



Research article

The effect of income inequality on carbon dioxide emissions: A case study of Indonesia

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ABSTRACT

The main objective of this study was to investigate the effect of income inequality on carbon dioxide (CO₂) emissions in Indonesia from 1975 to 2017 using the Autoregressive Distributed Lag (ARDL) technique. Per capita GDP, urbanization, and dependency ratio are included as additional variables in the analytical models. The statistical estimation and tests showed that income inequality has a negative effect on CO₂ emissions but the relationship pattern depends on the level of per capita GDP. An inverted U-shaped relationship was also observed between per capita GDP and CO₂ emissions. This indicates the existence of an Environmental Kuznets Curve (EKC) in Indonesia. Moreover, both urbanization and the dependency ratio have a negative effect on CO₂ emissions. This study suggests that income equality should be added to the policies formulated to aid economic growth in order to ensure that there is a reduction in CO₂ emissions.

1. Introduction

The United Nations Statistics Division - UNSD (2016) grouped Indonesia into the top 10 emitters of carbon dioxide (CO₂) alongside developed countries such as China, the United States, Russia, Japan and Germany in 2015. Indonesia is the biggest contributor of the CO₂ emissions in the Southeast Asia region with a yearly increase in the amount produced. Climate Transparency (2018) reported an average annual increase of 18 percent in Indonesia between 2012 and 2017. If this trend is allowed to continue, 2,000 out of the 17,000 islands in the country are feared to disappear due to global warming and climate change triggered by the increasing concentration of CO₂ emissions in the atmosphere (Lean and Smyth, 2010). Furthermore, the Intergovernmental Panel on Climate Change - the IPCC (2014) - emphasized the wide range of impacts due to global climate change on both nature and human life, especially in relation to food production, health, and the economy.

The IPCC (2014) argued that the increase in CO₂ emissions is driven by anthropogenic factors, especially by people in the economic field. Several empirical studies have been conducted to determine the appropriate anthropogenic models to identify the main driving forces behind the CO₂ emissions and environmental degradation in general. Ehrlich and Holdren (1970) introduced the IPAT (Impact-Population-Affluence-Technology) model to explain the effect of the interaction

between population, affluence, and technology on the environmental impact. Grossman and Krueger (1991) reproduced the Kuznets Curve to define the specific pattern of affluence measured by the inverted-U shaped relationship between income and environmental degradation. This curve later became known as the Environmental Kuznets Curve - EKC (Chow and Li, 2014; Dinda, 2004). Meanwhile, Dietz and Jorgenson (2015) developed a structural human ecology approach based on interactions between humans and the environment in order to explore the effect of demographic variables such as population, urbanization, dependency ratio and household size on environmental degradation (Li and Zhou, 2019; McGee and Greiner, 2018). Among these variables, urbanization and the dependency ratio have been widely recognized as the factors affecting CO₂ emissions (Hamza and Gilroy, 2011; Li and Zhou, 2019; McGee and Greiner, 2018; O'Neil et al., 2012).

In recent years, income inequality has been assumed to influence CO₂ emissions and this has become a major issue in academic circles and policy considerations (Baloch et al., 2018). As previously stated, several empirical studies have been conducted in many countries to determine the relationship between income inequality and environmental degradation. No definite conclusion has been produced despite the fact that different concepts, theories, and hypotheses were used. Galor and Moav (2004), for example, found there to be no direct relationship between high-income inequality and sustainable economic development.

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Moreover, income inequality was reported to have a positive influence on environmental degradation by Baek and Gweisah (2013), Boyce (1994), Hao et al. (2016) and Magnani (2000). However, other studies argued that the influence between these variables is negative (Ali et al., 2016; Coondoo and Dinda, 2008; Heerink et al., 2001; Ravallion et al., 2000) or that they exhibit a 'trade-off' relationship.

The main objective of this study was to investigate the effect of income inequality on CO₂ emissions in Indonesia. This is considered to be important considering the increase in CO₂ emissions and income inequality as observed in the rising increment in the Gini coefficient from 0.30 in 2000 to 0.41 in 2014. This is the highest ever recorded in the country (Badan Pusat Statistik - BPS, 2015). In the same period, 63 percent of countries around the world experienced a reduction in income inequality. However, Indonesia instead recorded an approximately 30 percent increase. This was the highest compared to all other developing countries in the world (Yusuf, 2018).

The framework with four proposed empirical models employed by McGee and Greiner (2018) was adopted to examine the effect of per capita GDP, urbanization, and dependency ratio on CO₂ emissions using the IPAT Model. It was also used to investigate the relationship between per capita GDP and CO₂ emissions using the EKC hypothesis framework and to evaluate the effect of income inequality on CO₂ emissions. Moreover, it was also applied to verify the effect of income inequality and its interaction with per capita GDP on CO₂ emissions. This study is expected to connect the three pillars of sustainable development including the economic, social, and environmental aspects in Indonesia and to also fill in the research gap observed in the relationship between income inequality and CO₂ emissions.

