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Palm Oil Export and Environmental Pollution in Malaysia: Evidence from ARDL Approach

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Abstract

This paper seeks to identify the effect of palm oil export on environmental pollutants. The National Income (GDP) and Foreign Direct Investment (FDI) were also included in the model as control variables. This study employs the auto-regressive distribution lag (ARDL) econometric technique, and the analysis is based on time series data from 1990 to 2020. The bound F-test and Johansen cointegration tests confirmed that palm oil export significantly accelerates environmental pollution. However, the results from the short-run estimate explore that all the variables are insignificant. This study concludes that Malaysia should control international trade activities to deal with pollution problems.

Keywords: Palm Oil Export; Agricultural Methane Emissions; ARDL Bounds Testing.

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1.0 Introduction

Commodity export revenues are essential for some commodity-dependent developing countries, and Malaysia is no exception. As a small, open economy, the concern about environmental measures such as greenhouse gas emissions (GHG) may affect Malaysia's market access and export competitiveness. Malaysian palm oil products are being exported to over 150 nations globally (Othman et al., 2023), and the lower price compared to other vegetable oils accounts for the increased export demand (Santeramo, 2017). In 2022, India, with a population of 1.42 billion people, was the largest importer of Malaysian palm oil goods, followed by China and the European Union.

Palm oil significantly contributes to the Malaysian economy, supplying more than 40% of the global palm oil. However, palm oil is claimed to significantly impact the quality of the environment, particularly in European countries (Kumaran, 2019 & Sundram, 2018). In short, Malaysia's palm oil export growth can no longer be sustained at the expense of the environment. Therefore, this study aims to identify the effect of palm oil export on environmental pollutants.

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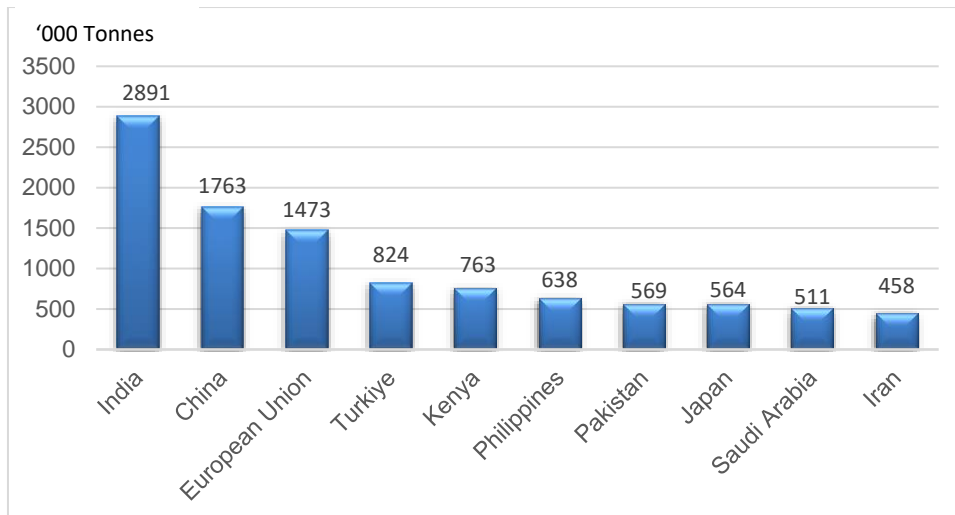


Figure 1: Top 10 Malaysia's Palm Oil Export Destinations in 2022
 Source: Malaysian Oil Palm Statistics 2022, 42nd Edition (2023)

The influence of palm oil export on environmental deterioration is empirically equivocal yet being investigated, particularly in Malaysia. Thus, the objective of this study is to identify the long-run effects of palm oil export on environmental degradation in Malaysia. The annual data were collected for 31 years, from 1990 to 2020. The remainder of the paper is structured as follows: Section 2 provides a brief review of the literature on the relationship between palm oil trade and environmental effects, while Section 3 describes the method used. Section 4 presents the empirical data findings, section 5 concludes the paper, and section 6 addresses the study's limitations.

