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The Carbon-Neutral Energy Consumption and Emission Volatility: The Causality Analysis of ASEAN Region

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Abstract: The use of renewable energy sources and carbon emissions has been debated from various perspectives throughout recent decades. However, the causal relationship between green energy sources and carbon emissions volatility has received limited attention. This study aims to close a knowledge gap in this area. The current study analyzes the renewable energy sources (wind, hydro, and geothermal) and carbon emissions of four ASEAN countries (Indonesia, Thailand, Vietnam, and the Philippines) between 2000 and 2019. The present study combined Chudik and Pesaran's (2015) newly developed Dynamic Common Correlated Effects (DCCE) with cutting-edge investigation tools such as first- and second-generation unit root tests; CS-dependence; Variance inflation factor test for multicollinearity; and Pedroni, Kao, and Wester Lund tests of co-integration. The Granger causality test is also used to check the short-term and long-term causal effects within the renewable energy sources and green energy sources, and carbon volatility. According to the empirical results, green energy sources make a positive and vital contribution to reducing carbon emissions growth in the above-noted ASEAN economies. Furthermore, short- and long-run causality runs from green energy sources to carbon emission volatility in the region. A significant causality relationship has also been observed within the green energy sources of ASEAN.

Keywords: carbon-neutral; green energy; climate change; ASEAN; granger causality

1. Introduction

The world's climate is changing because of promoting prosperity to the detriment of the atmosphere. Since the dawn of the industrial era, economies have shifted their focus to large-scale production and commerce, resulting in a rise in energy use. Historically, economies have relied heavily on conventional energy sources, including oil, gas, and coal, which are key market sources of the greenhouse effect (GHG) [1]. Increased GHG concentrations have impacted climatic changes by accelerating greenhouse gases. Global warming poses a challenge, especially with the rise in the world's surface temperature caused by GHG emissions. Carbon dioxide accounts for the most considerable portion of GHG emissions (CO₂). According to [2], CO₂ accounted for approximately 60% of GHG and posed a significant threat to environmental quality. By the end of 2050, the average

warming is expected to exceed 3 °C, resulting in increased natural disaster risks and increased biosphere pressure [3]. In this context, [4] hypothesized that the impact of temperature disruption could result in a drop in growth in countries worldwide if there are no environmentally sustainable measures to tackle emerging global stress. In particular, the researchers contend that the developing nations are more sensitive to climate change and are projected to see an annual growth drop of 2–4% by 2040 and 10% by 2100.

Among emerging regions, ASEAN economies maintain a crucial status for continuing faster productivity, particularly in Asia. Notably, the area is recognized as the center of major economies that have succeeded in changing growth [5]. The economic activity of the area is primarily due to high industrialization, modernization, and urban sprawl. Nevertheless, ASEAN countries are also blamed for polluting the climate.

In these circumstances, [6] concluded that the increase in prosperity, financial progress, and foreign direct investment are among the key factors responsible for the ASEAN region's environmental decline. Given that the ASEAN's economy is still developing, its carbon pollution rates, particularly in Malaysia, the Philippines, Indonesia, Vietnam, and Thailand, are considerably large.

Industrial production, chemicals, and automation—labeled energy-intensive—are all critical sectors committed to ASEAN development. Therefore, because of the increasing climate turmoil in the ASEAN area, the ASEAN economies' prosperity in the age of globalization is associated with environmentally sustainable economic activity. Due to these increased evolutionary challenges, the area experienced an increased incidence of ecological and climate change through rising temperatures and resource depletion, demanding economic progress that is found to be environmentally acceptable. Testifying that traditional energy sources have a detrimental impact on carbon emission, several experiments aim to explore environmental solutions to meet countries' energy requirements. The global economy, in the Paris Climate Convention, affirms decarbonization of the energy market by reducing carbon emissions' atmospheric concentrations [1]. In this respect, the economy will be focused on adopting energy policies that are environmentally sustainable and concentrate on alternative energy sources.

Renewable energy (henceforth GE) is energy produced from the earth's renewable energies. The aim of generating GE is to take advantage of the planet's ecological assets, such as water, sun, wind, and biomass, to meet countries' inescapable energy needs for household and commercial usage. Observing administrations' growing preference for GE acceptance, various researchers evaluated the effect of GE in a country's social [7], economic [8], and financial [9] development. Concerning ASEAN economies, [10] asserted that since early 2000, the region had faced increased concerns about future sustainability due to deteriorating energy supplies, emissions, and resource innovation obstacles. Similarly [11], advocated for increased economic integration, sustainable energy, and socioeconomic growth through greener fuels. They did, nevertheless, criticize the ASEAN economies under the growth of GE schemes. In recent times, critical ASEAN nations have increased their focus on renewable energy generation outlets. Intending to transition ASEAN economies to green growth by 2030, the ASEAN region's economies have also committed to increasing GE's share of their energy mix by 23%. By the end of 2030, the Philippines is expected to reduce its GHG emissions by 65%, led by Malaysia at 40%, Singapore at 35%, Indonesia at 27%, Thailand at 22%, and Vietnam at 9% [12,13].

Due to the countries' increasing focus on GE, the present study will examine GE's effect on environmental pollution in the top four ASEAN economies of Indonesia, Thailand, the Philippines, and Vietnam. The objective of this research is to determine the contribution of GE utilization to Decarbonisation in the area. The recent analysis provides value to the current body of knowledge in two distinct ways: (I) This review focuses exclusively on the relationship between GE use and CO₂ emissions of ASEAN economies. (ii) Chudik and Pesaran's (2015) novel Dynamic Common Correlated Effects (DCCE) model is used to investigate the causal relationship between GE use and CO₂ emissions.

