Final Draft EKC Deforestasi_ME1

by Turnitin Indonesia

Submission date: 29-Oct-2022 02:03AM (UTC-0700)
Submission ID: 1938453704
File name: Final_Draft_EKC_Deforestasi_ME1.docx (120.63K)
Word count: 5340
Character count: 30121

DEFORESTATION-INDUCED THE EKC FRAMEWORK: THE ROLE OF CORRUPTION CONTROL AND TRADE OPENNESS IN SOUTHEAST ASIA

Abstract

Reducing the deforestation rate and formulating sustainable forest governance are still challenging for Southeast Asia. This paper intends to investigate the dynamic connection between GDP, trade openness, corruption, and deforestation within the Environmental Kuznets Curve (EKC) framework by considering controls over agriculture and population. This study uses panel data from nine countries from 1996 to 2018. Pooled Mean Group (PMG) estimation and panel data causality tests (DH) were applied to examine the variables' long-term relationships and the direction of the causality. This article also features unit root and cointegration tests. The estimation results confirm that cointegration is evident. The results support the EKC hypothesis that the relationship between economic growth and deforestation forms an inverted-U curve. The turning point of the per capita GDP is USD 26785, i.e. the advanced stage of development. Other findings are that trade openness is a driver of deforestation and that governance (control over corruption) is an effective instrument to reduce the deforestation rate in the long term. Deforestation will still occur in Southeast Asia because only Brunei Darussalam has passed the turning point. However, implementing development programs while reducing the deforestation rate can be done because the bidirectional causality between GDP and deforestation is not confirmed. Improving trade regulations and governance is a necessary scheme to reduce deforestation rates in the future.

1. Introduction

Improving forest governance, reducing the rate of deforestation, and promoting sustainable development are notable agendas to battle the 21st-century climate crisis. Forests are essential in sustainable development because they absorb 2.4 billion tons of carbon emissions annually and are home to 80% of terrestrial biodiversity (IUCN, 2021). In addition, 606 gigatons of biomass reserves are stored in forests, potentially as inputs for green growth (FAO, 2020). However, the remarkable benefits forest resources provide are threatened by the current situation in line with issues of forest degradation and fragmentation.

The global deforestation rate for 2015-2020 is still relatively high, with nearly 10 million hectares per year (FAO & UNEP, 2020). However, deforestation rates also vary widely among regions. Southeast Asia is one of the regions with the highest deforestation rate. During 1990-2020, the forest cover area decreased by 376,000 km2 (Russell, 2020). This condition shows that forest governance has not been robust enough, where expansion for agriculture and public infrastructure development is enforced by converting forests. Deforestation occurs in all types of forests. Deforestation of mangrove

forests is widely found in Myanmar, while deforestation of peat swamps and tropical rain forests is markedly confirmed in Indonesia (Gandhi & Jones, 2019).

2. Literature Review

The deforestation rate is generally associated with development processes. It follows an inverted-J curve pattern, which is divided into four stages: pre-transition, early transition, late transition, and post-transition (Hosonuma et al., 2012). The pre-transition phase is closely related to low-income nations that are characterized by sub-optimal forest resource management. The early transition phase is closely tied to developing countries that are high deforestation rates. Deforestation is carried out for agricultural expansion and industrialization inputs, widely confirmed in Southeast Asia, Sub-Saharan Africa, and Latin America. However, North American and European countries benefit from the late and post-transition phases. The Forest Transition Theory is in line with the Environmental Kuznets Curve (EKC) that the relationship between economic growth and deforestation forms an inverted-U curve or N curve (Caravaggio, 2020). The inverted-U curve occurs due to the effects of scale, decomposition, and technology, in line with the economic transition stage (Usman et al., 2019). Figure 1 is the general shape of the EKC curve.
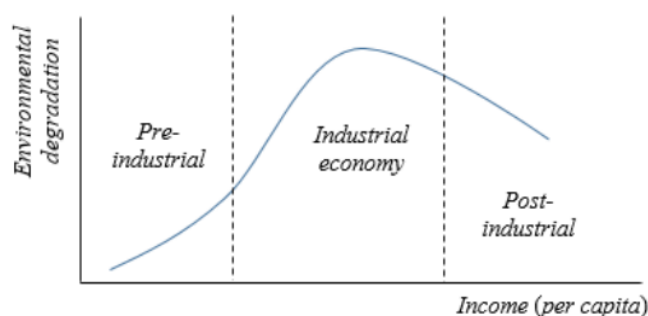
Source: Rashid Gill et al. (2018)

