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Forecasting Carbon Dioxide Emission and Sustainable Economy: Evidence and Policy Responses

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ABSTRACT

Forecasting CO_2 emissions have been of importance as it could help the government to improve energy policies and plans. In this paper, we forecast the future carbon dioxide emission (CO_2) through estimating the short and long-run causal correlation between CO_2 emission, economic growth (*Y*), oil price (*OP*), consumption of renewable (*RE*), energy (*E*) in Thailand for the period 1990-2016 using autoregressive distributed lag approach. The result indicates that in the long term, consumption of renewable, energy and oil price (*OP*) increase of 1% each decrease CO_2 emission by 5.66%, 14.73% and 5.07% respectively. The result of forecasting CO_2 emission base on variance decompositions found that in the future next 14-year decrease CO_2 emission 30.17%, which is higher than the target set to reduce CO_2 emissions by 20-25% within 2030 year. The country should be adjust the structure of energy use to reduce pollution.

Keywords: Forecasting, Carbon Dioxide Emission, Variance Decomposition
JEL Classifications: P28, Q42, Q43, Q47, Q48

1. INTRODUCTION

Global economic fluctuations and energy prices, including global warming and environmental impacts. All factors that affect and influence the situation of the energy use and supply of energy in the country. Scenario planning is one way of looking at the future. Analysis of factors that may affect future events, the linking of various factors, including the uncertainty that may occur, is able to cope with the changing world. Emerging developing countries play an important role in climate change because these countries generally have high economic growth affecting rapid pollution emission.

Thailand is one of the developing countries with the use of energy more steadily and affects carbon dioxide emissions increases causing air pollution. Thailand has been aware of the problem of global warming 20 years ago by signing and ratifying international law related to this issue. Both the United Nations Convention on Climate Change (1994), the Kyoto Protocol (2002) and the Paris Agreement (2016). Thailand is a medium-level greenhouse gas emission of 350 million tons of carbon dioxide per year, accounting for 0.8% of the total, ranking 21st in the world. Thailand focuses on energy security by distributing energy sources, reduce fossil energy consumption and increasing the proportion of renewable energy consumption. Thailand has established a plan to reduce greenhouse gases to at least 20-25% by 2030 (Banchanont, 2017). The government target low carbon along with the sustainability of economic growth. Therefore, the transition to low-carbon technology may help to achieve reduces carbon dioxide emission and sustainable economic growth (Zhao and Luo, 2018). In order to improving the government's targets of CO_2 emission. We will be forecasting carbon dioxide emission for the next 13 years, whether they can achieve the goals set in 2030 to improving energy policies and plans in the further.

2. LITERATURE REVIEW

The problem of greenhouse gas and energy consumption increases have led to restore interest in forecasting of CO_2 emissions in the future. There are considerable amounts of literature that discussed and reviewed this issue (Abdullah, 2015). According to Suarez and Menendez (2015) study forecasting CO_2 emissions, they plan 25% decrease in CO_2 emissions by 2050 according to an economic and population growth that is more consistent with recent global trends. Wu et al. (2015) focus on forecasting CO_2 emissions in the BRICS countries found that economic growth has effect on the CO_2 emissions. Pao and Tsai, (2011) and Pao et al. (2012) study modeling and forecasting the CO_2 emissions, energy consumption, and economic growth. They found of the inverted U-shaped relationships of both emissions and energy consumption.

According to Lotfalipour et al. (2013) prediction of CO_2 emissions in Iran, they found that carbon dioxide emissions will increase to 66% in 2020 compared to 2010. Appiah et al. (2019) report that joint effect of energy intensity, economic progress and industrialization at constant decrease emissions by 2.46% in Uganda. According to He et al. (2019), Al Mamun et al. (2014), Ahmed et al. (2017), Salahuddin et al. (2018), Sasana and Aminata (2019) and Kalaycı and Hayaloglu, (2019) analyze the effect of energy-based on economic growth to CO_2 emissions. They found that positive relationship between energy and economic impacted CO_2 emissions. According to Saudi et al. (2019), Appiah (2018), Heidari et al. (2015), Lean and Smyth, (2010), Mirza and Kanwal (2017) and Alshehry and Belloumi (2015) they study relationship between energy consumption, renewable energy consumption, economic growth, and CO_2 emissions. The results also showed that renewable energy consumption impact to reduces carbon dioxide emission but energy consumption and economic growth lead to increase CO_2 emission. This paper aims to forecast carbon dioxide emission and sustainable economy in Thailand evidence and policy responses. Therefore, we analyze that country will achieve the goal of reducing greenhouse gases by at least 20-25% by the year 2030 as the target or not. The results are to be used in the policy planning of Thailand. Hence, this research will be beneficial to national management and future applications. The research process was as follows in Figure 1, framework for Time Series Analysis.