It is a one-of-a-kind approach that transcends techniques in various corresponding patterns. For example, DCCE estimation acknowledges the underlying structure of interconnectedness between the examined data and is therefore considered robust against overestimated residuals. This approach provides causality with the mean but not with the variance and appraises the causality that exists at the extremes of the cumulative relationship between variables. Additionally, these predictions support the current study's review of causal relationships with variance. The results of this study aid in determining the causal relationship between GE and CO₂ in ASEAN member countries.

The remaining analyses are as follows: Section 2 summarizes the literature review on geothermal energy and CO₂ emission use. Section 3 described the methods for DCCE and short- and long-run causality while discussing and identifying the advanced econometric results. The fifth and final section is dedicated to the conclusion and policy suggestions.

Literature Review

In light of the ecological concerns, existing literature has concentrated on finding potential products and services to satisfy economic needs while still addressing climate change [14]. Carbon dioxide is the primary greenhouse gas responsible for global warming, accounting for about 60% of greenhouse gas emissions [2]. Recognizing the significant negative impact of carbon emissions into the environment, several studies explored causes that could result in a decrease in CO₂ emissions, including innovation [15], plantations [16], and energy conservation [17]. In recent times, clean energy has been described as a critical element in mitigating climate change by reducing greenhouse gases into the air [18].

The authors of [3] examined the impact of GE on environmental damage in OECD economies using panel FMOLS and DOLS techniques. The results indicated that an increase in GE decreased greenhouse gases in the underlying economies. Additionally [3], investigated GE's impact on environmental pollution in African countries utilizing Panel GMM econometric techniques to carry out the quantitative assessment. The statistical research findings indicate that increasing GE reduces CO₂ emanation in the test database. Additionally, for the G-7 countries, [1] examined the impact of GE on environmental devastation using Granger causality approaches; the findings verified the existence of a significant causal relationship between the factors in the nations of Germany and the United States. More precisely, the results indicated that GE has a one-way causal impact on the USA's CO₂ emissions. Conversely, in the case of Germany, there was a bi-directional causal relationship between the factors. Additionally, [19] examined GE's effect on the degradation of the BRICS regions' climate factors employing panel co-integration and Granger causality to the proposed task. The findings of this study established a feedback relationship between variables in the BRIC countries.

Another research [20] examined GE's impact on environmental destruction in Europe using panel DOLS econometric techniques. The study outcome showed a consistent GE role in influencing environmental protection and the negative relationship between GE and CO₂ emissions in Europe. Additionally, [21] investigates the impact of GE on the environment. Using panel FMOLS procedures, the findings showed that GE has a substantial impact on ecological sustainability. The research results indicated that an increase in GE lessened carbon emissions in the economies studied.

Correspondingly, [22] examined GE's effect on environment destruction, and utilized System GMM and FMOLS econometrics for its proposed assessment. The quantitative findings demonstrated GE's substantial effect on environmental factors, indicating that GE inflation is significantly correlated with CO₂ emissions in the cases studied. The authors of [23] examined the impact of GE on environmental devastation, emphasizing Asia's developing countries using panel FMOLS and DOLS methods, indicating that GE has a negligible influence on global sustainability in Asian developing economies. Similarly, [24] investigated the impact of GE on environmental pollution in a group of four ASEAN economies, utilizing panel FMOLS and DOLS econometric techniques to assess

the situation. The study's findings indicate that GE has a substantial influence on global circumstances, with GE negatively correlated to greenhouse gas emissions in the four ASEAN economies. In [25], GE's effect on China's ecological degradation was examined using time series analysis. Based on the ARDL analysis method, the review discovered that GE has a substantial long-run effect on the environmental factors. According to the research evidence, GE's growth is inversely linked to CO₂ emissions in the Chinese economy. Comparable findings were published by [14,19,26] in their investigations of the renewable-CO₂ nexus in China.

Additionally, [27] explored GE's impact on India's atmosphere using ARDL methods' econometrics to propose task measurement. The study's findings, comparable to those of [26], established that GE has a sizable impact on various factors, emphasizing that GE's inflation is significantly linked to its carbon dioxide emissions. Another research [28] evaluated the effect of GE on Malaysia's environmental pollution. The experiment concluded that an increase in GE decreased carbon emissions in the Malaysian economy when the F-bounds, VECM Granger causality, CUSUM, and CUSUMSQ hypotheses were used. Similarly, in Thailand, [29] investigated the impact of GE on environmental degradation. The inquiry used the econometrics of J-J co-integration and ECM methods to conduct the empirical evaluation.

In contrast to [27,28], the study's findings indicate that renewable energy has a negligible effect on environmental deterioration at the source of carbon dioxide emissions in Thailand. Additionally [30], examined the role of GE in contributing to Indonesia's environmental destruction. Using ARDL analysis techniques, the results suggested GE's critical position in influencing environmental protection by demonstrating that GE's improvement decreased carbon emissions in Indonesia.

