THE IMPACT OF ENVIRONMENTAL-RELATED TECHNOLOGY INNOVATION ON GREEN GROWTH IN CHINA, JAPAN, SOUTH KOREA, MALAYSIA, AND THE PHILIPPINES

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Abstract - As the problems caused by environmental damage become urgent, green growth becomes an important strategy to achieve sustainable goals. Firstly, this study constructs a green growth index system and uses the entropy-weight TOPSIS method to calculate the index. Then panel least square method is employed to analyze the ETI effect on green growthin China, Japan, Malaysia, the Philippines, and South Korea from 1990 to 2021. The results show that ETI can significantly positively impact green growth. Besides, innovation, export of goods and services, human capital, urbanization level and technology can significantly explain the green growth index.

Keywords - Green Growth; Green Technology Innovation

I. INTRODUCTION

Economic growth is essential for countries to solve poverty and well-being problems, especially for developing and emerging countries. As the problems of increasing carbon dioxide emission, climate change, environmental disruption and biodiversity reduction occurred, environmental issues got more attention from many scholars. In 2012, the world bank pointed out that our growth patterns are highly inefficient and the environmental burdens a high cost in economic growth, which gives a grave warning to human well-being. Moreover, despite the poverty rate significantly decreasing, many basic needs remain unmet, such as water scarcity, a mass of carbon dioxide emissions, and the fully exploited of ocean fisheries (World Bank, 2012). The seventeen's sustainable development goals (SDGs) proposed by the United Nations in 2015 will be achieved by 2030, which involve solving the problem of poverty, protecting the earth, and improving living standards worldwide. The UN environment programme warns that humans have many unfulfilled promises for environmental protection. Climate change, biodiversity loss, and environmental degradation have become emergencies (UNEP, 2021). However, the emergence of COVID-19 has brought massive health and development problems to the world, making sustainable development realisation more challenging. The world must transform traditional economic activities into a new, green, and efficient model so that humans can better make peace with nature.

The green growth strategy is a vital pattern for an economy developed with more consideration the environment protection, resource limitation, and biodiversity, not only focusing on the social and humankind. World Bank, United Nations (UN), the Organization for Economic Co-operation and Development (OECD), and Global Green Growth Institute (GGGI) give different definitions of green growth. However, the core idea is to reduce the damage of human activities to the environment while improving human well-being.

Human knowledge, innovation, technology, and cooperation are the most likely to help humans achieve green growth and a sustainable future (UNEP, 2021; UNCTAD, 2021; Guo et al., 2022). United Nations Conference on Trade and Development (UNCTAD) (2021) claims that each country should adopt technology and innovation policies according to its actual situation, which stage of economic development, social system, and specific environmental conditions. Environmental-related technology innovation (ETI) is an innovation in the technologies directly appertaining to water-related adaption, environmental management, and climate change mitigation that improves resource efficiency and minimizes the impact on the environment and other species. Furthermore, ETI is directly related to environmental protection technology.

Thus, the main objective of this study is to analyze the impact of ETI on green growth. According to the GGGI technical report No 16, green growth index 2020, China, Japan, South Korea, Malaysia, and the Philippines are in the top six ranks in 2019 for green growth index performance in Asia (Acosta et al., 2020). Hence, this study selects the five countries. Besides, this study selects seven other feasible control variables, including industrial structure upgrading, urbanization level, innovation, technology, FDI dependence, export of goods and services, and human capital, into the analysis.

In the rest of this study, the author reviews the existing literature in section 2. Section 3 shows the research methodology and Section 4 presents the results. Finally, the author gives the conclusion and policy suggestions in section 5.

II. LITERATURE REVIEWS

2.1. Studies on green growth and its influence factors

In the exploration of green growth's influence factors related studies, technological innovation, industrial structure, level of opening up, technology innovation, education, government intervention degree, environmental regulation, foreign direct investment (FDI), urbanization level and innovation are considered as factors (Liu, 2022; Wu & Zhou, 2018; Lin & Zhou, 2022; Hao, 2018; Zhao, 2018; Bu, 2017; Chen, 2021; Sun, 2020; Zhou et al., 2022; Feng et al., 2017). Some studies show that foreign direct investment (FDI) can positively impact green growth (Zhao, 2018; Chen, 2021;), but Lin and Zhou (2022) show that the impact is insignificant. Bu (2017) claimed that FDI dependence increases capital and energy use but reduces the utilization of labour and technology. Government intervention degree has different results, positive impact (Liu, 2022), also negative impact (Zhao, 2018). Industrial structure upgrading can have a significant positive effect on green growth (Lin & Zhou, 2022), but Liu (2022) gets an adverse effect (Liu, 2022). The level of urbanization is a significant positive effect on green growth (Lin & Zhou, 2022; Wu & Zhou, 2018; Zhao, 2018). Technological innovation positively affects green growth (Liu, 2022; Wu & Zhou, 2018; Lin & Zhou, 2022; Zhao, 2018;), but Hao (2018) claimed that technology patent stock has an insignificant impact on green growth. Feng et al. (2017) concluded that driven innovation could significantly promote regional green total factor productivity in China. Environmental regulation positively influences green growth (Lin & Zhou, 2022; Hao, 2018; Sun, 2020; Feng et al., 2017).

