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Article

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Does the Linkage between GDP, Renewable Energy, and Methane Validate the EKC hypothesis? Evidence from Indonesia

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ABSTRACT

Is it feasible for Indonesia to sustain economic growth while simultaneously reducing methane emissions? This paper aims to unravel the Environmental Kuznets Curve (EKC) hypothesis for methane by integrating the role of renewable energy by employing annual data for the period 1990-2020. Autoregressive distributed lag (ARDL)-bounds testing is applied to estimate the dynamic and cointegration relationships. Also, this paper performs both traditional and breakpoint unit root tests. The EKC hypothesis is confirmed since there is an inverse U-curve nexus between GDP and methane per capita. The income turning point is 14,516 USD per capita. Indonesia's income level is still below its estimated EKC threshold, implying that economic growth forces methane emissions to scale up. A 1% increase in GDP per capita leads to a 4.59% increase in methane per capita. However, renewable energy has a beneficial role in tackling methane emissions. A 1% increase in the share of renewable energy use leads to a 0.36% decrease in methane per capita. It is therefore recommended that to mitigate the damaging impact of economic growth, governments should enhance the share of energy use from renewable sources.

Keywords: Methane, Renewable Energy, EKC, Indonesia, ARDL
JEL Classification: O13, O44, Q43, Q56

1. INTRODUCTION

Promoting the principles of sustainable development is a pivotal action with the aim of declining methane emissions while simultaneously preserving economic growth in an emerging country such as Indonesia. In 2020, Indonesia generated approximately 333,994.9 kilotons (kt) of CO_2 equivalent and it was recorded as the 6th largest methane emitter on a global scale (World Bank, 2023). For note, neglecting the amount of methane emissions implies a process of acquiring social and economic costs in the future and doubles its harmful effect (Azar et al., 2023). Methane is confirmed to have an essential role in maintaining the earth's temperature; however, the uncontrolled level of methane emissions can drive environmental degradation to the environment, humans, and living things (Ari and Şentürk, 2020).

Numerous papers reported that the major sources of anthropogenic methane emissions have been identified and are grouped into three sectors, i.e., agriculture, energy, and waste (Djoukouo, 2021; Yusuf et al., 2012; and Global Methane Initiative, 2010). However, underlying drivers are still under debate, giving room for scholars to take it into account. Following the Stochastic Impacts by Regression on Population Affluence and Technology (STRIPAT) model, the nexus between income (affluence) and emissions should be a positive monotonic (Ji and Chen, 2017). Growth in income per capita implies an increase in purchasing power parity so that people can buy more commodities which in turn drives methane emissions. However, following the EKC framework proposed by Grossman and Krueger (1991), the linkage between economic growth and methane should be non-monotonic; Instead, it forms an inverted U shape.

The presence of the EKC framework will be confirmed if the development in particular regions consists of three stages, i.e., agricultural, industrial, and post-industrial economies, generating scale, decomposition, and technological effects (Balsalobre-Lorente et al., 2017). At the early stage, the amount of pollution tends to increase gradually as a result of early industrialization and natural resource extraction (Kaika and Zervas, 2013). The scale effect yields the upward trend of the Kuznets curve along with the shifting of the economy from conventional to industrial productions. Nonetheless, the industrial phase offers many opportunities to invest in technology-based products and services that can improve production processes through clean resource adoption (Sohag et al., 2019).

Previous studies either using a time-series or panel data by Cho et al. (2014), Yusuf et al. (2020), Djoukouo (2021), and Adeel-Farooq et al. (2021) found that the EKC framework in the case of methane emissions is strongly evident. Those findings pointed out that the nexus between per capita income and methane levels is non-monotonic increasing. Instead, it is argued to follow an inverted U-curve relationship. The difference findings are only in terms of income turning point. However, a study conducted by Ari and Şentürk (2020) noted that the traditional EKC hypothesis in a group of seven (G-7) countries is not verified. Meanwhile, there was an inverted N-curve relationship between income and methane.

Furthermore, previous EKC studies generally modify the empirical model by integrating the role of energy, demography, macroeconomic, institutional, or agricultural factors (Rosado-Anastacio, 2018; Cho et al., 2014; Benavides et al., 2017; Adeel-Farooq et al., 2021; Islam, 2021; Yusuf et al., 2020; Hassan and Nosheen, 2019; Aung et al., 2017). Energy is one of the most common variables included with the aim of investigating emissions under the extended EKC model. It is foremost that energy-based fossil is strongly associated with GHG pollution, largely due to the utilization of non-efficient energy consumption (Azhar Khan et al., 2014; Sarkodie and Strezov, 2019; Cho et al., 2014). As of 2023, global energy sectors released around 135 million tonnes of methane emissions (International Energy Agency, 2023).

In practice, not all types of energy drive emissions. Renewable energy use is one of the alternatives that can be emphasized in order to reduce methane emissions while simultaneously meeting energy demand (Owusu and Asumadu-Sarkodie, 2016). Clean energy drives low pollution so that it positively assists in reducing methane (Güney, 2019). A previous study by Sarkodie and Strezov (2019) found that renewable energy use significantly declines emissions in emerging economies. Thus, clean energy can be utilized as a tool to accelerate the EKC turning point. However, Benavides et al. (2017) showed that electric consumption from renewable energy still positively impacts methane emissions in Austria.