2. Materials and Methods

This study investigates the relationship between green energy sources and carbon emission in the selected countries of ASEAN. For this purpose, a dataset from 2000–2019 of green energy sources (wind, hydro and geothermal) and carbon emission has been collected from world bank indicators 2019. The literature survey reveals that investigators did not understand transversal effects and instead focused on homogeneous pathways in past findings [31]. The corresponding studies reveal multiple panel data regression tools such as GMM, random effect, and fixed-effect models. The interaction shifts between the transverse units in these models leave a high level of homogeneity. This statement is not accurate, and findings could be deceptive.

Because of these factors, in recent years, researchers have been drawn to panel data evaluation with heterogeneous coefficients between cross-sections across extended durations [32]. Experts are also concerned about cross-sectional units' reliance [33]. This analysis has implemented [33] dynamic standard correlated effect methodology (DCCE). This method is based on the concepts of the [34] PMG evaluation, the Pesaran and Smith evaluation of MG (1995) [35], the Pesaran CCE calculation (2006) [36], and the Chudik and Pesaran analyses (2015). However, for large non-stationary and heterogonous databases, [37] proposed the `xtpmg` command (pooled mean group estimator) because the PMG estimation method somehow does not accept cross-sectional dependency. Without pooled coefficients or DCCE, [38] reported typical corresponding results. Furthermore, the CCE estimate does not regard the endogenous variable's lag-value as an explanatory variable [33]. In contrast, the DCCE approach recognizes the importance of homogeneous and heterogeneous parameters and the DCCE and even transversal dependency. This approach includes heterogeneous paths and cross-sectional dependency by considering cross-sectional means and taking delay into account.

Besides, this process works well for limited data sets using correction procedures [33]. Another significant advantage of using this technique is its complete description,

leading to structural database breakage [39]. This method also works adequately for uneven dynamic panels [40]. We have used the dynamic equation of Chudik and Pesaran's (2015) DCCE framework:

$$CO2_{it} = \alpha_i CO2_{it-1} + \delta_i x_{it} + \sum_{p=0}^{P_T} \gamma_{xip} \bar{x}_{t-p} + \sum_{p=0}^{P_T} \gamma_{yip} \bar{y}_{t-p} + \mu_{it} \quad (1)$$

CO_2 belongs to carbon dioxide emission in Equation (6); α_i is CO_2 (i -1) is the lag of CO_2 in an explanatory variable; $\beta_i \times it$ refers to several predictor variables; and PT is the limit of lags found in averages through cross-sections.

This study used Pesaran's unit root test (2004) [41], which dealt with the null hypothesis's false refusal in cross-sectional dependency statistics.

$$a_{it} = \delta_i + \beta_{it} b_{it} + \mu_{it} \quad (2)$$

Equation (1) shows the connection between a_{it} that relies on residuals μ_{it} and time-invariant dimensions of nuisance δ_i . The pitches to be measured are β_{it} , and b_{it} is the volume of regressors. The "i" belongs to the cross-section and "t" in the subscription to the span. The subsequent dimension is measured to determine cross-sectional dependency between sample sizes.

$$H_0 = p_{iz} = p_{zi} = \text{cor}(\mu_{it}, \mu_{it}) = 0 \text{ for } i \neq z \quad (3)$$

$$H_1 = p_{iz} = p_{zi} = \text{cor}(\mu_{it}, \mu_{it}) \neq 0 \text{ for some } i \neq z \quad (4)$$

The connection between both roots confirms the CSD as mentioned above in Equations (3) and (4). The null hypothesis (H_0) shows no cross-cutting dependency between cross-cutting units and vice-versa for alternating ones (H_1).

Pedroni (2004) [42] indicates that the model with heterogeneous co-integration vectors is subject to two different test metrics. Let $\hat{u}_{it} = y_{it} - \hat{\delta}_i' d_{it} - \hat{\beta}_i' x_{it}$. Denote the OLS residual of the co-integration regression. Pedroni identifies two different groups of t -tests: (i) a "panel statistics" equal to root units for homogenous alternatives and (ii) the "mean statistics group" like root panel tests for heterogeneous substitutes. The t statistical versions are described as follows:

As Panel

$$Z_{Pt} = \left(\sigma_{NT}^2 \sum_{i=1}^N \sum_{t=1}^T \hat{u}_{i,t-1}^2 \right)^{\frac{1}{2}} \left(\sum_{i=1}^N \sum_{t=1}^T \hat{u}_{i,t-1}^2 \hat{u}_{it} - T \sum_{i=1}^N \hat{\lambda}_i \right) \quad (5)$$

group-mean

$$\tilde{Z}_{Pt} = \sum_{i=1}^N \left(\sigma_{ie}^2 \sum_{t=1}^T \hat{u}_{i,t-1}^2 \right)^{\frac{1}{2}} \left(\sum_{t=1}^T \hat{u}_{i,t-1}^2 \hat{u}_{it} - T \hat{\lambda}_i \right) \quad (6)$$

where $\hat{\lambda}_i$ is a stable one-sided long-term volatility estimation method $\lambda_i = \sum_{j=1}^{\infty} E(e_{it} e_{i,t-j})$, $e_{it} = u_{it} - \delta_i u_{i,t-1}$, $\delta_i = E(u_{it} u_{i,t-1}) / E(u_{i,t-1}^2)$, σ_{ie}^2 denotes the estimated variance of e_{it} and $\sigma_{NT}^2 = N^{-1} \sum_{i=1}^N \sigma_{ie}^2$. Pedroni presents values of μ_p , σ_p^2 and μ_p , σ_p^2 such that $(Z_{Pt} - \mu_p \sqrt{N}) / \sigma_p$ and $(\tilde{Z}_{Pt} - \mu_p \sqrt{N}) / \sigma_p$. The regular natural null hypothesis restricts probabilities. The latest update from Westerlund (2005a) [43] is supported by data from the Variance Ratio, which does not include modifications for the residual serial correlations.

