# Symmetric and Asymmetric Impacts on Carbon Dioxide Emissions in Palm Oil Industry, Malaysia

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**ABSTRACT**
The inconclusive evidence for the environmental Kuznets curve (EKC) hypothesis has led to proliferating asymmetric studies of carbon dioxide emissions, as scarce findings are observed in the agriculture-$CO_2$ EKC literature. Prior studies have commonly focused on the linear impact of agriculture on carbon dioxide emissions. To bridge the research gap, this study investigates the symmetric and asymmetric impacts of palm oil on $CO_2$ emissions within the EKC hypothesis framework using linear and nonlinear ARDL models. An estimation based on Malaysian time series data from 1978 to 2018 identifies significant symmetries and asymmetries between palm oil and $CO_2$ emissions. The asymmetric NARDL reveals that the rise in palm oil production reduces $CO_2$ in the long run, while reducing palm oil production increases emissions. Significant effects of renewable energy, oil demand, and trade openness on $CO_2$ emissions are also found. This study confirms the evidence supporting the EKC hypotheses for both linear and nonlinear analyses, verifying the relevance of symmetric and asymmetric EKC studies for Malaysia. This study provides significant implications for policymaking, where the expansion in palm oil production represents a solution to environmental degradation.

*Keywords:* Carbon dioxide ($CO_2$) emissions, Palm oil, NARDL model, Environmental Kuznets curve (EKC)

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## 1.0 INTRODUCTION

Countries worldwide are accelerating their efforts to increase sustainability and reduce their carbon dioxide ($CO_2$) emissions level. Green growth and development are preferred as a replacement for the conventional growth model, which focuses on economic growth alone. Simple as it may sound, green economic growth is challenging to achieve, as most countries are still highly dependent on fossil fuels: more than 81% of world energy production was derived from fossil fuels in 2018 (International Energy Agency, 2020). Since fossil fuel plays a vital role in world economic performance, implementing clean growth strategies requires in-depth planning to prevent any economic turbulence. The environmental and economic policies that effectively boost economic growth while simultaneously reducing $CO_2$ emissions and improving environmental quality are still ongoing debated; however, $CO_2$ emissions studies are complex, particularly in terms of the optimal environment-economic growth relationship. Prior studies showed mixed and inconclusive environmental Kuznets curve (EKC) results for $CO_2$ emissions linear studies, hinting at the nonlinearities possibility between $CO_2$ emissions and its determinants and thus calling for nonlinear EKC studies of $CO_2$ (Apergis & Gangopadhyay, 2020; Bhutto & Chang, 2019; Malik et al., 2020).

For instance, Zafeiriou et al. (2018) highlighted agriculture is the major $CO_2$ contributors and emissions caused by agriculture are generated by energy consumption at all stages of agricultural production. A higher production volume requires more energy and leads to a higher carbon emissions level. Such a phenomenon is portrayed by the parallel movement of worldwide agricultural production and emissions curves in Figure 1. Manning et al. (2019) echoed that among types of agricultural production, palm oil production is one of the major contributors to $CO_2$ emissions. Land conversion for oil palm plantations is the main culprit for the $CO_2$ emissions increase associated with the crop production and the loss of carbon stocks from peat forests is damaging because it takes centuries to recover from this conversion of land (Warren et al., 2017). European Union Parliament (2018) and Sertoglu & Dogan (2016) approved and discussed a resolution in 2017 to seek palm oil use restrictions by 2021 and this ban is deemed non-sustainable for the countries relied on palm oil as a significant GDP generator. Malaysia is highly dependent on its export of palm oil and palm products to generate major economic profits (Alam et al., 2015). In 2017, 13% of palm oil and palm oil shipments from Malaysia were exported to the EU, and 9% of Malaysia's biodiesel exports went to Europe and provides job opportunities for Malaysian smallholders and serves as the palm oil product supplier for large businesses (Lim & Biswas, 2018; MPOB, 2018). In 2018, palm oil was the highest contributor to Malaysia's agricultural GDP, representing 37.9% (DOSM, 2019).

The downturn in palm oil and palm product exports could impact Malaysia's growth, necessitating an investigation of the following research issues: (1) determining whether palm oil production is the primary source of $CO_2$ emissions and (2) verifying the Malaysian Palm Oil Council's (MPOC's) defence of palm oil sustainability. The MPOC claimed that although palm oil production does contribute to increased emissions, palm oil plantations can provide carbon dioxide sequestration, generating oxygen to be released back into the

atmosphere and converting solar energy into biomass. Rare studies have considered the claiming the harmfulness of Malaysian palm oil plantations nexus often lacked real evidence and contained statistical bias. Prior study is unclear whether the $CO_2$ emissions trajectory is linear, and it is possible that increases and decreases in palm oil production affect changes in carbon dioxide emissions levels differently. These uncertainties can be eliminated by empirically investigating the impacts of palm oil production on Malaysia's $CO_2$ emissions in an asymmetrical manner.

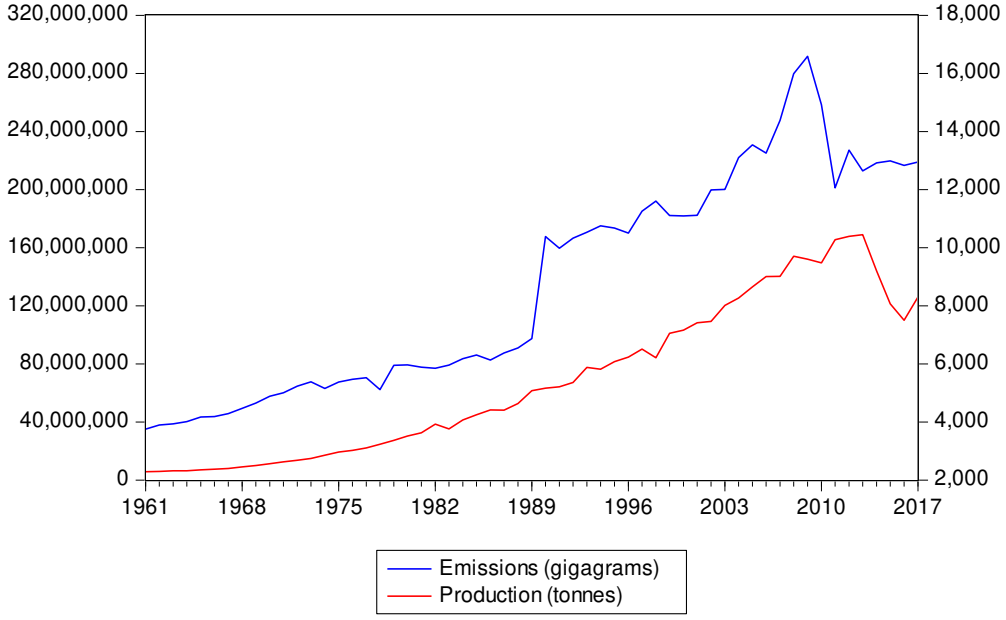


Figure 1: Malaysian agricultural emissions and agricultural production for 1961 to 2017 (*Source: FAOSTAT, 2019)*

Prior studies are lacking to be consensus or guidance to this debate in the specialist literature, and existing theoretical gaps make this debate inconclusive. (1) the literature mostly centres on the relationship between $CO_2$ emissions and agriculture as a whole; and only a few studies have initiated an investigation into the impacts of specific agricultural products on $CO_2$ emissions (Asumadu-Sarkodie & Owusu, 2016); (2) different agricultural products may have different impacts on $CO_2$ emissions; this type of empirical study is undoubtedly significant for economic and environmental policies; (3) few studies have been made to investigate the linkages between $CO_2$ emissions and the agriculture sector (palm oil) in Malaysia; (4) existing studies tend to emphasise the linear and dynamic relationship between agriculture and $CO_2$ emissions and remaining inconclusive on the relationship with asymmetric or nonlinea (Ridzuan et al., 2020 for Malaysia; Gokmenoglu & Taspinar, 2018 for Pakistan; Jebli & Youssef, 2016 for Tunisia). Xu et al. (2020) argued that the complexity and changeability of economic events often lead to a nonlinear relationship between economic attributes. There is a need to test for the nonlinearity of the relationship between agriculture and $CO_2$ emissions or, between palm oil and $CO_2$ emissions.

Yet, if a nonlinear relationship between the two attributes is found, negative values for the explanatory attribute have different effects than positive values on the dependent attribute and if a nonlinear relationship is found between palm oil and $CO_2$ emissions and signifies that the increase and decrease in palm oil production impact $CO_2$ emissions levels

differently. (Ahmad et al., 2020; Awodumi & Adewuyi, 2020). This study aims to answer the questions that reflects on the palm oil production.

1. How are $CO_2$ emissions affected by an increase and by a decrease in palm oil production in Malaysia? Are the effects significant?
2. Does an increase in palm oil production increase or decrease $CO_2$ emissions? Or is there no significant effect at all?

To fill the gap, this study aims to investigate the asymmetric or nonlinear relationship between palm oil production and $CO_2$ emissions within the EKC hypothesis to decompose into partial negative and positive sums in Malaysia palm oil production by employing the nonlinear autoregressive distributed lag model. Shin et al. (2014) proposed asymmetric $CO_2$ emissions mostly employed the nonlinear autoregressive distributed lag (NARDL) model to estimatesboth the short- and long-run asymmetries (Luqman et al., 2019; Brown et al., 2020; Malik et al., 2020). This method highlights any potential significant difference in how the dependent attribute reacts to changes in the explanatory attribute within a different time frame. Moreover, this method can detect changes in the direction and magnitude of the asymmetries between the short run and long run by estimating the asymmetric dynamic multipliers. In this case, one of two possible scenarios can be seen from the estimation: whether a positive (negative) shock has a greater effect in the short run while a negative (positive) shock has an effect in the long run.

This study analyses the impacts of agriculture type, i.e., palm oil, on $CO_2$ emissions in an asymmetric manner. This study extends the existing EKC studies that mostly employed traditional linear methods and neglected the nonlinear relationship that may exist between the attributes in question and often delivering mixed and inconclusive EKC hypothesis results. The NARDL results provide a specific and inputs to policymakers on how the variation in the explanatory attribute affects the dependent attribute in the short and long run and which type of shock (i.e., positive or negative) is more significant in influencing the changes in the dependent attribute in the short run and long run.

