IMPACT OF CLIMATE CHANGE AND ECONOMIC FACTORS ON MALAYSIAN FOOD PRICE

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ABSTRACT

This paper is motivated by the increasing food price over the recent years (2010 – 2017) in Malaysia. Food is a necessity for mankind and everyone has equal rights to enjoy adequate food protecting from hunger and malnutrition. In general, we understand that food and agriculture production are highly related. Crop production is affected biophysically by climatic variables, *i.e.* suitable rainfall and temperature for photosynthesis process to take place. If these climatic variables alter extremely in a long-term period, crop production will be affected and crop damage can occur due to the climate change effect such as extreme flood and drought. Hence, if climate change effect is defined as a linear relationship, it will result in a misleading explanation whereby as long as rainfall and temperature increase (or decrease) it will cause the crop production to decrease (or increase). Given the problem associated with food price, this paper investigated the food price determinants by looking at both economic factors and climate change. Non-linear time series analysis namely Engle-Granger (EG) cointegration test and Error Correction Mechanism (ECM) were performed by including the determinants such as Carbon Dioxide (CO_2), crude oil price, exchange rate and real gross domestic product (RGDP). The results showed that both economic Real Gross Domestic Product and climate factors jointly affect food price significantly and climate factor (CO_2) exhibits a strong non-linear U-shaped impact on food price in the long run. In addition, the Error Correction Term (ECT) showed that food market will have a slower self-recovery mechanism to adjust and return the temporary food market demand-supply shock to the equilibrium.

Key words: food price, nonlinear cointegration

INTRODUCTION

From 2010 to 2017, the Malaysian food price exhibited a steep growth which surpassed the consumer price index (CPI) (Fig. 1). In 2017, the Malaysian food price index soared to a high record of 128.6 which indicates that the general level of food price has increased by about 28.6% compared to the year 2010. However, the CPI for 2017 was 119.4 which means that the national inflation had increased by 19.4% compared to the year 2010. This implies that food inflation is serious in Malaysia and CPI may no longer be an appropriate measurement for the cost of living in the country. The higher food price inflation will affect the social welfare especially by putting more burden on the lower income group. In general, the lower income group has to spend a greater proportion of income on food (Ibrahim, 2015). When the food price increases more than the consumers' food purchasing power, then the food may become a luxury good and consumers may be at risk of being on the food insecurity path. This could have an alarming effect among the low income group who may not have access to food and eventually suffer from chronic undernourishment situation. On the other hand, this posed danger to the nation's food price stability and food sustainability, which major concerns of the policy makers.

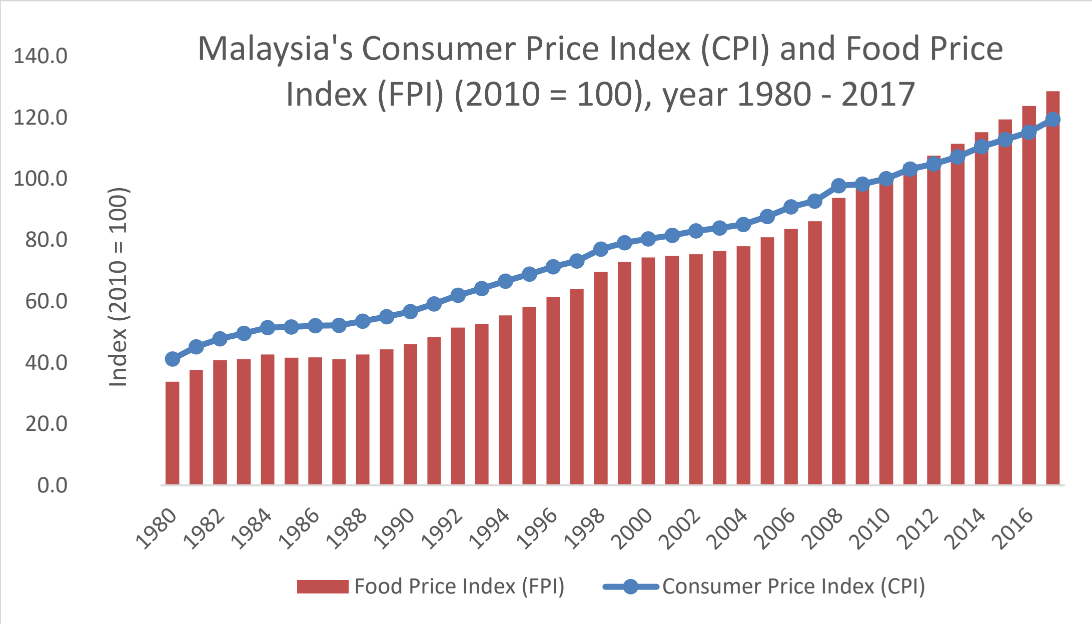

Fig. 1. Malaysia's Consumer Price Index and Food Price Index (2010 = 100), 1980 – 2017
Source: Bank Negara Malaysia's Monthly Statistical Bulletin, January 2018