A literature review demonstrates that co-integration methods have already been used extensively in scientific studies. Such co-integration strategies have traditionally been closely monitored to estimate long-term data. Several studies have suggested that these integration procedures show more significant application problems with time and much less data frequency [44]. In this analysis, we explored the long-term association between the variables under analysis, using the co-integration illustration of the process by

[45]. It is more effective than many other strategies of co-integration. For instance, it considers systemic breakdowns into view, compared to [42] guide to joint integration. Besides, were applying to short-term results, this theory utilizes lead-lag longness [46].

Equation (7) means the solution suggested by Westerlund and Edgerton for the bootstrap panel co-integration.

$$\Delta y_{it} = \delta' d_t + \alpha_i (y_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=-qi}^{qi} a_{ij} \Delta y_{i,t-1} + \sum_{j=-qi}^{qi} \gamma_{ij} \Delta x_{i,t-1} e_{i,t} \quad (7)$$

The equation mentioned above illustrates the connection between the dependent variables Δy_{it} , y_{it} , and the probabilistic portion in three different cases. Subscript t and i refer respectively to the period and cross-sectional units.

The goal is to transform data into two unnoticed subsystems for all those experiments: one with a highly cross-sectional correlation and a largely unit-specific characteristic. The test process is constantly the same and composed of two essential stages: the first stage includes data de-factored, consisting of panel unit root test statistics based on defaced data or established practices. These metrics do not struggle as they influence generic assessments focused on the presumption of cross-sectional freedom while common factors occur aboard. In this sense, the [47] include an entire process for checking the level of serial integration.

y_{it} = a Component of determinism + common element of factor structure + error unorthodox.

Rather than checking the existence of a root in y_{it} explicitly, Bai and Ng recommend testing common factors and the peculiar elements independently.

Let us introduce a framework with specific features and no pattern in period:

$$y_{it} = \alpha_i + \lambda_i' F_t + e_{it} \quad (8)$$

when F_t is a $r \times 1$ general parameters vector, and μ_i is a composite reliability vector? In the first differences, the relevant version is as follows:

$$\Delta y_{it} = \lambda_i' f_t + z_{it} \quad (9)$$

where $z_{it} = \Delta e_{it} \wedge f_t = \Delta F_t$ with $E(f_t) = 0$.

The likely consequences in Δy_{it} The primary component process calculates something. We should indicate \hat{f}_i , $\hat{\lambda}_i$, the relevant charging factors, and \hat{z}_{it} , the residuals estimated. The analysis approach for 'differentiation and re-cumulation' is based on the cumulative parameters defined as follows:

$$\hat{F}_{mt} = \sum_{s=2}^t \hat{f}_{ms} \quad \hat{e}_{it} = \sum_{s=2}^t \hat{z}_{is} \quad (10)$$

$$for\ t = 2, \dots, T, m = 1, \dots, r \wedge i = 1, \dots, N.$$

with the method utilizing \hat{F}_{mt} and \hat{e}_{it} , both Bai and Ng evaluate the unit root hypothesis in the individual portion \hat{e}_{it} and in the usual factors F_t .

To measure the non-stationary nature of the particular element

$$\Delta \hat{e}_{it} = \delta_{i,0} \hat{e}_{i,t-1} + \delta_{i,1} \Delta \hat{e}_{i,t-1} + \dots + \delta_{i,p} \Delta \hat{e}_{i,t-p} + \mu_{it} \quad (11)$$

Enable $ADF_{\hat{e}}^c(i)$ to be t-statistical for the i^{th} country's peculiar part. The asymptotic distribution of $ADF_{\hat{e}}^c(i)$ agrees with the range of Dickey-Fuller in the event of no static.

Let denote $P_{\hat{e}}^c(i)$ the p -value of the $ADF_{\hat{e}}^c(i)$ test, this statistic is

$$Z_{\hat{e}}^c = \frac{-\sum_{i=1}^N \log [P_{\hat{e}}^c(i)] - N}{\sqrt{N}} \xrightarrow[T, N \rightarrow \infty]{d} N(0, 1) \quad (12)$$

Only 1 Number (N) of factors is standard ($r = 1$); a regular ADF test in a template with an intercept is used.

$$\Delta \hat{F}_{1t} = c + \gamma_{i,0} \hat{F}_{1,t-1} + \gamma_{i,1} \Delta \hat{F}_{1,t-1} + \dots + \gamma_{i,p} \Delta \hat{F}_{1,t-p} + v_{it} \quad (13)$$

The subsequent ADF t-statistical, delineated $ADF_{\hat{\rho}}^c$, has the same limiting distribution for the static only case as the Dickey-Fuller test.

