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Impact of greenhouse gas emission, renewable energy, and economic growth on health expenditure in Southeast Asia: A comparative analysis of econometric models

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Abstract

Purpose — The study explores the effects of greenhouse gas emissions, renewable energy, and economic growth on health expenditures across Southeast Asia while comparing the performance of different econometric models for accuracy in analysis.

Method — The relationships among variables in this study are analyzed using three econometric models: the Autoregressive Distributed Lag Model, the co-integration Model, and the Quantile Regression Model, using annual data from 2000 to 2020.

Findings — The results reveal that greenhouse gas emissions and GDP significantly influence health expenditure in all three models. However, the significance of renewable energy consumption varies, with only the quantile regression model indicating a significant relationship with health expenditure. A model comparison based on Mean Squared Error (MSE) suggests that the autoregressive distributed lag (ARDL) model provides the most accurate predictions. Also, it found that there is a short-run and long-run causal effect of GHG and GDP on health expenditure and health spending on GDP.

Implication — This study helps to understand how economic growth, environmental factors, and healthcare spending interact to develop sustainable policies to address health and environmental problems in Southeast Asia.

Originality — This research contributes to the body of knowledge examining the impact of economic and environmental factors on health expenditures in Southeast Asia through a comparative analysis of different econometric models.

Keywords — Autoregressive distributed lag model, co-integration model, quantile regression model, mean squared error

Introduction

The relationship between environmental quality, economic growth, and health expenditure has become a critical area of study in recent years, especially in developing regions, with no exception in Southeast Asia. Many developed and developing countries aim for economic growth and development without considering the environmental impact, such as access to clean water and air quality. Rapid industrialization, urbanization, and energy consumption contribute to environmental degradation, affecting human health and threatening healthcare systems. Air pollutants, particularly

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carbon dioxide (CO2) emissions, have been linked to adverse health outcomes, leading to increased healthcare spending (Ibukun & Osinubi, 2020; Atuahene, et. al., 2020; Li, et al., 2022). Greenhouse gases are a consequence of anthropogenic activities, that is, raising the temperature in the environment, resulting in global warming (Xie, 2024). Human activities are the primary drivers of climate change, creating carbon dioxide emissions that significantly increase risks to human health, ecosystems, and economies (Loucks, 2021). The degradation of the environment will lead to increased expenditure on health treatments to sustain a healthy lifestyle (Manisalidis et al., 2020). Human activities increase environmental pollution, such as CO_2, which affects healthcare spending (Alhassan & Kwakwa, 2023), and the cost of reducing greenhouse gas emissions is high (Gillingham & Stock, 2018).

According to the study by (Ebi & Hess, 2020), climate change harms human health; that is, as the greenhouse gas levels increase, health risks also increase. Respiratory illnesses are caused by air pollution such as CO_2, and many people suffer from the effects of air pollution (Mujtaba & Shahzad, 2021). Public funding for facilities and access to universal health services is a challenge, especially among Southeast Asian nations (Lim et al., 2023). The proportion of health expenditure allocated to direct costs is relatively high (Kong et al., 2022) (Behera & Dash, 2020) and the absence of systematic or potentially remediable differences in health status (WHO, 2020).

This current study uses CO_2 emission as a proxy for greenhouse gas emission. As of 2023, the top global greenhouse gas emitters are China (28%), United States (15%), India (14%), the European Union (10%), Russia (5%), and Brazil (4%). When combined, these six emitter countries contribute to over 76% of the total greenhouse gas in the world (European Commission, 2023). Greenhouse gas emissions in various regions of Southeast Asia have been increasing rapidly (Lamb et al., 2021). The world's top energy-consuming nations make a significant contribution to CO_2 emissions. Increasing energy demand drives economic expansion. However, energy consumption also leads to the emission of greenhouse gases. Thus, the goal is to reduce CO_2 emissions by implementing sustainable development practices, focusing on the strategies for sustainable development, and promoting a green economy (Mentes, 2023).