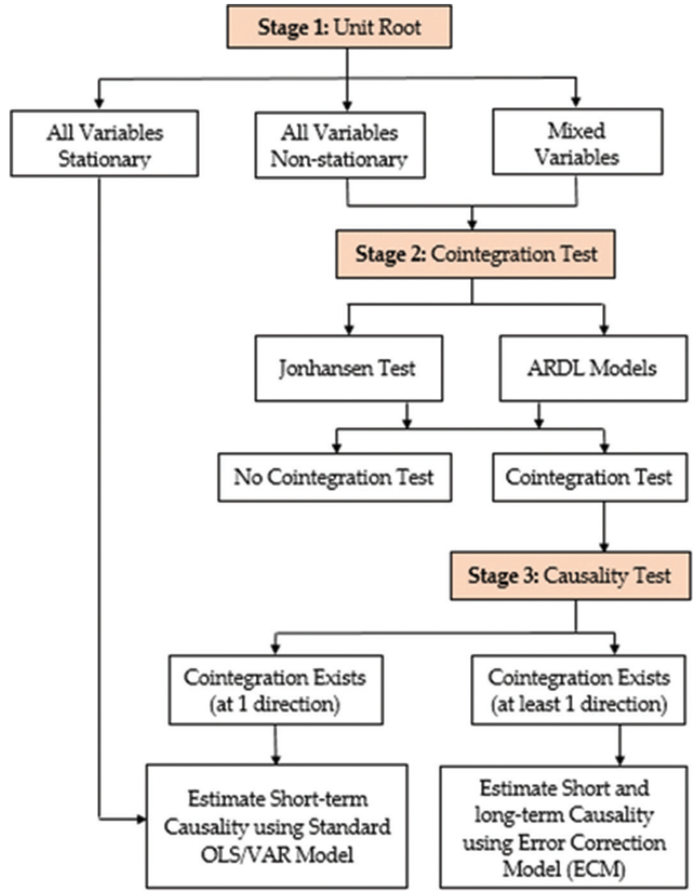
3. DATA AND METHODOLOGY

We start by estimating the long- and short-term relationship between consumption of energy, renewable, oil price (*OP*), economic growth, and CO_2 emissions. Then we forecasting CO_2 emissions for the next 14 year.

3.1. Data

Annual data covering the period of 1990 to 2016 were obtained from World Development Indicators and Energy Policy and Planning Office. The empirical analysis includes five factors: Economic growth (*Y*) measured in constant billion 2005 USD $/Ktoe, renewable energy consumption (*RE*) measured in Ktoe, energy consumption (*E*) measured in Ktoe, Carbon dioxide emissions (CO_2) measured in $MtCO_2$, and *OP* measured in USD $/Ktoe.

Figure 1: Framework for time series analysis



3.2. Methodology

This study employs time series data to analyze this relationship, we following method framework proposed in Figure 1. Three testing procedures were used in this study. After that, forecasting the CO_2 emission base on Variance Decomposition and Impulse Response analysis.

Stage 1: Unit root test to determine the stationarity of the time series.

Stage 2: We carry out the test of cointegration by employing autoregressive distributed lag (ARDL) method developed by Pesaran et al. (2001) and followed by Johansen cointegration technique.

Stage 3: Causality test. If found that no causality can use estimate short term causality using standard Ordinary Least Squares (OLS)/Vector autoregression model (VAR), if found that causality can use estimate short-term and long-term causality error correction model (ECM).

3.2.1 The description of the model

Stage 1: Stationary test

Firstly, the testing unit root examines the time-series variables for stationarity. We apply the Augmented Dickey and Fuller

(ADF) and Phillips and Perron tests (PP) were performed to test whether the data indicate a difference in stationarity or trend stationary, and to define the number of unit roots at their levels. Both tests are used to check the robustness of the results (Magazzino, 2015). We estimate the regression equation in the following manner:

$$\Delta y_t = \alpha + \beta_t + \theta y_{t-1} + \sum_{i=1}^{n} \mu_i \Delta y_{t-i} + e_t \tag{1}$$

Where α, β, μ_i, n and denote the intercept, the coefficient on the time trend T, the coefficient on the lagged dependant variable, number of lags and random error, respectively. Phillips and Perrom also suggested the method for unit root test and given the following equation:

$$\Delta y_t = \alpha + \beta_t + \theta y_{t-1} + e_t \tag{2}$$

Stage 2: Testing for cointegration

The term cointegration basically refers to that one or more linear combinations of time-series data are stationary even though they are individually non-stationary (Chen et al., 2019). Before proceeding with cointegration analysis, it was essential to determine the optimal lag length using the Likelihood Ratio (LR), Schwartz Criterion (SC), and Akaike Information Criterion (AIC) (Achour and Belloumi, 2016). The Johansen cointegration test is designed to obtain likelihood-ratios. There are two tests: the maximum eigenvalue test and the trace test. For both test statistics, the initial Johansen test is used for testing the null hypothesis of no cointegration against the alternative of cointegration. The tests differ in terms of alternative hypothesis (Shahbaz et al., 2017), trace test, and maximum eigenvalue as follows:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} ln\left(1 - \hat{\lambda}_i^2\right)$$