2. Theoretical background

2.1. Impact-Population-Affluence-Technology (IPAT) model

The IPAT model was first introduced by Ehrlich and Holdren (1970) to identify the anthropogenic drivers of environmental impacts. To overcome the weaknesses of the original version built by identity equations, Dietz and Rosa (1994) modified the model into a stochastic form known as the STIRPAT (Stochastic Estimation of Impact by Regression on Population, Affluence, and Technology) in order to allow for random errors in the parameter estimation. This was calculated using the following relationship.

$$I_i = aP_i^b A_i^c T_i^d e \quad (1)$$

Where I stands for impact measured by several environmental indicators, P is the population size, A represents affluence or economic activity usually expressed in terms of per capita and T is technology, evaluated as the environmental impact per unit of economic activity.

Other authors have expanded the demographic aspects of the original IPAT model by replacing population with several other indicators. For example, an increase in urbanization has been widely accepted as a driver of CO₂ emissions, particularly in developing countries (Al-Mulali et al., 2012; Martinez-Zarzoso and Maruotti, 2011; Zhu et al., 2012). Urbanization is defined as the increase in the population of people living in urban areas causing increased economic activity, energy consumption, and emissions. However, the accumulation of urban population may lead to economies of scale in the use of public goods, lifestyle changes, and technological diffusion to reduce the level of energy consumption and emissions (Hao et al., 2016; Martinez-Zarzoso and Maruotti, 2011). It is also important to note that there is no general conclusion on the effect of urbanization on CO₂ emissions according to previous empirical studies. For example, Hao et al. (2016) found a positive effect of inequality on CO₂ emission while Chikaraishi et al. (2015) and Poumanyong and

Kaneko (2010) reported a negative effect. Moreover, Martinez-Zarzoso and Maruotti (2011) suggested that the relationship between urbanization and CO₂ emissions in developing countries is an inverted-U shape. This means that there is an increase in the quantity of CO₂ emitted through urbanization in the initial stage but a reduction recorded after a given turning point.

Dependency ratio is another demographic factor believed to have an effect on CO₂ emissions as indicated by the consumption of more energy and resources by the working-age population. This age group is also associated with a higher labor participation rate and this further leads to more production and consumption (Dietz and Rosa, 1994; Liddle, 2011; Lugauer et al., 2014). It was also reported that the increase in the elderly population tends to reduce the level of CO₂ emissions due to the changes in their consumption pattern (Menz and Welsch, 2012; Okada, 2012; Yamasaki and Tominaga, 1997). This means the aging population is negatively correlated with CO₂ emissions (Hamza and Gilroy, 2011; Kronenberg, 2009; Li and Zhou, 2019).

2.2. Environmental Kuznets Curve (EKC) hypothesis

The EKC hypothesis assumes that the relationship between income and environmental degradation is inverted-U shaped, not linear. This means that environmental degradation, CO₂ emissions in this case, may initially increase with the level of income but after reaching a turning point, it decreases with a further increase in income level. This shows that there is a positive relationship between the variables in the early stages of development that are negative in the final stage (Miah et al., 2010). Several arguments have been made to explain the EKC phenomenon. Panayotou (1993) showed that in the early stages of development, expansion on an economic scale leads to negative environmental impacts. At a higher level, there were several structural changes to economic growth due to the focus on intensive industries and services coupled with increased awareness, enforced regulations and environmentally-friendly technologies. This led to the reduction of the degradation.

The validity of the EKC hypothesis is very important for policy recommendations. If the hypothesis is accepted, this means that economic growth has led to better environmental quality. Thus there is no need to limit growth to protect the environment. However, in contrast, if the hypothesis is rejected then public policies would be necessary to mitigate environmental degradation while economic growth is still increasing in the direction of sustainable development (Perman et al., 2003).

Several studies have been conducted to prove the existence of the EKC hypothesis using different types of environmental indicator, especially CO₂ emissions as seen in the studies by Ahmad et al. (2016), Al-Mulali et al. (2012), Azwar (2019), Lau et al. (2014), Pao and Tsai (2011), and Shahbaz et al. (2012). However, most of the results are "ambiguous" with no empirical evidence to generally support the hypothesis (Egli, 2004). Some of them are strongly dependent on and very sensitive to indicators of environmental degradation such as functional form, methods, variables, countries and time (Jaunky, 2011).