In this paper, we intend to examine empirical evidence for the EKC hypothesis for methane emissions in the context of Indonesia. This paper attempts to respond to the following questions: is it possible to decline the level of methane emissions while simultaneously improving income per capita? For this concern, we establish a quadratic function of an econometric model, under the EKC framework for the nexus between GDP and methane per capita. The next question is, does clean energy have a technological impact? For this case, we modify the EKC model by incorporating renewable energy in the right-hand-side equation along with the additional control variables.

The reasons for and contribution of this paper are: To begin with, although numerous studies have investigated the EKC model in Indonesia (Sugiawan and Managi, 2016; Darwanto et al., 2019; Prastiyo et al., 2020; Massagony and Budiono, 2023; Adebayo, 2021; and Sasana and Aminata, 2019), all of these studies are focused on carbon dioxide emissions. There is no single EKC study in the specific context of Indonesia that utilizes methane as a proxy for environmental degradation. Hence, this paper attempts to bridge the gap by examining the short- and long-run dynamic nexus between GDP and methane per capita using annual series over the period 1990-2019. Moreover, we modify the EKC model by incorporating the role of renewable energy use. It is pivotal to unravel whether the beneficial role offered by clean energy is evident or in doubt.

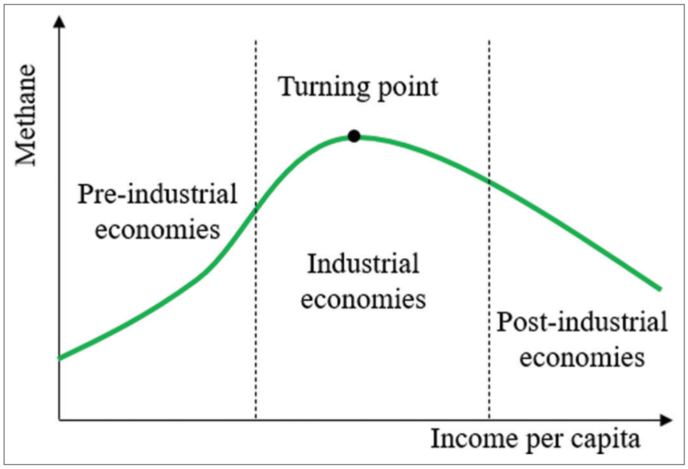
This paper employs autoregressive distributed lag (ARDL)-bounds testing given that it has some advantages for time series analysis. The ARDL produces a dynamic relationship and cointegration equation, and it is unbiased for a small sample series. This paper also considers pieces of information from unit root tests in order to ensure that the estimator is proper for application. For the robustness check, the Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) are performed. The empirical results confirm the existence of the EKC hypothesis with an income turning point of 15,413 USD. Furthermore, renewable energy use has a negative impact on methane emissions. Thus, clean energy has a pivotal position in supporting sustainable development and accelerating the EKC turning point.

2. LITERATURE REVIEW

The inverse U-curve for the nexus between economic growth and pollution (incl. methane) is supposed to be present as suggested by the EKC hypothesis. Environmental quality worsens during the early stage of economic development; however, after achieving a certain threshold, emissions depreciate as the economy continues to advance, and the trade-off is eliminated gradually (Stern, 2018; Shahzad and Aruga, 2023). In other words, it is assumed that the development-emissions trade-off is only evident in low or middle-income countries. Figure 1 depicts stages of economic development, i.e., pre-industrial, industrial, and post-industrial economies associated with scale, decomposition, and technology impacts, and their relationships toward methane (Stern, 2004).

To this day, numerous studies confirmed the presence of the EKC model in various types of environmental degradation indicators; for instance, EKC-carbon dioxide (Prastiyo et al., 2020; Danish et al., 2021; Koshta et al., 2021; Ntim-Amo et al., 2022; Massagony and Budiono, 2023), EKC-ecological footprint (Ulucak and Bilgili, 2018; Ansari, 2022; Fatima et al., 2021; Ozturk et al., 2023); EKC-deforestation (Waluyo and Terawaki, 2016; Ajanaku and Collins, 2021; Destiartono and Ekananda, 2023 Caravaggio, 2020 and Tsiantikoudis et al., 2019); and EKC-nitrous oxide (Islam, 2021

Figure 1: Illustrative of the EKC for methane



Source: Adopted from Kaika and Zervas, 2013

and Cho et al., 2014). In accordance with methane emissions, the Kuznets' turning point can be smoothed by advancing the role of renewable energy, crop diversification, and technological innovation (Islam, 2021).

