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A Heterogeneous Relationships between Urbanization, Energy Consumption, Economic Growth on Environmental Degradation: Panel Study of Malaysia and Selected ASEAN+3 Countries

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Abstract

This paper aims to analyse the association among urbanization, economic growth, energy consumption and environmental degradation based on estimates in the context of second-generation techniques. A Malaysian economy and selected ASEAN+3 were estimated using Pesaran (1999) Pooled Mean Grouped (PMG) and a panel dynamic common correlated effects (DCCE) technique pioneered by Pesaran and Chudik (2015) that measures a model of error correction (EC) which is resilient to cross-sectional dependency and co-integration. Evidence from the findings shows that the main actors or driving forces leading to a high level of environmental degradation are urbanization, economic growth, and energy consumption for Malaysia and selected ASEAN+3 nations. Also found was the existence of one-way causality running from economic growth to environmental degradation. It also indicates another one-way causality running from square of economic growth to environmental degradation. Whereas, a bidirectional causality is found between urbanization and environmental degradation, as well as a feedback causality among energy consumption and environmental degradation.

Keywords: Urbanization, environmental degradation, Energy consumption, Economic growth, Heterogeneous panel, Malaysia and Selected ASEAN+3

1 Introduction

The most challenging phenomenon facing humanity in the 21st century is global climate change, which is increasingly destroying ecosystems. Over the past few decades, global consensus has shown that carbon dioxide (CO_2) emissions are one of the primary sources of global warming due to rising energy consumption (25) and (35). Since after the industrial age, the rate of growth in CO_2 emissions has been 2.0 ppm per year and in 2017, this crossed the net figure of 410 ppm. This record will hit a current pace of up to 450 ppm within a few short decades (1). Achieving a high rate of economic growth through industrial production and technological progress is a primary concern for newly developed countries, which are reciprocally enhancing international trade, urban population and financial development. The recently industrialized nations (NIC) contribute 42% of total global CO_2 emissions as a result of increased economic growth (40) Stable economic growth with that of the least environmental damage from the climate is a severe challenge to the modern world. Academics and decision-makers are curious to find out which determinants are responsible for environmental damage (43). Besides, many contributing factors like energy usage, power usage, economic growth, trade openness, urban growth and transportation are responsible for environmental degradation (20"16"13). Energy usage in the Association of Southeast Asian Nations (ASEAN) economies has significantly increased as a result of steady growth in urbanism and industrial development. ASEAN. The Center for Energy (ACE) forecast a rise in the energy usage of ASEAN nations by 4.4% in 2030, which is higher than the global average demand for energy growth of 1.4%.

Nonetheless, a comprehensive greenhouse gas emission study continues to be restricted to ASEAN plus Three (ASEAN+3) member states. Numerous researches cantered on estimating the

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deterioration of the environment, energy usage and economic growth in ASEAN economies. (23), and (17) analyzed the interconnections between CO_2 pollution and powerful influences in ASEAN nations, whereas (6) based on only ASEAN 8. (36) and (10) evaluated the impact of ASEAN-5 nations on foreign direct investment, energy consumption and CO_2 pollution. This research, therefore, aims to bridge the gap in the research by examining the role of global warming among ASEAN+3 nations, especially CO_2 emissions. The slow growth to Japan has indeed been consumed by the rise of Korea, China, and ASEA (30), which has expanded the percentage of ASEAN+3 in the world GDP.

The contribution of ASEAN+3 nations in world GDP exceeded the United States of America (US) by 2.05 percent and the members of the European Union (EU) by 1.49 percent in 2012. However, the ASEAN+3 rate of growth GDP is projected to rise by 27% by 2018. The ASEAN plus 3 (APT) was institutionalized at the Third ASEAN+3 Conference in Manila of 1999 (Association of Southeast Asian Party, 2014) in a joint declaration on East Asian Cooperation. The APT Work Plan for Cooperation 2013-2017 was subsequently adopted at the 14th meeting of APT Foreign Ministers on 30 June 2013. One outline of the APT Work Plans is to reinforce environmental and sustainable development cooperation and address climate change impacts. The rest of the current paper will be structured as follows. The next chapter includes a review of past studies, followed by the paragraph on methods. The following section discusses the experimental findings, and in the last chapter, the article concludes with the conclusion.

2 Literature Review

The The study of carbon dioxide emission drivers is not a new research subject. Since the age of industrial development, global economies have been reorganized from organic to inorganic, pushing the consumption of fossil fuels for industrial production in order to meet population demands (28). Such structural change raises the use of fossil fuel resulting in climate change and drastic climate change (1). Environmental damage and climate change are currently a significant concern for policymakers to remedy a healthier environment by shocking CO_2 emissions. It is time to examine and build the conceptual framework by government measures to prevent environmental damage. A large number of studies examined environmental pollution control performers on various dimensions, such as population impact on CO_2.

