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Deforestation-induced the EKC framework: The role of corruption control and trade openness in Southeast Asia

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Abstract: Reducing the deforestation rate and formulating sustainable forest governance are still challenging for Southeast Asia. This empirical research intends to explore the dynamic connection between GDP, trade openness, corruption, and deforestation within the EKC framework by considering controls over agriculture and population. This article uses panel data from nine countries from 1996 to 2018. Pooled Mean Group (PMG) procedure and Dumitrescu-Hurlin (DH) causality tests were applied to examine the variables' long-term relationships and the direction of the causality. This article also features the unit root and cointegration tests. The estimation supports the EKC hypothesis that the nexus 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, while control of corruption is an effective instrument to reduce the deforestation rate in the long run. 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.
Keywords: Deforestation; GDP; trade openness; corruption; EKC; Southeast Asia
JEL Classification: O44; Q56; Q23; F18

Introduction

Improving forest governance and promoting sustainable development are notable agendas to battle the 21st-century climate crisis. Developing countries, however, deal with political-economic pressures to achieve environmental advancement (Tester, 2020). Forests are vital in sustainable development because they absorb approximately 2.4 billion tons of carbon emissions annually and are home to 80% of terrestrial biodiversity (IUCN, 2021). Six hundred six gigatons of biomass reserves are stored in forests, potentially as inputs for green economic growth (FAO, 2020). However, the remarkable benefits of forest resources are threatened by the current situation in line with forest degradation and fragmentation issues.

The global deforestation rate for 2015-2020 is still relatively high, with nearly 10 million hectares yearly (FAO & UNEP, 2020). However, deforestation rates also vary widely among regions. Southeast Asia is one of the territories with the highest deforestation rate. During 1990-2020, the forest cover area declined by 376,000 km2 (Russell, 2020). This phenomenon indicates 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).

The deforestation rate is generally associated with development processes. It follows an inverted-J curve pattern, divided into four stages: pre-transition, early transition, late transition, and post-transition (Hosonuma et al., 2012). The pre-transition phase is closely linked to low-income nations characterized by sub-optimal forest resource management. The early transition phase is closely tied to developing countries with high deforestation rates. Deforestation is carried out for agricultural expansion and industrialization, widely confirmed in Southeast Asia, Latin America, and Sub-Saharan Africa (Ordway et al., 2017; Tester, 2020). However, North American and European countries benefit from the late and post-transition phases. The Forest Transition theory aligns with the Environmental Kuznets Curve (EKC) that the relationship between economic growth and deforestation follows an inverted-U shaped or N curve (Caravaggio, 2020a). The inverted-U curve occurs due to the effects of scale, decomposition, and technology, in line with the stage of economic development (Usman et al., 2019).

Since the 21st century, the focus on the drivers of forest depletion has shifted from proximate (direct) to underlying (indirect) causes. The underlying drivers consist of socio-cultural, economic, demographic, governance, and technological elements (Carodenuto et al., 2015). Economic factors at the root of the forest cover changes in the tropics are Gross Domestic Product (GDP) 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.

Economic growth has long been linked to deforestation in emerging markets, including tropical countries. The research of Yameogo (2021) in Burkina Faso and Nathaniel and 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 forest degradation. Ajanaku and Collins (2021) reported that the nexus between per capita GDP and deforestation rates in Sub-Saharan Africa follows an inverted-U curve, in line with the EKC framework. Economic growth will not promote deforestation once per capita income reaches USD 3,000. In addition, there is unidirectional causality from per capita GDP to deforestation (Ajanaku & Collins, 2021).

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 and 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 and 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 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. Thuy Van et al. (2020) reported that controlling corruption has a beneficial role in achieving sustainable development. For the case of Southeast Asia, Handalani (2019) noted that the effect of corruption perceptions index (CPI) on forest cover is positive. Nonetheless, Mendes and Junior (2012) reported found that corruption has no significant impact on deforestation rates in the Amazon Rainforest in Brazil.