The employed NARDL method investigates on how changes in palm oil production affect the $CO_2$ emissions level in Malaysia. This study serves as an effective input for policy formulation and implementation relating to the sustainability of the Malaysian palm oil industry. These results distinguish the responsiveness of $CO_2$ emissions towards the palm oil production elasticity in the short and long run. Empowering policymakers to plan is for holistic mitigation and development policies that best safeguard Malaysia's position as the second-largest palm oil exporter in the world. This study acts as a countermeasure against the palm oil ban by the EU because the significant findings regarding the nonlinear relationship between palm oil production and $CO_2$ emissions in Malaysia provide strong arguments against the unfavourable claims that palm oil harms the environment.

The rest of the study is organised as follows: Section 2 briefly discusses the literature review, Section 3 describes the econometric model, methodology, data, and estimation procedure, Section 4 reports the empirical results, and Section 5 concludes the study.

## 2.0 Literature Review

This study proposes the environmental Kuznets curve theory and postulates that an inverted U curve reflects the relationship of environmental impact against the level of income (Kuznets, 1955; Grossman and Krueger, 1991). The theory reflects that a country needs to reach a threshold wealth value before starting to enjoy a cleaner environment and

argues that the EKC does not provide automatic correction for environmental degradation (Grossman & Krueger, 2015). For instance, Brown et al. (2020) highlighted that even though countries have reached the peak of curve, active economic and environmental policies need to be in place to realise the goal of a greener environment. The relationship between economic growth and the environment established in the EKC hypothesis is mostly studied to find practical and feasible policies to simultaneously balance economic growth and the environment. Myriad studies have supported the EKC in their sample, e.g., Ahmad et al., 2017 (Croatia); Ahmad et al., 2016 (India); and Apergis & Ozturk, 2015 (14 Asian countries). In contrast, Lacheheb et al. (2015; Algeria) and Mikayilov et al. (2018; Azerbaijan) rejected the EKC hypothesis. Some studies have found mixed EKC results (Narayan et al., 2016, for 181 countries; Baek, 2015, for 12 major nuclear-generating countries). The generalisability of the inverted-U shape of the EKC has also been contested. Zanin and Marra (2012), studying Austria, and Kang et al. (2016), studying China, concluded that the relationship between economic growth and $CO_2$ emissions is rather N-shaped. Although a positive relationship between economic growth and $CO_2$ emissions is found in both studies, the EKC hypothesis is instead found to be dependent on the country's development stage (Apergis, 2016).

The mixed EKC results, which are often estimated using income or GDP for economic growth and $CO_2$ emissions for environmental degradation, suggest that the EKC findings are inconclusive. $CO_2$ emissions have been a popular and critical indicator of green growth and a cleaner environment, while other possible determinants have been introduced to extend the theoretical understanding of the EKC hypothesis due to the broad evidence and arguments on the EKC discourse. For instance, energy consumption is found to positively affect $CO_2$ emissions and supports the EKC hypothesis (Ahmad et al., 2016; Shahbaz et al., 2015). For the question of whether renewable energy reduces $CO_2$ emissions, studies have both supported the EKC (Danish et al., 2017; Al-Mulali & Ozturk, 2016; Baek, 2016) and rejected the EKC (Dogan & Ozturk, 2017; Jebli & Youssef, 2015; Al-Mulali et al., 2015). A positive urbanisation-$CO_2$ emissions relationship supported the EKC in some studies (Pata, 2018; Ozatac et al., 2017, both for Turkey), but such relationship was not found in other studies that rejected the EKC (Hao et al., 2016, for China).

Agriculture has emerged as a major $CO_2$ emissions contributor, and more research has started to investigate the impacts of agriculture on $CO_2$ emissions. Gokmenoglu and Taspinar (2018) established a positive relationship between agriculture and $CO_2$ emissions, and the EKC was found to be valid for Pakistan, while Jebli and Youssef (2016) failed to establish the EKC for a study of Tunisia. Although agriculture is found to increase $CO_2$ emissions, this need not always be the case. Agriculture has the capability to sequester carbon dioxide and provide a carbon sink (Johnson et al., 2007) and is able to remove approximately 80-88% of $CO_2$ emissions (Reynold & Wenzlau, 2012). Liu et al. (2017), in an agricultural EKC study of the ASEAN-4, demonstrated that agriculture reduced $CO_2$ emissions and that the EKC was not valid. The mixed and inconclusive findings from the EKC evidence and the varied relationship between agriculture and $CO_2$ emissions suggest that existing studies have overlooked some critical aspects that the current study aims to further improve. As agriculture comprises several subsectors with various agricultural products, different agricultural products may have different impacts on $CO_2$ emissions. Asumadu-Sarkodie and Owusu (2016) attempted to study agricultural products and $CO_2$ emissions in Ghana. Agricultural products such as cocoa bean production, total fruit production, and total livestock production were found to positively correlate with $CO_2$ emissions, while total

primary vegetable production was found to reduce $CO_2$ emissions. However, they did not explicitly study palm oil, even though it is considered one of Ghana's major crops.

In the context of the Malaysian EKC hypothesis study, Gill et al. (2018) found a significant inverted relationship between $CO_2$ emissions and renewable energy, signifying that renewable energy is a remedy for Malaysia's environmental degradation. This relationship was later confirmed by Bekhet and Othman (2018) with similar findings. On the other hand, Saboori et al. (2016) included urbanisation as an explanatory attribute in their EKC framework and found that urbanisation significantly increased $CO_2$ emissions. Solarin et al. (2017) also found that urbanisation increased $CO_2$ emissions. Ridzuan et al. (2020) investigated agricultural subsectors' impacts on $CO_2$ emissions, finding that crops and fisheries reduced $CO_2$ emissions, while livestock had no significant impact. All these Malaysian studies contradict each other regarding the evidence for the EKC hypothesis: the EKC was valid in Ridzuan et al. (2020), Bekhet and Othman (2018) and Saboori et al. (2016) but invalid in Gill et al. (2018) and Solarin et al. (2017). The inconclusive results of the EKC hypothesis indicate that there is room for improvement in testing the EKC hypothesis for Malaysia.

The aforementioned studies in this section only focused on the linear relationship between the attributes using traditional linear models for the regression estimation. As an economic phenomenon may be affected by shocks or other significant economic events that create structural changes, some argue against the ability of traditional linear methods to provide a good fit. In other words, studies of the relationship between economic attributes using linear methods are incapable of capturing the nonlinearity between the attributes (Ye & Zhang, 2018). If scholars superficially assume that the correlation between economic attributes is linear, research applying linear models may suffer from model-related errors and high variance (Xu et al., 2020). In response to this concern, EKC studies employing nonlinear methods to find the asymmetric impacts of various attributes and $CO_2$ emissions have emerged (e.g., Brown et al., 2020; Malik et al., 2020; Şentürk et al., 2020). Novel asymmetric studies on EKC theory are limited in terms of guidance and research availability, especially those addressing agriculture. Mahmood et al. (2019) studied the nonlinear relationship between agricultural development and $CO_2$ emissions in Saudi Arabia by employing the NARDL method, wherein they discovered that, in the long run, there was a negative asymmetrical effect between the share of agriculture in GDP and $CO_2$ emissions and that the effect of the increase in agriculture's share of GDP was greater than that of a decreasing share. When these two findings were integrated, the study concluded that the increase in the share of agriculture in Saudi Arabia's GDP would reduce its $CO_2$ emissions in the long run.

Asumadu-Sarkodie and Owusu (2016) and Mahmood et al. (2019) both attempted to study the impacts of agricultural products on $CO_2$ emissions, but essential issues remain unaddressed. First, Asumadu-Sarkodie and Owusu (2016) did not include the EKC hypothesis framework in their study and only focused on the linearity between agricultural products and $CO_2$ emissions. Second, although Mahmood et al. (2019) investigated the asymmetric impacts of agriculture on $CO_2$ emissions, their study only considered such impacts of agriculture as a whole by employing agricultural value-added into the framework of the study without considering the asymmetric impacts of individual agricultural products, specifically palm oil. Accordingly, this study intends to improve the shortcomings of the existing research by investigating the asymmetric relationship between palm oil production and $CO_2$ emissions in Malaysia within the EKC hypothesis framework using the NARDL

method. This study attempts to extend the existing literature by becoming among the seminal empirical studies to investigate the impacts of palm oil production on Malaysia's $CO_2$ emissions, which is a topic requiring urgent attention from scholars, particularly following the recent palm oil ban by the EU Parliament. There are indeed existing studies relating to the Malaysian palm oil industry, but those studies generally focused on scientific fields (see Begum et al., 2019; Nadzir et al., 2020; Sarkar et al., 2020). In addition, estimating the EKC hypothesis with an econometric model enables this study to identify whether Malaysia's $CO_2$ emissions trajectory changes with palm oil production. Through this nonlinear study, this study is able to discover the relationship between palm oil production and $CO_2$ emissions, focusing on the elasticity of palm oil production in affecting $CO_2$ emissions for both the short and long run in Malaysia.

## 3.0 MODEL, DATA AND METHODOLOGY

### 3.1 Theoretical framework

This study employs the basic EKC model provided by Grossman and Krueger (1995) to explore the relationship between environmental degradation and economic growth as expressed in (1), where $E_{it}$ refers to per capita carbon dioxide emissions, Y and $Y^2$ represent per capita GDP and its square, respectively, $\varepsilon_{it}$ is the error term, $_i$ represents the country, and $_t$ represents the sample year:

$$E_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Y^2{}_{it} + \varepsilon_{it} \quad (1)$$

This study uses $CO_2$ emissions to represent environmental degradation, which takes a quadratic function of per capita income or GDP due to their nonlinear relationship. Specifically, $CO_2$ emissions first increase during the early stage of growth, reach the maximum when a threshold income is achieved, and eventually decline with more growth, revealing an inverted U-shaped relationship with economic growth (Grossman & Krueger, 1991). The initial positive growth-$CO_2$ relationship is captured by $Y_{it}$, while the EKC turning point representing the level of income or growth where $CO_2$ emissions start to decline is denoted by $Y^2{}_{it}$.

