

Tiawon, Harin; Itta, Irawan; Miar

Article

Empirical assessment for driving forces of CO₂ emissions: Application of STIRPART model on the leading ASEAN countries

Contemporary Economics

Provided in Cooperation with:

VIZJA University, Warsaw

Suggested Citation: Tiawon, Harin; Itta, Irawan; Miar (2020) : Empirical assessment for driving forces of CO₂ emissions: Application of STIRPART model on the leading ASEAN countries, Contemporary Economics, ISSN 2300-8814, University of Economics and Human Sciences in Warsaw, Warsaw, Vol. 14, Iss. 4, pp. 453-465,
<https://doi.org/10.5709/ce.1897-9254.418>

This Version is available at:

<https://hdl.handle.net/10419/297541>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>

Empirical Assessment for Driving Forces of CO₂ Emissions: Application of STIRPART Model on the Leading ASEAN Countries

Harin Tiawon, Irawan, and Miar

ABSTRACT

The aim of this empirical research study is to investigate the effect of different driving forces of the CO₂ emission for a set of leading ASEAN countries. The sample for this purpose included leading ASEAN countries; Indonesia, Thailand, Malaysia, Singapore, the Philippines and Myanmar due to the availability of the data from year 1992 to 2016. The study used panel data modelling techniques, such as fixed effect regression estimation, random effect regression estimation, as well as the pooled ordinary least square method of estimation. The dependent variable of the present study was CO₂ emissions while the independent variables were Total Population, GDP per capita, Urban Population, Environmental tax, Environmental patent count and CO₂ intensity. The study used a total number of three models for estimation purpose. Model 1 validated fixed effect estimation after conforming the significant value of Hausman test. Model 2 validated random effect estimation after conforming from LM test while pooled OLS was applied in case of Model 3. The findings of the study suggested that GDP as a proxy of affluence and environmental patent count as a proxy of technology are the important driving factors of CO₂ emissions in the ASEAN region. The findings of the current study are generalizable on the other countries of the same region and are affective for the policy makers to enlighten their ideas for making affective policies at national and international level for controlling the CO₂ emissions. The future researchers are advised to include more countries in the panel to strengthen the generalizability of the data as well as extent the STIRPART model as per the requirements of their studies.

KEY WORDS: CO₂ emissions, STIRPART model, panel data modelling, pooled OLS.

JEL Classification: Q50, Q56

Universitas Palangka Raya

1. Introduction and Background

Operative application for the regulations relating to environment and the use of eco-friendly technologies are the major compounds for modifying the trends of global warming and restructuring the strategies for the reduction of carbon in a region (Huisingsh et al., 2015). Though, such aspects are not undeviating amongst countries in any region of the world but their controlling technique for the reduction of carbon is very lim-

ited (Hashmi & Alam, 2019). They considered STIRPAT model as the popular model for empirically analyzing the factors that drive any effect on environmental aspects. The STIRPAT model considers the driving factors like the population factor, the affluence factors and the factors relating to technology and their effect is analyzed on CO₂ emissions using ordinary least square method. A lot of development was done in the past to decompose the STIRPAT model by including different factors in affluence and technology side. (Hashmi & Alam, 2019) argued that another factor like regulation can also affect the CO₂ emissions. So, they decomposed the STIRPAT model into STIRPART model by including the compo-

Correspondence concerning this article should be addressed to: **Harin Tiawon**, Universitas Palangka Raya, Kota Palangka Raya, Kalimantan Tengah 74874, Indonesia,
E-mail: harintiawon@gmail.com

ment of regulation as another factor that may affect carbon emissions. The present study is meant to investigate the empirical effect of driving forces for CO₂ emission on leading ASEAN countries. For this purpose, six leading countries (Indonesia, Thailand, Malaysia, Singapore, the Philippines and Myanmar) from the ASEAN group were finalized on basis of availability of complete set of data from the year 1992 to 2016 using extended STIRPART model with the help of panel data estimation of fixed effect, random effect and pooled ordinary least square.

The present empirical research study is meant to explore the research questions as follows:

RQ 1: What are driving factors of CO₂ emissions in the leading ASEAN countries and up to what level these factors are affecting CO₂ emissions in these countries?

RQ2: Is the STIRPART model applicable in case of ASEAN countries?