2.3. Relationship between income inequality and environmental degradation

Around the mid-1990s, economists developed theoretical arguments to explain the relationship between income inequality and environmental degradation (Grunewald et al., 2017). This has continuously been subject to further debate (Baloch et al., 2018). Boyce (1994) considered the inequality in power and wealth to be causing more environmental degradation. This was associated with the ability of the rich to degrade and pollute the environment in pursuit of profit without any regard for sustainability. While they obtain more benefits, the poor bear the consequences and cost. Torras and Boyce (1998) examined the

environmental policies for 18–52 cities from 19 to 42 countries. Using seven types of pollution indicators, he proved that income inequality causes environmental degradation in low-income countries. The result was also confirmed by Shafik and Bandyopadhyay (1992), Selden and Song (1994), and Grossman and Krueger (1995). Furthermore, Magnani (2000) also reported that rising income inequality was compounded by a lack of public attention focused on the environment. Hao et al. (2016) examined the income inequality and CO₂ emissions of 23 provinces in China in 1995–2012 and found there to be a positive relationship between income inequality and environmental degradation.

Conversely, Ravallion et al. (2000) showed that higher inequality reduces CO₂ emissions. It was discovered that the reduction of poverty through income redistribution changes the consumption of the rich from low-polluted to high-polluted products. Meanwhile, according to Gas-sebner et al. (2008), income inequality influences CO₂ emissions through the ownership of factors involved in production and power. In under-developed and developing countries, there is strong political power in the industrial sector controlled by the rich and strong. This leads to tighter environmental regulations. However, since most of the poor do not have access to electricity or energy, they produced fewer emissions.

Grunewald et al. (2017) found out about the existence of a trade-off between income inequality and CO₂ emissions in developing countries through the research conducted in 158 countries between 1980 and 2008. The government's effort to reduce income inequality by redistributing income was discovered to have led to an increase in environmental degradation. The trade-off was not confirmed in developed countries. Some studies have tried to explain the effect of the interaction between income inequality and economic growth on CO₂ emissions (Hao et al., 2016; McGee and Greiner, 2018) by answering questions such as ‘Will high-income inequality adversely affect the environment?’ They have also tried to determine if income inequality influences economic growth and aggravates environmental pollution in the process (Hao et al., 2016). Furthermore, McGee and Greiner (2018) emphasized the influence of income inequality on CO₂ emissions at a certain level depending on the dynamic relationship between income inequality and either income level or economic growth.

3. Methodology

This study adopted the Autoregressive Distributed Lag (ARDL) method first introduced by Pesaran and Shin (1999) and later expanded by Pesaran and Shin (2001). It was selected because ARDL can be used in short time-series data or on small samples. It has the ability to attenuate the problem of omitted variables and autocorrelations (Narayan, 2004). ARDL does not require the classification of pre-estimated variables before they are implemented at level I (0), the first difference I (1) or in a combination of both (Baloch et al., 2018).

3.1. Empirical model

The McGee and Greiner Framework, 2018 was adopted and this involved the application of four types of model. Model 1 shown in Eq. (2) represents the IPAT model used to examine the effect of income measured by per capita GDP (GDP), the urbanization rate (URB) and the dependence ratio (DEP) on CO₂ emissions (C O₂).

$$\begin{aligned} \Delta \ln CO_{2t} = & \alpha_1 + \sum_{i=1}^p \beta_1 \Delta \ln CO_{2t-i} + \sum_{i=0}^p \beta_2 \Delta \ln GDP_{t-i} + \sum_{i=0}^p \beta_3 \Delta \ln URB_{t-i} \\ & + \sum_{i=0}^p \beta_4 \Delta \ln DEP_{t-i} + \delta_1 \ln CO_{2t-1} + \delta_2 \ln GDP_{t-1} + \delta_3 \ln URB_{t-1} \\ & + \delta_4 \ln DEP_{t-1} + \theta ECT_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

Model 2 represented by Eq. (3) was used to investigate the EKC hypothesis postulating the existence of an inverted-U shaped relationship between per capita GDP and CO₂ emissions. This model modified Eq. (2) by extending per capita GDP into quadratic form. The existence of EKC was determined when sign ‘δ₂’ is positive and ‘δ₃’ is negative and statistically significant.

$$\begin{aligned} \Delta \ln CO_{2t} = & \alpha_1 + \sum_{i=1}^p \beta_1 \Delta \ln CO_{2t-i} + \sum_{i=0}^p \beta_2 \Delta \ln GDP_{t-i} + \sum_{i=0}^p \beta_3 \Delta \ln GDP_{t-i}^2 \\ & + \sum_{i=0}^p \beta_4 \Delta \ln URB_{t-i} + \sum_{i=0}^p \beta_5 \Delta \ln DEP_{t-i} + \delta_1 \ln CO_{2t-1} + \delta_2 \ln GDP_{t-1} \\ & + \delta_3 \ln GDP_{t-1}^2 + \delta_4 \ln URB_{t-1} + \delta_5 \ln DEP_{t-1} + \theta ECT_{t-1} + \varepsilon_t \end{aligned} \tag{3}$$