After reviewing the methods used, three methods are usually selected to evaluate green growth or growth efficiency. The first method is valuing green growth. Based on GDP (gross domestic production) indicators, they combine other costs and benefits of the environmental sources into a formula to evaluate green growth (Li, et al., 2022; Ulucak, 2020; Sohag et al., 2021; Fu, 2021). The second method calculates green total factor productivity by taking input factors, labour, resource, capital, desirable and undesirable output, like GDP, carbon emissions and pollution (Zhao et al., 2022; Liu, 2022; Zhai & An, 2021; Yang et al., 2022; Zhao, 2018; Sun, 2020).The third method is constructing an indicator system from different dimensions, like society, environment, resource, and economy (Lin & Zhou, 2022; Hao, 2018; Wu & Zhou, 2018; Cao et al., 2022; Guo, 2016; Koçak, 2020; Zhou et al., 2022). The method commonly used to calculate the green growth index is the entropy weight method (EWM) (Wu & Zhou, 2018; Cao et al., 2022). Besides, Lin and Zhou (2022) use the entropy weight Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to get the index.Guo (2016) compared the advantage and disadvantages of the DEA, EWM, Fuzzy Comprehensive Evaluation (FCE), Analytical Hierarchy Process (AHP), the technique for order of Preference by similarity to ideal solution (TOPSIS), Grey Relational Analysis (GRA), and employed combined with AHP and EWM to adopt a combination of AHP and EWM to give the weight of the decision indicators. And then, TOPSIS and GRA are integrated as an evaluation model for the degree of regional green growth. Koçak (2020) applied EWM and GRA methods to analyze OECD countries' green growth dynamics, then identify crucial indicators and measure the critical of these indicators on green growth.

2.2. Studies on impact of technology innovation on green growth

Through the literature review, the impact of green technological innovation on green growth mainly focuses on two aspects. One is taking green technology innovation as the primary variable to analyze the impact (Suki et al., 2022a; Mensah et al., 2019; Khurshid & Deng, 2021; Zhai & An, 2021; Ulucak, 2020; Ahmad & Zheng, 2021; Abedi &Moeenian, 2021; Fu, 2021). Mensah et al. (2019) and Khurshid and Deng (2021) use IPAT, STIRPAT model and multiple linear regression (MLR) to investigate the relationship between technological innovation with total, production-based, and demand-based carbon emission. Both studies confirm that climate change mitigation technologies linked to transportation positively affect green growth, and technologies with energy generation and transmission negatively impact green growth. Suki et al. (2022a) and Ulucak (2020) revealed that renewable energy with carbon emission and production-based carbon emission have a negative relationship with green technology innovation but a positive relationship between green technology and non-renewable energy. Zhai and An (2021) and Fu (2021) conclude that technological innovation has a significant positive spatial effect on the green economy by employing Spatial Durbin Model. Some of these studies specifically explore the effect of environmental-related technology on economic growth or carbon dioxide emissions (Ulucak, 2020; Ahmad & Zheng, 2021; Abedi &Moeenian, 2021). Ahmad and Zheng (2021) identify the cyclical and asymmetrical impact of environmental-related technology innovation on carbon dioxide emissions in BRICS countries. Abedi and Moeenian (2021) investigate environmental-related technology innovation for sustainable economic growth. However, this study only considers the real GDP growth, not the ecological and climate problems in the sustainable process in the decades we faced.

The other is taking green technology innovation as an

intermediate factor to analyze (Li et al., 2022; Guo et al., 2017;) or combines with another element to study the three-nexus effects (Talebzadehhosseini& Garibay, 2022; Su& Fan, 2022; Cao et al., 2022; Suki et al., 2022b; Sohag et al., 2021; Yang et al., 2022; Zhang & Chen, 2022; Li & Gao, 2022).

2.3. Literature gaps

After literature reviews, most studies that use green technology innovation as the primary objective measure green growth through production-based and demand-based carbon emissions or combine GDP growth and carbon dioxide emissions. Furthermore, in these studies, fewer use comprehensive evaluation methods to present green growth. Some studies comprehensively evaluate green growth, but green technological innovation is a mediating driving factor in the analysis. Fewer studies investigate the impact of environmental-related technology innovation on green growth. Moreover, they only choose a straightforward indicator to measure green growth. This study comprehensively evaluates green growth and investigates the impact of environmental-related technology innovation on green growth. Also, this study analyses the impact of China, Japan, South Korea, Malaysia, and the Philippines, which have good green growth and innovation index performance in Asia. Enrich the gap of effects of environmental-related technology innovation on green growth in these countries.

III. METHODOLOGY

3.1. Conceptual framework

3.1.1. Green growth index system design

This study builds an indicator system mainly according to the green growth indicator report by OECD (2017) to evaluate green growth. The author constructs the green growth index system from three dimensions: environmental and resource productivity, the environmental dimension of quality of life, and the social-economic context. Due to the data limitation of the five countries (China, Japan, South Korea, Malaysia, and the Philippines), only selected indicators in **Table 3.1**.

Following, the author briefly explains the selection of the indicators. Furthermore, more details of each indicator can refer from the OECD. Stat (2022), green growth indicators, database documentation and the OECD (2017). The unemployment rate indicator is according to the indicator system constructed by Zhao et al. (2022) selecting.

3.1.2. Conceptual framework design for investing influencing factors

One explanatory variable and seven control variables are selected to explore the impact on green growth as follows:

GGI=f(ETI, IS, Ur, In, Tec, FDI, Ex, HC), (1)

where GGI is the explained variable, it represents the green growth index; ETI represents the explanatory variable and environmental-related technology innovation. ETI is measured by the percentage of environmental-related inventions in all domestic inventions (among all technologies). An environmental-related patent is an essential indicator of a country's environmental protection technology innovation capability. Technological progress has dramatically reduced the cost of renewable energy. At the same time, new technologies can also help reduce pollution and promote sustainability (Dutta et al., 2021). As such, ETI is expected to impact green growth positively.