The linkage between energy consumption, economic growth, and carbon emissions is a topic that has become the order of recent times for quite a period in the literature on energy and climate economics. This connection can be classified into four factions by several quantitative results; although the first cohort of results suggests that energy usage induces growth and a one-way linkage exists, the second group asserts that energy usage improves as a result of economic growth, the third group claims that the causality connection is bidirectional. There is no causal link between energy usage and economic growth, as per the conclusions of the last factions. Nevertheless, with the Environmental Kuznets Curve (EKC) theory in research, the association between economic development and greenhouse gas emissions is established. Under this theory, the pollution rates are very high during the first phase of the country's development, but after a certain developmental level, the emissions are decreased and lower due to further economic growth. Studies focus on the linkage among energy consumption – economic growth and carbon-economic growth when analysing the empirical study (3)

Given that the sincerity of climate change and its negative environmental impact has been given more considerable attention to the global community, several studies have focused primarily on the relationship among energy usage, in specific the use of fossil fuels and CO_2 pollution (38). Looking at the researches on power-growth-environment (PGE), Soytaş et al. find Granger non-causality for the US economy among economic growth and greenhouse gases. (2) notes that both power use and emission growth are driven by economic development in France. Although (45), (11) and (44) find that economic growth drives carbon emissions in China, Jalil and Mahmud (21) accept proof that the EKC hypothesis is correct. While (18) promotes bi-directional connections, neither Soytas and (38) and (15) consider causal links between Turkey's variables. For the board containing six Central American nations, the EKC theory was endorsed by (15). (28) for the USA, (27) for India (37) highlighted the results endorsing a strong association among economic growth and energy usage. When the findings are regarded in research, it is hard to say that there is agreement on the course of the energy-economic growth-environment partnership. It can be said, though, that energy usage massively increases economic growth and production of coal.

2.1 Econometrics Estimation

The study used the annual data for the period 1970-2018 for Malaysia and Identified ASEAN+3 nations. State choice was based on a few criteria; covering developing and emerging economies, recognizing economic proximity and rate of integration, and eventually representing Annex B states and non-Annex B nations in the Kyoto Protocol. The study's variables included urbanization (population growth), economic growth (GDP percentage growth), energy consumption (EC, kg of oil equivalent per capita), GDP square, and environmental degradation (CO_2 emission per capita metric ton). This study involves parameters in logarithmic terms. The data is collected from the Development Indicators of the World Bank (2019). STATA 15 and EViews 10 program for analysis.

2.2 Testing slope homogeneity

The second problem in a panel statistical analysis is whether or not the parameters of the slope are heterogeneous. A strong null hypothesis is the causality of the entire panel from one parameter to another by applying the mutual constraint (14). Moreover, due to the specific characteristics of the region, the parameter homogeneity assumption is not capable of capturing heterogeneity (8).

A standard F-test is the most common way of testing the null hypothesis of the slope homogeneity: $H_0 : \beta_i = \beta\ upon\ all\ i$ in contrast to the hypothesis of heterogeneity: $\beta_i \neq \beta_j$ Representing a fraction of non-zero pair-wise slope for $i \neq j$. The validity of F test can be seen in a scenario where the cross-section dimension (N) is small relatively, and the panel's time dimension (T) is enormous; the explanatory variables are strictly exogenous, and the variances of errors are homoscedastic. (41) developed the test of slope homogeneity on the dispersion of individual slope estimates from an appropriate pooled estimator by relaxing the homoscedasticity assumption in the F test. Moreover, both the F test and the Swamy test require models of panel data where N is small relative to T (41).

2.3 Testing the cross-sectional dependency

Cross-section dependency must be tested once proceeding for further steps. Otherwise, outcomes may be bias and contradictory (7). Therefore, the presence of cross-section dependence in the series and the equation of cointegration should be checked before further studies. The presence of cross-sectional dependence between countries is tested through the (7) LM test when the time dimension exceeds the cross-sectional dimension. (8) has improved this test if the time dimension is smaller than the cross-section dimension, and the time dimension is larger than the cross-section continuum. If the average group is zero, this test is biased, but the average individual is distinct from zero. By applying the variance and the mean to the test statistics, Pesaran (7) modified this variation. Therefore, the bias-adjusted LM test (LM_{adj}) is named. The adjusted statistical form of the LM_{adj} test is as follows:

$$LM_{adj} = \left(\frac{2}{L(L-1)}\right)^{\frac{1}{2}} \sum_{i=1}^{L-1} \sum_{j=i+1}^{L} \left(\hat{\rho}_{ij}^2 \frac{(R-T-1)\hat{\rho}_{ij} - \hat{\pi}_{\gamma ij}}{\vartheta_{\gamma ij}}\right) \sim L(0,1) \quad (1)$$

where $\hat{\pi}_{\gamma ij}$ stands as the average, $\vartheta_{\gamma ij}$ Stands as the variance. The test of the statistics to be generated here reveals a typical normal distribution as asymptotic (8). The null hypothesis of the LM_{adj} is the absence of cross-sectional dependence.