Hypothesis as follows: H_0: $r \leq k$, $H_1 = r > k$, $k = 0,\ldots, n$

λ_{max} (r, r+1) = −Tln (1−λ_{r+1})

Hypothesis as follows: H_0: $r = k$, H_1: $r = k+1$, $k = 0,\ldots, n$

Where λ_i is the estimated ordered eigenvalue obtained from the estimated matrix and T is the number of usable observations after lag adjustment. The trace statistics test the null hypothesis that the number of the distinct cointegrating vector (r) is less than or equal to r against a general alternative. The maximal eigenvalue tests the null hypothesis that the number of the cointegrating vector is r against the alternative of r + 1 (Esso and Keho, 2016). The result of lag length criteria and Johansen test showed in Table 1 and Table 2, respectively.

Table 1: Result of lag length criteria

Lag	LR	AIC	SC
1	169.19*	–17.64*	–16.17*

(*) indicates lag order selected by the criterion, LR: Sequential modified Likelihood Ratio test statistic (each test at 5% level), AIC: Akaike information criterion, SC: Schwarz information criterion

The ARDL approach developed by Pesaran et al. (2001) was used to test cointegration. The ARDL bounds test is used to test the long-term relationship among variables. This approach has many econometric advantages compared to the standard Johansen cointegration test. To demonstrate the ARDL modeling approach, the following simple model can be considered:

$$y_t = \alpha + \beta x_t + \delta z_t + e_t$$

The equation with β, δ *and* e represent short term dynamic of the model. The error correction version of the ARDL model is given by:

$$\Delta y_t = \alpha_0 + \sum_{i=l}^{p} \beta_i \Delta y_{t-i} + \sum_{i=l}^{p} \delta_i \Delta x_{t-i} + \sum_{i=l}^{p} \varepsilon_i \Delta z_{t-i} + \lambda_1 y_{t-l} + \lambda_2 x_{t-l} + \lambda_3 z_{t-l} + u_l$$

The equation with λ represents long term relationship. The null hypothesis in the equation is $\lambda_1 + \lambda_2 + \lambda_3 = 0$, which means non-existence of long-term relationship (Ftiti et al., 2016).

The ARDL approach leads to estimation of the following unrestricted ECM by the OLS Method (OLS) (Ftiti et al., 2016), as presented by Equations (3) to (7):

$$\begin{aligned}\Delta yt = {} & \alpha_{0Y} + \sum\nolimits_{i=1}^{p1} \beta_{iY} \Delta Y_{t-i} + \sum\nolimits_{j=0}^{q1} X_{jRE} \Delta RE_{t-j} \\ & + \sum\nolimits_{k=0}^{r1} \delta_{kE} \Delta E_{t-k} + \sum\nolimits_{l=0}^{s1} \phi_{kCO2} \Delta CO_{2,t-l} \\ & + \sum\nolimits_{m=0}^{g1} \sigma_{mOP} \Delta OP_{t-m} + \varphi_Y Y_{t-1} + \gamma_{RE} RE_{t-1} \\ & + \eta_E E_{t-1} + \lambda_{CO2} CO_{2,t-1} + \theta_{OP} OP_{t-1} + \varepsilon_{1t}\end{aligned} \tag{3}$$

$$\begin{aligned}\Delta RE_t = {} & \alpha_{0RE} + \sum\nolimits_{j=1}^{q2} \beta_{iRE} \Delta RE_{t-j} + \sum\nolimits_{i=0}^{p2} X_{jY} \Delta Y_{t-i} \\ & + \sum\nolimits_{k=0}^{r2} \delta_{kE} \Delta E_{t-k} + \sum\nolimits_{l=0}^{s2} \phi_{klc} \Delta CO_{2,t-l} \\ & + \sum\nolimits_{m=0}^{g2} \sigma_{mOP} \Delta OP_{t-m} + \varphi_Y Y_{t-1} + \gamma_{RE} RE_{t-1} \\ & + \eta_E E_{t-1} + \lambda_{CO2} CO_{2,t-1} + \theta_{OP} OP_{t-1} + \varepsilon_{2t}\end{aligned} \tag{4}$$