In 2022, the study of Li et al., (2022) analyzed the impact of carbon emissions, economic growth, and health expenditure in the BRICS countries that utilized the Fourier ARDL model. The result shows that Brazil and China have cointegration relationships in health expenditure, CO2 emissions, and economic growth. Moreover, there is a negative causal relationship between India's CO_2 emissions and health expenditure; other countries only show a one-way relationship between CO_2 emissions, health expenditure, or economic growth. Using the ARDL method, Zaidi and Saidi (2018) reveal that economic growth positively impacts health expenditure (HE), while CO2 emissions and Nitrous Oxide Emissions negatively impact HE in the long run. On the other hand, the Vector Error Correction Model (VECM) Granger causality results show a one-way relationship between the HE and GDP per capita. On the contrary, a two-way causality relationship is found between CO_2 emissions and GDP per capita and between the HE and CO_2 emissions. Another study in Asian countries conducted by Slathia et al., (2024), investigated how carbon emissions, renewable energy use, and economic growth affect healthcare expenditure in 36 Asian countries. The study employs Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) models to analyze the data, revealing that higher levels of carbon emissions and economic growth are associated with increased healthcare costs. At the same time, the consumption of renewable energy contributes to lowering healthcare expenditure. The important finding is the direct and indirect relationships between these variables, particularly how carbon emissions from energy use affect health costs in various Asian sub-regions, offering valuable policy implications for sustainable healthcare. Haseeb et al., (2019) explored the influence of environmental pollution, energy consumption, and economic growth on health expenditure using again the ARDL approach. A related study by Wang et al., (2020) explored the impact of CO2 emissions, health expenditure, and economic growth using the cointegration approach. And finally, Bilgili et al., (2021) used a quantile regression model to assess the effects of health expenditure and economic growth on carbon dioxide emissions while (Apergis et al., 2018) and (Farooq et al., 2019) used the quantile regression approach to understand the effect of carbon emissions on health outcomes.

In recent years, many studies have been conducted on the determinants of health expenditure. However, the intersection of economic and environmental factors in influencing health expenditure, especially in Southeast Asia, has not been explored. This study introduces an approach that compares different econometric models to identify the most accurate and robust method for analyzing the impact of these factors on health expenditure. Previous studies also focused only on one or two aspects and a limited geographic scope. This research offers a comprehensive analysis that integrates economic and environmental variables, providing new insights into the drivers of health expenditure.

(Zhang et al., 2022), (Jian et al., 2019), and (Vo et al., 2019) administered the testing for stationarity using the Dickey-Fuller and causality estimates through the autoregressive distributed lag approach, which was also employed in the paper of (Li et al., 2022) and (Çobanoğulları, 2024). While in the study of Arı (2021) and Camba Jr and Camba (2021), they employed the Engle-Granger causality test model. Lastly, two research, Jian et al., (2019) and Vo et al., (2019) used the Johansen cointegration test.

This study aims to explore the impacts of economic growth, renewable energy consumption, and greenhouse gas emissions on health expenditure among the ten (10) Southeast Asian countries. It also seeks to compare the performance of different econometric models, such as the Autoregressive Distributed Lag (ARDL) Model**,** Cointegration Model, and Quantile Regression Model from the Mean Squared Error (MSE) value. This comparison will determine which of the proposed models provides a more accurate way of analyzing the impact of economic factors and health spending.

Methods

Data Summary and Source

The study used the annual data from 2000-2020, considering the variables of greenhouse gas emissions, economic growth such as gross domestic product (GDP), renewable energy consumption, and health expenditure across Southeast Asia. Southeast Asia is a diverse and dynamic region located in the southeastern part of Asia, consisting of countries such as the Philippines, Thailand, Vietnam, Indonesia, Malaysia, Cambodia, Myanmar (Burma), Brunei, Timor-Leste, and Laos. The secondary data were collected over 21 years from the World Bank's open data. Table 1 describes the summary of the variables.

Table 1. Summary of Variables across Southeast Asia countries (2000-2020)

	HE		**GHG**		**EC**		**GDP**	
	Average	*Total*	*Average*	*Total*	*Average*	*Total*	*Average*	*Total*
Philippines	85.69	1799.55	171029.90	3591627.9	31.42	659.75	2171.79	45607.7
Thailand	168.09	3529.99	355518.79	7465894.55	22.01	462.21	4637.15	97380.2
Vietnam	84.37	1771.78	260909.12	5479091.56	38.02	798.46	1738.29	36504.05
Indonesia	73.88	1551.58	809660.87	17002878.3	34.35	721.45	2560.03	53760.61
Malaysia	280.84	5897.72	242801.12	5098823.44	3.59	75.34	8046.83	168983.5
Cambodia	57.80	1213.81	28269.30	593655.34	68.44	1437.28	867.81	18223.91
Myanmar	30.44	639.248	94601.25	1986626.2	75.84	1592.55	809.59	17001.34
Brunei	683.83	14360.33	8902.66	186955.9	0.01	0.11	30142.19	632985.97
Timor-Leste	56.97	1196.367	5484.76	115179.9	26.56	557.76	898.54	18869.43
Laos	35.46	744.6178	15542.13	326384.73	64.65	1357.72	1322.25	27767.29