Figure 1. The EKC Curve

Since the 21st century, the focus on the drivers of deforestation has shifted from proximate (direct) to underlying (indirect) causes. The underlying factors consist of economic, demographic, institutional, technological, and socio-cultural dimensions (Carodenuto et al., 2015). Economic factors at the root of the forest cover changes in the tropics are economic growth, urbanization, industrialization, trade, and prices of agricultural commodities. However, the relationship between economic variables and deforestation may not be linear and is influenced by other factors such as environmental regulations, quality of human resources, and clarity of property rights. The concept of "degradation first, clean up later" is a generally applicable framework in developing countries.

Economic growth has long been linked to deforestation in emerging markets, including tropical countries. The research of Yameogo (2021) in Burkina Faso and Nathaniel & Bekun (2020) in Nigeria found that per capita income has a positive and significant effect on deforestation rates in the short term. The increase in per capita GDP will be followed by growth in the consumption of forestry and agricultural products, which drives deforestation. Ajanaku & Collins (2021) noted that the relationship between per capita GDP and deforestation rates in Sub-Saharan Africa follows an inverted-U curve, in line with the EKC hypothesis. Economic growth will not drive deforestation once per capita GDP reaches USD 3,000. In addition, there is unidirectional causality from per capita GDP to deforestation (Ajanaku & Collins, 2021).

More comprehensively, Caravaggio (2020) tested the EKC hypothesis using PMG and differentiated the sample based on income classification. The results of the study confirm that the inverted-U curve is only found in middle-income countries and that the turning point occurred when the per capita GDP had reached USD 3,790. The relationship between per capita GDP and deforestation in low-income and high-income countries follows a U-curve, indicating that deforestation will continue. However, Manivong et al. (2021) used the ARDL method to investigate EKC in Laos and reported that their results contradicted the EKC curve hypothesis. It should be noted that the causes of deforestation in Laos are the growth of the rural population and agricultural production.

In addition to economic growth, trade openness is suspected as another economic factor that drives changes in forest areas in the tropics. The increasing demand for agricultural commodities and forestry products from the global community incentivizes tropical countries to convert forests and extract trees. Defries et al. (2010) found that trade in agricultural commodities is the leading cause of deforestation in this century. Expanding agriculture and increasing forestry products in Southeast Asia is done mainly by clearing forests. Palm oil is an export commodity from forest conversion that causes deforestation (Austin et al., 2019). The results of the study by Faria & Almeida (2016) in the Brazilian Amazon Forest also confirm that trade openness, in both primary and total products, is a driver of deforestation. In contrast, Nathaniel & Bekun (2020) found that trade openness in Nigeria in the long term does not lead to deforestation. Trade can help meet the demand for agricultural commodities so that openness can reduce the potential of forest conversion.

In addition to economic factors, governance and institutions are other underlying factors for forest cover changes in the tropics. Wehkamp et al. (2018) used several governance indicators to investigate deforestation and found that environmental policies, clarity of property rights, and the presence of environmental NGOs and rules of law have been proven able to reduce deforestation. In addition, Pachmann (2018) emphasized that improving governance through corruption prevention and control is crucial because corruption at regional levels helps illegal logging in Indonesia. Corrupt conduct can also hinder forest conservation, certification, and REDD+ programs. For the context of Southeast Asia, Handalani (2019) noted that the effect of corruption perception index (CPI) on forest

cover is positive. However, Mendes & Junior (2012) found that corruption has no significant impact on deforestation rates in the Amazon Rainforest in Brazil.

The empirical literature on the underlying causes of deforestation in Southeast Asia is limited; this paper intends to examine the nexus between per capita GDP, trade openness, corruption, and deforestation rates within the EKC framework. We also consider population and agriculture as control variables. This study performs the Pooled Mean Group (PMG) and panel data causality tests. Regarding the research contributions, we propose four novelties. First, as the EKC deforestation article for the Southeast Asian context by Thi & Nguyen (2018) adopts a static panel (Fixed Effect Model), this study applies the PMG method, which can capture the short-term heterogeneity and the dynamics of the model. The weakness of FEM is that it cannot capture individual heterogeneity of time-varied panel data (Hill et al., 2020). Second, this deforestation study utilizes panel data with a larger sample size (N = 9 and T = 23) (see Kustanto, 2022; Handalani, 2019; Le & Nguyen, 2020). Third, we present the causality test for heterogeneous panels proposed by Dumitrescu & Hurlin (2012). Fourth, the measure of deforestation employed in this investigation is net rates of forest changes, while previous studies use forest cover. Differences in deforestation indicators may give different empirical results, both the coefficient direction and the magnitude.