### 3.2 Model specification

From equation (1), this study, following Waheed et al. (2018), Mahmood et al. (2019), and Ridzuan et al. (2020), extended the model by introducing agriculture, AGRPC, to capture the impact of agriculture on carbon emissions, giving equation (2) as follows:

$$CO2PC_t = f(GDPPC_t, GDPPC2_t, AGRPC_t) \quad (2)$$

This study intends to specifically investigate palm oil's impact on $CO_2$ emissions; thus, agriculture was substituted by palm oil production, POPROD, as in (3):

$$CO2PC_t = f(GDPPC_t, GDPPC2_t, POPROD_t) \quad (3)$$

Next, all attributes were transformed into their natural logarithms (ln) for more straightforward interpretation, error reduction, and model efficiency (Lüetkepohl & Xu, 2009). The specified econometric model, therefore, is as follows:

$$LNCO2PC_t = \alpha_0 + \alpha_1 LNGDPPC2_t + \alpha_2 LNGDPPC2_t + \alpha_3 LNPOPROD_t + \mu_t \quad (4)$$

where $\alpha_0$ and $\mu_t$ are the constant and error terms, respectively, while $\alpha_1$, $\alpha_2$, and $\alpha_3$ represent the estimated coefficients for $GDPPC_t$, $GDPPC2_t$, and $POPROD_t$, respectively. This model is treated as the baseline model and henceforth classified as Model 1.

For validity and reliability purposes, this study employed a few models by incorporating several control attributes that may influence the carbon emissions level into Model 1. Such an approach aims to ensure that the employed key explanatory attribute, i.e., palm oil production, behaves consistently, albeit under different assumptions (Lenz & Sahn, 2020), and to prevent the omission of any essential attributes in the extended EKC model (Cosmas et al., 2019; Haug & Ucal, 2019; Malik et al., 2020). Each model's results are compared, and inferences on the relationship between palm oil and $CO_2$ emissions are drawn based on the best model results, using past studies' findings as supporting arguments.

In Model 2, this study extended the baseline model in (4) by adding renewable energy, non-renewable energy proxied by oil demand, and trade openness into Model 1, denoted by RENEWPC, OILDDPC, and OPEN, respectively. This model is expressed as in equation (5) below and classified as Model 2:

$$LNCO2PC_t = \alpha_0 + \alpha_1 LNGDPPC2_t + \alpha_2 LNGDPPC2_t + \alpha_3 LNPOPROD_t + \alpha_4 LNRENEWPC_t + \alpha_5 LNOILDDPC_t + \alpha_3 LNOPEN_t + \mu_t \quad (5)$$

Model 2 was modified into Model 3 for a robustness check, such that palm oil production was substituted with palm oil consumption, or POCON, to evaluate the consistency of the correlation between palm oil and $CO_2$ emissions when an alternative proxy of palm oil was used in the analysis. The following equation expresses Model 3, where:

$$LNCO2PC_t = \alpha_0 + \alpha_1 LNGDPPC2_t + \alpha_2 LNGDPPC2_t + \alpha_3 LNPOCON_t + \alpha_4 LNRENEWPC_t + \alpha_5 LNOILDDPC_t + \alpha_6 LNOPEN_t + \mu_t \quad (6)$$

Theoretically, although the EKC hypothesis should be inversely U-shaped, different economic development stages may affect countries' environmental quality differently (Hafeez et al., 2019), varying the forms of the economic-environmental relationship described as follows:

1. If $\alpha_2 = \alpha_1 = 0$, an inverted U-shaped hypothesis for the relationship between environmental degradation and economic growth is rejected; no relationship exists between them (Bello & Abimbola, 2010; Rehman & Rashid, 2017);
2. If $\alpha_2 = 0$ and $\alpha_1 > 0$, a monotonically increasing linear causality exists between economic growth and environmental degradation (Farhani & Ozturk, 2015);
3. If $\alpha_2 = 0$ and $\alpha_1 < 0$, a monotonically decreasing linear causality exists (Baek, 2015; Dong et al., 2016);
4. If $\alpha_2 > 0$ and $\alpha_1 < 0$, it represents a positive U-shaped EKC hypothesis curve (Dogan et al., 2015; Dogan & Turkekul, 2016);
5. If $\alpha_2 < 0$ and $\alpha_1 > 0$, an inverted U-shaped EKC hypothesis curve is found, indicating the non-rejection of the hypothesis of the EKC (Ouyang & Lin, 2017; Churchill et al., 2019).

As mentioned above, if $\alpha_1$ is positive and $\alpha_2$ is negative, the EKC hypothesis exists for Malaysia's case. As for $\alpha_4$, it is expected to be negative and smaller than zero since renewable energy has been found to improve environmental quality (Ridzuan et al., 2020); $\alpha_5$ (oil demand) and $\alpha_6$ (trade openness), on the other hand, are expected to be positive, in line with (2019) for the former and Mahmood et al. (2019) for the latter. For palm oil production and palm oil consumption, $\alpha_3$, the signs of the attributes are dependent on the sustainability of Malaysian palm oil.

### 3.3 Data description

To conduct the analyses, this study utilised (1) the most updated Malaysia annual data ranging from 1978 to 2018, where GDP per capita data in constant 2010 US$ were collected from the World Development Indicators by World Bank; (2) data on $CO_2$ emissions per capita in metric tonnes were gathered from the World Data Atlas by Knoema Corporation; per capita renewable energy consumption data and oil demand per capita data in tonnes of oil equivalent were extracted from Malaysia Energy Information Hub; and (3) data on palm oil production and consumption, also per capita, were obtained from Datastream and the United States Department of Agriculture (USDA) in thousands of tonnes. Note that all employed data are in per capita units to keep all the tested models in line with the EKC model by Grossman and Krueger (1995), which postulates the relationship between per capita income and per capita $CO_2$ emissions. Table A1 in the Appendices presents and describes all the attributes and data employed by this study, while Table A2 provides the attributes' descriptive statistics.

### 3.4 Methodology

This study performed a series of econometric procedures to identify both symmetric and asymmetric relationships between the employed attributes. First, this study performed unit root and stationarity testing using multiple tests, including the augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Lee-Strazicich-(LEE), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, to complement the unit root analysis (El Montasser, 2015). Second, both symmetric and asymmetric cointegration tests were carried out to identify the linear and nonlinear relationship between all the attributes: the autoregressive distributed lag model (ARDL) by Pesaran and Smith (1995) and Pesaran et al. (2001) for linear cointegration testing, followed by nonlinear or asymmetric cointegration testing using nonlinear ARDL by Shin et al. (2014). Even though nonlinearity between the attributes is the primary concern of this study, performing ARDL estimation is essential prior to utilising the NARDL. Third, diagnostic and stability testing was carried out to verify that this study's ARDL and NARDL models are stable and reliable.

#### 3.4.1 Unit root tests

The stationarity of the data is key to valid estimated results because it guarantees the reliability of the employed time series. The conclusion drawn based on the estimation of any time series data is confirmed as valid only if the data are stationary, i.e., free from the unit root. Time series data are nonstationary and tend to falsify a noncorrelation as a correlation, giving spurious results and hence inaccurate forecasting. This study is necessary to commence the econometric analysis with stationarity testing on the employed data before performing subsequent tests.

3.4.2 Autoregressive distributed lag methodology (ARDL)

This study performs the ARDL test for cointegration by Pesaran and Smith (1995) and Pesaran et al. (2001) to investigate the long-run relationship between the attributes. Although there are many cointegration techniques seen in the literature, such as the Engle-Granger (1987) test and the Johansen (1988) and Johansen and Juselius (1990) maximum likelihood method, these methods may produce biased results if the tested attributes are integrated on the order of I(0) or I(1) (Le et al., 2019). However, that is not the case for ARDL, since this method can give unbiased estimations even with the existence of I(0) or I(1) attributes in the estimated model, and it has been employed by many (see Malik et al., 2020; Apergis & Gangopadhyay, 2020). Moreover, the ARDL method has several other qualities as follows: i) it adjusts for autocorrelation and endogeneity among the attributes to ensure estimation robustness and provides appropriate lag-length selection; ii) it is applicable to small samples; and iii) it simultaneously estimates both the long-run and short-run dynamics of the models, allowing for estimation flexibility (Pesaran et al., 2001).

In sum, this study employed the ARDL model to identify the dynamic relationship between the following attributes: income, palm oil production, and $CO_2$ emissions for Model 1; income, palm oil production, renewable energy, oil demand, trade openness, and $CO_2$ emissions for Model 2; and income, palm oil consumption, renewable energy, oil demand, trade openness, and $CO_2$ emissions for Model 3. The ARDL representation was formulated for each of the models. For Model 1, equation (5) is rewritten and expressed as follows:

$$\Delta\mathrm{LNCO2PC}_t = \lambda_0 + \sum_{k=1}^{m} \lambda_{1k}\, \Delta\mathrm{LNCO2PC}_{t-k} + \sum_{k=1}^{m} \lambda_{2k}\, \Delta\mathrm{LNGDPPC}_{t-k} + \sum_{k=1}^{m} \lambda_{3k}\, \Delta\mathrm{LNGDPPC2}_{t-k} + \sum_{k=1}^{m} \lambda_{4k}\, \Delta\mathrm{LNPOPROD}_{t-k} + \beta_1 \mathrm{LNCO2PC}_{t-1} + \beta_2 \mathrm{LNGDPPC}_{t-1} + \beta_3 \mathrm{LNGDDPC2}_{t-1} + \beta_4 \mathrm{LNPOROD}_{t-1} + \varepsilon_t \quad (7)$$

Equation (7) indicates the unrestricted error correction model (UECM) corresponding to the ARDL bound test, where ΔLNCO2PC, ΔLNGDPPC, ΔLNGDPPC2, and ΔLNPOPROD represent their respective difference values. $\lambda_1$-$\lambda_4$ represent short-term dynamic relationships, while $\beta_1$- $\beta_4$ each represent the long-run dynamic relationship. Using the F-test, cointegration between the attributes was performed where the null hypothesis of no cointegration is

(H0: $\beta_1=\beta_2=\beta_3=\beta_4=0$) against the alternative hypothesis of (H1: $\beta_1\neq\beta_2\neq\beta_3\neq\beta_4\neq0$).

