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Economic Growth and Changes in Forested Areas in Southeast Asia: Is Environmental Kuznets Curve Still Relevant?

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Abstract

The environmental history of the twentieth century in Southeast Asia reveals tremendous loss of forested areas as a consequence of unprecedented economic transformations and unrestrained globalization. Featuring some of the world's fastest-growing economies, Southeast Asia has been experiencing fundamental changes in its economic structure, sociopolitical institutions, and the rate of natural resource extraction and depletion, including deforestation. This study reexamines evidence of the Environmental Kuznets Curve (EKC) hypothesis in light of the deforestation the above region experienced over the period 1990-2013. We use the change in forest cover as an indicator for environmental degradation. A panel cointegration approach is invoked to investigate the presence of the EKC hypothesis for two different data panels, gauging the effects of changes in economic structure, agricultural productivity, institutional factors, demographic transformation, renewable energy, and international trade across Southeast Asian countries. We do not find the evidence of the EKC. However, our results confirm the negative impacts of increasing agricultural productivity on forest stocks. We identify major Granger causality relationships between economic growth, the ratio of the value of exported forest products to the value of imported manufactures, the share of agriculture, forestry, and fisheries over total manufacturing, the debt ratio, trade openness, and renewable energy consumption. A variable capturing institutional change is found to play an important role in the management of forest resources. Southeast Asian countries should develop strong political foundations, using international trade to foster sustainable development paths compatible with growth and less pressure on forested land.

Key words: Southeast Asia, Environmental Kuznets Curve, deforestation, agricultural productivity, economic structure, international trade, panel cointegration, Granger causality.

I/ Introduction

Southeast Asia is an essential region for long-term world economic performance and global ecological sustainability (Asian Development Bank and International Food Policy Research Institute, 2009). This region is comprised of eleven countries, namely: Brunei, Cambodia, Indonesia, Lao People's Democratic Republic (PDR), Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, and Vietnam. Southeast Asia serves as a vital center of trade in the greater Asia and the Pacific. Located in the tropic region near the Equator, Southeast Asia is well-known for its richness in forest resources that support some of the highest biodiversity levels in the world. The region covers four global biodiversity hotspots, where substantially-high biodiversity is under insurmountable threats (Food and Agricultural Organization (FAO), 2011). While several country members in this region are experiencing changes in their economic structures, moving away from agriculture towards industry and services, the pressure on land has not been offset (FAO, 2011). It is essential for the region as a whole to take immediate action to resolve growing concerns on how to commit to the establishment of regional policies aimed at harnessing sustainable development paths and resiliency in response to climate change impacts.

Six countries of the region, including Cambodia, Indonesia, Lao PDR, Myanmar, Philippines, and Vietnam, are classified as low-middle income countries (The World Bank, 2017). In recent years, these six countries have experienced high economic growth rates, and are in the midst of transitioning from the early stages of economic development, whereby food security and self-sufficiency are top economic priorities, to stages wherein economic programs are introduced in an effort to develop sustainable goals to improve wellbeing and human development (Raitzer et al., 2010). Thailand and Malaysia, two countries whose economies are classified as upper-middle income countries, are experiencing the rapid changes in their economic development (The World Bank, 2017). Besides food security and self-sufficiency, these two economies have been diversifying their agricultural production activities towards market-oriented farming in response to the impacts of increased off-farm employment and improvements in agricultural labor productivity (Raitzer et al., 2010). The economic structure of Brunei Darussalam and Singapore, the two high-income countries, as defined by The World Bank, is highly dependent on manufacturing and services rather than agricultural activities thanks to technological intensification (The World Bank, Raitzer et al., 2010). However, the average relative contribution of the agricultural sector throughout the entire region's economy is still much higher than the relative agricultural sector contributions in other regions across the world (Figure 1).

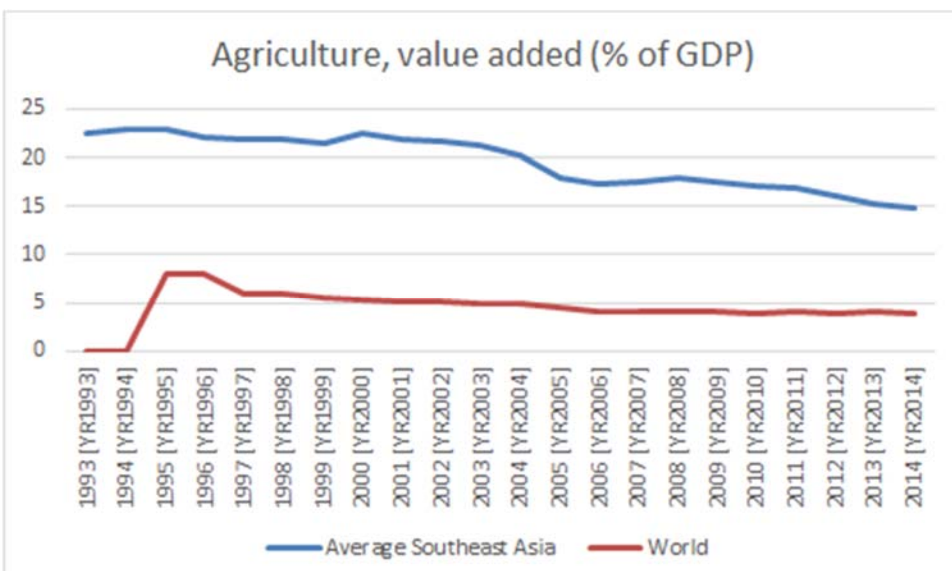

Figure I.1: Author's calculations based on The World Bank's WDI data.

Agricultural production plays an important role in the economies in Southeast Asia given the need for domestic food supply and the high export values of agricultural products. Among the top nineteen most valued commodities, since pre-industrialization, rice production has been dominating the agricultural production values with major contributions from the two world-leading rice exporters: Thailand and Vietnam (FAO, 2008). Since the 1970s and 1980s, many countries have diversified their agricultural sector, producing new cash crops and developing highland agricultural practices to complement the traditional lowland production. As the region is still heavily dependent on the growth of its agricultural sector, the majority of Southeast Asian populations are facing tremendous challenges associated with the ecological consequences of the long history of an agriculture-based economy, including climate change impacts, habitat loss, land degradation, and deforestation.

Forest land plays a prominent role in building resilience across the region in the wake of climate change impacts, coastal protection, and increasing demand for bioenergy and clean water resources. From 2005 to 2010, the forest areas of Southeast Asia declined at an annual rate of 0.5%, occurring most intensively in Cambodia, Indonesia, Philippines, Malaysia, and Myanmar (FAO, 2011). The loss of this major carbon sink, and accompanying severe loss in biodiversity across this region, is driven by a wide range of factors, including infrastructure development, agricultural expansion via monoculture cash crop plantations, and population growth.

The Environmental Kuznets Curve (EKC) literature on deforestation has discerned the environmental impacts associated with agricultural sector growth under increasingly dynamic economic conditions. Southeast Asia is an ideal case study to investigate the EKC hypothesis given the increase in trade of food staples and agricultural products. As Harris and Roach (2013) discuss, the increasing export values of major crops can drive increases in land conversion devoted to cash crop farming, which can result in rapid deforestation especially under weak political foundations and lack of defined property rights. One of the earliest EKC studies looking at deforestation as a proxy for environmental quality may be interpreted as cornerstone in understanding how a conversion from fuelwood energy to petroleum-based fuels, and then to cleaner energy, at early stages of development, can generate a hypothetical inverted U-shape relationship between deforestation rates and economic growth (Cropper and Griffiths, 1994). Examining a sample of developing countries, Cropper and Griffiths (1994) conducted a panel analysis under a fixed effects model using the percentage change in forest areas as dependent variable for deforestation as a function of multiple explanatory variables, including: population growth, population density, urbanization rates, and the price of forest products. Even though population growth is hypothesized to drive increases in deforestation rates, in more recent EKC studies institutional variables have also been identified as major factors impacting deforestation (Bhattarai and Hammig, 2004).

Invoking a modified EKC approach to account for renewable energy use and trade, this paper examines the evidence of the EKC for deforestation across Southeast Asian countries from 1990 to 2013. We examine interactive impacts on deforestation arising from changes in agricultural productivity, the share of value added in the agricultural sector to value added arising from manufactures, the debt to GDP ratio, population density, the ratio of the value of exported forest products to the value of imported manufactures, trade openness, renewable energy, and political freedom. The above study period is chosen to capture the impacts of trade liberalization on individual countries' economies throughout the region, especially during the 1990s, a period in which several economies, including Vietnam, Myanmar, Cambodia, and Laos, introduced major trade liberalization reforms aimed at the removal of artificial trade barriers across several economic sectors. We look at multiple variables in an attempt to incorporate the dynamic interactions among demographic, economic, and political changes across countries in this region. We hypothesize that there is evidence of a "race to bottom" scenario given the fact that forest stocks take a longer time to recover, and international trade triggers more pressure on land. Thus, we expect the conventional EKC to level off instead off curving down.

The rest of the paper is laid out as follows. The second section discusses the literature on deforestation and the EKC. This section addresses the theoretical models and concepts behind our chosen explanatory variables, and justifies the contributions of this study. The third section of the paper consists of the methods, variable descriptions, the panel analysis models for the sample data, and the econometric techniques implemented to undertake our empirical analysis, including the use of panel unit root tests, the Engle-Granger panel cointegration test, and the Granger causality test. The fourth section provides key findings light of our hypothesis. Lastly, the final section discusses policy implications, conclusions, and potential avenues for future research.

II/ Literature Review

II.1/ Theoretical Background of the EKC

The patterns of deforestation in Southeast Asia reflect one of the major environmental issues in the developing world. Similar to tropical deforestation in other parts of the world, forest loss in Southeast Asian countries is driven by a combination of factors. To analyze leading forces behind forest clearing, economic models have tested the magnitude and location of deforestation as a function of multiple variables that explain rationalities of agent decisions concerning the allocation of land among competing uses (Angelson & Kaimowitz, 1999).

Two of the most prominent sources of forest exploitation are agricultural expansion and logging. In light of these motivations, several important deforestation studies have identified and examined the interactions among the immediate and underlying causes of forest clearing at local, regional, and global levels (Allen and Barnes, 1985; Geist & Lambin, 2002; Mather et al, 1999). Some of these studies feature empirical analyses suggesting that there is evidence that deforestation in certain areas initially surged and then declined with economic development (Mather et al., 1999). For instance, time-series data on the relationship between deforestation and income growth in Philippines and Thailand serve as examples of potential evidence behind the EKC across developing countries (Refer to Figures II.1 and II.2 below). Similar patterns of changes in forest areas pitted against income per capita were found in global cross-sectional analyses during the 1980s (Mather et al., 1999).