2.4 Unit root Test (CADF)

In this analysis, because cross-section dependence between the countries in the panel among the variables used was established, one of the second-generation unit root tests developed by (7) was used to evaluate stationary of the variables. Unit root testing can be carried out in the series forming the panel in each cross-section unit through CADF. So, it is also possible to estimate the sequence stationary one by one for the overall panel and each cross-section. CADF test assumes that each country is affected differently from time effects and that in T > N and N > T circumstances, spatial autocorrelation is used. By comparing the statistical values of this test with the CADF critical table values of Pesaran, stationary for each country is tested. If the value of CADF's critical table is higher than the value of CADF's statistics, the null hypothesis is rejected and only that country's series is found to be stationary. The statistics of the CADF test are estimated as follows:

$$Y_{i,t} = (1-\varphi_i)\alpha_i + \varphi_i y_{i,t-1} + \pi_{i,t} i = 1,2,3, \dots\dots, N \; and \; t = 1,2,3, \dots\dots, T \quad (2)$$

$$\pi_{it} = \gamma_i f_t + \mu_{it} \quad (3)$$

Here f_t displays unobservable prevalent influence of each country, μ_{it} Reveals the error of individual-specific. Equation (2) and (3), as well as unit root hypothesis, can be given as follows:

$$\Delta y_{it} = \delta_i + \beta y_{i,t-1} + \tau_i f_i + \mu_{it} \qquad i = 1,2,3, \dots\dots, N \; and \; t = 1,2,3, \dots\dots, T \quad (4)$$

$$H_0: \beta_i = 0 \; upon \; all \; i \qquad (non-stationarity) \quad (5)$$

$$H_1: \beta_i < 0 \; i = 1,2,3, \dots, N_1 \beta_i = o \quad i = N_1+1, N_1+2 \dots\dots, N. \quad (the \; series \; is \; stationary) \quad (6)$$

As shown in Table 1, because the series likelihood values and co-integration formula are less than 0.05, H0 hypotheses are firmly denied and the cross-sectional correlation between these countries has been determined. It indicates that a significant change in the series often impacts the others in one of the nations. So, when decision-makers in these countries set their policy, other nations ' reforms and other external determinants should be taken into account. Moreover, as cross-section dependence has been established, this condition should be assessed when selecting the unit root and co-integration testing technique. Nevertheless, panel unit root checks and study of co-integration were also used taking into account the cross-sectional dependence. Findings in Table 2 demonstrate that the sequence at levels are non-stationary, although at first differences get to be stationary; they are shown to be first-order integrated, I (1). In this scenario, it was established that the co-integration association between these patterns could be checked as the sets under consideration are incorporated in the same order.

2.5 Wasteland Cointegration Test

In the research, many panel co-integration tests allow CSD between the different groups in the panel. In our statistical estimation, the (32) board co-integration experiment will only be implemented and adopted. This test does not only provide robust results in small sample sizes, but it could also be adhered in all instances, whether or not CSD exists, and can handle both nation-specific intercept and slope dimensions together with trends. However, (32) adopts systemic (instead of just residual) dynamics by easing the assumption that the unit root first-generation panel experiment typically imposes a common factor constraint. (32) then suggested four residual-based experiments that could be used to determine the null hypothesis of non-co-integration. Four of these measures are table statistics, while the other four are team statistics that are usually shared. The test mainly analyses whether or not co-integration happens by evaluating whether there is an error correction for the diverse panel groups and the panel itself.

The measurements are based on a simple error correction model:

$$\Delta y_{it} = \delta_i + \delta_{0i}\left(y_{i,t-1} - \beta_i X_{i,t-1}\right) + \sum_{j=1}^{k1i} a_{1ij} \Delta y_{i,t-j} + \sum_{j=k2i}^{kji} a_{2ij} \Delta X_{i,t-j} + \mu_{it} \quad (7)$$

Where δ_i is the error correction term, which already provides projections of the pace of adjustment to the long-run equilibrium of the group. Therefore, the panel hypothesis and group are estimated as:

$$H_0: i\delta_{0i} = 0 \; there \; is \; no \; presence \; of \; cointegration \; for \; \forall_i$$
$$H_1: \delta_{0i} < 0 \; there \; exist \; a \; cointegration \; for \; \forall_i \quad (8)$$

In the panel study, the alternative hypothesis suggests that equilibrium change is homogeneous around the various groups. Rejecting the null hypothesis thus means that there is proof of co-integration in the board as a whole.

