, research and development expenditure, foreign direct investment, and financial markets, respectively. CDE for total CO2 emissions (kt); FDI for foreign direct investment, net inflows (% of GDP); PI for GDP per capita (constant 2015 U.S.$); POP for total population; R&D for research and development expenditure (% of GDP); and FM for market capitalization (% of GDP).

We begin our investigation by applying three-panel unit root tests. We use the common unit root process is examined using the Levin, Lin, and Chu (2002) (LLC) test while the individual unit root processes are investigated by employing the Im, Pesaran, and Shin (2003) (IPS) test as mentioned in Paramati, S.R., et.al. (2021). Then, we use the cross-sectional augmented panel unit root (CIPS) test, which is proposed by Pesaran (2007) based on the assumption of cross-sectional dependence. As we use in the equation, all variables had stationer in the first difference then we use 1st difference in the equation.

We explore the long-run association among these models using the Pedroni (1999, 2004) panel cointegration framework mentioned in Paramati, S.R., et.al. (2021).

Results and Discussion

Panel cointegration framework

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-1.06845	0.8573	-2.29785	0.9892
Panel rho-Statistic	-1.09162	0.1375	0.281544	0.6109
Panel PP-Statistic	-8.2976	0.0000**	-8.86259	0.0000**
Panel ADF-Statistic	-7.68459	0.0000**	-4.12603	0.0000**

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	1.065127	0.8566
Group PP-Statistic	-10.8732	0.0000**
Group ADF-Statistic	-5.53825	0.0000**

The findings of panel cointegration framework show that out of the test's seven statistics, two statistics under the within-dimension and two statistics under the in between-dimension statistics is statistically significant. This means that there is a considerable long-run relationship among the variables under consideration.

We followed Paramati, S.R. et.al. (2021) who used the cointegrating regression FMOLS in all countries and specified countries. The result is described follow:

All countries (cointegrating regression FMOLS)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI_INFLOWS)	406.2972	450.2411	0.902399	0.3695
D(POP)	0.005733	0.000995	5.764072	0.00**
D(RD)	-5411.77	14170.75	-0.3819	0.7035
D(MARKETCAP)	-39.471	57.38996	-0.68777	0.4935

Based on this results, fdi_inflows and population had positive coefficients and the population had a significant effect on carbon emissions in 5 Southeast Asia countries. Detailed investigation is needed to examine this finding.

Specified analysis per countries (cointegrating regression FMOLS)

Country	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Indonesia	D(FDI_INFLOWS)	-10.0952	4881.486	-0.00207	0.9984
	D(POP)	0.004668	0.001892	2.46741	0.0261**
	D(RD)	-6081.44	213705.4	-0.02846	0.9777
	D(MARKETCAP)	317.0707	452.7372	0.700341	0.4944
Malaysia	D(FDI_INFLOWS)	2121.961	770.1413	2.755288	0.0147**
	D(POP)	0.014372	0.002612	5.501711	0.0001**
	D(RD)	-17997.5	12309.89	-1.46204	0.1644
	D(MARKETCAP)	-142.93	44.04514	-3.24507	0.0054**
Singapore	D(FDI_INFLOWS)	117.7192	54.32429	2.166972	0.0467**
	D(POP)	0.004101	0.002681	1.529832	0.1469
	D(RD)	-2677.18	1989.517	-1.34565	0.1984
	D(MARKETCAP)	-16.9374	8.518715	-1.98826	0.0653**
Thailand	D(FDI_INFLOWS)	1897.72	856.0207	2.216909	0.0425**
	D(POP)	0.014357	0.003374	4.254437	0.0007**
	D(RD)	-24581.7	14466.31	-1.69924	0.1099
	D(MARKETCAP)	-27.7464	66.69197	-0.41604	0.6833
Vietnam	D(FDI_INFLOWS)	2828.159	8021.16	0.352587	0.7348
	D(POP)	0.027732	0.00626	4.430183	0.003**
	D(RD)	-165785	100673.4	-1.64676	0.1436
	D(MARKETCAP)	306.4117	783.8324	0.390915	0.7075

Based on the results, the results displayed varied between countries. Indonesia had a significant population impact on carbon emissions, and the coefficient is positive. Malaysia had fdi_inflows, population, and market cap significant on carbon emissions. The market cap coefficient in Malaysia is negative. Singapore had fdi_inflows positive coefficient significant to carbon emissions. Furthermore, Singapore had a significant market cap on carbon emissions, and the market cap coefficient in Singapore is negative. Thailand had fdi_inflows, a population significant on carbon emissions, and their coefficient is positive. Vietnam had a significant population contribution to carbon emissions, and the coefficient is positive. The R&D coefficient is negative in all countries but not significant.

As a result of these findings, which are aligned with Paramati, S.R., et al. (2021), it is hoped that growth in R&D, FDI, and financial markets will help those economies minimize CO2 emissions. Specifically, the argument that the financial markets reflect the increase in the listed shares of the service companies that consume less fossil fuel than the good-producing companies. The stock markets may also show support for companies with new technologies that reduce pollution, which may reflect an increase in awareness of the dangers of climate change. However, the analysis of the market cap should be deepened, as the market cap follows the market trend itself. A more detailed investigation with more data about green investments is needed to examine the green policies in these countries.