$$\begin{aligned}\Delta E_t = {} & \alpha_{0E} + \sum\nolimits_{k=1}^{r3} \beta_{KE} \Delta E_{t-k} + \sum\nolimits_{i=0}^{p3} X_{jY} \Delta Y_{t-i} \\ & + \sum\nolimits_{k=0}^{r3} \delta_{iRE} \Delta RE_{t-j} + \sum\nolimits_{l=0}^{s3} \phi_{lCO2} \Delta CO_{2,t-l} \\ & + \sum\nolimits_{m=0}^{g3} \sigma_{mOP} \Delta OP_{t-m} + \varphi_Y Y_{t-1} + \gamma_{RE} RE_{t-1} \\ & + \eta_E E_{t-1} + \lambda_{CO2} CO_{2,t-1} + \theta_{OP} OP_{t-1} + \varepsilon_{3t}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta CO_{2,t} = {} & \alpha_{0CO2} + \sum\nolimits_{l=1}^{s4} \beta_{lCO2} \Delta CO_{2,t-1} + \sum\nolimits_{i=1}^{p4} X_{jY} \Delta Y_{t-i} \\ & + \sum\nolimits_{j=0}^{q4} \delta_{iRE} \Delta RE_{t-j} + \sum\nolimits_{k=0}^{r4} \phi_{kE} \Delta E_{t-k} \\ & + \sum\nolimits_{m=0}^{g4} \sigma_{mOP} \Delta OP_{t-m} + \varphi_Y Y_{t-1} + \gamma_{RE} RE_{t-1} \\ & + \eta_E E_{t-1} + \lambda_{CO2} CO_{2,t-1} + \theta_{OP} OP_{t-1} + \varepsilon_{4t}\end{aligned} \tag{6}$$

$$
\begin{aligned}
\Delta OP_t = {} & \alpha_{0OP} + \sum\nolimits_{m=1}^{p5} \beta_{lOP} \Delta OP_{t-m} + \sum\nolimits_{i=0}^{q5} X_{jY} \Delta Y_{t-i} \\
& + \sum\nolimits_{k=0}^{q5} \delta_{kE} \Delta E_{t-k} + \sum\nolimits_{l=0}^{s5} \phi_{lCO2} \Delta CO_{2,t-1} \\
& + \sum\nolimits_{m=0}^{g5} \sigma_{mRE} \Delta RE_{t-J} + \varphi_Y Y_{t-1} + \gamma_{RE} RE_{t-1} \\
& + \eta_E E_{t-1} + \lambda_{CO2} CO_{2,t-1} + \theta_{OP} OP_{t-1} + \varepsilon_{5t} \qquad (7)
\end{aligned}
$$

Where Δ is the first difference and ε_{jt}, (j = 1, 2, 3, 4, 5) are white noise error terms. The existence of a cointegration relationship between the variables from Equations (3) to (7) was investigated by testing the significance of the lagged levels of variables using the computed F-statistic. Pesaran et al. (2001) and Brini et al. (2017) suggested testing H_0: $\varphi_Y = \gamma_{RE} = \eta_E = \lambda CO_2 = \theta_{OP} = 0$, which means that the absence of cointegration cannot be rejected, against the alternative, and H_1: $\varphi_Y \neq \gamma_{RE} \neq \eta_E \neq \lambda CO_2 \neq \theta_{OP} \neq 0$, which implies that the hypothesis of there being such a relationship cannot be rejected. Following Pesaran et al. (2001) and Brini et al. (2017), the F-statistic used for this test has a non-standard asymptotic distribution and generates two sets of critical value bounds. The lower critical value corresponds to the case where all variables are I (0), and the upper critical value corresponds to the case where all variables are I (1). If the computed F-statistic surpasses the upper critical bound, then the null hypothesis of no cointegration is rejected and it can be concluded that there is evidence of a long-term relationship. If it falls below the lower critical value, the null hypothesis of no cointegration is not rejected, and if the F-statistic is between the lower and upper critical bounds, the result is inconclusive (Fatai et al., 2004).

Stage 3: Testing for causality

After the appearance of a long-term association amongst the variables, but it does not indicate the direction of causality. For this aim, the Granger-causality tests based on vector error correction model (VECM) are carried out to the empirical analysis involved testing both short- and long-term causality between variables (Alshehry and Belloumi, 2015), applying the VECM approach established in the following equation:

$$
\begin{bmatrix} \Delta Y \\ \Delta RE \\ \Delta E \\ \Delta CO_2 \\ \Delta OP \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \end{bmatrix} + \sum\nolimits_{i=1}^{n} \begin{bmatrix} \beta_{11,i} & \beta_{12,i} & \beta_{13,i} & \beta_{14,i} & \beta_{15,i} \\ \beta_{21,i} & \beta_{21,i} & \beta_{21,i} & \beta_{21,i} & \beta_{21,i} \\ \beta_{31,i} & \beta_{31,i} & \beta_{31,i} & \beta_{31,i} & \beta_{31,i} \\ \beta_{41,i} & \beta_{41,i} & \beta_{41,i} & \beta_{41,i} & \beta_{41,i} \\ \beta_{51,i} & \beta_{51,i} & \beta_{51,i} & \beta_{51,i} & \beta_{51,i} \end{bmatrix} \begin{bmatrix} \Delta Y_{t-i} \\ \Delta RE_{t-i} \\ \Delta E_{t-i} \\ \Delta CO_{2,\,t-i} \\ \Delta OP_{t-i} \end{bmatrix} + \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \\ \gamma_5 \end{bmatrix} \begin{bmatrix} ECT_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix} \qquad (8)
$$