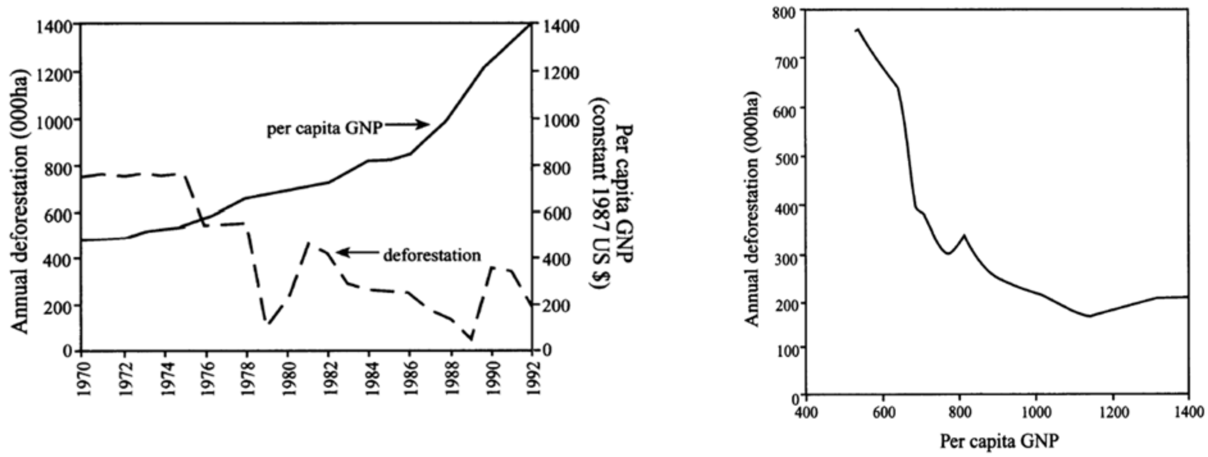

Figure II.1: Deforestation rates and economic growth in Philippines from 1970-1992. Source: Summers and Heston (1988) and Remigio (1993)

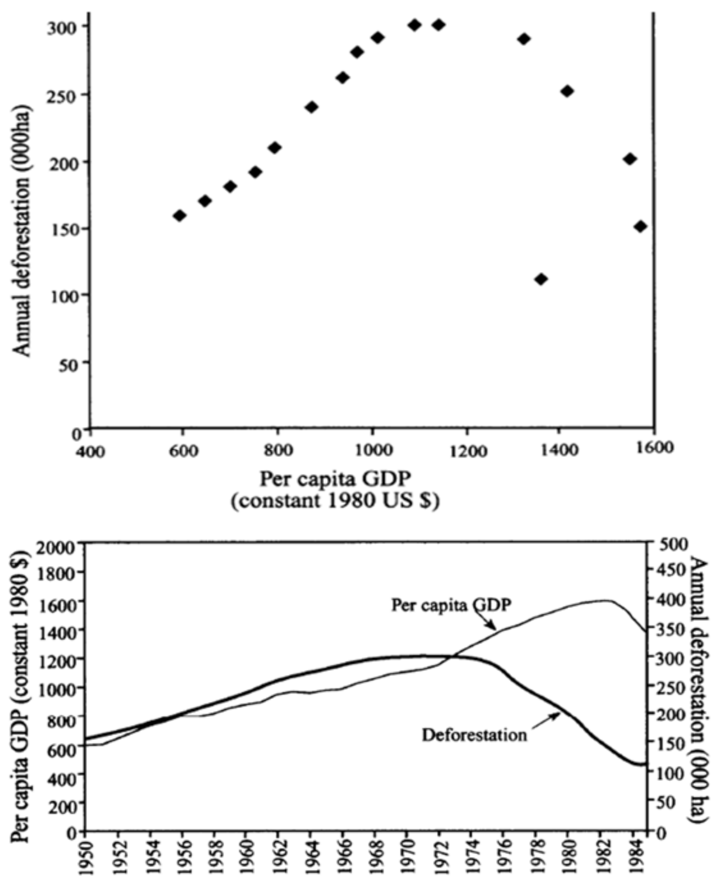

Figure II.2: Deforestation rates from 1950 to 1984 in Thailand and the relationship between economic growth trends and deforestation rates. Source: Rigg (1993)

Based on this empirical evidence, researchers began to invoke the EKC hypothesis to discern major driving forces behind forest clearing activities in an effort to identify courses of action (Allen and Barnes, 1985; Cropper and Griffiths, 1994; Marther et al, 1999; Bhattarai and Hammig, 2004; Ehrhardt-Martinez et al., 2002; Marquart-Pyatt, 2004; Culas, 2006). Similar to the original Kuznets Curve hypothesis pitting economic growth vs. inequality, after Kuznets (1955), the EKC hypothesizes that the interaction between environmental degradation and economic growth undertakes the pattern of an inverted U-shaped relationship. Applying the EKC to examine deforestation implies that at the early stages of economic development, the rate of deforestation will go up as income rises, but then forest coverage will expand at higher levels of development. The EKC hypothesis for deforestation provides lessons concerning the environmental impacts of previous and existing economic development paths undertaken by emerging and developing economies. The utilization of EKC in examining deforestation across developing countries can encourage sustainable development policies to protect forest resources (Panayotou, 1997). Although there is a consensus amongst some leading researchers over empirical evidence of the EKC for deforestation, varying independent variables utilized to explain the driving forces for the EKC patterns can be grouped into four major underlying forces, namely: demographic, economic, technological, and institutional factors (Geist and Lambin, 2002).

The empirical EKC studies have identified the scale, composition, and technological effects of economic growth on the environment (Dasgupta et al., 2002; Dinda, 2004; Stern, 2004). The positive slope of the EKC can be explained by the scale effect, which occurs and predominates during the beginning stages of economic development. Capital accumulation consumes a greater amount of natural capital and increases the throughput, accelerating pollution levels, depleting natural resources, and causing biodiversity loss (Antweiler et al., 2001; Cole and Elliott, 2003; Dinda, 2004; Stern, 2004). The composition and technological effects will eventually offset the scale effect to generate the negative relationship between economic growth and environmental degradation (Dinda, 2004; Lorente and Alvarez-Herranz, 2016). As income grows, the structure of the economy often transitions from a less pollution-intensive agrarian economy to more pollution-intensive growth in manufacturing and then cleaner service industries. This conventional process of economic development generates the composition effect with a mixture of positive and negative effects on the environmental quality (Panayotou, 1993; Antweiler et al., 2001; Dinda, 2004; Stern, 2004). Income growth often can lead to technological progress that increases efficiency, introducing cleaner technologies beneficial for the environment (Antweiler et al., 2001; Andreoni and Levinson, 2001; Cole and Elliott, 2003; Dinda, 2004; Sica and Susnik, 2014; Ben Jebli et al., 2015). Coupled with international trade and enhanced international cooperation, technology transfers can help developing countries achieve economic growth while reducing the negative impacts of growth on the environment. However, high-income countries can potentially induce a growth in the outflows of dirty industries to developing countries or inflows of natural resources from the developing world through international trade (Suri and Chapman, 1998; Dinda, 2004; Jayanthakumaran and Liu, 2012).

II.2/ Criticism of the General EKC and the EKC for Deforestation

The confounding findings of multiple EKC models do not reflect the complexity of the ecological systems on our planet. The censure behind the EKC hypothesis originates from various ecological perspectives, arguing that the EKC studies have seldom incorporated the

Earth's finite carrying capacity, irreversible losses of resource stocks, feedback loops of natural ecosystem cycles, and ecosystem resilience (Arrow et al., 1995; Meadows et al., 1972; Stern et al., 1996). Additionally, major literature surveys on the empirical findings of the EKC conclude that the EKC models have never included all pollutants, or examined more comprehensive groups of variables of environmental quality, which leads to a significant amount of conflicting arguments, interpretations, and criticisms among researchers and policy makers. (Stern et al., 1996; Dasgupta et al., 2002; Dinda, 2004; Stern, 2004)

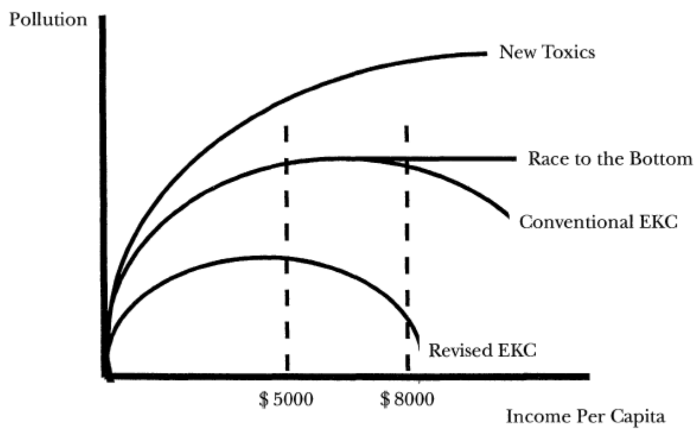

Figure II. 3: Theoretical depiction of the EKC hypothesis. Source: Dasgupta et al. (2002)

The relationship between economic growth and environmental degradation may follow different modified shapes of the conventional inverted-U shape (Refer to Figure II.3). Pessimistic critics discern two main hypotheses: the "Race to the Bottom" scenario with the ease of environmental standards by developed countries to cease outflows of dirty countries and "New Toxics" cases concerning potentially rising new toxics (Dasgupta et al., 2002; Dinda, 2004; Stern, 2004). Optimistic economists have postulated that developing and emerging economies might follow a revised EKC thanks to technology transfers under international assistance for environmental protection and economic liberalization with increasing international pressures from market agents on the environmental impacts of economic growth (Dasgupta et al., 2002; Dinda, 2004; Stern, 2004).[1]

Rather than emphasizing the impact of economic development, the evidence of the EKC for deforestation might be driven by natural ecosystem forces that, after a certain period, the rate of deforestation will decline due to the contraction in forested areas in the short run (Mather et al., 1999). Existing empirical studies mix different independent variables together without categorizing different layers of the driving forces behind deforestation (Angelsen and Kaimowitz, 1999). There is a limitation to the application and interpretation of the EKC for deforestation: this independent variable only represents environmental destruction, since it does not reflect the afforestation rate (Mather et al., 1999). It is necessary to broaden the variable as the changes in forest areas indeed account for both deforestation and reforestation. Moreover, there is neither consensus on the definition of deforestation nor consistent pooling time-series data of forested areas across nations. Even though the United Nations Food and Agriculture Organization (FAO) provides the most consistent annual data since 1990 on forest coverage through the FAO Global Forest Resource Assessments (FAO FRA), validated by annual questionnaires for each surveyed country, this database still contains missing data filled by the FAO's estimates using linear interpolation (FAO, 2016).

II.3/ Deforestation and Demographic Changes

Population growth is one of the most commonly cited causes of deforestation in developing countries (Allen and Barnes, 1985; Myers, 1994; Cropper and Griffiths, 1994; Lambin et al., 2001). This variable represents an internal factor of environmental change, which may result in negative effects on resource availability or environmental quality, as Malthus'

[1] See Nguyen (2016) for detailed discussion on different shapes of the EKC and evidence of the revised EKC.

theory suggests. Rapid population growth requires higher yields from agriculture, which triggers pressure on agricultural land and the conversion of forest areas to other uses to meet the increasing food demand (Mather et al., 1999; Jayasuriya, 2001). At local and regional levels, however, population growth might interact, and be driven by, economic, technological, and institutional factors (Angelson and Kaimowitz, 1999). Thus, population growth might better serve as an endogenous variable for deforestation models and might not play an important role as other factors have such as property rights and institutional factors, including XYZ. (Angelson and Kaimowitz, 1999; Cropper and Griffiths, 1994). Given the direct and indirect relationship with deforestation patterns, other demographic factors like population density and distribution should be considered. An increase in population density and the rural to urban population ratio is expected to exert harmful pressure on forests (Kahn and McDonald, 1995). Unequivocally, certain demographic factors, including population growth and density, can help explain the scale effect or the negative slope of the EKC.