In the recent decades, studies have showed that the crude oil price is the main factor that influences the increase in food price (*e.g.* Kwon and Koo, 2009; Nazlioglu and Soytas, 2011; Reberedo, 2012; Ibrahim, 2015; and Abdlaziz et al. 2016). Crude oil price is a direct factor influencing the producers' cost of production, such as transportation cost, product processing cost, etc. Hence, the impact of increase in crude oil price will drive food price to hike, and ultimately will generate the cost-push inflation in the food market. Due to Malaysian economy transformation from agriculture- and commodity-based to industrial-based economy, this increases the possibilities for the country to be exposed to global food and oil crisis (Ibrahim 2015). For instance, the global and Malaysia's food price crisis which occurred in 2008 and 2011 were impacted by the international crude oil price shock. Besides that, the other economic factors also will elevate food inflation. When Malaysian currency depreciated, a higher price will be paid for the imported food. Therefore, it will lead to the increase in food import bills and cause a higher increase in the food price.

However, food production and food price are also affected by the non-economic factors such as climate change. In general, we understand that the production of crops is affected biophysically by climatic variables. Without rainfall or temperature, crops will not grow. Increased rainfall and temperature at a lower level will enhance crop production. However, if these climatic variables rise extremely or over the optimum level, flooding or drought may occur which will damage crop production. According to Cai, Bandara, and Newth (2016), climate change has posed a major threat to agriculture which could be highly vulnerable to it. Some international non-government organizations (NGOs) and experts found that the climate change will cause a negative impact on food production. This explains that the extreme increase in temperature will reduce agriculture production (food availability decreases) (Sivakumar and Stefanski, 2011). Consequently, the yield loss will push the food inflation up. In a nutshell, if only linear analysis is applied, the effect of climate change on crop production will give a misleading explanation whereby as long as rainfall and temperature increase it will cause to the crop production to decrease.

In the recent decades, food price in Malaysia has increased and fluctuated with the changes in economic factors and also as a result from climate change. In order to address the food price movement, it is important to confirm the most pertinent variables to be controlled in order to tackle the fluctuation of food price in Malaysia. Therefore, this study aimed to determine the impact of economic factors (economic growth, exchange rate, and crude oil price) and climate change on the Malaysia's food price fluctuations.

The study on oil price pass-through effect into the food price fluctuation has captured much interest of many researchers (e.g. Nazlioglu and Soytas, 2011; Ibrahim and Said, 2012; Reberedo, 2012; Ibrahim, 2015; Abdlaziz et al., 2016). Besides that, Harri et al. (2009), Kwon and Koo (2009) and Baek and Koo (2010) found that the exchange rate movements and petroleum price played a significant role in determining the food price inflation. This indicates that the exchange rate itself is playing an important role in determining the food price fluctuation (Roache and Rossim, 2010). According to Abdlaziz, et al. (2016), the depreciation of US dollar was one of the important factors that influences global food prices and this was supported by Nazlioglu and Soytas (2012)'s findings. Hence, exchange rate is expected to show a positive causal impact on food price in Malaysia. Ibrahim (2015) has posited that the depreciation of Malaysian Ringgit will lead to the increase in Malaysia's food import bill and subsequently drive the domestic food price upwards. Futhermore, most of the studies also included real GDP to determine the food price changes (Ibrahim and Said, 2012; Ibrahim, 2015; Abdlaziz et al. 2016; and Tadasse et al. 2016). The real GDP was found to have a significant positive impact on agriculture commodity and food price in many literatures. This indicates that the rise of economic productivity will increase the national income which would result in the upward shift of the aggregate demand curve and consequently drive the food price hike.

The likely negative impact of climate change on agriculture has important implications for the developing countries and temperature increases will led to the decrease in agriculture productivity (Cervantes-Godoy and Dewbre, 2010). According to Bandara and Cai (2014), climate change will cause agriculture yield losses and drive the food price to increase. This implies that climate change will give some negative impacts on the food production through the decrease of agriculture production and then increase in market food price. According to Parry et al. (2004), biophysical effects explain the linkages between climate change and agricultural responses. Accordingly, the production of crop is affected biophysically by climatic variables, such as the rise in temperatures, changes in precipitation regimes, and increase in atmospheric carbon dioxide levels. However, the direct effects of CO_2 on crops' yield are widely used as a proxy for the temperature raise in climate change impact studies[1] (Kimball et al. 2002; Derner et al. 2003; Tubiello and Ewert, 2003; Parry et al. 2004). For instance, Ekpenyong and Ogbuagu (2015) employed the sum of the three popular greenhouse gas emission (CO_2, methane and nitrous oxide emissions) as a proxy for climate change and found that the climate change has a negative impact on the agricultural productivity.