Primary index	Secondary index	Tertiary index
Green growth index	Environmental and resource productivity	Production-based CO2 productivity, GDP per unit of energy-related CO2 emissions
		Demand-based CO2 productivity, GDP per unit of energy-related CO2 emissions
		Energy productivity, GDP per unit of TPES
		Non-energy material productivity, GDP per unit of DMC
	The environmental dimension of quality of life	Mean population exposure to PM2.5
		Mortality from exposure to ambient ozone
		Population with access to improved sanitation, % total population
		People using at least basic drinking water services, % of the population
	social-economic context	life expectation at birth
		Unemployment, total, % of total labor force
		Environmentally related taxes, % GDP
		Real GDP per capita ,US dollar, 2015

Table 3.1: Indicator system of green growth

Others (IS, Ur, In, Tec, FDI, Ex, HC) are control variables: IS represents industry structure upgrading measured by the percentage of service value added to GDP. Low-level industrial structures usually damage the ecological environment and are not conducive to green growth (DRC&OECD, 2017; Sun, 2020). With the continuous progress of economic development,

the proportion in primary and secondary sectors tends to reduce, and the tertiary sector will be prominent. The more developed economies have a more excellent opportunity to achieve green growth than lower developed economies. Thus, IS is expected to affect green growth positively. Ur represents urbanization level, and the percentage of the urban population in the total population measures it. Urbanization is essential in driving economic growth and social progress (Todaro & Smith, 2015). The efficient urban scale may drive knowledge and technological progress spillover. However, the increase in the proportion of the urban population in the process of urbanization is inevitable, and the formation of urbanization often accompanies the emergence of industrialization. In the early stage of industrialization, the environmental situation has been deteriorating. Many industrial emissions create a series of threats to humankind in developing countries as well. Thus, the author hypothesis that two relationships (positive or negative) are possible between Ur and green growth. Innovation can achieve industrial empowerment and promote the development of industries towards high-end, green, intelligent, and emerging industries. In represents the innovation level measured by the patent application of residents. Innovation can achieve industrial empowerment and promote the development of industries towards high-end, green, intelligent, and emerging industries. Innovation is also the driving force for reconstructing economic growth and is a critical element in promoting economic growth from quantitative growth to qualitative growth, thereby improving the efficiency of economic development (Zhao et al., 2019; Feng et al., 2017). This study expected that innovation positively impacts green growth. Tec represents the technology level and is measured by the percentage of research and development expenditure to GDP. Tec is expected to affect green growth positively. FDI represents foreign direct investment (FDI) dependence, measured by the net foreign direct investment inflows as a percentage of GDP. Because FDI directly provided funds to the host country, which enriched the actual available funds in the host country and made up for the host country's capital and reserves. Besides, FDI also can be directly translated into productivity, thus improving the production efficiency of the host county.Although some FDI flows into polluting enterprises, the strong pollution control capacity and relatively advanced technology level of FDI can improve local polluting enterprises' technical level and pollution control ability. (Sun, 2020; Bu, 2017) As such, FDI dependence is expected to have a positive relationship with green growth. Ex represents export of goods and services, measured by the percentage of exported goods and services on GDP. The results of some studies (Michieka, 2013; Ahmad & Zheng, 2021; Ahmad et al., 2021) show that increased demand for export commodities encourages entrepreneurs to manufacture more products at lower costs. As such, industries have chosen low-cost technologies but harmful to the environment to reach a low price in the international market and contribute to carbon dioxide emissions. Hence, Ex is expected to impact green growth negatively. HC represents human capital. A percentage of government expenditure on education in total GDP plus the percentage of current health expenditure in total GDP is used to measure a country's human capital. Improved health and education are important ways to help families eliminate the vicious circles of poverty. Besides, technology and innovation cannot leave the accumulation of human capital. Education plays a crucial role in absorbing modern technology and developing self-sustain growth and development capacity in developing countries. Meanwhile, education also depends on appropriate health conditions (Todaro & Smith, 2015). As such, a positive relationship between investment in HC and green growth is expected.

3.2. Model and data source

Based on Eq (1) in the framework design, the author established the following regression model of environmental-related technology innovation impact on green growth.

$$\begin{aligned}\ln GGI_{it} = {} & \beta_{oi} ETI_{it} + \beta_{1i} IS_{it} \\ & + \beta_{2i} Ur_{it} + \beta_{3i} \ln In_{it} + \beta_{4i} Tec_{it} \\ & + \beta_{5i} FDI_{it} + \beta_{6i} Ex_{it} + \beta_{7i} HC_{it} + \mu_i \\ & + \varepsilon_{it}\end{aligned}$$

where, β_{si} (s=0, 1, 2, ..., 7) are the coefficients of independent variables (ETI, IS, Ur, lnIn, Tec, FDI, Ex, HC) in the panel model for long-run equilibrium; μ_i is the fixed effect of cross-section data; $\varepsilon_{it}$is the white noise process. The author takes the natural logarithm of the green growth index and the innovation (the patent application of residents), so that the author can use the percentage to interpret the data in which units of the variables are inconsistent and eliminate problems with outliers.

The source of data used to conduct green growth systems comes from OECD.Stat, (2022), except the data of the unemployment rate and people using at least basic drinking water services (% of the population), are collected from the world bank (2022). Data of ETI comes from OECD. Stat, (2023). Data of seven controls variables comes from world bank (2022).For the missing data in some variables, the author uses the SPSS programmer to do an imputation.

