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Assessing Human Factors in Environmental Degradation: A Panel Data Analysis of Asean Countries Using Stirpat and Cross-Sectional Dependency Models

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Abstract
Many theories have been developed to analyse the nexus and solve environmental issues linked to human factors. In contributing to the existing literature, this study has two main objectives: (1) to examine the human factors that affect environmental degradation by considering the cross-section dependency effect; and (2) to determine the appropriate model for explaining the relationship between the factors. Using panel data from 2000 to 2019, this study employs the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model to assess human environmental impacts, focusing on ASEAN countries. The factors tested include population, GDP and energy intensity, with CO2 emissions as the dependent variable. To overcome the issue of ignoring the cross-section dependency effect in panel data regression in past literature, the heterogeneous panel estimators of the mean group, common correlated effects mean group and augmented mean group (MG, CCEMG and AMG) are employed. The results reveal that CCEMG is the best estimator, with the smallest root mean square error (RMSE). The estimated GDP and energy intensity significantly contribute to higher CO2 emissions. The findings also show that cross-sectional dependency influences GDP. The results of this study may provide a perspective into how the economy should be developed without affecting the environment.
Keywords: Environmental Degradation, STIRPAT, Panel Data, Cross-sectional Dependency

Introduction

The relationship between environmental degradation, economic growth, and energy has long been studied, but more research using extended research methods is needed to provide insightful findings. The relationships between the three variables are significant because they will reveal information for better policy planning and decision-making to achieve sustainable growth while monitoring and maintaining environmental quality.

Carbon dioxide (CO2) emissions account for approximately 75% of the global greenhouse (GHG) effect in the atmosphere (Atasoy, 2017; Sirag et al., 2018). The global temperature is expected to rise between 1.4 and 5.8 degrees Celsius by 2100 (Pachauri, 2014).

Air pollution is only one aspect of larger environmental and health issues in ASEAN's major cities. Data from the World Bank reveals that ASEAN countries that produced the highest CO2 over the period 2000 to 2018 are Indonesia (413,532 kt), Thailand (226,897 kt), and Malaysia (188,151 kt). The Action Plan represents a significant milestone for ASEAN, indicating a renewed, bolder collective commitment to tackling a critical environmental challenge through regional actions aligned with national agendas. ASEAN has joined the rest of the world in reaching a significant milestone in the fight against climate change. GHG emissions in the region have been increasing with fossil-fuel-based industrialization and associated land-use change, resulting in the loss of biodiversity-rich tropical forests and peatland. Given current policy and Nationally Determined Contribution (NDC) targets, GHG emissions will continue to rise globally in the years leading up to 2030 (Zhou et al., 2020).

Researchers are working to resolve the problem by looking for new, less expensive technologies that can completely replace fossil fuel energy. Most of the world's energy is generated from fossil fuels, making efforts to reduce global temperatures difficult. If a region's economic growth relies heavily on energy consumption, it is unlikely to reduce its consumption. Coal and fossil fuel-based energy should be limited to reduce the GHG effect. However, this action is problematic because it may slow economic growth (Dasgupta & Maler, 2000; Dechert, 2001). This situation challenges many countries worldwide, as these factors are mutually beneficial (Apergis & Payne, 2009). Unsustainable development has the potential to devastate ecosystems as well as human health.

Asia has the world's highest energy consumption, increasing at an unprecedented rate (Aruga, 2019). In Asia, the rise in energy consumption is increasingly harming environmental quality. As a result of the consequences, policymakers are constantly debating how to continue to develop the economy without destroying the environment. The statistics and circumstances discussed above show a strong link between energy consumption and environmental issues and the need for policymakers to maintain environmental quality while pursuing economic development/progress.

According to the EKC theory, when an economy reaches its optimal growth rate, continued growth will trigger a turning point in environmental quality. Economic growth is associated with lower environmental quality after the optimal point. However, EKC does not consider the influence of the population factor. As described in Dietz & Rosa (1997) and Fan et al. (2006), the population is one of the critical drivers of accelerating air pollution in the next decade. Thus, it is appropriate to include such a variable in the study. In the STIRPART framework, the link between environmental quality and human systems is well documented.

Past studies indicated inconsistent findings due to the studies' different sample periods or regions. This is also possible due to the limitations of estimation techniques. The differences in estimates in studies on the environmental impacts of population and affluence could be explained by different functional forms of STIRPAT (Wei, 2011). The use of classical estimation models in panel data analysis, which does not account for the effect of cross-section dependence, is one of the main flaws of previous studies. Because of the lack of knowledge about such an effect, inaccurate estimates may be made, leading to different conclusions.