In Southeast Asia, the rate of population growth was an essential internal factor inducing forest loss across predominantly agrarian societies, especially during the colonial period of the 1870s through the 1940s, as well as the modern era after the 1970s (Boomgaard, 2007). However, the negative impacts of population growth, especially in rural areas, are limited to the early stages of development, as the rate of population growth has been leveling off during more recent decades and declining with economic development (Ehrhardt-Martinez et al., 2002). Many countries in this region have been experiencing urban migration and demographic changes, but the shares of rural population in some countries remain high even after urbanization picked up. Thus, it is critical to examine which demographic factors can best explain the patterns of deforestation in the context of economic development in this region.

II.4/ Deforestation and Technological Change in Agriculture

With the impacts of population growth, technological change in the agricultural sector must proceed to accommodate increasing food demand and decreasing availability of natural resources as production inputs. Technological improvement enhances agricultural productivity and, theoretically, reduces the rate of natural resources exploitation, such as forest clearing (Bhattarai and Hammig, 2004). This notion is supported by the ecological modernization theory, which posits that the commercialization and mechanization of agriculture increases land productivity, which can attenuate deforestation and even generate reforestation (Ehrhardt-Martinez, 2002). Thus, if labor supply is inelastic with the introduction of new labor-intensive technologies, technological progress in agriculture can serve as the driving force behind the bending down portion of the EKC, which embodies the Borlaug hypothesis (Angelsen and Kaimowitz, 1999; Schmitz et al., 2015). Borlaug (2007) postulates that increasing agricultural yields lead to a reduced demand for croplands, resulting in the decline in prices of major staples and cultivated areas, a phenomenon displayed in Figure II.5 below. Empirical evidence of the land-sparing effect of increasing agricultural productivity at the global level can be found in the study by Rudel et al., (2009), as shown in Figure II.5.

Conversely, land conversion for agricultural uses can be accelerated by technological intensification, assuming exogenous commodity prices (Jayasuriya, 2001). Technological change can negatively influence forest cover, usually in the case of upland agricultural expansion (Jayasuriya, 2001; Geist and Lambin, 2002). The land-consuming effects of agricultural intensification supported by technology manifest the incentives of clearing the remaining forest areas if output demand is relatively elastic and prices of major commodities do not largely drop (Rudel et al., 2009). Moreover, FAO has revealed that small peasant farmers produce most of the food consumed using only 25% of the world's arable land, a finding which lies in stark contrast with the land-sparing effect associated with the moves toward corporatization hypothesized by the ecological modernization theory. Additionally, in the developing world the labor supply is usually elastic in contrast to the assumption by the Borlaug hypothesis. Henceforth, depending on the type of technology and market elasticities, agricultural intensification through technological amendments might yield perplexing interactions between deforestation and economic growth.

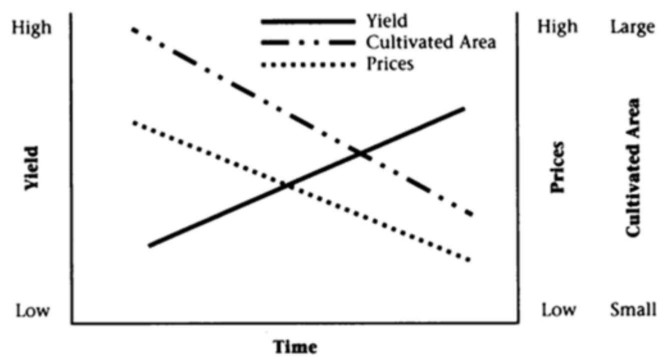

Figure II.4: Borlaug hypothesis on the relationship between changes in yields per hectare, prices, and cultivated areas. Source: Rudel et al. (2009)

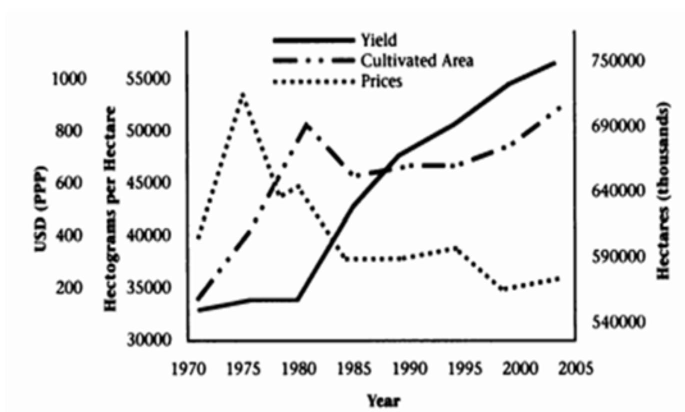

Figure II.5: Global trends over time in yield, cultivated area, and prices for ten major crops. Source: Rudel et al. (2009)

Forests in Southeast Asia might experience the land-consuming impacts of technological progress, which stimulates the expansion of lowland agriculture with wet rice cultivation and upland agriculture with cash crops like rubber and palm oil (Jayasuriya, 2001; Boomgaard, 2007). As farmers were able to increase productivity through the Green Revolution during the 1970s, most of the lowland forested areas were substituted by irrigated land. Over the past few decades, however, the introduction of cash crops and and increased demand for commercial crops has triggered the invasions of upland productions in the area (Boomgaard, 2007; Schmitz et al., 2015). Moreover, with the support of technology, residents living near the forests find it easier to clear forests for timber sale and property reclamation, as property rights are not well defined and the majority of forested areas are controlled by the government authorities in many Southeast Asian countries (Jayasuriya, 2001). Despite the rapid rate of technology adoption as well as forest loss in Southeast Asia, literature on deforestation in this region has not found consensus at the empirical level regarding whether there is consistent evidence on the role of technology in the relationship between changes in forest coverage and economic growth.

II.5/ Deforestation and Institutional Factors

The structure of socio-political institutions has recently received more attention from deforestation studies in developing countries, as supported by increasing empirical data on socio-political and institutional frameworks. Institutional factors can affect the EKC relationship as one of the major driving forces behind market and political activities, which might have a larger impact than population growth alone (Bhattarai and Hammig, 2001). Countries experiencing weak institutions with lacking property rights and policy climates are found to experience higher rates of deforestation in the short run, and face greater detrimental impacts on the surrounding environment and production of forest services in the long run (Geist and Lambin, 2002).

However, if economic growth brings about institutional improvements with better environmental policies and well-defined property rights, the inclusion of institutional variables might help shift the EKC relationship downward (Bhattarai and Hammig, 2001; Culas, 2007). Empirical evidence on the EKC for deforestation accounting for the institutional factors divulged the roles nation states play in securing sustainable uses of natural resources and enhancing environmental quality (Bhattarai and Hammig, 2001; Ehrhardt-Martinez, 2002; Culas, 2007).

One reason why forest clearing for agriculture can also be associated with property reclamation over land in Southeast Asia, as aforementioned, is due to the strong control the State has over forests as public lands. Besides individual expansion into forests, economic land concessions, particularly during the 1970s, have been granted by government officials to private logging companies (Sandler, 1997; Boomgaard, 2007). This corrupted behavior expedited the massive loss of forest coverage in Southeast Asia, especially in Philippines and Cambodia.

II.6/ Deforestation and the Changes in Economic Structure

One of the underlying factors behind the inverted U-shape between deforestation and economic growth refers to the changes in the economic structure, which reflects the composition effects of the conventional EKC within a given economy. The outgrowth of traditional agrarian techniques and agricultural intensification at the early stages of the industrial transformation initiate and push deforestation to reach its peak (Ehrhardt-Martinez et al., 2002). During these stages of development, the dominance of fuelwood energy in the context of increasing population can also explain the positive relationship between the growth of income and forest loss (Bhattarai and Hammig, 2004). The negative slope of the EKC for deforestation infers the relief of pressure on forests as a result of the structural changes in the economy towards industry and services-dominated urban economies (Ehrhardt-Martinez et al., 2002, FAO, 2011).

Furthermore, the patterns of deforestation leveling off and declining at later stages of economic development also elucidate the transformation of energy use towards coal and petroleum-based fuels (Bhattarai and Hammig, 2004). The impacts of urbanization and structural changes in the economy on deforestation can be evaluated by investigating off-farm employment, lower agricultural wages, and the amount of road construction as immediate factors of forest exploitation (Angelsen and Kaimowitz, 1999).

In the modern era, especially beginning the 1970s, as the rate of urbanization picked up the demand for timber used in building wooden houses, warehouses, and industrial establishments accelerated deforestation (Boomgaard, 2007). Additionally, urbanization and industrialization have provoked further development of infrastructures that require more land acreage, which then competes with forested areas.

II.7/ Deforestation and Macroeconomic Variables: Debt, and International Trade

Deforestation in low-income countries is considered a by-product of the interactions between the developed core and the developing periphery and semi-periphery, as suggested by leading international political economy theorists (Ehrhardt-Martinez et al., 2002; Marquart-Pyatt, 2004). In the context of international trade, the evidence of the EKC for deforestation in developed countries might result from exploiting natural resources in peripheral and semi-peripheral countries to feed the production process in the core as raw materials (Ehrhardt-Martinez et al., 2002). Due to the inferior position of the periphery and semi-periphery, developing nations have no alternative but to depend on forest and agricultural exports for economic growth, which in turn accentuates the rate of deforestation. The export flows of forest products and agricultural inputs often generate “boom-and-bust” cycles for peripheral and semi-peripheral economies, as the increasing exploitation rate exceeds the recovery rate or natural growth of forests, leading to a depleted forest stock (Ehrhardt-Martinez et al., 2002).

Trade flows of agricultural and timber products from developing countries toward their developed counterparts are partly driven by the debt dependency and debt servicing. The role of debt in the nexus of economic development and deforestation patterns is often included in the deforestation models of developing countries. As the shares of debt service account for large portions in the national budgets of developing countries, many countries in the underdeveloped periphery and semi-periphery have been facing rising tradeoffs between debt relief and forest conservation (Bhattarai and Hammig, 2001). In the short run, developing nations may sacrifice forest resources to escape debt constraints and secure inflows of credit loans and foreign investment (Kahn and McDonald, 1995; Bhattarai and Hammig, 2001; Ehrhardt-Martinez et al., 2002). If credit expansion is dedicated to forest management, this variable can help explain the reduced pressure on forests. Policies promoting trade in agriculture and forest products, such as export subsidies and tax incentives, tend to raise the output prices or benefits earned by farmers, consequently driving up forest exploitation (Angelsen and Kaimowitz, 1999).