To determine the existence of the cointegrating relationship between the attributes, the F-statistic obtained from the UECM was compared against the critical values derived by Narayan (2005), since such critical values are more effective for the case of small samples. If the F-statistic exceeds the upper critical values, the null hypothesis is rejected, indicating long-run cointegration between attributes, while when the F-statistic is smaller than the lower critical values, the null hypothesis cannot be rejected, and the attributes are not cointegrated. The analysis is inconclusive if the obtained F-statistic falls between the lower and upper critical values.

The next step is to estimate the employed model's long-run and short-run results once the attributes' cointegration is established. The long-run coefficients for the attributes of Model 1 were calculated by estimating the following long-run model, which is respecified from the UECM in (7), giving the following equation:

$$\mathrm{LNCO2PC_t} = \lambda_0 + \sum_{k=1}^{m} \lambda_{1k}\, \mathrm{LNCO2PC_{t-k}} + \sum_{k=1}^{m} \lambda_{2k}\, \mathrm{LNGDPPC_{t-k}} + \sum_{k=1}^{m} \lambda_{3k}\, \mathrm{LNGDPPC2_{t-k}} + \sum_{k=1}^{m} \lambda_{4k}\, \mathrm{LNPOPROD_{t-k}} + \varepsilon_t \quad (8)$$

Finally, the short-run coefficients were estimated using the error correction model (ECM) per the ARDL method such that:

$$\Delta\mathrm{LNCO2PC_t} = \lambda_0 + \sum_{k=1}^{m} \lambda_{1k}\, \Delta\mathrm{LNCO2PC_{t-k}} + \sum_{k=1}^{m} \lambda_{2k}\, \Delta\mathrm{LNGDPPC_{t-k}} + \sum_{k=1}^{m} \lambda_{3k}\, \Delta\mathrm{LNGDPPC2_{t-k}} + \sum_{k=1}^{m} \lambda_{4k}\, \Delta\mathrm{LNPOPROD_{t-k}} + \beta_1 \mathrm{LNCO2PC_{t-1}} + \beta_2 \mathrm{LNGDPPC_{t-1}} + \beta_3 \mathrm{LNGDDPC2_{t-1}} + \beta_4 \mathrm{LNPOROD_{t-1}} + \theta \mathrm{ECT_{t-1}} + \varepsilon_t \quad (9)$$

where θ denotes the error correction term (ECT) coefficient, indicating the dependent attribute's speed of adjustment after a change in the other attributes in the short run. In other words, the ECT shows how fast the dependent attribute returns to the long-run equilibrium following shocks to the other attributes in the short run. The ECT coefficient should be statistically significant and negative.

To certify that the model is reliable such that the hypothesis drawn is correct, the model should be confirmed to be free from i) autocorrelation, ii) heteroscedasticity, and iii) multicollinearity, and the error term $\varepsilon_t$ in the model should have i) a normal distribution and ii) a constant mean of zero value and variance (Bekhet & Othman, 2018). Thus, several diagnostic tests, such as the ARCH White heteroscedasticity test, Breusch-Godfrey LM serial correlation test, Breusch-Pagan-Godfrey heteroscedasticity test, and Jarque-Berra normality test, were conducted to confirm that the model follows all the specified criteria. For model stability testing, this study employed the CUSUM and CUSUMSQ tests.

Since this study has three different models, i.e., Model 1, Model 2, and Model 3, all the ARDL procedures done for Model 1 were repeated for Model 2 and Model 3, such as the formulation of the UECM as in (5) for F-bound testing; the estimation of the long-run and short-run coefficients, respectively using the long-run model derived as in (6) and the ECM as extracted in (7). The same applies to diagnostic and stability testing.

### 3.4.3 Nonlinear autoregressive distributed lag methodology (NARDL)

In the event that the relationship between studied attributes is likely not to be linear, the utilisation of ARDL may lead to a misleading conclusion about the actual relationship (Kocaarslan & Soytas, 2019; Huang et al., 2018) or may even suggest a nonsignificant symmetric relationship (Bhutto & Chang, 2019). Economic attributes are often affected by fluctuations in the economic cycle, making the relationship between economic attributes nonlinear in nature (Xu et al., 2020), and some macroeconomic attributes are more responsive to bad news or negative shocks, e.g., stock prices, as suggested by Koutmos (1999). The ARDL model is enhanced by applying asymmetry or nonlinearity to it to capture any possible nonlinearities between attributes (Shin et al., 2014). The statistically insignificant linear relationship deduced by ARDL becomes significant if the explanatory attributes are separated into positive and negative shocks to determine any hidden asymmetric cointegration that may exist (Bhutto & Chang, 2019). This study extends linear cointegration testing by examining the asymmetric relationship between palm oil and $CO_2$ emissions using the NARDL approach, as described next.

The NARDL allows for cointegration testing irrespective of the order of integration, provided that the attributes are integrated at level I(0) or first difference I(1), but never I(2). The model simultaneously estimates the long-run and short-run coefficients, and it is more appropriate for small sample sizes. The methodology decomposes the exogenous attribute X into the positive and negative partial sums of increases and decreases in regressors. Following the 3 models for the ARDL cointegration estimation employed by this study, the NARDL model is classified into NARDL Model 1, NARDL Model 2, and NARDL Model 3. Specifically, NARDL Model 1 decomposes the changes in the values of palm oil production into positive (+) and negative (-) partial sums of increases and decreases; NARDL Model 2 decomposes the changes in the values of palm oil production, renewable energy, oil demand, and trade openness into positive and negative partial sums of increases and decreases. For Model 3, NARDL Model 2 was modified by replacing palm oil production with palm oil consumption; the other attributes remained unchanged. Starting with the first NARDL model, Model 1, as in equation (4), it is extended in the following form:

$$LNCO2PC_t = \alpha_0 + \alpha_1 LNGDPPC_t + \alpha_2 LNGDPPC_2 + \alpha_3 LNPOPROD_t{}^{+} + LNPOPROD_t{}^{-} + \mu_t \quad (10)$$

where $LNPOPROD_t{}^{+}$ and $LNPOPROD_t{}^{-}$ represent the positive and negative partial sum process variation in palm oil production derived from equation (9):

$$LNPOPROD_t{}^{+} = \sum_i^t \Delta LNPOPROD_i{}^{+} + \sum_i^t max(\Delta LNPOPROD_i, 0)$$
$$LNPOPROD_t{}^{-} = \sum_i^t \Delta LNPOPROD_i{}^{-} + \sum_i^t min(\Delta LNPOPROD_i, 0) \quad (11)$$

Similarly, the asymmetric testing of the attributes follows the steps executed under the ARDL methodology, whereby unit root testing was done to check the order of integration for $LNPOPROD_t^{+}$ and $LNPOPROD_t^{-}$. If the tests employed confirmed the attributes' stationarity condition, this study proceeded to apply the NARDL method to investigate the asymmetric relationship in Model 1. The equation is written as:

$$\Delta LNCO2PC_t = \alpha_0 + \sum_{k=1}^{m} \alpha_{1k} \Delta LNCO2PC_{t-k} + \sum_{k=1}^{m} \alpha_{2k} \Delta LNGDPPC_{t-k} + \sum_{k=1}^{m} \alpha_{3k} \Delta LNGDPPC2_{t-k} + \sum_{k=1}^{m} \alpha_{4k} \Delta \mathrm{LNPOPROD}^{+}{}_{t-k} + \sum_{k=1}^{m} \alpha_{5k} \Delta LNPOPROD^{-}{}_{t-k} + \beta_1 \mathrm{LNCO2PC}_{t-1} + \beta_2 \mathrm{LNGDPPC}_{t-1} + \beta_3 \mathrm{LNGDDPC2}_{t-1} + \beta_4 \mathrm{LNPOPROD}^{+}{}_{t-1} + \beta_5 \mathrm{LNPOPROD}^{-}{}_{t-1} + \varepsilon_t \quad (12)$$

where $\sum_{k=1}^{m} \alpha_{4k}$ and $\sum_{k=1}^{m} \alpha_{5k}$ capture the short-run positive and negative effects of palm oil production on carbon emissions, while $\beta_4$ and $\beta_5$ capture the long-run positive and negative effects of palm oil production on $CO_2$ emissions. The ECM of (10) is represented as follows:

$$\Delta \mathrm{LNCO2PC}_t = \alpha_0 + \sum_{k=1}^{m} \alpha_{1k} \Delta \mathrm{LNCO2PC}_{t-k} + \sum_{k=1}^{m} \alpha_{2k} \Delta \mathrm{LNGDPPC}_{t-k} + \sum_{k=1}^{m} \alpha_{3k} \Delta \mathrm{LNGDPPC2}_{t-k} + \sum_{k=1}^{m} \alpha_{4k} \Delta \mathrm{LNPOPROD}^{+}{}_{t-k} + \sum_{k=1}^{m} \alpha_{5k} \Delta \mathrm{LNPOPROD}^{-}{}_{t-k} + \theta \mathrm{ECT}_{t-1} + \varepsilon_t \quad (13)$$

θ represents the ECT, denoting the adjustment speed to the long-run equilibrium after the shocks in the short run, while $\alpha_{4k}$ and $\alpha_{5k}$ represent short-run adjustment asymmetries. Next, bounds testing was employed using the F statistic to test for the long-run cointegration between attributes with the null hypothesis of no cointegration:

($H_0$: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$) against the alternative of cointegration ($H_1$: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$).