Model 3 as shown in Eq. (4) examines the effect of income inequality (GINI) on CO₂ emissions while per capita GDP, urbanization rate, and dependency ratio are considered to be additional variables.

$$\begin{aligned} \Delta \ln CO_{2t} = & \alpha_1 + \sum_{i=1}^p \beta_1 \Delta \ln CO_{2t-i} + \sum_{i=0}^p \beta_2 \Delta \ln GDP_{t-i} + \sum_{i=0}^p \beta_3 \Delta \ln GINI_{t-i} \\ & + \sum_{i=0}^p \beta_4 \Delta \ln URB_{t-i} + \sum_{i=0}^p \beta_5 \Delta \ln DEP_{t-i} + \delta_1 \ln CO_{2t-1} + \delta_2 \ln GDP_{t-1} \\ & + \delta_3 \ln GINI_{t-1} + \delta_4 \ln URB_{t-1} + \delta_5 \ln DEP_{t-1} + \theta ECT_{t-1} + \varepsilon_t \end{aligned} \tag{4}$$

Lastly, Model 4 shown in Eq. (5) augments Eq. (4) by adding the interaction variable between income inequality and per capita GDP with a consequent effect on CO₂ emissions.

$$\begin{aligned} \Delta \ln CO_{2t} = & \alpha_1 + \sum_{i=1}^p \beta_1 \Delta \ln CO_{2t-i} + \sum_{i=0}^p \beta_2 \Delta \ln GDP_{t-i} + \sum_{i=0}^p \beta_3 \Delta \ln GINI_{t-i} \\ & + \sum_{i=0}^p \beta_4 \Delta \ln GINI * \ln GDP_{t-i} + \sum_{i=0}^p \beta_5 \Delta \ln URB_{t-i} + \sum_{i=0}^p \beta_6 \Delta \ln DEP_{t-i} \\ & + \delta_1 \ln CO_{2t-1} + \delta_2 \ln GDP_{t-1} + \delta_3 \ln GINI_{t-1} + \delta_4 \ln GINI * \ln GDP_{t-1} \\ & + \delta_5 \ln URB_{t-1} + \delta_6 \ln DEP_{t-1} + \theta ECT_{t-1} + \varepsilon_t \end{aligned} \tag{5}$$

All of the variables in the models can be expressed in the natural logarithm (ln) to reduce the possibility of the heteroscedasticity problem arising in the model estimation. Moreover, Δ is the differenced operator, ε_t is the error term, t is the time period, β₁, β₂, β₃, β₄, β₅ and β₆ correspond to the short-run parameters, δ₁, δ₂, δ₃, δ₄, δ₅, δ₆ indicate the long-run dynamic coefficients of the ARDL model, and θECT_{t-1} refers to the error-correction term (ECT) which indicates the adjustment speed and convergence of the long-run equilibrium.

3.2. Data and the descriptive statistics

This study used time series data from 1975 to 2017 with the CO₂ emissions defined as a result of the total combustion from fossil fuels expressed in tons per capita (tCO₂ per capita). The per capita Gross Domestic Product (GDP) was calculated based on the 2010 base year (US\$) expressed by a natural logarithm which represents economic growth. Income inequality was measured using the Gini coefficient (GINI), urbanization rate (URB) was measured by the percentage of the total population living in urban areas and the dependency ratio (DEP) was the ratio of the population aged under 15 years old and over 64 years old through to those between 15 - 64 years old known as the productive age.

All of the data used was secondary and obtained from official institutions. For example, the CO₂ emission data was from the International Energy Agency (IEA), the Gini coefficient was from Badan Pusat Statistik

Table 1. Descriptive statistics.

Variables	Obs.	Mean	Min.	Max.	SD
CO ₂ emission (ton per capita)	43	1,031	0,289	1,880	0,499
Gini coefficient	43	0.349	0.300	0.410	0.030
Per capita GDP (constant 2010, US\$)	43	2,184	949.08	4,120.43	882.09
Urbanization rate	43	36.956	19.317	54.659	11.449
Dependency ratio	43	63.934	48.714	85.967	12.561

Table 2. Stationary test.

Variables	t-statistics		Results
	Level	First Difference	
LnCO ₂	-3.066459**	-6.013644***	I(1)
LnGDP	-0.592268	-4.775942***	I(1)
LnGDP ²	-0.170755	-4.784953***	I(1)
LnGINI	-1.064368	-5.991690***	I(1)
LnGINI*lnGDP	-2.052510	-6.919935***	I(1)
LnURB	-2.660642*	-0.033619	I(0)
LnDEP	-2.690273*	-0.922306	I(0)

***, **, and * significance level at 1, 5, and 10 percent, respectively.

Table 3. Cointegration test.