Macroeconomic policies play an important role in creating, or strengthening, the linkages between indebtedness, forest and agricultural trade, and deforestation patterns. Among leading macroeconomic policy variables, exchange rate policies are often chosen to serve as one of the major driving factors linking domestic production and export activities (Bhattarai and Hammig, 2001). The fluctuations in prices of different crops, livestock products, and timber exports are important variables demonstrating immediate causes of the underlying macroeconomic combination factors of foreign debt, foreign investment, and international trade.

In Southeast Asia, trade liberalization in conjunction with currency devaluations helped raise agricultural and timber prices, and, as a result, partially drove up short-term forest loss (Angelsen and Kaimowitz, 1999). The increase in the volume and changes in the direction of trade flows of agricultural commodities were found to increase the prices of key crops. The process of trade liberalization took place during the 1970s, thus occurring after the economic stagnation period of 1946 to 1957, a period in which almost all Southeast Asian countries became independent (Boomgaard, 2007). The increasing demand from European and North American markets introduced upland production of commercial crops alongside with increased mono-cropping of wet rice irrigation (Boomgaard, 2007). Intensive exports not only help countries in Southeast Asia pay their debts, but also enhanced an increasing rate of economic growth. This process coincides with the transition away from labor-intensive manufacturing industries due to losses in the comparative advantage held by agriculture and forestry industries (Jha et al., 2010). As Southeast Asia has experienced the largest decline in forested areas in the late twentieth century (FAO, 2011), environmental concerns have risen due to agricultural expansion and logging, which are often externally driven by international market demand. These mounting pressured have led to rising concerns to induce forest conservation efforts. However, recent literature on Southeast Asian deforestation has not determined the magnitude of how two coexisting trade flows in agriculture and forestry (driven by trade liberalization and agricultural intensification) interact and influence the changes in forest coverage.

II.8/ Deforestation and renewable energy consumption

The consumption and generation of renewable energy can serve as one of the major solutions to lessen the extraction pressure on natural resources and pollution due to fossil fuel dependence. Several leading case studies have examined the impact of the energy sector, especially the renewable energy production stimulated by the adoption of new technologies (Ang, 2007; Lopez-Menedez et al., 2014. Renewable energy consumption is found to have a positive and statistically significant association with an increase in per capita income (Sadorsky, 2009). Indeed, the empirical evidence from a panel of emerging economies illustrates that fluctuations in income have a larger impact on increasing renewable energy consumption than fossil fuel electricity consumption (Sadorsky, 2009). Renewable energy consumption also has a long-run causality to trade and income growth (Ben Jebli et al., 2015), while in the short run, it has a causal association with CO_2 emissions (Salim and Rafiq, 2012).

Countries with high renewable energy resource intensity are found to experience the EKC patterns at lower levels of pollution and environmental degradation (Lopez-Menedez et al., 2014; Nguyen, 2016). This empirical evidence urges countries to diversify their energy sectors by promoting incentives to renewable energy generation when striving to meet economic priorities and combat environmental challenges (Ben Jebli et al., 2015; Al-Mulali et al., 2015; Lorente and Alvarez-Herranz, 2016). While literature has paid much attention on how renewable energy can reduce pollution levels, there is little discussion on whether cleaner energy sources can influence the rate of natural resource extraction like the rate deforestation, except for the debatable case concerning the potential effects of biofuels on forest land and economic growth. Renewable energy consumption patterns by sector and by energy source could possess different impacts on the fluctuations of natural capital stocks, especially in terms of forest land. The inclusion of renewable energy as one of the control variables is important in light of the evidence of an EKC hypothesis for deforestation.

III/ Methods

III.1/ Data

To analyze the EKC model for deforestation this study collects a data panel of eleven countries in Southeast Asia over the period 1990-2013.[2] We use the level of forest area, an indicator for deforestation, as our dependent variable. According to FAOSTAT, forest area is defined as land covered with trees higher than 5 meters and canopy of more than 10%, including areas with bamboo and palms, forest roads, firebreaks, forest in protected areas, and areas under reforestation potentially reaching 10 percent of canopy cover (FAO, 2016). This new definition of forest cover excludes the areas covered by trees in agricultural production systems and in urban parks and gardens. Several previous studies on deforestation estimate the rate of deforestation as the annual rate of change in forest cover to serve as the dependent variable regressed against a mix of independent variables in both levels and first differences, which has not taken into account the issues of non-stationarity among variables. To resolve that problem, in this paper we regress the level of forest areas as a function of other dependent variables in levels and repeat the process for the first differenced data of all variables. Since this dependent variable does not measure environmental damage directly, if there is evidence of an EKC for deforestation, we expect to find the reflection of the EKC shape, meaning a U-shape rather than an inverted one.

Given the conditions of data availability, we apply panel analysis for two different panel datasets: The first set includes all eleven countries in Southeast Asia for the period 1990-2013; whereas, the second set contains only six countries, namely Cambodia, Indonesia, Malaysia, Philippines, Thailand, and Vietnam, over the period 2000-2013, to incorporate the impacts of

[2] See Appendix VII.1/ for the list of countries

debt, renewable energy use, and international trade. For both panels, observations for 8 independent variables are calculated based on information collected by FAOSTAT, the United States Department of Agriculture (USDA), the International Monetary Fund (IMF). Variables include: Per capita real GDP measured in U.S. dollars at constant 2005 prices (GDPpc), the square of per capita real GDP (sqGDPpc), the share of the value of agriculture, forestry, and fisheries to the value of total manufacturing (Agmu), an agricultural total factor productivity growth index[3] (1992 = 100) (Agriproductivity) measured based on the rate of output growth versus input growth, the net capital stocks of agriculture, forestry, and fishing in million U.S. dollars at constant 2005 prices (Ncs), population density measured as number of inhabitants per square Km of land area (Pdensity), the ratio of rural population to urban population (Ruralurban), and the political institutional index with values from 2 to 14 (Freedom).

Three variables *Agmu*, *Agriproductivity*, and *Ncs* serve as proxies to capture the impacts of technological intensification in agriculture and the change in the economic structure. As discussed in the literature, the coefficients of these three variables are not predicted since technological change can carry out both negative and positive impacts on forest areas. Demographic factors and the impacts of industrialization and urbanization are examined through the *Pdensity* and *Ruralurban* variables, which are expected to take negative signs since increasing population pressure triggers more deforestation. *Freedom* is the institutional variable that serves as a proxy for the presence of property rights and political foundation, an underlying factor behind our EKC model for deforestation. This variable is measured as the sum of political

[3] According to USDA, the index is measured based on the growth rate of gross agricultural output versus the weighted-average growth in quality-adjusted land, labor, machinery power, livestock capital, synthetic NPK fertilizer, and animal feed.

rights and civil liberty indices[4] collected from Freedom House data. The lower the index value, the more political and individual freedom a country will have. An improvement in political institutions will reduce deforestation, meaning that as the value of the freedom index is smaller forest cover will increase. Thus, we expect the coefficient of the variable *Freedom* to take a negative sign in relation to our dependent variable *Forest*.

For the panel with six cross-sectional countries over a shorter time period, from 2000 to 2013, we introduce four more variables in addition to the six aforementioned variables. The ratio of the exported value of primary forest products (round wood, sawn wood, wood-based panels, pulp, and paper and paperboard) to the imported value of manufactures (chemicals, basic manufactures, machinery and transport equipment, and miscellaneous manufacture goods) (Pxpm). *Pxpm* intends to capture the impacts of international markets and trade transactions on forest levels. The debt to GDP ratio (Debt) is interpreted as the driving force behind the negative impact of trade on deforestation in developing countries, as discussed in section II. Given our previous work on the EKC and the roles of trade and renewables on environmental quality, we include in our current analysis the trade openness index (TO), which is measured by the sum of exports and imports expressed as a percentage of GDP, and renewable energy consumption defined as the share of renewable energy in total energy consumption (Renewable) (Nguyen, 2016. Observations to produce *Pxpm*, *Renewable*, and *TO* were retrieved from the World Bank's World Development Indicators (2017); whereas, observations to produce the variable *Debt* were retrieved from the International Monetary Fund (IMF, 2017). All variables underwent natural log

[4] These indices are constructed and published annually in the Freedom House website. The political rights index and civil liberties index is estimated by the scores for seven subcategories drawn from the Universal Declaration of Human Rights, including voting freedom in legitimate elections, free participation in the political process, having accountable political representatives, exercising freedoms of expression and belief, freedom to assemble and associate, free access to an established and equitable system of rule of law, and equal access to economic opportunities and the right to hold private property.

transformations and a first difference obtained, in most cases using RStudio 1.0.136. Descriptive statistics of the raw data for the both panel datasets are shown in Table 2 (Appendix VII/2) and Table 6 (Appendix VII/6).

III.2/ Model

For two different panel datasets, we have two EKC regression models with the natural log of forest areas as a quadratic function of the natural log of per capita real GDP and natural logs of other independent variables. The first equation is used for the panel including our entire sample of eleven countries in Southeast Asia, while the second equation is applied to the panel including six countries, as discussed above. Following are the equations for both models:

$$\begin{aligned} lnForest_{it} = \alpha_i + \gamma_t + \beta_1 lnGDPpc + \beta_2 (lnGDPpc)^2 + \beta_3 lnAgmu \\ + \beta_4 lnAgriproductivity + \beta_5 lnNcs + \beta_6 lnPdensity + \beta_7 lnRuralurban \\ + \beta_8 lnFreedom + \varepsilon_{it}, \end{aligned} \quad (1)$$

$$\begin{aligned} lnForest_{it} = \alpha_i + \gamma_t + \beta_1 lnGDPpc + \beta_2 (lnGDPpc)^2 + \beta_3 lnAgmu \\ + \beta_4 lnAgriproductivity + \beta_5 lnNcs + \beta_6 lnPdensity + \beta_7 lnRuralurban \\ + \beta_8 lnFreedom + \beta_9 lnPxpm + \beta_{10} lnPxpm + \beta_{11} lnDebt \\ + \beta_{12} lnRenewable + \beta_{13} lnTO + \varepsilon_{it}, \end{aligned} \quad (2)$$

where i = 1,..,11 and t = 1990,...,2013 for equation (1) and i = 1,..,6 and t = 2000,...,2013 for equation (2) indicate the country and year, respectively α_i and γ_t denote the country and time fixed effects. The turning point in income is defined as the maximum level of forest cover τ, which we obtain by determining the first order conditions for each equation:

$$\begin{aligned} lnCO2'_{it} &= \beta_1 + 2\beta_2 lnrealGDP = 0 \\ lnrealGDP &= \frac{-\beta_1}{2\beta_2} \\ realGDP &= \tau = e^{(-\beta_1/(2\beta_2))} \end{aligned}$$

Once a country reaches this threshold level of income, an increase in every unit of income will correspond to an increase in the level of forest area. The above equations assume that although each considered country may have different EKC shapes and turning points, at a given income level all the countries have the same income elasticity. The two models capture several relationships between per capita real GDP and deforestation depending on the coefficients of $\beta_1$and β_2 (Refer to Appendix VII/4). Our empirical findings are consistent with an EKC when $\beta_1 < 0$ and $\beta_2 > 0$, meaning there is a U-shape relationship between income and the level of forest areas, supporting the evidence of the EKC for deforestation.