In their 2017 study, Hanif, I., et.al., proposed that there might be an Environmental Kuznets Curve (EKC) for developing economies, which relates to greenhouse gas emissions. They indicated that a turning point in emissions levels could be imminent, but warned that failure to address population growth and economic instability due to inflation could undermine progress in increasing per capita income and reaching the projected turning point of the EKC. In this scenario, the connection between economic advancement and environmental deterioration may not follow the expected inverted U-shaped curve but may instead show a direct positive correlation between income growth and greenhouse gas emissions in developing nations.

The impact of environmental deterioration in developing countries is largely attributed to low per capita income and economic instability, which hinder these countries from reaching their EKC turning point. National policies should focus on ensuring macroeconomic stability and population control to reduce the negative effects of economic development on the environment in developing economies.

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Annex

Econometric result

unit root test

Panel unit root test: Summary
Series: FDI_INFLOWS
Date: 07/05/24 Time: 14:06
Sample: 2000 2023
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.13230	0.0000	5	108
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.25489	0.0000	5	108
ADF - Fisher Chi-square	44.5428	0.0000	5	108
PP - Fisher Chi-square	58.2697	0.0000	5	110

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

Panel unit root test: Summary
Series: D(MARKETCAP)
Date: 07/05/24 Time: 14:08
Sample: 2000 2023
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.8541	0.0000	5	94
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-10.7830	0.0000	5	94
ADF - Fisher Chi-square	95.7423	0.0000	5	94
PP - Fisher Chi-square	166.846	0.0000	5	97

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

Panel unit root test: Summary
Series: D(POP)
Date: 07/05/24 Time: 14:09
Sample: 2000 2023
Exogenous variables: None
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.05586	0.0011	5	103
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	25.4239	0.0046	5	103
PP - Fisher Chi-square	33.0005	0.0003	5	110

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

Panel unit root test: Summary
Series: D(RD)
Date: 07/05/24 Time: 14:10
Sample: 2000 2023
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.03079	0.0000	5	108
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.95939	0.0000	5	108
ADF - Fisher Chi-square	53.7461	0.0000	5	108
PP - Fisher Chi-square	71.5574	0.0000	5	110

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

Panel unit root test: Summary
Series: D(Y)
Date: 07/05/24 Time: 14:13
Sample: 2000 2023
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.96644	0.0000	5	94
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.91646	0.0000	5	94
ADF - Fisher Chi-square	58.4824	0.0000	5	94
PP - Fisher Chi-square	63.3218	0.0000	5	95

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

Panel unit root

Panel unit root tests with cross-sectional dependence: Pesaran - CIPS
Series: FDI_INFLOWS
Date: 07/09/24   Time: 14:44
Sample: 2000 2023
Cross-sections: 5
Balanced observations: 22
Total observations: 110
Deterministics: Constant

CIPS unit root test
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.29261	<0.10
Truncated CIPS:	-2.29261	<0.10

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.59	-2.59
5%	-2.34	-2.34
10%	-2.21	-2.21

Panel unit root tests with cross-sectional dependence: Pesaran - CIPS
Series: GDP_PER_CAPITA
Date: 07/09/24 Time: 14:53
Sample: 2000 2023
Cross-sections: 5
Balanced observations: 23
Total observations: 115
Deterministics: Constant

CIPS unit root test
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.64215	<0.01
Truncated CIPS:	-2.64215	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.59	-2.59
5%	-2.34	-2.34
10%	-2.21	-2.21

Panel unit root tests with cross-sectional dependence: Pesaran - CIPS
Series: RD
Date: 07/09/24 Time: 14:59
Sample: 2000 2023
Cross-sections: 5
Balanced observations: 23
Total observations: 115
Deterministics: Constant

CIPS unit root test
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.59234	<0.01
Truncated CIPS:	-2.59234	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.59	-2.59
5%	-2.34	-2.34
10%	-2.21	-2.21

Panel unit root tests with cross-sectional dependence: Pesaran - CIPS
Series: DMARKETCAP
Date: 07/09/24 Time: 15:04
Sample: 2000 2023
Cross-sections: 5
Balanced observations: 13
Total observations: 65
Deterministics: Constant

CIPS unit root test
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-4.63831	<0.01
Truncated CIPS:	-3.89688	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.78	-2.74
5%	-2.43	-2.41
10%	-2.26	-2.24

Panel unit root tests with cross-sectional dependence: Pesaran - CIPS
Series: DPOP
Date: 07/09/24   Time: 15:07
Sample: 2000 2023
Cross-sections: 5
Balanced observations: 22
Total observations: 110
Deterministics: Constant

CIPS unit root test
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-0.9844	>=0.10
Truncated CIPS:	-2.7941	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.594	-2.594
5%	-2.338	-2.338
10%	-2.21	-2.21

Panel unit root tests with cross-sectional dependence: Pesaran - CIPS
Series: DY
Date: 07/09/24 Time: 15:12
Sample: 2000 2023
Cross-sections: 5
Balanced observations: 19
Total observations: 95
Deterministics: Constant

