ASYMMETRIC EFFECTS OF CLIMATE CHANGE ON PALM OIL PRICES IN MALAYSIA

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Abstract: *Of all major vegetable oils, palm oil remains extremely productive crop. Malaysia is currently the world's second-largest producer and also the world's second-largest exporter of palm oil. However, the sector most vulnerable to climatic condition is agriculture. Extreme climatic events include high temperature levels, drought and flash floods. Such events affect oil palm growth and promote plant disease which then, increase the palm oil price. Previous understandings suggest that the changing climate and palm oil prices follow similar behaviour patterns. Therefore, this study aims at exploring the asymmetric relations between climate change and palm oil prices from 1964-2016. A nonlinear autoregressive distributed lag (NARDL) cointegration methodology was employed for the estimations. Overall, the results suggest the presence of a significant and asymmetric relation between palm oil prices and temperature in the long run, the impact of a fall in the temperature is more pronounced than when the temperature increases. In contrast, the responses of the palm oil prices to the rainfall show a symmetric but insignificant in the long run. Such findings are of great importance in showing that palm oil price reacts differently to rising and falling temperature, but not for rainfall. Therefore, long-term sustainability requires a diverse and robust technological and knowledge base to enhance palm oil productivity and efficiency in order to reduce the vulnerability of palm oil to climate change.*

Keywords: *Climate change, palm oil prices, asymmetry, NARDL, Malaysia.*

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1. INTRODUCTION

Compared to alternative vegetable oils, palm oil remains important due to its crop efficiency, large productivity, long life span and oil versatility. According to USDA (2019), in 2018/19 palm oil contributed 36.40% of the world's vegetable oil supply. In terms of efficiency and high productivity, the average annual palm oil yield is approximately 4.2t/ha compared to 0.4 and 1.2t/ha for soybean and rapeseed, respectively (Tan, Lee, Mohamed, & Bhatia, 2009). In other words, oil palm yields indeed ten times and four times more productive than soybean and rapeseed yields on a per hectare basis. The annual global production of palm oil rose by 15 times to nearly 74 million MT in 2018 from 4.9 million MT in 1980; while Indonesia and Malaysia nominate the bulk of the world palm oil production with about 70%-80% in that period (USDA, 2019). For oil versatility, it offers a broad range of benefits including food products, cosmetics, biofuel and engine lubricants. In fact, food consumption dominated around 80%- 90% of the production of palm oil while the rest was *channelled* to industries (Shimizu & Desrochers, 2012). Besides that, palm oil requires a relatively lower production cost than other vegetable oils (Shimizu & Desrochers, 2012; Tan et al., 2009).

Currently, Malaysia consistently produces and exports almost 20 million MT of palm oil annually This makes Malaysia the second-largest producer and exporter of palm oil globally (Ubilava & Holt, 2013; USDA, 2019). According to the USDA (2019), Malaysia contributed 25% of global palm oil production and 34% of the global export market after its neighbouring country, Indonesia, in 2018. Palm oil production has benefited greatly millions of smallholder farmers and their families in Malaysia. Contribution of agriculture sector in Malaysia's Gross Domestic Product (GDP) is about 7.3% according to latest statistics in 2018 (DOSM, 2019). Over the same period, oil palm continues to be the leading driver of agriculture growth, makes up 37.9% of GDP for the agriculture sector, followed by other types of agriculture namely livestock, fishing forestry and logging, and rubber at 25.1%, 14.9%, 12.5%, 6.9% and 2.8%, respectively.

However, the earth faces potentially disastrous impacts of global warming. Growing emission of carbon dioxide (CO2) leads to irreversible global climate change. The changing climate will probably increase the likelihood of extreme weather, warmer temperature, frequency and intensity of rainfall and frequency and severity of extreme events (Wheeler & von Braun, 2013). According to the 5th Assessment Report of Intergovernmental Panel on Climate Change (IPCC), the global mean temperature rose by 0.85°C between 1880 and 2012 while the global mean average sea level increased by 0.19 m from 1901 to 2010. In comparison to 1986-2005, the IPCC predicts that further rise in mean global temperature rise between 1 to 2°C by 2065 and 1 to 3.7°C by 2100; while projected change in global average sea level to be 0.24 to 0.30m by 2065 and 0.40 to 0.63m by 2100 (Pachauri et al., 2014). Out of the 30 top emitters, Malaysia stands out to be the biggest emitter of CO2, a 221% rise between 1990 and 2004 (Watkins, 2007). In 2014, around 243 million MT of CO2 were emitted or 8.1 MT/person in Malaysia (WDI, 2019).