3.3. Research Methodologies

3.3.1. Entropy weighted TOPSIS

TOPSIS method is a multi-standard decision method proposed by Hwang and Yoon in 1981 (Hwang & Yoon, 1981). This study refers to Sun et al. (2017)

and Lin and Zhou (2022) employed method, entropy weighted TOPSIS method. It includes following seven steps:

1) Build the initial decision matrix

Assume m is the number of years, and there are m indicators. The value of the indicator is x_{ij} $(1 \le i \le m, 1 \le j \le n)$, and the decision matrix is $X = (x_{ij})_{n\times m}$, where x_{ij} presents the value of the j indicator in the year i

2) Standardization of data.The author standardizes the indicators to eliminate the impact that comes from different dimensions on the evaluation results.

If x_{ij} is the benefit indicator, the making standardization formula is $x_{ij}^{'} = \frac{x_{ij} - \min_{1\le i\le m}(x_{ij})}{\max_{1\le i\le m}(x_{ij}) - \min_{1\le i\le m}(x_{ij})}$;

if x_{ij} is the cost indicator, the making standardization formula is $x_{ij}^{'} = \frac{\max_{1\le i\le m}(x_{ij}) - x_{ij}}{\max_{1\le i\le m}(x_{ij}) - \min_{1\le i\le m}(x_{ij})}$.

3) The entropy method calculates objective weights.

First, get the proportion of the$j$ indicator during year i: $y_{ij} = \frac{x_{ij}^{'}}{\sum_{i=1}^{m} x_{ij}^{'}}$. Second, get the entropy value of indicator $j$by formula: $e_j = -\frac{x_{ij}^{'}}{\ln m}\sum_{i=1}^{m} y_{ij} \ln y_{ij}$.

Third, calculate the coefficient of variation, and the formula is $\gamma_j = 1 - e_j$. Fourth, figure out the weight in index j: when subjective preference for indicator j is not existence, its weight factor is $w_j = \frac{\gamma_j}{\sum_{j=1}^{n}\gamma_j}$; when subjective preference for indicator j exist, its weight factor is $w_j^{'} = \frac{\lambda_j \gamma_j}{\sum_{j=1}^{n}\lambda_j\gamma_j}$,where λ_j is the weight coefficient.

4)Figure out the weighted matrix of indicator value

The formula is $U = (u_{ij})_{m\times n} = (w_j x_{ij}^{'})_{m\times n} = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ u_{m1} & u_{m2} & \cdots & u_{mn} \end{bmatrix}$.

5) The fifth step is to determine the ideal solution that includes positive and negative two types. Positive ideal solution: $U^{+} = (u_1^{+}, u_2^{+}, \cdots, u_n^{+})$, where $u_i^{+} = \{(\max u_{ij} \mid j \in J_1), (\min u_{ij} \mid j \in J_2)\}$. Negative ideal solution: $U^{-} = (u_1^{-}, u_2^{-}, \cdots, u_n^{-})$, where $u_i^{-} = \{(\min u_{ij} \mid j \in J_1), (\max u_{ij} \mid j \in J_2)\}$. J_1 presents the indicator set including indicators which are as big as possible, J_2 presents the indicator sets including indicators which are as small as possible.

6) Calculate the separation measures for each alternative. The separation from positive ideal alternative is: $S_i^{+} = \sqrt{\sum(u_i^{+} - u_{ij})^2}$. The separation from negative ideal alternative is: $S_i^{-} = \sqrt{\sum(u_i^{-} - u_{ij})^2}, i = 1, \cdots, m.$

7) Finally step, calculate the relative closeness to the ideal solution, which present proximity of the green growth index in this study. $C_i = S_i^{-}/(S_i^{+} + S_i^{-})$.

3.3.2. Cross-section dependency, slope heterogeneity, and panel unit roots tests

1)Cross-sectional dependency (CD) test

With the popularity of nationalization, economic activities between countries become more frequent (such as sharing in inter-region policies, financial crises, and oil prices), making countries share the burden of floating, which makes it possible to exist cross-sectional dependence. Therefore, consider the CD problem to avoid biased results and ambiguous interpretations (Suki, et al., 2022a). The null hypothesis: disturbance, u_{it} is assumed to be independent and identically distributed (iid) over all t and cross-sectional units, which means the series no cross-section dependence. Otherwise, the alternative hypothesis, u_{it}, is correlated across cross sections, CD existence. Statistics of CD test is

$$CD = \left(\frac{2T}{N(N-1)}\right)^{\frac{1}{2}} \left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2\right),$$

where $CD \xrightarrow{d} N(0,1)$ for $N \to \infty$ and T sufficiently lager. When the values of $T$and $N$are fixed, the CD statistic has mean at exactly zero, and the CD test is still valid for homogeneous and heterogeneous dynamic models. (Pesaran, 2007)

2) Slope heterogeneity test

In panel data, slope heterogeneity is another potential problem that might be cause the false estimates and invalid inferences. As such, the author checks the slope homogeneity refered to Pesaran Yamagata (2008). The standardized dispersion statistics, $\hat{\Delta}$, which is alculate by follow formula, $\hat{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right)$ .Furthermore, if the ε_{it} is satisfied normally distributed, the statistic,$\hat{\Delta}$, can be adjusted by mean-variance bias adjusted, and then get the adjusted $\hat{\Delta}$, denoted by $\hat{\Delta}_{adj}$, which equals $\sqrt{N}(\frac{N^{-1}\tilde{S} - E(\tilde{Z}_{iT})}{\sqrt{Var(\tilde{Z}_{iT})}})$. (Pesaran& Yamagata, 2008)

3) panel unit root test

The cross-sectional Im-Pesaran-Shin unit root test (CIPS) is a technique for panel unit root testing. CADF regression equation is

$$\Delta y_{it} = \alpha_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{it}$$

where $t = 1, \ldots, T$, $i = 1, \ldots, N$, and $\bar{y}_t$ presents the cross section mean of y_{it}, which extracted from $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$. The null hypothesis is $b_i = 0$for all i, and alternative hypothesis is $b_i < 0$for some i. The CIPS test based on

$$CIPS(N,T) = N^{-1}\sum_{i=1}^{N} t_i(N,T),$$

where $t_i(N,T)$ is statistic of the CADF for thei^{th}cross section unit given by the t-ratio of the coefficient of $y_{i,t-1}$in CADF regression.