CIPS unit root test
Null hypothesis: Unit root

Test results:

Statistic	t-stat	p-value
CIPS:	-2.6293	<0.01
Truncated CIPS:	-2.6293	<0.01

Critical values:

Level	CIPS	Trunc. CIPS
1%	-2.612	-2.612
5%	-2.346	-2.346
10%	-2.212	-2.212

Pedroni Residual Cointegration Test
Series: FDI_INFLOWS GDP_PER_CAPITA MARKETCAP POP RD Y
Date: 07/05/24 Time: 14:42
Sample: 2000 2023
Included observations: 120
Cross-sections included: 5
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend
Automatic lag length selection based on SIC with lags from 1 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-1.068451	0.8573	-2.297849	0.9892
Panel rho-Statistic	-1.091623	0.1375	0.281544	0.6109
Panel PP-Statistic	-8.297604	0.0000	-8.862587	0.0000
Panel ADF-Statistic	-7.684592	0.0000	-4.126027	0.0000

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	1.065127	0.8566
Group PP-Statistic	-10.87316	0.0000
Group ADF-Statistic	-5.538251	0.0000

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
1	-0.008	0.467270	0.467270	0.00	20
2	-0.070	1.097219	0.416041	7.00	20
3	-0.392	7.420448	6.893841	2.00	20
4	-0.450	0.439582	0.073580	10.00	20
5	-0.164	0.283650	0.126758	5.00	12

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
1	-0.008	0.467270	0	3	20
2	-0.840	0.649215	2	3	18
3	-0.392	7.420448	0	3	20
4	-4.003	0.163007	3	3	17
5	-0.164	0.283650	0	1	12

Cointegrating result

Dependent Variable: D(Y)
Method: Panel Fully Modified Least Squares (FMOLS)
Date: 07/07/24 Time: 17:41
Sample (adjusted): 2002 2020
Periods included: 19
Cross-sections included: 5
Total panel (unbalanced) observations: 87
Panel method: Pooled estimation
First-stage residuals use heterogeneous long-run coefficients
Coefficient covariance computed using default method
Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI_INFLOWS)	406.2972	450.2411	0.902399	0.3695
D(POP)	0.005733	0.000995	5.764072	0.0000
D(RD)	-5411.767	14170.75	-0.381897	0.7035
D(MARKETCAP)	-39.47104	57.38996	-0.687769	0.4935

R-squared	0.057789	Mean dependent var	7910.709
Adjusted R-squared	0.023733	S.D. dependent var	16083.55
S.E. of regression	15891.55	Sum squared resid	2.10E+10
Long-run variance	1.64E+08		

Multicollinearity test

Variance Inflation Factors
Date: 07/07/24 Time: 17:44
Sample: 2000 2023
Included observations: 87

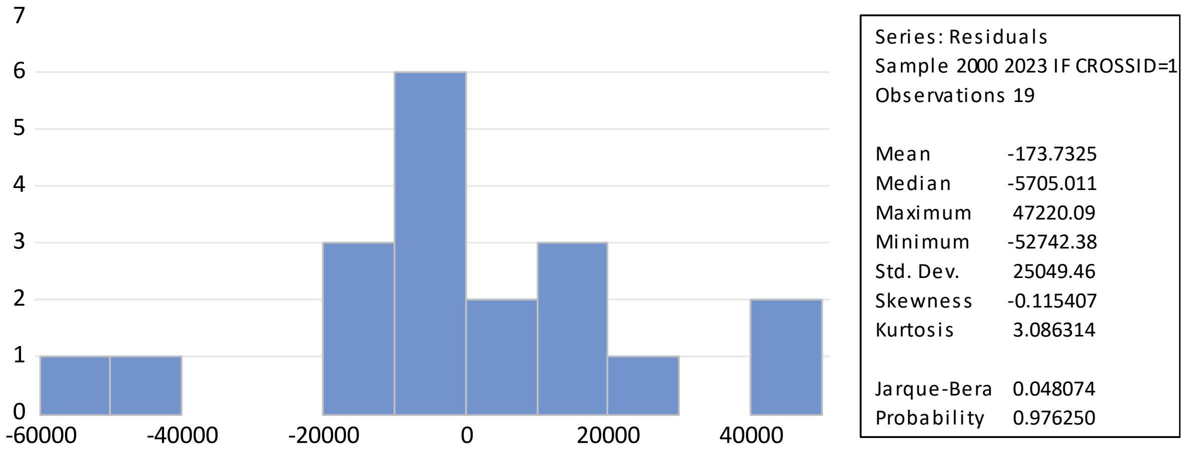
Variable	Coefficient Variance	Uncentered VIF
D(FDI_INFLOWS)	202717.1	1.587807
D(POP)	9.89E-07	1.019741
D(RD)	2.01E+08	1.249850
D(MARKETCAP)	3293.607	1.606088