Where ECT_{t-1} is the lagged error correction term derived from the long-term cointegration functions; α_1, α_2, α_3, α_4, and α_5 are constant trends; γ_1, γ_2, γ_3, γ_4, and γ_5 are the adjustment coefficients; and ε_1, ε_2, ε_3, ε_4, and ε_5 are the serially uncorrelated error terms. A significant t-statistic on the Error Correction Model (ECM) indicates the presence of a long-term causality relationship, while the significant variables in first differences provides evidence of short-term causality relationships. The ECM reflects the speed of the adjustment and how quickly the variables return to the long-term equilibrium with a statistically significant coefficient (Alshehry and Belloumi, 2015).

3.2.2. Forecasting CO_2 emission and economic growth

After determining the directions of causality from the application of the VECM. We apply the generalised impulse responses and variance decomposition following Koop et al. (2015) and Pesaran and Shin (Pesaran and Shin, 1998; Georgantopoulos, 2012) innovative studies. Hence, the Impulse Response analysis to find responsiveness outcome variable in the VAR when a shock is put to error term. Consequently, unit shock is applied to each of variables in order to see its effects on VAR system (Appiah et al., 2019). After that, this study predicts a causal link between economic growth, renewable energy consumption, energy consumption, CO_2 emissions and OP in Thailand for the next 14-year period.

4. EMPIRICAL RESULTS

4.1. Results of Stationary Test

We begin with the screening of influencing factors for model input. That regression results may be spurious if the estimated variables are non-stationary and/or not cointegrated (Tang et al., 2016). Therefore, we testing for a unit root of each series is necessary. To investigate the order of integration, we began by applying the ADF and PP. The ADF test and PP test show that all variable causal factors are stationary at the First Difference I (1), as presented in Table 3.

Table 3 showed that all factors are non-stationary at Level I (0), it was found that those factors became stationary at first difference I (1). Once the factors were identified as stationary, they were taken for a co-integration test, as next step by Johansen Juselius and ARDL approach as shown reported in Tables 2 and 4, respectively.

4.2. Results of the Cointegration Test

For estimate the long-term relationship through bound testing approach, there are essential tests which are used to select appropriate lag selection criteria. We employed LR, SC, and AIC to identify appropriate lag length, as reported in Table 1. The optimal lag length is found to be one, thus we performed the Johansen cointegration test with this lag structure.

We perform Johansen's cointegration tests to assess the evidence of cointegration. In Table 2, both the results of trace tests and maximum eigenvalue tests unanimously point to the same conclusion that there is at most one cointegrated relationship, at the 1% level of significance. The results investigate each causal factor was cointegrated at a confidence interval 95%.

In addition, we performed using the ARDL bounds test for compared to the standard Johansen cointegration test, we investigate F-value to confirm the existence of cointegration

Table 2: Results of Johansen's cointegration test

Variables	Hypothesized no. of cointegrating equations	Trace statistic test	Max-eigen statistic	MacKinnon critical value	
				1%	5%
$\Delta\ln(Y)$, $\Delta\ln(RE)$, $\Delta\ln(E)$, $\Delta\ln(CO_2)$, $\Delta\ln(OP)$	None***	85.35	34.67	39.37	33.87
	At Most 1**	50.67	22.64	32.71	21.58

(***) denotes a significance, α=0.001, (**) denotes a significance, α=0.01, (*) denotes a significance, α=0.1

between variables for long term relationship. The results of bound F-statistics shown in Table 4. If the F-statistic is below the lower critical bound, I (0), then one accepts the null hypothesis of no cointegration between the variables which implies that the series are not cointegrated. However, if the F-statistic is below the upper critical bound, I (1), then one rejects the null hypothesis of no cointegration and therefore, concludes that the series are cointegrated. Furthermore, if the F-statistic falls in-between the four critical bounds, the decision becomes inconclusive (Ang, 2008). The calculated F statistic $F_y(Y/OP, RE, E, CO_2) = 2.79$, $F_{op}(OP/Y, RE, E, CO_2) = 2.58$, $F_E(E/OP, RE, Y, CO_2) = 2.46$, $FCO_2(CO_2/OP, RE, E, Y) = 4.69$, are greater than the upper bound critical value of Pesaran et al. (2001) at the 10% significance level (3.52). This result indicates that the null hypothesis of cointegration was rejected. $F_{RE}(RE/Y, OP, E, CO_2) = 2.05$ is the lower critical bound, I (0), at the 10% significance level (2.45) then one accepts the null hypothesis of no cointegration between the variables which implies that the series are not cointegrated.