3. Research Method

3.1 Data

This empirical study uses secondary data, i.e. panel data from nine Southeast Asian countries in the period of 1996-2018. The research period was determined by the availability of the data. The samples are Indonesia, Malaysia, Thailand, Vietnam, the Philippines, Laos, Brunei Darussalam, Cambodia, and Myanmar. The data needed to form the variables are forest cover area (% of land area), export value (% of GDP), import value (% of GDP), per capita GDP (constant prices in 2015), the estimated value of the corruption control index (from -2.5 to 2.5), arable land area (% of land area), and population growth. These data were obtained from the annual statistics of World Development Indicators (WDI) and World Governance Indicators (WGI) published by the World Bank. Since corruption control indices for 1997, 1999, and 2001 were not available, the gap was filled by applying the linier interpolation technique. The number of observations in this study is 207, acquired from nine countries and 23 series.

3.2 Model Specification

This study intends to investigate the nexus between economy, governance, and deforestation using the EKC framework. The selected economic indicators are per capita GDP and trade openness, while governance is proxied by corruption control index. Referring to previous studies on EKC

deforestation (Caravaggio, 2020; Ajanaku & Collins, 2021; Culas, 2007), equation 1 is the empirical model.

$$DEF_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 TO_{it} + +\beta_4 COR_{it} + \beta_5 ARABLE_{it} + \beta_6 POPG_{it} + e_{it} \quad (1)$$

In the equation above, DEF is deforestation, GDP is per capita income, GDP2 is the quadratic form of per capita GDP, COR is corruption control index, TOP is trade openness, POPG is population growth, ARABLE is arable land area, subscripts i and t are countries and periods (1996 – 2018), β_1 ... β_6 is the coefficient of the explanatory variable, β_0 is the intercept, and e_{it} is the error term. The EKC (inverted-U curve) hypothesis is confirmed only if the coefficient values of β1 > 0 and β2 < 0. The EKC turning point can be obtained through equation 2.

$$t^* = exp\left(-\frac{\beta_1}{2 \times \beta_2}\right) \quad (2)$$

Deforestation is the removal of forest cover and changes in vegetation, from forestry to non-forestry (Hosonuma et al., 2012). Deforestation is proxied by net rates of forest changes, as used by Waluyo & Terawaki (2016). The net deforestation rate was obtained using equation 3. FC_{it} denotes the forest cover area (%) of country i in period t. If the DEF value is positive, i.e. the forest cover area in the analysis period (t) is lower than the forest cover area in the previous period (t-1), deforestation is indicated, and vice versa.

$$DEF_{it} = \left(\frac{FC_{it-1} - FC_{it}}{FC_{it}}\right) \quad (3)$$

Per capita income was measured according to the per capita Gross Domestic Product (GDP) value at constant prices in 2015, following previous studies (Ajanaku & Collins, 2021; Caravaggio, 2020). The quadratic variable of per capita GDP was established to test the EKC hypothesis. The GDP coefficient is expected to be positive, while the GDP2 coefficient is supposed to be negative, so the link between per capita GDP and deforestation follows the inverted-U curve, which supports the EKC hypothesis. Trade openness was measured using the ratio between total trade (exports + imports) and GDP. Trade openness is categorized as the underlying factor of deforestation. The empirical findings of Faria & Almeida (2016) and Kustanto (2022) confirm that trade openness and globalization are the top drivers of deforestation in the tropical forest.

In this research, governance is considered as a fundamental factor that prevents practices leading to forest depletion. Ajanaku & Collins (2021) found that political rights and civil independence have a negative and significant effect on deforestation. This study opted for corruption control index as the proxy for governance. This index measures the extent to which public power is used for personal gain (small- and large- scale corruption) and for arrests based on elite and private interests. The

corruption control index is published by the World Governance Indicator (WGI). The index ranges between -2.5 and 2.5. A higher index indicates better governance.