However, Huong, Bo, and Fahad (2018), using quadratic Ricardian model, found that the climate change or meteorological variables have an inverted U-shaped relationships with agriculture revenue. This indicates that the agriculture productivity will increase up to a certain level of CO_2 but will decrease when the temperature or CO_2 greenhouse gas emission increases over the threshold value. Hence, climate change is also believed to have a nonlinear U-shaped relationship with the food price.

[1] Most of the researchers have agreed that the greenhouse gas emission (CO_2) could serve as a proxy to capture the temperature and climate change effect (Nelson et al. 2009; Sivakumar and Stefanski, 2011; and Bandara and Cai, 2014).

In terms of the normal biophysical effects, increased temperatures below the threshold level will increase the agricultural productivity and subsequently it will drive the food price to decrease. In this situation, temperature and food price have a negative relationship. In contrast, excessive temperatures are amplifying drought effects and consequently cause a loss of crops and agricultural production (Bates et al. 2008; Brown and Funk 2008; Adhikari et al. 2015). Consequently, the decrease in food supply will drive the soaring food price when the temperature rises higher than the threshold value.

In the past, most of the researchers only focused either the impact of economic factors (Aker and Lemtouni, 1999; Arshad, 2012; Applanaidu et al. 2013, Ibrahim 2015) or climate change effects on the food price movement (Ericksen, 2008; Gregory and Ingram, 2008; Ericksen et al. 2009). However, there are limited food price studies that covered both climate change and economic factors on their research works. The impact of temperature on the food price is not yet analyzed in literature especially in the case of Malaysia. In order to fill in this research gap, this study examined the impacts of both economic factors and climate change on the Malaysia's food price movement in a non-linear analytical approach.

METHOD OF ANALYSIS

Cointegration test is one of the basic approaches to confirm that estimated time series regression does not produce a spurious regression. In this study, the Engle-Granger cointegration test (hereafter EG) and Error Correction Mechanism (ECM) regression were adopted. The first step to test the cointegration in EG test was to estimate the long-run equation with Ordinary Least Square (OLS) method, which is:

$$Y_t = c + \beta_1 X_t + \varepsilon_t \tag{1}$$

where Y_t denotes the endogenous variable and X_t denotes the exogenous variable(s).

In this study, the food price was estimated based on the supply-demand theory. The food demand (Qd) was determined by the food price index (FPI), currency exchange (MYR) which captured the food trade effect whereas the RGDP captured the aggregate demand for food:

$$Qd_t = \alpha_1 - \lambda_1 \, FPI_t + \lambda_2 \, MYR_t + \lambda_3 \, RGDP_t + \varepsilon_{1t} \tag{2}$$

In supply theory, quantity supplied (Qs) is determined by the market food price (FPI), and crude oil price (COP) which captures the cost of production. However, according to the Ricardian quadratic model, agriculture production is affected by the climate change in a non-linear inverted U-shape (see Huong, Bo, and Fahad, 2018). As mentioned before, the normal increase in temperature will increase crop production due to the biophysical effects. However, the decrease in agriculture production due to the excessive temperatures such as CO_2 gas emission (Parry et al., 2004) will drive the market food supply shock and then food price hike (Edoja et. al. 2016). Hence, the climate change variable should be included into the food supply model which is as follows: [2]

$$Qs_t = \alpha_2 + \lambda_4 \, FPI_t - \lambda_5 \, COP_t + \lambda_6 \, CO_{2\,t} - \lambda_7 \, CO_2{}^2{}_t + \varepsilon_{2t} \tag{3}$$

Under the market equilibrium situation, the Qs is equal to the Qd or the equation (2) is equal to the equation (3). Hence, the market food price can be estimated as:

$$\alpha_1 - \lambda_1 \, FPI_t + \lambda_2 \, MYR_t + \lambda_3 \, RGDP_t + \varepsilon_{1t} = \alpha_2 + \lambda_4 \, FPI_t - \lambda_5 \, COP_t + \lambda_6 \, CO_{2\,t} + \lambda_7 \, CO_2{}^2{}_t + \varepsilon_{2t}$$

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[2] The CO_2-squared represents the nonlinear U-shaped effects of climate change on the food price as mentioned before.

$$\lambda_1 \text{ FPI}_t + \lambda_4 \text{ FPI}_t = \alpha_1 + \lambda_2 \text{ MYR}_t + \lambda_3 \text{ RGDP}_t + \varepsilon_{1t} - \alpha_2 + \lambda_5 \text{ COP}_t - \lambda_6 \text{ CO}_{2t} + \lambda_7 \text{ CO}_2{}^2{}_t - \varepsilon_{2t}$$

$$\text{FPI}_t = \alpha_1 - \alpha_2 + \lambda_2 \text{ MYR}_t + \beta_3 \text{ RGDP}_t + \beta_5 \text{ COP}_t - \beta_6 \text{ CO}_{2t} + \beta_7 \text{ CO}_2{}^2{}_t + \varepsilon_{1t} - \varepsilon_{2t} \quad (4)$$