The vast majority of the EKC in Southeast Asia focuses on co2 emission (Saboori & Sulaiman, 2013; Nosheen et al., 2019; Ansari, 2022; Pata et al., 2022) and few researchers focused on deforestation. Therefore, this paper intends to investigate the presence of EKC deforestation in Southeast Asia and consider the role of control over corruption and trade. To the best of our knowledge, testing the EKC hypothesis for deforestation in Southeast Asia using a comprehensive panel method is still neglected. The previous articles by Thi & Nguyen (2018), Handalani (2019), and Kustanto (2022) solely employed a within estimator (fixed effect model), which ignored some critical issues in panel data, i.e., dynamics processes and heterogeneity slope (Hill et al., 2020). Hence, this paper uses the Pooled Mean Group (PMG) estimator that can perform better in long panels ($T > N$). Moreover, the method is appropriate to tackle endogeneity problems via sufficient lags.

To give more insight, we consider the impact of corruption and trade openness on deforestation. As Caravaggio (2020b) proposed, governance and trade openness are vital drivers of forest cover change. Moreover, the current study revises the previous paper conducted by Handalani (2019) by employing more expanded panel data (9 countries over the period 1996 – 2018). Finally, we also performed the Dumitrescu-Hulin (DH) test to examine panel causality among variables.

The EKC, inverted U-shape hypothesis, has been utilized as an empirical framework to investigate the connection between initial level of economic growth and environmental degradation. It states that degradation of the environment grows along with the initial output growth (scale effect) and declines at a specific point when the economy advances a certain level of economic development (Ganda, 2019). Therefore, the EKC framework represents a dynamic process in which technological innovation and structural changes emerge along with output growth (Darwanto et al., 2019). To this day, the EKC has been widely used in various proxies of environmental degradation (Stern, 2018), such as carbon dioxide (Mahmood et al., 2019), methane (Adeel-Farooq et al., 2021), ecological footprint (Al-mulali et al., 2015), water pollution (Thompson, 2012), and deforestation (Caravaggio, 2020a). The EKC-deforestation mainly comprises single- or cross-country analysis focused on tropical regions. Figure 1 presents a general shape of the EKC curve.

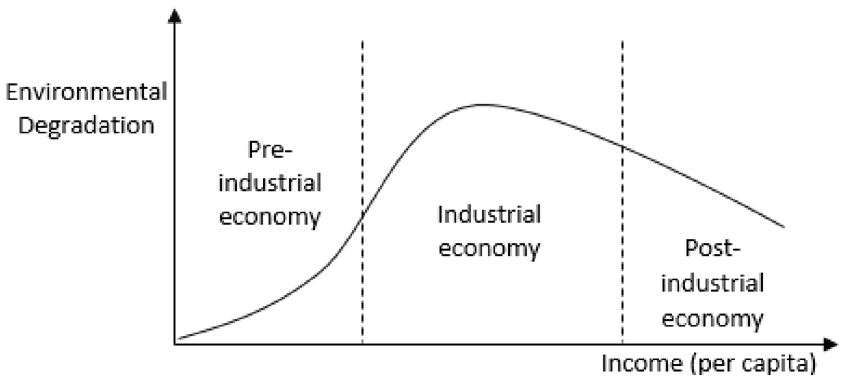

Figure 1 The EKC Curve
Source: Rashid Gill et al. (2018)

The EKC has been widely tested and discussed, but there are heterogeneity findings among samples that considerably limit the overall significance and sign of coefficients of the results. An empirical meta-analysis conducted by Caravaggio (2020b) noted that EKC-deforestation related to two theories, i.e., the von Thünen-like competing land use Forest Development Path (FDP) and Forest Transition (FT). The results revealed that the EKC framework leaves open the question of whether it does hold or not. Put simply, Studies of EKCs remain unresolved. It needs to consider the length of periods, the thoroughness of the data, the cross-sectional sample selection, and the potential of a second threshold. However, the second turning point may only be relevant for high-income samples. Align with Stern (2018) who stated that the EKC hypothesis is not statistically robust. EKC estimation results are sensitive to additional control variables, measurement variables, length of the data, and size of cross-sections (Aquilas et al., 2022; Sapkota & Bastola, 2017). Currently, EKC deforestation studies expand its empirical model concerning the proximate and underlying drivers of forest cover change. Previous studies incorporated the role of agricultural, trade, energy use, demographic, macroeconomic, and governance (see Aquilas et al., 2022; Ajanaku & Collins, 2021; Manivong et al., 2021; Tsiantikoudis et al., 2019; Caravaggio, 2020a; Ogundari et al., 2017; Waluyo & Terawaki, 2016; Yustisia & Sugiyanto, 2014; Wafiq & Suryanto, 2021).