Table 1: Cross-sectional Dependency Test, Testing of Slope Homogeneity and Unit root test

Variables	CD	CIPS Level	CIPS First Difference	CADF Level	CADF First Difference
$LNCO2_{it}$	18.15*	0.584	-4.564*	-0.906	-3.799*
$LNGDP_{it}$	8.52*	-3.640	-6.190*	-3.735*	-6.776*
$LNGDP_{it}^2$	6.82*	-0.643	-6.190*	-3.925*	-7.343*
$LNURB_{it}$	36.75*	-1.769	-2.763*	-4.138*	-6.664*
$LNEC_{it}$	20.50*	-1.038	-5.333*	-1.039	-4.001*
Test of Homogeneity					
LM	320.80*				
$LM\ adj^*$	69.41*				
$LM\ CD^*$	3.795*				

Table 2: Summary results of heterogeneous cointegration tests

Test type	Dependent Variable is CO_2				
		With Trend		Without Trend	
	Statistic	Value	*p*-value	Value	*p*-value
Westerlund	G_t	4.860*	0.000	-4.703*	0.000
	G_a	23.034*	0.009	-22.803*	0.000
	P_t	12.155*	0.000	-11.508*	0.000
	P_a	-27.309*	0.000	-18.215*	0.000

* and ** denotes rejection of the null hypothesis of no cointegration at 1% and 5% levels of significance respectively for Westerlund estimates. AIC is, therefore, used in selecting lag.

Group Statistics:

$$H_0: i\delta_{0i} = 0 \text{ there is no presence of cointegration for } \forall_i$$
$$H_1: \delta_{0i} < 0 \text{ there exist a cointegration for some groups, but not for others}$$

The alternative hypothesis in group analysis also assumes that the transition in equilibrium is diverse around the various groups, and denial of the null hypothesis implies evidence of co-integration in at least one member of the group.

In order to determine the vibrant assimilation between Urbanization, Energy usage, Economic Growth on Environmental Deterioration in Malaysia and Selected ASEAN+3 nations, this study includes a time series panel method, notably (32) error-based tests to measure the long-term connection between Urbanization, Energy usage and Economic Growth on Environmental damage. The main advantage of the operation is to analyse the variables ' pre-movement without any endogeneity concerns. The tests are premised on (31) suggested structural instead of residual nuances. (32) show better smaller sample characteristics with small size biases and high voltage relative to residual-based co-integration technique in the error typo-based tests.

This study of 10 emerging countries (Malaysia and Selected ASEAN+3 nations) also suits well. Both experiments are evenly distributed and can integrate unit-specific short-run trends, unit-specific pattern and slope factors, and cross-sectional dependence (32). Table 2 above indicates that all four figures refute the null hypothesis of no cointegration in both trendy and trend-free economies in Malaysia and chosen ASEAN+3. This means that in Malaysia and Selected ASEAN+3 nations, there are long-run connections between both the parameters in trend and trend-free instances. The group means statistic ($G\tau$ *and* $G\alpha$) rejects the null at both 1% and 5% level of significance and both panel statistics ($P\tau$ *and* $P\alpha$) at the 1%, 5% and 10% level of significance, respectively.

2.6 Long-run and Short-run Estimates

Report on IPAT identity by Ehrlich and Holdren (1971) provides the basis for many work relevant to the detection of environmental degradation drivers. The well-known identification indicates that environmental destruction is the result of population (P), affluence (A), and technology (T) and can be defined as follows:

$$I = P.A.T \tag{9}$$

$$I = \varphi P^{\sigma}.A^{\rho}.T^{\tau} \tag{10}$$

After taking the logarithm, Eq. (9) is transformed into Eq. (10) as follows.

$$\ln I = \ln\varphi + \sigma\ln P + \rho\ln A + \tau\ln T + ln\varepsilon \tag{11}$$

where φ is the coefficient of the model, σ, ρ, τ are exponentials of independent variables and STIRPAT model random error term is represented by ε. In this research, (7) and the Dynamic Panel Common Correlated Effects (DCCE) method established by (7), which calculates an error correction (EC) model, scientifically evaluate the impacts of population (P), affluence (A), technology (T) and other actors on environmental damage. The (7) assumptions that variables are exogenous and require feedback effects among eigenvalues that can lead to problems of consistency. (7) tackles three main issues, the first issue being cross-sectional correlations, which are addressed by taking cross-sectional averages and lagging cross-sectional averages of predictive factors on the right-hand side of the equation with predictor variables. The second problem is parameter variability, which can be overcome using Eberhardt and Presbitero's (2015) mean group model. The third problem is nuances that can be solved by introducing the explanatory determinants lag in the model. The common correlated effects dynamic panel (DCCE) method solves all the problems mentioned above and provides more accurate predictions for the expanded STIRPAT model. The model in question consists of the preceding equations:

$$I_{it} = k_i + \coprod_i l_{i,t-1} + \rho P_{it} + \tau A_{it} + \varphi T_{it} + \mu'_{oi} IV + Q_{it} \quad (12)$$

$$Q_{it} = Q'_{irt} + \forall_{it} \quad (13)$$

$$r_{it} = \binom{IV_{it}}{a_{it}} = kr_i + \beta_i l_{i,t-1} + Q'_i g_t + M_{it} \quad (14)$$

where $i = 1, to\ N; t = 1\ to\ T$; l_{it} is a dependent variable that represents CO2 emission; P_{it} is a measure of the population; Ait is a measure of affluence; Tit is a measure of technology and IV_{it} Denotes multiple predictor variables for the extended STRIPAT system, including energy output, labor productivity, residential housing, density population, energy mix and market accessibility. Also k_i represents effects specification to the country which are unobserved; a_{it} consistent parameters contingent on some possible determinants but not dependent on parameter dependency. g_t is the economy specific impacts of time-varying determinants that are not noted and also reflect downturns that impact all the newly industrialized nations with the same extent on a world level. $\forall_{it}$ Represent errors which are not correlated with regressors. Also $\forall_{it}$ exhibit shocks which are common and unobserved as well, furthermore these errors are also weakly independent across countries and are also serially correlated. ωi denotes matrix for factor loadings, β_i represents the vector of coefficients and M_{it} is a stationary covariance process regardless of error M_{it} . Further, it is assumed that vector consisting of factor loadings (∂_i, π_i) and coefficients such as $\Omega_i = (Q_i, \rho, \tau, \varphi, \mu'_{oi})'$ follow the below models with random coefficients.

$$Q_i = \check{z} + \theta_{0,i,} \vartheta_{0,i} \sim IID(0, \delta_z) \quad (15)$$

$$vec(z_i) = vec(z) + \theta_{z,i,} \vartheta_{z,i} \sim IID(0, \delta_z) \quad (16)$$

$$\Omega_i = \Omega + \theta_{\Omega,i,} \vartheta_{\Omega,i} \sim IID(0, \delta_\Omega) \quad (17)$$

$$\sum — MG = \frac{1}{N-1} \sum_{i=1}^{N} (\breve{\Omega}_i - \dot{\Omega}_{MG})(\breve{\Omega}_i - \Omega_{MG})' \quad (18)$$

We embraced the method of dynamic joint-related effect assessment (7) for the measurement equation used as cross-sectional averages dependent variable greenhouse gases. The model in Eq. (18) also includes lag of the dependent variable as a proxy for common factors effect along with P, A, and T and extended variables.

$$I_{it} = k_i + \coprod_i l_{i,t-1} + \rho P_{it} + \tau A_{it} + \varphi T_{it} + \mu'_{oi} IV + Q_{it} + \sum_{x=0}^{y} \emptyset_{1ix} \overline{I_{t-x}} + \sum_{x=0}^{y} \emptyset_{2ix} \overline{PI_{t-x}} + \sum_{x=0}^{y} \emptyset_{3ix} \overline{AI_{t-x}} + \sum_{x=0}^{y} \emptyset_{4ix} \overline{TI_{t-x}} + \sum_{x=0}^{y} \emptyset_{5ix} \overline{IVI_{t-x}} + \varepsilon_{it} \quad (19)$$

where $\overline{I_{t-x}}, \overline{PI_{t-x}}, \overline{AI_{t-x}}, \overline{TI_{t-x}}, \overline{IVI_{t-x}}$ represents the dependent variable cross-sectional average, and y represents cross-sections averages lags. Dependent variable $(I_{i,t-1})$ included as an explanatory variable because models with dynamic properties such as Dynamic Common Correlated Estimator (DCCE) uses lag of independent variable (7).

However, the PMG estimators illustrate both the pooling suggested by the drawbacks of homogeneity on the long-run coefficients and the median through classes used to obtain process for the analyzed model's other short-run parameters and error correction coefficients. The Pooled Mean group model, including the long-term relationship between variables, that obey the methods of Pesaran et al. (1999):

$$\begin{aligned} \Delta LNCO2_{it} = \beta_1 &+ \sum_{j=1}^{p-1} \partial_{ij} \Delta LNCO2_{it-j} + \sum_{1=0}^{q-1} \gamma_{ij} \Delta LNGDP_{ij-1} \\ &+ \sum_{1=0}^{r-1} \delta_{ij} \Delta LNGDP^2{}_{ij-1} \\ &+ \sum_{1=0}^{s-1} \varphi_{ij} \Delta LNURB_{ij-1} + \sum_{1=0}^{z-1} \omega_{ij} \Delta LNEC_{ij-1} \\ &+ \pi_1 LNCO2_{ij-1} + \pi_2 LNGDP_{ij-1} \\ &+ \pi_3 LNGDP^2{}_{ij-1} + \pi_4 LNURB_{ij-1} \\ &+ \pi_5 LNEC_{ij-1} + \mu_{1it} \\ &+ \varepsilon_{1it} \end{aligned} \quad (20)$$