To simplify equation (4), we re-write the food price function as:

$$\text{FPI}_t = c + \beta_1 \text{ COP}_t + \beta_2 \text{ MYR}_t + \beta_3 \text{ RGDP}_t - \beta_4 \text{ CO}_{2t} + \beta_5 \text{ CO}_2{}^2{}_t + \varepsilon_t \quad (5)$$

where the $c = \frac{\alpha_1 - \alpha_2}{\lambda_1+\lambda_4}$, $\beta_1 = \frac{\lambda_5}{\lambda_1+\lambda_4}$, $\beta_2 = \frac{\lambda_2}{\lambda_1+\lambda_4}$, $\beta_3 = \frac{\lambda_3}{\lambda_1+\lambda_4}$, $\beta_4 = \frac{\lambda_5}{\lambda_1+\lambda_4}$, $\beta_5 = \frac{\lambda_7}{\lambda_1+\lambda_4}$, and $\varepsilon_t = \frac{\varepsilon_1 - \varepsilon_2}{\lambda_1+\lambda_4}$.

Oil price hike, depreciation of domestic currency and economic expansion will lead to increase in food price. Following this, COP, MYR, and RGDP were expected to have positive sign. However, the climate change should have U-shaped relationship, indicating that the CO_2 and CO_2-squared were expected to have negative and positive sign, respectively.

Therefore, we can estimate the Equation (5) using simple OLS and then obtain and use the residual series from this estimated regression to estimate a *k* lag augmented regression which can be expressed as:

$$\Delta\hat{\varepsilon}_t = (\rho - 1)\hat{\varepsilon}_{t-1} + \sum_{j=1}^{k} \delta_j \Delta\hat{\varepsilon}_{t-j} + u_t \quad (6)$$

where the $\Delta\hat{\varepsilon}_t$ indicates the first difference of estimated error term which is obtained from the Equation (5). If the null hypothesis of ρ-1=0 is rejected in the Augmented Dickey Fuller (ADF) test, it indicates that the estimated variables (COP, MYR, RGDP, CO_2, CO_2^2 and FPI) have a long-run cointegrated relationship and the long-run estimated regression or Equation (5) do not produce a spurious regression. After the cointegration test, we proceeded to the ECM estimation in order to confirm the short-run equilibrium among the estimated variables. In ECM, we considered the error term ($\hat{\varepsilon}_t$) in the Equation (5) as the long-run equilibrium error or the disequilibrium magnitude. Hence, we can use the error term to tie the short-run behaviour of food price (FPI) to its long-run value. In general, the ECM is written as:

$$\Delta y_t = \Omega_0 + \alpha\hat{\varepsilon}_{t-1} + \sum_{i=1}^{k} \Phi_i \, \Delta y_{t-i} + \sum_{h=0}^{r} \theta_h \, \Delta x_{jt-h} + u_t \quad (7)$$

where the u_t is the stochastic term and $\hat{\varepsilon}_{t-1}$ is the lagged value of the error term in Equation (5). Besides that, the y_t represents the FPI_t and the x_j represents the exogenous, including COP, MYR, RGDP, and CO_2. The *k* and *r* are the optimum lag length selected based on the general to specific approach and in order to avoid the auto-serial correlation on u_t. In addition, α is the long-run speed of adjustment, also known as error correction coefficient, while Φ_i and θ_h illustrate that short-run elasticities.

In this study, ECM Equation (7) can be re-written as:

$$\Delta \text{lnFPI}_t = \Omega_0 + \alpha \text{ ECT}_{t-1} + \sum_{i=1}^{k} \Phi_i \, \Delta lnFPI_{t-i} + \sum_{h=0}^{r} \theta_h \, \Delta lnCOP_{t-h} + \sum_{h1=0}^{p} \theta_{h1} \, \Delta lnMYR_{t-h1} + \sum_{h2=0}^{q} \theta_{h2} \, \Delta lnRGDP_{t-h2} + \sum_{h3=0}^{r} \theta_{h3} \, \Delta lnCO_{2_{t-h3}} + \sum_{h4=0}^{s} \theta_{h4} \, \Delta lnCO^2_{2_{t-h4}} + u_t \quad (8)$$

where: the $\text{ECT}_{t-1} = \ln \text{FPIt} - c - \beta_1 \ln \text{COP}_t - \beta_2 \ln \text{MYR}_t - \beta_3 \ln \text{RGDP}_t - \beta_4 \ln \text{CO}_{2t} - \beta_5 \ln \text{CO}_2{}^2{}_t$ and α in Equation (8) is the magnitude of self-adjustment which expected to be negative if the variables are cointegrated.