Definition and Measurement of Variables

The dependent variable in this study is health expenditure per capita, defined in the Table 2. The independent variables are greenhouse gas emissions, renewable energy consumption, and GDP per capita.

Table 2. Definition and measurement of variables

Variable	Notations	Measurement	Type
Health expenditure per capita	HE	Health expenses per capita through out-of-pocket spending (in U.S. dollars).	Dependent
Greenhouse gas emission	GHG	Overall greenhouse gas emissions (in kilotons of CO2 equivalent) consist of fluorinated gases, all anthropogenic methane sources, nitrous oxide sources, and carbon dioxide (CO2).	Independent
Renewable Energy Consumption	REC	Renewable energy consumption represents the proportion of energy in the total final renewable energy consumption.	Independent
GDP	GDP	Gross domestic product per person.	Independent

Source: World Bank Open Data

Econometrics Models

Autoregressive Distributed Lag (ARDL) Model

The ARDL technique examines time series data and uncovers short-term and long-term connections among variables within the specified time frame. One of the benefits of using the ARDL approach is that it can reveal both intra-model and inter-model dimensions. Furthermore, it offers asymptotic properties facilitating the independent variable estimation for stationary and non-stationary series data. ARDL model is expressed as follows:

$$\Delta HE_{it} = a_i + \sum_{j=1}^{m-1} b_{ij}\Delta HE_{i,t-j} + \sum_{z=0}^{n-1} \varphi_{il}\Delta GHG_{i,t-z} + \sum_{r=0}^{p-1} \gamma_{ir}\Delta REC_{i,t-r} + \sum_{u=0}^{s-1} \theta_{iu} GDP_{i,t-u} + \delta_1 HE_{i.t-1} + \delta_2 GHG_{i.t-1} + \delta_3 EC_{i.t-1} + \delta_4 GDP_{i.t-1} + e_{1i,t}, \quad (1)$$

where Δ is the first-order differential operator and the $e_{1i,t}$ is the error term. The dependent variable in the above model is health expenditure (HE); GHG stands for greenhouse gas emission; REC is the amount of renewable energy used; and GDP represents gross domestic product, measured with GDP per individual. The parameter α in the models represents the speed of alteration towards equilibrium (Haseeb et al., 2019).

The first step of the ARDL approach is to decide the length of optimal lag for each variable. The goal is to minimize using the Schwarz Information Criterion (SIC). The null hypothesis was formulated as follows:

$$H_0: \rho_1 + \rho_2 + \rho_3 + \rho_4 = 0$$
$$H_1: \rho_1 + \rho_2 + \rho_3 + \rho_4 \neq 0 \quad (2)$$

If the null hypothesis was not rejected after testing for co-integration, then the long-term association between the variables was evaluated.
After developing a long-run association, error correction terms were determined in equation (3)

$$\Delta HE_{it} = a_i + \sum_{j=1}^{m-1} b_{ij}\Delta HE_{i,t-j} + \sum_{l=0}^{n-1} \varphi_{il}\Delta GHG_{2i,t-l} + \sum_{r=0}^{p-1} \gamma_{ir}\Delta EC_{i,t-r} + \sum_{u=0}^{s-1} \theta_{iu}\Delta GDP_{i,t-u} + aECT_{t-1} + e_{1i,t} \quad (3)$$

where and ECT_{t-1} is the error correction term that defines the long-run equilibrium relationship among variables.

Cointegration Model

The last model is the Granger causality test, where a strong causal relationship was examined. The cointegration approach needs to test three null hypotheses:

$$H_o: \varphi_1 = \varphi_2 = \varphi_3 = 0\ (R1 - test),$$
$$H_o: \varphi_2 = \varphi_3 = 0\ (R2 - test), and$$
$$H_o: \varphi_1 = 0\ (A - test). \quad (4)$$

The Bootstrap ARDL cointegration is the new cointegration test, satisfying the above null hypotheses (McNown et al., 2018). In case 1, the null hypotheses are rejected in both the R1 test and the R2 test. In case 2, the null hypotheses in R1 and A test while the R2 test is not rejected. An additional test for $\varphi_2 = 0$ or $\varphi_3 = 0$ is conducted if cointegration exists. If cointegration does not exist, then the Bootstrap ARDL model is used.