Using annual data over the 1962 – 2007 periods and the ARDL procedure, Waluyo and Terawaki (2016) tested the EKC hypothesis in the case of Indonesia and modified the EKC model by incorporating the role of agriculture and demographic factors. Deforestation was proxied by the change in forest cover over the forest cover in the previous period $(\mathrm{FC}_{t-1} - \mathrm{FC}_t/\mathrm{FC}_{t-1})$. The inverse U-shape for the nexus between income per capita and deforestation was evident. Surprisingly, the income turning point was US$ 990.4. The results indicate that Indonesia is in a technological step in which GDP growth supports improving forest cover. In addition, the study revealed the unidirectional causality from GDP per capita to deforestation.

In the same vein, Kustanto (2022) examined the impact of trade openness on forest cover and tested the existence of the EKC hypothesis by employing pooled data (20 provinces over the 2002 – 2018 periods) and running the fixed effect estimator. Instead of using the annual rate of deforestation, he preferred to use forest cover as a proxy for environmental degradation. Trade openness, income per capita, and loggings, respectively, negatively contribute to changes in forest cover. Advancing trade openness, economic growth, and logging activities cause forest cover to decrease. The results align with Tsurumi and Managi (2014) and Faria and Almeida (2016). In addition, the ECK framework was verified. The results align with Adila et al. (2021), who examined the EKC deforestation in the case of Indonesia using provincial panel data (32 states for the period of 2013 – 2018) and by employing the feasible GLS method. The turning point was approximately US$10,055.

Naito and Traesupap (2014) tested the EKC framework in Thailand, used mangrove deforestation as a proxy for environmental depletion, and expanded its empirical model by considering the impact of shrimp farm expansion. The research employed provincial panel data, i.e., mangrove loss and Gross Regional Domestic Product (GRDP) per capita, over the 1975 – 2004 period. The results support the EKC framework that the nexus between income per capita and mangrove loss follow the inverse U-shape. In addition, results noted that the development of extensive and semi-intensive shrimp aquaculture quickens mangrove depletion. However, intensive shrimp aquaculture developed during the 1990s effectively declined mangrove loss.

By adopting a sophisticated empirical strategy, Caravaggio (2020a) examined the EKC hypothesis using PMG and differentiated samples based on income classification. Findings were heterogeneous based on income group. The results, surprisingly, found that the inverted U-curve is only verified in middle-income countries and that the turning point occurred when the level of income per capita attained USD 3,790. Meanwhile, the link between income per capita and deforestation in low-income and high-income countries follows a U-curve, interpreting that forest depletion is predicted to persist. Nonetheless, join samples confirmed that the EKC hypothesis was evident, with its relatively elevated threshold and the even higher level of development at which forests cover begins to expand and recover.

Among the recent studies, not all findings verify the EKC hypothesis. Manivong et al. (2021) examined the short- and long-run relationship between income per capita and the rate of deforestation in Laos within the EKC framework and considered additional control variables (debt, rural population growth, and agricultural production). The study engaged the annual data spanning 1991 – 2015 and the ARDL method. Results disputed the EKC framework and showed that the significant causes of deforestation are rural population and agricultural production. Similarly, empirical analyses by Minlah et al. (2021) and Tsiantikoudis et al. (2019) failed to verify the EKC hypothesis; instead, the link between income per capita and deforestation follows an inverted N-curve.

