Relationship between Bioethanol Production and Agricultural Commodity Prices: for the case of Thailand

Thurai Murugan Nathan[a,*], Abdelhak Senadjki[b], Chee-Keong Choong[c] and Ismail Nor Asmat[d]

[a,b,c] Department of Economics, Faculty of Business and Finance,
Universiti Tunku Abdul Rahman, 31900 Kampar,
Perak, MALAYSIA

[d] Department of Economics, School of Social Science,
Universiti Sains Malaysia, 11800 Minden, Pulau Pinang, MALAYSIA

Abstract

This paper examines the relationship between bio-ethanol production and agricultural commodity prices in Thailand. The main feedstocks for producing bioethanol in Thailand are sugarcane, cane molasses and cassava. Monthly data has been used from January 2006 to March 2014 to conduct this research. The existence of long-run relationships among the four variables i.e. bioethanol production, sugarcane farm gate price, cane molasses export price and cassava farm gate price detected through the Auto Regressive Distributive Lag (ARDL) framework. Then, the Granger Causality Test (Wald Test) used to investigate the short-run causal relationship among those variables. From the result found that when bioethanol production act as independent variable, long-run equilibrium exist between bioethanol production and sugarcane farm gate price, cane molasses export price and cassava farm gate price, respectively. Besides that, Granger causality exists among the variables as well. Sugarcane farm gate price and bioethanol production as well as cassava farm gate price and bioethanol production are found to be having unidirectional Granger causality effect. Meanwhile, bidirectional Granger causality effect is found between cane molasses export price and bioethanol production. The results of this study would contribute towards significant policy making in Thailand.

Keywords: *Bio-ethanol production, Agricultural commodity prices, Thailand, econometrics, Economy*

1. Introduction

Along with India, China, Philippines, and Indonesia, Thailand has recently emerged to be one of the leading producers of biofuels in Asia (Zhou & Thomson, 2009). The accelerated production of biofuels over years is the result of Thailand's serious effort to reduce oil import dependency (Russell & Frymier, 2012). National Alternative Energy Development Plan (2004-2011) was the first plan adopted by Thai government (Preechajarn & Prasertsri, 2010). In year 2009, Thai government implemented the second plan for biofuels known as Alternative Energy Development Plan (2008-2022). This plan has been divided into three phases in order to achieve the final goal, which is the share of alternative energy mix to be increased to 20 percent of the country's final energy demand by 2022 (Morgera, Kulovesi & Gobena, 2009). The target of both bioethanol production and consumption for short term plan (2008-2011), medium term plan (2012-2016) and long term plan (2017-2022) are 3.0 million liters per day, 6.2 million liters per day and 9.0 million liters per day, respectively (Preechajarn & Prasertsri, 2010).

[*]Corresponding author. PhD student, Department of Economics, School of Social Science, Universiti Sains Malaysia, 11800 Minden, Pulau Pinang, MALAYSIA. E-mail: thurai@utar.edu.my. Tel: (605) 468 8888 ext:4632.

However, the Alternative Energy Development Plan (2008-2022) was unsuccessful due to the fall short in achieving its short term target, especially in bioethanol consumption. Therefore, Thai government had replaced it with the new 10-year Alternative Energy Development Plan (2012-2021) in year 2012 (Preechajarn & Prasertsri, 2012). The target of bioethanol consumption for the new plan remained at 9.0 million liters per day by 2021. Today, the bioethanol is commonly used to blend with gasoline at the concentrations of 10%, 20% and 85% by volume to form different grades of gasohol fuel in Thailand market (Silalertruksa & Gheewala, 2010).