Then, given the presence of a long-run relationship, this study investigated the null hypothesis of long-run symmetry $\beta = \beta^+ = \beta^-$ and short-run symmetry $\alpha = \alpha^+ = \alpha^-$ for palm oil production using standard Wald tests. After the long-run relationship was confirmed, the dynamic multiplier effect was examined, where a 1% change in $LNPOPROD^+_{t-k}$ and $LNPOPROD^-_{t-k}$ were estimated. The estimated dynamic multipliers denote the dynamic adjustment of the dependent attribute, $CO_2$ emissions, to the new equilibrium following different shocks (positive and negative) to palm oil production. The adjustment patterns can be observed in the dynamic multiplier graphs. To conclude, the NARDL estimation and diagnostic and stability testing were carried out, similar to the testing employed in the ARDL approach, to verify that the model was stable, reliable and free from estimation bias. All of the NARDL procedures described were then repeated for Model 2 and Model 3.

## 4.0 RESULTS AND DISCUSSION

### *4.1 Unit root and stationarity tests*

The results of all the unit root and stationary tests of this study are presented in Table 1. The results of the ADF, PP, and LEE tests suggest that the attributes have a mixed order of integration, i.e., they are integrated at level I(0) and first difference I(1), rejecting the null hypothesis of a unit root, while the KPSS test reveals that all attributes are significant at I(0) except for GDP and renewable energy. The structural breaks shown in LEE relate to events at the national and global levels. Since no unit root is found and all attributes are stationary, the data satisfy the statistical needs for this research.

Table 1: Unit root tests

| **Methodology** | **ADF** | **PP** | **KPSS** | **LEE** | |
|---|---|---|---|---|---|
| Attribute | t-stat. | t-stat. | t-stat. | t-stat. | Break-years |
| ***At Level I(0)*** | | | | | |
| LNCO2PC | -2.151 | -1.993 | 0.757*** | -4.053 | 1990, 2008 |
| LNGDPPC | -0.794 | -0.777 | 0.789*** | -3.977 | 1989, 1999 |
| LNGDPPC2 | -0.523 | -0.524 | 0.790*** | -3.980 | 1990, 1999 |
| LNRENEWPC | -1.383 | -1.479 | 0.619** | -6.121* | 1985, 2010 |
| LNPOPROD | -2.973** | -5.824*** | 0.775*** | -6.311* | 1990, 2007 |
| LNPOCON | -2.863* | -3.413 | 0.762*** | -5.871* | 1981, 1992 |
| LNOPEN | -2.393 | -2.393 | 0.614** | -4.685 | 1992, 2009 |
| LNOILDDPC | -2.415 | -2.272 | 0.7257** | -4.261 | 1985, 1995 |
| ***At First Difference, I(1)*** | | | | | |
| LNCO2PC | -4.929*** | -4.936*** | 0.385* | -6.970*** | 1984, 1988 |

| | | | | | |
|---|---|---|---|---|---|
| LNGDPPC | -5.295*** | -5.295*** | 0.084 | -6.072* | 1986, 2000 |
| LNGDPPC2 | -5.375*** | -5.375*** | 0.063 | -6.032** | 1986, 2000 |
| LNRENEWPC | -5.114*** | -5.021*** | 0.166 | -6.259** | 1983, 2003 |
| LNPOPROD | -7.481*** | -7.509*** | 0.812*** | -9.751*** | 1993, 2001 |
| LNPOCON | -8.393*** | -8.819*** | 0.514** | -8.864*** | 1981, 1985 |
| LNOPEN | -4.735*** | -4.730*** | 0.638** | -6.715** | 1986, 2000 |
| LNOILDDPC | -5.177*** | -5.156*** | 0.394* | -6.312** | 1982, 1986 |

*Note: ***, ** and * show significance at the 1,5 and 10% level respectively.*
*Null hypothesis for ADF test: Attribute has a unit root*
*Null hypothesis for PP test: Attribute has a unit root*
*Null hypothesis for KPSS test: Attribute has no unit root*
*Null hypothesis for LEE test: Attribute has a unit root*

### *4.2 Autoregressive distributed lag methodology (ARDL)*

Table 2 shows the results for the lag order selection, where all four criteria, i.e., LR, FPF, AIC, and HQ, indicate that a lag length of 2 is desirable for cointegration testing. In fact, the maximum lag length of 2 conforms to the rule of thumb for the annual data used in this study, and the lag selection under the vector autoregressive (VAR) model is confirmed in Figure 2 by the polynomial graph—that all dots are within the circle (except for one dot that is just across the border) signify the appropriateness of lag length 2 for decision and policy reliability.

Table 2: Lag Selection

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | -1856.880 | NA | 2.91E+30 | 95.686 | 96.070 | 95.824 |
| 1 | -1527.270 | 490.188 | 9.39E+24 | 82.937 | 86.776* | 84.314 |
| 2 | -1415.270 | 114.871* | 3. 89e+24* | 81.347* | 88.641 | 83.964* |

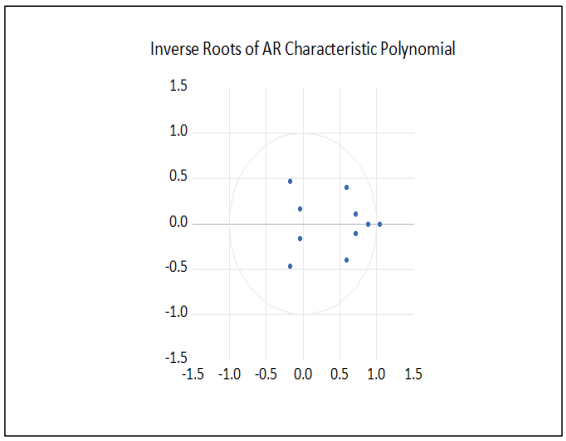


Figure 2: Lag selection criteria under VAR in a polynomial graph

The bound F-test was conducted between the attributes of Model 1, Model 2, and Model 3 for the cointegration test, and the results are tabulated in Table 3. The F-statistic of Model 1 (4.294) exceeds the 10% upper bound critical value; the F-statistic of Model 2 (6.535) exceeds the 1% upper bound critical value; and the F-statistic of Model 3 (2.402)

falls between the upper and lower bound critical values at the 10% significance level. According to Narayan (2005), these results confirm that there exists a significant long-run relationship between the attributes in Model 1 and Model 2 and inconclusive long-run cointegration between those of Model 3.

Once cointegration evidence has been found, the long-term and short-term ARDL coefficients for models with significant cointegration, i.e., Model 1 and Model 2, are estimated. Table 3 reports the long-run coefficients of the ARDL estimates, while Table 4 reports the short-run coefficients. For Model 1, the ARDL results for the relationship between economic growth (proxied by per capita income or GDP) and carbon dioxide emissions per capita are positive and significant in both the long run and short run, suggesting that a 1% increase in GDP increases $CO_2$ emissions by 14.109% in the long run and 3.948% in the short run. For the square term of per capita income denoted by LNGDPPC2, both the long-run and short-run coefficients are negative and significant, verifying the existence of the EKC hypothesis for the case of Malaysia. The EKC hypothesis is clearly not only a long-run occurrence for the Malaysian case. The coefficient of the ECT ($ECT_{t-1}$) is negative and statistically significant, implying a highly stable long-run relationship between attributes in the model. Palm oil production (0.378) has a significant positive relationship with $CO_2$ emissions in the long run, suggesting that a 1% increase in palm oil production in Malaysia raises the country's $CO_2$ emissions level by 0.0.378%.

Similar steps were taken for Model 2, where the long-run results of Model 2 reveal insignificantly negative GDP (-2.824) and insignificantly positive squared GDP (0.168), rejecting the EKC hypothesis for Malaysia. However, the impact of the key explanatory attribute, palm oil production (0.369), on $CO_2$ emissions remains significantly positive even after incorporating the control attributes into the model. An increase of 1% in palm oil production increases $CO_2$ emissions by 0.369% in the long run for Model 2. Meanwhile, the ARDL estimation of the control attributes produces the expected results for renewable energy and trade openness in both the short run and long run. The results show that an increase of 1% in renewable energy reduces $CO_2$ emissions by 0.043%, while a rise of 1% in trade openness increases carbon emissions by 0.468% in the long run. For the other control attribute, oil demand, both the short-run and long-run ARDL estimates show that oil demand has an insignificantly negative impact on $CO_2$. In terms of the ECT, $ECT_{t-1}$ in Model 2 has a negative and significant coefficient, certifying the existence of long-run cointegration between palm oil production, renewable energy, oil demand, trade openness, and $CO_2$ emissions.

Model 1's reliability was tested through several diagnostic tests, as depicted in Table 3, and all tests confirmed that Model 1 was free from the problems of heteroscedasticity (the Breusch-Pagan-Godfrey and ARCH tests) and autocorrelation (the Breusch-Godfrey serial correlation LM test) and that the model's residuals were normally distributed (the Jarque-Bera normality test). The results of the CUSUM and CUSUMSQ stability tests proved that Model 1 is stable, as indicated by Figure 2, where both the CUSUM and CUSUMSQ diagrams show that the values stay within the 0.05 significance level boundaries. Similarly, Model 2 passed the tests of normality, serial correlation, heteroscedasticity, CUSUM, and CUSUMSQ, concluding that the results generated by the ARDL method in Model 2 are unbiased and accurate.