RQ3: What are the policy implications of the current empirical research study?

The policy makers, by considering the conclusion and findings of the study, can update the knowledge of the countries in the ASEAN region regarding CO₂ emissions and their controlling factors effects. They can notify about the important factor that may weaker the CO₂ emissions level and also that may increase the level of CO₂ emissions in this region. By using the suggestions by policy makers, the Government of the relevant countries in ASEAN region can implement some important rules to control the level of CO₂ emissions

2. Literature Review

There is an extensive set of findings available in the past that uses the STIRPAT model to analyze the effect on carbon emissions for different regions in the world specially in case of china. The researcher tried to analyze past ten years literature to conclude the possible effect of different factors that drives effects on CO₂ emissions.

A past study by Liddle and Lung (2010) used the framework of the STIRPAT model. They found that there is different impact of age-specific population groups on carbon emission. They also concluded that the level and size of urbanization in the developed countries positively and significantly affect the carbon emission. Poumanyvong and Kaneko (2010) also used the framework of the STIRPAT model on 99

countries by utilizing the balance dataset in panel form for the year 1975 to 2005. They concluded that the urbanization level can negatively affect carbon emission in the groups of low income while the same can positively affect the groups of middle income. Another empirical research study was conducted by Siiton et al. (2010), studied the relationship between consumption of energy through primary sources and through secondary sources. They suggested that a well-defined system by an industry can control the carbon emission. Martinez-Zarzoso and Maruotti (2011) conducted a research study for investigating the effect of urbanization level on CO₂ emissions by taking the sample of developed countries from the year 1975 up till 2003 data. They concluded that for different groups, the impact of urbanization differs significantly. A similar study conducted on OECD group of countries using the STIRPAT model by Liddle (2011) found that younger and older groups of population have a positive and significant relationship with carbon emission while the middle aged group of population had a negatively significant relationship with carbon emissions. Behera and Vishnu (2011) conducted an empirical study using STIRPAT framework model on India for the period of study 1960 to 2007 found that a statistically negative and significant relationship was found between urbanization level and carbon emissions, subsequently the result was same for GDP per capita, populations, industrial as well as for service sector. A study led on 12 countries from the region of middle-eastern for the year 1990 to 2009 by Al-mulali (2012) considered GDP per capita as an important factor determining the level of carbon emissions in this region. Wang et al. (2012), conducted a similar investigation using STIRPAT model and revealed that urbanization level is the main factor that determine the carbon emission in China's financial hub; Beijing. Another study conducted on Iran for the data period of 1973 to 2008 by Abouie-Mehrizi et al. (2012), revealed that the forces like CO₂ intensity, GDP growth rate, urbanization and the level of population increases significantly the level of CO₂ emissions in this region. Zhang and Nian (2013) conducted a similar study by applying STIRPAT framework on china region by using the data from 1995 to 2010 period revealed that the population growth has a statistically negative and significant relation with carbon emissions. Another

Table 1. Variable Description and Literature Sources

	Title of Variable	Explanation	Data Source	Literature Source
D.V	CO ₂ Emissions	Total Carbon dioxide Emissions	WDI	(Hashmi & Alam, 2019), (Akram et al., 2019), (Dong et al., 2019), (Chontanawat, 2019), (Mohmmed et al., 2019)
P	Population (POP)	Total Population size	WDI	(Hashmi & Alam, 2019), (Akram et al., 2019), (Dong et al., 2019), (Chontanawat, 2019), (Mohmmed et al., 2019)
	GDP	GDP per capita	WDI	(Hashmi & Alam, 2019), (Akram et al., 2019), (Dong et al., 2019), (Chontanawat, 2019)
A	Urban Population	Total Urban Population size	WDI	(Lin et al., 2017), (Martínez-Zarzoso & Maruotti, 2011), (Poumanyvong & Kaneko, 2010), (Liddle & Lung, 2010)
R	Environmental Tax (REG)	Environmental tax revenue per capita	OECD Statistics	(Hashmi & Alam, 2019)
	Environmental Patent Count (Tech1)	Number of applications filed for environmental patents	OECD Statistics	(Hashmi & Alam, 2019)
T	CO ₂ Intensity (Tech2)		WDI	(Akram et al., 2019), (Dong et al., 2019), (Mohmmed et al., 2019)