Let us consider the following ADF model:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (14)$$

$$\rho_i = \left[F(y_{1,i})' y_{1,i} - F(y_{1,i})' X_i (X_i' X_i)^{-1} X_i' y_{1,i} \right]^{-1} \left[F(y_{1,i})' \varepsilon_i - F(y_{1,i})' X_i (X_i' X_i)^{-1} X_i' \varepsilon_i \right] \quad (15)$$

$$Z_i = \frac{\hat{\rho}_i}{\hat{\sigma}_{\hat{\rho}_i}} \xrightarrow[T \rightarrow \infty]{d} N(0, 1) \quad \text{for } i = 1, \dots, N \quad (16)$$

The experimental and quasi, and the short-and long-run stability can be represented using an error correction model, according to co-integration theory (ECM). The residual panel co-integration impact assessment process co-integrates renewable energy, CO₂ emissions, and economic development. The co-integrating partnerships, however, could not offer guidance. Consequently, the short- and clear long-term correlation was investigated with a panel-based error correction model with error correction representation. The Granger causality process was conducted in the Vector Error Correction Model (VECM). The cause test Granger is defined as follows along with the error correction term (ECT):

$$\Delta CO2_{it} = \phi_0 + \sum_{i=1}^p \phi_{1i} \Delta Hydy_{t-1} + \sum_{i=1}^p \phi_{2i} \Delta Wind_{t-1} + \sum_{i=1}^p \phi_{3i} \Delta Geo_{t-1} + \rho_1 \varepsilon_{t-1} + \mu_{1t} \quad (17)$$

$$\Delta Hydy_{it} = \phi_0 + \sum_{i=1}^p \phi_{1i} \Delta CO2_{t-1} + \sum_{i=1}^p \phi_{2i} \Delta Wind_{t-1} + \sum_{i=1}^p \phi_{3i} \Delta Geo_{t-1} + \rho_2 \varepsilon_{t-1} + \mu_{2t} \quad (18)$$

$$\Delta Wind_{it} = \phi_0 + \sum_{i=1}^p \phi_{1i} \Delta Hydy_{t-1} + \sum_{i=1}^p \phi_{2i} \Delta CO2_{t-1} + \sum_{i=1}^p \phi_{3i} \Delta Geo_{t-1} + \rho_3 \varepsilon_{t-1} + \mu_{3t} \quad (19)$$

$$\Delta Geo_{it} = \phi_0 + \sum_{i=1}^p \phi_{1i} \Delta Wind_{t-1} + \sum_{i=1}^p \phi_{2i} \Delta Hydy_{t-1} + \sum_{i=1}^p \phi_{3i} \Delta CO2_{t-1} + \rho_3 \varepsilon_{t-1} + \mu_{3t} \quad (20)$$

where, Δ and ρ mark the first means of expressing and lag framework. The residual ($\mu_1, \mu_2, \mu_3, \mu_4 \wedge \mu_5$) were presumed to be sequentially separate with a zero mean and ε_{t-1} was the error correction term for a time.

Multicollinearity appears if a regression model is strongly correlated with two or more explanatory factors. The Variance Inflation Factors (VIF) is one method of measuring multicollinearity, evaluating how much the variance of an expected regression coefficient rises if factors are associated. A 5 to 10 VIF is indicative of a highly troubling correlation. The value of R² is calculated to decide how well the certain predictor parts of a parameter are represented. A higher value of R² shows a strong connection between the parameter and the other parameters. It is reflected in the following VIF:

$$VIF = 1/(1 - R^2) \quad (21)$$

Thus, the closer the value R² to 1, the greater the value VIF and the greater the multicollinearity with the separate variable. In comparison, multicollinearity can be used in the correlation matrix and dispersion plots. However, their results suggest only the bivariate effect of predictor variables. Therefore, VIF is chosen because its connection to a group of other variables can be seen. Panel data can be subject to overwhelming cross-sectional dependency, which correlates all units in the same cross-section. It is often due to the influence, while possible in various ways, of certain unknown factors, specific to all units and affecting each.

3. Results

This study investigates green energy causal effect in the four leading ASEAN countries, including Philippines, Thailand, Indonesia, and Vietnam, concerning Carbon emissions. Current research utilizes renewable energy as a metric for green energy determined by the percentage of renewable energy from energy content for the statistical analysis. Recent studies have also used Carbon emission as a pollution reduction instrument expressed in metric tons per capita to mitigate environmental consequences. The present research utilizes an annual dataset from 2000–2019. The current research is intended to apply DCCE, which prescribes the application of numerous observations. This study also measures the short and long-run causality between variables in the said countries of ASEAN. The following step is the descriptive statistics mentioned in the proposed investigation in Table 1.

Table 1 describes the description of significant data characteristics in the descriptive metrics and correlation metrics, LFDI L. Hydyl, L. wind, and L.Geo separately. The correlation analysis between the parameters is shown in the table, and there is an essential connection between pollution and clean energy. Table 1 provides descriptive statistics consisting of average, minimum, maximum value, standard deviation, skewness, kurtosis, Jarque-Bera, statistics on probability. The result showed that the mean value in each variable flatter for all countries. Hydyl (23.2742) accompanied by Geo is the highest average GE value (18.4631). The lowest average value for CO₂ (0.5381) and the wind is (17.6101). Moreover, the Kurtosis results are around 1–3 for almost all variables, suggesting an indication of linearity between the variable in all variables.

Furthermore, the Kurtosis outcomes for nearly all parameters are around 1–3, which implies linearity between the variables. Additionally, the current research utilized the Jarque-Bera test to verify data normality. The results demonstrated that the null hypothesis is rejected at a mixed level by all variables being statistically significant and that all variables are normally distributed. The results of the JB tests have also verified the linearity of the parameters for all ASEAN countries.