Country specified analysis

Dependent Variable: D(Y)
Method: Panel Fully Modified Least Squares (FMOLS)
Date: 07/06/24 Time: 14:38
Sample: 2000 2023 IF CROSSID=1
Periods included: 19
Cross-sections included: 1
Total panel (balanced) observations: 19
Panel method: Pooled estimation
Coefficient covariance computed using default method
Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI_INFLOWS)	-10.09518	4881.486	-0.002068	0.9984
D(POP)	0.004668	0.001892	2.467410	0.0261
D(RD)	-6081.438	213705.4	-0.028457	0.9777
D(MARKETCAP)	317.0707	452.7372	0.700341	0.4944

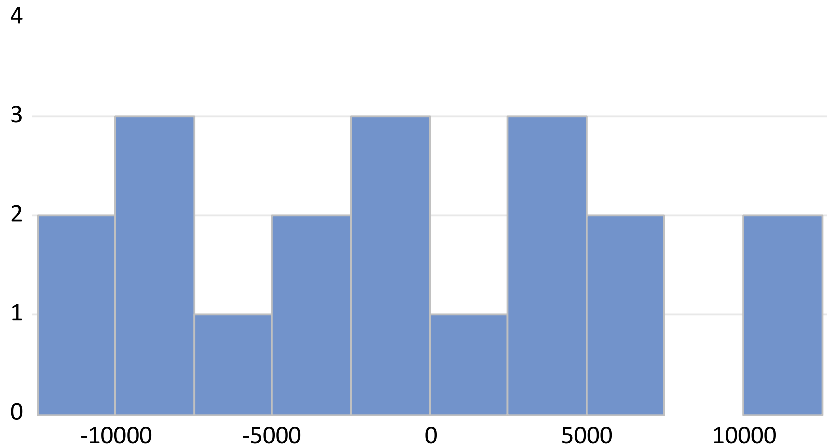
R-squared	0.051502	Mean dependent var	13744.32
Adjusted R-squared	-0.138198	S.D. dependent var	25721.20
S.E. of regression	27441.00	Sum squared resid	1.13E+10
Long-run variance	3.02E+08		


7
6
5
4
3
2
1
0
-60000
-40000
-20000
0
20000
40000
Series: Residuals
Sample 2000 2023 IF CROSSID=1
Observations 19
Mean -173.7325
Median -5705.011
Maximum 47220.09
Minimum -52742.38
Std. Dev. 25049.46
Skewness -0.115407
Kurtosis 3.086314
Jarque-Bera 0.048074
Probability 0.976250

Dependent Variable: D(Y)
Method: Panel Fully Modified Least Squares (FMOLS)
Date: 07/06/24 Time: 14:40
Sample: 2000 2023 IF CROSSID=2
Periods included: 19
Cross-sections included: 1
Total panel (balanced) observations: 19
Panel method: Pooled estimation
Coefficient covariance computed using default method
Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI_INFLOWS)	2121.961	770.1413	2.755288	0.0147
D(POP)	0.014372	0.002612	5.501711	0.0001
D(RD)	-17997.51	12309.89	-1.462036	0.1644
D(MARKETCAP)	-142.9295	44.04514	-3.245069	0.0054

R-squared	0.477243	Mean dependent var	6088.453
Adjusted R-squared	0.372691	S.D. dependent var	9898.313
S.E. of regression	7839.744	Sum squared resid	9.22E+08
Long-run variance	25085743		



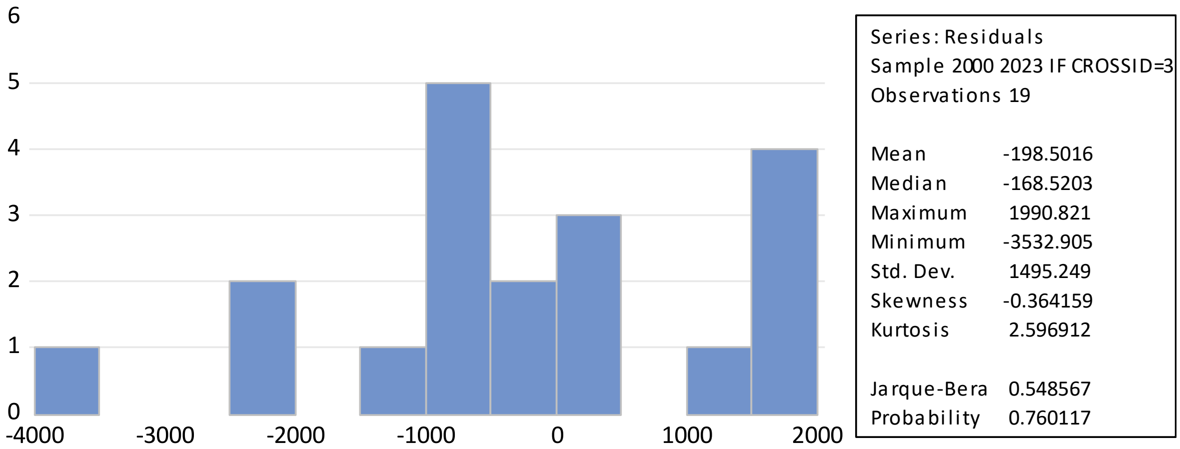
Series: Residuals
Sample 2000 2023 IF CROSSID=2
Observations 19