3.3.3. Co-integration test

The purpose of a co-integration test is to confirm whether there is a long run relationship between the variables. The Johansen Fisher-type panel co-integration test introduced by Maddala and Kim (1998) underlies the Johansen methodology applied

in this study. Two statistics techniques are applied to test panel co-integration among variables in Johansen Fisher-Types approach. The first statistics technique is named the maximum eigenvalue statistics (the formula is Eq (3.1)) and the second statistics technique is called the trace statistics (the formula is Eq (3.2)).

$\lambda_{max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1})$ (3.1)

$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\hat{\lambda}_i)$ (3.2)

where T is sample size, and n is the numbers of variables used to test for long-run relationship by the panel co-integration model. $\hat{\lambda}_i$ is the correlation between the residuals of *i* (*i*is number of cross-sectional data) and the residuals from *i* which were differentiated already.

3.3.4. Panel least square test

Suppose the data series, for each variable is$t = 1, 2, \dots, T$ (time periods of panel data) and $i = 1, 2, \dots, N$ (number of groups in panel data). The multiple linear regression model assumes a linear (in parameters) relationship between a dependent variable y_{it} and a set of explanatory variables $\mathbf{X}_{it}^{'} = (x_{1it}, x_{2it}, \dots, x_{Kit})$. The model can write be as follow: y_{it}=$\alpha_i^* + \mathbf{X}_{it}^{'}\boldsymbol{\beta}$+$u_{it}$,where $\boldsymbol{\beta}$is K× 1 vector of constants and α_i^* is a 1×1scalar constant representing the effects of those variables peculiar to the *i*th individual in more or less the same fashion over time; u_{it} is error term and be assume that is uncorrelated with ($\mathbf{X}_{i1}, \dots, \mathbf{X}_{iT}$). Besides the error term is an independently identically distributed random variable with mean 0 and variance σ_u^2. Based on above assumption of error term, the ordinary least-squares (OLS) estimator of α_i^* and $\boldsymbol{\beta}$ are obtained by minimizing the residual sum of squares, S.

$S = (y - \tilde{x}\boldsymbol{\theta})'(y - \tilde{x}\boldsymbol{\theta}) = \sum_{i=1}^{N}\mathbf{u}_i'\mathbf{u}_i = \sum_{i=1}^{N}(y_{it} - \mathbf{e}\alpha_i^* - X_i\boldsymbol{\beta})'(y_{it} - \mathbf{e}\alpha_i^* - X_i\boldsymbol{\beta})$, (4.1)

where $\tilde{x} = (\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_N, X)$, and let $\mathbf{d}_i$ is $NT \times 1$ vector dummy variable; $\boldsymbol{\theta} = (\alpha_1^*, \dots, \alpha_N^*, \boldsymbol{\beta}')'$. And then, taking partial derivatives of S with respect to α_i^* and setting them equal to 0 can get the

$\hat{\alpha}_i^* = \bar{y}_i - \bar{\mathbf{X}}_i'\boldsymbol{\beta}$. (4.2)

Substituting Eq (4.2) into (4.1) and taking thepartial derivative of S with respect to $\boldsymbol{\beta}$ can get the estimator of $\boldsymbol{\beta}$,

$\widehat{\boldsymbol{\beta}}_{cv} = [\sum_{i=1}^{N}\sum_{t=1}^{T}(\mathbf{X}_{it} - \bar{\mathbf{X}}_i)(\mathbf{X}_{it} - \bar{\mathbf{X}}_i)']^{-1}[\sum_{i=1}^{N}\sum_{t=1}^{T}(\mathbf{X}_{it} - \bar{\mathbf{X}}_i)(\mathbf{X}_{it} - \bar{\mathbf{X}}_i)']$.(Hsia, 2014)

IV. ESTIMATIONS AND RESULTS

4.1. Results of green growth index

Firstly, the author uses the entropy weighted get the weight of each indicator, the results show in the **Table 4.1**. The maximum indicator weight is X4 (18.513%), non-energy material productivity and the minimum value is X12, real GDP per capita. (1.969%).

Then, the author calculates the green growth index through the TOPSIS method, and the result is shown in **Table 4.2**. In order to see the data more intuitively, the author made a plot (**Figure 4.1**) where CHN, JPN, MYS, PHL, and KOR represent China, Japan, Malaysia, the Philippines and South Korea, respectively. **Figure 4.1** shows the green growth index and changes in five countries from 1990 to 2021. Overall, the green growth index of all five countries showed an upward trend. Japan and South Korea performed better than the other three countries, reaching more than 0.7, while China had the lowest green growth index value, 0.396 in 2021. Malaysia and the Philippines have similar Green Growth Index values. The growth trend is most pronounced in China and South Korea.

4.2. Results of cross-sectional dependency (CD) test and slopeheterogeneity test

The results summarized in **Table 5** confirmed the existence of cross-section dependence for all variables at the 1% significant level. The FDI cannot pass the Pesaran CD test. However, it can pass the other three cross-section dependence tests (Breusch-Pagan LM, Pesaran scaled LM and Bias-corrected scaled LM tests) at the 1% significant level, and the result of FDI shown in **Table 4.4** is obtained by Pesaran scaled LM method.