where: Δ is the first difference operator, and $LNCO2, LNGDP, LNGDP^2, LNURB, and\ LNEC$ Are the five variables selected in the study. The constants is β_1, the short-run and long-run coefficients on the trends are $\partial_{ij}, \gamma_{ij}, \delta_{ij} \varphi_{ij}, \vartheta_{ij}, and\ \omega_{ij}\ and\ \pi_1, \pi_2 \pi_3 \pi_4\ and\ \pi_5$, respectively. $p, q, r, s, and\ z$ represents the maximum lag length,ε_{1it} are error terms,

The table above shows the long-run results of DCCE and PMG estimates. These results revealed that at a 1% level of significance, a unit increase in GDP leads to 16% and a 29% rise in CO_2 emissions, respectively. While at a 1% level of significance, a 1 unit rise in GDP^2will bring about a 69% decrease in CO_2 emissions, and subsequently, at a 5% level of significance, a 1-unit increase in GDP^2 will result in 24% decrease in CO_2 emissions. Whereas, at a 1% level of significance, a 1-unit increase in POP will leads to 36% and 31% decline in CO_2 emission, respectively. However, at a 5% significance level, a 1-unit increase in EU leads to 21% and a 35% increase in CO_2 emission.

Meanwhile, in the short-run, at a 1% significance level, a unit increase in GDP leads to 34% and a 13% increase in CO_2 emission. Also, a unit change in GDP^2, 27% and 48% increase in CO_2 emission will result in restively at a 1% level of significance. While at a 5% level of significance, a unit change in POP will result in a 35% decrease in CO_2 emission. Whereas, at a 5% level of significance, a unit increase in the EU will lead to a 21% and 35% increase in CO_2 emission, respectively.

Table 3: Estimates Results

Dependent variable: $LNCO_{2it}$						
DCCE Variables	Coefficients	Standard error	p-value	PMG Coefficients	Standard error	p-value
Long-run estimates				*Long-run estimates*		
$LNGDP_{it}$	0.299* [4.220]	0.071	0.000	0.163* [-3.805]	0.043	0.000
$LNGDP_{it}^2$	-0.698* [-4.179]	0.167	0.000	-0.248** [-2.640]	0.087	0.046
$LNURB_{it}$	-0.369* [-3.806]	0.097	0.000	-0.590* [2.861]	0.249	0.002
$LNEU_{it}$	-0.801* [-3.221]	0.249	0.002	-1.192* [-8.576]	0.139	0.000
Short-run estimates				*Short-run estimates*		
$\Delta LNGDP_{it}$	0.347* [3.343]	0.104	0.000	0.137* [2.322]	0.059	0.006
$\Delta LNGDP_{it}^2$	0.274* [2.686]	0.102	0.008	0.487* [3.122]	0.156	0.000
$\Delta LNURB_{it}$	-0.369** [-2.119]	0.174	0.035	-0.315* [-4.565]	0.069	0.000
$\Delta LNEU_{it}$	0.210** [2.386]	0.088	0.005	0.350** [2.52]	0.139	0.012
ect_{t-1}	-0.438* [-6.147]	0.071	0.000	-0.557* [-3.115]	0.179	0.002
Observation	598					
Cross-section	13					
F(P)	299.15(0.000)					
R^2	0.68					
Adj-R^2	0.57					
CD Statistics	4.77(0.000)					
Optimal lag length	(1,1,1,1,1)			(1,1,1,1,1)		

The results are in line with EKC, as the combination of economic development and greenhouse gas emissions is developed with the Environmental Kuznets Curve (EKC) concept study. Under this hypothesis, pollution rates are very high in the first stage of development of the country, but after a certain level of development, emissions are lowered and lower due to more economic growth, just like the findings of the current study.