Data collection. In this study, time series data from 1980 to 2017 were used to estimate the factors determining the food price in Malaysia. The Food Price Index (FPI) was adopted to represent Malaysian food price. Furthermore, the crude oil price (COP) was proxied by the West Texas Intermediate crude oil price in US dollar per barrel and the Malaysian exchange rate (MYR) measured in ringgit per US dollar. All of these variables were adopted from the Monthly Statistical Bulletin published by the central bank of Malaysia *(www.bnm.gov.my)*. However, the CO_2 gas emission is a proxy for the climate changed effects and the real income was represented by the real gross domestic product (RGDP) and measured in millions ringgit as adopted from *https://data.worldbank.org/indicator*.

RESULTS AND DISCUSSION

In this study, secondary data was used to determine the food price fluctuation. Hence, the basic requirement of time series data was to examine the data stationary level. It is necessary to check the unit roots whether the data are stationary at order zero or $I(0)$ or stationary at order one or $I(1)$. Table 1 shows the summarized results of the unit root test using the Augmented Dickey-Fuller (ADF) and Philip-Perron (PP) test. The ADF and PP tests showed that all variables had failed to reject the null hypothesis of unit roots in level form, indicating that all the variables were not stationary at order zero. Hence, the data was transformed into first difference form to re-test the stationarity of the data. Consequently, the ADF and PP tests confirmed that all data rejected the null hypothesis of unit roots at 1% significance level. This indicated that these data were stationary at order one or $I(1)$.

Table 1. Augmented Dickey Fuller (ADF) and Philip-Peron (PP) Unit root tests

	Level		**First Difference**	
Variables	**ADF**	**PP**	**ADF**	**PP**
FPI	-0.396	-0.414	-4.659***	-4.664***
	(0)	(2)	(0)	(2)
COP	-1.206	-1.261	-5.567***	-5.567***
	(0)	(2)	(0)	(0)
RGDP	-1.147	-1.094	-4.824***	-4.838***
	(0)	(1)	(0)	(1)
MYR	-1.131	-1.157	-6.032***	-6.031***
	(0)	(2)	(0)	(2)
CO_2	-1.355	-1.417	-6.554***	-6.517***
	(0)	(1)	(0)	(3)
CO_2^2	-1.133	-1.173	-6.570***	-6.540***
	(0)	(1)	(0)	(2)

Note: All variables are converted into the form of logarithm, *** represents as significant at 1% significance level. The number in the parenthesis (…) represents the optimum lag selected for the test. To select optimum lag order in ADF test, the Schwarz Info Criterion (SIC) is adopted and to select the best lag order in PP test, Newey-West Bandwith (NWB) is used.

Engle-Granger Cointegration Test. The result for the Engle- Granger cointegration test showed that the model's stochastic term (u_t) is stationary at order zero or $I(0)$ and rejects the null hypothesis of no cointegration relationship at 1% significant level (Table 2). Therefore, all the exogenous variables (COP, MYR, RGDP, CO_2, and CO_2^2) showed that a long-run cointegration relationships with the food price movement.

The long-run regression showed that all the explanatory variables followed the expected sign but only RGDP and CO_2 were highly significant at 1% significance level while CO_2^2 were statistically significant at 5% significance level. The estimated elasticity of RGDP is 0.7806 which defines that 1%

increase in RGDP will lead to food price rise about 0.7806%, holding other factors constant. Similar with the finding of other researchers, climate change was found to have a nonlinear impact on the food price. The long-run regression showed that the gas emission (CO_2) had a U-shaped relationship on the food price movement.[3] The elasticity of CO_2 showed that 1% increase of CO_2 will reduce the food price by 1.867%. The threshold value of the CO_2 is 286,244.04 kiloton (kt) which indicates that if the gas emission CO_2 raise more than this level, agriculture production will decrease and drive the food price to increase.[4] In 2017, the total greenhouse gas CO_2 emission in Malaysia was recorded at 280,908.09 kt which is close to the threshold level.[5]

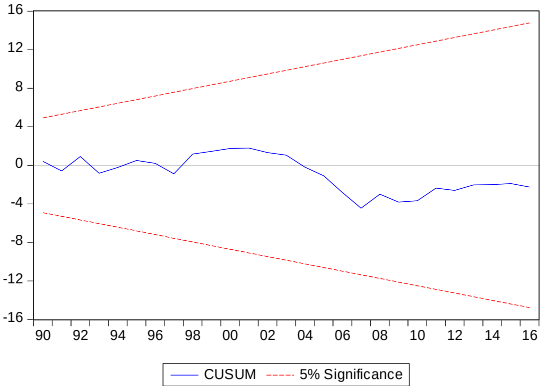
Table 2. Summary of Engle – Granger Cointegration Test

