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Development of Ecological Patent in Southeast Asian Countries: Linkages between Economic Growth, Environment and Innovation

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ABSTRACT

This study examines the impacts of gross domestic product (GDP), carbon emission, and renewable energy consumption on ecological innovation patent of five countries in Southeast Asian region, namely Indonesia, the Philippines, Singapore, Thailand, and Malaysia, for the period 2000-2019. Two methods are applied; those are Ordinary Least Squared (OLS) and Generalized Least Squared (GLS). The results show that GDP provides a positive and significant impact on ecological innovation patent in the five countries. Similarly, carbon emission leads the ecological innovation patent. The same finding prevails in the impact of renewable energy consumption, in which it leads to further ecological innovation. The implication of this study is on the urgency for policies toward ecological innovation patent in reducing environmental damage in Southeast Asian countries.

Keywords: Eco-innovation, Carbon Emission, Gross Domestic Product, Renewable Energy Consumption
JEL Classifications: O1, O4, Q2, Q5

1. INTRODUCTION

Economic growth and environmental protection do not always go hand on hand. In some cases, these two agenda run into an opposite direction. An increase in economic growth might accompany with an environmental degradation (Ben Amara et al., 2023). The destruction of nature is often characterized by an increase in carbon emissions and a high level of energy consumption Mohsin et al., 2019; Ozcan et al., 2020). In response to the environmental degradation, many countries are trying to prepare a transition to sustainable development and raise environmental protection as a key agenda (Browne et al., 2023; Long, 2022).

The environmental issue has led to a growing concern in adopting technological innovations that are environmentally friendly in supporting economic growth and at the same time maintaining environmental integrity (Güven et al., 2024). This process reflects a paradigm shift in development, where environmental considerations and sustainability aspects are becoming increasingly important in economic decision-making and public policy. When it comes to carbon emissions, it is important to know the sources. The increased use of fossil fuels since the industrial revolution has led to various increases in the amount of greenhouse effect in the atmosphere, thus becoming the main cause of global warming or climate change, which eventually led to various environmental problems (Yurdakul and Kazan, 2020).

Climate change and environmental problems are certainly affecting an economy and become a major problem in the future (Tol, 2024). Economic growth and technology transfer sound good, but they will raise a certain problem, such as carbon emission and environmental degradation, when they do not manage properly (Chien et al., 2021). Ecological innovation (eco-innovation) can be an alternative way in reducing environmental problems. Wang et al., (2020) shows that an increase in carbon emission in China triggers acceleration in eco-innovation. Similarly, Sadiq et al.,

(2023) pictures the relationship between carbon emission and eco-innovation in BRICS, while Wang et al., (2020) shows the relationship in G7 countries.

An increase in carbon emissions becomes an impetus for companies to adopt environmentally friendly innovation solutions. In addition, a higher carbon emission triggers a significant impact on environmental regulations by many countries around the world. It is necessary for the governments to respond to carbon emissions through the implementation of policies based on command and control. Through this, an attention to the increase in carbon emissions highly related to the issue of climate change, and in turn increases an awareness for environmental innovations

Innovation and technology transfer allow companies to replace traditional technologies with renewable technologies in their production processes. Although many people today are highly educated who are able to absorb and adapt to technology from the results of innovation or technology transfer, in fact, improper use of technology can also lead to unexpected risks such as ecological footprints that can damage the surrounding environment (Destek and Manga, 2021; Bakhtina, 2011)**.** If this unexpected risks keep continue and to be ignored, it can be a potential cause for a large loss for a country or even for a mother nature. Although this issue has been a long-term awareness, the impacts on environmental degradation are still felt between generations, characterized by the buildup of carbon emissions in the atmosphere that last for 100-1000 of years to come (Attenborough and Lagarde, 2019). In addition, climate change can also increase the likelihood of natural disasters. The impact of these natural disasters is very difficult to avoid, but at least through real action it can be anticipated or become an early warning. Awareness of the importance of protecting the environment and innovating to reduce the ecological footprint can help civilization overcome this challenge (Murshed et al., 2021)

As part of efforts to reduce the impact of climate change and to improve environmental sustainability, the development of renewable energy resources is of critical importance. According to Shinn, (2022), renewable energy or clean energy comes from natural sources or processes that are continuously renewed. Renewable energy includes resources such as solar, wind, water, and biomass can be a major focus in providing environmentally friendly solutions to global energy needs. One of the drivers of the increase in renewable energy is ecological technology innovation (Khan et al., 2021). This is due to the transition, where the manufacturing industry is starting to reduce the amount of energy use obtained from fossils which certainly causes carbon emissions by replacing it with more sustainable energy such as renewable energy.