III.3/ Econometric Techniques

This study estimates both random and fixed effects (country and time specific) models for the above regression equations. Under the fixed-effects models, α_i and γ_t are treated as regression parameters; whereas, in the random-effects models, α_i and γ_t represent components of a random disturbance term (Stern, 2004). If and when the explanatory variables are correlated, the random-effects model cannot be estimated consistently, meaning the fixed-effects model is preferred over the random-effects model. If the error terms are correlated, the random-effects, rather than the fixed-effects model, is more suitable to infer the regression results. The random-effects model assumes that the variation across entities is random and uncorrelated, which allows for time-invariant variables to influence the model as explanatory variables (Torres-Reyna, 2007). Conversely, the fixed-effects model removes the effects of time-invariant characteristics that are unique to the individuals, so they do not influence the regression outcomes (Torres-Reyna, 2007). The results of the fixed-effects model, however, cannot be generalized to a population or another sample since the estimated parameters depend on the country-and time-effects in the selected sample (Stern, 2004).

Prior to running the regression equations (1) and (2), this study also examines the following tests[5] to choose the most appropriate models:

1. The Breusch-Pagan Lagrange multiplier (B-P/LM) for random effects;
2. The Hausman test;
3. The F test for time-fixed effects;
4. The Breusch-Godfrey/Wooldridge test for cross-sectional dependence;
5. The Breusch-Godfrey/Wooldridge test for serial correlation;
6. The Breusch-Pagan test for heteroskedasticity;
7. The augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) test for unit roots/stationarity with lags of 1 and 2;
8. Engle-Granger cointegration test;
9. Granger causality test.

[5] Refer to Appendix VII.10/ for the definitions and hypotheses of these tests

IV/ Empirical Analysis

IV.1/ Empirical results for the first data panel

The results of the statistical tests for the first panel containing eleven countries in Southeast Asia across a 24-year time series are recorded in Table 3 (Refer to Appendix VII.3/). The Breusch-Pagan Lagrange multiplier (B-P/LM) test for random effects suggests that there is evidence of significant differences across countries within the panel, so the random-effect model is preferred over the pooled ordinary least squares (OLS) (Table 3, Appendix VII.3/). The result of the Hausman test then rejects the random effect model with significant test statistics, meaning the fixed-effect model is a better fit for the selected panel compared to the random effects model (Table 3, Appendix VII.3/). With a p-value larger than 0.1, we fail to reject the null hypothesis of the F test, and therefore time-fixed effects do not need to be considered (Table 3, Appendix VII.3/).

As a result, we will focus on the outcomes of the country-fixed effect model. The results of the tests for cross-sectional dependence, serial correlation, and heteroscedasticity yield very small p-values, which reject the null hypothesis for these three tests (Table 3, Appendix VII.3/). The evidence of cross-sectional dependence, serial correlation, and heteroscedasticity is present in this panel. Thus, we want to apply Arellano robust covariance errors to correct for these problems.

Unit Root

The results of the ADF and PP unit root tests are provided in Table 4 (Refer to Appendix VII.4/). Both of the ADF and PP test statistics show that all the variables, except *Ncs* and *Ruralurban*, are non-stationary at levels and become stationary at the first difference or I(1).

Panel cointegration

Using the results of the unit root tests, we obtain the result of the Engle-Granger cointegration test with a very small p-value that rejects the null hypothesis and confirms that there is evidence of long-run relationships between variables. Since most of the variables in the regression models are cointegrated, the regression model using first difference cannot solve the issues of serial correlation.

Augmented Dickey-Fuller Test Unit Root Test

Value of test-statistic is: -4.8268 (p-value = 0.000003244)

Critical values for test statistics: 1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

Granger causality

Given the outcome of the Engle-Granger cointegration test, the Granger causality test is conducted to examine the direction of causality between forest areas, real GDP per capita, the ratio of the share of agriculture, forestry, and fisheries over the share of manufacturing, agricultural factor productivity, population density, and the ratio of the share of rural population over the share of urban population. The test is conducted at lags of 1 and 2, as recorded in Table 5a and Table 5b, respectively (Refer to Appendix VII.5/). There is a long-run unidirectional causality running from real GDP per capita to the ratio of the share of agriculture, forestry, and fisheries over the share of total manufacturing. An increase in income causes the ratio to decrease, which reflects the increase in the share of total manufacturing or the reduced share of agriculture, forestry, and fisheries. Other unidirectional causality relationships run from agricultural factor productivity and population density to real GDP per capita. While there is no statistically significant correlation between agricultural productivity and economic growth, we find that population density can affect, and has a positive relationship with, economic growth (Figure IV.1). The Granger causality test shows no evidence of a causality relationship between forest areas and other variables.

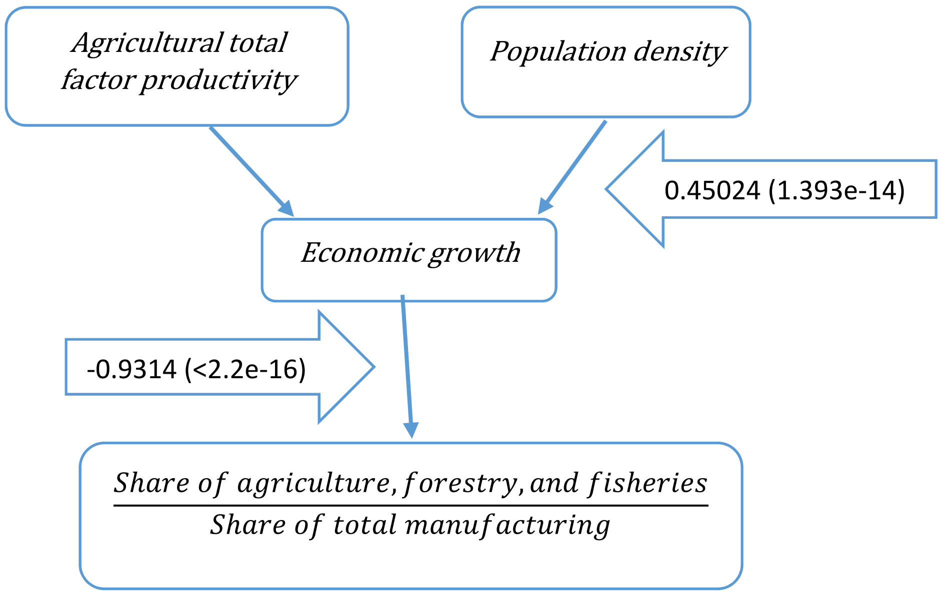

Figure IV.1: Evidence of long-run Granger causality for the first panel. The direction of the errors represents the direction of the causality. The correlation coefficients which are statistically significant between these variables are recorded inside the arrow features, along with the p-values in parentheses. (Author's diagrammatic interpretation).

Regression results

Excluding two variables *Ncs* and *Ruralurban* due to different orders of integration from the models, we obtain the regression results for pooled ordinary least squares (Pooled OLS), random effects, country-fixed effects, country-and-time fixed effects, and first difference, as recorded in Table 1. Since we are interested in the country-fixed effect model, there is no evidence of a statistically significant EKC curve for deforestation, or the U-shape between real GDP per capita and forest cover in this panel. According to the country-fixed model, *Agmu* has a positive relationship with forest areas at a one percent level of significance. This result indicates that as the ratio of the value of agriculture, forestry, and fisheries in income to total manufacturing increases, the levels of forest coverage will increase. The agricultural total factor productivity index is another variable that has a statistically significant association with forest levels. As agricultural productivity increases or is intensified, forest land is compressed and reduced.

Table 1: Panel regression models for the first panel

	Dependent variable: LnForest (Robust standard errors using sandwich estimator)				
	Pooled OLS	Random effects	Entity-fixed effects	Entity & time fixed effects	First difference
	(1)	(2)	(1)	(2)	(1)
GDPpc	3.9400** (1.8228)	-0.0180 (0.3026)	-0.0053 (0.2972)	-0.0366 (0.3141)	-0.0447 (0.2202)
sqGDPpc	-0.3132** (0.1254)	0.0207 (0.0185)	0.0203 (0.0185)	0.0380 (0.0251)	0.0055 (0.0131)
Agmu	-0.1750 (0.7337)	0.1662*** (0.0564)	0.1770*** (0.0544)	0.2626*** (0.0791)	0.0155*** (0.0047)
Agriproductivity	0.0124 (0.4616)	-0.0826 (0.0550)	-0.0977** (0.0464)	-0.0906* (0.0525)	-0.0105 (0.0101)
Pdensity	-0.8327* (0.4259)	0.0064 (0.1219)	0.0606 (0.0612)	0.3842 (0.3644)	-0.0670 (0.1291)
Freedom	-0.5174 (0.7313)	0.0494 (0.1035)	0.0560 (0.1053)	0.0542 (0.0902)	0.0038 (0.0056)
Constant	2.8236 (7.7645)	8.1403*** (1.3106)			
Observations	264	264	264	264	253
R2	0.8693	0.1256	0.1592	0.2155	0.0191
Adjusted R2	0.8662	0.1052	0.1047	0.0789	-0.0048
F Statistic	284.8576***	6.1532***	7.7940***	10.2571***	0.7994
Note:	***Significant at the 1 percent level of significance; **Significant at the 5 percent level of significance; *Significant at the 10 percent level of significance. Robust standard errors are presented in parentheses.				

IV.2/ Empirical results for the second data panel

After running the pre-regression statistical tests for the second panel, we conclude that the time-fixed effects should be considered and controlled for the selected data (Table 7, Appendix VII.7/). The evidence of cross-sectional dependence, serial correlation, and heteroscedasticity is also present in this panel (Table 7, Appendix VII.7/). Thus, the Arellano robust standard errors are used for the fixed-effect models. For this panel, we pay closer attention to the country-and-time fixed effect model, as controlling for year effects allows the models to capture the influence of both aggregate time trends and differences across entities in the panel.

Unit root

The results of the ADF and PP unit root tests are recorded in Table 8 (Refer to Appendix VII.8/). The ADF and PP test statistics both confirm that all the variables, except *Ncs*, *Pdensity*, and *Ruralurban*, are non-stationary at levels and become stationary at the first difference or I(1). After excluding *Ncs*, *Pdensity*, and *Ruralurban*, we can test the long-run relationship between the non-stationary variables using the Engle-Granger cointegration test.