Mean	-858.4061
Median	-1231.470
Maximum	11021.64
Minimum	-12335.27
Std. Dev.	7102.126
Skewness	0.024552
Kurtosis	1.941257
Jarque-Bera	0.889317
Probability	0.641043

Dependent Variable: D(Y)
Method: Panel Fully Modified Least Squares (FMOLS)
Date: 07/06/24 Time: 14:42
Sample: 2000 2023 IF CROSSID=3
Periods included: 19
Cross-sections included: 1
Total panel (balanced) observations: 19
Panel method: Pooled estimation
Coefficient covariance computed using default method
Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI_INFLOWS)	117.7192	54.32429	2.166972	0.0467
D(POP)	0.004101	0.002681	1.529832	0.1469
D(RD)	-2677.182	1989.517	-1.345645	0.1984
D(MARKETCAP)	-16.93740	8.518715	-1.988257	0.0653

R-squared	0.247263	Mean dependent var	88.08947
Adjusted R-squared	0.096716	S.D. dependent var	1739.380
S.E. of regression	1653.129	Sum squared resid	40992532
Long-run variance	1196607.		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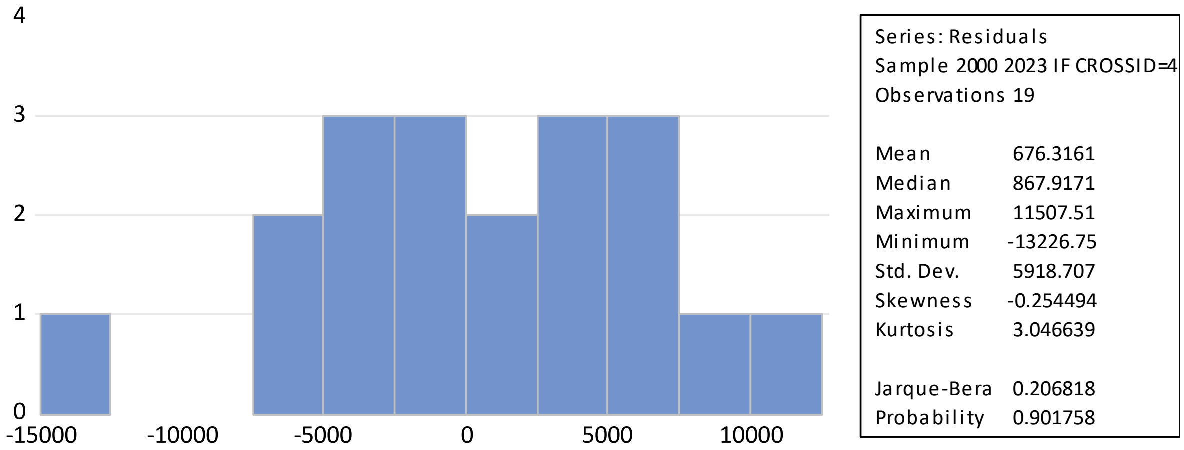
5
4
3
2
1
0
-4000
-3000
-2000
-1000
0
1000
2000
Series: Residuals
Sample 2000 2023 IF CROSSID=3
Observations 19
Mean -198.5016
Median -168.5203
Maximum 1990.821
Minimum -3532.905
Std. Dev. 1495.249
Skewness -0.364159
Kurtosis 2.596912
Jarque-Bera 0.548567
Probability 0.760117

Dependent Variable: D(Y)
Method: Panel Fully Modified Least Squares (FMOLS)
Date: 07/06/24 Time: 14:42
Sample: 2000 2023 IF CROSSID=4
Periods included: 19
Cross-sections included: 1
Total panel (balanced) observations: 19
Panel method: Pooled estimation
Coefficient covariance computed using default method
Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI_INFLOWS)	1897.720	856.0207	2.216909	0.0425
D(POP)	0.014357	0.003374	4.254437	0.0007
D(RD)	-24581.65	14466.31	-1.699235	0.1099
D(MARKETCAP)	-27.74643	66.69197	-0.416039	0.6833