Table 3: The ARDL long-run results

| Attributes | Model 1 | Model 2 | Model 3 |
|---|---|---|---|

| | | | |
|---|---|---|---|
| LNGDPPC | 14.109*** (0.001) | -2.824 (2.475) | -12.350 (0.346) |
| LNGDPPC2 | -0.674*** (0.002) | 0.168 (0.117) | 0.627 (0.317) |
| LNPOPROD | 0.378** (0.038) | 0.369*** (0.063) | |
| LNPOCON | | | 0.069 (0.711) |
| LNRENEWPC | | -0.043* (0.022) | 0.046 (0.727) |
| LNOILDDPC | | -0.074 (0.271) | 0.225 (0.653) |
| LNOPEN | | 0.468*** (0.133) | 1.002* (0.089) |
| CONSTANT | -21.832*** (0.002) | 5.265 (9.899) | 17.674 (0.254) |
| Selection Model | 1,2,2,1 | 2, 2, 2, 2, 2, 1, 2 | 128, 2, 2, 0, 2, 0, 0 |
| R-square | 0.997 | 0.999 | 0.997 |
| Adjusted R-square | 0.996 | 0.998 | 0.996 |
| F-stat. | 968.323 | 1043.711 | 753.430 |
| *ARDL Bound Test Estimate* | | | |
| F.stat | 4.294* | 7.313*** | 2.402 |

| Narayan (2005) Critical Values | | | | | | |
|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| 10% Significance Level | 2.933 | 4.02 | 2.353 | 3.599 | 2.353 | 3.599 |
| 5% Significance Level | 3.548 | 4.803 | 2.797 | 4.211 | 2.797 | 4.211 |
| 1% Significance Level | 5.018 | 6.61 | 3.8 | 5.643 | 3.8 | 5.643 |

| *Diagnostic Testing* | | | |
|---|---|---|---|
| Normality | 0.158 | 0.491 | 0.644 |
| Serial correlation | 0.938 | 0.217 | 0.447 |
| Heteroscedasiticy (BPG) | 0.502 | 0.358 | 0.928 |
| ARCH | 0.542 | 0.034** | 0.803 |
| CUSUM | Stable | Stable | Stable |

*Note: ***, ** and * show significance at the 1, 5 and 10% level respectively. Standard errors are in brackets. Jarque-Bera (normality) test; Breusch-Godfrey LM serial correlation test; Breusch-Pagan-Godfrey heteroscedasticity test; LM-ARCH heteroscedasticity test; Cumulative sum (CUSUM) stability test; Cumulative sum of square (CUSUM-SQ.) stability test.*

Table 4: The ARDL short-run results

| Attributes | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| LNGDPPC(-1) | 3.948*** (0.003) | -2.229 (1.925) | -3.557 (0.230) |
| LNGDPPC2(-1) | -0.189*** (0.003) | 0.133 (0.091) | 0.181 (0.201) |
| LNPOCON(-1) | | | |
| LNRENEWPC(-1) | | -0.034 (0.020) | 0.013 (0.686) |
| LNPOPROD(-1) | 0.106** (0.049) | 0.291*** (0.063) | |
| LNOILDDPC(-1) | | -0.059 (0.213) | |
| LNOPEN(-1) | | 0.369*** (0.105) | |
| D(LNCO2PC(-1)) | | 0.168 (0.134) | |
| D(LNGDPPC) | -5.009 (0.429) | -20.728*** (5.233) | -15.828** (0.039) |
| D(LNGDPPC(-1)) | 17.302***(0.009) | 18.875***(4.898) | 15.379** (0.027) |
| D(LNGDPPC2) | 0.279 (0.378) | 1.056*** (0.260) | 0.811 (0.034) |

| | | | |
|---|---|---|---|
| D(LNGDPPC2(-1)) | -0.864*** (0.009) | -0.952*** (0.244) | -0.772** (0.027) |
| D(LNPOPROD) | -0.037 (0.642) | -0.050 (0.071) | |
| D(LNPOPROD(-1)) | | -0.224*** (0.065) | |
| D(LNOILDDPC) | | 0.075 (0.128) | |
| D(LNOILDDPC(-1)) | | 0.285 (0.134) | |
| D(LNRENEWPC) | | 0.041 (0.029) | -0.007 (0.843) |
| D(LNOPEN) | | 0.026 (0.088) | -0.080 (0.032) |
| D(LNOPEN(-1)) | | -0.137 (0.113) | |
| D(LNPOCON) | | | |
| ECT(-1) | -0.280*** (0.005) | -0.789*** (0.136) | |

*Note: ***, ** and * show significance at the 1,5 and 10% level respectively. Standard errors are in brackets.*

*4.3 Nonlinear autoregressive distributed lag methodology (NARDL)*

Macroeconomic attributes may not be linear due to the presence of asymmetric effects in some regressors, such that an increase or a decrease in the explanatory attributes affects the response attributes differently (Apergis & Gangopadhyay, 2020). This study argues that the attributes in Model 1, Model 2, and Model 3 are actually nonlinearly cointegrated, and the results of the estimated ARDL models are mis-specified and inaccurate. Therefore, this study attempts to check for any nonlinearities that may exist among the employed attributes to examine how the dependent attributes respond to the presence of different shocks on the independent attributes.

Table 5: The NARDL long-run results

| Attributes | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| LNGDPPC | 13.741*** (4.084) | 51.828** (20.360) | 3.865 (3.421) |
| LNGDPPC2 | -0.656 *** (0.205) | -2.380** (0.942) | -0.189 (0.169) |
| LNPOPROD_POS | 0.361**(2.043) | -1.889* (0.877) | |
| LNPOPROD_NEG | 0.326 (0.682) | 2.645* (1.202) | |
| LNOILDDPC_POS | | -2.571* (1.150) | 0.023 (0.135) |
| LNOILDDPC_NEG | | -1.071 (0.710) | 0.391 (0.302) |
| LNRENEWPC_POS | | 1.051** (0.439) | 0.078 (0.050) |
| LNRENEWPC_NEG | | -1.235** (0.404) | -0.242*** (0.030) |
| LNOPEN_POS | | -0.522 (0.435) | 0.201 (0.137) |
| LNOPEN_NEG | | 2.087** (0.656) | 0.049 (0.167) |
| R-squared | 0.999 | 0.972 | 0.932 |
| Adjusted R-square | 0.998 | 0.970 | 0.931 |
| F-stat. | 1089.416 | 1078.314 | 937.512 |
| *NARDL Bound Test Estimate* | | | |
| F.stat | 3.329 | 4.451*** | 7.491*** |

| Narayan (2005) Critical Values | | | | | | |
|---|---|---|---|---|---|---|
| | I(0) | I(1) | I(0) | I(1) | I(0) | I(1) |
| 10% Significance Level | 2.45 | 3.52 | 1.83 | 2.94 | 1.83 | 2.94 |
| 5% Significance Level | 2.86 | 4.01 | 2.06 | 3.24 | 2.06 | 3.24 |
| 1% Significance Level | 3.74 | 5.06 | 2.54 | 3.86 | 2.54 | 3.86 |

| *Diagnostic Testing* | | | |
|---|---|---|---|
| Normality | 0.528 | 0.491 | 0.704 |
| Serial correlation | 0.105 | 0.034** | 0.016** |
| Heteroscedasiticy (BPG) | 0.696 | 0.326 | 0.759 |
| ARCH | 0.662 | 0.044** | 0.200 |
| CUSUM | Stable | Stable | Stable |
| CUSUM-SQ | Stable | Stable | Stable |

*Note: ***, ** and * show significance at the 1, 5 and 10% level respectively. Jarque-Bera (normality) test; Breusch-Godfrey LM serial correlation test; Breusch-Pagan-Godfrey heteroscedasticity test; LM-ARCH heteroscedasticity test; Cumulative sum (CUSUM) stability test; Cumulative sum of square (CUSUMSQ) stability test. Standard errors are in brackets.*

This study applied the NARDL approach by Shin et al. (2014) to explore asymmetry issues that may exist between the employed attributes. The F-statistic (3.329) obtained for NARDL Model 1 presented in Table 5 falls between the 10% significance level of the upper and lower bound critical values, suggesting an inconclusive long-run cointegration between the attributes (Narayan, 2005). Therefore, this study proceeded with only the short-run NARDL estimation on Model 1. As shown in Table 6, economic growth has a positive and significant relationship with carbon dioxide emissions (3.933) at the 1% significance level in the short run.

The coefficient for squared GDP is negative (-0.188) but significant, verifying the presence of the EKC hypothesis for Malaysia in the short run. The rise in palm oil production (0.103) increases the level of $CO_2$ emissions significantly in the short run, while the decrease in palm oil production (0.093) has no significant short-run impact on carbon emissions. The Wald test results of NARDL Model 1 in Table 7 show that positive and negative shocks to palm oil production significantly support asymmetry in the short run. Meanwhile, the model's ECT is found to be negative (-0.286) and statistically significant, implying that any disequilibrium in past years is corrected within one year at a speed of 28.6%, representing a slow adjustment speed. In terms of model reliability, the diagnostic tests presented in the lower part of Table 5 show no evidence pertaining to the problems of model misspecification, heteroscedasticity, serial correlation, and normality for NARDL Model 1. The stability of the model is confirmed by the CUSUM and CUSUMSQ test charts, as displayed in the Appendices.

Table 6: The NARDL short-run results

| Attributes | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| LNGDPPC(-1) | 3.933*** (1.291) | 38.201** (12.046) | 5.606 (4.994) |
| LNGDPPC2(-1) | -0.188*** (0.059) | -1.754** (0.561) | -0.273 (0.246) |
| LNPOPROD_POS(-1) | 0.103* (0.052) | -1.392** (0.503) | |
| LNPOPROD_NEG(-1) | 0.093 (0.211) | 1.950** (0.629) | |
| LNOILDDPC_POS(-1) | | -1.895** (0.673) | 0.034 (0.197) |
| LNOILDDPC_NEG(-1) | | -0.789 (0.452) | 0.567 (0.442) |
| LNRENEWPC_POS(-1) | | 0.775** (0.241) | 0.114 (0.072) |
| LNRENEWPC_NEG(-1) | | -0.910*** (0.236) | -0.352*** (0.057) |
| LNOPEN_POS(-1) | | -0.384 (0.308) | 0.291 (0.199) |

| | | | |
|---|---|---|---|
| LNOPEN_NEG(-1) | | 1.538*** (0.363) | 0.072 (0.242) |
| LNPOCON_POS(-1) | | | 0.281** (0.107) |
| LNPOCON_NEG(-1) | | | 0.604* (0.286) |
| C | -20.224*** (6.872) | -202.981** (64.523) | -27.781 (25.202) |
| ECT(-1) | -0.286** (0.107) | -0.737*** (0.175) | -1.450*** (0.225) |

*Note: ***, ** and * show significance at the 1,5 and 10% level respectively. Standard errors are in brackets.*