Further, Liu et al. (2017) examined the Forest Transition (FT) for nine Asian countries for the period 1960-2010 and tested the EKC hypothesis independently. The OLS is employed to test any significant link between variables. The results, however, reported that the inverted U-shaped curves for each country were not robust, i.e., there is no consistency when the model omits control variables. After adding control variables; however, the EKC hypothesis was only verified in South Korea and Indonesia. Regarding the FT, results showed that Indonesia, Malaysia and Laos still experience forest cover decline, indicating that rapid forest loss is still ongoing. In the same vein, Leblois et al. (2017) combined the OLS and fixed effect estimators to test the EKC deforestation in developing countries. Results cannot validate the EKC hypothesis and note that agricultural trade, previously relatively neglected, is found to be one of the main drivers of deforestation.

Research Method

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 the corruption data indices for 1997, 1999, and 2001 were not available, these gaps were filled by applying the linear interpolation technique. The number of observations in this study is 207, acquired from nine countries and 23 series.

Model Specification

This study aims to examine the nexus between economy, governance, and deforestation under the EKC hypothesis. The selected economic indicators are per capita income and trade openness, while governance is proxied by the control of corruption index. Referring to previous articles on EKC deforestation by Caravaggio (2020a), Minlah et al. (2021), and Liu et al. (2017), an empirical model can be specified as follow:

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

In the equation above, DEF is the deforestation rate; GDP is per capita income, GDP2 is the quadratic form of per capita income, COR is corruption control index, TRADE 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 hypothesis (inverted-U shaped) is confirmed only if the coefficient values of β1 > 0 and β2 < 0. The EKC turning point can be obtained through Equation 2.

$$t^* = exp(-\beta_1/2\beta_2) \tag{2}$$

Operational Variables

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. The positive value of DEF_{it} represents that forests in the current period (t) are lower than in the prior period (t-1), deforestation is indicated, and vice versa.

$$DEF_{it} = (FC_{it-1} - FC_{it})/FC_{it} \tag{3}$$

Per capita income was measured according to the per capita GDP value at constant prices in 2015, following previous studies by Ajanaku & Collins (2021) and 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 calculated 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 and Almeida (2016) and Kustanto (2022) confirm that trade openness and globalization are the top drivers of deforestation in tropical forests.

In this research, governance is considered a fundamental factor that prevents practices leading to forest depletion. Ajanaku and Collins (2021) found that political rights and civil independence have a negative and significant impact 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 arrests based on elite and private interests. The corruption control index is published by the World Governance Indicator (WGI). The index ranges from -2.5 to 2.5. A higher index indicates better governance.

To tackle the Omitted Variable Bias (OVB) issue, this research includes control variables related to agricultural and demographic factors. Previous studies 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 and population growth are expected to have a positive impact on deforestation. Table 1 summarizes research variables, a unit of measurement, and expected signs.

Table 1 Summary of Research Variables

Variable	Unit of Measurement	Source	β Exp.
DEF	Net deforestation rate (%)	WDI	
GDP	GDP per capita (constant 2015 US$)	WDI	+
GDP2	GDP per capita (Constant 2015 US$) squared	WDI; author's calculation	-
TRADE	The ratio of export plus import over GDP (%)	WDI	+
COR	Control of corruption index (-2.5 – 2.5)	WGI	+
ARABLE	Share of arable land (%)	WDI	+
POPG	Population growth rate (%)	WDI	+

Estimation Method

This study utilizes the Panel ARDL (PMG) procedure to examine the nexus between per capita income, openness, governance, and deforestation under the EKC theory. Prior to executing the PMG method, this article conducted stationary and cointegration tests. The stationary check 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). Hence, this article uses the unit root detection proposed by Levin et al. (2002). LLC calls for ADF equations to test stationarity.

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

where y_{it} = a variable in the form of panel data, Δ = differentiation, q = a number of ADF regression lags, θ = the coefficient of ΔY_{it-1}, Z = deterministic component, and e_{it} = error term. LLC assumes homogeneity in the autoregressive parameters for all individual panels ($\rho_i = \rho$) in the initial model. y_{it} is stationary if $|\rho| < 1$. The null hypothesis of non-stationary variables is rejected when the corresponding p-value of t-statistics is less than 5% critical value.