Both Johansen cointegration approach and the ARDL bounds test approach confirm that these variables form a long-term relationship with each other; however, the presence of a long-term relationship does not imply causality. Therefore, we employed different variants of the Granger causality test to study the direction of the causality between these variables (Heidari et al., 2015). Table 5 reported in the estimated long-term and short-term by the estimate ARDL model. In the long term, consumption of renewable, energy and OP increase of 1% each decrease CO_2 emission by 5.66%, 14.73% and 5.07% respectively. In the short term, consumption of renewable, energy and *OP* increase of 1% each decrease CO_2 emission by 10.08%, 26.22% and 9.03% respectively. But economic growth increase of 1% each increase CO_2 emission by 76.49%. Furthermore, the lagged error correction term (ECT_{t-1}) is of the right negative sign, which means that an equilibrium relationship could be restored any time there are deviations. The coefficient of lag error correction term (ECT_{t-1}) −1.7796 implies that approximately 1% of the shocks to the system are restored in the next period. The same results suggest that a deviation from the long-term equilibrium level of CO_2 emission in 1 year is corrected by 17.79% in the next year.

4.3. Results of the Granger Causality based on VECM approach

After estimating the long-and short-term estimate, we find the direction of causality by Granger causality base on the VECM in order to find the direction of causality between variable. To calculate short term causality, we apply Wald test to difference and lag difference coefficient of all independent variables. We also calculate short term and long-term joint causality (Inglesi-Lotz, 2016). Table 6 reported results from Granger Causality based on VECM test, the results of the Wald-test are provided in Table 7 and depicted in Figure 2 following below.

According to these results, the ECT_{t-1} coefficients of renewable energy (*RE*), CO_2 emissions (CO_2) and *OP* are both comprised

Table 3: ADF and PP tests

At 1st difference	ADF Test	PP tests
Variables	Value	Value
$\Delta\ln(Y)$	−3.56**	−3.56*
$\Delta\ln(RE)$	−4.94***	−5.36***
$\Delta\ln(E)$	−3.75*	−3.85*
$\Delta\ln(CO_2)$	−3.45*	−3.48*
$\Delta\ln(OP)$	−4.39*	−4.38*

Y is economic growth; RE is renewable energy consumption; E is energy consumption; CO_2 is carbon dioxide emissions; OP is oil price. The values in this table are t-statistics. (***) denotes a significance, α=0.001, (**) denotes a significance, α=0.01, (*) denotes a significance, α=0.1, Δ is the first difference, and ln is the natural logarithm. ADF: Augmented Dickey and Fuller, PP: Phillips and Perron

Table 4: Results of bounds cointegration test – ARDL approach

Equation	F-statistics
$F_Y(Y/OP, RE, E, CO_2)$	2.79*
$F_{OP}(OP/Y, RE, E, CO_2)$	2.58*
$F_{RE}(RE/Y, OP, E, CO_2)$	2.05
$F_E(E/OP, RE, Y, CO_2)$	2.46*
$FCO_2(CO_2/OP, RE, E, Y)$	4.69*
Critical values of F-statistics	I (0)=2.45, I (1)=3.52

Critical values for $K = 4$ and n = 27 at 10%, (*) denotes a significance, α=0.1. ARDL: Autoregressive distributed lag

Table 5: Results of long-and short-term estimates of ARDL model (Dependent Variable: CO_2)

Variable	Coefficient	P value
Long term estimates		
ΔY	1.1382	0.0000
ΔRE	−0.0566	0.3312
ΔE	−0.1473	0.1365
ΔOP	−0.0507	0.0420
ECT_{t-1}	−1.7796	0.0000
Short term estimates		
Constant	−0.0133	0.0974
Y	0.7649	0.0001
RE	−0.1008	0.3329
E	−0.2622	0.1339
OP	−0.0903	0.0358

ARDL model (1, 1, 0, 0, 0); R^2=0.83; Adj. R^2=0.77; F-Stats=3.58; Prob. (F-Stats)=0.00; DW=2.01; Normality test: Jarque-Bera test=4.89; Hetero. Test=0.71; ARDL: Autoregressive distributed lag

Table 6: Result from Granger Causality based on VECM test

Dependent variable	Short-term causality					Long-term causality
	ΔY_{t-1}	ΔE_{t-1}	ΔRE_{t-1}	$\Delta CO_{2,t-1}$	ΔOP_{t-1}	ECM_{t-1}
ΔY_t	-	–0.13 (0.7538)	–0.03 (0.8516)	0.08 (0.8130)	–0.10 (0.1672)	–0.60 (0.2714)
ΔE_t	1.27 (0.0196)*	-	–0.61 (0.0050)***	0.63 (01214)	–0.17 (0.0322)*	–0.20 (0.5213)
ΔRE_t	0.60 (0.2549)	–0.24 (0.5564)	-	–0.57 (0.2719)	0.22 (0.0161)*	–0.35 (0.0768)*
$\Delta CO_{2,t}$	0.76 (0.0408)*	0.51 (0.0970)*	–0.48 (0.0118)*	-	–0.12 (0.0850)*	–1.53 (0.0072)***
ΔOP_t	0.98 (0.5258)	0.23 (0.8591)	0.50 (0.4630)	–1.46 (0.2992)	-	–0.48 (0.0796)*