Environmental protection is not only an urgent need, but can be a potential key to economic growth through ecological innovation. There are concerns about environmental degradation caused by the economic activities of several countries in Southeast Asia, so through this research it is hoped that it can provide an insight and awareness of a solution to the environmental problems that are happening. Meanwhile, this study uses research objects covering five countries in Southeast Asia. Amheka et al., (2022) stated that countries in the Southeast Asia region have experienced significant economic growth and industrialization in recent years, which has led to an increase in energy consumption and greenhouse gas emissions, which now account for 90% of total greenhouse gas emissions in Indonesia, Malaysia, the Philippines and Thailand. These countries have high emission levels and are therefore important targets for carbon emission reduction efforts and a transition to low-carbon economies.

The main contribution of this current research is twofold. Firstly, it adds renewable energy consumption as a new variable within an environment Kuznets model, in order to grasp the effect of demand side economy. Secondly, it focuses on the major Southeast Asian countries that have an increasing awareness about environmental issue and ecological innovation due to the increasing gas emission and economic growth.

The rest of this paper will proceed as followed. The second part provides reviews on the related literature, followed by the methods in the third section. The fourth section shows the empirical results and analysis. The conclusion and implications are given in the last section.

2. LITERATURE REVIEW

2.1. Environmental Kuznets Curve

The theoretical ground for the environmental issue and economic growth is provided by Kuznets (1955). The term Environmental Kuznets is named after Simon Kuznets, who argued that income inequality would increase and then decrease with economic development (Stern, 2004). According to the Environmental Kuznets hypothesis, environmental degradation starts to increase during economic growth (Kuznets, 1963). This is because in the early stages of economic growth, awareness of protection, environmental care is still low, and also advanced technology to prevent damage is still not available (Mahmoodi and Dahmardeh, 2022). This hypothesis also explains that at the beginning of economic growth, pollution emissions increase and environmental quality deteriorates. However, there is also a phenomenon at the per capita level where when there is economic growth, income increases, which will encourage the improvement of the environment Galeotti, (2007) arguments, the Kuznets curve has an inverted U-shape and the effect of economic growth to environmental degradation has a quadratic function.

2.2. Effect of Gross Domestic Product on Eco-Innovation

According to Hu (2021) the long run gross domestic product (GDP) have a significant positive effect on increasing innovation technology, this certainly includes eco-innovation. This study was supported by a research by Costantini et al., (2023) whose suggesting that the higher the level of GDP of a country, the higher the development of a country and also awareness or interest in eco-innovation. Costantini et al., (2023) highlighted further that there are a factor accelerating awareness for eco-innovation, namely openness to innovation science. In addition, Mačiulytė-Šniukienė and Sekhniashvili, (2021) states that eco-innovation helps a

country to increase its potential economic growth, by creating new opportunities, helping companies to grow their business, reducing costs, as well as protecting environment for resource efficiency which might helps many companies achieve both economic and environmental benefits. Based on these previous studies, one can hypothesize that the effect of GDP on eco-innovation is positive at the beginning of environmental degradation, but then the magnitude of the positive effect will slowing down through time when the governments enact several regulations in preventing environmental degradation. Thus, the hypothesis in relation to the impact of GDP to ecological innovation can be divided into two parts, as followed:
H1: GDP increases ecological innovation.
H2: the magnitude of GDP effect is slowing down through time (i.e. the squared-GDP has a negative effect on ecological innovation).

2.3. Effect of Carbon Emission on Ecological Innovation

(Hordofa et al., 2023) shows that ecological innovation has been an important factor in reducing carbon emission. Among several efforts in dealing environmental degradation, ecological innovation has been a more significant determinant in reducing carbon emissions compared to other variables, such as green investment. Another perspective is highlighted in (Wang et al., 2020) that shows the direction of effect can go from carbon emission to ecological innovation. The increase in carbon emission has a significant positive effect on the tendency of the Chinese states to make environmentally friendly innovations. Hashmi and Alam, (2019) also found that carbon emission increases the awareness for environmental friendly innovation and triggers the innovation patent. Following these previous research, this current study puts forward a hypothesis that:
H3: Carbon emission generates a positive impact on ecological innovation patent.

2.4. Effect of Renewable Energy Consumption on *Eco-Innovation*

Research conducted by Solarin et al*.* (2022) found that ecological innovation has a significant positive relationship with renewable energy in BRICS countries. The findings of this study indicate that in order to increase ecological innovation, policy makers need to increase GDP, reduce carbon emissions, which will then affect the consumption of renewable energy, and in turn generate ecological innovation. In addition, Popp, (2001) analyzed data on patents in the United States and the impact of energy prices on innovations has founded two-sided results. On the demand side, the rise in the renewable energy consumption encourages innovation activities through increasing the value of innovation, and from the supply side the investment in renewable energy production induces scientific breakthroughs that make innovation more highlighted. Based on these previous studies, the hypothesis is:
H4: Renewable energy consumption provides a positive effect on ecological innovation.