If climate change continues, agricultural lands become not suitable for cultivation and hence reduce crop yields area (Murad, Molla, Mokhtar, & Raquib, 2010). For instance, Sub-Saharan Africa, South East Asia and South Asia may suffer from the crop yields failure and production losses if the global warming causes temperature increases of above 1.5°C to 2°C (Schellnhuber et al., 2013). At a country like Malaysia, the rice production is predicted to experience a reduction in rice yield of 0.36t/ha resulting from a rise in temperature by 2°C, and this is equivalent to annual economic loss of RM162.531 million (Vaghefi, Shamsudin, Makmom, & Bagheri, 2011). Similarly, Zainal et al. (2012) revealed that an increase in rainfall and temperature has an adverse impact on palm oil production and thereby reduces the annual net revenue. For instance, the marginal impact calculations suggest that net revenue decreases by RM 44.52 (Peninsular), RM 45.60 (Sabah) and RM 37.70 (Sarawak) with every 1°C increase of temperature. Crops production is responsive to the climatic conditions and consequently influences the price movement of agricultural products (Bandara & Cai, 2014; Brunner, 2002; Nsabimana & Habimana, 2017; Ubilava & Holt, 2013). Nevertheless, it has been argued that the climate change, i.e., rainfall, and El Nino southern oscillation (ENSO) and crop or vegetable oil prices follow asymmetric behaviour patterns (Nsabimana & Habimana, 2017; Ubilava & Holt, 2013).

The potential impacts of uncertain weather and climatic conditions on palm oil production are closely related. Extreme weather conditions are likely to have an adverse effect on palm oil production in the leading palm oil producing countries such as Indonesia and Malaysia and thus, affect the palm oil prices (Ubilava & Holt, 2013). In Malaysia, many studies as such assumed that the link between climate changes and palm oil production (or prices) is linear (Ab Rahman, Abdullah, Balu, & Shariff, 2013; Ab Rahman, Abdullah, & Shariff, 2012; Adnan, 2015; Hassan, Ahmad, & Balu, 2018; Kamil & Omar, 2016). Nevertheless, climate change is found to have a significant nonlinear effect on net revenue from oil palm production (Zainal et al., 2012) and on food price (Wong, Lee, & Wong, 2019). Additionally, Wong, Lee, and Wong (2019), concluded that the explanation may be misleading if only linear impacts of climate change on crop production are captured. Therefore, this study aims at examining the possible asymmetric effects of climate changes on palm oil prices in Malaysia over the period of 1964 – 2016.

2. LITERATURE REVIEW

The effects of climate change on crop production has been discussed extensively (Challinor et al., 2014; Knox, Hess, Daccache, & Wheeler, 2012; Lobell & Gourdji, 2012; Peng et al., 2004; Rosenzweig & Parry, 1994; Schellnhuber et al., 2013; Schlenker & Lobell, 2010; Schlenker & Roberts, 2009; White, Hoogenboom, Kimball, & Wall, 2011). Referring to a report of World Bank (Schellnhuber et al., 2013), major crop yields for instance, rice, wheat, maize are affected as a result of extreme high temperatures, affecting the food security negatively. According to White et al. (2011), the studies on wheat, maize, soybean and rice were the highest at 170 papers out of a total of 221 peer-reviewed studies, while the papers on the USA and Europe region contributed 55 papers and 64 papers respectively. Similarly, Knox et al. (2012) collected the findings of the impacts of changing climate on the crop yields from a systematic review and a meta-analysis in 52 publications from an initial screen on 1144 studies. They suggested that the average change of eight major crop yields in Africa and South Asia is projected to be -8% by 2050. Specifically, the average yield changes are estimated to be -17%, -15% and -10% and -5% for wheat, sorghum, millet and maize, respectively across Africa; while across South Asia, the mean change in yield of maize and sorghum are estimated to be -16% and -11%, accordingly.