FPI	**C**	**COP**	**MYR**	**RGDP**	**CO_2**	**CO_2^2**
	α	**β_1**	**β_2**	**β_3**	**β_4**	**β_5**
	-5.2288	0.0046	0.0830	0.7806***	-1.8671***	0.0743**
	(-0.929)	(0.205)	(1.189)	(5.291)	(-2.814)	(2.358)
Engle-Granger Cointegration Test: (Δu_t = -ρu_{t-1} + $\sum_{i=1}^{k} \beta_i$ Δu_{t-1})					-4.0772*** [0]	
Critical Values:				**1%** -4.07	**5%** -3.37	**10%** -3.03

Notes: ***, ** and * denotes significant at 1%, 5% and 10% respectively. The figure in the parenthesis (…) represents the t-statistic for the coefficient. The figure in the bracket […] denotes the optimum lagged selected based on the SIC.

Error Correction Mechanism (ECM). In order to show the unbiased estimation of ECM model, some crucial diagnostic tests were applied *i.e* R-squared, auto-serial correlation test, Jarque-Bera normality test, and ARCH test. In this ECM model, the R-squared was 0.564 which indicates 56.4% of the variation of ΔFPI is explained by ΔCOP, ΔMYR, ΔRGDP, ΔCO_2 and ΔCO_2^2, while the remaining 43.6% were not explained by other factors that are not included in the estimated regression. In addition, the F-statistic was statistically significant at 1% significance level which indicates that the model was fitted and explained by the all independent variables. In order to confirm that the estimated regression was free from the auto-serial correlation problem, the auto-serial correlation test was applied and result was not significance to reject the null hypothesis that the residuals are serial correlated. On the other hand, the estimated regression's residual was not correlated and the ECM model was confirmed unbiased. In addition, the regression's residual was found normally distributed and the variance of the residual was homoscedasticity and constant. This was confirmed by the Jarque-Bera test and ARCH test, both of which failed to reject the null hypothesis. In addition, the CUSUM and CUSUM square (Figure 3) showed that the coefficients in this estimated ECM were stable and the model was Best Linear Unbiased Estimator (BLUE).

[3] The F-statistic for the null hypothesis $\beta_4 = \beta_5$ is 19.22 and the p-value is 0.0001, which reject the null hypothesis and this infer that the quadratic relationship exist in this model.
[4] The threshold value is calculated based on the first derivative on the long-run regression, which is $\frac{\partial FPI}{\partial CO2} = -1.8671 + 0.1486\, lnCO_2 = 0$. After the mathematic solution on this derivative function, the exp(CO_2) is equal to exp(12.5646) = 286,244.04.
[5] The Malaysia's CO_2 is based on the World Bank Indicator and retrieved from *https://data.worldbank.org/indicator.*



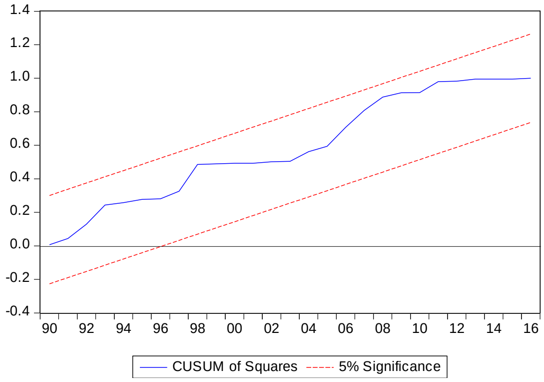


Fig. 3. CUSUM and CUSUM square for the ECM model

In this study, the findings of ECM showed that all short-run variables bore the expected signs (Table 3). The negative coefficient for the error correction term (ECT) lagged one was estimated in value of -0.3975 and it was statistically significant at 1% significance level. This indicates that the food market adjustment is playing a significant impact on auto-convergence which is the short-run disequilibrium and will automatically return to the initial equilibrium point. Moreover, the magnitude of the speed of adjustment (-0.3975) showed that the market itself has a moderate speed to converge into the long-run.

Based on the estimated ECM, the short-run elasticity for FPI lagged one was statistically significant at 1% level. However, the exogenous variables were not significant in affecting the short-run changes of FPI. This indicates that the changes of food price in short-run was based on the food market itself but not on the external factors. Furthermore, the estimated F-statistic 2.933 (p-value = 0.0978) showed a non-significant relationship to reject the null hypotheses that the short-run elasticities of CO_2 is equal to the elasticities of CO_2^2. This indicates that the CO_2 still has a quadratic relationship with the changes of food price but it was at a lower confidence level.