2.0 Literature Review

The impact of agricultural trade on the agricultural environment is uncertain theoretically. However, several studies have explored the different perspectives on the relationship between agriculture trade and environmental pollution. A recent study by Ghimire, Lin and Zhuang (2021) examined the impacts of agricultural trade on economic growth and overall agricultural GHG as a proxy for agricultural environmental pollution in Bangladesh using an Auto-Regressive Distributed Lag (ARDL). Their finding indicates that an increase in agriculture trade led to a reduction in environmental pollution in the long run. Their result is contradicted by Lorente et al. (2019), who found that agricultural activity negatively impacts the carbon emissions in BRICS (Brazil, Russia, India, China and South Africa) countries.

Other than that, Opoku (2020) used the Pooled Mean Group estimation technique to examine the environmental impact of foreign direct investment (FDI) in 36 selected African countries by proxied the environment with several factors, including carbon dioxide, nitrous oxide, methane, and total greenhouse gases emissions. However, the effect of foreign direct investment on the environment is found to be largely significant. The benefits of FDI are good for developing the industrial sector (Sutton et al., 2016).

The influences of food trade on carbon dioxide emission were evaluated intensively. However, there needs to be more investigations of the nexus between Methane emissions and agriculture product trade available, which fails to consider new and important food import/export countries, such as Malaysia, the second largest palm oil producer. Methane is the primary contributor to the formation of ground-level ozone, a hazardous air pollutant and greenhouse gas. Over 20 years, it is 80 times more potent at warming than carbon dioxide (Mar et al., 2022).

Considering that palm oil production contributes to agricultural methane emissions, this study will quantify how and to what extent the palm oil trade could alleviate agriculture methane emissions by conducting an ARDL analysis. Zhao et al. (2020) and Han et al. (2019) have applied multiregional input-output (MRIO) analysis to quantify the trade-related GHG emissions and redistribute GHG emission responsibilities to different countries. The drawback of this method is that the data are not available annually, and it cannot assess a quantitatively long-term trend of agriculture trade as factors contributing to methane emissions. Pazienza et al. (2020) also used Agriculture Methane Emissions as a proxy for environmental pollution to see the impact on FDI in agriculture and fisheries sector.

The limitations of previous research are twofold. First, most previous studies only focus on the overall agriculture industry. Secondly, the proxy used for environmental pollution is limited to carbon emissions. The present study fills the abovementioned gaps and assesses the long-run relationship between palm oil export and environmental pollution by using Agriculture Methane Emissions as a proxy.

3.0 Methodology

This study uses the ARDL bounds testing technique to analyze the long-run relationship among the variables since the dataset is integrated with a combination of I(0), I(1) in a small sample size. The ARDL model proposed by Pesaran, Shin, and Smith (2001), is a flexible and popular approach for testing for cointegration in a multivariate setting. To examine the relationship between environmental

pollution and palm oil export in Malaysia. The Agriculture Methane Emissions are used as a proxy for environmental pollution variables. Based on the previous literature, a model framework based on the selected variables takes the form as follows:

$$\ln AME_t = \beta_0 + \beta_1 \ln POE_t + \beta_2 \ln Y_t + \beta_3 \ln FDI_t + e_t \tag{1}$$

Where AME indicates Agriculture Methane Emissions, POE is Palm Oil export value, Y is Malaysia’s GDP (constant 2015 US\$), FDI represents Foreign direct investment, net inflows (BoP, current US\$) and e_t is the error term. This study transforms all variables into natural logarithms. The data for the analysis were obtained from the World Development Index (WDI), and the analysis covers annual data from 1990 to 2020. Stationarity is important because if a series is nonstationary, all results from the regression analysis would be invalid. Therefore, the augmented Dickey–Fuller (ADF) and Phillip–Perron (PP) tests will be utilized to ascertain the stationarity of a variable. The general specification of the ARDL bound test approach of this study is given in the form of an unrestricted error correction model to test for cointegration as follows:

$$\Delta \ln AME_t = \alpha_0 + \sum_{k=1}^t \alpha_k \Delta \ln AME_{t-k} + \sum_{l=0}^u \gamma_l \Delta \ln POE_{t-l} + \sum_{i=m}^v \tau_m \Delta \ln Y_{t-m} + \sum_{n=0}^w \partial_n \Delta FDI_{t-n} + \phi_1 \ln AME_{t-1} + \phi_2 \ln POE_{t-1} + \phi_3 \ln Y_{t-1} + \delta_4 \ln FDI_{t-1} + \varepsilon_t \tag{2}$$