Although great efforts have been made continuously to maintain a stable food production, agriculture remains highly vulnerable to weather particularly in developing economies since the greenhouse farming is yet to be formed (Nsabimana & Habimana, 2017). According to Rosenzweig and Parry (1994), climate change has led to an imbalance of cereal production between developed and developing nations but developing nations are expected to receive more effects of the climate change. For instance, Haile, Wossen, Tesfaye, and von Braun (2017) projected that climate change may reduce crop production globally (such as maize, wheat, rice and soybeans) on average by 9% and by 23 % in the 2030s and 2050s, respectively. As a result of climate change impacts, Sub-Saharan Africa (SSA) is expected to experience reduction in maize (22%), sorghum (17%), millet (17%), groundnut (18%), and cassava (8%) yields by 2050 (Schlenker & Lobell, 2010).

Since weather conditions and crop production are closely related, it also has a great incidence on agricultural product prices (Bandara & Cai, 2014; Brunner, 2002; Nsabimana & Habimana, 2017; Ubilava, 2017; Ubilava & Holt, 2013). For instance, chronic floods, high temperature levels, changes in precipitation pattern, droughts and heat waves tend to reduce the food production by reducing the crop growth, encouraging crop disease and increasing sensitivity of crops to insect pests (CCSP, 2008). Thereby, this changing climate leads to a rise in crop prices (Nsabimana & Habimana, 2017). On the other hand, South Asia is known as one of the regions that are affected by global climate change the most (Bandara & Cai, 2014). They further found that there is an adverse impact of climate change on food production in Bangladesh, India, Nepal, Pakistan and Sri Lanka which subsequently, pushes up the market food prices.

In Malaysia, palm oil production will be more vulnerable to uncertain weather conditions (Ab Rahman et al., 2013; Adnan, 2015). According to a 2000 MOSTE report, the average annual temperature, ranging from 28°C to 31°C, is often favoured for higher fruit production. As the average temperature continues to rise and subsequently increases the likelihood of drought, it could be estimated that about 12% of the current oil palm areas would be unsuitable for growing oil palm. In the event of extreme temperature, an increase in rainfall favours productivity of oil palm provided unless it causes prolonged flooding (Fleiss, Hill, McClean, & Lucey, 2017; MOSTE, 2000); while rainfall reduction will lead to yield loss (Fleiss et al., 2017).

The strong occurrences of La Niña and El Niño will affect the palm oil supply from producing countries and thereby influence the price movements (Ab Rahman et al., 2013; Kamil & Omar, 2016). An El Niño induces severe drought, which leads to low rainfall and high temperatures resulting in a reduction of palm oil yield. The El Niño phenomenon could cause various lagged effects which last to two years including bunch failure, abortion of floral bud and this is favourable to the formation of male flowers production (Adnan, 2015). Thus, the effects of El Niño are not immediate but seem to occur on a long-term basis. On the other hand, La Niña-induced high rainfall often leads to floods in major planted areas, and can disrupt harvesting, collecting activities and fresh fruit brunches of palm oil (Ab Rahman et al., 2013, 2012). During the strong El Niño event in 1997/1998, there has been a massive reduction in the production of crude palm oil from 907 000t (1997) to 832 000t (1998) (Hassan et al., 2018) while its prices spiked 78% to RM2400/t from RM1350/t (Kamil & Omar, 2016).

One problem with the previous results in favour of the argument that the changes of climate and crop prices follow similar behaviour patterns. Nevertheless, climate change is found to have a significant nonlinear effect on net revenue from oil palm production from 1980 to 2010 (Zainal et al., 2012) and on food price from 2010 to 2017 (Wong et al., 2019). Wong, Lee, and Wong (2019) concluded that the explanation may be misleading if only linear impacts of climate change on crop production are captured. As evidenced by Peng et al. (2004) between the period of 1979-2003 at the International Rice Research Institute (IRRI) Farm, rice grain yield declined by about 10% for every 1°C increase in growing-season minimum temperature during the dry season; while there was no significant effect of maximum temperature on crop yield. On a similar note, Nsabimana and Habimana (2017) suggested that food crop prices namely cassava roots, beans and potatoes respond asymmetrically to rainfall shocks in Rwanda between 2000-2012. On the other hand, Ubilava and Holt(2013) also evidenced that there were potential nonlinearities in the El Nino southern oscillation (ENSO) on major vegetable oil prices spanning from 1972 to 2010. Their results reveal that positive deviations, El Nino events, result in the vegetable oil price increase; whereas negative deviations, La Nina events, result in decrease in prices.