This study is motivated by the urgent need to understand and mitigate environmental degradation linked to human and economic activities in ASEAN countries. Examining key factors—population, GDP, and energy intensity—addresses gaps in prior research that overlooked cross-sectional dependency in panel data analysis. Considering the abovementioned issues and limitations, we aim to fill the gaps by examining the STIRPAT framework in ASEAN countries. Heterogeneous panel estimators are used to model the relationship by including the cross-section dependence effects of each panel country. The study adds to the body of knowledge on environmental quality, population, energy, and economic views by revealing the best estimator to explain the relationship for ASEAN. The findings provide policymakers with helpful information and recommendations for policy decisions and planning.

The remainder of this work's contents are divided into five sections: The literature review is in Section 2, the data and methodology are in Section 3, and the empirical results are in Section 4. In section 5, the study's findings are summarised.

Literature Reviews

Increased greenhouse gas emissions and a worsening environmental problem due to development have alarmed the world, raising concerns about environmental sustainability. Theoretically, there is a well-established link between environmental quality, economic growth, and energy consumption. The environmental Kuznets curve is one of the most well-known theories (EKC). This curve shows that economic growth and environmental degradation are inverted.

Recent studies have explored the relationship between economic growth, human activities, and environmental degradation, focusing on sustainability. Xing et al. (2023) analyzed the Environmental Kuznets Curve (EKC) and STIRPAT model using panel data from Asian economies (1990–2019), finding that innovations could help achieve sustainable development despite rejecting the inverted U-shaped EKC relationship. Quan et al. (2024) used the STIRPAT framework and ecological footprint (EF) indicator to examine 31 OECD countries (2000–2021), revealing that urbanization and renewable energy reduce environmental degradation, while economic growth and energy intensity exacerbate it, especially at higher quantiles. Finally, Kostakis (2024) studied ASEAN countries (1996–2018) and Nordin and Sek (2024) for European Countries (2000-2018) found that renewable energy is critical in reducing environmental harm, though financial openness increases CO2 emissions. The EKC hypothesis was only supported in Singapore, with policy recommendations emphasizing the need for sustainable practices in these regions.

However, there is no conclusive finding to describe the nexus. For instance, Dasgupta & Heal 1979) and Sun (1999), outlined that environmental degradation is not an issue when a country's economy is developing. Tang and Tan (2016), discovered that CO2 emissions, energy, and economic growth are all linked and that reaching a long-run equilibrium takes about 11 years. Energy consumption and economic growth have a statistically significant impact on environmental degradation in the long run, according to Kebede (2017).

Some other studies have recognized the importance of energy consumption as a critical determinant of environmental degradation (Saboori & Sulaiman, 2013; Baek, 2015). Energy consumption contributes to CO2 emissions Pablo et al. (2017) and causes environmental problems. Obradović and Lojanica (2017), and Odularu and Okonkwo (2009), discovered that energy consumption and economic growth have a long-term relationship. These findings are similar to those of Naser (2015), and Chen et al. (2016). Naser examined leading emerging economies: Russia, China, South Korea, and India, and Chen et al. used data from three countries.

Aruga (2009), claimed that reducing energy consumption per capita with GDP per capita is difficult because the region's economic growth heavily depends on energy. However, if the region is willing to improve the technology by introducing energy-saving technology, there is a way to address this issue. Furthermore, mass adoption of the traditional capital-driven production technique in the industrial sector would increase CO2 emissions (Shafik & Bandyopadhyay, 1992; Shahbaz et al., 2014).

Previous empirical studies primarily used panel data regression, which ignored the cross-section dependence effect between cross-section units. Sohag et al. (2017) discussed the consequences of neglecting the cross-section dependence (CSD) effect in panel data regression. In fixed-effects and random-effects regressions, the presence of a CSD effect due to common factors uncorrelated with the regressors may lead to inefficient but consistent estimates. However, if the regressors correlate, the estimators may be inefficient and inconsistent. This could lead to a misleading conclusion.