In the next stage, the author tests the slope heterogeneity of the panel data with two tests ($\hat{\Delta}$ and $\hat{\Delta}_{adj}$) by running Stata software. The null hypothesis is that slope coefficients are homogeneous. The results in **Table 4.5** demonstrated that statistical heterogeneity exists in slope coefficients.

4.3. Results of panel unit root test

Results of the unit root test are presented in Table 4.6. Results show that the series of ETI, IS, Ur, lnIn, Tec, FDI, and HC are stationary at 1% significant level. The IS and Ex are non-stationary at level, but their first-difference series are stationary at the 1% significant level. The author retests the cross-section dependence of the first difference of IS and Ex. The results are shown in **Table 4.4**. The D(IS) and D(Ex) are existing cross-section dependence.

4.4 Results of integration test

The Johansen-Fisher panel cointegration test is used to test the cointegration relationship of the explained variable with explanatory variables. The trend assumption is no deterministic trend. Furthermore, the lag intervals are typing "1 1", which means the test regresses in terms of the first difference on one lag of the first difference. The results are presented in **Table 4.7**. The first column is the number of cointegrating relations under the null hypothesis. The third and fifth columns are p-values of Johansen's cointegration trace test and maximum eigenvalue test. The results show that reject the null hypothesis at most seven cointegrating relations at a 5% significant

level, which means that there are at least seven cointegrating relations among the variables. As such, the existence of cointegration implies a long-run relationship existing.

4.5 Benchmark regression

Before estimating the coefficients, the author identifies which types of suit panel data, pool, random, or effect models. The results of the slope heterogeneity test find that the panel data has the problem of heterogeneity problem, so the pool model is not suitable. Next, due to a random effects estimation requiring the number of cross sections larger than the number of coefficients for between estimator of estimate of random effect innovation variance, but this study's data set cannot satisfy this condition. As such, the fixed effects model is chosen in this study. After comparing three types of fixed models, the cross-section fixed model, the period fixed model, and the cross-section and period fixed model (double fixed model), the author chooses the cross-section fixed model. The regression estimate results are shown in **Table 4.8**. **Table 4.8**, Model (1) shows that the R-squared is 0.9782, and the adjusted R-squared is 0.9763, which implies the explanatory degree of the explanatory variables to the explained variable is 97.82%. The F-statistic is 530.5268, and the probability of the F-statistic is less than 0.01, which means the eight explanatory variables are jointly explained the dependent variable at a 1% significance level. The primary explanatory variable, ETI, is significant in explaining ln(GGI) at 1% significant level. Besides, in the other seven control variables, excepted individual D(IS) and FDI are not statistically significant in explaining ln(GGI); the other five variables, lnIn, D(EX), HC, Tec and Ur are statistically significant in explaining ln(GGI). Then the author eliminates insignificant variables step by step. Firstly, eliminating the FDI and the regression result is presented in Model (2) of **Table 4.8**, and the D(IS) still cannot pass the statistically significant test. Consequently, the author continues to remove the insignificant variable, D(IS), based on Model (2) and then gets Model (3).

In Model (3), all explanatory variables pass the statistically significant test at a 5% significant level. Moreover, the explanatory degree of the explanatory variables to the explained variable is 97.78%. The probability of the F-statistic is less than 0.01, which means the six explanatory variables are jointly explained the dependent variable at a 1% significance level.

The final model of benchmark regression can present as follows:

lnGGI = 0.00444*ETI + 0.1550*lnIn + 0.00318*D(Ex) + 0.0447*HC - 0.0376*Tec - 0.0034*Ur - 2.4275 + [CX=F]

Model (3) suggests a positive relationship between environmental-related technology innovation and a green growth index, which is consistent with the expected result. Holding other factors fixed, if the percentage of the environmental-related inventions in all domestic inventions increases by 1%, the percentage of the green growth index increase by 0.0044%. Besides, the empirical results of the impact of innovation and human capital on green growth are consistent with the expected result. Innovation and human capital have a significantly positive relationship with green growth. According to the result, urbanization development and green growth are a positive relationship, implying that urbanization's positive effects outweigh the harmful effects of urbanization on green growth. However, the empirical results of exports of goods and services show a positive impact on green growth, which is inconsistent with the expected result. The reason is that more export activity means more openness for a country. The open market can improve access to new technologies that make production more efficient. Besides, as the environmental problem becomes international attention, many countries provide incentives to adopt stringent environmental standards and raise standards for import products; hence exporting countries be encouraged to use and development of sanitary products in order to export, thereby promoting local green growth. The result shows a negative relationship between TEC and lnGGI, which is inconsistent with the expected result.

4.6 Robustness test

In this study, the panel Full Modified Least Squares (FMOLS) and panel Dynamic Least Squares (DOLS) co-integrating regression methods are adopted to test the robustness of the benchmark regression results (See **Table 4.9**). The results show that the coefficient of the primary core explanatory variable, ETI is consistent with the above regression results. As such, the previous empirical results are robust.

4.7 Heterogeneity test

In order to investigate heterogeneity and the individual effects of environmental-related technology innovation (ETI) on green growth (lnGGI) of China, Japan, Malaysia, the Philippines and South Korea, the author separates do OLS regressions of each country. The results are presented in **Table 4.10**.

The results revealed that except China cannot pass the statistically significant test, the other four countries' ETI can significantly impact green growth. The ETI of Japan, the Philippines and South Korea are statistically significant in explaining their lnGGI, consistent with the previous whole regression result. Holding other factors, if the percentage of environmental-related technologies in all technologies, the corresponding green growth index of Japan, the Philippines and South Korea will

increase. However, the ETI of Malaysia is a negative relationship with its lnGGI. According to the result in **Table 4.10**, except for China, the most independent variable can pass the statistically significant test, which means the previous benchmark regression model is relatively valid and can pass the heterogeneity test. Besides, the result concludes the model is more efficient in countries with better-developed levels.