2.7 Dumitrescu and Hurlin heterogeneous Panel Granger Causality Estimates

In heterogeneous panel data models with defined coefficients, (14) developed the non-causality test. The rise in generic causality checks for panel data suggests evaluating cross-sectional longitudinal constraints on design coefficients in the context of a linear autoregressive information generation process. The use of cross-sectional data will expand the causality data set from one parameter given to another. The composite board figures of causality of Dumitrescu and Hurlin Granger are:

$$\begin{aligned}\Delta LNCO2_{i,t} = \beta_i &+ \sum_{k=1}^{K} \partial_i^{(k)} \Delta LNCO2_{i,t-k} \\ &+ \sum_{k=1}^{K} \gamma_i^{(k)} \Delta LNGDP_{i,t-k} \\ &+ \sum_{k=1}^{K} \gamma_i^{(k)} \Delta LNGDP^2{}_{i,t-k} \\ &+ \sum_{k=1}^{K} \delta_i^{(k)} \Delta LNURB_{i,t-k} \\ &+ \sum_{k=1}^{K} \theta_i^{(k)} \Delta LNEC_{i,t-k} \\ &+ \varepsilon_{i,t} \qquad (21)\end{aligned}$$

$$\begin{aligned}\Delta LNGDP_{i,t} &= \beta_i + \sum_{k=1}^{K}\gamma_i^{(k)}\Delta LNGDP_{i,t-k} + \sum_{k=1}^{K}\partial_i^{(k)}\Delta LNCO2_{i,t-k} \\ &+ \sum_{k=1}^{K}\gamma_i^{(k)}\Delta LNGDP^2{}_{i,t-k} + \sum_{k=1}^{K}\delta_i^{(k)}\Delta LNURB_{i,t-k} \\ &+ \sum_{k=1}^{K}\theta_i^{(k)}\Delta LNEC_{i,t-k} \\ &+ \varepsilon_{i,t}\end{aligned} \quad (22)$$

$$\begin{aligned}\Delta LNGDP^2{}_{i,t} &= \beta_i + \sum_{k=1}^{K}\gamma_i^{(k)}\Delta LNGDP^2{}_{i,t-k} + \sum_{k=1}^{K}\gamma_i^{(k)}\Delta LNGDP_{i,t-k} \\ &+ \sum_{k=1}^{K}\partial_i^{(k)}\Delta LNCO2_{i,t-k} + \sum_{k=1}^{K}\delta_i^{(k)}\Delta LNURB_{i,t-k} \\ &+ \sum_{k=1}^{K}\theta_i^{(k)}\Delta LNEC_{i,t-k} \\ &+ \varepsilon_{i,t}\end{aligned} \quad (23)$$

$$\begin{aligned}\Delta LNURB_{i,t} = \beta_i &+ \sum_{k=1}^{K}\delta_i^{(k)}\Delta LNURB_{i,t-k} \\ &+ \sum_{k=1}^{K}\gamma_i^{(k)}\Delta LNGDP^2{}_{i,t-k} \\ &+ \sum_{k=1}^{K}\gamma_i^{(k)}\Delta LNGDP_{i,t-k} \\ &+ \sum_{k=1}^{K}\partial_i^{(k)}\Delta LNCO2_{i,t-k} \\ &+ \sum_{k=1}^{K}\theta_i^{(k)}\Delta LNEC_{i,t-k} \\ &+ \varepsilon_{i,t}\end{aligned} \quad (24)$$

$$\begin{aligned}\Delta LNEC_{i,t} = \beta_i &+ \sum_{k=1}^{K}\theta_i^{(k)}\Delta LNEC_{i,t-k} + \sum_{k=1}^{K}\delta_i^{(k)}\Delta LNURB_{i,t-k} \\ &+ \sum_{k=1}^{K}\gamma_i^{(k)}\Delta LNGDP^2{}_{i,t-k} \\ &+ \sum_{k=1}^{K}\gamma_i^{(k)}\Delta LNGDP_{i,t-k} \\ &+ \sum_{k=1}^{K}\partial_i^{(k)}\Delta LNCO2_{i,t-k} \\ &+ \varepsilon_{i,t}\end{aligned} \quad (25)$$

Where β_i Remain steady in the dimension of the time, and K denotes steady lag orders for all cross-sections of the panel. This allows $\gamma_i^{(k)}$, $\partial_i^{(k)}$, $\delta_i^{(k)}$ and $\theta_i^{(k)}$ As an autoregressive parameters and coefficients of slope to differ across the groups. The model uses a fixed special effect and a fixed coefficient model. The heterogeneous no-causality hypothesis the null hypotheses: ($H_0: \partial_i^{(k)}, \delta_i^{(k)}, \gamma_i^{(k)}\ and\ \theta_i^{(k)} = 0 \forall_{ij} = 1, .. N$). The value of F-statistics and p-value, which indicates whether to reject or not to reject the null hypothesis, documents no, or the existence of causality.

Table 4 below shows the causality relationship between the determinants concerning CO_2 emissions, which highlights that there is an existence of one-way causality running from economic growth to CO_2 emission. It also indicates another one-way causality running from GDP^2 to CO_2 emission. Whereas, a bidirectional causality is found between urbanization and CO_2 emission, as well as a feedback causality among energy used and CO_2 emission. This is very consistent with the findings of (18) While (11), (12) and (25) found economic growth driving carbon emissions (1) accept evidence that the EKC hypothesis is right.