The number of scholars who used heterogeneous models to study energy-economic growth is considered limited among all the studies conducted. From 1980 to 2012, Fazli and Abbasi (2018) investigated GDP and CO2 emissions for middle-income economies. According to the coefficients of heterogeneous estimators, energy consumption is the main contributor to CO2 emissions in upper and lower-middle-income countries. From 1975 to 2015, Churchill et al. (2018) used eight developing countries to test the impact of energy intensity. The study discovered that as these countries' industrialization and urbanization progressed, their energy consumption increased, supporting the inversed U-shape pattern. In the meantime, Shahbaz et al. (2017) examined 20 OECD countries from 1870 to 2014. According to the MG, AMG, and PMG estimators, environmental degradation and growth are linked. The authors agree with Yassin and Aralas (2019), and claim that pollution is not a serious issue because, in the long run, the rate of pollution will decrease once technological advancements are widely used.

Studies mainly applied the STIRPAT framework, among others are Yassin and Aralas (2019), Gani (2021), and Yeh and Liao (2017). Yassin and Aralas analysed 34 selected ASIAN countries using homogeneous and heterogeneous estimators to examine pollution in the region from 1990 to 2016. According to the study, Asian countries' CO2 emissions could rise as carbon-intensive activities and industrialization grow. Gani (2021), and Wu et al. (2021) used the extended STIRPAT framework in cross-country analysis. Gani applied different fossil fuel sources (natural gas, oil, and coal) to see their environmental effects. The results indicate that coal and oil negatively correlate to environmental quality. However, Wu et al. revealed reduced emissions in 18 developed countries using the extended STIRPAT model. The model suggests such a decline due to the higher consumption of renewable energy and adaptations in energy intensity. On the other hand, Yeh and Liao provide evidence of a relationship between population and GDP and emissions in Taiwan. The environment is affected by the increase in population. Nevertheless, the effect of GDP is negative. Lohwasser et al. (2020) argued the different impacts of population and economic growth on the environment. Based on a sample of 84 countries, the results show that the effect size of population growth on environmental degradation is more obvious than economic growth. However, Ma et al. (2022) found that energy consumption affects environmental quality more than economic growth and urbanization in China. The study used a spatial-temporal approach that was not considered in the STIRPART framework works of literature. Regarding dependency among ten countries with the highest healthcare expenditure, Yang et al. (2021) used AMG and CCEMG to regress the STIRPART framework. The findings show that economic growth is one factor contributing to higher emissions.

Data and Methodology

This study examines the driving factors of environmental degradation using a stochastic model based on the STIRPAT framework. The idea was started with IPAT formulation by Ehrlich and Holdren (1971) to study the effect of population on the environment, where the environmental impacts (I) are a multiplication function due to population (P), affluence (A) and technology (T). This original idea was later reformulated and improved by Dietz and Rosa (1994) into a stochastic form called STIRPAT (stochastic estimation of environmental impacts by regression on population, affluence, and technology). The standard model is:

$$I = \alpha P^b A^c T^d \tag{1}$$

where b, c and d are coefficients to be estimated. By taking the natural logarithm of both sides, the equation can be rewritten as:

$$lnI = \alpha + b(lnP) + c(lnA) + d(lnT) + \ln{(e)} \tag{2}$$

where α is the constant and e is the error term.

The study used an annual panel dataset from 2000 to 2019 (t =20) from the World Development Indicators (WDI) of the World Bank. The variables used are CO_2 emissions (CO2) (kt) as a dependent variable (a proxy for I), the remaining population growth (POP) (annual %) (a proxy for P), GDP (current US$) (a proxy for A) and energy intensity level of primary energy (ENE) (MJ/$2017 PPP GDP) (a proxy for T) are independent variables. We use energy intensity to represent T similar to Zhang and Zhao (2019) and Yang et al. (2018), where energy intensity reflects the technological level (technology-based efficiency). We transformed the data into a natural logarithm (lnCO2, lnPOP, lnGDP, lnENE) for consistency. The data comprises 10 ASEAN countries: Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand and Vietnam.

The analysis begins by checking the properties of the variables through several tests. The existence of the cross-section dependence (CSD) effect is confirmed by the Lagrange Multiplier (LM) test developed by Breusch and Pagan (1980), the Pesaran scaled LM test introduced by Pesaran (2004), and the Pesaran CD estimator developed by Pesaran et al. (2008). Secondly, if CSD is detected, the stationarity of the series is tested by performing the second-generation unit root tests, Pesaran (2007) and Bai and Ng (2004). The tests allow the CSD effect to be examined in terms of stationarity. The null hypothesis is no CSD (correlation) in residuals vs the alternative hypothesis of CSD (correlation) in residuals. Next, the Westerlund test determines whether the variables are cointegrated. The *allpanels* option in the STATA package tests the null hypothesis of no cointegration vs. the alternative cointegration hypothesis.