Additionally, a number of empirical studies have focused on the asymmetric effects in food price (Ibrahim, 2015), agricultural commodity prices (Nazlioglu, 2011), gold price (Kumar, 2017), gasoline price (Lamotte, Porcher, Schalck, & Silvestre, 2012), stock prices (Raza, Jawad Hussain Shahzad, Tiwari, & Shahbaz, 2016), housing price (Katrakilidis & Trachanas, 2012) and gasoline and natural gas prices (Atil, Lahiani, & Nguyen, 2014). Subsequently, it could be argued that the changes of climate on crop prices are likely to follow asymmetric behaviour patterns. Overall, it is worthy to indicate that the previous studies have made notable contributions in understanding the response of climate change on palm oil prices. However, empirical results have insufficiently accommodated the asymmetric effects in the palm oil price. In this regard, more empirical studies are needed to quantify the asymmetric pattern of palm oil price.

3. DATA AND METHODOLOGY

3.3 Data

The study used annual time series data, covering the period 1964 – 2016. The choice of the length of the study period depended solely on data availability. Data on the annual prices palm oil and soybean oil) were collected mainly from the World Bank commodity price while the data for climate change indicators (temperature and rainfall) were obtained from the World Bank's climate change knowledge portal, respectively.

3.4 The Nonlinear Autoregressive Distributed Lag (NARDL) Cointegration

Previous studies assumed symmetric relations between palm oil price and climate change. However, potential nonlinearities in the palm oil price dynamics were not well captured. To highlight this issue, a relatively more advanced cointegration methodology of NARDL cointegration developed by Shin, Yu, and Greenwood-Nimmo (2014) was employed. The NARDL cointegration is an extension of the linear ARDL model (Pesaran & Shin, 1999; Pesaran, Shin, & Smith, 2001) which allows for estimating asymmetric relations in the short-run as well the long-run among variables examined. Following Nsabimana and Habimana (2017), the specification for long-run equation of palm oil price can be specified as below:

$$\mathrm{LPO_t} = \theta_0 + \theta_1 \mathrm{LCC_t} + \theta_2 \mathrm{LSO_t} + \mathrm{e_t} \tag{1}$$

where t = 1, …, T, L denotes natural logarithms, PO is the real prices of palm oil (US dollars per metric ton), CC is the climate change indicator (temperature (TEM) in °C and rainfall (RF) in mm), SO is the real soybean oil prices (US dollars per metric ton) and e is the error term. All the explanatory variables have theoretically expected positive sign except rainfall is expected to be negatively related with palm oil price. Based on equation (1), the asymmetric long-run palm oil equation can be specified in the following form:

$$\mathrm{LPO}_t = \theta_0 + \theta_1^{+}\mathrm{LCC}_t^{+} + \theta_1^{-}\mathrm{LCC}_t^{-} + \theta_2 LSO_t + \mathrm{e}_t \quad (2)$$

where $\theta = (\theta_0, \theta_1^{+}, \theta_1^{-}, \theta_2)$is a cointegrating vector.

In equation (2), LCC_t can be decomposed as:

$$\mathrm{LCC}_t = \mathrm{LCC}_0 + \mathrm{LCC}_t^{+} + \mathrm{LCC}_t^{-} \quad (3)$$

where LCC_0 is the initial value, $\mathrm{LCC}_t^{+}$and $\mathrm{LCC}_t^{-}$are the positive and the negative partial sum changes in LCC_t:

$$\mathrm{LCC}_t^{+} = \sum_{i=1}^{t} \Delta\mathrm{LCC}_i^{+} = \sum_{i=1}^{t} \max(\Delta\mathrm{LCC}_i, 0) \quad (4)$$

$$\mathrm{LCC}_t^{-} = \sum_{i=1}^{t} \Delta\mathrm{LCC}_i^{-} = \sum_{i=1}^{t} \min(\Delta\mathrm{LCC}_i, 0) \quad (5)$$