Empirical studies on the EKC hypothesis for methane have been growing. For instance, Yusuf et al. (2020) tested the nexus between GDP per capita and GHG components using balanced panel data from African Organization of Petroleum Exporting Countries (OPEC) for the period 1970-2016 by employing the Pooled Mean Group (PMG) and incorporating the role of energy use. Surprisingly, the results showed that the EKC model for carbon dioxide and nitrous oxide is not confirmed; instead, the EKC framework was only verified for methane. Furthermore, energy consumption was not the key driver of methane emissions. In another paper, Cho et al. (2014) examined the EKC model for Organizations for Economic Cooperation and Development (OECD) members from 1970 to 2000 by utilizing FMOLS and confirmed that the EKC model holds for all the GHG components. In addition, there was a significant impact of energy consumption on GHG emissions.

More recently, Adeel-Farooq et al. (2021) tested the presence of the EKC model for methane in selected Southeast Asia countries, including Indonesia, by employing PMG and incorporating the role of energy use and trade openness. The findings denoted that the inverse U-curve relationship is validated. Furthermore, energy usage was positively and significantly associated with methane. Using annual data from 1975 to 2014 in Pakistan, a positive nexus between energy consumption and methane was also reported by Tanveer et al. (2022). Additionally, energy consumption has a positive impact on methane.

Moving to time-series studies, Aung et al. (2017) examined the EKC model for three types of emissions in Myanmar over the period of 1970 to 2014 by adopting the ARDL-bounds testing. The results denoted that the inverse U-shaped relationship is confirmed for methane and nitrous oxide while it does not hold for carbon dioxide. Additionally, trade intensity and financial openness had a negative impact on all GHG components, indicating that they provide a technological role in declining pollution. In a similar vein, Rosado-Anastacio (2018) estimated the nexus between income and methane in Argentina by integrating the role of electricity power consumption and agricultural land use. The EKC hypothesis was confirmed with an income turning point of 6,994 USD.

Empirically, the presence of the EKC model does not consistently hold. For instance, Ari and Şentürk (2020) found that the EKC hypothesis is not evident for the linkage between income and methane from solid waste. In a similar context, Islam (2021) tested the inverse U-curve relationship for the degradation indicators of nitrous dioxide and methane in Bangladesh from 1990 to 2010. The results denoted that the EKC model is not observed for methane; instead, there is a bell-shaped relationship. Al-mulali et al. (2015) unraveled that the EKC model is not validated for low-and lower-middle-income groups. In addition, Dogan and Inglesi-Lotz (2020) found that the EKC hypothesis is not evident in European countries. Furthermore, Sasana and Aminata (2019) noted that the EKC model for emissions in the case of Indonesia is not confirmed. To sum up, there are various possible findings in the analysis of the EKC hypothesis, depending on the types of emissions, number of observations, additional variables, and econometrics methods applied.

3. METHODS

3.1. Model Specification

This research attempts to unravel the EKC model for methane emissions in Indonesia and incorporates the role of renewable energy use using a time-series approach. Following previous studies by Adeel-Farooq et al. (2021), Yusuf et al. (2020), and Aung et al. (2017), a model can be specified as Eq. (1):

$$\ln CH4p_t = \gamma_0 + \gamma_1 \ln GDPp_t + \gamma_2 GDPp_t^2 + \gamma_3 \ln REU_t + \gamma_4 \ln TOP_t + \gamma_5 \ln POPD_t + \varepsilon_t \quad (1)$$

where CH4p stands for methane emissions per capita; GDPp is Gross Domestic Product per capita; $GDPp^2$ is GDP per capita squared; REU is renewable energy use; TOP is trade openness; POPD is population density; γ_0 is the constant term; $\gamma_1 \ldots \gamma_5$ are coefficients for each variable to be estimated, respectively; ε_t is the error term and it is expected to be independent and identically distributed, i.e., $\mu(I, \sigma^2)$; the subscript t refers to year t; ln the logarithm operator. Following the EKC hypothesis, it is supposed that $\gamma_1>0$ while $\gamma_2<0$, indicating an inverse U-curve relationship. As for renewable energy use, given that higher clean energy consumption leads to a decrease in the share of fossil energy use; therefore, it is predicted that $\gamma_3<0$. Outside the EKC framework, functional forms in terms of the linkage between income and methane are explained in Table 1.

3.2. Data and Variable

This EKC paper utilizes annual data on methane and its determinants, consisting of economic, demography, and energy factors, in the context of Indonesia. The dataset used was collected from the World Development Indicators (WDI) database, spanning from 1990 to 2020. The length of the series used relies on the presence of methane data. Thus, the number of observations for each variable is 31 units.

Methane is the dependent variable in this paper, and it is measured in tonnes of CO_2 equivalent per capita. The independent variable of GDP per capita (constant 2015 USD) is utilized as a proxy for economic growth. Further, GDP per capita squared is computed in order to establish the EKC model. Renewable energy use was measured as a percentage of total final energy consumption. In addition, this paper includes additional variables namely trade openness and population density in order to avoid omitted variables bias. Population density is the number of inhabitants per unit (square kilometer-km^2) of land area whilst trade openness is defined as the share of total trade (the sum of exports plus imports) over GDP. Table 2 shows a summary of variables.