Table 1. Results of Descriptive Statistics.

| | CO ₂ | Hydyl | Wind | Geo |
|-----------------|-----------------|----------|----------|----------|
| Mean | 0.5381 | 23.2742 | 17.6101 | 18.4631 |
| Median | 0.4819 | 23.0145 | 18.1508 | 18.5144 |
| Maximum | 1.4386 | 25.2117 | 22.4582 | 23.3753 |
| Minimum | −0.3983 | 21.9837 | 13.8155 | 13.8155 |
| Std. Dev. | 0.5388 | 0.77385 | 2.4489 | 4.5612 |
| Skewness | 0.2220 | 1.0103 | −0.2424 | −0.0016 |
| Kurtosis | 1.8634 | 3.3661 | 1.8794 | 1.0103 |
| Jarque-Bera | 4.9630 | 14.0567 | 4.9684 | 13.1963 |
| Probability | 0.0536 | 0.0008 | 0.0533 | 0.0013 |
| Sum | 43.0499 | 1861.936 | 1408.812 | 1477.052 |
| Sum Sq. Dev. | 22.9361 | 47.3092 | 473.7898 | 1643.586 |
| Observations | 80 | 80 | 80 | 80 |
| CO ₂ | 1 | | | |
| Hydyl | −0.1931 | 1 | | |
| Wind | 0.4834 | −0.1466 | 1 | |
| Geo | −0.5028 | −0.2246 | −0.2192 | 1 |

To avoid cross-sectional dependency [48] against cross-sectional units and deceptive criteria, we utilized the [49] cross-sectional dependence (CD) test in consideration of transversal dependency between transversal entities. We have used CD-testing, scaled LM-testing, and bi-corrected scaled LM [49,50], which are more accurate for CSD and direct

the methods in that case as mentioned in Table 2. The null hypothesis of the CD test reflects independence in cross- or non-sectional groups. The results presented in the table conclude that there is cross-sectional dependency across cross-sectional units. The CD test also makes it convenient to determine whether first-generation root unit panel tests or second-generation panel tests are needed [51].

Table 2. Panel Unit Root Test for Cross-Sectional Dependence.

| | Pesaran CD | | Pesaran Scaled LM | | Breusch-Pagan LM | |
|-----------------|------------|----------|-------------------|----------|------------------|----------|
| CO ₂ | 8.29 *** | (0.0000) | 18.66 *** | (0.0000) | 70.64 *** | (0.0000) |
| Hydyl | 0.36 | (0.7114) | 5.54 *** | (0.0000) | 25.21 *** | (0.0003) |
| Wind | 8.95 *** | 0.0000 | 21.69 *** | (0.0000) | 81.16 *** | (0.0000) |
| Geo | −0.96 | (0.3352) | 1.37 | (0.1699) | 10.75 ** | (0.0503) |

Source: Authors' Estimations using STATA. Note: ***, ** indicate the level of significance at 1% and 5% respectively.

The variance inflation factor (VIF) test of multicollinearity performed in Table 3. Based on equation No.21 statement, there is no issue of multicollinearity in the underline dataset.

Table 3. Variance inflation factor (VIF Matrix) testing multicollinearity).

| | CO ₂ | Hydyl | Wind |
|-------|-----------------|-------|------|
| Hydyl | 1.04 | - | - |
| Wind | 1.31 | 1.02 | - |
| Geo | 1.34 | 1.05 | 1.05 |

Source: Authors' Estimations using STATA.

The unit root test for accurate results was performed in first-generation (see Table 4) [51], however, the cross-sectional dependence is ignored in the first-generation unit root analysis. For this, second-generation unit root test of CIPS trial by [41] also applied. Results demonstrate that the parameters are of mixed integrative order since the variables are stationary at 1st difference with different significance level.

Table 4. Unit Root (First & Second Generation) Tests Results.

| First-Generation Unit Root Tests (LLC & IPS) | | | | |
|--|---------------------|------------------------------|------------------------------|------------------------------|
| Level | | | 1st Difference | |
| Variables | Levin, Lin, and Chu | Im, Pesaran, and Shin W-stat | Levin, Lin, and Chu | Im, Pesaran, and Shin W-stat |
| CO ₂ | −2.2065 *** | 0.4793 ** | −4.9751 *** | −3.4264 *** |
| Hydyl | −0.0571 | 0.3054 | −6.4232 *** | −5.5715 *** |
| Solar | −0.5633 | 0.6721 | 0.2866 | 0.7493 |
| Wind | 2.0002 | 3.3803 | −2.0246 ** | −1.6716 ** |
| Geo | −0.1411 | 0.2247 | −4.7077 *** | −4.1577 *** |
| 2nd-Generation Unit Root Tests (LLC & IPS) | | | | |
| Level | | | 1st Difference | |
| Variables | CIPS | | Im, Pesaran, and Shin W-stat | |
| CO ₂ | 1.369 | | −2.825 ** | |
| Hydyl | −0.643 | | −2.601 *** | |
| Wind | −0.508 | | −2.624 *** | |
| Geo | −0.208 | | −2.502 ** | |

Source: Authors' Estimations using STATA. Note: ***, ** indicate the level of significance at 1% and 5%, respectively.

The results of cointegration tests by Pedroni demonstrate that there is no long-term correlation among the intended factors. In Table 5, the findings from the Pedroni are discussed within and between co-integrated studies. We can refute from seven tests the non-cointegration hypothesis in one test (at 10 percent significance) while maintaining its near p-value. We assume a long-term relationship between renewable energy and CO₂ per capita as such. Therefore, we follow various co-integration tests to verify these findings for the reliability coefficient. However, all the panels in Pedroni text are not showing co-integration. Therefore, we conduct a further co-integration test like Kao and Westerlund to make a confirmation statement in this regard.