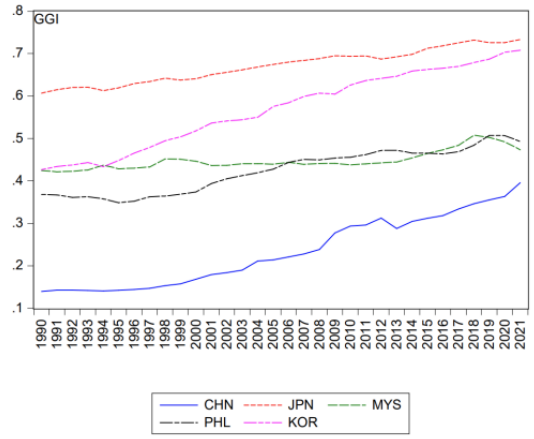

Figure 4.1: Green growth index trend

V. CONCLUSION

Dealing with climate change problems and achieving sustainable development goals in 2030 have become important goals for humans. Technology innovation is a crucial factor in achieving these goals. This study analyzes the impact of environmental-related technology innovation on green growth in China, Japan, Malaysia, the Philippines and South Korea. In order to investigate this relationship, the author first calculates each country's green growth index by establishing a green growth indicator system. Applied the entropy-weighted TOPSIS method, getting the green growth and results show that the green growth index of the five countries showed an overall growth trend. Besides, the green growth index of two developed countries, Japan and South Korea, were higher than those of the other three developing countries. Among the five countries, China has the lowest green growth index. This study considers the environmental-related technology innovation as the primary explored explanatory variable and adds industry structure upgrading, urbanization level, innovation, technology level, foreign direct investment dependence, export of goods and services and human capital seven variables as control variables. The explained variable is the green growth index. The empirical results show that environmental-related technology innovation is statistically significant in explaining the green growth index.

Furthermore, a positive relationship exists between environmental-related technology innovation and green growth. The foreign direct investment dependence and industry structure upgrading cannot statistically impact the green growth index. However, the other five control variables can explain the green growth index statistically significantly. Furthermore, innovation, export of goods and services, and human capital can positively impact the green growth index. However, technology development and urbanization level negatively impact the green growth index. Based on empirical results, the author suggests that the government should encourage to develop the environmental-related technology innovation, which is beneficial to improve countries' green growth.

variable	Test Statistics	P-values
lnGGI	15.8458***	0.0000
ETI	4.5483***	0.0000
IS	13.6058***	0.0000
D(IS)	5.6329***	0.0000
Ur	8.6014***	0.0000
lnIn	3.3861***	0.0007
Tec	16.3758***	0.0000
FDI	3.3036***	0.0010
Ex	5.2329***	0.0000
D(Ex)	4.0864***	0.0000
HC	13.0179***	0.0000

Table 4.1: Results of cross-section dependence analysis

Note: *** explain the level of significance at 1%.

Indicators	Notation	Weight (%)
Production-based CO2 productivity, GDP per unit of energy-related CO2 emissions	X1	8.878
Demand-based CO2 productivity, GDP per unit of energy-related CO2 emissions	X2	5.823
Energy productivity, GDP per unit of TPES	X3	8.413
Non-energy material productivity, GDP per unit of DMC	X4	18.513
Mean population exposure to PM2.5	X5	4.156
Mortality from exposure to ambient ozone	X6	4.908
Population with access to improved sanitation, % total population	X7	7.435
People using at least basic drinking water services, % of the population	X8	3.658
life expectation at birth	X9	14.528
Unemployment, total, % of total labor force	X10	15.008
Environmentally related taxes, % GDP	X11	6.709
Real GDP per capita ,US dollar, 2015	X12	1.969

Table 4.2:The results of entropy weighted

Date	CHN	JPN	MYS	PHL	KOR
1990	0.139	0.607	0.424	0.368	0.426
1995	0.142	0.619	0.428	0.349	0.448
2000	0.168	0.641	0.446	0.374	0.518
2005	0.214	0.675	0.439	0.428	0.575
2010	0.294	0.693	0.437	0.456	0.626
2015	0.312	0.712	0.464	0.465	0.662
2020	0.363	0.726	0.492	0.507	0.703
2021	0.396	0.733	0.473	0.493	0.708

Table 4.1: The green growth index of CHN,JPN, MYS, PHL and KOR

Statistics	Test value(P-Value)
$\hat{\Delta}$	2.708^{***}(0.007)
$\hat{\Delta}_{adj}$	3.372^{***}(0.001)

Table 4.4: Results of slope heterogeneity test

Note: *** explain the level of significance at 1%.

Series	Test for unit root in	Type of test equation	CIPS-test statistics	conclusion
lnGGI	level	Constant	−2.3502	I(0)
ETI	level	None	-2.5113^{*}	I(0)
IS	first difference	None	-3.2488^{*}	I(1)
Ur	level	None	-2.1033^{*}	I(0)
lnIn	level	Constant	-3.3779^{*}	I(0)
Tec	level	Constant	−3.0666	I(0)
FDI	level	None	−2.4241	I(0)
Ex	first difference	None	−4.5161	I(1)
HC	level	Constant and trend	−3.2299	I(0)

Table 4. 5: Results of panel unit root tests

Note: ***, ** & * explain the level of significance at 1%, 5% and 10% respectively.