3. RESEARCH DATA AND METHODS

The type of this current research is explanatory research that explores phenomenon occurred based on empirical data. The main focus of this research is to examine the relationship between GDP, carbon emissions, energy consumption and ecological innovation in five Southeast Asian countries, namely Indonesia, Malaysia, Thailand, the Philippine and Singapore. Based on its purpose, this research can be categorized as a conclusive research since it re-verifies the phenomena that are happening. This research also is quantitative research, as it uses statistical tools to examining data.

As discussed in the Literature Review section, there are five variables to be examined in this current research. The dependent variable is ecological innovation, whereas the independent variables are Gross Domestic Product (GDP), the squared value of GDP, carbon emission, and renewable energy consumption. The use of the squared value GDP is aimed at evaluating the environmental Kuznets hypothesis. Table 1 provides the definitions of the variables.

3.1. Data Type and Data Sources

The data used in this research is secondary data obtained from World Bank online database, OECD online dataset, and Our World in Data. The final dataset consists of a period from 2000 to 2019 and five Southeast Asian countries, namely Indonesia, the Philippines, Singapore, Thailand, Malaysia. The five variables are ecological innovation (eco-innovation), gross domestic product (GDP), the quadratic value of gross domestic product (GDP^2), carbon emission (CE), and renewable energy consumption (REC). Data for eco-innovation is obtained from the OECD (*Organization for Economic Co-operation and Development*) online dataset, defines as collaboration in the development of technologies that focus on addressing climate change or pollution problems in order to help local businesses utilize existing technologies. The data for

Table 1: Definitions of the variables

Variables	Symbol	Definitions	Sources of data
Ecological Innovation	EI	Numbers of innovations produced to reduce impacts of climate (percentage of technology).	(OECD, 2023)
Gross Domestic Product	GDP	The sum of the gross value added by the producer as well as the product tax is then reduced by subsidies that are not included in the product value. The units used are constant US dollars which then be logged.	(The World Bank, 2023a)
Gross Domestic Product Squared	GDP^2	The natural logarithm of the quadratic value of GDP	(The World Bank, 2023a)
Carbon Emission	CE	Total emissions from fossil fuels plus emissions of industry, with units of percentage which will then be logged	(Our World in Data, 2023)
Renewable Energy Consumption	REC	Percentage of renewable energy consumption in total final energy consumption.	(The World Bank, 2023b)

GDP is from the World Bank website, which is used to measure economic growth. The data for the third variable Carbon Emission is collected from the Our World in Data website, measured in tons, covering all emissions from fossil fuel consumption. The last is data from Renewable Energy Consumption, obtained from the World Bank website, measured in percentage of renewable energy consumption in total final energy consumption.

3.2. Analysis Method and Model

There are two estimation methods used in this current research. They are Ordinary Least Squared (OLS) regression method and Generalized Least Squared (GLS) regression method. OLS is the early method of regression that is used to estimate the effect of one variable to another (Gujarati and Porter, 2009). There are 10 Gauss-Markov assumptions for linear regression that should be fulfilled in OLS in order to be BLUE (Best Linear Unbiased Estimator), four of the assumptions are tested in this paper. The GLS method is conducted when the assumption of homocedasticity and no-autocorrelation are violated. In this study, the two methods are performed because the autocorrelation test shows that the decision is in the inconclusive area. GLS has a minimum variance when there is an autocorrelation or heteroscedasticity in the model (Wooldridge, 2019).

In constructing empirical model in this research, four variables are used as independent variables affecting ecological innovation patent (EI). The four independent variables aregross domestic product (GDP), the squared value of GDP, carbon emission (CE), and renewable energy consumption (REC). FiveAsian countries, namely Indonesia, Malaysia, Singapore, Thailand, and the Philipines, are examined within the periode 2000-2019. The empirical model for this current research is:

$$lnEI_{it} = \beta_0 + \beta_1 lnGDP_{it} + \beta_2 lnGDP_{it}^2 + \beta_3 lnCE_{it} + \beta_4 REC_{it} + \varepsilon_{it} \quad (1)$$

where *ln* represents natural logarithm, *EI* represents ecological innovation, *GDP* is gross domestic product, GDP^2 is the quadratic value of gross domestic product, *CE* represents carbon emission, *REC* is renewable energy consumption, β_i represents parameters to be estimated, *i* is the i-th countries, and t is the t-year.

3.3. Classical Assumption Test

The Gauss-Markov assumptions for regression analysis are also known as classical assumptions. Testing for the assumption is mandatory to check for the fulfillment of BLUE for an estimator (Qotrun, 2021). This study presents four assumptions tests, namely normality, multicollinearity, autocorrelation, and heteroscedasticity.