Model	Optimal Lag	F-statistic	Critical Value			Results
			Sig.	I(0)	I(1)	
1	(1,3,1,2)	5.400560***	10%	2.37	3.20	Cointegrated
			5%	2.79	3.67	
			1%	3.65	4.66	
2	(1,0,2,3,0)	4.333978**	10%	2.20	3.09	Cointegrated
			5%	2.56	3.49	
			1%	3.29	4.37	
3	(1,3,0,1,2)	4.380079***	10%	2.20	3.09	Cointegrated
			5%	2.56	3.49	
			1%	3.29	4.37	
4	(4,3,0,0,3,4)	4.877909***	10%	2.08	3.00	Cointegrated
			5%	2.39	3.38	
			1%	3.06	4.15	

*** and ** significance level at 1 and 5 percent, respectively.

(BPS) and per capita GDP, urbanization, and dependency ratio were from the World Bank. Table 1 shows the descriptive statistics of the variables used in all of the models.

3.3. Estimation procedures

Modeling in time series data requires a pre-estimation evaluation using a stationary test due to its stochastic or non-stationary trend which has the ability to produce spurious regression (Gujarati and Porter, 2015). There are three types of stationary test and they include graph analysis, a correlogram and unit root. In line with several of the previous studies, the Augmented Dickey-Fuller (ADF) root unit test was applied. This was followed by the determination of the possible optimum length of the lag to be selected using different methods such as the Akaike Information Criteria (AIC), Schwartz-Bayesian Criteria (SBC) and Hanna Quinn Criterion (HQ). The AIC criteria was applied due to its ability to provide better and more consistent results compared to the others (Uddin et al., 2013).

The cointegration test was conducted to investigate the possibility of a long-run equilibrium relationship between the independent and dependent variables. In line with the previous studies by Baloch et al.

(2018), Khemili and Belloumi (2018), and Lau et al. (2014), the Bound Test was adopted to compare the F-statistic to the critical value constructed by Pesaran and Pesaran (1997). It is therefore important to note that if the F-statistic value is below the lower bound value - I (0) then it means that there is no long-run relationship in the model and vice versa. However, if the F-statistic value is between I (0) and I (1), then the result is inconclusive.

A diagnostic test was also conducted to ensure the robustness and stability of the model to ensure that it was able to produce an unbiased estimation. This involved investigating normality, no autocorrelation and homoscedasticity using the Jarque-Bera, Breusch-Godfrey LM and Breusch-Pagan-Godfrey tests respectively. The decision rule for all assumptions is to accept the null hypothesis (H₀) if the probability is greater than 0.05. Moreover, CUSUM and CUSUM Square (CUSUMQ) tests were also employed to determine the stability of the model.

4. Results and discussion

The Augmented Dickey-Fuller (ADF) unit root test showed that the urbanization and dependency ratio were stationary at level [I(0)] while CO₂ emissions, per capita GDP, per capita GDP squared, the Gini

Table 4. Long-run estimations.

Variables	Model 1	Model 2	Model 3	Model 4
C	31.9816*** (6.7210)	-9.6273 (8.4841)	31.4240*** (5.8907)	33.7602*** (3.1056)
LnGDP	0.2467* (0.1260)	10.7787*** (2.1150)	0.4415*** (0.1567)	1.7192*** (0.2861)
LnGDP ²	–	-0.6392*** (0.1282)	–	–
LnGINI	–	–	-0.3476* (0.1992)	-5.5528*** (1.0653)
LnGINI*GDP	–	–	–	0.0867*** (0.0173)
LnURB	-2.2230*** (0.7303)	-3.1281*** (0.5066)	-2.4771*** (0.6649)	-3.4518*** (0.4185)
LnDEP	-6.3465*** (1.1244)	-5.8142*** (0.6586)	-6.4322*** (0.9906)	-8.5984*** (0.7024)

***, **, and * significance level at 1, 5, and 10 percent, respectively; parentheses () are the standard error.

Table 5. Short-run estimations.