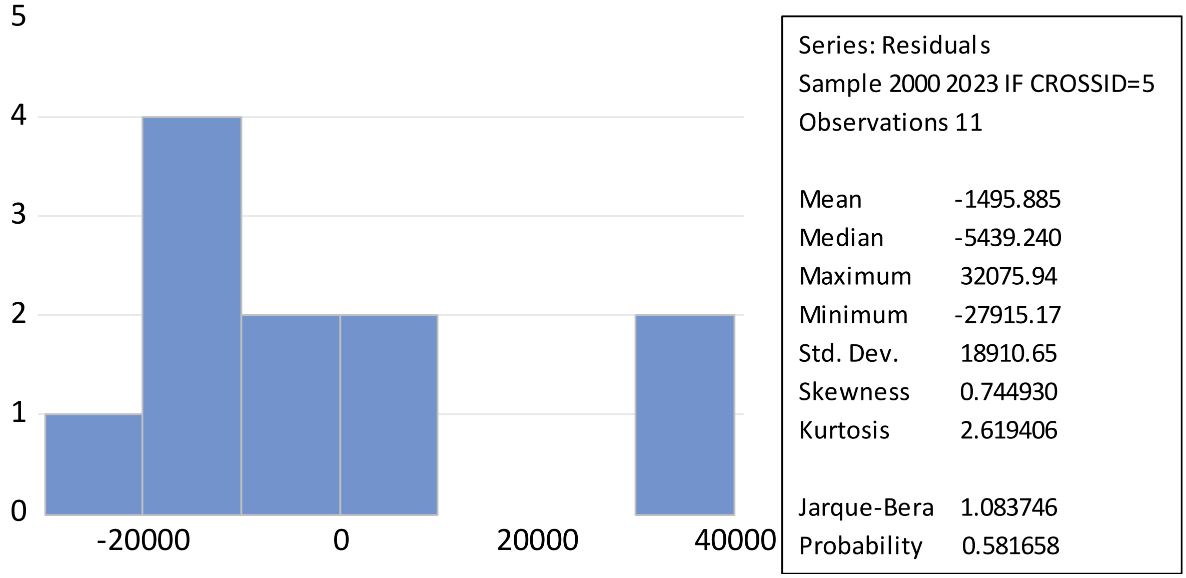
R-squared	0.461596	Mean dependent var	4563.279
Adjusted R-squared	0.353915	S.D. dependent var	8121.666
S.E. of regression	6528.145	Sum squared resid	6.39E+08
Long-run variance	25181746		


4
3
2
1
0
-15000
-10000
-5000
0
5000
10000
Series: Residuals
Sample 2000 2023 IF CROSSID=4
Observations 19
Mean 676.3161
Median 867.9171
Maximum 11507.51
Minimum -13226.75
Std. Dev. 5918.707
Skewness -0.254494
Kurtosis 3.046639
Jarque-Bera 0.206818
Probability 0.901758

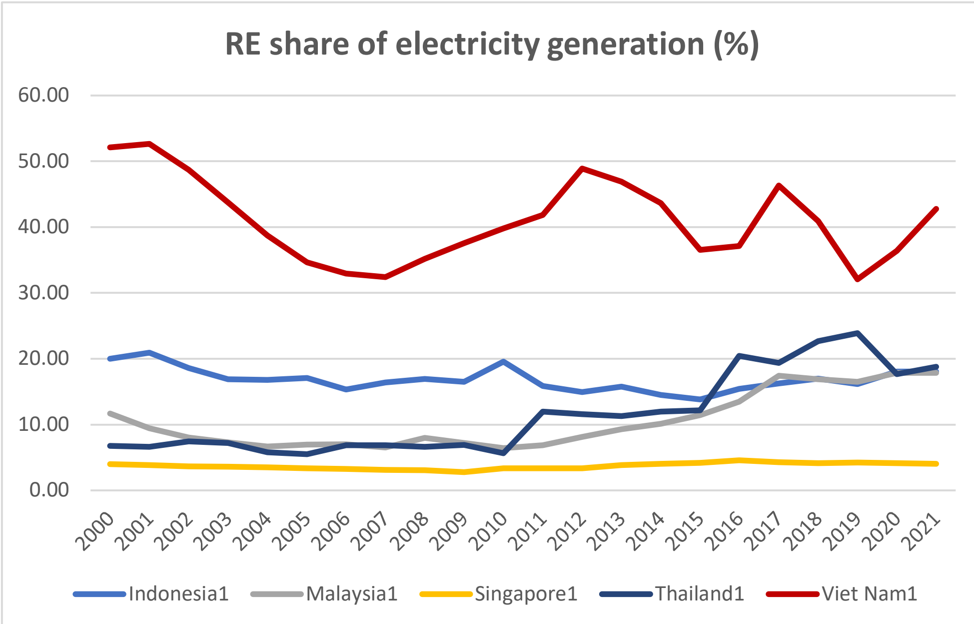
Dependent Variable: D(Y)
Method: Panel Fully Modified Least Squares (FMOLS)
Date: 07/06/24 Time: 14:44
Sample: 2000 2023 IF CROSSID=5
Periods included: 11
Cross-sections included: 1
Total panel (balanced) observations: 11
Panel method: Pooled estimation
Coefficient covariance computed using default method
Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