3.3. The Unit Root Test

Checking the presence of unit roots is necessary prior to applying the ARDL method. Therefore, this study employs the augmented Dickey and Fuller (1981) test in order to check the presence of unit roots for each variable. The ADF method has the power to capture any serial correlation by adding the lagged difference form of the variable (Δy_{i-1}) on the right-hand side equation (RSH) (Tanaya and Suyanto, 2022). Models for the ADF test can be specified as Eq. (2) and Eq. (3).

A model with constant and no trend:

$$\Delta Y_t = \theta_0 + \theta_i Y_{i-1} + \sum_i^m \phi" \, Y_{i-1} + e_t \quad (2)$$

A model with constant and trend:

$$\Delta Y_t = \theta_0 + \theta_1 Y_{i-1} + \theta_2 t + \sum_i^m \phi" \, Y_{i-1} + e_t \quad (3)$$

where y is a time-series variable; θ_0 is the constant term; θ_1 = 1-p. y is stationary if |p|<1, and vice versa. The null hypothesis of non-stationary data is proposed. All the variables are assumed to be stationary at the level or first difference. The ARDL necessitates variables used to be either integrated into I(0), one, I(1), or mixed order of integration. This method is no longer appropriate for use if any variable is found to be integrated into I(2). For the robustness check, we also perform the DF-Generalized Least Square (DF-GLS) and Zivot-Andrew (ZA) tests. The advantage of the DF-GLS test is that it has the power in the case of small-sample size (Enders and Liu, 2014). The DF-GLS test consists of two steps namely the de-trending using the GLS technique and the ADF procedure (Tanaya and Suyanto, 2022). The ZA test is used to check the presence of unit roots with potential structural breaks in the series.

Table 1: Possible functional form for GDP-methane nexus

Functional form	Implication
γ_1=γ_2=0	No association between GDPp and CH4p
γ_1>0 and γ_2=0	Linear increasing association between GDPp and CH4p
γ_1<0 and γ_2=0	Linear decreasing association between GDPp and CH4p
γ_1<0 and γ_2>0	U-shaped association between GDPp and CH4p

Table 2: Summary of variables

	Notation	Unit of measurement	Exp.
Methane per capita	CH4p	tonnes of CO_2 equivalent	
GDP per capita	GDPp	constant 2015 US$	+
GDP per capita square	$GDPp^2$	constant 2015 US$	-
Renewable energy use	REU	% of final total energy consumption	-
Trade openness	TOP	the sum of export and import over GDP	+
Population density	POPD	the number of inhabitants per km^2	+

3.4. ARDL-bounds Testing

This paper applies the ARDL procedure developed by Pesaran et al. (2001) given that the method offers several advantages as follows: The ARDL was chosen instead of, for instance, the Engle-Granger and Johansen-Juselius tests, because it can be applied to check the cointegration relationship even if variables are I(0), I(1), or mixed order integration (Hadi and Chung, 2022). The ARDL-bounds testing only utilizes a single reduced form of a model rather than system equations (Pradhan et al., 2013). Also, this method simultaneously provides the dynamic relationship of short- and long-run coefficients. Furthermore, the ARDL is proper to be applied for a small sample, for instance, n ≤ 30 observation, and it provides unbiased estimates (Tinoco-Zermeño et al., 2014). Hence, this is more proper in our case where the number of series is 30 observations. Previous small sample studies also applied the ARDL method (Takentsi et al., 2022; Hadi and Chung, 2022; Deka et al., 2023; and Raihan et al., 2022). Last, of all, the ARDL method eliminates the problems of endogeneity and serial correlation by plugging sufficient lags for both the dependent and independent variables (Latif et al., 2015).

The ARDL method consists of two critical steps. The first step is that it is necessary to identify the maximum lag length since the long-run estimates are sensitive to lag length. For this purpose, we adopted the Akaike Information Criterion (AIC) technique since it has the power to balance the trade-off between model complexity and goodness of fit (Kubara and Kopczewska, 2024). The second step is to check the presence of a cointegration relationship between methane and its determinants. For this case, we utilized the joint -statistics in the bound test. Following Pesaran et al. (2001), Eq. (1) can be written as the ARDL () model as Eq. (4)

$$\begin{aligned}\Delta \ln CH4p_t = {} & \delta_0 + \sum_{i=1}^{B} \delta_1 \Delta \ln CH4p_{t-i} + \sum_{i=0}^{B} \delta_2 \Delta \ln GDPp_{t-1} + \\ & \sum_{i=0}^{B} \delta_3 \Delta \ln GDPp_{t-1}^2 + \sum_{i=0}^{B} \delta_4 \Delta \ln REU_{t-1} + \\ & \sum_{i=0}^{B} \delta_5 \Delta \ln TOP_{t-1} + \sum_{i=0}^{B} \delta_6 \Delta \ln POPD_{t-1} + \beta_1 \ln CH4p_{t-1} + \\ & \beta_2 \ln GDPp_{t-1} + \beta_3 \ln GDPp_{t-1}^2 + \beta_4 \ln REU_{t-1} \\ & + \beta_5 \ln TOP_{t-1} + \beta_6 \ln POPD_{t-1} + \mu_t \end{aligned} \quad (4)$$