The relationship in equation (2) is regressed using the heterogeneous estimators, namely mean group (MG), augmented mean group (AMG) and the common correlated effect mean group (CCEMG). AMG and CCEMG are estimators that consider the CSD effect, while the MG estimator does not consider such an effect. All mean group type estimators generally have the same formulation: 1) estimate a group-specific regression and 2) average the estimated coefficients among groups. The MG was developed by Pesaran and Smith (1995). The estimator allows for parameter heterogeneity and OLS regression is estimated separately for each panel. The mean of the parameters across groups is estimated by calculating the average of the coefficients. This estimator works consistently when the sample and time-period dimension are sufficiently large. For example:

$$Y_{it} = \alpha_i + \gamma_i Y_{i,t-1} + \beta_i X_{it} + u_{it} \tag{3}$$

where i is the country. The long-run parameter for the country i is:

$$\theta_i = \frac{\beta_i}{1-\gamma_i} \tag{4}$$

Thus, the MG estimators for the whole panel is:

$$\theta = \frac{1}{N}\sum_{i=1}^{N} \widehat{\theta_\iota} \tag{5}$$

CCEMG estimator was developed by Pesaran (2006) and established based on the MG estimator. Unlike MG, CCEMG considers the CSD effect and is robust to slope heterogeneity and endogeneity. However, for sample size, the estimator is robust to structural breaks and non-stationary and non-cointegrate. The average of the variables is calculated for the whole panel and each equation includes the average cross-section terms of y and x. The equation is written as follows:

$$y_{it} = \alpha_i + b_i x_{it} + c_{1i}\bar{y}_t + c_{2i}\bar{x}_t + c_{3i} trend + e_{it} \tag{6}$$

$$\hat{b}_{CCEMG} = N^{-1}\sum_i \hat{b}_i$$

AMG was introduced by Eberhardt and Bond (2009) and Eberhardt and Teal (2010) to handle CSD and slope heterogeneity. AMG estimator contains a "common dynamic process" in the country regression, k_i as given in equation (7). This variable is obtained through the year dummy coefficients of a pooled regression in first differences (FDOLS). Next, the cointegrating relation formed by the unobserved common factors is included in the second regression stage. AMG is an unbiased estimator, efficient at any dimension of sample and time-period and unaffected by degrees of freedom. The equations are:

Stage 1: $$\triangle y_{it} = b \triangle x_{it} + \sum_{s=2}^{T} c_s \triangle D_s + \triangle e_{it} \quad (5)$$

Stage 2: $$y_{it} = a_i + b_i x_{it} + k_i \hat{\mu}_t^{\cdot} + c_i trend + e_{it} \quad (6)$$

$$\hat{b}_{AMG} = N^{-1}\sum_i \hat{b}_i$$

Results

In this study, ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. The CSD tests are employed to check the presence of the CSD effect. Table 1 shows that all tests reject the null hypothesis of no CSD effect among the countries. Hence, the results suggest the CSD effect in ASEAN countries. Because of the dependency results, the first-generation panel unit root test is not valid. Allowing for cross-sectional unit dependence, we proceed with the second-generation panel unit root test. Table 2 reports the results of the panel unit-root test of Pesaran (2007) CIPS and Bai and Ng (2004). After differencing, the test statistics suggest that the null hypothesis of the unit root in the series should be rejected. Therefore, we can conclude that they are integrated of order 1 or I (1).

Next, since all variables are I (1), we can continue the analysis by checking if the variables are cointegrated. Table 3 provides the results of the Westerlund (2005) cointegration test. The large statistic variance ratio in the table shows that the null hypothesis of no cointegration can be rejected. Thus, we can say the relationship among all panels is cointegrated. Consequently, the heterogeneous models are eligible to apply.