Next, this study applies the cointegration test proposed by Kao (1999). The procedure employed the DF- and ADF-equation tests for the residuals. Cointegration signifies the existence of long-run nexus, i.e., the combination of a number of variables that contain unit roots 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. The Kao's residual test can be calculated based on the following procedure (Al-Mulali et al., 2015):

$$\hat{e}_{it} = \rho\hat{e}_{it-1} + \sum_{j=i}^{p} \varpi \Delta e_{it-j} + v_{it} \tag{5}$$

$\hat{e}_{it}$ expresses the residual equation. If $\rho < 0$, cointegration is evident. The ADF statistic equation can be formed as follows:

$$ADF = \frac{t_p + \sqrt{6N\hat{\sigma}_v}/2\hat{\sigma}_{0v}}{\sqrt{(2\hat{\sigma}_{0v}/2\hat{\sigma}_r) + (3\hat{\sigma}_v/10\hat{\sigma}_{0v}^2)}} \quad (6)$$

To verify the long-run relationship, we consider the cointegration tests proposed by Pedroni (1999; 2004) as a robustness check. Unlike the Kao residual test, the method permits intercept heterogeneity and comprehends a trend in an equation (Ekananda, 2014). The Pedroni test offers seven alternative statistical tests, estimated using within- and between-dimension approaches. However, to simplify results, we only consider panel ADF- and Group ADF-statistics.

Then, this research employs the PMG or Panel ARDL procedure proposed by Pesaran et al. (1999). This method accommodates issues concerning panel data heterogeneity and allows for different intercepts and parameters among individuals in the short-run model; however, long-run parameters are assumed to be homogeneous (Pesaran et al., 1999). The estimator utilizes maximum likelihood, assumes errors with a normal distribution, and is based on Newton-Raphson's optimized algorithm. Previous studies, however, have applied the MPG method in order to test the existence of the EKC hypothesis (Attiaoui et al., 2017; Ari & Şentürk, 2020; Ampon-Wireko et al., 2021). The PMG equation (p,q) can be arranged as follows.

$$DEF_{it} = \sum_{i=1}^{p} \pi'_{ij} DEF_{it-j} + \sum_{j=0}^{q} \omega'_{ij}\, X_{it-j} + v_i + \varepsilon_{it} \quad (7)$$

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

$$\begin{aligned} \Delta DEF_{it} = \phi_i[DEF_{it-1} - \alpha'_i X_{it}] + \sum_{j=1}^{p-1} \pi'_{ij} \Delta DEF_{it-j} + \sum_{j=0}^{q-1} \omega'_{ij}\, \Delta X_{it-j} \\ + v_i + \varepsilon_{it} \end{aligned} \quad (8)$$

where π_i and ω_i represent the short-run coefficients of the lags of deforestation and explanatory variables. α_i shows the long-run parameters of the explanatory variables. ϕ_i denotes the coefficient of Error Correction Term (ECT). For verification, the ECT parameter must be negative and statistically significant, at least at the 10% level. ϕ_i demonstrates the speed of adjustment towards long-term equilibrium.

Finally, this research incorporates a panel causality test. The presence of cointegration among variables verifies that there must be at least, one causal connection; yet, it fails to explain its direction (Saidi & Ben Mbarek, 2016). Therefore, this paper performs the DH causality method proposed by Dumitrescu and Hurlin (2012). Several advantages of this method are that it allows cross-sectional dependency problems, heterogeneity of panel data and can be applied to panel structures with large N and T or small N and T (Lopez & Weber, 2017). The DH causality test adopts the Wald statistics. Referring to the article of Dumitrescu & Hurlin (2012), the panel causality equation is arranged as follows.

$$y_{it} = \alpha_i + \sum_{k=1}^{k} \gamma_i^{(k)} y_{it-m} + \sum_{k=1}^{k} \beta_i^{(k)} x_{it-m} + \epsilon_{it} \quad (9)$$

where x_{it} and y_{it} are assumed to be stationary variables and proven to be cointegrated. t, i, and m denote the period of estimation, country, and lag order, respectively. The null hypothesis of no causal nexus in each subgroup is proposed in the DH causality; whereas, the alternative hypothesis is that there is a causal nexus, at least in one subgroup. The DH causality test comprises three statistics, i.e., the average Wald ($\bar{W}$), z-bar ($\bar{z}$), and z-bar tilde ($\tilde{z}$) statistics (Lopez & Weber, 2017).