Eq. (4) represents the unrestricted ARDL model. Δ is the first difference notation; B denotes the lag order for each variable; $\delta_1 \ldots \delta_3$ show the dynamic short-run parameters; $\beta_1 \ldots \beta_6$ signify the dynamic long-run parameters; δ_0 is the constant term. μ_t signifies the error term. ln is the natural logarithm operator; The existence of the cointegration relationship is checked by comparing the calculated F-statistic with respect to critical values of lower- and upper-bounds. The null hypothesis of no levels linkage and the alternative hypotheses can be specified as Eqs. (5) and (6):

$$H_0: \beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=0 \tag{5}$$

$$H_0: \beta_1\neq\beta_2\neq\beta_3\neq\beta_4\neq\beta_5\neq\beta_6\neq 0 \tag{6}$$

The null hypothesis should be rejected if the calculated F-statistic is higher than the upper critical bound either at a 10, 5, or 1% significance level. There is an inconclusive result if the joint calculated F-statistic ranges between upper- and lower-critical bounds. The bound test can adopt asymptotic samples ($n \geq 1000$) or finite samples ($n \leq 30$) assumptions as suggested by Narayan (2005). Once a cointegration nexus among variables is established, the next procedure is to examine the long-run equilibrium equation.

The short-run dynamics of the ARDL coefficients can be specified by integrating the error correction model (ECM) as Eq. (7)

$$\begin{aligned}\Delta \ln CH4p_t = \delta_0 &+ \sum_{i=1}^{B}\delta_i \Delta \ln CH4p_{t-i} + \sum_{i=0}^{B}\delta_i \Delta \ln GDPp_{t-i} \\ &+ \sum_{i=1}^{B}\delta_i \Delta \ln GDPp^2_{t-i} + \sum_{i=1}^{B}\delta_i \Delta \ln REU_{t-i} + \\ &\sum_{i=1}^{B}\delta_i \Delta \ln TOP_{t-i} + \sum_{i=1}^{B}\delta_i \Delta \ln POPD_{t-i} \\ &+ \varpi \mathrm{ECM}_{t-1} + u_t\end{aligned} \tag{7}$$

where the ECM parameter ϖ signifies the speed of adjustment from short-run disequilibrium. It is supposed to have a negative sign and varies from −1 to 0. For estimating the significance level relationship between methane per capita and the lagged level of the variables, the ARDL applies both F and t-statistics. Critical values depend on whether all variables are integrated into $I(0)$, $I(1)$, or fractionally integrated which can be accessed in Pesaran et al. (2001).

Following Noorunnahar et al. (2023), this paper also performs several diagnostic and stability tests in order to ensure that the estimated model fulfills regression assumptions and the stability parameters. Last, of all, cointegrated regressions, i.e., FMOLS and DOLS methods, are utilized for robustness checks.

4. RESULTS AND DISCUSSION

This section displays and discusses the empirical findings from the methods used. To begin with, we present jointly the standard unit root test, i.e., ADF and DF-GLS, in Table 3. The results are similar in that all the variables used are not stationary at level. Nonetheless, they switch to become stationary after taking the first difference. Thus, they are integrated of order one, $I(1)$. Since none of the series are $I(2)$, the ARDL is proper to be applied.

In order to check the presence of a unit root with a structural break in the data, the ZA test was employed. The findings presented in Table 4 denote that all series checked, that is, CH4p, GDPp, REU, POPD, and TOP, are stationary at their level. Thus, they are $I(0)$. Even if these findings are distinct from the standard unit root test of ADF, DF-GLS, and PP, these results clearly confirm that the ARDL method is a fit method to be applied. The year breakpoints for CH4p, GDPp, REU, POPD, and TOP are 2001, 1998, 2002, 2000, and 1998, respectively.

The other necessary preliminary step in time-series modeling, including ARDL, is lag selection. The ARDL coefficients are sensitive to the lag length. Therefore, this study uses the Akaike Information Criteria (AIC) method to select the maximum lag length as well as the ARDL lag structure. As presented in Table 5, order 2 is the optimal lag length of vector autoregressive (VAR). This finding aligns with Narayan (2005) who suggested the optimal lag of 2 in the case of yearly data. Additionally, Figure 2 denotes that the ARDL (2,0,2,1,1,0) is the most proper model.

Following the model selection, the bound test produces a cointegration check in Table 6. The findings show that the H_0: No levels relationship between methane per capita and its set of determinants cannot be accepted given that the calculated F-statistic (9.829) exceeds the upper critical bound (4.21) at a 1% level. Thus, the presence of a cointegration nexus is confirmed. This finding implies that the long-run relationship

Table 3: Conventional unit root test results

Tests	Level		1st difference	
	Statistics	p-value (lag)	Statistics	p-value (lag)
ADF test				
CH4p	−0.409	0.895 (1)	−3.182**	0.032 (0)
GDPp	0.919	0.994 (0)	−3.409**	0.019 (0)
REU	−0.504	0.877 (0)	−5.668***	0.000 (0)
POPD	−0.406	0.896 (0)	−5.387***	0.000 (0)
TOP	−2.391	0.153 (1)	−5.369***	0.000 (7)
DF-GLS test				
CH4p	−0.234	0.817 (1)	−3.056***	0.005 (0)
GDPp	−0.159	0.875 (1)	−3.450***	0.002 (0)
REU	0.803	0.429 (0)	−5.281***	0.000 (0)
POPD	0.295	0.770 (2)	−5.427***	0.000 (0)
TOP	−2.457	0.020 (1)	−5.809***	0.000 (7)

The number of lag lengths for each variable in ADF and DF-GLS tests was selected by the AIC technique and it set 7 for the maximum lags

Table 4: Break-point unit root test results.