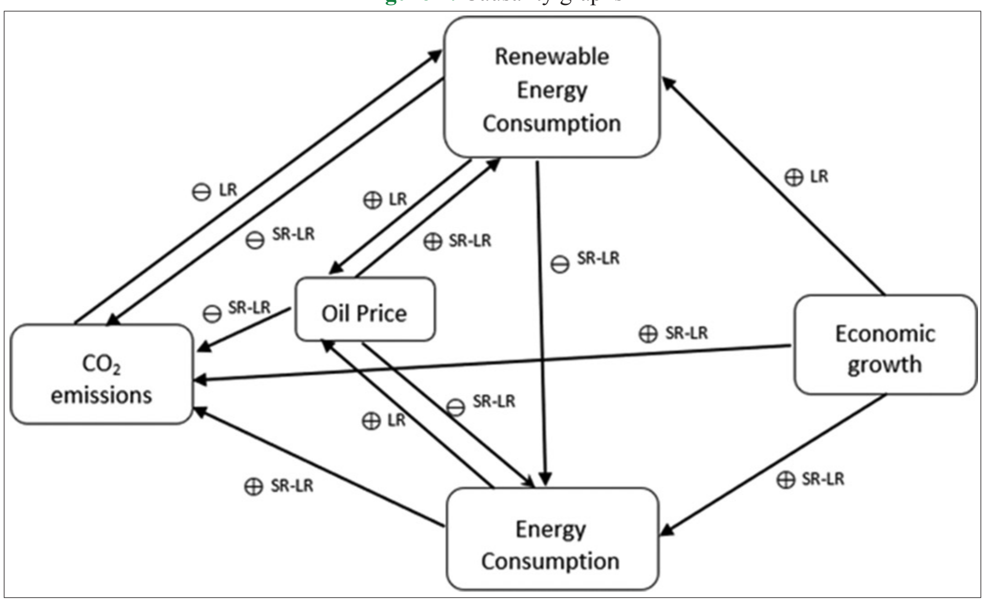
Associated *P* value are provided in parentheses. (***) P<0.001; (**) P<0.05; (*) P<0.1. VECM: Vector error correction model

Table 7: Result from the wald test

dependent Variable	Long-term causality				
	ΔY_{t-1} ECM_{t-1}	ΔE_{t-1} ECM_{t-1}	ΔRE_{t-1} ECM_{t-1}	$\Delta CO_{2,i-1}$ ECM_{t-l}	ΔOP_{t-1} ECM_{t-1}
ΔY_t	-	0.64 (0.5366)	0.67 (0.5236)	0.68 (0.5190)	1.73 (0.2045)
ΔE_t	4.30 (0.0297)*	-	−5.27 (0.0158)*	1.92 (0.1751)	−4.24 (0.0309)*
ΔRE_t	2.77 (0.0888)*	1.85 (0.1857)	-	−2.66 (0.0971)*	4.74 (0.0222)*
$\Delta CO_{2,t}$	8.07 (0.0031)***	5.10 (0.0175)*	−6.75 (0.0065)***	-	−8.11 (0.0031)***
ΔOP_t	1.72 (0.2056)	2.77 (0.0891)*	3.40 (0.0555)*	−2.36 (0.1226)	-

Associated *P* values are provided in parenthesis. *** P < 0.01; **P < 0.05; *P < 0.1

Figure 2: Causality graphs



between −1 and 0, which are statistically significant. Therefore, there exists causality in the Granger sense running from Y to RE, E, CO_2 in the long-term. These results verify the cointegration test analysis. In addition, there exists a long-term Granger causality running from E, Y, and negative OP, RE to CO_2. And then we found causality running from RE to OP and negative E, CO_2. In the short-term, there is a uni-directional causality from running Y to E, CO_2 at 5% level of significance. This may explain that the proportion of economic growth in energy consumption and CO_2 emission are increasing, thus, the demand for energy consumption also would increase. Simultaneous, the demand for renewable energy consumption also would increase too. In the short-term and long term, there is a unidirectional causality running from E to CO_2 at 1% level of significance which means that increasing in energy consumption could promote the more energy efficiency and conservation policy. It can be explained that with the deterioration of the environment, Thailand will take a series of measures to prevent the further atrophy of environmental pollution.