Quantile Regression Model

The quantile regression approach addresses both the heterogeneity and structure of quantile data. These models demonstrate greater flexibility and robustness than the ordinary least square approach because they do not rely on assumptions about the error term distribution (Belaïd et al., 2020). This model aims to estimate the median or quantities (Chernozhukov et al., 2022). The model of the quantile regress can be written as,

$$Q_T z_{it}\left(\tau | z_{i,t-1}, x_{it}\right) = c_i + \gamma(\tau) z_{i,t-1} + x_{it}^T \beta(\tau)\ , i = 1, \ldots, n \ and \ t = 1, \ldots, T_i \quad (5)$$

where z_{it} is the output, $z_{i,t-1}$ is the z_{it} lag, x_{it} is the exogenous variable, $c = (c1, \ldots, cN)'$.

Stationarity Test

Assessing the data's stationariness is necessary before conducting econometric analysis, as this was a prerequisite for econometric modeling. This ensures that the stationarity of variables is imperative to prevent issues associated with spurious regression in the event of non-stationary variables. Typically, stationarity tests like the Augmented Dickey-Fuller test are conducted for macroeconomic data.

Results and Discussions

Data Summary and Correlation Test

Table 3 displays the summary statistics of four (4) variables from the Southeast Asia datasets from 2000 to 2020. All the variables' mean is larger than the corresponding standard deviation, indicating low volatility and an increasing trend. The skewness values are nearly zero, suggesting the distribution is roughly symmetric. Additionally, all the kurtosis values are less than 3, indicating lighter tails. Furthermore, the Jarque-Bera Test results fail to reject the null hypothesis, concluding that all the variables follow a normal distribution. The Box-Pierce test results indicate rejecting Ho, suggesting the absence of serial correlation. Figure 1 displays a time plot of the four variables. It shows that HE, GHG, and GDP are on an upward trend, while REC shows a downward trend as the years progress.

Table 3. Summary statistics of the variables

	HE	GHG	REC	GDP
Mean	155.74	199272	36.49	5319
Median	166.06	195904	37.73	5830
Maximum	221.52	266179	44.46	7645
Minimum	76.05	146265	26.91	2573
Std. Dev.	50.947	36768	5.705	1708.13
Skewness	-0.3315	0.3260	-0.4402	-0.3472
Kurtosis	1.5913	2.0452	1.8076	1.8062
Jarque-Bera	2.1211	1.1741	1.9223	1.6689
Box-Pierce	16.233	15.357	16.365	15.481
Sample	21	21	21	21
Year	2000-2020	2000-2020	2000-2020	2000-2020