Variable	Model 1 (1,3,1,2)	Model 2 (1,0,2,3,0)	Model 3 (1,3,0,1,2)	Model 4 (4,3,0,0,3,4)
D(LnCO2(-1))	–	–	–	0.729*** (0.178)
D(LnCO2(-2))	–	–	–	0.331** (0.119)
D(LnCO2(-3))	–	–	–	0.120 (0.095)
D(LnGDP)	0.312* (0.154)	11.307*** (2.580)	0.488*** (0.153)	3.350*** (0.553)
D(LnGDP(-1))	0.035 (0.164)	–	0.048 (0.159)	0.090 (0.132)
D(LnGDP(-2))	0.550** (0.161)	–	0.609*** (0.158)	1.045*** (0.141)
D(LnGDP ²)	–	-0.713*** (0.167)	–	–
D(LnGDP ² (-1))	–	-0.041*** (0.011)	–	–
D(LnGINI)	–	–	-0.337*** (0.147)	-10.164*** (1.905)
D(LnGINI*LnGDP)	–	–	–	0.158*** (0.032)
D(LnURB)	4.881*** (1.394)	-2.942 (2.394)	4.858*** (1.329)	17.026*** (3.309)
D(LnURB(-1))	–	-0.256 (3.614)	–	10.192** (4.211)
D(LnURB(-2))	–	-6.079* (2.523)	–	5.775* (2.968)
D(LnDEP)	-7.342*** (2.252)	-6.429*** (0.145)	-7.787*** (2.238)	-7.414*** (1.801)
D(LnDEP(-1))	2.854 (1.808)	–	4.605** (1.852)	12.042*** (2.556)
D(LnDEP(-2))	–	–	–	1.385 (2.446)
D(LnDEP(-3))	–	–	–	9.268*** (2.108)
ECT	-0.747*** (0.134)	-1.062*** (0.146)	-0.820*** (0.138)	-1.908*** (0.255)

***, **, and * significance level at 1, 5, and 10 percent, respectively; parentheses () are the standard error.

Table 6. Diagnostic test.

Model	Normality	Autocorrelation	Homoscedasticity
1	0.728429	0.1096	0.3296
2	0.530790	0.6680	0.3287
3	0.943029	0.0820	0.3887
4	0.428148	0.1601	0.6550

coefficient and interaction variables (LnGINI*LnGDP) were stationary at the first difference [I(1)] as shown in Table 2. The AIC criteria indicated that the optimum length of lag for Models 1 to 4 were (1,3,1,2) (1,0,2,3,0) (1,3,0,1,2, and (4,3,0,0,3,4) respectively as presented in Table 3.

The cointegration test showed that the F-statistic values for all of the models was greater than the upper bound value I (0) at a significance level of 1 percent for models 1, 3, 4. Model 2 was at 5 percent as shown in Table 3. Therefore H_0 was rejected. This means that the variables are cointegrated or there is an adjustment process from the short-run to long-run equilibrium.

The estimation results showed that per capita GDP has a statistically significant and positive effect on CO₂ emission both in the long-run and short-run in all models as shown in Tables 4 and 5. This is in line with the findings of some of the previous studies conducted in different countries such as China (Shuai et al., 2018), Tunisia (Cherni and Jouini, 2017) and

West Africa (Adu and Denkyirah, 2018). The increase in CO₂ emissions in Indonesia is mainly driven by its output and energy consumption contributed to especially by the industrial sector (Hwang and Yoo, 2014). Moreover, the country's GDP is dominated by the manufacturing industry sector even though its value has been declining over the past few years. Due to the high production, it is the highest consumer of energy and the biggest contributor of CO₂ emissions followed by transportation. In addition, Indonesia is highly dependent on fossil fuels. For example, in 2015, the energy consumption was dominated by oil at 41 percent, natural gas at 24 percent and coal at 29 percent (Kementerian ESDM, 2016a).

The relationship between per capita GDP and CO₂ emissions was found to be non-linear according to the EKC hypothesis. The estimation results of Model 2 show that the EKC was in both the long-run and short-run was indicated as statistically significant and positive for per capita GDP² which confirmed the inverted-U shaped relationship as shown in