To tackle the issue of Omitted Variable Bias (OVB), this study includes control variables related to agricultural and demographic factors. Previous researchs indicate that they are prominent drivers of forest cover change (Nathaniel & Bekun, 2020; Yameogo, 2021; Acheampong et al., 2019; Ngwira & Watanabe, 2019; Plata-Rocha et al., 2021). Agriculture is proxied by arable land area (% of land area), while demography is proxied by population growth rate (%). Arable land area and population growth are expected to positively affect deforestation. Table 1 contains the summary of research variables, operational definitions, and expected signs.

Table 1 Summary of Research Variables

Variable (notation)	Unit	Operational	Expected sign
Deforestation (DEF)	%	Net deforestation rate	
Per capita income (GDP)	Dollar	Per capita Gross Domestic Product (constant price in 2015)	+
Trade openness (TOP)	%	Ratio between total trade values (exports + imports) and GDP	+
Arable land (ARABLE)	%	Share of arable land area	+
Population growth (POPG)	%	Annual population growth rate	+
Corruption (COR)	index	Corruption control index (-2.5 – 2.5)	+

4. Estimation Method

This study adopts the Pooled Mean Group (PMG) estimation method to investigate the nexus between income, openness, governance, and deforestation in Southeast Asia in the EKC framework. Prior to implementing PMG, this paper conducted unit root and cointegration tests. Unit root test is essential for avoiding spurious regression and checking the model fit. The nature of the ARDL model can only be applied if there is a combination of variable stationarity at the level and first differentiation (Ekananda, 2022). This article employs the unit root detection proposed by Levin et al. (2002). LLC assumes homogeneity (slope and intercept) in the first stage of regression and calls for ADF equations to check stationarity.

$$\Delta Y_{it} = (1 - \rho)Y_{it-1} + \sum_{j=1}^{q_i} \theta \Delta Y_{it-j} + Z_{it}^* \delta + e_{it} \qquad (4)$$

Y_{it} = a variable in the form of panel data, Δ = differentiation, q = number of ADF regression lags, θ = the coefficient of ΔY_{it-1}, Z = deterministic component, and e_{it} = error. LLC assumes homogeneity in the autoregressive coefficients for all individual panels ($\rho_i = \rho$). Y is stationary if $|\rho| <$

1. Reject the null hypothesis if the t-statistic is greater than the critical values or the p-value is smaller than the 10% significance level. To check the robustness, we present the IPS unit root test as proposed by Im et al. (2003).

Next, this study applies the cointegration test proposed by Kao (1999). Cointegration indicates a long-term relationship, i.e. the combination of a number of variables that are not stationary yet become stationary and integrated in the same order. Kao (1999) assumes the homogeneity of the intercept and the slope for individual panels in the first stage of regression.

$$y_{it} = \alpha_i + \beta x_{it} + e_{it} \tag{5}$$

where:

$$\hat{e}_{it} = \rho \hat{e}_{it-1} + v_{it} \tag{6}$$

$\hat{e}_{it}$ expresses the equation residual, while y and x are cointegrated if $\rho < 1$. To verify the robustness, this paper performs the cointegration tests of Pedroni (2004) and Westerlund (2005). In contrast to Kao, Pedroni's cointegration test allows intercept heterogeneity and adds trend (Ekananda, 2014). There are seven statistical tests: panel v-stat, rho-stat, PP-stat, and ADF-stat, Group rho-stat, PP-stat, and ADF-stat; they were estimated using the within- and between-dimension approaches.

Then, this study implements the PMG or Autoregressive Distributed Lags (ARDL) panel proposed by Pesaran et al. (1999). PMG accommodates issues concerning panel data heterogeneity and allows for different slopes and intercepts between individuals in the short term, but is assumed to be homogeneous in the long term (Pesaran et al., 1999). The estimator utilizes maximum likelihood, assumes errors with a normal distribution, and is based on Newton-Raphson's optimized algorithm. Several recent empirical studies also apply this method. Attiaoui et al. (2017) used PMG to investigate the nexus between renewable energy consumption, GDP growth, and carbon emissions in Africa. Ampon-Wireko et al. (2021) employed PMG to examine the effect of health expenditures on CO2 emissions in developing countries. Currently, Islam (2021) applied PMG to test the EKC hypothesis in South Asia. The PMG panel equation (p,q) can be arranged as follows.

$$\Delta DEF_{it} = \alpha_i DEF_{i,t-1} - \beta_i X_{it} + \sum_{i=1}^{p-1} \lambda'_{ij} \Delta DEF_{it-j} + \sum_{j=0}^{q-1} \delta'_{ij} \Delta X_{it-j} + v_i + \varepsilon_{it} \tag{7}$$