Table 5. Pedroni Co-integration Test.

| Alternative Hypothesis: Common AR Coefficients. (within-Dimension) | | | | |
|--|------------|----------|--------------------|--------|
| | Statistic | Prob. | Weighted Statistic | Prob. |
| Panel v-Statistic | −1.5488 | 0.9393 | −1.6910 | 0.9546 |
| Panel rho-Statistic | 1.23477 | 0.8915 | 1.33050 | 0.9083 |
| Panel PP-Statistic | −0.9948 ** | 0.0599 | −1.0082 ** | 0.0567 |
| Panel ADF-Statistic | −0.9599 | 0.1685 | −0.8954 | 0.1853 |
| Alternative Hypothesis: Individual AR Coefficients. (between-Dimension) | | | | |
| | Statistic | Prob. | | |
| Group rho-Statistic | 1.7134 | 0.9567 | | |
| Group PP-Statistic | −0.7119 | 0.2382 | | |
| Group ADF-Statistic | −1.6155 | 0.0531 * | | |

Source: Authors' Estimations using STATA. Note: **, * indicate the level of significance at 5% and 10% respectively.

Table 6 reports the summary of the Cointegration test for the Kao residual column. The result strongly rejects the null hypothesis of no cointegration as it significant at 1% level. It confirms the existence of a long-term correlation between the independent.

Table 6. Results of Kao Test.

| Null Hypothesis | No Co-Integration | |
|------------------------|--------------------------|-------|
| | Kao t-Stat | Prob. |
| ADF | −3.987 *** | 0 |
| Residual variance | | 0.005 |
| HAC variance | | 0.006 |

Source: Authors' Estimations using STATA. Note: *** indicate the level of significance at 1%.

Furthermore, we have also performed the Westerlund Cointegration test, the second generation [52], which is superior to the standard cointegration test for various reasons. It includes crucial issues neglected by the conventional co-integration test, including [53] cross-sectional dependency, structural data breaks, heteroscedasticity, and serial correlation [52]. The [54] co-integration test discusses cross-sectional dependency, systemic breakdowns, serial correlation, and hetero scene problems and offers consistent results compared to conventional co-integration studies. The co-integration findings from the bootstrap panel in [52] confirm the existence of a long-term association or co-integration among CO₂, Hydyl, Wind, and Geo. The probability rates for co-integration tests of Gt and Pt [46] are less than 0.05 that rejects the null hypothesis of no co-integration. The co-integration test findings are shown in Table 7 below, which provides the varying findings.

Table 7. Westerlund co-integration tests.

| H ₀ : No Co-Integration | Value | p-Value |
|------------------------------------|-----------|---------|
| Gt | −3.483 ** | 0.012 |
| Ga | −3.119 | 0.998 |
| Pt | −6.072 ** | 0.049 |
| Pa | −2.813 | 0.988 |

Source: Authors' Estimations using STATA. Note: ** indicate the level of significance at 5%.

Table 8 displays the findings of the Dynamic Common Correlated Effects (DCCE). As per the empirical investigation results, the dependent variable of all independent variables has a mixed effect. All the independent indicators of renewable energy have a significant and negative impact on carbon emissions. The Hydyl coefficient is 0.06 and statistically significant, which means that one percent growth in Hydyl would support 0.06 percent to impose environmental impact of these nations of the ASEAN region. The hydropower infrastructure makes a significant contribution to reducing emissions in this area. Also, the wind energy source is statistically significant. According to its coefficient, 0.6% environmental restoration in the ASEAN region can be improved due to a 1% increase in the level of wind-induced green energy. Lastly, with a negative sign, Geo-Thermal also has a significant effect on carbon emissions. The Geo-Thermal Coefficient shows that a 1% rise in this green energy source factor would contribute to 0.1% environmental improvements in selected ASEAN countries. Overall results show that the ASEAN green energy source contributes to restoring environmental status in the region.

Table 8. Long-run results (DCCE).

| Regressors | Coefficient | p-Value |
|----------------------|-------------|---------|
| CO ₂ (−1) | −0.44 *** | 0.009 |
| Hydyl | −0.06 ** | 0.049 |
| Wind | −0.01 ** | 0.038 |
| Geo | −0.01 ** | 0.041 |

Source: Authors' Estimations using STATA. Note: ***, and ** show the significance levels at 1% and 5%, respectively.

The results of short and long-run Granger causality presented in Table 9. According to long-run results, there is Granger causality running from Hydyl to CO₂ and Geo to Hydyl in the case of Indonesia. There is Granger causality running from Geo to CO₂ at a 1% significant level, while from Hydyl to Wind there is a 10% significant level in Thailand. There is a 10% long-run Granger causality from wind to CO₂ and Geo to Hydyl for the Philippines. The long-run Granger causality runs from CO₂ to Hydyl at a 5% significant level, while wind to CO₂ has a 10% significant level in Vietnam.

Based on the outcome of short-run Granger Causality, Hydyl Granger-causes CO₂ to 10% of its significance, and Geo causes Hydyl to 10% of its significance in Indonesia. In the Philippines, short-term Granger Causality results indicate that wind causes Hydyl at 10% significance. In Thailand, the results estimated demonstrate that Granger causality runs from Hydyl to CO₂ at a 10% significant level. In the Vietnam case, approximate findings indicate that Hydyl causes CO₂ at 10% significance.