In the short-term, there is a unidirectional causality running from RE to negative E, CO_2 which means that use of renewable energy effect in decreasing energy consumption from fossil and decreasing carbon emissions could promote the consumption of renewable energy. This result is consistent with the fact that Thailand is constantly increasing the use of renewable energy in recent years. In the long-term, renewable energy consumption causes negative CO_2 emissions. This result has been confirmed by the long-term estimates coefficient in ARDL model showing that increasing renewable energy consumption reduces of CO_2 emissions. In the short-term and long-term, there's a unidirectional causality running from OP to RE, negative E, CO_2 at 1% level of significance. This means that OP affects the use of energy, renewable energy and CO_2 in Thailand. The conclusion is consistent with the actual

Table 8: Result from variance decompositions

Variance Decomposition of CO_2						
Period	Standard error	*Y*	*RE*	*E*	CO_2	*OP*
3	0.074458	5.774378	0.065181	5.777781	62.63071	25.75195
7	0.094857	5.062426	0.267859	25.98938	46.63098	22.04935
14	0.139598	3.629858	7.959773	29.58542	30.17206	28.65289

Economic growth (Y), renewable energy consumption (RE), energy consumption (E), Carbon dioxide emissions (CO_2) and OP

situation in Thailand that the *OP* expensive effect to decreasing use of energy and pollution emissions but when *OP*s fluctuate effect to the production of more renewable energy. Figure 2 sums up short-term and long-term Granger causalities between variables.

4.4. Result of forecasting CO_2 emission and economic growth

Table 8 shows the estimations of the variance decomposition for CO_2 emission. These results indicate that form of CO_2 emission initially explains relatively of the future variation in CO_2 emission. In the short run, that is year 3 about 62.63% of CO_2 emission are caused by its own standard innovation shock. CO_2 emission reacts by 5.77%, 0.06% and 25.75% when a one standard deviation change is imputed in economic growth, renewable energy consumption, energy consumption and *OP,* respectively.

In the long term, that is year 14, impulse or innovation or shock to CO_2 emission account for 30.17 percent variation of the fluctuation in CO_2 emission, shock to economic growth, renewable energy consumption, energy consumption, *OP* can cause 3.62%, 7.95%, 29.58% and 28.65% respectively, fluctuation in CO_2 emission. As a result, total fluctuation become 100 percent. However, as the forecast horizon widens the explanatory of CO_2 emission decreases by 30.17% at year 14. The results indicate that a decrease in economic growth in Thailand would lead to a decrease in carbon dioxide emissions as 1% decrease in economic growth would give abate to 5.06% in carbon dioxide in year 7. Results of the impulse response function the negative effects of the various independent variables on the environment of Thailand. The result shows that in the next 14 years, Thailand cannot reduce carbon dioxide emissions to meet the goals of the policy that in 2030 will reduce greenhouse gas emissions by 20-25%.

5. CONCLUSION AND POLICY RECOMMENDATIONS

The main objective of this study is to forecast the CO_2 emission in the future (for the next 14 years) that are sufficient to the goals set by the government or not, using Johansen cointegration and ARDL models for test of long-term cointegration. Granger causality test for direction causality and apply to forecast based on VAR model. We analyzed the causal relationship between CO_2 emissions, renewable energy consumption, energy consumption, *OP*s, and economic growth in Thailand from 1990 to 2016. The results of estimate cointegrating relationships between variable, there exist positive and statistically significant coefficients of CO_2 emission with respect to economic growth, renewable energy consumption, energy consumption, *OP* is short and long-term. The Granger causality testing results show that there exists long-term and strong bi-directional causality relationship between renewable energy consumption and CO_2 emission, *OP* respectively. As well as we found that strong bi-directional causality relationship between *OP* and energy consumption, CO_2 emission respectively. This indicates each consumption of renewable, energy, CO_2 emission, *OP* is highly interrelated to each other.

We have predicted the CO_2 emission based on VAR model within 2017-2030 for next 14 year. The results show CO_2 emission is forecasted to decrease 30.17% in the next year 14. Thailand has implemented an action plan to reduce greenhouse gases by 20-25 percent by 2030, aiming to reduce the use of fossil energy and use more renewable energy to be environmentally friendly. Increase the proportion of renewable energy use and sustainable development to achieve the goal of reducing greenhouse gas and sustainable development in year 2030. The results found that in the next 14 years, carbon dioxide emissions were 30.17%. Which has more carbon dioxide emissions than the target set to reduce carbon dioxide emissions by 20-25% in 2030.

We should encourage more renewable energy production to reduce carbon emissions. Therefore, improving energy efficiency and reduce pollution the long-term environmental would support enhancing the sustainability of further economic growth and target in Thailand. Additionally, this study's it attempts to pave a guideline for future research and in different research contexts. Moreover, it will help national policy planning in the future. However, should be the difference various concepts are to produce a useful result to achieve goals sustainable policy.

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