3.3.1. Normality test

The normality test is to check whether the residual value is *iid* (independent and identically distributed). The Gauss Markov assumption (also known as Classical assumptions) requires the residuals in the model are random and normally distributed with mean value μ and variance σ. The Jarque-Bera (JB) test is used to perform the normality in this study. The null hypothesis of Jarque-Bera is the residuals are normally distributed. The decision is checked through the comparison of the probability value of JB with the critical value of 5%. When the probability is greater than the critical value, the null hypothesis JB is not rejected, suggesting for normality distribution. In contrast, if the probability is less than the critical value 5%, the null hypothesis JB is rejecting, implicating of not normal in the distribution of residuals.

3.3.2. Multicollinearity test

The multicollinearity test is to check whether the correlation between independent variables is larger than the correlation between independent and dependent variables (Gujarati and Porter, 2009). The perfect or near perfect correlation between independent variables can resulted in the OLS estimator is no longer efficiency or has a minimum variance. This study uses partial Pearson correlation test to check for multicolinearity.

3.3.3. Autocorrelation test

The autocorrelation test is to evaluate whether the residual in the data series is correlated (Hansen, 2022). For an estimator to be BLUE in conducting regression analysis, the data used in estimation should free from autocorrelation. If the autocorrelation exists in the dataset, the OLS is no longer the best (or efficient) and could be replaced by GLS. The autocorrelation test that uses in this study is Durbin-Watson d-test.

3.3.4. Heteroscedasticity test

Heteroscedasticity test is to determine whether there are deviations in classical assumptions, namely the non-constant in the variance of the residuals for all observations in a linear regression model (Wooldridge, 2019). Residual heteroscedastic diagram is used as a detection tool for the heteroscedasticity in this study. Alternatively, the statistical test for heteroscedasticity is Likelihood Ratio (LR) test for panel data.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. Descriptive Statistics

The first section of the results shows descriptive statistics of the variables. Table 2 presents data in a concise, structured, and easy to understand manner in order to describe the distribution patterns and characteristics of the observed data. Descriptive statistics consist of Mean (average), Minimum (smallest value), maximum (largest value), Standard Deviation (data distribution).

From Table 2, one can see that the mean value of ecological innovation (EI) is 10.06%, with a minimum value 1.15% and the maximum value 23.78%. The mean value of natural logarithm GDP is 11.41, whereas the minimum value is 10.90 and the maximum value is 12.45. The natural logarithm of quadratic GDP is calculated from the squared value of GDP and then calculates

Table 2: Descriptive statistic

Variables	Measure	Mean	Minimum	Maximum	Std. Dev.
EI	%	10.05740	1.150000	23.78000	4.304064
GDP	Ln	11.40792	10.89719	12.04887	0.287047
GDP^2	Ln	130.2221	118.7488	145.1752	6.567863
CE	Ln	0.716064	0.111234	1.093382	0.290887
REC	%	18.52540	0.330000	45.63000	14.71419

the logarithm value, therefore the value is relatively high. Carbon emission also presented as the natural logarithm, with mean value 0.72. Lastly, the renewable energy consumption is in a percentage, with the mean value 18.53% and the minimum and maximum values are 0.33% and 45.63% respectively.

4.2. Results of Classical Assumption Tests

To perform multiple regression analysis, the Gauss-Markov Classical assumptions should be met. As mentioned in sub-section 3.3, there are four Classical assumptions are performed in this study, those are normality, multicolinearity, autocorrelation, and heteroscedasticity. The results for the four classical assumptions are presented below.

4.2.1. Normality test

The result of normality testing is to check for the normal distribution of the dataset. Table 3 shows that results of Jarque-Bera (JB) test for normality check. The JB probability is compared with the critical value of 5%, in determining the acceptance or rejection of JB hypothesis. The null hypothesis of JB test is that the residuals of the linear regression model are normally distributed, whereas the alternative hypothesis is that the residuals are not normally distributed.

Table 3 shows that the JB probability is 0.089592 and if it is compared to the critical value 5%, it is larger. This finding highlight that the JB null hypothesis is not rejected, suggesting that the residual of the linear regression model is normally distributed. Hence, the normality assumption is fulfilled.

4.2.2. Multicollinearity test

As suggested in Gujarati and Porter (2009), the rule of thumb for multicolinearity is that the correlation coefficients between independent variables (or regressors) should be <0.8. Table 4 presents the Pearson partial correlation for each variables and points out that the values of correlation coefficients between independent variables are all <0.8, suggesting for no multicollinearity in the model. Therefore, the dataset that used for estimation is free from multicolinearity.