Following Shin et al. (2014), equation (2) is associated with the linear ARDL(p,q) model (Pesaran& Shin, 1999; Pesaran et al., 2001) which becomes NARDL (p, q) model:

$$\Delta LPO_t = \gamma_0 + \beta_0 LPO_{t-1} + \beta_1^{+} LCC_{t-1}^{+} + \beta_1^{-} LCC_{t-1}^{-} + \beta_2 LSO_{t-1}$$
$$+ \sum_{i=1}^{p-1} \alpha_{0i} \Delta LPO_{t-i} + \sum_{i=0}^{q-1} (\alpha_{1i}^{+} \Delta LCC_{t-i}^{+} + \alpha_{1i}^{-} \Delta LCC_{t-i}^{+} + \alpha_{2i} \Delta LSO_{t-i}) + \mu_t \quad (6)$$

where $\theta_1^{+} = -\frac{\beta_1^{+}}{\beta_0}$ and $\theta_2^{-} = -\frac{\beta_1^{-}}{\beta_0}$ represent the long-run impacts of climate increase and climate decrease on the palm oil prices. While $\sum_{i=0}^{q-1} \alpha_{1i}^{+}$ and $\sum_{i=0}^{q-1} \alpha_{1i}^{-}$ measure the short-run effects of an increase in climate and a decrease in climate, respectively on palm oil price. The long-run symmetry of the null hypothesis $(\theta_1^{+} = \theta_1^{-})$ and the short-run symmetric of the null hypothesis $(\alpha_1^{+} = \alpha_1^{-})$ are tested using the Wald test.

4 ESTIMATION RESULTS

Table 1 reports the descriptive statistics for all the variables. The annual palm oil price ranged from the minimum value of \$350.48/MT in 1990 to the maximum value of \$1777.51/MT in 1974, with an annual average value of 806.23/MT. Meanwhile, the annual average soybean price was approximately \$888.52/MT and reached its peak in 1974 of \$2210.86/MT. For climate change indicators, the mean annual temperature was 25.5°C, with the highest temperature recorded was 26.4°C in 2016 and the lowest temperature recorded was 24.8°C in 1976. The average value of rainfall was 252.6 mm, ranging from the lowest rainfall of 208.1886 mm (1990) to the highest rainfall of 311.0 mm occurring in 2008. The Jacque-Bera test suggests normality of all the series, except the soybean oil price.

Table 1. Descriptive statistics.

	PO	TEM	RF	SO	
Mean	806.2314	25.4939	252.5730	888.5203	
Maximum	1777.5090	26.3753	311.0423	2210.8610	
Minimum	350.4799	24.8180	208.1886	425.0146	
Std. Dev.	299.6262	0.3680	24.5273	331.0260	
JB	3.6860	0.9444	1.2845	31.5643	***

Notes: *** denotes 1% significance level. JB represents the Jacque-Bera test for normality.

Table 2 displays the results for the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root tests. The results indicate that all the series are I(1) at the 1% level, except the rainfall (LRF) is stationary in level. Therefore, the NARDL bounds test was employed to examine the cointegrating relation between the variables of the studied since it allows for the variables to be integrated in different orders. The computed F-statistic reported in Table 3 is larger than the upper critical bound value at 1% (for models 2 and 4), 5% (for model 1) and 10% (for model 3) significance levels, supporting cointegration relationship between the variables.

Table 2. Unit root tests results.

	Level							
	Augmented Dickey-Fuller (ADF)				**Phillips-Perron (PP)**			
	Intercept		**Trend and Intercept**		**Intercept**		**Trend and Intercept**	
Variable	***t*-Stat.**		***t*-Stat.**		***t*-Stat.**		***t*-Stat.**	
LPO	-1.9168		-1.6940		-2.5729		-2.4601	
LTEM	-0.6594		-5.4064	***	-1.5242		-5.3619	***
LRF	-5.3069	***	-5.4769	***	-5.2564	***	-5.3751	***
LSO	-1.6702		-1.4274		-2.4611		-2.5206	

	First Difference							
	Augmented Dickey-Fuller (ADF)				**Phillips-Perron (PP)**			
	Intercept		**Trend and Intercept**		**Intercept**		**Trend and Intercept**	
Variable	***t*-Stat.**		***t*-Stat.**		***t*-Stat.**		***t*-Stat.**	
LPO	-9.2612	***	-9.2870	***	-9.4160	***	-15.8612	***
LTEM	-6.6995	***	-6.6319	***	-25.2230	***	-26.4622	***
LRF	-7.5824	***	-7.4978	***	-18.8133	***	-18.0921	***
LSO	-9.2374	***	-9.2441	***	-8.2971	***	-10.8594	***

Notes: *** denotes 1% significance level.

Table 3. Bound tests results.