similar study conducted by Zhao et al. (2013), using STIRPAT model on the power sector of china using the data from 1980-2010, revealed that added value of power industry had a statistically positive and significant influence on carbon emission. In addition, a study conducted by Wang et al. (2013), used an extended version of STIRPAT modelling framework on china by taking the 1980 to 2010 found that GDP per capita as well as urbanization level as a proxy of affluence are the important determining factors of CO₂ emissions. Lin et al. (2017), conducted a similar study found that the only factors influencing carbon emissions are population and urbanization using the STIRPAT model framework. Ren et al. (2018), found

that the environmental regulations do not have any significant impact of CO₂ emissions.

The researcher analyzed the past literature and concluded that there is a need to decompose the STIRPAT model which was used in the past extensively to study this domain of research. Hashmi and Alam (2019) decomposed the STIRPAT framework by including the environmental regulation as another component and tested another framework as STIRPART model on OECD countries. The researcher was motivated to use this model on the ASEAN region as no study exploring the impact on carbon emission in this region could be found.

3. Variable Description

Table 1 denotes the output and input variables of the study. The CO₂ emission was used as output variable while considering STIRPART model as suggested by Hashmi and Alam (2019) the input variable like population size as a proxy for population (P), GDP per capita income and urban population size as a proxy for affluence (A), environmental tax revenue per capita as a proxy for regulation (R), finally the environmental patent count and CO₂ intensity as proxy for technology (T). The detail of each variable as well as their explanation, data source and literature are included in Table 1.

4. Sample and Methodology

The present study is meant to investigate the empirical effect of driving forces for CO₂ emission on leading ASEAN countries. For this purpose, six leading countries (Indonesia, Thailand, Malaysia, Singapore, the Philippines and Myanmar) from the ASEAN group were finalized on basis of availability of complete set of data from the year 1992 to 2016. The dependent variable of the present study was CO₂ emissions while the independent variables were Total Population, GDP per capita, Urban Population, Environmental tax, Environmental patent count and CO₂ intensity (Hussain et al., 2020). The present research uses panel data modelling for analyzing the impact of driving forces for CO₂ using a long form of panel. According to Cameron and Trivedi (2010), "a panel data is considered to be long panel when the number of time period is large as compared to number of countries". The panel data denotes the combination of cross sectional units with a series of time (Baltagi, 2008). The study uses the panel data modelling techniques like fixed effect regression estimation, random effect regression estimation as well as the pooled ordinary least square method of estimation. The decision to choose between fixed effect and random effect is based on a test named Hausman specification test (Hausman, 1978) while the decision of selecting an appropriate model between random effect and pooled OLS is LM test (Breusch & Pagan, 1980). The previous studies used the STIRPART model to analyze the impact of driving forces on CO₂ emissions while the

current study used its extended form STIRPART model as developed by Hashmi and Alam (2019) and denotes the stochastic impacts by regression on population, affluence, regulation and technology. As a part of STIRPART model "P" states the total Population, "A" states affluence which is denoted by GDP per capita as well as urban population, "R" states Environmental regulations and "T" states technology which is denoted by Environmental patent count and CO₂ intensity. The researchers used natural log of each variable of the study in order to avoid heterogeneity issue in the sample data of the study that also ensures that variables having co-integration association should be affected at all as per the directions by Chen et al. (2019).

The panel econometric modelling in line with direction of Baltagi (2008) and relevant equation with required variables are given below;

4.1. Model 1

The first equation is based on fixed effect modelling.

$$(CO^2)_{it} = (\beta_0 + \mu_i) + \beta_1(POP)_{it} + \beta_2(GDP)_{it} + \beta_3(REG)_{it} + \beta_4(Tech1)_{it} + \nu_{it} \quad (1)$$

The second equation is based on random effect modelling.

$$(CO^2)_{it} = \beta_0 + \beta_1(POP)_{it} + \beta_2(GDP)_{it} + \beta_3(REG)_{it} + \beta_4(Tech1)_{it} + (\mu_{it} + \nu_{it}) \quad (2)$$

The third equation is based on Pooled OLS modeling.