4.2.3. Autocorrelation test

The autocorrelation test employed in this study is Durbin-Watson d-test and the result is presented in Figure 1. With the numbers of data is 100 (5 countries for the period 2000-2019) and the numbers of independent variables (k) is 4 variables, the Durbin Watson table for α=5% suggests for DL (lower limit) value 1.461 and the DU (upper limit) value 1.625. The Durbin-Watson

Table 3: Normality test results

Jarque-Bera	Probability
4.824974	0.089592

Table 4: Pearson correlation results

Variable	EI	GDP	REC	CE
EI	1.000000	0.243836	0.321447	0.201047
GDP	0.243836	1.000000	0.212398	−0.437117
REC	0.321447	0.212398	1.000000	−0.307716
CE	0.201047	0.212398	−0.307716	1.000000

(DW) statistic that calculated using Eviews software has a value 1.655549, as presented in Table 5. When the statistic is put in the normal distribution of DW test, the statistic value is located in the no-autocorrelation area, but very near to the DU value.

The area of Durbin-Watson test is presented in Figure 1. One can see that Durbin Watson statistics is located in the area of No-autocorrelation, with a value is slightly larger than DL value. This finding indicates a No-autocorrelation in the dataset. The implication of this finding is that OLS is still Best Linear Unbiased Estimator (BLUE). Considering that the DW-statistic has a value that just slightly larger than DL value, this study applies an alternative estimator, namely the GLS (*Generalized Least Square)* as a robustness check for the results of OLS.

4.2.4. Heteroscedasticity test

The result for heterocedasticity test is presented in Figure 2. From the figure, one can see that the residual values are fluctuated between 5 and −5, with the mean value is close to zero. This figure suggests for no symptoms of heteroscedasticity.

Besides the residual test, this time, the statistical test is performed to test the heteroscedasticity for panel data. The Likelihood Ratio (LR) test is employed as the statistical test and the results are presented in Table 6. The probability value of LR test is 0.0001, suggesting that the null hypothesis of heteroscedasticity is rejected. This finding indicates no heteroscedasticity in the dataset.

4.3. Results of Regression Estimations

After testing for the classical assumptions of OLS, the regression estimation is performed. The estimation is to check the direction

Figure 1: Result of Durbin – Watson d-test

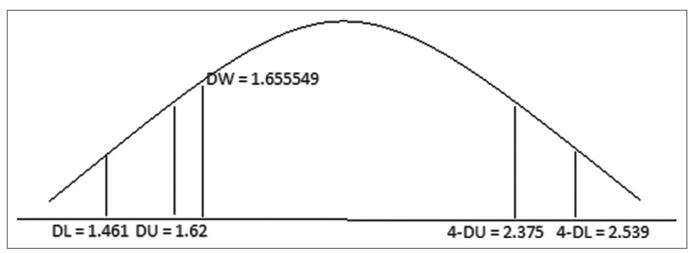
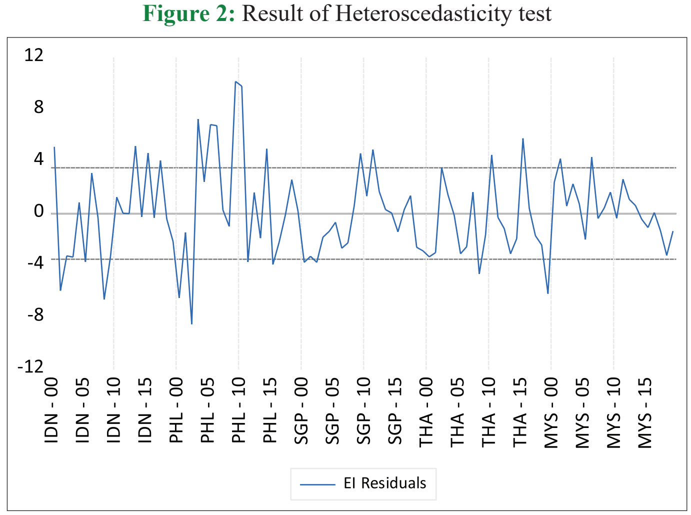


Figure 2: Result of Heteroscedasticity test



of influence as well as the magnitude of influence from GDP, carbon emission, and renewable energy consumption to ecological innovation patent. The regression estimation is also to calculate the statistical significance of the impact of GDP, carbon emission, and renewable energy consumption on ecological innovation patents. In this study, two regression estimations are conducted, namely Ordinary Least Squared (OLS) and Generalized Least Squared (GLS).