Where j denotes the number of lag, v_i represents fixed effect, and X is the vector of independent variables. Next, the error correction equation is formed through equation 8.

$$\Delta DEF_{it} = \psi_i \left[DEF_{i,t-1} - (\gamma_0 + \gamma_1 X_{it-1}) \right] + \sum_{j=1}^{p-1} \lambda'_{ij} \Delta DEF_{it-j} + \sum_{j=0}^{q-1} \delta'_{ij} \Delta X_{it-j} + v_i + \varepsilon_{it} \tag{8}$$

Where λ_i and δ_i represent the short-run coefficients of the lags of the independent and dependent variables, while i shows the long-run coefficients of the independent variables. Ψ represents the coefficient of error correction term (ECT). For verification, the ECT coefficient must be negative and significant, at least at the 10% significance level. Ψ also denotes the speed of adjustment towards long-term equilibrium.

Finally, this study incorporates a causality test. It is important to investigate the direction of the causality when a number of variables are shown to be cointegrated (Nathaniel & Bekun, 2020). This article uses the DH non-causality test proposed by Dumitrescu & Hurlin (2012). The advantages of this method are that it allows cross-sectional dependency problems, heterogeneity of panel data and that it can be applied to panel structures with large N and T or small N and T (Lopez & Weber, 2017). This causality test adopts the Wald's statistic. Referring to the article of Dumitrescu & Hurlin (2012), the panel causality test equation is arranged as follows.

$$y_{it} = \alpha_i + \sum_{k=1}^{k} \gamma_i^{(k)} y_{it-k} \sum_{k=1}^{k} \beta_i^{(k)} x_{it-k} + \epsilon_{it} \qquad (10)$$

Where x_{it} and y_{it} are assumed to be stationary variables and proven to be cointegrated. t, i, and k denote period, country, and lag order, respectively. The null hypothesis is that there is no causal link in each subgroup. Reject the null hypothesis if there is a causal relationship, at least in one subgroup. The hypotheses were tested using the mean value of the Wald statistic ($\bar{W}$). Reject the null hypothesis if the z-bar ($\bar{z}$) is greater than the average value of the Wald statistics obtained through equation 11 (Lopez & Weber, 2017).

$$\bar{W} = \frac{1}{N} \sum_{1}^{N} W_i \qquad (11)$$

5. Result and Discussion

Table 2 displays the statistical description of the research variables. The standard deviation of DEF and COR is greater than the mean value, representing a high deviation rate. In contrast, the standard deviations of GDP, TOP, ARABLE, and POPG are smaller than the mean value, indicating a low degree of variation. All the variables, besides DEF, tend to be positive-skewed. Furthermore, all variables are not normally distributed and form a platykurtic curve, except for POPG. The total observations of this study are 207 units from nine countries and 23 series.

Table 2. Descriptive Statistics of Variables

	DEF	GDP	TOP	ARABLE	POPG	COR
Mean	0.248	7.874	1.009	14.175	1.414	-0.541
Median	0.239	7.659	0.969	16.185	1.380	-0.570

Max.	3.790	10.488	2.204	32.903	3.020	0.990
Min.	-6.822	5.473	0.119	0.380	0.315	-1.670
Std. Dev.	1.057	1.225	0.446	9.472	0.526	0.609
Skewness	-0.994	0.604	0.603	0.132	0.265	0.360
Kurtosis	13.639	2.901	2.922	2.102	2.972	2.419
P (J-B)	0.000	0.002	0.002	0.023	0.298	0.025
N	207	207	207	207	207	207

Table 3 reveals the outcomes of the LLC and IPS unit root tests. A number of variables were found to be non-stationary at the level; they are GDP, DEF, TOP, ARABLE, and COR. However, they were stationary in the first differentiation, both in the LLC and IPS unit root tests. It can be concluded that the variables in this research are integrated in the first order, I(I). Because a number of variables are not stationary at the level, the cointegration test is necessary to examine the existence of a long-term relationship.

Table 3. Unit Root Test Result

	LLC		IPS	
	I(0)	I(1)	I(0)	I(1)
DEF	-3.971	-10.754***	-0.899	-10.823***
GDP	0.398	-21.316***	5.252	-8.680***
TOP	-3.717	-13.603***	-3.717	-13.603***
ARABLE	-2.994*	-10.774***	-4.567	-10.561***
PG	-8.780***	-13.226***	-2.994*	-10.774***
COR	-4.5666	-10.5612***	1.787	-11.791***

Notes: I(0) and I(1) represent level and first difference.
*,**, and *** indicate significant at 10, 5, and 1% level.