Result and Discussion

Panel Unit Root Test

To begin with the analysis, we check the order of integration of the variables by employing the LLC unit root test. We present the outcomes in Table 2. The findings reveal that GDP and ARABLE are stationary at level (at a 5% significance level). However, a number of variables, i.e., DEF, TRADE, POPG, and COR, are stationary after taking the first difference. Since the LLC test reveals mixed order of integration, i.e., $I(0)$ and $I(1)$, the PMG method (panel-ARDL) is an appropriate method to examine the nexus between deforestation and explanatory variables.

Table 2 LLC Unit Root Test Results

	Level		First difference	
	Statistic	p-value	statistic	p-value
DEF	-1.2468	0.1062	-11.3428***	0.0000
GDP	-1.9681**	0.0245	-8.2684***	0.0000
TRADE	-0.9967	0.1595	-9.9523***	0.0000
ARABLE	-1.6576**	0.0487	-4.7605***	0.0000
POPG	1.5265	0.9366	-5.0406***	0.0000
COR	0.1164	0.5463	-6.0727***	0.0000

Note: ** and *** indicate a significance of 5% and 1%, respectively.

Panel Cointegration Tests

Since a number of variables are not stationary at the level, the panel cointegration check is necessary to check the presence of a long-run relationship. Table 3 presents the results of the Kao residual test. The ADF statistic is -2.2840, which is significant at the 5% level. It can be stated that a long-term relationship is evident. DEF, GDP, GDP2, TRADE, ARABLE, POPG, and COR are cointegrated, i.e., moving together towards long-run equilibrium. For the robustness check, the Pedroni (Group- and panel- ADF statistics) and Westerlund (variance ratio) also exhibit the presence of cointegration between deforestation and the explanatory variables.

Table 3 Panel Cointegration Tests

Method		t-statistic	p-value
Kao	ADF	-2.2840**	0.011
Pedroni (Individual AR)	Group-ADF	-7.3665***	0.000
Pedroni (Common AR)	Panel-ADF	-6.1979***	0.000
Westerlund	Variance ratio	-2.2337**	0.013

Note: ** and *** indicate a significance of 5% and 1%, respectively.

PMG Estimation Results

The estimated PMG results in Table 4 present both the short-run and long-run coefficients and record the impact of explanatory variables on deforestation. Based on the automatic lag selection, the ARDL (2, 2, 2, 2, 2, 2) is the most appropriate model, following the AIC method. The long-run PMG 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 validate the EKC framework that the nexus between per capita GDP and deforestation is non-linear, i.e., following the U-shaped. The increase in per capita GDP initially drives deforestation; however, after reaching a certain threshold, it generates growth in forest cover. These findings are in line with Waluyo & Terawaki (2016), Caravaggio (2020), Adila et al. (2021), and Ajanaku and Collin (2021). These findings also align with the argument proposed by Crespo Cuaresma et al. (2017) that the marginal effect of income growth on environmental depletion is strong at the initial development; however, 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 income per capita of USD 26,875, i.e., the advanced stage of economic development. This figure is much higher than previous related studies by Kustanto (2022), Caravaggio (2020a), Adila et al. (2021), and Waluyo and Terawaki (2016). However, this calculated turning point is relevant because Southeast Asia is one of the global deforestation hotspots, where forest loss remains substantial (Estoque et al., 2019). Referring to the EKC turning point of USD 26,875, Brunei Darussalam is the only emerging country in Southeast Asia that has passed the turning point. In contrast, the per capita GDP of Indonesia, Malaysia, Thailand, Laos, Myanmar, Vietnam, the Philippines, and Cambodia is still far below the EKC turning point. These results indicate that deforestation will continue in Southeast Asia, in line with the advancement of income per capita and economic growth. In other words, output growth causes national welfare to improve, which in turn drives forest cover to decrease. These findings also suggest to policymakers that the integration between development policies and forest governance should be strengthened. Improved environmental policies and forest governance can accelerate the threshold of the nexus between GDP per capita and deforestation.