Model	***F*-stat.**		**k**	**Signif.**	**I(0)**	**I(1)**
1. LPO = *f*(LTEM^{+} LTEM^{-} LSO)	**4.9982**	**	3	10%	2.5380	3.3980
				5%	3.0480	4.0020
				1%	4.1880	5.3280
2. LPO = *f*(LTEM^{+} LTEM^{-} LRF LSO)	**7.1764**	***	4	10%	2.3720	3.3200
				5%	2.8230	3.8720
				1%	3.8450	5.1500
3. LPO = *f*(LRF^{+} LRF^{-} LSO)	**3.8978**	*	3	10%	2.5380	3.3980
				5%	3.0480	4.0020
				1%	4.1880	5.3280
4. LPO = *f*(LRF^{+} LRF^{-} LTEM LSO)	**5.9374**	***	4	10%	2.3720	3.3200
				5%	2.8230	3.8720
				1%	3.8450	5.1500

Notes: ***, ** and *imply significant at the 1%, 5% and 10% levels, respectively. The optimal lag selection is based on Akaike Information Criterion (AIC).

Table 4 contains the estimation results for the four NARDL models with the variables of primary interest namely temperature and rainfall split into two partial sums. The first two models report the asymmetric impact of temperature on palm oil price while the final two models record the asymmetry in palm oil price changes to rainfall. The results suggest several points. First, in the last part of the Table 4, all models were found to be free from a battery of diagnostic tests; for instance, no model specification errors, independence, constant variance, normal distribution of residuals except for the specification errors (models 2 and 4) as well as heteroscedasticity (model 4) at the 5% level. Moreover, CUSUM and CUSUMSQ tests on residuals also highlight that the parameter estimates of NARDL are stable over the sample period for all models.

Second, the lagged error correction term (ECT_{t-1}) carries a negative sign and is highly significant at the 1% level which suggests that palm oil price, climate change variables (temperature and rainfall) and soybean price are cointegrated. The coefficients of ECT in absolute value are 0.4945, 0.6765, 0.2333 and 0.5097 for model 1, model 2, model 3 and model 4, respectively, signifying that palm oil price converges to equilibrium with the speed of adjustment of between 23.3% and 67.7% annually. This is consistent with empirical finding by Hassan et al. (2018), which shows that there was 23.3% short-run adjustment towards long-run equilibrium each month.

Third, the standard Wald tests were employed to test for symmetry in both the short-run (W_{SR}) and the long-run (W_{LR}). For models 1 and 2, the Wald test rejects the null hypothesis of short-run symmetry at the 1% level while the long-run symmetry is rejected at the 5 % level. The results suggest that palm oil price reacts asymmetrically to positive and negative changes of the temperature. Moreover, the long-run parameter estimates of temperature for $LTEM^{+}$ ranges from 11.5651 to 12.7340 and for $LTEM^{-}$ ranges from 14.4073 to 15.2606 and are statistically significant at conventional level. This concludes that a 1% increase in the temperature leads to a 11.57% (model 1) and 12.73% (model 2) rise in palm oil price; on the other hand, a 1% decrease in the temperature is associated with a 14.41% (model 1) and 15.26% (model 2) decrease in the price of palm oil. Specifically, palm oil prices react more strongly to negative temperature shocks in response to positive temperature shocks. For comparison's sake, the last model in Table 4 examines both the rainfall and temperature variables simultaneously. Once again, the estimated coefficient of temperature reveals a significant positive effect, with a 1% rise of temperature yielding an increase of 9.44% on palm oil price. This same finding from models 1, 2 and 4 reveals that temperature has an explanatory power for palm oil price.

Fourth, turning to the rainfall (models 3 and 4), the Wald test results confirm the existence of asymmetric links between rainfall and palm oil price in the short-run but a weak asymmetric impact (only at the 10% level) for model 4 in the long-run. Nevertheless, both positive and negative long-run coefficients of rainfall (LRF^{+} and LRF^{-}) carry the expected negative sign but insignificant in models 3 and 4. For comparison purposes, model 2 was estimated by considering the two climate change variables together; the estimated coefficient on rainfall remains insignificant but negative. Hence, palm oil prices display evidence of insignificant symmetric response to positive and negative rainfall shocks.