$$(CO^2)_{it} = \beta_0 + \beta_1(POP)_{it} + \beta_2(GDP)_{it} + \beta_3(REG)_{it} + \beta_4(Tech1)_{it} + \varepsilon_{it} \quad (3)$$

4.2. Model 2

The fourth equation is based on fixed effect modeling.

$$(CO^2)_{it} = (\beta_0 + \mu_i) + \beta_1(POP)_{it} + \beta_2(URB)_{it} + \beta_3(REG)_{it} + \beta_4(Tech2)_{it} + \nu_{it} \quad (4)$$

The fifth equation is based on random effect modeling

$$(CO^2)_{it} = \beta_0 + \beta_1(POP)_{it} + \beta_2(URB)_{it} + \beta_3(REG)_{it} + \beta_4(Tech2)_{it} + (\mu_{it} + \nu_{it}) \quad (5)$$

The sixth equation is based on Pooled OLS modeling.

$$(CO^2)_{it} = \beta_0 + \beta_1(POP)_{it} + \beta_2(URB)_{it} + \beta_3(REG)_{it} + \beta_4(Tech2)_{it} + \varepsilon_{it} \quad (6)$$

4.3. Model 3

Seventh equation is based on Pooled OLS using all independent variables.

$$(CO^2)_{it} = \beta_0 + \beta_1(POP)_{it} + \beta_2(GDP)_{it} + \beta_3(URB)_{it} + \beta_4(REG)_{it} + \beta_5(Tech1)_{it} + \beta_6(Tech2)_{it} \varepsilon_{it} \quad (7)$$

5. Results and Discussion

The presented study was analyzed on the basis on different statistical techniques like panel descriptive statistics, Pearson correlation and regression analysis using panel data estimation. Table 2 denotes the panel descriptive statistics measures of the present study using overall observation of 150 and time period as 25 years from 1992 to 2016 with six leading ASEAN countries (like Indonesia, Thailand, Malaysia, Singapore, the Philippines and Myanmar). The measures estimated by way of panel descriptive are mean, standard deviations, minimum and maximum values. The detailed measures are described in Table 2.

Table 2 indicates that CO₂ emissions having the overall average value trend of .64 with overall standard deviation as 1.35 which slightly double from its mean value.

Table 2. Panel Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
CO	Overall	.64	1.35	-2.30	2.89
	Between		1.44	-1.65	2.35
	Within		.27	-.25	1.40
POP	Overall	17.54	1.23	14.93	19.36
	Between		1.34	15.24	19.19
	Within		.13	17.23	17.82
GDP	Overall	9.10	1.13	6.57	11.31
	Between		1.18	7.44	10.91
	Within		.33	8.23	10.12
URB	Overall	16.80	.98	14.93	18.72
	Between		1.04	15.24	18.33
	Within		.21	16.30	17.19

Table 2. Panel Descriptive Statistics (Continued)

Variable	Observations	Mean	Std. Dev.	Min	Max
REG	Overall	-3.83	3.45	-9.18	.19
	Between		3.09	-8.96	-.99
	Within		1.98	-7.99	-.62
Tech1	Overall	2.18	.69	-.40	3.77
	Between		.32	1.73	2.58
	Within		.63	-.25	3.58
Tech2	Overall	.59	.50	-.92	1.35
	Between		.50	-.39	1.01
	Within		.21	-.22	1.21

Note: Total Observations ($n \times T = N$) = 150, Number of countries (n) = 6, Time Period (T) = 25 years

CO = CO₂ emissions, POP = Total Population, GDP = GDP per capita, URB = Urban Population

REG = Environmental Tax as proxy of regulation, Tech 1 = Environmental Patents counts, Tech 2 = CO₂ intensity

The between effect shows that the standard deviation from country to country deviates 1.44 from its mean which is also more than the double from its overall average value while the within effect shows that the trend of standard deviation from year to year deviated from its mean trend by .27 which is approximately less than the half of its overall mean trend. The first independent variable total population size denotes an overall average value trend of 17.54 with overall standard deviation as 1.23 overall, 1.34 country to country deviation and .13 as year to year deviation from its overall average trend. The GDP per capita which a proxy for affluence shows an average value trend as 9.10 with overall standard deviation as 1.13, 1.18 value deviates from overall mean trend as country to country deviation and .33 deviates year to year from its overall mean trend. Urban population rate as another proxy for affluence shows as average value trend of 16.80 with overall deviation as .98, country to