Another result, the coefficient of trade openness is positive and significant at the 1% level. It can be noted that trade openness is the underlying driver of deforestation in Southeast Asia. This finding is in line with a previous article conducted by Faria and Almeida (2016), who reported that openness to trade, either primary or all products, generates forest depletion. Openness is an incentive for forest conversion. The main link is that openness caused deforestation through export-oriented agricultural and processed forest products (Defries et al., 2010; Ajanaku & Collins, 2021). The increase in demand for agricultural commodities and processed forestry products will boost tropical countries to expand their agriculture sectors through forest conversion and logging activities. Palm oil and timber products are an example of notable export-oriented commodities in Southeast Asia that cause deforestation (Dohong et al., 2017; Austin et al., 2019).

Table 4 PMG Estimation Results

		Dependent: Deforestation	
		Coefficient	**Standard Error**
Short-run equation	GDP	6.43270***	2.37494
	GDP2	-0.31536**	0.14159
	TRADE	1.37076***	0.15356
	COR	-0.71906***	0.12752
	ARABLE	0.17693***	0.01530
	POPG	0.50326***	0.18775
Error correction	ECT	-0.88848***	0.25876
Long-run equation	Δ(DEF(-1))	-0.16117	0.22396
	Δ(GDP)	-408.47750	327.92710
	Δ(GDP(-1))	417.60540	341.07720
	Δ(GDP2)	26.66266	22.30920
	Δ(GDP2(-1))	-29.19596	23.79855
	Δ(TRADE)	0.31645	1.62792
	Δ(TRADE(-1))	1.13132	1.92194
	Δ(COR)	1.30910*	0.75498
	Δ(COR(-1))	1.35803*	0.78587
	Δ(ARABLE)	0.44326	0.33045
	Δ(ARABLE(-1))	0.09890	0.15955
	Δ(POPG)	11.66357	15.60363
	Δ(POPG(-1))	-8.87007	12.72662
	C	-32.14371***	9.43864

Note: Δ denotes the first difference operator. The lag order is specified using the AIC. *, ** and *** indicate a significance of 10%, 5% and 1%, respectively.

Furthermore, corruption negatively affects deforestation at a 1% level of significance. The negative impact of the corruption control index on the 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; the International Country Risk Guide (ICRG), Corruption Perceptions Index (CPI), and Business Intelligence (BI) index. They negatively affect forest product smuggling and illegal logging. In contrast, corrupt behaviours support forest resource management practices that neglect sustainability principles (Pachmann, 2018). This finding shows that control over corrupt practices is indispensable in combating deforestation and supporting sustainable forest governance.

Concerning the control variables, the empirical estimation reveals that the coefficients for arable land and population growth are positive and significant at a 1% level, confirming that both are the drivers of deforestation. The agricultural expansion generates the forest cover to decrease. This finding aligns with a previous study by Austin et al. (2019), who reported that both small and large-scale agricultures were the driver of deforestation. Next, the positive impact of population growth on deforestation aligns with the Neo-Malthusian hypothesis and previous research of Ngwira and Watanabe (2019), who found that rapid population growth was strongly associated with deforestation. In practice, growing population size will be followed by expanded land demand for housing, cattle ranching (grazing), and food- and non-food crops, which drive forest conversion (Richards & Friess, 2016; Hughes, 2017).