Table 4 shows the results of the panel cointegration test. The statistical values of the Kao (MDF-t, DF-t, ADF-t, Unadjusted MDF-t, and Unadjusted DF-t), Pedroni (Group rho-stat, Group PP-stat, Group ADF-stat, Panel PP-stat, Panel ADF-stat), and Westerlund (Variance Ratio) represent the rejection for the null hypothesis, i.e. no cointegration. Each is significant at the 5% or 1% significance level. A proven long-term relationship is evident. A number of variables (DEF, GDP, GDP2, TOP, ARABLE, POPG, and COR) are cointegrated, i.e. moving together towards long-run equilibrium. The existence of cointegration confirms that adopting the PMG estimation method is appropriate.

Table 4. Cointegration Test Result

		t-statistic	p-value
Kao	MDF-Stat	-5.0896***	0.000
	DF-Stat	-3.9119***	0.000
	ADF-Stat	-2.2840**	0.011
	Unadjusted MDF-Stat	-5.6490***	0.000
	Unadjusted DF-Stat	-4.0522***	0.000
Pedroni Individual AR	Group rho-Stat	2.0242**	0.022
	Group PP-Stat	-7.7297***	0.000
	Group ADF-Stat	-7.3665***	0.000
Pedroni	Panel v-Stat	1.0734	0.142

Common AR	Panel rho-Stat	1.2227	0.111
	Panel PP-Stat	-6.3422***	0.000
	Panel ADF-Stat	-6.1979***	0.000
Westerlund	Variance ratio	-2.2337**	0.013
	Variance ratio (all panels)	-2.01770**	0.022

Note: *,**, and *** indicate significant at 10, 5, and 1% level.

Table 5 presents the result of short- and long-term PMG estimation. PMG (2, 2, 2, 2, 2, 2) is the best model, according to AIC's suggestion. The long-term estimation results find that the coefficient of GDP is positive, while the coefficient of GDP2 is negative; each of which is significant at the 1% level. These results support the EKC hypothesis. The increase in per capita income initially encourages deforestation, then, after reaching a certain threshold, promotes an upgrade in forest cover area. This finding is similar to that of Ajanaku & Collin (2021) for the context of Sub-Saharan Africa, Caravaggio (2020) for the sample of middle-income countries, and Handalani (2019) for the context of Southeast Asia. The estimation results are also in line with the results of Crespo Cuaresma et al. (2017) that the marginal effect of income growth is the strongest at the beginning of development, but then it weakens at the more advanced stages of the economy.

Based on the coefficient values of β_1 and β_2, the turning point is reached at the per capita of USD 26875. This figure is much higher than previous empirical results. However, this figure is relevant because the deforestation rate in Southeast Asia is still positive. Forest cover tends to decrease every year. Referring to the turning point figure (USD 26875), Brunei Darussalam is the only developing country in Southeast Asia that has passed the turning point. In contrast, the per capita income of Indonesia, Malaysia, Thailand, Laos, Myanmar, Vietnam, the Philippines, and Cambodia is still far from the turning point. Deforestation will continue in Southeast Asia, in line with economic growth and per capita income increase. This finding also suggests that the integration between development policies and forest governance should be strengthened. Improved forest governance and environmental policies can accelerate the threshold of the relationship between GDP and deforestation.

Table 5. The PMG Estimation Result

	Coefficient	Standard Error
Long-Run Equation		
GDP	6.43270***	2.37494
GDP2	-0.31536**	0.14159
TOP	1.37076***	0.15356
COR	-0.71906***	0.12752
ARABLE	0.17693***	0.01530
POPG	0.50326***	0.18775
Short-Run Equation		
ECT	-0.88848***	0.25876
D(DEF(-1))	-0.16117	0.22396
D(GDP)	-408.47750	327.92710
D(GDP(-1))	417.60540	341.07720
D(GDP2)	26.66266	22.30920

D(GDP2(-1))	-29.19596	23.79855
D(TOP)	0.31645	1.62792
D(TOP(-1))	1.13132	1.92194
D(COR)	1.30910*	0.75498
D(COR(-1))	1.35803*	0.78587
D(ARABLE)	0.44326	0.33045
D(ARABLE(-1))	0.09890	0.15955
D(POPG)	11.66357	15.60363
D(POPG(-1))	-8.87007	12.72662
C	-32.14371***	9.43864

Note: D represent difference
*,**, and *** indicate significant at 10, 5, and 1% level.