Variables	Statistics	p-value (lag)	Breakpoint
CH4p	−3.474	0.001 (1)	2001
GDPp	−7.535	0.000 (0)	1998
REU	−3.482	0.049 (0)	2002
POPD	−9.736	0.000 (0)	2000
TOP	−8.467	0.000 (0)	1998

The maximum lag length was set to be 4

Table 5: Optimal lag test results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	251.0811	NA	1.84E-15	−16.90214	−16.61925	−16.81354
1	464.7146	324.1336	9.32E-21	−29.15273	−27.17251*	−28.53255
2	517.3799	58.11344*	4.20e-21*	−30.30206*	−26.62451	−29.15030*

*Represents the optimal lag order

Table 6: Cointegration test results

Tests	Value	Sign.	Lower bound	Upper bound
F-statistic	9.871	10%	1.81	2.93
k	5	5%	2.14	3.34
Actual sample size	29	2.5%	2.44	3.71
		1%	2.82	4.21

Signifies the number of regressors

Table 7: Long-run estimates of the ARDL

Variables	Coeff.	SE	t-stat.	p-value
Ln (GDPp)	4.59161***	0.65382	7.02	0.000
Ln ($GDPp^2$)	−0.23957***	0.03260	−7.35	0.000
Ln (REU)	−0.36086***	0.10839	−3.33	0.004
Ln (POPD)	−4.15519***	0.68118	−6.1	0.000
Ln (TOP)	0.12298**	0.05303	2.32	0.032

SE stands for standard error. *P<10%; **P<5%; ***P<1%

Table 8: The EKC turning point

$T^* = \exp\left(-\frac{\beta_1}{(2\beta_2)}\right)$	$T^* = \exp\left(-\frac{4.59161}{2\times(-0.23957)}\right)$	T*=14, 516.19 USD

β_1 and β_2 are long-run coefficients of ARDL. *T** stands for the EKC turning point

among the variables used is not spurious and there is no spurious information.

Given that a cointegration relationship is evident, there is no spurious regression and the long-run estimates of the ARDL are meaningful to be interpreted. The results are recorded in Table 7. In the long run, GDPp has a positive impact on methane at a 1% significance level. An increase of 1% in income per capita has a scale effect to cause an increase of 4.59% in methane per capita. However, $GDPp^2$ has a negative impact on methane at a 10% level of significance. This indicates that the effect of income on methane emissions is non-monotonic increasing. Instead, there is a non-linear relationship between economic development and methane, following an inverse U curve. Therefore, the EKC hypothesis for methane emissions in the context of Indonesia is validated. Importantly, this finding is consistent with previous studies by Adeel-Farooq et al. (2021), Djoukouo (2021), Aung et al. (2017), and Benavides et al. (2017).

Following the estimated parameters of β_1 and β_2, the income turning point is 14,516 USD (Table 8). This monetary value is within the range of high-income status, and it is higher than the calculated turning point in central African countries (12.860 USD) reported by Djoukouo (2021) and in Argentina (6,990 USD) declared by Rosado-Anastacio (2018). With a 2019 GDP per capita of 4,100 USD (constant 2015 USD), Indonesia has not yet surpassed its EKC turning point. The country is still in the early stage of development. As a result, it is acceptable that total output growth is more prioritized instead of meeting the principles of sustainable development such as reducing methane emissions.

As expected, renewable energy use has a negative impact on methane per capita at a 1% significance level. Following the long run ARDL estimates, an increase in 1% share of renewable energy use with respect to total energy consumption drives a decline of 0.36% in methane per capita. This finding indicates that clean energy has a technological effect, and it can be utilized to accelerate the EKC turning point. The more green energy is used and the less share of fossil fuel energy is consumed, in turn, reduces methane levels. In other words, enhancing investment in green energy sectors is pivotal with the aim of declining methane emissions and promoting better air quality.

Following the empirical results, Renewable Energy Transition (RET) is one of the most remarkable policies that need to be addressed to tackle methane pollution. Consuming clean energy has a serviceable role in reducing industrial-based emission levels (Sarkodie and Strezov, 2019). The more clean energy is consumed, the less methane drivers are activated, and vice versa. The good tiding is that numerous eco-friendly energy potentials are embodied in Indonesia. Nyasha and Odhiambo (2015) noted that Indonesia has a total capacity of 400 gigawatts of renewable energy. Several feasible green energies that can be developed are geothermal, hydropower, wind power, biomass, solar photovoltaic, and ocean energy (Langer et al., 2021).