country deviation as 1.04 and year to year variation as .21 from its overall mean trend value. Environmental tax revenue as proxy of regulation denotes an average trend value as -3.83. It is only negative trend value on average basis with an overall standard deviation as 3.45, country to country deviation as 3.09 and year to year variation as 1.98 from its overall average trend value. Environmental patents count as a first proxy of technology shows an average value of 2.18 with overall standard deviation as .69, country to country deviation as .32 and year to year deviation as .63 from its overall average mean value. Finally, the second proxy for technology with the name of CO₂ intensity shows an overall mean trend of .59 with overall standard deviation as .50, country to country deviation as .50 and year to year deviation as .21 from its overall mean value trend.

Table 3 designates the association between the variables of the study. The table shows that there is a nega-

Table 3. Pearson Correlation

Variables	CO	POP	GDP	URB	REG	TECH1	TECH2
CO	1.000						
POP	-0.5623*	1.000					
		0.0000					
GDP	0.9452*	-0.6532*	1.000				
		0.0000	0.0000				
URB	-0.3429*	0.9501*	-0.4336*	1.000			
		0.0000	0.0000	0.0000			
REG	-0.0783	-0.0266	-0.0807	-0.0749	1.000		
		0.3411	0.7468	0.3264	0.3626		
TECH1	-0.3831*	0.2856*	-0.3228*	0.1881*	0.0222	1.000	
		0.0000	0.0004	0.0001	0.0212	0.7875	
Tech2	0.8196*	-0.1073	0.6641*	0.0977	-0.0860	-0.2569	1.000
		0.0000	0.1913	0.0000	0.2341	0.2951	0.0015

Note: *Denotes the statistical significance at the level of .05

tive and statistically high significant correlation between population size and CO₂ emissions. On the other hand, GDP per capita has positive and highly statistically significant association with CO₂ emissions. The same factor has a statistically negative and significant relationship with total population size. Urbanization size has negative and statistically highly significant correlation with CO₂ emissions, total population size and GDP per capita. Environmental tax revenue per capita as proxy of regulation as a negative and statistically insignificant association with CO₂ emissions, population size, GDP per capita and urbanization size. Environmental patent count as a first proxy of technology has a negatively significant correlation with CO₂ emission and GDP per capita size

while the same has a positive & significant correlation with population and urbanization size. CO₂ intensity as a second proxy for technology shows a positive and statistically highly significant correlation with CO₂ emissions, GDP per capita and urbanization size while the same has negatively insignificant association with population size and environmental tax revenue per capita.

Table 4 indicates and panel estimation results for fixed effect as well as for random effect for model 1 and model 2 of the current study. The output variable in both models was CO₂ emissions while the input variables in model 1 were Population size, GDP per capita as proxy of affluence, environmental tax revenue per capita as a proxy of regulation and Environmental patent count as

Table 4. Panel Regression Analysis

Variables	Model 1		Model 2	
	F.E	R.E	F.E	R.E
POP	-.1091951 (.2168956)	-.2446103* (.0851322)	-1.356908 * (.136262)	-1.4181* (.1280835)
GDP	.4597469* (.1038274)	.6696949* (.0654315)		
URB			1.448654* (.0853002)	1.47677* (.0825252)
REG	-.0175805 (.0128093)	.0004238 (.0122157)	.0099966* (.004442)	.0098649* (.0044266)
TECH1	-.0961815* (.0300547)	-.1105113* (.032628)		
TECH2			.9147663 (.0386996)	.9147336 (.038544)
CONS	-1.487769 (3.242526)	-.9221251 (1.646194)	-.3998746 (1.304583)	.2006526 (1.250649)
Observation	150	150	150	150
Countries	6	6	6	6
Years	25	25	25	25
R ²				
* Within	0.3673	0.3583	0.9012	0.9011
* Between	0.8841	0.8439	0.8639	0.8763
* Overall	0.8490	0.8206	0.8589	0.8717

Table 4. Panel Regression Analysis (Continued)