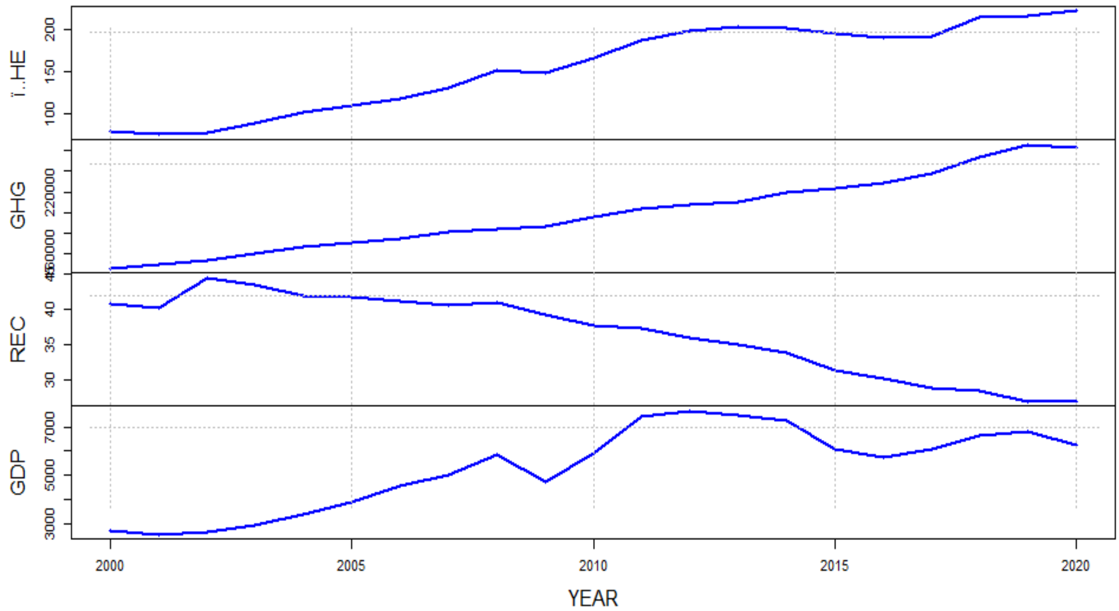

Figure 1. Sequence Plot from 2000-2020

Correlation Test

The correlation test for each variable is presented in Table 4. All the p-values are below 0.05, indicating a significant correlation exists between GHG, REC, GDP, and HE. The correlation reveals strong positive associations between Health Expenditure (HE) and Greenhouse Gas Emission (GHG), as well as Gross Domestic Product (GDP). Additionally, Renewable energy consumption (REC) is significantly inversely related to health expenditure (HE), with a correlation value of -0.874. This indicates that a unit increase in renewable energy consumption is associated with a decrease in health expenditure. The results of (Shahzad et al., 2020) also confirmed that economic growth and CO2 emissions have a positive impact on health expenditure, while renewable energy consumption has a negative impact on health expenditure. This implies that as the economy grows, Southeast Asian countries pay more attention to the healthcare system. However, Atuahene et al. (2020) claimed that economic growth negatively impacts health expenditure in China and India. This means that despite significant economic growth, there has been a lack of focus on healthcare.

Table 4. Correlation between variables

Variable		HE	GHG	REC	GDP
HE	correlation	-			
	p-value	-			
GHG	correlation	0.939	-		
	p-value	0.000*	-		
REC	correlation	-0.874	-0.959	-	
	p-value	0.000*	0.000)	-	
GDP	correlation	0.941	0.789	-0.688	-
	p-value	0.000*	0.000*	0.000*	-

Note: *p< 0.10, **p< 0.05, ***p< 0.01, respectively.

Unit Root Test

Before utilizing the three (3) approaches, testing the data stationarity for each variable is important. The Augmented Dickey-Fuller (ADF) test indicated that health expenditure (HE) and greenhouse gas emissions (GHG) are both stationary at the level, and all variables exhibit stationary after being differenced once. Unit root test for stationarity was also executed in the papers of (Çobanoğulları, 2024), (Haseeb et al., 2019), and (Wang et al., 2020).

Table 5. Test for Stationarity

	Augmented Dickey-Fuller (ADF)		Order of Integration
	Level	*First Difference*	
HE	5.518*	2.459*	I (0)
GHG	18.39**	1.541*	I (0)
REC	2.011	9.54**	I (1)
GDP	0.5218	5.019*	I (1)

Note: *p< 0.10, **p< 0.05, ***p< 0.01, respectively.

Test for Homogeneity

The result of the heteroscedasticity test gives a p-value (0.4912) greater than 0.05. This value indicates that there is no evidence to suggest that the variability of the errors changes across different levels of the independent variables, thereby satisfying the assumption of homoscedasticity (Haseeb et al., 2019).

Table 6. Test for Homogeneity of Variance

Dependent Variable	Statistic	DF	p-value	Decision
HE	2.4129	3	0.4912	Reject Ho

Cointegration Test

Table 7. Johansen cointegration analysis

Unrestricted Test			
	Trace Statistics	Rejection	P-value
None*	73.06	47.86	0.000
At most 1	27.80	29.80	0.0835
At most 2	9.77	15.49	0.2992
At most 3	0.22	3.84	0.6422
Unrestricted Cointegration Rant Test (Maximum Eigenvalue)			
None*	45.26	27.58	0.0001
At most 1	18.04	21.13	0.1285
At most 2	9.55	14.26	0.2432
At most 3	0.22	3.84	0.6422

The Johansen Cointegration test examines both long- and short-term relationships in health expenditure described in Table 7. The hypotheses is there is no cointegration exist (Wang et al., 2020)(Çobanoğulları, 2024). As depicted in the table 7, the trace statistics and max-eigen statistics were examined, and the null hypothesis was rejected at a 0.05 significance level. This result suggests there is a long-term relationship between the variables in the model.