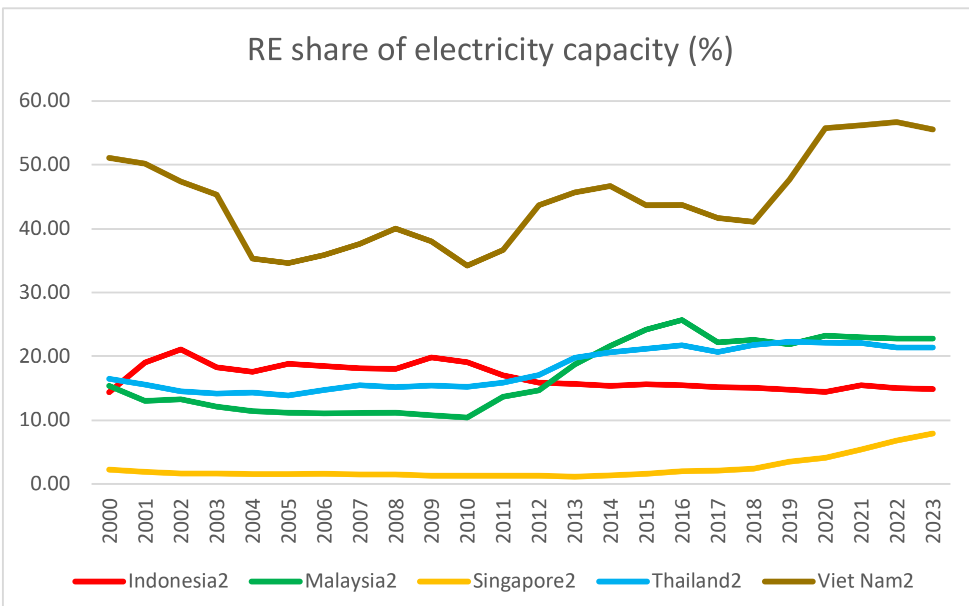
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI_INFLOWS)	2828.159	8021.160	0.352587	0.7348
D(POP)	0.027732	0.006260	4.430183	0.0030
D(RD)	-165784.9	100673.4	-1.646760	0.1436
D(MARKETCAP)	306.4117	783.8324	0.390915	0.7075

R-squared	-0.009840	Mean dependent var	20275.74
Adjusted R-squared	-0.442628	S.D. dependent var	18882.94
S.E. of regression	22680.20	Sum squared resid	3.60E+09
Long-run variance	1.24E+08		



5
4
3
2
1
0
-20000
0
20000
40000
Series: Residuals
Sample 2000 2023 IF CROSSID=5
Observations 11
Mean -1495.885
Median -5439.240
Maximum 32075.94
Minimum -27915.17
Std. Dev. 18910.65
Skewness 0.744930
Kurtosis 2.619406
Jarque-Bera 1.083746
Probability 0.581658





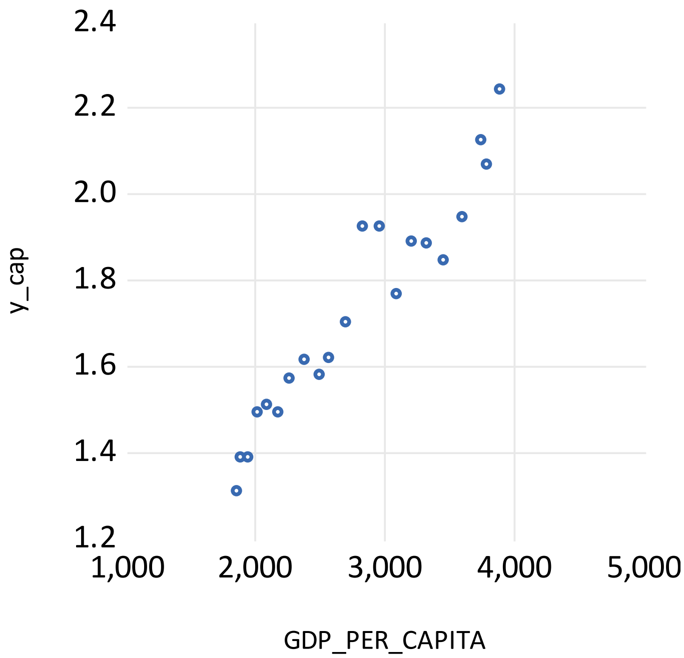
[1]**RE share of electricity generation (%)**

[2]**RE share of electricity capacity (%)**

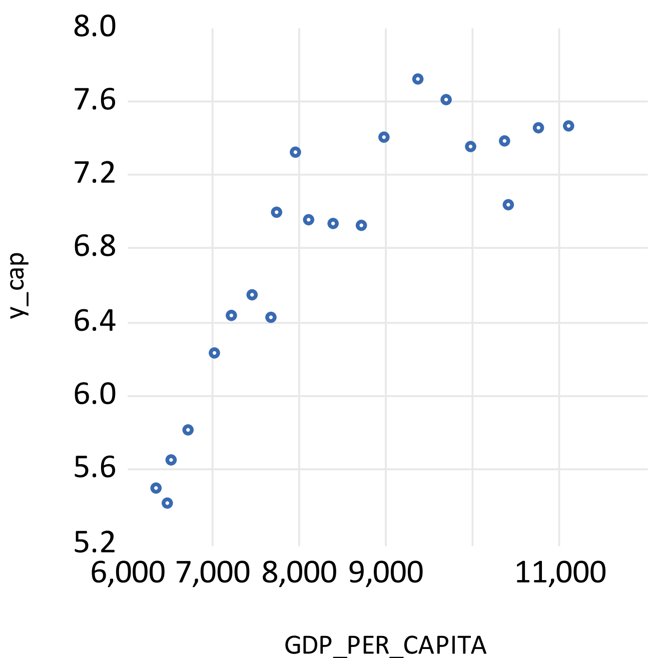
Source:

IRENA (2024), Renewable Capacity Statistics 2024; & IRENA (2023), Renewable Energy Statistics 2023, The International Renewable Energy Agency, Abu Dhabi.