Panel cointegration

The results of the Engle-Granger cointegration test with a small p-value of close to zero provide evidence of the long-run relationship among the selected non-stationary variables of the second panel.

```
# Augmented Dickey-Fuller Test Unit Root Test #
Value of test-statistic is: -6.9824 (p-value = 0.000000004932)
Critical values for test statistics:    1pct  5pct 10pct
                                   tau1 -2.6   -1.95 -1.61
```

Granger causality

We use the Granger causality test to determine the direction of causality among these cointegrated variables at two different lags of 1 and 2. The results of this test are recorded in Table 9a and Table 9b (Appendix VII.9/). With the inclusion of additional independent variables compared to the first panel, there is one bidirectional long-run negative causality relationship between renewable energy consumption and the debt to GDP ratio (Figure IV.2)

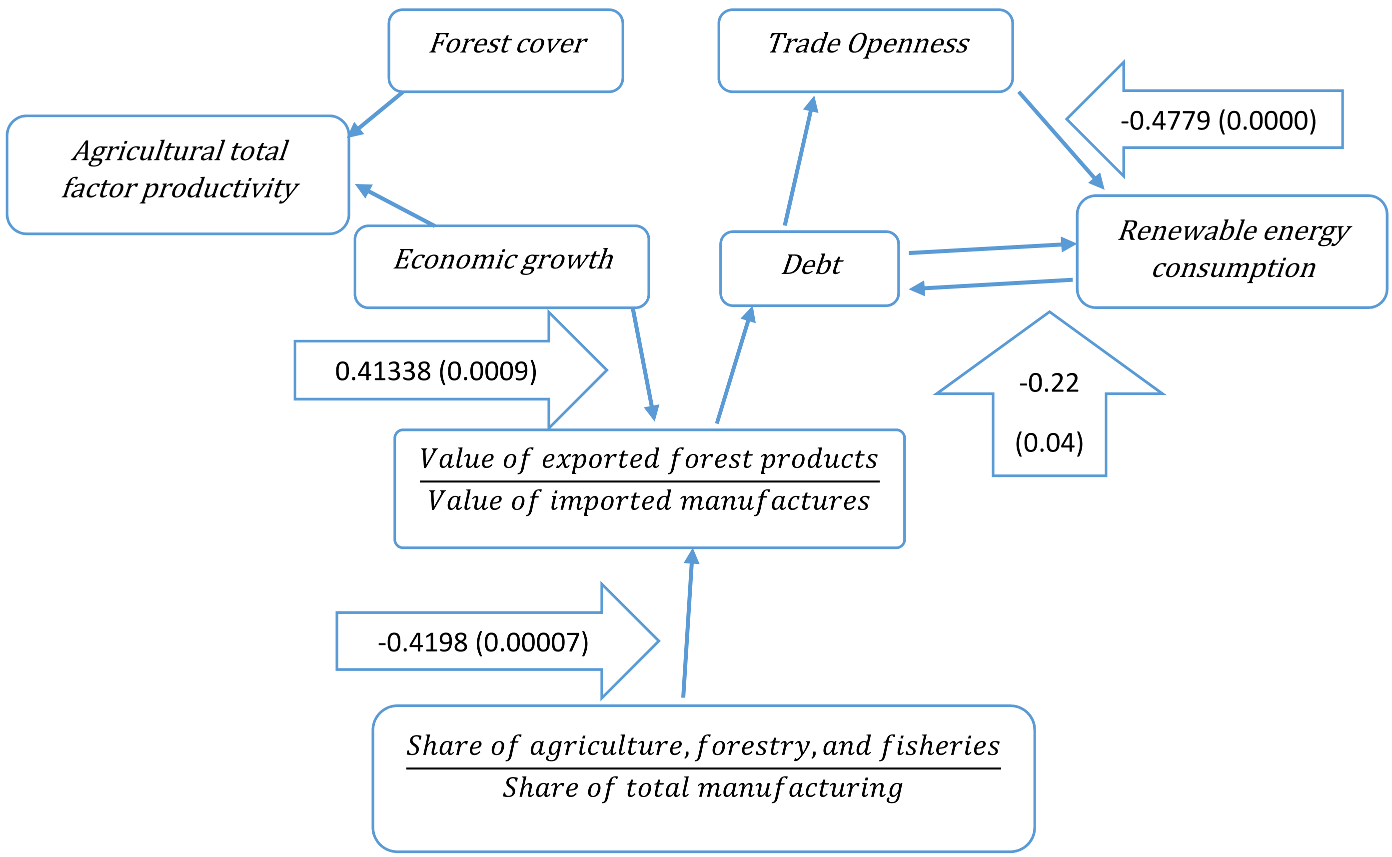

Figure IV.2: Evidence of long-run Granger causality for the second panel. The direction of the errors represents the direction of the causality. The statistically significant correlation coefficients between these variables are recorded inside the arrow features with the p-values in parentheses. Results are drawn from Appendix VII.9/ (Author's diagrammatic interpretation).

Other negative causality relationships run from the trade openness index to renewable energy consumption and from the ratio of the contribution of agriculture, forestry, and fisheries over the contribution of total manufacturing to the ratio of the exported value of forest products to the imported values of manufactures (Figure IV.2). We observe a statistically significant positive correlation and causality association from real GDP per capita to the ratio of the exported value of forest products to the imported value of manufactures. Meanwhile, this ratio Granger drives the debt to GDP ratio. Unidirectional causality is then found to run from the debt to GDP ratio to the trade openness index, which also Granger causes renewable energy consumption. Other important causality relationships include the case that forest land and income Granger cause agricultural productivity.

Regression results

Incorporating the results of the unit root tests, we omit three variables *Ncs*, *Pdensity*, and *Ruralurban* in equation (2), under section III, and obtain the regression outcomes in Table 2. There is no evidence of the EKC under the country-and-time fixed effects, which is preferred by the pre-regression statistics tests (Table 2). The agricultural factor productivity index has a negative relationship with the forest areas, at 1% significance level under the country-and-time fixed effects, which coincides with the regression result from the first panel (Table 2). The coefficient of the freedom index is also found to bear a negative sign, meaning that as the countries become more politically and civic-free, the forest areas will expand (Table 2). At 5% significant level, the forest cover is positively related to the ratio of the exported value of forest products over the imported value of manufactures (Table 2). The Debt to GDP ratio, the ratio of the exported value forest products over the imported value of manufactures, and trade openness have positive relationships with the forest cover at 5% significance level (Table 2). When renewable energy consumption is added to the model, it takes a negative coefficient with the levels of forest land (Table 2).

Table 2: Regression results for fix-effect models for the second panel

	Dependent variable: LnCO2 (Robust standard errors using sandwich estimator)					
	Entity-fixed effects	Entity & time fixed effects	First difference	Entity-fixed effects	Entity & time fixed effects	First difference
	(1)	(1)	(1)	(2)	(2)	(2)
GDPpc	-0.3289 (0.5290)	-0.0321 (0.5289)	-0.0492 (0.6533)	-0.4882 (0.3446)	-0.0120 (0.0671)	-0.1204 (0.6087)
sqGDPpc	0.0509* (0.0301)	0.0068 (0.0311)	0.0011 (0.0417)	0.0585*** (0.0201)	-0.0232*** (0.0076)	0.0081 (0.0373)
Agmu	-0.0116 (0.0844)	-0.0863 (0.0860)	-0.0123 (0.0137)	0.0185 (0.0439)	-0.0208 (0.0214)	-0.0087 (0.0163)
Agriproductivity	-0.6205* (0.3445)	-0.7755** (0.3601)	-0.2303** (0.1057)	-0.5832*** (0.1269)	-0.6905*** (0.0539)	-0.2452** (0.1186)
Freedom	-0.0699 (0.0473)	-0.0884* (0.0493)	-0.0031 (0.0045)	-0.0443** (0.0192)	-0.0410** (0.0160)	-0.0027 (0.0065)
Pxpm				0.0304*** (0.0076)	0.0155** (0.0076)	0.0057*** (0.0020)
Debt				0.0519** (0.0206)	0.0300** (0.0138)	0.0231 (0.0153)
Renewable				-0.1549** (0.0618)	-0.2389*** (0.0555)	-0.0230 (0.0389)
TO				0.0083 (0.0325)	0.1313*** (0.0284)	0.0053 (0.0152)
Constant			0.0076** (0.0037)			0.0069 (0.0045)
Observations	84	84	84	84	84	78
R2	0.2908	0.3753	0.0928	0.6788	0.8411	0.1472
Adjusted R2	0.1937	0.1358	0.0298	0.6136	0.7645	0.0343
F Statistic	5.9868***	7.2081***	1.4731	16.2034***	32.9430***	1.3041
Note:	***Significant at the 1 percent level of significance; **Significant at the 5 percent level of significance; *Significant at the 10 percent level of significance.					

Robust Standard errors are presented in parentheses.

V/ Conclusion, Policy Implications, Limitations, and Potential Avenues for Future Research

In this study, we use the fixed-effect panel analysis applying panel unit root, panel cointegration, and Granger causality for two different data panels to test the long-run relationship between forest cover and economic growth, a reflection of the EKC for deforestation under different groups of factors. After testing for panel cointegration and unit root, which might cause spurious regression and different time-series trends, the regression outcomes of forest cover against the independent variables integrated in the same order show no evidence of the EKC hypothesis for two different data panels. The first panel included all eleven countries in Southeast Asia from 1990 to 2013, investigating the EKC hypothesis for the whole region by capturing the factors of technological change in agriculture, economic structural change, population density, and the quality of political institutions. The second panel has a smaller dimension across six countries with less variations in the levels of economic growth and deforestation rates, including Cambodia, Indonesia, Malaysia, Philippines, Thailand, and Vietnam from 2000 to 2013, adding the driving factors of the market values of international commodities, international trade, debt service, and renewable energy consumption.

The study provides a complex picture of long-run causality relationships between forest cover, economic growth, and different factors, including agricultural intensification, the change in economic structure, international market values of forestry and manufactures, debt service, trade openness, and renewable energy. For both data panels, the negative impact of agricultural intensification, as illustrated by the agricultural total factor productivity index, is present as the literature on deforestation in South Asia has discussed. The fluctuations of this indicator are affected by the changes in forest area and economic growth rates. This result reflects how the compression or depletion of a limited natural resource stock drives technological improvements to meet the increasing demand for land and food production, particularly in a developing region like Southeast Asia.

The results of the second panel embody the dynamic interactions between different sectors of the economy in the relationship with international trade and energy use. The study reflects economic transitions across the majority of Southeast Asian economies, from agriculture to manufacturing. The positive relationship between forest cover and the ratio of exported value of forest products over imported values of manufactures implies that the expansion of domestic manufacturing production can help reduce pressure on forest resources, which is theorized under the EKC hypothesis for deforestation. This indicator is an essential variable, which Granger causes the debt to GDP ratio and is simultaneously driven by economic growth and the ratio of the share of agriculture over the share of total manufacturing. Having a causality relationship, the debt to GDP ratio and trade openness both yield a positive relationship with the level of forest coverage, which suggests that as trade barriers are removed, more development flows to agricultural research and environmental protection can lessen the rate of forest loss. Institutional factors also play an important role in managing natural resources, since this underlying force drives both social and economic changes in developing countries.

The results of this study suggest that as a region, Southeast Asia has the potential to draw investment in sustainable development programs to reduce pressure on natural resources, moving away from the periphery standing positions. By continuing on an economic development transition from agriculture to manufactures and services, it is vital that this region develop a strong political foundation in preparation for opening its markets and adopting innovations to relieve pressure on land and other natural resources.