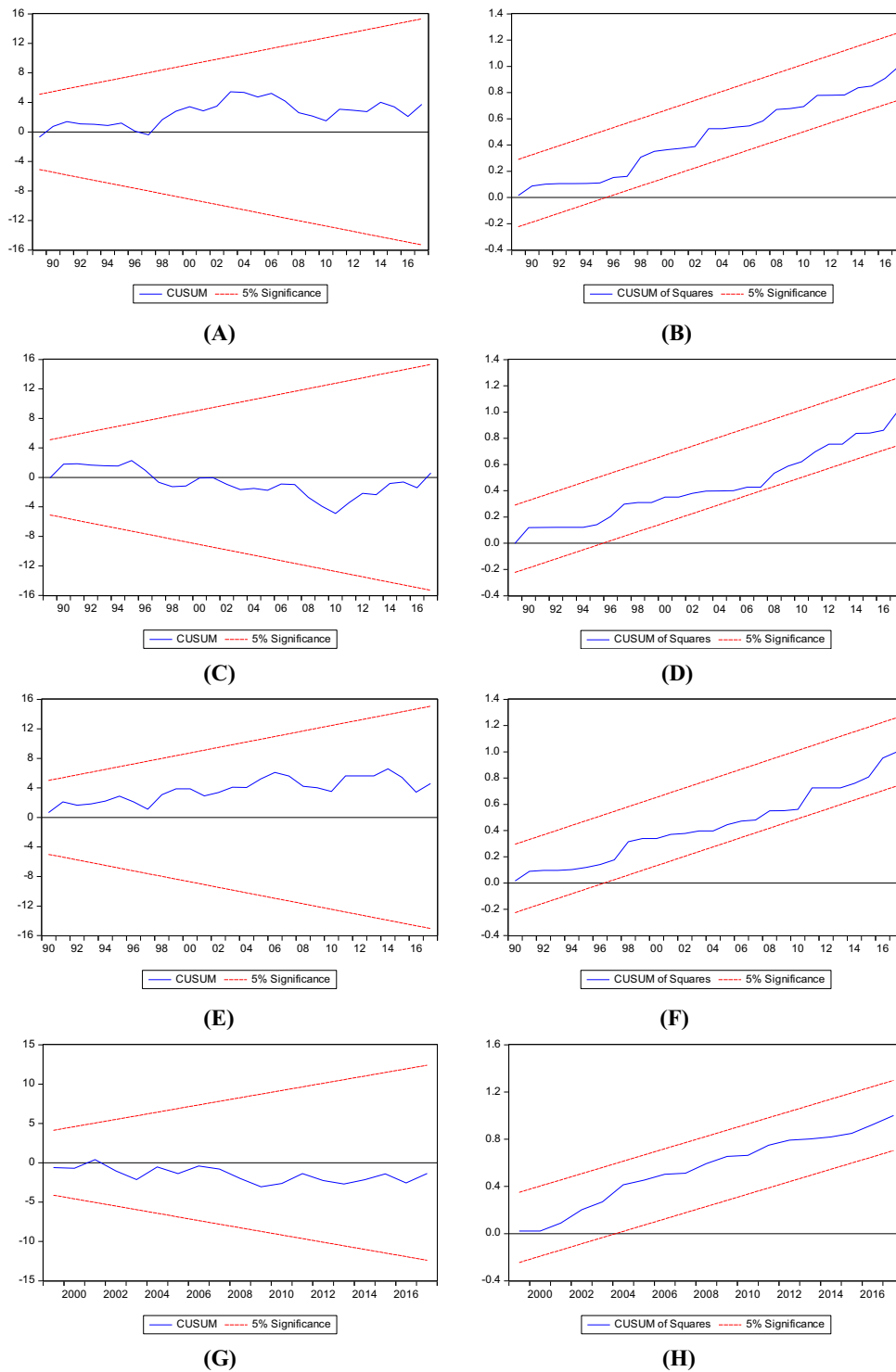


Figure 1. CUSUM and CUSUMQ for coefficient stability.

Tables 4 and 5. The mathematical calculation showed that the turning point was at US \$8,431 per capita GDP in the long-run and US \$7,927 in the short-run. According to Panayotou (1993), these phenomena can be justified using two arguments. First there is the primary intensity energy. As one of the technological progress indicators, this tends to decrease and has done particularly since 2001 (Ministry of Energy and Mineral Resources – MEMR, 2017). Second, the Indonesian Government is actively

committed to the reduction of greenhouse gases (GHG) emissions by 26 percent and by 41 percent if there is a provision of international assistance by 2020 (Kementerian ESDM, 2016b). As a follow-up to that commitment, the government issued Presidential Regulation No. 61 on the National Action Plan for Reducing GHG Emissions and Presidential Regulation No. 71 on the Implementation of the National Greenhouse Gas Inventory in 2011.

The estimation results of Model 3 show that income inequality has a significant negative effect both in the long-run and short-run as shown in Tables 4 and 5. This means a decrease in income inequality leads to an increase in CO₂ emissions. This finding confirms the Marginal Propensity to Emit (MPE) Hypothesis adopted from the Keynesian concept of Marginal Propensity to Consume (MPC). This was empirically proven by Hailemariam et al. (2019) in OECD countries and by Hao et al. (2016) in China. This suggests that the efforts undertaken to improve income equality through increasing the income level of poor households to pursue an income level closer to the richer households will increase their energy consumption and CO₂ emissions as a consequence (Ravallion et al., 2000). Sager (2019) formulated and quantified what they call the “equity-pollution dilemma”—positive income redistribution may raise aggregate household carbon” using micro-data on the household consumption within a single country. The result estimated that a marginal transfer of \$1000 from a richer to a poorer household in 2009 may increase the CO₂ content of that income by about 5.1% or 28.5kg in the US.