Finally, the estimation results of the long-run PMG must be confirmed using the short-run ECT model. The short-run PMG model shows that the ECT coefficient is negative (-0.888) and significant at the 1% level. There is a confirmed long-term equilibrium. The existence of shocks in the short run will be corrected by independent variables with 0.89 units of speed toward long-run equilibrium.

DH Causality Test Results

This section discusses the causal connection between deforestation, per capita income, corruption, and trade openness, employing the heterogenous panel causality method proposed by Dumitrescu and Hurlin (2012). The results are displayed in Table 5. There is a bidirectional causality between deforestation and control of corruption, implying that governance has a feedback effect from forest degradation. A change in the corruption index will cause a shift in the deforestation rates and vice versa. These findings also point out that the existence of forests is an incentive for corrupt practices.

Table 5 Pairwise DH Causality Test

T: 1996 – 2018, N: 9 n: 153 lags: 3			
H_0	$\overline{W}$	$\bar{z}$	**p-value**
GDP →DEF	10.17290	5.50683***	0.000
DEF → GDP	3.36819	-0.14729	0.883
TRADE → DEF	7.02337	2.88982***	0.004
DEF → TRADE	4.44805	0.74998	0.453
COR → DEF	12.70460	7.61043***	0.000
DEF → COR	7.01338	2.88152***	0.004
TRADE → GDP	4.12859	0.48453	0.628
GDP → TRADE	8.33763	3.98185***	0.000
COR → GDP	3.72417	0.14849	0.882
GDP → COR	8.68606	4.27136***	0.000
COR → TRADE	7.80269	3.53736***	0.000
TRADE → COR	4.68545	0.94723	0.344

Note: (→) represents the direction of causality.). $\overline{W}$ and $\bar{z}$ are the average Wald and z-bar statistics, respectively. The lag length selection is based on information criterion (AIC, SC, and HQ. ** and *** denote a significance of 5% and 1%, respectively.

Other findings, there are unidirectional causalities: from trade openness and per capita GDP toward deforestation. The one-way causality from per capita GDP to deforestation is in line with previous studies by Waluyo and Terawaki (2016), Ajanaku and Collins (2021), and Yameogo (2021). This finding implies that deforestation is not the driver of the change in per capita income. On the contrary, a change in per capita GDP significantly causes changes in the forest cover. In addition, changes in trade openness also lead to changes in the deforestation rate. These findings support the PMG estimation results, confirming that commercial liberalization is the significant driver of forest degradation in Southeast Asia. Nonetheless, the unidirectional causality of per capita GDP towards deforestation represents that the region has an excellent potential to promote economic development programs while simultaneously reducing the deforestation rate. Promoting forest-friendly products trade and strengthening controls over corruption are conceivable policies to combat deforestation.

Conclusion

Achieving net zero deforestation and sustainable economic development remains a substantial challenge for Southeast Asia. Deforestation, along with forest degradation and fragmentation, is an factual form of environmental degradation caused by the expansion of agriculture, the development of public infrastructure, and a lack of robust governance that neglect sustainable development principles. Nevertheless, the underlying cause of forest depletion is still in debate. Hence, this empirical study presents empirical evidence about the relationship between GDP, trade openness, corruption, and deforestation rates in Southeast Asia in the EKC hypothesis by considering the impact of agricultural and demographic factors. This research employs pooled data from nine developing countries in Southeast Asia from 1996 to 2018. PMG and DH Causality methods were applied to investigate the long-term nexus and the direction of causality.

Cointegration between deforestation, per capita GDP, trade openness, and control of corruption is strongly 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 26,875, 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 income per capita will be followed by deforestation. Other findings are that trade openness is the driver of deforestation, while governance (control over corruption) is the suitable instrument to reduce the deforestation rate. For the record, there are unidirectional causalities from income per capita and trade openness toward deforestation. A development economy that simultaneously reduces deforestation rates should likely be enforced. We emphasize that robust integration between economic growth programs, trade policies, and forestry resource governance must be improved to reduce deforestation rates, promote forest cover to increase, and accelerate the EKC turning point. Furthermore, reconstructing the quality of national institutions through strengthening control over corruption is required to prevent actions that drive deforestation.

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