Renewable energy consumption unexpectedly has a negative relationship with forest land. This indicator currently reported by the World Bank does not justify the renewable consumption by sector and the contributions of different types of renewable energy sources, which makes it harder to determine its impacts on deforestation. Literature on deforestation has yet to pay closer attention on how the composition of energy use across sectors can drive or hinder the rate of deforestation. As the puzzles between the use of biofuels, deforestation, and methane pollution have not been solved, and renewable energy consumption stands at the ending causality chain in this study, it is critical that future research take on the task of breaking down energy use sources to assess the loss of natural resources, such as forests in relation to economic growth.

Given the dynamic interactions among international trade, macroeconomic indicators, and energy use, we acknowledge that our case study has not included the role of commodity prices as well as the real exchange rate. As we cannot control the trading unit value and price effects of forest products and other commodities, our results cannot be used to address in more detail the tangled nexus between macroeconomic conditions, especially the business cycles, and the rate of natural resource exploitation, such as deforestation. Using the trade openness index to examine the role of international trade on deforestation, this study has not accounted for the endogenous characteristics of import and export values, which might result from changes in prices overseas or an appreciated foreign currency (U.S dollars) vis-à-vis the local currencies. Moreover, two high income countries including Singapore and Brunei Darussalam do not have enough forest stocks to experience the changes in deforestation, which might affect the results of our first data panel. Future studies should apply a distributed lag model for panel analysis to incorporate the long-term fluctuations in forest stocks in relation to economic development.

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VII/ Appendix

VII.1/ Table 1: List of selected countries in the sample

Country List	Income Group
Brunei Darussalam	High income
Cambodia	Low middle income
Indonesia	Low middle income
Lao People's Democratic Republic	Low middle income
Malaysia	Upper middle income
Myanmar	Low middle income
Philippines	Low middle income
Singapore	High income
Thailand	Upper middle income
Timor-Leste	Low middle income
Vietnam	Low middle income

VII.2/ Table 2: Quadratic EKC patterns using the levels of forest cover as the dependent variable

Inverted-U EKC	U-shaped EKC	Monotonically increasing EKC	Monotonically decreasing EKC	Leveled-off EKC
$\beta_1 < 0$	$\beta_1 > 0$	$\beta_1 < 0$	$\beta_1 > 0$	$\beta_1 = \beta_2 = 0$
$\beta_2 > 0$	$\beta_2 < 0$	$\beta_2 = 0$	$\beta_2 = 0$	

Notes: Author's adjustments on the coefficients based on Lopez-Menendez et al. (2014).

VII.2/ Table 2: Descriptive statistics of first data panel

Statistic	N	Mean	St. Dev.	Min	Median	Max
Forest (in 1000 ha)	264	21,315.93	27,328.47	16.35	13,602.50	118,545.0
GDPpc (constant $US 2005 prices)	264	6,185.99	10,482.06	76.83	1,039.14	37,626.86
sqGDPpc	264	147,723,896.0	322,088,500.0	5,903.13	1,079,834.0	1,415,780,228.0
Agmu (ratio)	264	1.82	2.32	0.001	0.57	11.40
Agriproductivity (index base 1992 = 100)	264	132.79	56.92	36.35	121.03	381.95
Freedom (2 to 14)	264	10.42	2.92	5	11	14
Ncs (in millions value $US, constant 2005 prices)	264	9,839.31	12,009.49	57	3,453	55,013
Pdensity (people per km^2 of land area)	264	670.92	1,732.81	18.40	113.79	7,636.72
Population (total number)	264	48,449,966.0	61,288,308.0	256,939	24,161,470	251,268,276
Ruralurban (ratio)	264	1.99	1.44	0.00	1.99	5.48

Notes: Data was collected from the FAOSTAT (2017) and The World Bank's World Development Indicators (2017).

VII.3/ Table 3: Summary of statistical tests for the first data panel

Pre-statistical tests	Equation (1)
Breusch-Pagan Lagrange multiplier (B-P/LM) for random effects	chisq = 242.86, df = 1, p-value < 2.2e-16
Hausman test	chisq = 3829.9, df = 8, p-value < 2.2e-16
F test for time-fixed effects	F = 0.95533, df1 = 23, df2 = 222, p-value = 0.5247
Breusch-Pagan LM test for cross-sectional dependence in panels	chisq = 400.49, df = 55, p-value < 2.2e-16
Breusch-Godfrey/Wooldridge test for serial correlation	chisq = 202.22, df = 24, p-value < 2.2e-16
Breusch-Pagan test for heteroskedasticity	BP = 205.88, df = 41, p-value < 2.2e-16

VII.4/ Table 4: Results of the ADF and PP unit root tests for the first data panel

	ADF (with intercept and trend)				PP (with trend)			
	Statistic	1pct	5pct	10pct	Statistic	1pct	5pct	10pct
Forest	-2.4562	-3.98	-3.42	-3.13	-2.51321	-3.996246	-3.42822	-3.137204
Δforest	-5.12713	-3.98	-3.42	-3.13	-5.00297	-3.997694	-3.42891	-3.137615
GDPpc	-2.9338	-3.98	-3.42	-3.13	-2.98177	-3.996246	-3.42822	-3.137204
ΔGDPpc	-7.73615	-3.98	-3.42	-3.13	-10.6421	-3.997694	-3.42891	-3.137615
sqGDPpc	-2.86475	-3.98	-3.42	-3.13	-2.98177	-3.996246	-3.42822	-3.137204
Δsqgdp	-6.69836	-3.98	-3.42	-3.13	-11.0413	-3.997694	-3.42891	-3.137615
Agmu	-2.59176	-3.98	-3.42	-3.13	-2.67315	-3.996246	-3.42822	-3.137204
Δagmu	-8.62823	-3.98	-3.42	-3.13	-13.9221	-3.997694	-3.42891	-3.137615
Agriproductivity	-3.55002	-3.98	-3.42	-3.13	-3.8187	-3.996246	-3.42822	-3.137204
Δagriproductivity	-3.72565	-3.98	-3.42	-3.13	-3.91485	-3.997694	-3.42891	-3.137615
Ncs	-3.27946	-3.98	-3.42	-3.13	-3.42259	-3.996246	-3.42822	-3.137204
Δncs	-2.5174	-3.98	-3.42	-3.13	-2.81006	-3.997694	-3.42891	-3.137615
Pdensity	-2.38772	-3.98	-3.42	-3.13	-2.48298	-3.996246	-3.42822	-3.137204
Δpdensity	-6.75955	-3.98	-3.42	-3.13	-8.46744	-3.997694	-3.42891	-3.137615
Ruralurban	-3.24113	-3.98	-3.42	-3.13	-3.35184	-3.996246	-3.42822	-3.137204
Δruralurban	-2.49462	-3.98	-3.42	-3.13	-2.51459	-3.997694	-3.42891	-3.137615
Freedom	-2.45617	-3.98	-3.42	-3.13	-2.51321	-3.996246	-3.42822	-3.137204
Δfreedom	-10.8415	-3.98	-3.42	-3.13	-16.7527	-3.997694	-3.42891	-3.137615

VII.5/ Table 5: Results of Granger causality test for the first data panel

Table 5a: Granger causality test at lag of 1

Dependent variable	Δforest	ΔGDPpc	Δagmu	Δagriproductivity	Δpdensity	Δfreedom
Δforest	-	0.117 (0.7326)	0.0094 (0.9228)	0.7941 (0.3737)	0.3459 (0.557)	0.3563 (0.5511)
ΔGDPpc	0.6835 (0.4092)	-	0.0046 (0.9459)	3.3443 (0.0683) *	3.3973 (0.06649) *	0.0693 (0.7925)
Δagmu	0.0446 (0.833)	4.0434 (0.0454) **	-	6.0821 (0.01433)	0.2336 (0.6293)	2.0034 (0.1582)
Δagriproductivity	0.1571 (0.6922)	0.1291 (0.7197)	1.8433 (0.1758)	-	0.2329 (0.6298)	0.092 (0.7619)
Δpdensity	0.0182 (0.8929)	0.0901 (0.7643)	0.0001 (0.9905)	0.0331 (0.8557)	-	0.733 (0.3927)
Δfreedom	0.7308 (0.3935)	1.0142 (0.3149)	1.5833 (0.2095)	1.0047 (0.3171)	0.5413 (0.4626)	-

*p<0.1; **p<0.05; ***p<0.01

Table 5b: Granger causality test at lag of 2

Dependent variable	Δforest	ΔGDPpc	Δagmu	Δagriproductivity	Δpdensity	Δfreedom
Δforest	-	0.1589 (0.8532)	0.1696 (0.8441)	0.4998 (0.6073)	0.3077 (0.7354)	1.0306 (0.3583)
ΔGDPpc	0.2891 (0.7491)	-	0.0045 (0.9955)	1.4527 (0.2359)	1.6803 (0.1885)	1.8492 (0.1595)
Δagmu	0.1251 (0.8825)	1.2623 (0.2848)	-	2.2804 (0.1044)	2.0841 (0.1266)	2.7065 (0.06876)
Δagriproductivity	0.1048 (0.9005)	0.2581 (0.7727)	0.9051 (0.4058)	-	0.2405 (0.7864)	0.1443 (0.8657)
Δpdensity	0.142 (0.8677)	0.0607 (0.9412)	0.6414 (0.5274)	1.4754 (0.2307)	-	0.5569 (0.5737)
Δfreedom	1.1518 (0.3178)	0.6212 (0.5382)	1.5737 (0.2093)	0.5503 (0.5775)	0.3364 (0.7147)	-

*p<0.1; **p<0.05; ***p<0.01

VII.6/ Table 6: Descriptive statistics of the second data panel

Statistic	N	Mean	St. Dev.	Min	Median	Max
Forest (in 1000 ha)	84	27,552.24	31,338.11	6,840.00	15,307.50	99,409.00
GDPpc (constant $US 2005 prices)	84	2,140.34	1,879.72	330.11	1,331.75	7,050.43
Agmu (ratio)	84	0.79	0.59	0.27	0.51	2.57
Agriproductivity (index base 1992 = 100)	84	139.19	21.64	103.97	133.75	209.87
Ncs (in millions value $US, constant 2005 prices)	84	19,520.00	13,893.40	678	19,422.5	55,013
Pdensity (people per km2 of land area)	84	163.17	88.22	69.10	129.22	327.24
Ruralurban (ratio)	84	1.85	1.24	0.36	1.26	4.38
Freedom (2 to 14)	84	8.50	2.72	5	8	13
Pxpm (ratio)	84	0.04	0.05	0.003	0.02	0.22
Debt (% of GDP)	84	43.19	11.48	22.96	41.43	87.44
Renewable (% of total energy consumption)	84	36.23	21.82	3.82	34.82	83.02
TO (Imports plus exports as % of GDP)	84	118.95	43.52	45.51	120.50	220.41

VII.7/ Table 7: Summary of statistical tests for the second data panel

Pre-statistical tests	Equation (2)
F test for time-fixed effects	F = 4.2642, df1 = 13, df2 = 53, p-value = 0.00007728
Breusch-Pagan LM test for cross-sectional dependence in panels	chisq = 29.062, df = 15, p-value = 0. 01579
Breusch-Godfrey/Wooldridge test for serial correlation	chisq = 41.235, df = 14, p-value = 0.0001634

Breusch-Pagan test for heteroskedasticity	BP = 56.73, df = 30, p-value = 0.002249