Comparison of Econometric Models

The Mean Square Error (MSE) is used to assess the precision of a model's forecasts. Table 8 shows the results for the three econometric models with their respective MSE values and Figure 2 shows.

Table 8. Mean Square Error (MSE) of the Three Econometric Models

Models	Mean Square Error (MSE)
ARDL	235.12
Cointegration	587.66
Quantile Regression	712.18

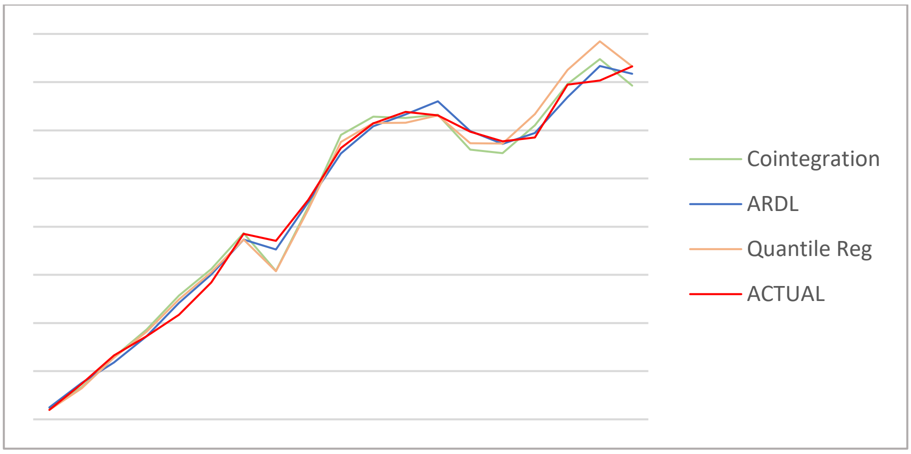

Figure 2. Actual vs fitted values of the three econometric models

The ARDL model performs better than the cointegration and quantile regression models in predictive accuracy, as indicated by the lower MSE value. A similar result was found in the study by (Adom & Bekoe, 2012), which concluded that the ARDL model is superior, particularly because it is more efficient at handling small sample sizes.

The ARDL model, for current analysis, is the most reliable for making accurate predictions. Conversely, the quantile regression model has the highest MSE, indicating the least accurate predictions among the three models. One of the primary reasons is that quantile regression focuses on estimating the conditional quantiles of the response variable rather than the mean (Chernozhukov et al., 2022). The cointegration model falls in between, performing better than the quantile regression model but not as well as the ARDL model.

Figure 2 shows the visual presentation of the original and fitted values from the three different econometric models. The graph visually assesses how closely the fitted values match the actual values. As observed, all the fitted values from the three models are close to the actual values, indicating that the econometric models are performing well in predicting the observed data.

Table 9. Coefficients' t-Statistics and probabilities across three econometric models

Variable	ARDL		Cointegration		Quantile Regression	
	t-value	prob	t-value	prob	t-value	prob
GHG	3.295	0.004***	2.931	0.009***	8.213	0.000***
REC	0.936	0.363	-1.395	0.181	-6.222	0.000***
GDP	10.569	0.000***	14.79	0.000***	8.737	0.000***

Note: *p< 0.10, **p< 0.05, ***p< 0.01, respectively.

Table 9 shows that all three models have a significant influence on GHG and GDP on health expenditure. However, REC's significance varies across models. The ARDL and cointegration models fail to reject the null hypotheses, indicating a non-significant relationship between REC and health expenditure. In contrast, the quantile regression model rejects the null hypothesis, implying a significant relationship between REC and the dependent variable.