Further, we discuss the empirical findings of the additional control variables which include demography and trade aspects. Surprisingly, the impact of population density on methane is negative and significant at a 1% level. An increase of 1% in population density is associated with a decline of 4.15% in methane level. This result implies that Indonesia benefits from economies of scale in the case of methane emission with respect to population size. This finding aligns with Onanuga (2017) and Danish et al. (2021) that population density assists in forming the EKC model. Along with the growth in population density, its scale effect on methane declined gradually.

The linkage between trade openness and methane was positive at a 1% significance level as expected. Other determinants held constant; a 1% advance in trade openness generates methane emissions by around 0.12%. This indicates that global trade activities such as exports and imports are observed as drivers (underlying cause) of methane emissions. This finding is consistent with Benavides et al. (2017) for Austria and Islam (2021) for Bangladesh. Consequently, it is necessary for Indonesia to revise current trade regulations and adjust them to the principles of sustainability.

Moving to the short-run estimation, the outcomes are presented in Table 9. The estimated parameter of ECM is negative and significant at a 1% level with a speed adjustment of −0.35321. This indicates that any shock that drives disequilibrium in the short run will be adjusted by nearly 35.32% within a year. In addition, The EKC model for methane emissions is strongly validated since the sign of ΔGDPp (ΔGDPp^2) is positive (negative) and significant at a 1% level. Furthermore, the impact of renewable energy use on methane is negative and significant at a 1% level. This implies that the technological effect of consuming green energy is not only beneficial in the long run but also evident in the short run. Thus, it is pivotal to invest in clean energy usage for the purpose of reducing methane gasses.

The ARDL estimates results are no longer insightful to be interpreted if the estimated model fails to satisfy its assumptions. The diagnostics tests of Jarque-Berra, Brauch-Pagan LM, Glejser, and RAMSEY reset in Table 10 signify results as follows; the error terms are normally distributed and have no serial correlation; the error variance is homoscedastic along the period of investigation; and there is no misspecification related to the model. Subsequently, the stability tests via the plots of CUSUM and CUSUMSQ recursive residuals are presented in Figures 3 and 4, respectively. Those tests are based on ECM residuals. The null hypothesis of consistency parameters is accepted since the blue plots fluctuate inside upper and critical values at a 5% confidence level (red plots). Thus, the long-run estimates of the EKC model for methane are stable during the analysis period.

Following Guan et al. (2020), this empirical study applied cointegrated regressions, i.e., FMOLS and DOLS as developed by Phillips and Hansen (1990) and Stock and Watson (1993), for the robustness check of ARDL coefficients. The notable advantages of these methods are that they accommodate serial correlation and endogeneity problems as well as a potential bias caused by a small sample size (Cui et al., 2022; Rosado-Anastacio, 2018). Also, these techniques are feasible to be employed either in non-stationary series. The empirical results in Table 11 point out that the estimated parameters derived from FMOLS and DOLS are identical to the results of ARDL long-run coefficients. Thus, the EKC hypothesis for methane emissions and the negative impact of renewable energy use on methane in the case of Indonesia are robust.

Table 9: Short-run estimates

Tests	Coeff.	SE	t-stat.	p-value
ECM_{t-1}	−0.35321***	0.08365	−4.22	0.001
ΔLn (CH4p)	−0.45372**	0.17571	−2.58	0.019
ΔLn (GDPp)	1.37766***	0.29767	4.63	0.000
	−0.35381***	0.07095	−4.99	0.000
ΔLn (GDPp^2)	−0.08462***	0.01900	−4.45	0.000
ΔLn (REU)	−0.21118***	0.04940	−4.27	0.000
ΔLn (POPD)	−1.91086***	0.35806	−5.34	0.000
ΔLn (TOP)	0.04344**	0.01900	2.29	0.035

*P<10%; **P<5%; ***P<1%

Table 10: Diagnostic test results

Tests	Hypothesis	F-stat.	P-value
Breusch-Pagan LM	There is no serial correlation	2.013	0.168
Glejser	There is no heteroscedasticity	1.070	0.436
Jarque-Berra	Residuals are normally distributed		0.161
Ramsey-RESET	There is no misspecification in the model	0.178	0.839

Figure 2: AIC (top 20 models)