Table 1

Cross-Sectional Dependence Test Results

Test	Statistic
Breusch-Pagan LM	413.873***
Pesaran scaled LM	38.882***
Pesaran CD	12.208***

Table 2
Panel Unit Root Test Results

	CIPS		**Bai and Ng**	
	Constant	Constant and trend	Constant	Constant and trend
Levels				
lnCO2	-1.876	-2.735	1.278	-2.501**
lnPOP	-2.078	-2.821*	-1.834	-1.270*
lnGDP	-2.812***	-3.789***	-2.230	-0.428
lnENE	-1.999	-2.019	-1.505	-1.452*
First difference				
lnCO2	-3.453***	-3.678***	-3.850***	-3.714***
lnPOP	-4.310***	-3.883***	-5.118***	-6.210***
lnGDP	-3.300***	-3.160**	-2.855*	-3.558***
lnENE	-2.709***	-3.616***	-4.784***	-4.828***

Table 3
Westerlund (2005) Cointegration Test

	statistic
Variance Ratio	-1.4406*

Table 4 summarises the regression results of heterogeneous models. Based on the results from the three estimators, it is observed that the signs of all the variables' coefficients are consistent in explaining their effects on environmental degradation. Among the three estimators, CCEM is the best estimator by showing the smallest RMSE value (0.032), implying the slightest forecast error of estimates. Therefore, the discussion of the analysis will focus on CCEMG. CCEMG estimator significantly affects cross-section dependence (mean_ln(GDP)). This implies that economic growth is similar among the countries. The economic interaction among the countries, on average, may contribute to the group's economic growth in the long run. If such effects are ignored, it may result in a severe estimation bias and inconsistency.

As observed in the main effect coefficients, although population growth is concerned in the STIRPAT framework, it has no significant impact on environmental issues. However, lnGDP and lnENE are highly significant and positive. The coefficient of 0.240 implies that for every 1% increase in GDP, CO_2 emissions will increase by 0.240%. Meanwhile, the coefficient of 1.080 implies that for every 1% increase in energy intensity, CO_2 emissions will increase by 1.080%. Higher energy intensity means more energy is used to produce a product. Energy intensity can be reduced when the use of renewable energy increases in addition to the efficient use of energy, as implemented by the Australian government to curb air pollution while not affecting economic growth (Marques et al. 2018; Shahiduzzaman & Alam, 2017). The results reveal that the estimator without the CSD effect (MG) has lower performance (higher RMSE) compared to the estimators with the CSD effect (AMG and CCEMG).

Table 4
Estimation Results

	MG	CCEMG	AMG
Long-run impacts			
lnPOP	-0.258 (0.188)	-0.210 (0.204)	-0.169 (0.166)
lnGDP	0.073 (0.074)	0.240*** (0.083)	0.264** (0.115)
lnENE	1.072*** (0.252)	1.080*** (0.264)	1.035*** (0.219)
constant	8.153*** (1.275)	3.553 (5.284)	3.313*** (2.691)
trend	0.049** (0.021)	0.026 (0.021)	0.005 (0.014)
$\hat{\mu}\cdot$			0.342 (0.128)
mean_lnCO2		0.232 (0.222)	
mean_lnPOP		-0.021 (0.052)	
mean_lnGDP		-0.246*** (0.088)	
mean_lnENE		-0.353 (0.276)	
RMSE	0.040	0.032	0.038

Conclusion

The relationship between environmental degradation and its factors has long been studied theoretically and empirically. The STIRPAT model is one of the frameworks used to explain the relationship between the variables. However, empirical examinations show inconclusive results due to the different time-period, approaches and sample countries.

Aside from inconsistency in results, previous studies have shortcomings, particularly in estimation techniques. In panel data analysis, disregarding the cross-section dependence (CSD) effect in the estimation can lead to misleading and accurate results. This study examined the STIRPAT model of ASEAN countries using three heterogeneous estimators from 200 to 2018 to address this issue. Our findings confirm the existence of the CSD effect and the cointegrating relationship, thereby validating the use of heterogeneous estimators. The results also show that estimators with the CSD effect (CCEMG and AMG) outperform estimators without the CSD effect (MG). The CSD effect (economic growth) is highly significant. The findings imply that the cross-section dependence effect affects energy intensity in ASEAN, as the behavior of one country in the group can influence the decision/behavior of the other members. The finding is similar to , where the main effects, economic growth and energy intensity, contribute to increased CO_2 emissions.

The outcomes point to the coexistence of environmental regulations and economic plans. More clean technology that produces low-carbon energy sources should be developed and improve the energy efficiency of all economic sectors. Policymakers can help accelerate the energy transition and reduce CO_2 emissions by promoting energy structure shifts and pollution-free economic development through effective environmental laws. Countries with fewer pollution problems benefit the environment and the economy as there is no need to allocate large expenditures for people's health. Finally, investments in research and development and technological innovation are critical to improving environmental quality. For future work, the spatial modeling approach is suggested to examine how spatial effects in the adjacent areas influence environmental degradation in ASEAN.

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