Where Δ refers to the first difference operator and, n is the lag order. $\Delta \ln AME_t = \alpha_0$ describes the changes in the lagged dependent variable. α_0 is the drift term and ε_t is the residuals. In the next step, this study determines the optimal lag length for p, q, r and s in Equation (3). The maximum lags are determined by using AIC information criteria. Pesaran et al (2001) used the uniform lag length (p, p, p, p). The calculated F-statistics in this study should be compared to its critical values tabulated by Narayan (2005) since the sample size is small (ranging from 30 to 80 observations). If the computed F-statistic is below the lower bound, the null hypothesis of no cointegration cannot be rejected. However, suppose the computed F-statistic is greater than the upper threshold. In that case, the null hypothesis of no cointegration can be rejected, which implies the existence of the cointegrating long-run relationship. However, the test is inconclusive when the calculated F-statistic falls between the two critical value limits. The optimal lag selection will be employed based on AIC. The diagnostic and stability tests are conducted to assess the adequacy of the ARDL model’s goodness of fit.

4.0 Findings

4.1 Unit Root Test

The results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests indicate that the p-values for all variables show significance and thus rejecting the null hypothesis of stationarity at level and first difference. Thus, the study concludes that it has a mixed stationary result for the unit root test. Given this condition, the next step is to proceed with the ARDL bounds testing approach to cointegration.

Table 4.1: Unit root test

Variables	ADF		PP	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
	Level			
InAME	-2.409024	-2.960176	-2.435087	-2.968120
InPOE	-1.738938	-1.593942	-1.740765	-1.797840
InY	-2.128052	-2.638690	-2.549817	-2.457530
InFDI	-4.773126***	-5.166470***	-4.767942***	-5.155908***
	First Difference			
InAME	-6.873507***	-7.134006***	-6.934569***	-7.134006***
InPOE	-4.778159***	-4.940418***	-4.150912**	-4.154689**
InY	-4.082488***	-4.620127***	-4.082488**	-4.615961**
InFDI	-6.449144***	-6.318519***	-24.95415***	-24.05948***

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Intercept and trend results are reported. The null hypothesis of the ADF and PP tests examines nonstationary panels. The default lag selected is the Schwarz info criterion.

4.2 Cointegration Bound Test

The initial step in the bound test approach of co-integration entails estimating the ARDL model by employing a suitable criterion for selecting the lag length. The present study employed the Schwarz criterion (SIC) to determine the appropriate lag order for the conditional ARDL model, with a maximum lag order of 2 being chosen. The subsequent analysis involved assessing the joint significance of the coefficients through Wald test where is a statistical procedure that entails the imposition of constraints on the estimated long-run coefficients of the variables. The results of the bound test are summarised in Table 4.2.

Table 4.2: Bounds Test for the presence of a relationship level.

Test Statistic	Value	Sig	I(0)	I(1)
F-Statistic	3.9433*		K=3 N=30	
		1%	3.65	4.66
		5%	2.79	3.67
		10%	2.37	3.2

*Denotes rejection of the null hypothesis of no cointegration at 10% significance level. #The critical values are obtained from Narayan (2005)

The result from Table 4.2 indicates that when AME is used as a dependent variable, the null hypothesis of no cointegration is rejected as the F-statistic value of 3.9433 exceeds the upper bound critical value at a 5% significance level. The obtained result demonstrates the rejection of the null hypothesis, which suggests no cointegration and provides evidence supporting a long-term relationship between the variables.

Table 4.3 presents the long-term coefficients of the ARDL model for each variable. The findings indicate that InPOE has positive while InY has negative coefficients towards InAME, and both are statistically significant at a 10% significance level. InFDI has a negative coefficient but is not significant.

Table 4.3: Long-run estimates based on the selected ARDL model (1,0,1,0)

Variable	Coefficient	t-Statistic	Prob.
InPOE	0.0352 (0.0172) *	2.0430	0.0522
InY	-0.0554 (0.0278) *	-1.9928	0.0578
InFDI	-0.0111 (0.0083)	-1.3328	0.1951
C	9.3473 (0.4358) ***	21.4474	0.0000

Notes: Standard errors in () and ***, **, * are significant at 1%, 5%, and 10%, respectively.