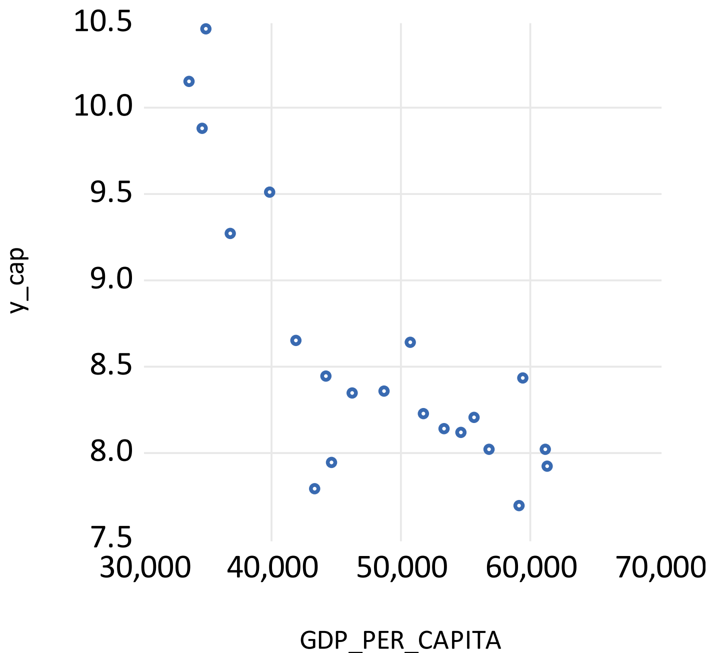
Graphic Environmental Kuznet Curve



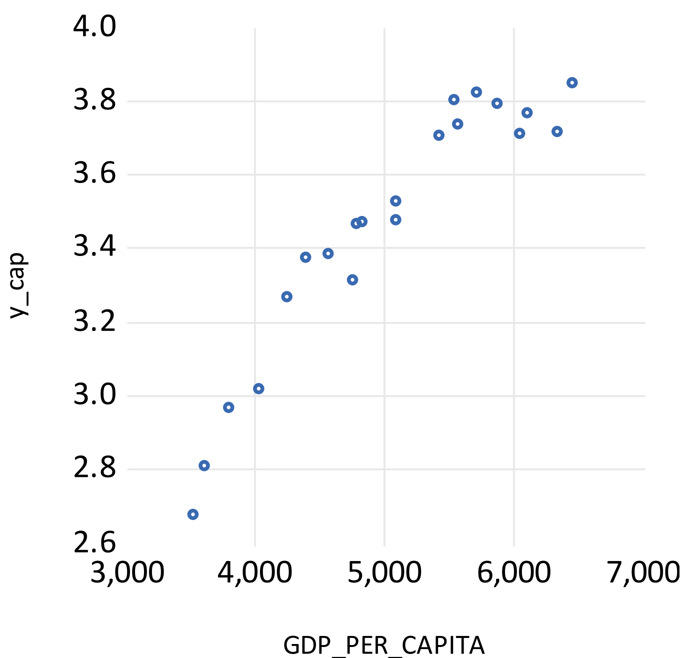
Indonesia



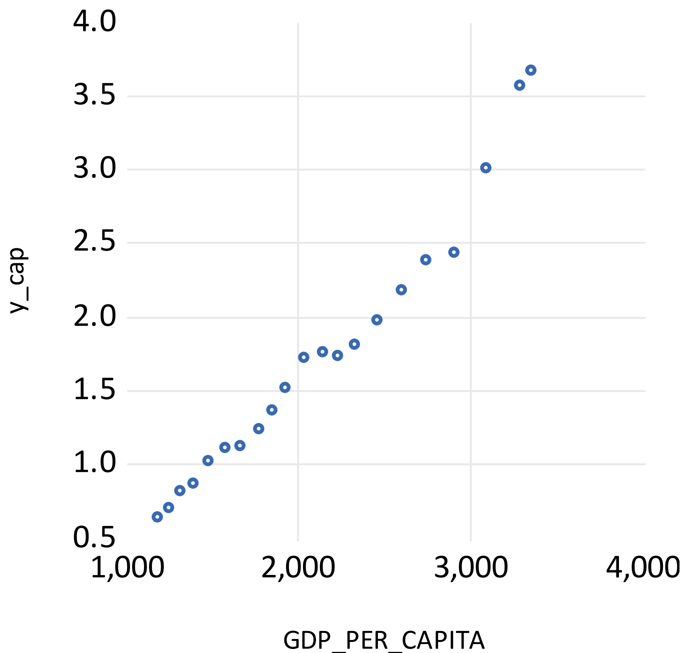
Malaysia



Singapore



Thailand



Vietnam

Discussion

The only results that showed a reverse U curve were from Singapore. That means Singapore is the only country to have reached the environmental Kuznet reverse U curve. Singapore had reached the knowledge economy, or post-industrialized phase. Meanwhile, the other countries had been in the industrial development phase.