Another result, the coefficient of trade openness is positive and significant at the 1% level. This finding confirms that trade openness is a driver of deforestation in Southeast Asia. It is in line with the results of previous studies (Defries et al., 2010; Faria & Almeida, 2016). Trade openness causes deforestation through the expansion of export-oriented agricultural commodities and processed forest products (Defries et al., 2010; Ajanaku & Collins, 2021). Openness is an incentive for deforestation. The increase in demand for agricultural commodities and processed forestry products will encourage tropical countries to expand agriculture through forest conversion and timber extraction. Palm oil is an example of an export-oriented commodity that causes deforestation (Austin et al., 2019).

Furthermore, corruption negatively affects deforestation at a 1% level of significance. The negative impact of corruption control index on deforestation rate indicates that regions with high levels of corruption tend to have high deforestation rates. This result is in line with the finding of Avnimelech & Zelekha (2014), who used three measures of corruption; International Country Risk Guide (ICRG) index, Corruption Perception Index (CPI), and Business Intelligence (BI) index. They negatively affect forest product smuggling and illegal logging. Corrupt conducts support forest resource management practices that are neglect sustainability principles (Pachmann, 2018). This finding shows that control over corruptive practices is indispensable in fighting deforestation and supporting sustainable forest governance.

Concerning the control variables, this research reveals that the coefficients for arable land and population growth are positive and significant, so both are the drivers of deforestation. The increase in arable land causes the forest cover to decrease. The result is in line with a previous study in Burkina Faso (Yameogo, 2021). The positive impact of population growth on deforestation is in line with the Neo-Malthusian hypothesis that population is the cause of environmental degradation.

Finally, the estimation results of the long-run PMG must be confirmed using the short-run ECT model. The estimation result of the short-run PMG shows that the ECT is negative (-0.888) and significant at the 1% level. There is a proven long-term balance. The existence of shocks in the short term will be adjusted by explanatory variables with 0.88 units of speed toward long-term equilibrium.

Table 6. Panel Causality Test Result

HO: x does not cause y	W-Stats	Zbar-Stats	p	Conclusion
GDP →DEF	10.185	5.517	0.000	One-way causality of GDP causes
DEF → GDP	3.858	0.260	0.795	DEF
TO → DEF	7.023	2,889	0.003	One-way causality TOP causes
DEF → TOP	4.448	0.750	0.453	DEF
ARABLE → DEF	7.128	2,976	0.003	ARABLE one-way causality
DEF → ARABLE	4.873	1.103	0.269	causes DEF
POPG → DEF	8.956	4.495	0.000	Bidirectional causality between
DEF → POPG	11,717	6,790	0.000	POPG and DEF
COR → DEF	12,704	7.610	0.000	Bidirectional causality between
DEF → COR	7.013	2.881	0.004	COR and DEF
TOP → GDP	5,293	1,452	0.146	One-way causality of GDP causes
GDP → TOP	7.146	2,992	0.003	TOP
ARABLE → GDP	8.323	3.970	0.000	Bidirectional causality between
GDP → ARABLE	7.079	2,936	0.003	ARABLE and PDB
POPG → GDP	10.019	5.379	0.000	GDP one-way causality causes
GDP → POPG	3,787	0.201	0.840	POPG
COR → GDP	4.094	0.456	0.648	One-way causality of GDP causes
GDP → COR	8,219	3,883	0.000	COR
ARABLE → TOP	4.470	0.768	0.442	One-way causality TOP causes
TOP → ARABLE	5.534	1,652	0.098	ARABLE
POPG → TOP	4.161	0.511	0.609	One-way causality TOP causes
TOP → POPG	7,997	3,699	0.000	POPG
COR → TOP	7,802	3,537	0.000	One-way causality COR causes
TOP → COR	4.685	0.947	0.343	TOP
POPG → ARABLE	5.487	1,613	0.106	There is no causal relationship
ARABLE → POPG	5.058	1.257	0.208	
COR → ARABLE	3.167	-0.314	0.753	ARABLE one-way causality
ARABLE → COR	5.579	1,689	0.091	causes COR
COR → POPG	2.417	-0.937	0.348	POPG one-way causality causes
POPG → COR	11.279	6.426	0.000	COR