Table 7: The NARDL Wald test results

| Models | Exogenous attribute | Short-run | | Long-run | |
|---|---|---|---|---|---|
| | | F-stat. | Probability | F-stat. | Probability |
| Model 1 | LNPOPROD | 6.719*** | 0.005 | 2.067 | 0.151 |
| Model 2 | LNPOPROD | 2.602 | 0.143 | 5.655** | 0.035 |
| | LNOILDDPC | 0.082 | 0.922 | 2.458 | 0.155 |
| | LNRENEWPC | 5.087** | 0.043 | 2.456 | 0.156 |
| | LNOPEN | 4.843** | 0.048 | 3.868* | 0.074 |
| Model 3 | LNPOCON | 3.403* | 0.068 | 1.646 | 0.234 |
| | LNOILDDPC | 1.254 | 0.320 | 1.144 | 0.351 |
| | LNRENEWPC | 8.772*** | 0.005 | 0.177 | 0.840 |
| | LNOPEN | 1.365 | 0.292 | 3.307* | 0.072 |

*Note: ***, ** and * show significance at the 1, 5 and 10% level respectively.*

The result of NARDL Model 2 found that the F-statistic (4.451) becomes statistically significant at the 1% level, revealing that the attributes (oil demand, renewable energy, and trade openness) are statistically cointegrated in the long run. The NARDL Model 2 short- and long-run estimation shows that most of the explanatory attributes have statistically significant asymmetric effects on $CO_2$ emissions. The control attributes have mixed asymmetric relationships with $CO_2$ emissions in the long run, specifically, (i) oil demand: a rise in oil demand (positive shock in the partial sum of oil demand) reduces $CO_2$ emissions significantly, while a decrease in oil demand (negative shock in the partial sum of oil demand) has no significant impact on $CO_2$; (ii) renewable energy: an increase in renewable energy (positive shock in the partial sum of renewable energy) increases $CO_2$ emissions significantly, while a decrease in renewable energy (negative shock in the partial sum of renewable energy) reduces $CO_2$ emissions significantly; and (iii) trade openness: a rise in trade openness (positive shock in the partial sum of trade openness) has no significant effect on $CO_2$ emissions, while a decline in trade openness (negative shock in the partial sum of trade openness) significantly increases $CO_2$ emissions.

A rise in palm oil production (positive shock in the partial sum of palm oil production) has a negative effect on $CO_2$ emissions (-1.889), meaning an increase of 1% in palm oil production reduces $CO_2$ emissions significantly by 1.889%. This is supported by the finding of Uning et al. (2020), who claimed that palm oil is capable of absorbing approximately 64 tons of $CO_2$ per hectare annually. In a situation where palm oil production declines (negative shock in the partial sum of palm oil production), it has a positive impact on $CO_2$ emissions (2.645), meaning that if palm oil production decreases by 1%, $CO_2$ emissions increase significantly by 2.645%. For the EKC hypothesis evidence, the nonlinear ARDL Model 2 supports the EKC path in the long run, since both per capita GDP (51.828) and

squared per capita GDP (-2.380) have positive and negative significant relationships with $CO_2$ emissions, respectively. For short-run asymmetric estimates, the nonlinearities between the model's independent attributes and $CO_2$ emissions are mostly consistent with their long-run estimates.

The same applies to the EKC hypothesis, wherein the NARDL estimation of Model 2 provides significant evidence of the EKC hypothesis for Malaysia in the short run. However, the Wald test statistics suggest mixed findings, such that the asymmetry between palm oil production and $CO_2$ emissions is significant only in the long run; asymmetry in renewable energy is significant only in the short run; and trade openness supports the asymmetry in both the short and long run. For oil demand, its asymmetries in both the short run and long run are insignificant and unsupported. NARDL Model 2 also passes the diagnostic tests of heteroscedasticity and normality, as well as the CUSUM and CUSUMSQ stability tests.

In NARDL Model 3, palm oil production in NARDL Model 2 was replaced with palm oil consumption. The purpose for such modification is for sensitivity and robustness analysis, and thus the results obtained in Model 3 are compared against the results of Model 2. This also aims to check whether the cointegration between the attributes changes if different proxies of palm oil and trade openness are used. As shown in Table 5, the result of long-run cointegration between the attributes in NARDL Model 3 is statistically significant at the 1% significance level. For the NARDL long-run and short-run estimates, there are some critical differences in the findings that are worth noting in the NARDL Model 3 estimation.

In sum, (1) the EKC hypothesis for Malaysia is not significant; (2) the rise in palm oil consumption (positive shock in the partial sum of palm oil consumption) increases $CO_2$ emissions significantly in the long run; the rise and fall in oil demand (positive and negative shocks in the partial sum of oil demand) have no significant impact on $CO_2$ emissions in the long run; (3) the rise in renewable energy (positive shock in the partial sum of renewable energy) has no impact on $CO_2$ emissions in the long run; (4) the increase and decrease in trade openness (positive and negative shocks in the partial sum of trade openness) have no significant impact on $CO_2$ emissions; and (5) NARDL Model 3 is reliable and stable, evidenced by the lack of heteroscedasticity and normality issues uncovered in diagnostic testing. The model is confirmed as stable since the values in both the CUSUM and CUSUMSQ diagrams stay within the 5% significance level boundaries.

To conclude, for the NARDL estimation, the asymmetric dynamic multiplier was executed to illustrate the adjustment pattern of the attributes to their new long-run equilibrium following shocks in the short run. Figure 3 illustrates the asymmetric dynamic multipliers assessed on Model 2, where the diagrams show the patterns of adjustment of $CO_2$ emissions to their new long-run equilibrium in response to positive and negative shocks on palm oil production, renewable energy, oil demand, and trade openness at a given forecast horizon. In the graphs, the lower and upper bands are represented by dotted lines, indicating symmetry at the 95% confidence interval. The positive change curves (the continuous black line) provide information on the asymmetric adjustments of the dependent attribute ($CO_2$ emissions) to positive shocks on the explanatory attributes, and the negative change curves (dashed black lines) show the asymmetric adjustment patterns of the dependent attribute ($CO_2$ emissions) to negative shocks on the explanatory attributes.

The difference between the positive component and negative component curves represents an asymmetry curve showing the linear mixture of the dynamic multipliers linked with positive and negative shocks on the explanatory attributes. As illustrated by the

diagrams, the asymmetry in palm oil production is significant in the long run, where the effect of a negative shock is deeper than that of a positive one; the asymmetry in renewable energy is significant in the short-run, where $CO_2$ emissions are seen to be more sensitive to a negative shock; positive and negative shocks to oil demand do not support asymmetry in either the short run or the long run; positive and negative shocks in trade openness support asymmetry in both the short run and long run, with a greater impact coming from a negative shock than from a positive shock, as shown in the diagram.

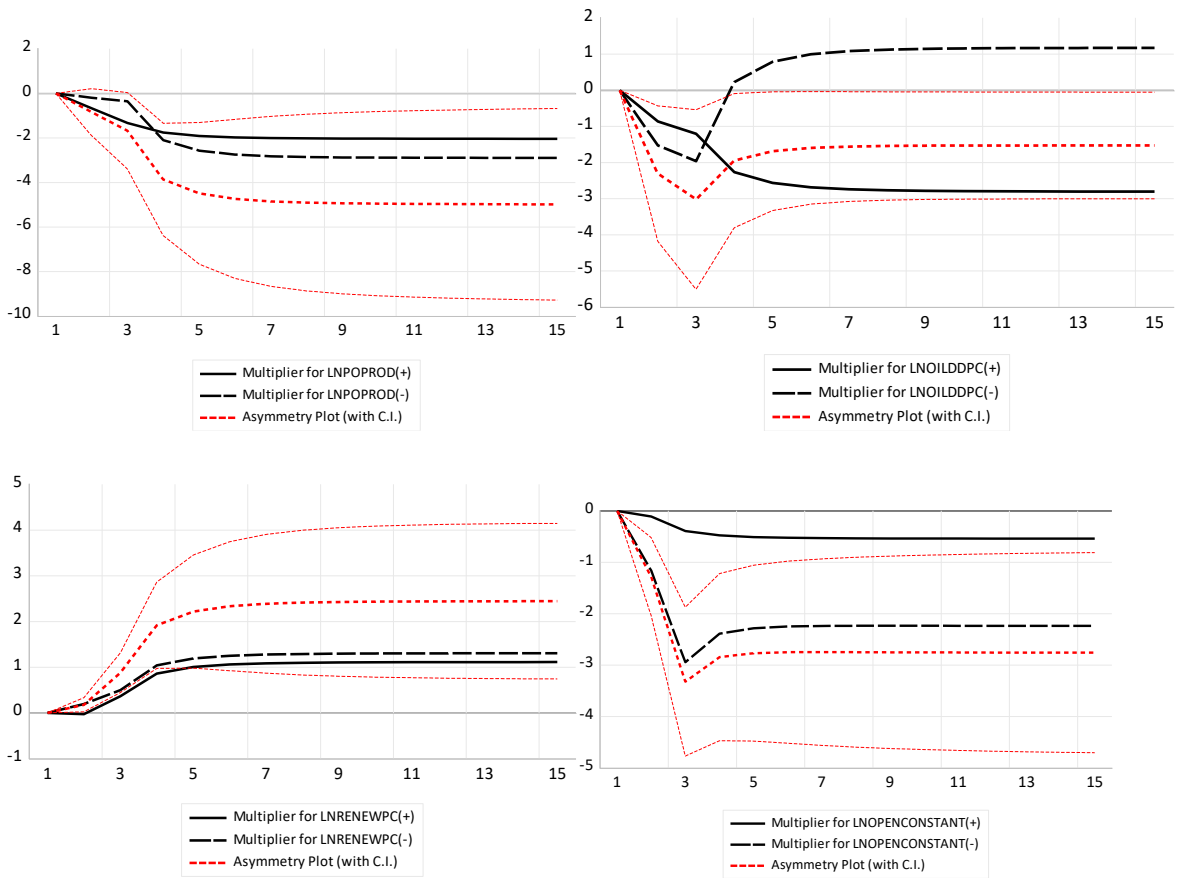


Figure 3: Nonlinear ARDL dynamic multiplier effect graphs (Model 2)

## 5.0 CONCLUSION

This study examines the symmetric and asymmetric relationship between palm oil and $CO_2$ emissions in the EKC hypothesis framework for Malaysia for the period of 1978 until 2018. For this purpose, the ARDL and NARDL methodologies are utilised to examine the long-run and short-run linearities and nonlinearities between the attributes, and a baseline model and modified models are employed to propose the palm oil-$CO_2$ emissions EKC model that can best capture the asymmetrical impacts of palm oil on $CO_2$ emissions for the case of Malaysia. The results reveal that palm oil and $CO_2$ emissions have a significant asymmetric relationship in the long run for Malaysia, as a rise in palm oil production can bring the country's $CO_2$ emissions level down in the long run, while a reduction in palm oil production raises the emissions level instead. Thus, Malaysian palm oil production indeed contributes to the country's sustainable development goals, provided that the country continues to improve the sustainability of its palm oil sector. This study confirms the EKC hypothesis for Malaysia for both methodologies.