VII.8/ Table 8: Results of the ADF and PP unit root tests for the second data panel

	ADF (intercept and trend)				PP (with trend)			
	Statistic	1pct	5pct	10pct	Statistic	1pct	5pct	10pct
Forest	-2.178015	-4.04	-3.45	-3.15	-2.218481	-4.071325	-3.463851	-3.158133
Δforest	-4.531394	-4.04	-3.45	-3.15	-4.208149	-4.080282	-3.468062	-3.160581
GDPpc	-2.081294	-4.04	-3.45	-3.15	-2.086555	-4.071325	-3.463851	-3.158133
ΔGDPpc	-4.39783	-4.04	-3.45	-3.15	-6.909747	-4.080282	-3.468062	-3.160581
sqGDPpc	-2.081294	-4.04	-3.45	-3.15	-2.081294	-4.071325	-3.463851	-3.158133
Δsqgdp	-4.39783	-4.04	-3.45	-3.15	-6.909747	-4.080282	-3.468062	-3.160581
Agmu	-1.967197	-4.04	-3.45	-3.15	-2.004904	-4.071325	-3.463851	-3.158133
Δagmu	-6.614373	-4.04	-3.45	-3.15	-9.890104	-4.080282	-3.468062	-3.160581
Agriproductivity	-3.40468	-4.04	-3.45	-3.15	-3.552173	-4.071325	-3.463851	-3.158133
Δagriproductivity	-4.911369	-4.04	-3.45	-3.15	-8.314601	-4.080282	-3.468062	-3.160581
Exr	-1.331801	-4.04	-3.45	-3.15	-1.370963	-4.071325	-3.463851	-3.158133
Δexr	-7.152988	-4.04	-3.45	-3.15	-7.562726	-4.080282	-3.468062	-3.160581
Ncs	-2.256743	-4.04	-3.45	-3.15	-2.183007	-4.071325	-3.463851	-3.158133
Δncs	-1.858346	-4.04	-3.45	-3.15	-1.996428	-4.080282	-3.468062	-3.160581
Pdensity	-2.406794	-4.04	-3.45	-3.15	-2.519161	-4.071325	-3.463851	-3.158133
Δpdensity	-2.235928	-4.04	-3.45	-3.15	-2.314068	-4.080282	-3.468062	-3.160581
Ruralurban	-1.766368	-4.04	-3.45	-3.15	-1.726032	-4.071325	-3.463851	-3.158133
Δruralurban	-2.20436	-4.04	-3.45	-3.15	-2.297661	-4.080282	-3.468062	-3.160581
Freedom	-2.24588	-4.04	-3.45	-3.15	-2.240493	-4.071325	-3.463851	-3.158133
Δfreedom	-5.552293	-4.04	-3.45	-3.15	-7.908441	-4.080282	-3.468062	-3.160581
Pxpm	-2.615565	-4.04	-3.45	-3.15	-2.349791	-4.071325	-3.463851	-3.158133
Δpxpm	-9.896366	-4.04	-3.45	-3.15	-10.60342	-4.080282	-3.468062	-3.160581
Debt	-3.118168	-4.04	-3.45	-3.15	-3.074544	-4.071325	-3.463851	-3.158133
Δdebt	-5.051992	-4.04	-3.45	-3.15	-5.251555	-4.080282	-3.468062	-3.160581
Renewable	-1.826639	-4.04	-3.45	-3.15	-1.883322	-4.071325	-3.463851	-3.158133
Δrenewable	-6.197651	-4.04	-3.45	-3.15	-7.314249	-4.080282	-3.468062	-3.160581
TO	-2.432376	-4.04	-3.45	-3.15	-2.593786	-4.071325	-3.463851	-3.158133
Δto	-6.718035	-4.04	-3.45	-3.15	-8.443358	-4.080282	-3.468062	-3.160581

VII.9/ Table 9: Results of Granger causality test for the second data panel

Table 9a: Granger causality at lag of 1

Dependent variable	Δforest	ΔGDPpc	Δagmu	Δagriproductivity	Δfreedom	Δpxpm	Δdebt	Δrenewable	Δto
Δforest	-	0.1032 (0.7489)	0.1064 (0.7453)	1.1465 (0.2878)	0.3368 (0.5635)	0.4394 (0.5095)	0.8081 (0.3716)	0.3844 (0.5372)	1.7325 (0.1922)
ΔGDPpc	0.0235 (0.8785)	-	0.0266 (0.8708)	0.0408 (0.8404)	0.2748 (0.6017)	0.2357 (0.6288)	2.0406 (0.1574)	2.3845 (0.1268)	0.236 (0.6286)
Δagmu	0.0263 (0.8716)	0.0904 (0.7645)	-	1.6045 (0.2092)	0.2149 (0.6443)	0.5224 (0.4721)	0.7566 (0.3872)	0.024 (0.8772)	0.949 (0.3332)
Δagriproductivity	4.5585 (0.03607) **	5.371 (0.02324) **	0.9348 (0.3368)	-	1.0106 (0.318)	0.1004 (0.7522)	0.3169 (0.5752)	0.0296 (0.864)	0.6591 (0.4195)
Δfreedom	0.8804 (0.3511)	0.0746 (0.7856)	0.046 (0.8308)	0.2889 (0.5925)	-	0.2399 (0.6257)	0.0636 (0.8016)	1.4405 (0.2339)	0.3867 (0.536)
Δpxpm	0.0005 (0.9816)	3.3424 (0.07155) *	4.41446 (0.04535) **	0.6005 (0.4409)	0.0172 (0.8961)	-	0.0192 (0.8903)	0.076 (0.7835)	0.2767 (0.6005)
Δdebt	1.9707 (0.1646)	0.0341 (0.8539)	0.5374 (0.4658)	0.0543 (0.8164)	0 (0.9979)	3.1657 (0.0793) *	-	3.0577 (0.0845) *	0.3849 (0.5369)
Δrenewable	2.555 (0.1142)	2.0751 (0.1539)	0.1321 (0.7173)	0.6879 (0.4096)	1.1715 (0.2826)	0.8967 (0.3468)	6.979 (0.01006) **	-	2.9779 (0.08858) *
Δto	0.1388 (0.7105)	1.1836 (0.2802)	0.3983 (0.5299)	2.6409 (0.1084)	0.3435 (0.5596)	0.3799 (0.5396)	5.4392 (0.02241) **	0.4748 (0.4929)	-

*p<0.1; **p<0.05; ***p<0.01

Table 9b: Granger causality at lag of 2

Dependent variable	Δforest	ΔGDPpc	Δagmu	Δagriproductivity	Δfreedom	Δpxpm	Δdebt	Δrenewable	Δto
Δforest	-	0.1449 (0.8653)	0.0608 (0.941)	0.4637 (0.6308)	0.3631 (0.6968)	0.8678 (0.4243)	0.5556 (0.5762)	0.3498 (0.706)	0.9476 (0.3925)
ΔGDPpc	0.0297 (0.9708)	-	1.0415 (0.3583)	0.4209 (0.6581)	0.4153 (0.6617)	0.1629 (0.85)	1.2955 (0.2802)	1.7697 (0.1778)	1.25 (0.2927)
Δagmu	0.074 (0.9288)	0.1107 (0.8954)	-	0.5521 (0.5782)	0.0544 (0.9471)	1.3948 (0.2546)	0.4968 (0.6106)	1.2151 (0.3028)	0.7175 (0.4915)
Δagriproductivity	1.6547 (0.1984)	3.3097 (0.04224)	1.5847 (0.2122)	-	0.3085 (0.7355)	0.0409 (0.9599)	0.3135 (0.7319)	0.1744 (0.8403)	1.1957 (0.3085)
Δfreedom	0.4288 (0.653)	0.6311 (0.535)	0.2046 (0.8155)	0.1248 (0.8829)	-	0.1921 (0.8256)	0.13 (0.8783)	0.6837 (0.508)	2.3916 (0.09881) *
Δpxpm	0.9066 (0.4085)	3.3556 (0.0405)**	1.6696 (0.1956)	0.4975 (0.6102)	0.0681 (0.9342)	-	0.3002 (0.7416)	0.7802 (0.4622)	0.7547 (0.4739)
Δdebt	1.592 (0.2107)	0.075 (0.9278)	0.3403 (0.7127)	0.5437 (0.583)	0.0615 (0.9404)	0.931 (0.3989)	-	2.518 (0.0878) *	0.203 (0.8168)
Δrenewable	1.2303 (0.2984)	1.5904 (0.211)	0.3716 (0.691)	1.6495 (0.1994)	0.9613 (0.3873)	0.5876 (0.5583)	4.6378 (0.01279) ***	-	1.365 (0.262)
Δto	0.1748 (0.84)	0.7624 (0.4703)	1.5065 (0.2287)	1.2342 (0.2972)	0.1443 (0.8659)	1.1017 (0.3379)	2.541 (0.08594) *	0.2093 (0.8117)	-

*p<0.1; **p<0.05; ***p<0.01

VII.10/ Definitions and hypotheses of pre-statistical tests for panel analysis

(1) The Breusch-Pagan Lagrange multiplier (B-P/LM) for random effects where the null hypothesis is that variances across entities are zero or that there is no need to consider random effects;

(2) The Hausman test where the null hypothesis is that the preferred model is the random effects rather than the fixed effects model;

(3) The F test for time-fixed effects where the null hypothesis is that the coefficients for all years are jointly equal to zero or that there is no time fixed-effects model needed;

(4) The Breusch-Godfrey/Wooldridge test for cross-sectional dependence in panels where the null hypothesis states that there is no cross-sectional dependence in the panel model. If cross-sectional dependence is present, we will use robust standard errors for the models;

(5) The Breusch-Godfrey/Wooldridge test for serial correlation where the null hypothesis states that there is no serial correlation in the panel model;

(6) The Breusch-Pagan test for heteroskedasticity where the null hypothesis is that the panel data is homoscedastic, meaning the variance of the error term is constant for all levels of the explanatory variables. If there is evidence of heteroskedasticity and serial correlation, we will apply the Arellano robust covariance errors for the regression results;

(7) The augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) test for unit roots/stationarity with lags of 1 and 2, where the null hypothesis states that the time series data of the sample has a unit root, meaning the statistical properties like mean and variance are not constant over time. If there is evidence of a unit root in the data, we will examine the models using the first difference of the variables as well as examine the evidence of panel cointegration and long-term Granger causality among variables.

(8) Engle-Granger cointegration test is conducted to identify whether non-stationary variables that are integrated in the same order, meaning they are stationary after taking the differences by the same number of times, to find the evidence of long-run relationship between variable. The test consists of two main steps: First, regress non-stationary dependent variables on independent variables to extract the estimated residuals from the model, and then construct unit root test on such residuals. The null hypothesis of the test is that the residuals of this model are non-stationary. Rejecting the null hypothesis allows us to confirm the cointegration among the series of the chosen variables. If the series are cointegrated, differencing will not solve the problem of unit root.

(9) Granger causality test will be conducted if there is evidence of panel cointegration to examine spurious regression among cointegrated variables. If there are causality relationships among variables, the correlation test will be conducted to examine the magnitude of the relationships.