Variables	Model 1		Model 2	
	F.E	R.E	F.E	R.E
Prob>F	0.0000		0.0000	
Prob>Chi2		0.0000		0.0000
Statistics				
Hausman Test for Fixed Effect			Model 1	Model 2
Chi ² (4)			68.40	2.67
Probability > Chi ²			0.0000	0.6144
Lagrange Multiplier Test for Random Effect				
Chibar ² (1)			-	856.33
Probability > Chibar ²			-	0.0000

Note: *Denotes the statistical significance at the level of .05

a first proxy of technology. The second model comprises of Population size, Urban population size as a proxy of affluence, environmental tax revenue per capita as a proxy of regulation and CO₂ intensity as second proxy for technology. The Hausman test conforms the validity of fixed effect estimation for model 1 as probability > chi² value of (Hausman, 1978) test is highly significant at .05 level. In case of second model, the test value (Hausman, 1978) is not significant as probability > chi² = 0.6144. It further required to apply LM test (Breusch & Pagan, 1980) to decide between random effect and pooled OLS estimation which finally validates the random effect for second model as the value of this test probability > Chibar² = 0.000 shows a statistically significant value for this purpose.

Using fixed effect estimation for regression purpose in

case of model 1 indicates that a relationship of negative as well as statistically insignificant form was found between total population size and CO₂ emissions. The GDP per capita as first proxy of affluence denotes a positive and statistically significant connection with CO₂ emissions. There is a statistically not significant and negative relationship between CO₂ emissions and environmental tax revenue per capita as a proxy for regulation. Model 1 also states that environmental patent count as a first proxy of technology has statistically negative and significant connection with CO₂ emissions.

Using random effect estimation for regression purpose in case of model 2 indicates that a relationship of negative as well as statistically insignificant form was found between total population size and CO₂ emissions. The total urbanization size as a second proxy of affluence

Table 5. Pooled Regression Analysis

Variable	Model 1	Model 2	Model
POP	.1199617*	-1.233533*	-.0799205
	(.0370523)	(.1054222)	(.1021928)
GDP	1.177353*		.6903407*
	(.0410127)		(.0466541)
URB		.9182592*	-.0726758
		(.1329443)	(.1071446)
REG	.0024804	-.0015244	-.0000976
	(.0100081)	(.0090354)	(.005695)
TECH1	-.1885823*		-.114301*
	(.0527535)		(.0309169)
TECH2		1.706593*	1.126105*
		(.0807175)	(.064065)
CONS	-11.75738*	5.837379*	-3.433843*
	(.9335059)	(.6012663)	(.7371256)
Observation	150	150	150
Countries	06	06	06
Years	25	25	25
R ²	0.9069	0.9248	0.9705
Prob>F	0.0000	0.0000	0.0000

Note: *Denotes the statistical significance at the level of .05

has a statistically positive and highly significant connection with CO₂ emissions. There is a statistically significant and positive relationship between CO₂ emissions and environmental tax revenue per capita as a proxy for regulation. The model 2 also states that there is a non-significant and statistically positive connection between CO₂ intensity as second proxy for technology and CO₂ emissions.

Table 5 indicates pooled ordinary least square estimates for panel data modelling for model one, two and three. Using model one for this purpose states that population and GDP has a statistically positive and highly significant relationship with CO₂ emissions. The environmental patent count has a statistically negative and highly significant relationship with CO₂ emissions. Finally, the model 1 shows that there is a statistically positive but not-significant relationship between environmental tax revenue per capita and CO₂ emissions.

As per the estimates shown in Table 5 for model two for pooled OLS estimates designates that there is statistically negative and highly significant relationship between population size and CO₂ emissions. Urbanization size indicates a statistically positive and highly significant relationship with CO₂ emissions. There is a statistically negative but not-significant relationship between environmental tax revenue per capita and CO₂ emissions. CO₂ intensity has statistically positive and highly significant relationship with CO₂ emissions.

The third model as shown in Table 5 for pooled OLS indicates that statistically negative and non-significant relationship with CO₂ emissions. GDP per capita as a first proxy of affluence shows a statistically positive and highly significant connection with CO₂ emissions. Urbanization size as a second proxy of affluence shows a statistically negative and insignificant relationship with CO₂ emissions. There is a statistically negative but not-significant relationship between environmental tax revenue per capita and CO₂ emissions. The environmental patent count has a statistically negative and highly significant relationship with CO₂ emissions. Finally, the CO₂ intensity has statistically positive and highly significant relationship with CO₂ emissions.