Causality Test

Table 10 presents the causality analysis for both the long-run and short-run effects. It reveals that the long-run causal effects of GHG emissions and GDP on HE were significant, with t-statistics of 3.2956 (p-value 0.0049) and 10.5698 (p-value 0.0000), respectively. This result means that greenhouse gas emissions and gross domestic product significantly influence health expenditure in Southeast Asia over the long term. Also, health expenditure has a long-run causality effect on GDP, suggesting that an increase or decrease in health expenditure will lead to changes in GDP. These results were supported by the study of Ibukun and Osinubi (2020), Slathia et al. (2024), Haseeb et al. (2019), and Atuahene et al. (2020), which found that GHG emissions and GDP have a significant relationship with health expenditure. Additionally, renewable energy consumption (REC) does not significantly affect health expenditures (HE) in the short and long run. While Apergis et al. (2018) shows a unidirectional causality from REC to HE, and Dorbonova and Sugözü, (2024) advocate for the use of renewable energy, the lack of a significant effect in Southeast Asia may be due to several factors, including inadequate infrastructure to effectively translate renewable energy into health benefits, cultural practices and beliefs, and ineffective implementation of policies promoting renewable energy. Furthermore, the limited impact of REC might be influenced by other health challenges/factors and disparities across different countries.

Table 10. Causality analysis

Direction of Causality	t-Statistics	P-value
	Long-Run Causality Effect	
GHG → HE	3.295	0.004**
REC → HE	0.936	0.363
GDP → HE	10.569	0.000**
HE → GHG	-0.352	0.727
HE → REC	-1.282	0.219
HE → GDP	13.233	0.000**
	Short-Run Causality Effect	
GHG → HE	4.019	0.001**
REC → HE	1.033	0.317
GDP → HE	5.737	0.000**
HE → GHG	-0.504	0.621
HE → REC	-1.409	0.179
HE → GDP	5.546	0.000**

Note: *p< 0.10, **p< 0.05, ***p< 0.01, respectively.

In the short-run causality test, it was observed that greenhouse gas (GHG) emissions and gross domestic product (GDP) significantly affect health expenditure. This finding is supported by the results of (Wang et al., 2020), which suggest that increased CO_2 emissions and GDP help improve health expenditures. It was also observed that the short-run causality of health expenditure on GHG and REC was not significant. However, observing the health expenditure has a short-run causal effect on GDP, which implies a direct effect of healthcare spending on economic growth in the short run. This finding is consistent with the results of (Haseeb et al., 2019), who also found no short-term causality between health expenditures and energy consumption (EC), CO2 emissions, or GDP. This means that changes in health expenditures do not directly influence energy consumption, CO2 emissions, or GDP in the short run.

Conclusions

This study examines the impact of greenhouse gas emissions, economic performance, and renewable energy consumption on health expenditure, covering ten (10) Southeast Asian countries from 2000 to 2020. The primary goal of this paper is to address the gap in previous research by considering another set of variables and comparing the existing econometric models. The dependent variable considered in this study is health expenditure (HE), and the independent variables are greenhouse gas (GHG) emissions, renewable energy consumption (REC), and gross domestic product (GDP). These variables are used in the three econometric models: the Autoregressive Distributed Lag Model, the Cointegration Model, and the Quantile Regression Model.

The analysis shows a significant influence of greenhouse gas emissions (GHG) and gross domestic product (GDP) on health expenditure among the three models, but renewable energy consumption (REC) varies across the three models. In comparing the three models, the ARDL model performs better than the cointegration and quantile regression models, which means that the ARDL model is the most reliable in making accurate predictions of the annual health expenditure of Southeast Asian countries.

Lastly, this paper studied the relationship of the short-run and long-run causality among the variables and found a short-run and long-run causal effect of GHG and GDP on health expenditure. This leads to the conclusion that GHG emissions increase healthcare spending due to the deterioration of air quality, which results in high spending on healthcare services. On the other hand, health expenditure has short-run and long-run causality effects on GDP, indicating that healthcare spending changes impact a specific country's overall economic output.

While this study provides valuable insights into the relationship between greenhouse gas emissions, economic growth, renewable energy consumption, and health expenditure in Southeast Asia, it also has several limitations that must be acknowledged. First, it only considers the annual data from 2000 to 2020, which may limit the analysis and not fully capture recent trends regarding the impact of economic and environmental variables. Additionally, the econometric models employed consider only three models. They may not always hold in real-world scenarios, such as linearity and stationarity, which could affect the validity of the results. Lastly, the study does not account for other factors, such as socio-political changes or health policy interventions, which might influence health expenditure.

The research findings extend previous research by highlighting the importance of environmental and economic factors in influencing health expenditures in Southeast Asia. Future studies should explore other econometric models and consider additional data to better understand the broader impact of healthcare spending across diverse economic contexts.

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