Table 4: Granger causality results

	LNGDP−/→LNCO2	*LNGDP←/−LNCO2*
W^{Hnc}	1.703	
		3.078*
Z_{NT}^{Hnc}	1.546	
		4.778
$\tilde{Z}_{N}^{HNC}$		
	LNGDP²−/→LNCO2	*LNGDP²←/−LNCO2*
W^{Hnc}	1.227	
		3.383*
Z_{NT}^{Hnc}	0.424	
		5.494
$\tilde{Z}_{N}^{HNC}$		
	LNURB−/→LNCO2	*LNURB←/−LNCO2*
W^{Hnc}		
	7.560*	2.259*
Z_{NT}^{Hnc}		
	15.318	2.853
$\tilde{Z}_{N}^{HNC}$		
	LNEU−/→LNCO2	*LNEU←/−LNCO2*
W^{Hnc}		
	2.447*	3.292*
Z_{NT}^{Hnc}		
	40.337	92.398
$\tilde{Z}_{N}^{HNC}$		

3 Results and policy implications

This research used the sophisticated panel DCCE approach to analyse the expanded STIRPAT model for a panel of Malaysia and Identified ASEAN+3 economies from 1970 to 2018. The presence of cross-sectional dependence between the nations in the panel, in other phrases the hypothesis that a macroeconomic downturn in one of the nations examined might affect others, also analyzed using the CDLM test formulated by (8) and those whose variance was rectified by Pesaran, Ullah, and Yamagata and it was defined that cross-section existed In the co-integration equation and between the examined countries ' sequence of urbanization, economic growth, energy usage and environmental pollution. CADF test designed by (7) examined the presence of unit root in series in this analysis, taking into account the cross-section dependence in series, and it was noticed that series were not level consistent and stable when their first differences were taken.

In this case, the precondition for studying the co-integration linkage between series was determined. The presence of the co-integration relation between the series was tested by the test established by (32) and the cross-section dependence was considered and the co-integration connection between the series was observed. Then the calculation of the board is performed using the DCCE method. Co-integration analysis is also used for robustness to verify the co-integration relationship between variables. Also, compared to PMG techniques are the results of the DCCE method. Finally, the research applied causality checks for Dumitrescu and Hurlin to explore the causalities of course. The research to investigate essential factors that are the primary cause of rising CO_2 pollution is very important as total emissions rise sharply. Evidence from the findings shows that the main actors or driving forces leading to a high level of environmental damage are demographics, GDP per capita, and energy usage for Malaysia and selected ASEAN+3 nations.

It can, therefore, be inferred that, with higher population size, GDP per person, and energy consumption, the solution to supporting a level of CO_2 emissions and reducing energy usage will contribute to the rate of CO_2 emissions being regulated. In Malaysia and Selected ASEAN+3 states, on the other hand, labor productivity has no significant long-term effect on the rate of CO_2 pollution. Therefore, with the help of calculations, it can be advocated but the use of further labor productivity during industrial development would not cause deterioration of the environment. Likewise, the workforce holding the real economy's potential does not significantly contribute to a rise in CO_2 emission, which means that global economic growth will not affect the rate of CO_2 pollution. Therefore, the results suggest that the main factors that can decrease CO_2 emissions are energy usage, level of public work and efficiency of labor. The actors of expanded STIRPAT (population, economic growth, and energy usage) in all Malaysia and selected ASEAN+3 nations support long-term environmental damage.

These results provide a policymaker with useful information to control both safe industrialization speed and rate of CO_2 emissions. Industrialization is a fundamental element of economic growth and cannot be limited, while the primary cause for environmental damage is CO_2 emissions. Lawmakers in Malaysia and selected ASEAN+3 nations propose adding new industrial units with environmentally-friendly technology that consume low energy levels, leading to low levels of pollution. Managing energy usage can be a significant contributor to mitigating CO_2 pollution, particularly for the industry sector in Malaysia and selected ASEAN+3 nations, and this can be made possible through effective policies with government support. Such countries in Malaysia and Identified ASEAN+3 need to implement more restrictive energy policies for short- and long-term non-renewable sources of energy and should invest more in research and development to incorporate environmentally friendly sources of energy. Renewable and alternative energy options that are an alternative to non-renewable energy (oil) should be discussed being used on a massive scale. More notably, renewable energy will eventually replace fossil fuel energy because recent research and technological advances have resulted in an enormous cost decline in renewable energy. The decision-makers in Malaysia and selected ASEAN+3 nations should take some steps to personalize the need for energy and encourage the use of renewable energy at the commercial and industrial level by creating policies such as user tax subsidies. One of the effective measures to limit environmental damage in Malaysia and selected ASEAN+3 countries may be encouraging productive industrial and household power use.

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