6. Conclusion and Recommendations

The aim of the study was to explore empirically the effect of driving forces of CO₂ emission for leading

ASEAN countries (Indonesia, Thailand, Malaysia, Singapore, the Philippines and Myanmar) for the period 1992 to 2016 using extended STIRPART model as developed by Hashmi and Alam (2019). The study used the panel data modelling techniques like fixed effect regression estimation, random effect regression estimation as well as the pooled ordinary least square method of estimation. The decision to choose between fixed effect and random effect is based on a test named Hausman specification test (Hausman, 1978) while the decision of selecting an appropriate model between random effect and pooled OLS is LM test (Breusch & Pagan, 1980). The dependent variable of the present study was CO₂ emissions while the independent variables were Total Population, GDP per capita, Urban Population, Environmental tax, Environmental patent count and CO₂ intensity. The study used a total number of three models for estimation purpose. Model 1 validated fixed effect estimation after conforming the significant value of Hausman test. Model 2 validated random effect estimation after conforming from LM test while pooled OLS was applied in case of model 3.

The fixed effect regression estimation using first model shows two important factors as driving forces of CO₂ emissions; GDP per capita as a proxy of affluence and environmental patent count as a proxy of technology. The findings suggest that GDP per capita can increase the level of CO₂ emissions while the environmental patent count can decrease it. The random effect estimation using second model shows three important factors as driving force of CO₂ emissions; the level of population size can decrease the CO₂ emissions while the level of urbanization size and environmental tax revenue per capita can increase it. The pooled ordinary least square estimation for panel data using third model indicates three important driving forces of CO₂ emissions; GDP per capita and CO₂ intensity can increase it while environmental patent count can decrease it. The findings of the current study are generalizable on the other countries of the same region and are affective for the policy makers to enlighten their ideas for making affective policies at national and international level for controlling the CO₂ emissions. The future researchers are advised to include more countries in the panel to strengthen the generalizability of the data as well as extent the STIRPART model as per the requirements of their studies.

References

Abouie-Mehrizi, M., Atashi, S. M., & Elahi, M. (2012). The effect of variables population growth, urbanization and economic growth on CO2 Emissions in Iran. *African Journal of Business Management*, 6(28), 8414-8419. <https://doi.org/10.5897/AJBM11.2020>

Akram, Z., Engo, J., Akram, U., & Zafar, M. W. (2019). Identification and analysis of driving factors of CO2 emissions from economic growth in Pakistan. *Environmental Science and Pollution Research*, 6(19), 19481-19489. <https://doi.org/10.1007/s11356-019-05281-0>

Al-mulali, U. (2012). Factors affecting CO2 emission in the Middle East: A panel data analysis. *Energy*, 44(1), 564-569. <https://doi.org/10.1016/j.energy.2012.05.045>

Baltagi, B. (2008). *Econometric analysis of panel data*. John Wiley & Sons Ltd, Chichester.

Behera, B., & Vishnu, R. (2011). Analysing the impact of anthropogenic factors on the environment in India. *Environment and Natural Resources Research*, 1(1), 117-129. <https://doi.org/10.5539/enrr.v1n1p11>

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The review of economic studies*, 47(1), 239-253. <https://doi.org/10.2307/2297111>

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconomics using Stata, revised edition*. StataCorp LP.

Chen, Y., Zhao, J., Lai, Z., Wang, Z., & Xia, H. (2019). Exploring the effects of economic growth, and renewable and non-renewable energy consumption on China's CO2 emissions: Evidence from a regional panel analysis. *Renewable energy*, 140, 341-353. <https://doi.org/10.1016/j.renene.2019.03.058>

Chontanawat, J. (2019). Driving forces of energy-related CO2 emissions based on expanded IPAT decomposition analysis: evidence from ASEAN and four selected countries. *Energies*, 12(4), 764. <https://doi.org/10.3390/en12040764>

Dong, K., Dong, X., & Dong, C. (2019). Determinants of the global and regional CO2 emissions: What causes what and where?. *Applied Economics*, 51(46), 5031-5044. <https://doi.org/10.1080/00036846.2019.1606410>

Hashmi, R., & Alam, K. (2019). Dynamic relationship among environmental regulation, innovation, CO2 emissions, population, and economic growth in OECD countries: A panel investigation. *Journal of cleaner production*, 231, 1100-1109. <https://doi.org/10.1016/j.jclepro.2019.05.325>

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*, 46(6), 1251-1271. <https://doi.org/10.2307/1913827>.