Based on the findings, there are some policy implications that can be suggested. Firstly, this study showed that the food market has self-recovery mechanism to adjust to the temporary food market demand-supply shock back to the equilibrium. Hence, policy-maker should focus on the long-run food price hike than short-run price shock since the short-run market self-adjustment (ECT) was significant. Secondly, the economic growth will increase the household purchasing power and increase the market food price in long-run. This suggests that the food market should have a well-planned strategy on their agriculture or food supply and government has to ensure food self-sufficiency or not to decrease food production. Otherwise, the food crisis such as that of the 2007/2008 international food crisis can happen again. Finally, the non-linear climate change effect suggests that the importance of water supply facilities and good irrigation system to address the problem of drought when the temperature increases over the threshold value. Hence, the threshold level of the temperature provided a significant warning information for the farmers. In 2017, the greenhouse gas CO_2 emission in Malaysia was recorded close to the threshold level, hence, policy maker should strengthen the existing rules and regulations to restrict the manufacturing sector from producing more greenhouse gases in order to slow down the CO_2 emission and prolong the time to reach the threshold level. For example, government can sell permits to address the greenhouse gas issues or implement a pollution tax for such as gas emission. In addition, government also can provide research grant and subsidies to expand the sustainable energy source (solar energy) in order to reduce the coal and fossil fuel use.

Table 3. Summary findings of error correction mechanism

Variable	Coefficient	Standard Error	P- Value
C	0.0194**	0.0071	0.011
ECT_{t-1}	-0.3975***	0.0885	0.0001
ΔFPI_{t-1}	0.3885***	0.1148	0.0022
ΔCOP_t	0.0069	0.0127	0.5901
ΔMYR_t	0.0029	0.0350	0.9352
$\Delta RGDP_t$	0.1289	0.1005	0.2101
ΔCO_{2t}	-1.0353*	0.5997	0.0957
$\Delta {CO_2}^2_t$	0.0414	0.0267	0.1325
Diagnostic Checking:			
R square		0.564	
Adjusted R square		0.452	
F- statistics		4.999*** [0.001]	
Serial Correlation		4.4842 [0.1062]	
Normality Jarque-Bera		1.6572 [0.4366]	
ARCH		0.4867 [0.4854]	

Notes: ***, ** and * denotes significant at 1%, 5% and 10% respectively. The figure in the parenthesis (…) represents the standard error for the result. The figure in the bracket […] denotes the p-value.

CONCLUSION

In the recent decades, the food price in Malaysia has increased rapidly. Therefore, this study aimed to investigate the impact of economic factors (economic growth, exchange rate, and crude oil price) and climate changed towards Malaysia's food price fluctuation. This study had employed the cointegration method on data over 38 years from 1980 to 2017. As for the overall findings, for the ADF and PP tests, all the variables were stationary after transformed into first difference or $I(1)$. The test for cointegration showed that there is long run cointegration between the food price and the underlying variables (i.e. COP, MYR, RGDP and CO_2). This means that all the independent variables jointly and significantly affect the food price in the long-run. The result showed that in the long run, increase in RGDP, MYR, and COP will lead to increase in food price. However, in a short period, the crude oil price, currency exchange, and real GDP have insignificant impact towards food price fluctuations. The changes in food price in a short period were solely caused by its own lag and the ECT. As claimed by classical economists, market price always acts like an "invisible hand" to adjust the market shock back to the equilibrium situation in all free market. Furthermore, climate change is found to have a strong non-linear U-shaped impact on the food price change in the long-run but it was a weak quadratic impact in a shorter period which clarified the critics made in this study.

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REFERENCES CITED

Abdlaziz, R.A., Khalid, A.R. and A. Peter. 2016. Oil and food prices co-integration nexus for Indonesia: A non-linear autoregressive distributed lag analysis. International Journal of Energy Economics and Policy. 6(1): 82 – 87.

Adhikari, U., Nejadhashemi, A.P., and Woznicki, S.A., 2015. Climate change and eastern Africa: a review of impact on major crops. 4(2): 110 -132.

Aker, J.C. and Lemtouni, A. 1999. A framework for assessing food security in the face of globalization: The Case of Morocco. Agroalimentaria, 8, 13-26.

Applanaidu, S.D., Bakar, N.A.A. and A.H, Baharudin. 2014. An econometric analysis of food security and related macroeconomic variables in Malaysia: A vector autoregressive approach (VAR). UMK Procedia 1, 93 -102. Retrieved from: https://pdfs.semanticscholar.org/9af9/de090be7787395e28a95cbdd7e3be77e3bd2.pdf.

Arshad, F. M., and Abdel Hameed, A. A. 2010. Global Food Prices: Implications to Food Security in Malaysia, CRRC Consumer Review, 1(1), 21-38.

Baek, J. and W.W. Koo. 2010. Analyzing factors affecting U.S. food price inflation. Canadian Journal of Agricultural Economics. 58(3): 303 -320.

Bandara, J. S. and Cai, Y. 2014. The impact of climate change on food crop productivity food prices and food security in South Asia. Economic Analysis and Policy. 44(4): 451 – 465.