According to these results, there is running long-run causality from GE to CO₂ volatility in almost every ASEAN country at different significance levels. The same trend has also been observed in the short-run Granger causality from GE to Carbon volatility except in Thailand. Furthermore, it has also been observed that GE's elements (Hydro, Wind, and Geo) have Granger causality with each other. Additionally, the findings established a significant causal relationship between GE and CO₂ exposure volatility in the Philippines,

Thailand, Indonesia, and Vietnam. The results demonstrate a significant causal association between GE and the returns and volatility of CO₂ emissions in ASEAN member countries when the climate is worse.

Table 9. Results of Causality.

| Long-Run Granger Causality | | | | | | Short-Run Granger Causality | | | | |
|----------------------------|-----------------|-----------------|-------------|----------|---------|-----------------------------|-----------------|----------|--------|--------|
| | Variables | CO ₂ | Hydyl | Wind | Geo | Variables | CO ₂ | Hydyl | Wind | Geo |
| Indonesia | CO ₂ | 1 | 0.9074 | 0.7691 | 2.1000 | Δ CO ₂ | 1 | 1.0126 | 2.0945 | 2.1000 |
| | Hydyl | 4.3398 ** | 1 | 1.3921 | 1.1616 | Δ (Hydyl) | 3.1132 * | 1 | 0.4604 | 1.6462 |
| | Wind | 2.6514 | 0.2259 | 1 | 0.10747 | Δ (Wind) | 0.2548 | 0.0841 | 1 | 0.1268 |
| | Geo | 1.4604 | 13.7402 *** | 2.7116 | 1 | Δ (Geo) | 1.4604 | 3.2130 * | 1.7617 | 1 |
| Thailand | CO ₂ | 1 | 1.2509 | 0.0029 | 1.0089 | Δ CO ₂ | 1 | 0.9814 | 1.8099 | 0.0743 |
| | Hydyl | 1.5660 | 1 | 3.2034 * | 1.8419 | Δ (Hydyl) | 1.3117 | 1 | 1.7858 | 1.5147 |
| | Wind | 0.3272 | 2.0473 | 1 | 0.6291 | Δ (Wind) | 0.2868 | 2.9488 * | 1 | 0.0661 |
| | Geo | 9.1607 *** | 1.3160 | 1.1550 | 1 | Δ (Geo) | 0.9725 | 0.3300 | 0.0572 | 1 |
| Philippines | CO ₂ | 1 | 1.6336 | 0.2105 | 1.4700 | Δ CO ₂ | 1 | 1.3397 | 0.2105 | 0.2417 |
| | Hydyl | 2.2180 | 1 | 1.0200 | 0.4289 | Δ (Hydyl) | 2.1801 * | 1 | 0.4604 | 1.6462 |
| | Wind | 2.9353 * | 0.6206 | 1 | 1.0163 | Δ (Wind) | 0.5427 | 0.0841 | 1 | 0.1268 |
| | Geo | 0.8077 | 2.9452 * | 2.4239 | 1 | Δ (Geo) | 0.4091 | 1.7441 | 1.7617 | 1 |
| Vietnam | CO ₂ | 1 | 4.3914 ** | 1.7941 | 0.1145 | Δ CO ₂ | 1 | 0.5088 | 0.2039 | 2.1000 |
| | Hydyl | 1.1546 | 1 | 1.4314 | 0.0565 | Δ (Hydyl) | 2.9581 * | 1 | 0.1471 | 0.5595 |
| | Wind | 3.4533 * | 1.7207 | 1 | 0.2486 | Δ (Wind) | 0.3378 | 3.1201 | 1 | 0.1776 |
| | Geo | 1.7609 | 1.3456 | 0.0432 | 1 | Δ (Geo) | 1.4604 | 1.9616 | 5.0108 | 1 |

Source: Authors' Estimations using STATA. Note: ***, ** and * show the significance levels at 1% 5% and 10%, respectively.

4. Conclusions

With the onset of industrialization, societies shifted their focus to large-scale manufacturing and commerce, resulting in a rise in energy use. Historically, economies have relied heavily on conventional energy sources such as oil, gas, and coal, which are widely regarded as the primary indicators of environmental deterioration. To mitigate the destruction of the environment, economies' attention should be shifted toward ecologically responsible renewable energies, with a great reliance on alternative green energy sources. Due to the region's increasing focus on GE, the present study uses time-series data from 2000 to 2019 to examine GE's influence on environmental deterioration in the ASEAN countries, namely Indonesia, Thailand, Philippines, and Vietnam. The present study's task is to identify GE's contribution to regional decarbonization. For this purpose, the current study used a novel DCCE approach and Granger causality procedure. The results indicated that GE has a critical determinant effect on Carbon footprint levels in ASEAN member states.

Additionally, the findings established a significant causal relationship between GE utilization and Carbon emissions volatility in all nations in the long run. The analysis found a 5% significant long-run level of a causal relationship between renewable energy (Hydyl) and Carbon emissions volatility only in Vietnam. There is no causality between the abovementioned variables in any other country in the short or long run. The current study proposed that the policymakers and representatives implement various measures (such as wind or hydro energy investment) to mitigate environmental damage in ASEAN member states. The causality relationship between green energy sources and carbon emission must be accounted for during the policy design for carbon mitigation through renewable energy sources.

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