Huisingsh, D., Zhang, Z., Moore, J. C., Qiao, Q., & Li, Q. (2015). Recent advances in carbon emissions reduction: policies, technologies, monitoring, assessment and modeling. *Journal of Cleaner Production*, 103, 1-12. <https://doi.org/10.1016/j.jclepro.2015.04.098>

Hussain, H.I.; Slusarczyk, B.; Kamarudin, F.; Thaker, H.M.T.; Szczepańska-Woszczyna, K. (2020). An investigation of an adaptive neuro-fuzzy inference system to predict the relationship among energy intensity, globalization, and financial development in major ASEAN economies. *Energies*, 13(4), 850. <https://doi.org/10.3390/en13040850>

Liddle, B. (2011). Consumption-driven environmental impact and age structure change in OECD countries: A cointegration-STIRPAT analysis. *Demographic Research*, 24(30), 749-770. <https://doi.org/10.4054/DemRes.2011.24.30>

Liddle, B., & Lung, S. (2010). Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. *Population and Environment*, 31(5), 317-343. <https://doi.org/10.1007/s11111-010-0101-5>

Lin, S., Wang, S., Marinova, D., Zhao, D., & Hong, J. (2017). Impacts of urbanization and real economic development on CO2 emissions in non-high income countries: Empirical research based on the extended STIRPAT model. *Journal of Cleaner Production*, 166, 952-966. <https://doi.org/10.1016/j.jclepro.2017.08.107>

Martínez-Zarzoso, I., & Maruotti, A. (2011). The impact of urbanization on CO2 emissions: evidence from developing countries. *Ecological Economics*, 70(7), 1344-1353. <https://doi.org/10.1016/j.ecolecon.2011.02.009>

Mohammed, A., Li, Z., Arowolo, A. O., Su, H., Deng, X., Najmuddin, O., & Zhang, Y. (2019). Driving factors of CO2 emissions and nexus with economic growth, development and human health in the Top Ten emitting countries. *Resources, Conservation and Recycling*, 148, 157-169. <https://doi.org/10.1016/j.resconrec.2019.03.048>

Poumanyvong, P., & Kaneko, S. (2010). Does urbanization lead to less energy use and lower CO2 emissions? A cross-country analysis. *Ecological Economics*, 70(2), 434-444. <https://doi.org/10.1016/j.ecolecon.2010.09.029>

Ren, S., Li, X., Yuan, B., Li, D., & Chen, X. (2018). The effects of three types of environmental regulation on eco-efficiency: A cross-region analysis in China. *Journal of Cleaner Production*, 173, 245-255. <https://doi.org/10.1016/j.jclepro.2016.08.113>

Suutonen, S., Tuomaala, M., & Ahtila, P. (2010). Variables affecting energy efficiency and CO2 emissions in the steel industry. *Energy Policy*, 38(5), 2477-2485. <https://doi.org/10.1016/j.enpol.2009.12.042>

Wang, P., Wu, W., Zhu, B., & Wei, Y. (2013). Examining the impact factors of energy-related CO2 emissions using the STIRPAT model in Guangdong Province, China. *Applied Energy*, 106, 65-71. <https://doi.org/10.1016/j.apenergy.2013.01.036>

Wang, Z., Yin, F., Zhang, Y., & Zhang, X. (2012). An empirical research on the influencing factors of regional CO2 emissions: evidence from Beijing city, China. *Applied Energy*, 100, 277-284. <https://doi.org/10.1016/j.apenergy.2012.05.038>

Zhang, C., & Nian, J. (2013). Panel estimation for transport sector CO2 emissions and its affecting factors: A regional analysis in China. *Energy Policy*, 63, 918-926. <https://doi.org/10.1016/j.enpol.2013.07.142>

Zhao, X., Ma, Q., & Yang, R. (2013). Factors influencing CO2 emissions in China's power industry: Co-integration analysis. *Energy Policy*, 57, 89-98. <https://doi.org/10.1016/j.enpol.2012.11.037>