Bates, B. C., Z. W. Kundzewicz, S. Wu, and J. P. Palutikof. 2008. Climate change and water. Technical Paper of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change, IPCC Secretariat, Geneva, Switzerland.

Brown, M. E. and C. C. Funk. 2008. Food security under climate change. Science, 319: 580 – 581.

Cai, Y., Bandara, J.S., and Newth, D. 2016. A framework for integrated assessment of food production economics in South Asia under climate change. Environmental Modelling and Software. 75: 459 -497.

Derner, J.D., Johnson, H.B., Kimball, B.A., Pinter Jr, P.J., Polley, H.W., Tischler, C.R., Bouttons, T.W., LaMorte, R.L., Wall, G.W., Adam, N.R., Leavitt, S.W., Ottman, M.J., Matthias, A.D. and T.J. Brooks. 2003. Above-and below-ground responses of C3-C4 species mixtures to elevated CO_2 and soil water availability. Global Change Biology 9, 452–460.

Edoja, P.E., Aye, G.C., and Abu, O. 2016. Dynamic relationship among CO_2 emission, agricultural productivity and food security in Nigeria. Cogent Economics and Finance, 4, 1 – 13.

Ericksen, P.J. 2008. Conceptualizing food systems for global environmental change research. Global Environmental Change, 18, pp. 234-245.

Ericksen, P.J., Ingram, J.S.I., and D.M. Livernman 2009. Food security and global environmental change: Emerging challenges. Environmental Science and Policy, 12, 373 – 377.

Gornall, J., Betts, R., Burke, E., Robin, C., Joanne, C., Kate, W., Wiltshire, A., 2010. Implications of climate change for agricultural productivity in the early twenty-first century. Phil. Trans. B 365 (1554), 2973–2989.

Gregory, P., and J. Ingram. 2008. Climate change and the current ‘‘Food Crisis’’. CAB Reviews: Perspectives in Agriculture, Veterinary Sciences. Nutrition and Natural Resources 3, 1–10.

Harri, A., Nally, L., and D. Hudson. 2009. The relationship between oil, exchange rates, and commodity prices. Journal of Agricultural and Applied Economics. 41(2): 501–510.

Huong, N.T.L, Bo, Y.S., and Fahad, S. 2018. Economic impact of climate change on agriculture using Ricardian approach: A case of northwest Vietnam. Journal of the Saudi Society of Agricultural Sciences. Retrieved from https://ac.els-cdn.com/S1658077X17304290/1-s2.0-S1658077X17304290-main.pdf?_tid=e4b79122-fae6-4d7a-acba-4fd2f18c8d1b&acdnat=1522980484_d9521ecf2e5bc33abb576857a1e48507

Ibrahim, M.H. 2015. Oil and food prices in Malaysia: A nonlinear ARDL analysis. Agricultural and Food Economics. 3(1): 1-14.

Ibrahim, M.H. and R. Said. 2012. Disaggregated consumer prices and oil price pass-through: evidence from Malaysia. China Agricultural Economic Review. 4(4): 514–529.

Kimball, B.A., Kobayashi, K., M. Bindi 2002. Responses of agricultural crops to free-air CO_2 enrichment. Advances in Agronomy 77, 293–368.

Kwon, D. and W.W. Koo. 2009. Price transmission channels of energy and exchange rate on food sector: A disaggregated approach based on stage of process. Selected Paper Prepared for Presentation at the Agricultural & Applied Economics Association 2009 AAEA & ACCI Joint Annual Meeting, Milwaukee, Wisconsin, July 26-29, 2009.

Nazlioglu, S., and U. Soytas. 2011. World oil prices and agricultural commodity prices: evidence from an emerging market. Energy Economics. 33(3): 488–496.

Nelson, G.C, Rosegrant, M.W., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Msangi, S., Palazzo, A., Batka, M., Magalhaes, M., Valmonte-Santos, R., Ewing, M., Lee, D., 2009. Climate change: Impact on agriculture and costs of adaptation. Food Policy Reports, no. 21. International Food Policy Research Institute, Washington, DC.

Parry, M.L., Rosenzweig, C., Iglesias, A., Livermore, M., and Fischer, G. 2004. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Global Environmental Change. 14: 53 – 67.

Roache, S. K., and M. Rossi. 2010. The effects of economic news on commodity prices. The Quarterly Review of Economics and Finance. 50(3): 377-385.

Sivakumar, V.K.M., and Stefanski, R., 2011. Climate change in South Asia. In: Lal, R., Mannava, V.K., Sivakumar, S.M.A., Faiz, A.H.M., Rahman, M., Islam, K.R. (Eds.), Climate Change and Food Security in South Asia. Springer, London, pp. 13-30.

Tadasse, G., Algieri, B., Kalkuhl, M., and J.V. Braun. 2016. Drivers and triggers of international food price spikes and volatility. Food Policy. 47: 117-128.