Notes: ($\rightarrow$) indicates to the direction of causality
The causality test adopts lag 3 (as suggested by AIC, SC, and HQ)

Table 6 displays the results of the causality tests using the method of Dumitrescu & Hurlin (2012). In the forestry context, bidirectional causality is present between DEF and POPG and between DEF and COR. In addition, there are unidirectional causalities: from GDP to DEF, from TOP to DEF, and from ARABLE to DEF. Changes in per capita GDP, trade openness, and arable land area will drive changes in deforestation rate. Uniquely, there is a bidirectional causality between DEF and COR. Outside the forestry context, the DH causality test found unidirectional causalities from GDP to TOP, POPG, and COR; from TOP to ARABLE and POPG; from COR to TOP; from ARABLE to TOP; and from POPG to COR. Finally, there is a bidirectional causality between ARABLE and GDP.

The unidirectional causality from per capita GDP to deforestation is in line with the results of studies in Burkina Faso by Yameogo (2021) and in Sub-Saharan Africa by Ajanaku & Collins (2021). This finding indicates that deforestation is not a source of change for per capita income. Conversely, changes in per capita GDP will cause changes in the deforestation rate. In addition, changes in the trade

openness index will also lead to changes in the deforestation rate. The unidirectional causality of per capita GDP to deforestation indicates that there is excellent potential for Southeast Asian countries to promote economic development programs while reducing deforestation rates, one of which is through promoting trade policies that are in line with sustainability principles. Furthermore, improving governance through strengthening controls on corrupt action is also an essential agenda for reducing deforestation rates.

6. Conclusion

Achieving net zero deforestation and sustainable development remains a significant challenge for Southeast Asia. Deforestation, along with forest degradation and fragmentation, is an empirical form of environmental degradation caused by the expansion of agriculture, public infrastructure, and a lack of robust governance that neglect sustainable development principles. Nevertheless, the underlying cause of forest depletion is still in debate. This study presents empirical evidence about the relationship between GDP, trade openness, corruption, and deforestation rates in Southeast Asia in the Environmental Kuznets Curve (EKC) framework by considering the impact of agricultural and demographic factors. This study uses panel data from nine developing countries in Southeast Asia from 1996 to 2018. Pooled Mean Group (PMG) and heterogeneous panel (DH) causality tests were applied to investigate the long-term nexus and the direction of causality.

Cointegration between deforestation, per capita GDP, trade openness, and governance (control over corruption) is evident. The estimation results support the EKC hypothesis that the relationship between per capita GDP and deforestation rate follows the Inverted-U curve. The threshold for per capita GDP is USD 26875, i.e. the stage of advanced economic development. We emphasize that deforestation will continue because Southeast Asia is still dominated by lower middle-income countries with per capita GDP that is still far from the threshold. Brunei is the only sample that has passed the turning point. Southeast Asia is enjoying the effects of scale of development so that an increase in GDP will be followed by deforestation. Another result is that openness is the driver of deforestation, while governance (control over corruption) is the correct instrument to reduce the deforestation rate. For the record, there are unidirectional causalities from per capita GDP and trade openness to deforestation. Development that simultaneously reduces deforestation is very likely to be implemented. We emphasize that strong integration between economic growth programs, trade policies, and forestry resource governance must be improved to reduce deforestation rates and accelerate the EKC turning point. Furthermore, the reconstruction of national institutions through strengthening control over corruption is also essential to prevent actions that drive deforestation.

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Appendix

Table 7. The Optimal Lag Structure Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-943.1410	NA	0.051513	14.06135	14.19047	14.11382
1	722.2028	3157.985	1.69E-12	-10.07708	-9.173215	-9.709773
2	836.6655	206.8808	5.31E-13	-11.23949	-9.560886	-10.55735
3	979.7435	245.8822	1.10e-13*	-12.82583*	-10.37249*	-11.82886*
4	1011.854	52.32752	1.18E-13	-12.76820	-9.540118	-11.45640
5	1041.160	45.15316	1.33E-13	-12.66903	-8.666210	-11.04240
6	1066.686	37.05992	1.61E-13	-12.51386	-7.736299	-10.57239
7	1091.039	33.19290	2.02E-13	-12.34132	-6.789018	-10.08502
8	1134.904	55.88707*	1.93E-13	-12.45784	-6.130794	-9.886704

Note: * represents the optimal lag

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