Theoretically, ARDL cointegration testing reveals a mixed finding of long-run cointegration for all models, providing some interesting conclusions. First, palm oil, economic growth, and $CO_2$ emissions are statistically cointegrated in the long run when palm oil production is used, as in Model 1 and Model 2. Second, when palm oil consumption is used in Model 3, the relationship between palm oil, economic growth, and $CO_2$ emissions becomes insignificant. This finding justifies the employment of palm oil production rather than consumption in the baseline model investigating the impact of palm oil on $CO_2$ emissions. This study further strengthened the argument of Ridzuan et al. (2020) and Gokmenoglu and Taspinar (2018), where these studies also utilised production-based attributes, and this study contributes to the knowledge on the irrelevance of palm oil consumption to $CO_2$ emissions.

The question of whether $CO_2$ emissions are caused by the supply or demand of palm oil is answered in this study, as production has taken a greater toll. For example, palm oil requires the conversion of forests and peatland into oil palm plantations, and in this way, the production of palm oil contributes to the emissions of $CO_2$ in Malaysia (Jaafar et al., 2020). In contrast, the cointegration significance between palm oil and $CO_2$ emissions improves when the control attributes, namely, renewable energy, oil demand, and trade openness, are introduced in Model 2. Note how the significance level of Model 1 increases from 10% to 1% in Model 2 with the inclusion of the control attributes, justifying this study's decision to incorporate some control attributes to avoid the omission of any vital attributes in the EKC model, as suggested by Cosmas et al. (2019); Haug and Ucal (2019); Malik et al. (2020). Moreover, the significant improvement in Model 2 also proves that the addition of renewable energy, oil demand, and trade openness depicts a more stable long-run cointegration between palm oil and carbon dioxide emissions in the framework of the EKC hypothesis for Malaysia.

In addition, this study sheds some light on policy implications. Both ARDL Model 1 and Model 2 revealed a significantly positive long-run relationship between these two attributes, denoting that in the long run, Malaysian palm oil significantly increases $CO_2$ emissions. Since a significant value is not detected for palm oil consumption, the government should be more vigilant in finding the equilibrium between the supply and demand for palm oil. The mismatch of supply and demand may be caused by boycotts from European countries, for instance, but the longer run of the differentiation may further worsen the case, as the data do not support the current claim that palm oil plantations can replace what forests have offered. The findings signal that Malaysia needs to improve the sustainability of its palm oil production activities to sustain long-term growth in its palm oil sector, especially now that countries worldwide are shifting towards more sustainable and environmentally friendly substitutes for oil palm products, as described earlier in this study, thereby putting the Malaysian palm oil sector at risk should no significant green approach be implemented in the sector. This concern aside, the consistent ARDL long-run coefficients of palm oil production between Model 1 and Model 2 justify the utilisation of palm oil production as a proxy to examine the relationship between palm oil and $CO_2$ emissions for Malaysia as done in this study.

In the meantime, the ARDL results for renewable energy, oil demand, and trade openness suggest a few critical points, as the negative relationship found between renewable energy and $CO_2$ emissions implies that the usage of renewable energy can help to reduce emissions and that the Malaysian palm oil sector should employ more renewable energy in its production activities to improve the country's production of palm oil in the long

run. The positive relationship between trade openness and $CO_2$ emissions signifies that Malaysia's trade activities lead to more emissions in the long run. Such a case is worrisome for Malaysia, as its role as the world's second-largest palm oil exporter is at stake in the long run, since the increase in its palm oil export activities requires increased production of palm oil and hence more $CO_2$ emissions. Based on the insignificantly negative oil demand-$CO_2$ emissions correlation found in both the short run and long run, there may exist a possible asymmetric cointegration between oil demand and $CO_2$ emissions.

As such, it is relevant to check for the nonlinearities among the attributes so that the insignificant linear relationship found by the ARDL estimation is improved with asymmetric cointegration testing. On this note, the government should strengthen the other elements surrounding palm oil production. For example, a policy that focuses on the palm oil ecosystem should be carefully designed. $CO_2$ emissions should be countered with other greener practices as mitigation responses.

This study performed the NARDL estimation to establish some noteworthy findings explaining the mixed significance in the findings related to the linear relationship between the attributes of Model 1, Model 2, and Model 3. NARDL Model 2 yields the best results among all. The inclusion of control attributes such as renewable energy, oil demand, and trade openness into the model and the utilisation of palm oil production to examine the symmetric and asymmetric relationship between palm oil and $CO_2$ emissions in the EKC framework for Malaysia have provided better and more significant results in general. The results of Model 2 were improved when the ARDL model was extended into the NARDL model. The inequality in the effects of positive and negative shocks to palm oil production on $CO_2$ emissions in the short run, as represented by the model's Wald test results, provides justification for asymmetric cointegration testing using the nonlinear ARDL approach, as done by this study.

For the sensitivity analysis using Model 3, the ARDL cointegration results between Model 3 and Model 2 for palm oil and $CO_2$ emissions are quite consistent; however, the results produced by the NARDL method for Model 3 are not entirely consistent with those of Model 2. In addition, the results of NARDL Model 2 are better and more relevant for this study, verifying the suitability of palm oil production as the key indicator of palm oil employed in this study's symmetric and asymmetric EKC analysis. This finding also indicates that there are possibilities for asymmetric relationships in palm oil production contributions to $CO_2$ emissions. Therefore, it suggests that a clear and strategic direction for governmental policies will be helpful in justifying decisions made in the palm oil industry. Moreover, other green programs that may be attached to palm oil production should be explicitly measured and recorded, as evidenced by the existence of the asymmetric EKC effect.

**Author Contributions**

**Norlin Khalid**- Conceptualize, original version and finalized the final version; **Mohd Helmi Ali**- Conceptualize, original version and finalized the final version; **Nur Hilfa Awatif Mohamad Ridzuan**- Conceptualize, original version and finalized the final version; **Ming-Lang Tseng**- Conceptualize, original version and finalized the final version; **Mohd Shahrul Mohd Nadzir**- Conceptualize, original version and finalized the final version; **Shifa Md Nor**- Conceptualize, original version and finalized the final version

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**Appendices**

Table A1: Data elaboration and sources

| Attribute | Description | Main/ Control | Sources |
|---|---|---|---|
| CO2PC | Carbon emission per capita | Main | World Data Atlas by Knoema Corporation |
| GDPPC | Gross domestic product (GDP) per capita | Main | World Development Indicators by World Bank |
| GDPPC2 | Square of GDP per capita | Main | World Development Indicators by World Bank |
| POPROD | Palm oil production | Main | Datastream |
| RENEWPC | Renewable energy per capita | Main | Malaysia Energy Information Hub |
| POCON | Palm oil consumption | Control | United State Department of Agriculture (USDA) |
| OPEN | Trade openness in constant value | Control | Department of Statistics Malaysia |
| OILDDPC | Oil demand per capita | Control | Malaysia Energy Information Hub |

Table A2: Descriptive statistics

| | LNCO2PC | LNGDPPC | LNRENEWPC | LNPOPROD | LNPOCON | LNENERGYCON | LNOPEN | LNOPEN | LNOILDDPC |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 1.522 | 10.002 | -3.844 | 16.011 | 14.356 | 16.896 | 0.152 | 0.405 | -0.379 |
| Median | 1.647 | 10.085 | -3.856 | 16.094 | 14.613 | 17.080 | 0.277 | 0.410 | -0.188 |
| Max. | 2.111 | 10.673 | -2.601 | 16.836 | 15.440 | 17.985 | 0.519 | 0.790 | -0.008 |
| Min. | 0.593 | 9.267 | -5.138 | 14.599 | 12.269 | 15.448 | -0.460 | -0.078 | -1.080 |
| Observations | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 |

Figure A1: ARDL CUSUM and CUSUMSQ graphs

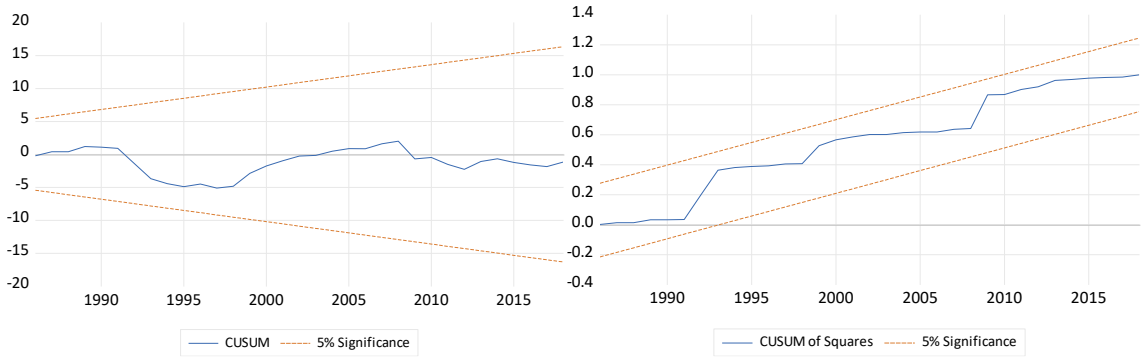


Figure A2: Non-linear ARDL CUSUM and CUSUMSQ graphs