Table 7 presents that estimation results for the two regression models. The sign of coefficients are similar for both models although the magnitude is slightly different. The significance tests for each coefficient between the two models suggest the same conclusions. For interpretation of the sign and the magnitude of each coefficient, the OLS results are used. The sign of GDP coefficient is positive with a magnitude 214.28, suggesting that GDP has a positive impact on eco-innovation. This result is in line with the findings in Hu (2021) and Ben Amara et al. (2023), which confirmed that an increase in GDP rise the ecological innovation patents. Furthermore, the sign of GDP2 coefficient is negative with magnitude −9.13, implicating for the inverted U-shape of the environmental Kuznets curve for the relationship between economic growth and ecological innovation patents. The impact of GDP on ecological innovation is increase with a smaller impact over time. This finding conforms the environmental Kuznets hypothesis and is similar to the results of previous study Khan et al. (2020) and Uddin et al. (2019).

For carbon emission, the sign of the CE coefficient is positive and the magnitude is 6.6382, suggesting that the increase in carbon emission by 1 percent leads to the increase in ecological innovation patent by more than 6%. This finding is consistent with the previous research in Wang et al., (2020) and Popp (2001) that point out the importance of awareness regarding carbon emission in trigger ecological innovation.

Table 5: Autocorrelation test (Durbin Watson method)

DW	DU	DL
1.655549	1.625	1.461

Table 6: Result of Heteroscedasticity LR Test

Measure	Value	df	Probability
Likelihood ratio	25.65881	5	0.0001
LR test summary			
	Value	df	
Restricted LogL	−265.1533	95	
Unrestricted LogL	−252.3239	95	

Table 7: Regression estimation results of OLS and GLS methods

Variable	OLS		GLS	
	Coefficient	Prob.	Coefficient	Prob.
C	−1251.860	0.0083	−1.199.304	0.0051
GDP	214.2850	0.0098	205.8384	0.0061
GDP^2	−9.135214	0.0118	−8.786224	0.0075
CE	6.638153	0.0000	4.622861	0.0002
REC	0.120133	0.0000	0.094255	0.0001

Lastly, the coefficient of renewable energy consumption REC is positive with magnitude 0.1201, showing that the awareness to use renewable energy trigger ecological innovation. Solarin et al., (2022) found a similar conclusion regarding the impact of renewable energy consumption on ecological innovation.

4.4. Results for Partial Significance Test (t-test)

The partial significance test employed in this study is student test (t-test). Referring to Table 6, the t-test probability value of GDP is 0.0098, which has a value smaller than 0.05, implicating that GDP generated a significant impact on eco-innovation. Moving to the squared-GDP variable, the probability value is 0.0118, which is smaller than 0.05, suggesting for a statistical significant effect of the squared-GDP on ecological innovation. Furthermore, the probability value of carbon emission (CE) is approaching zero, suggesting for a significant impact. The similar finding is emerged for REC variables with the probability value approaching zero, suggesting a statistical significant influence of renewable energy consumption on ecological innovation.

4.5. Results of Joint Significance Test (F-Test)

To test the joint significance, F-test is applied. The finding is presented in Table 8. The probability value is approaching zero, suggesting for the significant impact of the four exogenous variables on ecological innovation patent.

From the joint significant F-test, one can see that all independent variables are simultaneously affecting the ecological innovation patent. This finding is in line with Ben Amara et al. (2023) and confirms the theoretical framework of environmental Kuznets, suggesting that economic growth in the five Asian countries is a driving force for the creation of an awareness for the community to protect environment and to respond to environmental problems through technological innovation activities.

4.6. Results of Goodness of Fit Test

The estimation results for goodness of fit using R-Squared are presented in Table 9, for both OLS and GLS models. For the first interpretation, we will look at the results of OLS.

In accordance with the OLS results in Table 9, it can be interpreted that all independent variables affect the dependent variable by 35.8458% and the remaining 64.1542% is influenced by other variables besides the model. As for the GLS results, it can be seen that all independent variables affect the dependent variable by 38.7198% and the remaining 61.2802% is influenced by other variables besides the model.

Table 8: Results of joint significance test (F-Test)

OLS		GLS	
F- Statistic	1.8283	*F-Statistic*	15.00642
Prob (F-stat)	0.000000	Prob (F-stat)	0.000000

Table 9: Results of R squared goodness of fit

OLS	GLS
R-Squared=0.358458	R-Squared=0.387198

5. CONCLUSION AND IMPLICATIONS

5.1. Conclusion

This study investigates the impacts of three key determinants, namely GDP, carbon emission, and renewable energy consumption, on ecological innovation. Four important conclusions can be drawn from the findings. Firstly, GDP has a significant positive impact on eco-innovation in the five observed Southeast Asian countries, namely Indonesia, the Philippines, Singapore, Thailand, and Malaysia. Secondly, renewable energy consumption provides a positive and significant effect on eco-innovation. Thirdly, carbon emission influences eco-innovation positively and significantly. Lastly, the results of this study align with the Kuznets Environmental Curve theory, pictured from the negative sign of the GDP-squared variable. The environmental condition of a country undergoes degradation during economic growth phases due to insufficient awareness among the population regarding its impact, lack of innovation, and technological measures to mitigate environmental damage during economic expansion.