The relationship pattern between income inequality and CO₂ emissions also depends on the interaction between income inequality and economic growth (McGee and Greiner, 2018). The estimation results of Model 4 show that the interaction variable (GINI*GDP) has a significant and positive effect in both the long-run and short-run as shown in Tables 4 and 5 respectively. This means that the positive interaction coefficient suggests that the “equity-pollution dilemma” is smaller in relation to the higher aggregate income levels. This finding justifies the results of Hao et al. (2016) where negative income inequality may increase the aggregate CO₂ at higher aggregate income levels only. In addition, the Indonesian historical data showed that the level of income equality between 1975 and 2017 was not linear but U-shaped instead. The Gini coefficient between 1975 and 1999 was observed to be decreasing while the data for 2000 through to 2017 showed that it had increased (BPS, 2015). In contrast, both per capita GDP and CO₂ emissions between 1975 and 2017 increased (World Bank, 2019).

Urbanization has a significant and negative effect on CO₂ emissions in all models in the long-run as shown in Table 4. This is a confirmation of the results of some of the previous studies such as those by Chikaraishi et al. (2015) and Poumanyong and Kaneko (2010). However, according to the theoretical background, the relationship between urbanization and CO₂ emissions has the tendency to occur in different ways. First, it can occur as an inverted-U shape pattern, especially in developing countries (Martinez-Zarzoso and Maruotti, 2011). Second, it may be indirect, involving other moderating or intervening variables such as economic growth, according to the Kuznets Curve hypothesis. Lewis (2013) testified that there is a positive relationship between urbanization and economic growth in Indonesia. However, this is not the main objective of this study, therefore it has not been included in the analytical model.

The effect of the dependency ratio on CO₂ emissions was found to be statistically significant and negative for all models both in the long-run and short-run as shown in Tables 4 and 5. This is the same with the findings of most of the previous studies such as those by Okada (2012), Liddle (2011), Lugauer et al. (2014), and Menz and Welsch (2012). This means that an increase (decrease) in the proportion of productive (non-productive) age in the total population leads to a decrease (increase) in the dependency ratio followed by a CO₂ emission increase. There is a need to focus on this issue due to the improvements in the demographics of the country. This is creating both challenges and opportunities for development and future environmental quality improvements. For example, the historical data shows that the Indonesian dependency ratio has declined sharply from 85.97 in 1975 to 48.71 in 2017 (BPS, 2015). This means that those of a productive or young age are increasing while those in the non-productive or older generations are reducing in number across the population.

The ARDL estimation model applied did not have any diagnostic problems. The statistical tests conducted using a 0.05 significance level

showed that all of the models satisfy the assumption of normality, autocorrelation, and homoscedasticity as presented in Table 6. This means that the models have the ability to produce unbiased estimations. In addition, the CUSUM and CUSUMSQ plots showed that the ARDL parameters were stable over time at 0.05 for all models as shown in Figure 1. In the figure, Panels A and B are the CUSUM and CUSUMSQ for Model 1, Panels C and D are the CUSUM and CUSUMSQ for Model 2, Panels E and F are the CUSUM and CUSUMSQ for Model 3 and Panels G and H are the CUSUM and CUSUMSQ for Model 4. Therefore the two statistical analyses have confirmed that all of the models used have met the assumptions for robustness and stability.

5. Conclusions

Increasing CO₂ emissions and high-income inequality are two crucial problems requiring urgent attention in Indonesia. This study was conducted to examine the relationship between income inequality and CO₂ emissions using ARDL technique from 1975 to 2017. Moreover, anthropogenic models such as the IPAT and the EKC hypothesis were used. The explanatory variables applied include per capita GDP, urbanization and the dependency ratio.

The statistical estimation analysis shows that income inequality has a negative effect on CO₂ emissions both in the long-run and short-run. The pattern of the relationship is dependent on the level of per capita GDP. This study found there to be a positive effect of interaction between income inequality and per capita GDP on CO₂ emission. This means that an increase in economic growth due to high-income inequality will increase the level of CO₂ emissions and vice versa. Moreover, an inverted U-shaped relationship was also observed between per capita GDP and CO₂ emissions. This indicates the existence of the EKC in Indonesia. Both urbanization and the dependency ratio were also found to have a negative effect on CO₂ emissions. This means that an increase in urbanization or the dependency ratio causes an increase in CO₂ emissions.

It was recommended that for the purpose of policy-making, economic growth should be associated with income equality to reduce the gas emission level in accordance with the commitment to the national action plan for the reduction of greenhouse gases. Moreover, for advanced studies, the pattern of relationship between urbanization and CO₂ emissions should be explored by adding interaction variables or expanding the model, particularly into quadratic form in order to capture the inverted-U shaped relationship between the variables.

Declarations

Author contribution statement

Deni Kusumawardani: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Ajeng Kartiko Dew: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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The authors declare no conflict of interest.

Additional information

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