Hypothesized No. of CE(s)	Fisher Stat.(From trace test)	Fisher Stat.(From max-Eigen value)
None	424.9^{***}	192.4^{***}
At most 1	383.8^{***}	158.3^{***}
At most 2	198.2^{***}	87.02^{***}
At most 3	130.6^{***}	55.34^{***}
At most 4	83.6^{***}	41.53^{***}
At most 5	50.61^{***}	25.9^{***}
At most 6	33.52^{***}	24.07^{***}
At most 7	19.83^{*}	21.49^{**}
At most 8	5.412	5.412

Table 4.6: Results of cointegration tests

Note: ***, ** explain the level of significance at 1%, 5% and respectively. Probabilities (Prob.) are computed using asymptotic Chi-square distribution.

	Model (1)		**Model (2)**		**Model (3)**	
Variables	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
ETI	0.0043^{***}	-2.7726	0.0043^{***}	0.0015	0.0044^{***}	0.0015
	（0.0016）		(2.7547)		(2.8779)	
lnIn	0.1568^{***}	-17.5747	0.1561^{***}	0.0087	0.1550^{***}	0.0087
	（0.0089）		(17.9021)		(17.8062)	
D(Ex)	0.0031^{**}	2.4576	0.0031^{**}	0.0012	0.0032^{**}	0.0013
	（0.0013）		(2.4749)		(2.5442)	
HC	0.0444^{***}	7.0409	0.0448^{***}	0.0062	0.0447^{***}	0.0062
	（0.0063）		(7.2233)		(7.1855)	
Tec	-0.0381^{**}	-2.1228	-0.0385^{**}	0.0179	-0.0376^{**}	0.0179
	（0.0179）		(-2.1570)		(-2.1008)	
Ur	-0.0035^{***}	-3.0142	-0.0036^{***}	0.0011	-0.0034^{***}	0.0011
	（0.0012）		(-3.2088)		(-3.0499)	
D(IS)	-0.0067	-1.1524	-0.0074	0.0055		
	（0.0058）		(-1.3372)			
FDI	0.0023	0.4264				
	（0.0054）					
C	-2.4364^{***}	0.0886	-2.4192^{***}	0.0786	-2.4275^{***}	0.0785
	（0.0885）		(-30.7885)		(-30.9044)	
R-squared		0.9782		0.9781		0.9778
Adj.R-squared		0.9763		0.9764		0.9763

F-statistic	530.5269	582.0705	636.6145
Prob (F-statistic)	0.0000	0.0000	0.0000

Table 4.8: Estimation results of OLS (Cross-section fixed effects)

Note: ***, ** explain the level of significance at 1% and 5% respectively; the values in parentheses are t-statistics.

R-squared (R^2) is coefficient of determination; Adj. R-square ($\overline{R}^2$) is adjusted coefficient of determination, and$\overline{R}^2 = (1 - \overline{R}^2)\frac{n-1}{n-k}$. F-statistic is used to do an F-test (test whether the linear relationship between the explained variable and all the explanatory variables in the model is significant as a whole), and the null hypothesis of F-test is all the coefficient of parameters are equaled. Prob (F-statistic) present the concomitant probability of F-statistic.

	Countries				
	CHN	**JPN**	**MLS**	**PHL**	**KOR**
variables	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
ETI	0.0093	0.0051**	-0.0030**	0.0036***	0.0067**
	(1.6662)	(2.5179)	(-2.2913)	(3.7407)	(2.5736)
lnIn	0.0042	0.0778***	-0.0749***	0.0571*	-0.0405
	(0.1188)	(4.8431)	(-4.5272)	(1.9552)	(-1.3028)
D(Ex)	0.0014	-0.001032	0.0010	-0.0109***	-0.0003
	(0.4278)	(-1.2353)	(1.7093)	(-4.4797)	(-0.4186)
HC	0.0334	-0.0159***	-0.0126**	0.0353***	0.04634***
	(1.0863)	(-4.4574)	(-2.7418)	(3.2377)	(6.2910)
Tec	0.2942**	-0.0055	0.0642	0.5210***	-0.01026
	(2.8328)	(-0.4184)	(1.5236)	(3.0459)	(-0.4264)
Ur	0.0159***	0.0082***	0.0096***	-0.0389***	0.0409***
	(2.4816)	(13.4072)	(3.6039)	(-3.1570)	(4.5121)
R-squared	0.9898	0.9907	0.8398	0.9548	0.9918
Adjusted R-squared	0.9872	0.9884	0.7872	0.9435	0.9897

Table 4. 7: The results of OLS regression of individual countries

Note:***, **&*explain the level of significance at 1%, 5% and 10% respectively; the values in parentheses are t-statistics.

	FMOLS		DOLS	
variable	Coefficient	Std. Error	Coefficient	Std. Error
ETI	0.0057**	0.0026	0.0152***	0.0051
	(2.2336)		(2.9716)	
lnIn	0.1667***	0.0145	0.1500***	0.0187
	(11.4935)		(8.0056)	
D(Ex)	0.0050**	0.0021	0.0098	0.0080
	(2.4264)		(1.216863)	
HC	0.0539***	0.0105	-0.0193	0.0180
	(5.1449)		(-1.0737)	
Tec	-0.0578*	0.0230	0.0996*	0.0525
	(-1.9278)		(1.896348)	
Ur	-0.0046**	0.0019	0.0074**	0.0074
	(-2.3994)		(2.0717)	
R-squared		0.9763		0.9970
Adjusted R-squared		0.9746		0.9891

Table 4.8: The results of robustness check

Note:***, **, and * explain the level of significance at 1%, 5% and 10% respectively; the values in parentheses are t-statistics. R-squared is coefficient of determination; Adj. R-square is adjusted coefficient of determination.

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