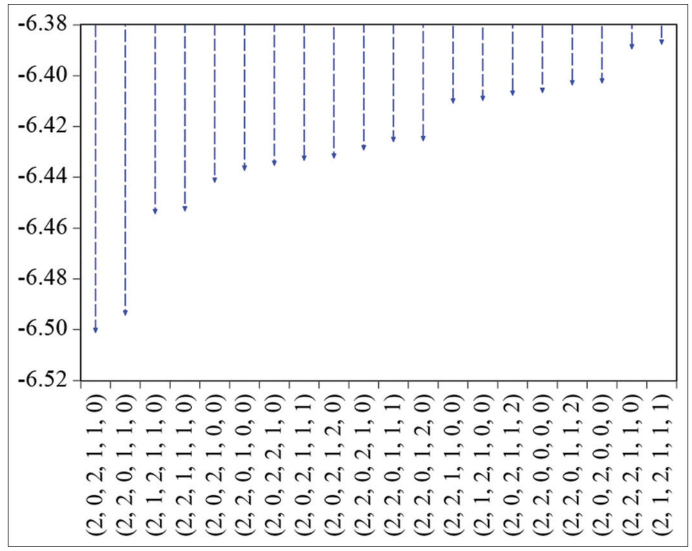


Figure 3: CUSUM test

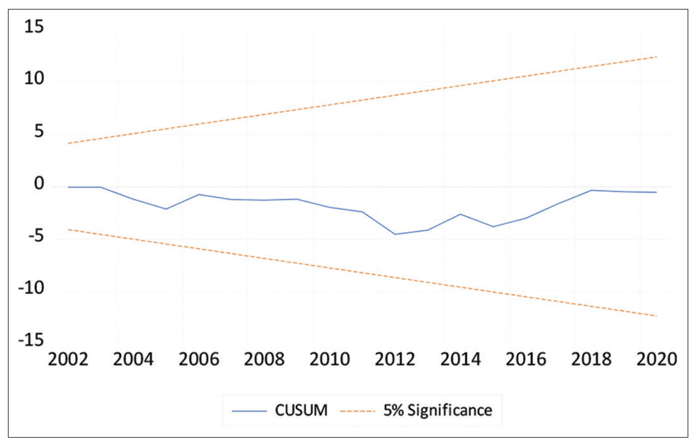


Figure 4: CUSUMSQ test

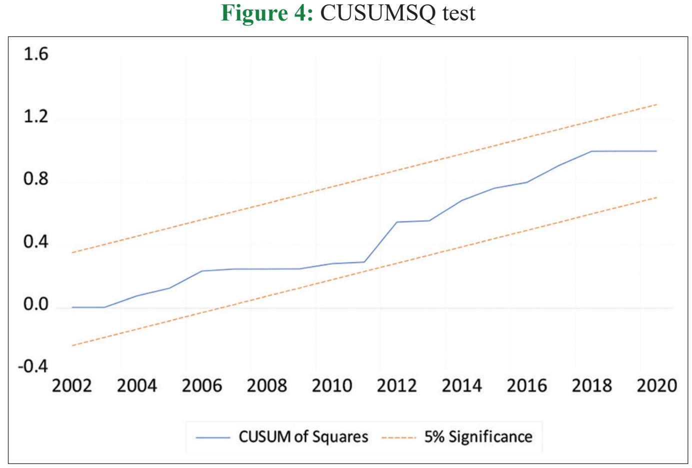


Table 11: Robustness checks

Variables	FMOLS		DOLS	
	Coeff.	t-stat.	Coeff.	t-stat.
Ln (GDPp)	4.3667* (2.3698)	1.843	9.6900** (2.84688)	3.404
Ln ($GDPp^2$)	−0.2813* (0.1536)	−1.832	−0.5983** (0.19052)	−3.140
Ln (REU)	−0.4694*** (0.14117)	−3.325	−0.7115*** (0.13982)	−5.088
Ln (POPD)	−1.9744*** (0.3776)	−5.229	−3.4333*** (0.32780)	−10.474
Ln (TOP)	0.13543** (0.0516)	2.627	0.1927 (0.14437)	1.335
Constant	−5.9165 (7.62462)	−0.776	−20.3141** (8.68866)	−2.338
R^2	0.92719		0.99725	
Adj R^2	0.91202		0.98940	

*P<10%; **P<5%; ***P<1%. Standard errors are in the parentheses

5. CONCLUSIONS

Achieving eco-sustainability indicators while simultaneously fostering economic development is a pivotal scheme to be adopted by emerging economies such as Indonesia. For the last three decades, the country has been recorded as one of the most prominent methane emitters on the global scale. By adopting the EKC framework, this paper intends to unravel the linkage between GDP per capita and methane by integrating the role of renewable energy use. This paper relies on yearly data over the period 1990-2020, retrieved from the WDI database. Traditional and breakpoint stationary tests are applied to identify the order of integration and the ARDL-bounds testing is applied to estimate dynamics and cointegration relationships.

The results validate the EKC hypothesis, i.e., an inverse U-curve relationship, for methane in the context of Indonesia. The estimated income turning point is 14,516 USD per capita. Indonesia's income level has not passed its turning point, indicating that current economic activities significantly contribute to methane emissions. Specifically, a 1% increase in GDP per capita has a scale effect to generate an increase of 4.59% in methane per capita. However, there is a technological impact of renewable energy on methane. A 1% increase in the share of renewable energy use leads to a 0.36% decrease in methane per capita. It is pivotal for Indonesia to constantly track and estimate the nexus between GDP and methane emissions with the aim of navigating potential damaging impacts caused by economic growth. Furthermore, it is recommended to foster energy transition since the beneficial role offered by renewable energy is confirmed. For the record, these empirical findings are robust with the alternative methods of DOLS and FMOLS.

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