Table 4.5 illustrates the short-run relationship between the variables using the error correction model (ECM). As expected, the ECM coefficient is negative and statistically significant at a 1% level, which means 75.96 % of the disequilibrium is corrected to reach its long equilibrium in one year. This suggests that any disequilibrium shock from the previous year adjusts rapidly towards long-run equilibrium, with a convergence speed of 74.18% per year, that it would take effect more than a year (1.34 years). Table 4.5 also indicates that there are no short-run relationships between the variables.

Table 4.4: Error correction model and short-run estimates

Variable	Coefficient	t-Statistic	Prob.
C	-0.006957 (0.008262)	-0.842083	0.4084
D InPOE	0.015947 (0.018956)	0.841287	0.4088
D InY	0.149805 (0.112834)	2.207398	0.1973
D InY(-1)	0.198724 (0.128323)	1.327658	0.1351
D InFDI	-0.004770 (0.004192)	1.548629	0.2669
ECM(-1)	-0.759692 (0.189963)	-3.999161	0.0006
Diagnostic test statistic			
R ²	0.490611	Prob(F-statistic)	0.005680
Adjusted R ²	0.379874	Durbin-Watson stat	2.061780
Log likelihood	76.62867	S.E. of regression	0.019343
F-statistic	7.430419		

Notes: Dependent variable: InAME. Standard error in () and *, **, *** denotes significance at 10%, 5% and 1% respectively

After establishing the long-run and short-run relationships between the variables, the subsequent step entails conducting diagnostic tests to identify potential concerns. To ensure that the selected model and results are unbiased, we conducted tests for serial correlation, heteroscedasticity, and stability (CUSUM stability tests) are conducted. The findings of the diagnostic tests are displayed in Table 4.5.

Table 4.5: Diagnostic test for ECM based ARDL model

Test Statistic	F-Statistic	Prob. Values
Serial Correlation	1.5414	0.4300
Normality	1.4138	0.4931
Heteroscedasticity	0.4676	0.7963
CUSUM	Stable (refer to fig. 4.1)	
CUSUMSQR	Stable (refer to fig.4.2)	

The diagnostic tests encompassed an examination of serial correlation, normality and heteroscedasticity—furthermore, the CUSUM Test and CUSUM Square. The critical boundaries are determined using a significance level of 5%. The model is deemed stable if the blue line is within the critical bounds, as illustrated in Figures 4.1 and 4.2. Nevertheless, if the blue line deviates beyond the critical

thresholds, it implies that the model's efficacy could be characterized by inconsistency or unpredictability. The results indicate that the model is unbiased and stable (Table 4.5).