In line with previous studies, climate change (measured by rainfall, temperature, and CO_2) was found to have a significant nonlinear effect on net revenue of palm oil production (Zainal et al., 2012) and food price (Wong et al., 2019). According to Wong et al. (2019), there is a U-shaped nexus between CO_2 emissions and food price, indicating that a 10% increase in CO_2 emissions leads to a decrease in food price of 18.67% in Malaysia. However, if CO_2 emissions are above certain threshold value, food price will continue to climb up. Likewise, La Niña and El Niño events are also found to have a positive impact on crude palm oil prices in Malaysia (Ab Rahman et al., 2013). They suggested that crude palm oil prices increase by about 0.03% and 0.02% during the La Niña and El Niño events, respectively. As pointed by Ubilava and Holt (2013), the El Niño Southern Oscillation (ENSO)-price nexus is characterized as nonlinear dynamics, showing that a positive ENSO shock of El Niño (a negative ENSO shock of La Niña) can lead to a reduction (rise) in wheat price. In contrast, Ubilava and Holt (2013) suggested that a positive deviation (El Niño events) has contributed to an increase in vegetable oil price while a negative deviation (La Niña events) will certainly cause a decrease in vegetable oil price. Ubilava (2017) and Ubilava and Holt (2013) provided an interesting finding that the negative ENSO shocks have greater impact on price than the positive ENSO shocks.

Fifth, another concern is the other type of oil, for instance soybean oil is found to be an important substitute for the palm oil. The long-run coefficients on soybean oil price for all models are positive and are highly significant at the 1% level. This indicates that an increase of 1% in soybean oil price raises palm oil price between 1.0% (model 3) and 1.2% (model 2). According to Awad, Arshad, Shamsudin, and Yusof (2007), prices of substitute oils such as soybean oil, corn oil, rapeseed oil and sunflower seed oils play a crucial role in stimulating the demand for palm oil in Middle East and North African (MENA) countries. Ab Rahman, Abdullah, Balu, and Shariff (2013) reported that soybean oil price is considered as one of the important factors in affecting the crude palm oil prices, suggesting that with a 10% rise of soybean oil prices, comes an increase of 4.6% on palm oil prices. There are many reasons for believing that both vegetable oils are closely related. A profound explanation is the high degree substitutability between major vegetable oils (palm oil, soybean, rapeseed and sunflower seed oils) traded globally, therefore their prices will likely to converge (In & Inder, 1997). Other reason is the vegetable oils have identical characteristics in terms of chemical composition and end-uses, sharing common end-users covering from food preparation to manufacturing products for example soap, paints and medicines (Ubilava & Holt, 2013). Similarly, soybean oil appears to be a substitute to palm oil in most of the Middle East and North African (MENA) countries (Awad et al., 2007).

Table. 4 NARDL results.

ARDL Error Correction Regression

	Model 1			**Model 2**			**Model 3**			**Model 4**		
Variable	**Coeff.**	***t*-Stat.**		**Coeff.**	***t*-Stat.**		**Coeff.**	***t*-Stat.**		**Coeff.**	***t*-Stat.**	
Δ(LPO(-1))	-0.1419	-1.2739		-0.122	-1.1257		-0.3183	-2.4891	**	-0.0547	-1.0639	
Δ(LPO(-2))	-0.4393	-4.1197	***	-0.3924	-3.8809	***	-0.2701	-2.4671	**	-0.0091	-0.1536	
Δ(LPO(-3))							0.0883	1.6437		0.0725	1.5164	
Δ(LPO(-4))							0.1699	3.309	***	0.1228	2.4651	**
Δ(LTEM$^+$)	-0.3375	-0.1754		2.4664	1.2574							
Δ(LTEM$^+$(-1))	-8.5842	-3.424	***	-8.1963	-3.272	***						
Δ(LTEM$^+$(-2))	-5.7359	-2.632	**	-8.1203	-3.9199	***						
Δ(LTEM$^+$(-3))	-14.6716	-6.9132	***	-11.6947	-4.9801	***						
Δ(LTEM$^+$(-4))	-5.2933	-1.9325	*	-3.2302	-1.3357							
Δ(LTEM$^+$(-5))	-8.5471	-3.2669	***	-6.8351	-3.0344	***						
Δ(LTEM$^-$)	0.8656	0.4228		3.8511	2.0449	*						
Δ(LRF$^+$)							-0.1299	-0.6122		0.054	0.359	
Δ(LRF$^+$(-1))							-0.0085	-0.0473				
Δ(LRF$^+$(-2))							-0.6492	-3.4258	***			