In summary, the findings support the notion that economic growth, renewable energy consumption, and carbon emissions are significant factors influencing eco-innovation in the five Southeast Asian countries. The trend of GDP growth is consistent with the theoretical framework provided by the Kuznets Curve, highlighting the importance of addressing environmental concerns alongside economic development.

5.2. Implication

Based on the findings, the implication is straightforward to three issues. The first implication related to the finding about a positive impact of GDP on eco-innovation, which suggests for continuing initiatives or policies toward accelerating GDP growth for an enhancement of ecological innovation patents. The second implication is regarding programs for enhancing boosting research and development in renewable energy in an agenda to stimulate the creation of eco-innovation patents in the five Southeast Asian countries. The third implication is on the efforts to develop patents for eco-innovation should be concentrated on effective solutions to mitigate or reduce carbon emissions.

5.3. Limitations

There are at least two limitation of the current research. Firstly, the data covers only five countries in Southeast Asian region due to the unavailability of balanced panel data for the other five countries. The future research can extend the observed countries to other regions of Asia to provide a bigger picture. Secondly, the time period of analysis is limited to the period 2000-2019. Future research can add a more recent data.

REFERENCES

Amheka, A., Nguyen, H.T., Yu, K.D., Noach, R.M., Andiappan, V., Dacanay, V.J., Aviso, K. (2022), Towards a low carbon ASEAN: An environmentally extended MRIO optimization model. Carbon Balance and Management, 17(1), 13.

Attenborough, D., Lagarde, C. (2019), The greatest balancing act. Finance and Development, 56(4), 68.

Bakhtina, V.A. (2011), Innovation and its potential in the context of the ecological component of sustainable development. Sustainability Accounting, Management and Policy Journal, 2(2), 248-262.

Ben Amara, D., Qiao, J., Zada, M. (2023), How to reconcile the climate change issue with economic growth? Spatial dual mediating effects of carbon emissions and foreign investment. Journal of Cleaner Production, 411, 137285.

Browne, K., Dzebo, A., Iacobuta, G., Faus Onbargi, A., Shawoo, Z., Dombrowsky, I., Fridahl, M., Gottenhuber, S., Persson, Å. (2023), How does policy coherence shape effectiveness and inequality? Implications for sustainable development and the 2030 Agenda. Sustainable Development, 31(5), 3161-3174.

Chien, F., Ajaz, T., Andlib, Z., Chau, K.Y., Ahmad, P., Sharif, A. (2021), The role of technology innovation, renewable energy and globalization in reducing environmental degradation in Pakistan: A step towards sustainable environment. Renewable Energy, 177, 308-317.

Costantini, V., Delgado, F.J., Presno, M.J. (2023), Environmental innovations in the EU: A club convergence analysis of the eco-innovation index and driving factors of the clusters. Environmental Innovation and Societal Transitions, 46, 100698.

Destek, M.A., Manga, M. (2021), Technological innovation, financialization, and ecological footprint: Evidence from BEM economies. Environmental Science and Pollution Research, 28(17), 21991-22001.

Galeotti, M. (2007), Economic growth and the quality of the environment: Taking stock. Environment, Development and Sustainability, 9, 427-454.

Gujarati, D.N., Porter, D.C. (2009), Basic Econometrics. United States: McGraw-Hill Irwin.

Güven, T., Çam, F.B., Bilgili, B., Erciş, A. (2024), The impact of social innovation on environmentally friendly product involvement. Innovation and Management Review, 21(2), 94-109.

Hansen, B. (2022), Econometrics. United States; Princeton University Press.

Hashmi, R., Alam, K. (2019), Dynamic relationship among environmental regulation, innovation, CO_2 emissions, population, and economic growth in OECD countries: A panel investigation. Journal of Cleaner Production, 231, 1100-1109.

Hordofa, T.T., Vu, H.M., Maneengam, A., Mughal, N., Cong, P.T., Liying, S. (2023), Does eco-innovation and green investment limit the CO_2 emissions in China? Economic Research-Ekonomska Istrazivanja, 36(1), 634-649.

Hu, G.G. (2021), Is knowledge spillover from human capital investment a catalyst for technological innovation? The curious case of fourth industrial revolution in BRICS economies. Technological Forecasting and Social Change, 162, 120327.

Khan, A., Chenggang, Y., Yi, W.X., Hussain, J., Sicen, L. (2020), Examining the pollution haven, and environmental kuznets hypothesis for ecological footprints: An econometric analysis of China, India, and Pakistan. Journal of the Asia Pacific Economy, 26, 462-482.