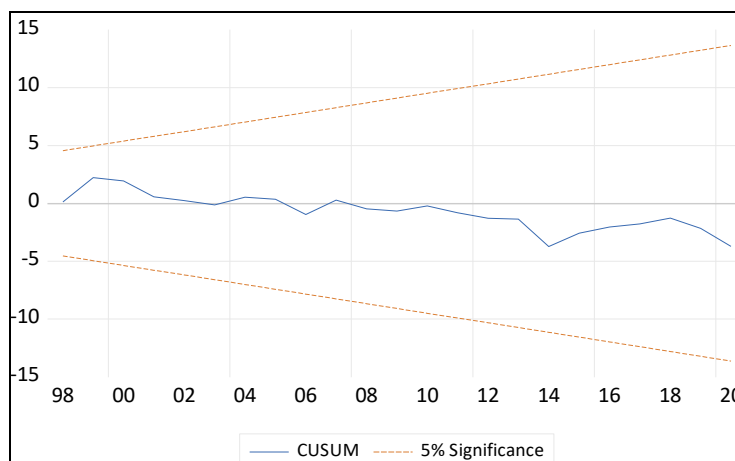


Figure 4.1: CUSUM Stability Tests

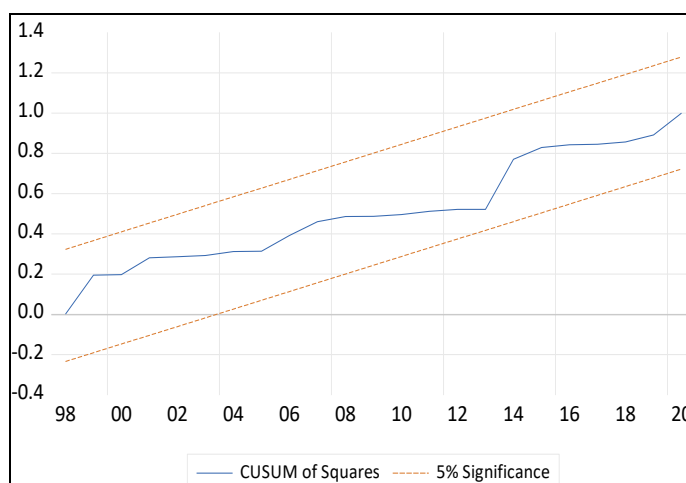


Figure 4.2: CUSUMSQ Stability Tests

5.0 Discussion

The effect of palm oil export (POE) towards (AME) was significant at a 10% level of significance. The coefficient (0.03) of POE shows that a 1% increase in palm oil export leads to a 0.03% increase in AME in the long run. The result from this study is consistent with Lorente et al. (2019), which suggests that agricultural activity positively impacts carbon emissions. Malaysia, the second largest palm oil producer, has been widely recognized as a major source of methane. Therefore, an increase in palm oil exports will contribute to methane emissions. Improved and effective technologies are meant to be resource-efficient and have a lower pollution effect.

Palm oil plantations' methane emissions contribute to climate change but could be turned into renewable energy, such as biodiesel. The high demand in the EU market had been due to using palm oil as the main feedstock for manufacturing industrial frying fats and expanding the biodiesel industry in EU countries. The EU has provided incentives to encourage the use of biodiesel. Palm-based biodiesel will only be eligible if the default value of greenhouse gas emission savings for palm oil indicated in the instructions is less than the defined level. This is also important to meet the required criteria such as (for biofuel derived from palm oil, the auditor shall verify that (i) the Palm Oil Mill Effluent (POME) is treated in a gas-tight digester system equipped with methane capture, and (ii) the methane is either used for energy generation purposes or flared). Despite these circumstances, the potential of palm oil as a biodiesel source can be rationalized.

The finding also indicates that there is an urgency for Malaysia to improve their role in the palm oil circular economic business ecosystem since the European Union (EU) has revised its biofuels policy to phase out palm oil-based biodiesel by 2030. Therefore, the industry player should integrate their resource and expand their investment into the high value-added downstream products such as high value food applications, biodiesel, pharmaceuticals and nutraceuticals.

6.0 Conclusion & Recommendations

This study concludes that Malaysia should control methane emissions in the palm oil industry trade to deal with pollution problems. Environmental protection policies should balance economic growth through exports and environmental protection. However, although palm oil plantations' methane emissions contribute to climate change, they could be turned into renewable energy. Malaysia should seek more advanced technology to turn methane generated in palm oil production into a biofuel. This serves as a source of renewable energy and helps reduce the immediate release of methane into the atmosphere. The policymaker should also consider carbon pricing mechanisms that include exported products and carbon footprints that would incentivize companies to reduce emissions. Moreover, the government can also make Environmental Impact Assessment (EIA) mandatory for exporting industries to mitigate potential environmental impacts throughout their supply chains. This will ensure that exports are not causing significant harm to the environment.

7.0 Limitations of the Study

This research, however, still offers preliminary scientific data, and there are still some limitations. To begin with, in this study, we used only Agriculture Methane Emissions as a proxy for agricultural environment pollution. Ultimately, it will be helpful to explore the overall agricultural GHG, which includes carbon dioxide (CO₂), sulfur hexafluoride (SF₆), nitrous oxide (N₂O), hydrofluorocarbons (HFC) and perfluorocarbons (PFC). Second, this study included only palm oil industries besides other agriculture sectors. As a result, in a future study of environmental pollution and trade, we will show the comparative analysis across other crops such as Rice, Rubber, Fisheries, etc. It will benefit policymakers in devising practical and tailored strategies to mitigate the impact of environmental pollution.

Paper Contribution to Related Field of Study

The study's findings imply critical policy recommendations that can be addressed by the government, producers, and stakeholders to improve the competitiveness of Malaysia's palm oil business without sacrificing environmental repercussions.

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