$\Delta(LRF^-)$							-0.0606	-0.3606		0.0626	0.4774	
$\Delta(LRF^-(-1))$							0.8881	3.8168	***	0.993	5.3687	***
$\Delta(LRF^-(-2))$							0.5109	1.9553	*			
Δ(LRF)				0.1285	1.1935							
Δ(LRF(-1))				0.6647	5.4466	***						
Δ(LRF(-2))				0.3408	2.4586	**						
Δ(LRF(-3))				0.2505	2.1024	**						
Δ(LRF(-4))				0.4078	3.1444	***						
Δ(LRF(-5))				0.1967	1.6407							
Δ(LSO)	0.8395	14.9792	***	0.8124	16.9852	***	0.9619	15.122	***	0.9864	18.0067	***
Δ(LSO(-1))	-0.0408	-0.3511		-0.1324	-1.2424		0.2987	2.2594	**			
Δ(LSO(-2))	0.3026	2.6201	**	0.1802	1.6892		0.3432	2.8974	***			
Δ(LSO(-3))	-0.1124	-2.0933	**	-0.1166	-2.481	**						
Δ(LSO(-4))	0.0803	1.4669										
ECT(-1)	-0.4945	-5.3566	***	-0.6765	-7.3014	***	-0.2333	-4.6998	***	-0.5097	-6.3925	***

ARDL Long Run Form

Variable	**Coeff.**	***t*-Stat.**		**Coeff.**	***t*-Stat.**		**Coeff.**	***t*-Stat.**		**Coeff.**	***t*-Stat.**	
$LTEM^+$	11.5651	2.1461	**	12.734	3.4876	***						
$LTEM^-$	14.4073	2.188	**	15.2606	3.4838	***						
LRF				-0.3465	-0.5109							
LRF^+							-2.4456	-0.9619		-0.6525	-1.2269	
LRF^-							-2.4834	-0.9471		-0.5287	-0.9602	
LTEM										9.4419	2.3407	**
LSO	1.0662	12.2572	***	1.1689	11.9948	***	1.0257	4.6947	***	1.1137	11.7256	***

C	-0.1703	-0.2733		0.876	0.2759		0.2181	0.1376		-31.1725	-2.3693	**
Symmetry tests												
W_{SR}	12.9001		***	8.9694		***	10.7301		***	4.6466		**
W_{LR}	4.8723		**	6.0228		**	0.1066			3.1516		*
Diagnostic Checks												
R^2	0.9617			0.9777			0.9525			0.9413		
Adjusted R^2	0.9445			0.9614			0.9344			0.9292		
x^2-BGLM	0.3707			0.7055			0.3947			2.7854		
x^2-ARCH	1.521			18.8156			4.1035			7.8603	**	
x^2-JB	0.5226			1.9056			0.2678			1.7219		
F -RESET	2.4239			3.6924	**		2.0335			3.637	**	
CUSUM	√			√			√			√		
CUSUMSQ	√			√			√			√		

Notes: ***, ** and *imply significant at the 1%, 5% and 10% levels, respectively.

5 CONCLUSION

This study explores the existence of asymmetrical relations between climate change and palm oil prices in Malaysia over the period 1964-2016. The nonlinear autoregressive distributed lag (NARDL) cointegration techniques was used to simultaneously examine both the long and short-run asymmetric responses of the palm oil prices to climate change shocks. There are several conclusions that can be drawn from the analysis. First, the findings of palm oil price according to climate change indicators vary significantly. Second, palm oil prices appear to respond asymmetrically to rising and falling temperature. Third, palm oil prices react more forcefully to negative temperature shocks than to positive ones, indicating that the decrease in temperature has a greater impact on the palm oil prices than the increase in the long-run. Lastly, palm oil prices respond to rainfall increases and decreases in a symmetrical manner but insignificant in the long run. Therefore, the assessment of asymmetric and nonlinear framework will lead to more accurate responses of palm oil price.

The presence of asymmetries in the long-run highlights the need to develop a sustainable agriculture and society. In order to reduce the vulnerability of palm oil to climate change, long-term sustainability requires a diverse and robust technological and knowledge base to enhance palm oil productivity and efficiency. The concept of sustainable plantation practices, applied to all agricultural crops, must fulfill the universal criteria of benefiting the 3Ps – profit, people and planet. For instance, during the dry weather season, replanting of oil palm plantation needs to be delayed due to insufficient water supply. While during high rainfall season, smart and intelligent water management system should be implemented. This includes the drainage system and the river reserves which serve as a natural filter and protect the banks of waterways.

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