Khan, S.A.R., Ponce, P., Yu, Z. (2021), Technological innovation and environmental taxes toward a carbon-free economy: An empirical study in the context of COP-21. Journal of Environmental Management, 298, 113418.

Kuznets, S. (1955), Economic growth and income inequality. American Economic Review, 45, 1-28.

Kuznets, S. (1963), Quantitative aspects of the economic growth of nations: Viii. distribution of income by size. Economic Development and Cultural Change, 11, 1-80. AQ1

Long, H. (2022), Analysis of the key factors of ecological environment protection in the national economic sustainable development goals. Journal of Environmental and Public Health, 2022, 3593587.

Mačiulytė-Šniukienė, A., Sekhniashvili, D. (2021), The eco-innovation impact on economic and environmental performance of EU member states. Business, Management and Economics Engineering, 19(2), 212-228.

Mahmoodi, M., Dahmardeh, N. (2022), Environmental kuznets curve hypothesis with considering ecological footprint and governance quality: Evidence from emerging countries. Frontiers in Environmental Science, 10, 849676.

Mohsin, M., Abbas, Q., Zhang, J., Ikram, M., Iqbal, N. (2019), Integrated effect of energy consumption, economic development, and population growth on CO_2 based environmental degradation: A case of transport sector. Environmental Science and Pollution Research, 26(32), 32824-32835.

Murshed, M., Rahman, M.A., Alam, M.S., Ahmad, P., Dagar, V. (2021), The nexus between environmental regulations, economic growth, and environmental sustainability: Linking environmental patents to ecological footprint reduction in South Asia. Environmental Science and Pollution Research, 28(36), 49967-49988.

OECD. (2023), Patents on Environment Technologies. Available from: https://data.oecd.org/envpolicy/patents-on-environment-technologies.htm

Our World in Data. (2023), Per Capita CO_2 Emissions. Available from: https://ourworldindata.org/explorers/co2?time=2000.2019&facet=none&country=idn&gas+or+warming=co₂&accounting=production-based&fuel+or+land+use+change=all+fossil+emissions&count=per+capita

Ozcan, B., Tzeremes, P.G., Tzeremes, N.G. (2020), Energy consumption, economic growth and environmental degradation in OECD countries. Economic Modelling, 84, 203-213.

Popp, D. (2001), Induced innovation and energy prices. American Economic Review, 92, 160-180.

Qotrun A. (2021), Pengertian Uji Asumsi dan Jenis-Jenisnya. Available from: https://www.gramedia.com/literasi/uji-asumsi

Sadiq, M., Chau, K.Y., Ha, N.T.T., Phan, T.T.H., Ngo, T.Q., Huy, P.Q. (2023), The impact of green finance, eco-innovation, renewable energy and carbon taxes on CO_2 emissions in BRICS countries: Evidence from CS ARDL estimation. Geoscience Frontiers, 15, 101689.

Shinn, L. (2022), Renewable Energy: The Clean Facts. NRDC (Natural Resources Defense Council). Available from: https://www.nrdc.org/stories/renewable-energy-clean-facts#sec-whatis

Solarin, S.A., Bello, M.O., Tiwari, A.K. (2022), The impact of technological innovation on renewable energy production: Accounting for the roles of economic and environmental factors using a method of moments quantile regression. Heliyon, 8(7), e09913.

Stern, D.I. (2004), The Rise and fall of the environmental kuznets curve. World Development, 32(8), 1419-1439.

The World Bank. (2023a), GDP (Current US$). Available from: https://data.worldbank.org/indicator/ny.gdp.mktp.cd

The World Bank. (2023b), Renewable Energy Consumption (% of Total Final Energy Consumption). Available from: https://data.worldbank.org/indicator/ny.gdp.mktp.cd

Tol, R.S.J. (2024), A meta-analysis of the total economic impact of climate change. Energy Policy, 185, 113922.

Uddin, G.A., Alam, K., Gow, J. (2019), Ecological and economic growth interdependency in the Asian economies: An empirical analysis. Enviromental Science and Pollution Research, 26, 13159-13172.

Wang, L., Chang, H.L., Rizvi, S.K.A., Sari, A. (2020), Are eco-innovation and export diversification mutually exclusive to control carbon emissions in G-7 countries? Journal of Environmental Management, 270, 110829.

Wang, W., Li, Y., Lu, N., Wang, D., Jiang, H., Zhang, C. (2020), Does increasing carbon emissions lead to accelerated eco-innovation? Empirical evidence from China. Journal of Cleaner Production, 251, 119690.

Wooldridge, J.M. (2019), Introductory Econometrics: A Modern Approach. 7th ed. United States: Cengage Learning Publisher.

Yurdakul, M., Kazan, H. (2020), Effects of eco-innovation on economic and environmental performance: Evidence from Turkey's manufacturing companies. Sustainability, 12(8), 3167.