Based on several studies on the overall effect of bioethanol program in Thailand, there is a rise in certain feedstock prices since the program was implemented (Mudiyanselage, Lin & Yi, 2013). This has substantially raised the concern on the potential food shortages problem in Thailand. Although the government has provided price supports, the prices of sugarcane and cane molasses have climbed and turned to be more volatile (Mudiyanselage et al., 2013). The food prices can be further increased if more farmers headed for higher-priced crops, thus leading to smaller areas of food crops (Business-in-Asia.com, 2007). These could create a competition among food and fuel as the present feedstock is also used for foods (Patumsawad, 2011). On the other hand, fluctuation in three feedstock prices may affect their ratio in bioethanol production. Thai government has given some flexibility to the sugarcane and sugar producers in which more sugarcane should be placed to produce sugar when the increment in sugar price is more profitable than bioethanol, whereas, more sugarcane should be placed as an input for bioethanol production when the sugar appears to be less profitable than bioethanol (Cane and Sugar Industry Policy Bureau, 2006). Turning to another focus, molasses is a by-product of sugar milling and has taken a major share of 80 percent of the total feedstock for ethanol production (Preechajarn & Prasertsri, 2013). Nevertheless, cassava-based bioethanol production seemed to be more favorable as the cane molasses prices are currently facing an upward pressure[72] (Preechajarn & Prasertsri, 2013). Price subsidies and discounted sales of government-owned cassava stocks are exercised to encourage the supplies of cassava-based bioethanol (Preechajarn & Prasertsri, 2013). In summary, all the concerns on food security and sustainability of feedstock supply above have drawn the interest to examine the correlation and causal relationship between bioethanol production and, sugarcane, cane molasses and cassava prices in Thailand.

The essence of this research paper is to serve as a guideline for Thailand policymakers in creating agricultural policies and biofuels policies. Thai government could determine whether and to which extent should both agricultural policies and biofuels policies coordinated with one another. Besides, Thailand can be claimed to be the best role model for other Asian countries who are still in the early stage of the bioethanol production such as Malaysia. Malaysia is in implementing its new strategy to produce second-generation biofuels, during its infant stage in bioethanol production[73]. Thailand is more advance and had initiated its second-generation biofuels pilot project by using sugarcane bagasse in 2010 (Preechajarn & Prasertsri, 2010). It is still remain at an experimental stage by producing at 10,000 liters per day. However, it is believed to be commercially practicable in the short term.

[72] This is resulted from the drop in cane molasses yield in 2013/14, which was a full 0.4% below 4.5% for previous year, leading to a fall in cane molasses supply by 500,000 million tonnes (UM Trading, 2014).
[73] In year 2011, a new strategy added into the National Biomass Strategy 2020 was introduced; highlighting the production of bioethanol from lignocellulosic biomass (second-generation biofuels) especially the oil palm biomass and wood waste (Chin & H’ng, 2013).

e-ISBN 978-967-11473-2-0

2. Literature review

A number of researchers have found to be using similar variables of fossil fuels, biofuels and agricultural commodities to fit into each different research objectives. However, mix outcomes are commonly resulted among similar researches.

There are several researchers looking at the relationships among oil, bioethanol and corn but the results are inconsistent among them. Natanelov, McKenzie and Huylenbroeck (2013) have shown that the relationship between corn and bioethanol appears to be less direct as well as the two markets are not firmly connected by a long-run cointegrating relationship. Their finding is supported by the result of Zhang, Lohr, Escalante and Wetzstein (2010), further suggesting that the sugar price is found to be the dominant force in influencing agricultural commodity prices as it acts as the largest input for world bioethanol production[74]. However, the results from Cha and Bae (2011) have somehow disagreed with those statements above. Even though the higher demand from bioethanol causes the price of feedstock to increase in short run, this price increment will eventually offset by the progress of quantity adjustments from the reduction in export demand for feedstock and feed demand for feedstock in the long run (Cha & Bae, 2011).

Several studies also examine the volatility transmission between oil, bioethanol and corn markets by accounting for the structural break on 2008, which are Algieri (2014), Gardebroek and Hernandez (2013), Wu and Li (2013), and Du and McPhail (2012). It is found that there is a single directional spillover from crude oil market to corn market but the spillover between bioethanol and corn are in the form of double directions (Wu & Li, 2013). However, this is partly supported by Algieri (2014) stating that oil and bioethanol have their impact on a range of agricultural commodities[75]. Nevertheless, the findings of Gardebroek and Hernandez (2013) have argued that none of volatility spillover from oil or bioethanol to corn is observed. Instead, it is only the shock in corn price volatility that induces a short-run shock in bioethanol price volatility (Gardebroek & Hernandez, 2013).

On top of that, these studies below are having different objectives to carry out their research but all of them are focusing on the relationship between oil price and agricultural commodities by taking the upsurge of bioethanol into account. Kanamura (2009) is testing the correlation while Ciaian and Kancs (2011a) and Ciaian and Kancs (2011b) are examining the cointegration as well as impact of these variables. According to Kanamura (2009), the researcher stated that there are significant strong correlations between energy and grain price return, between energy and biofuels and between petroleum and agricultural commodities excluding corn during high oil price[76]. The researcher added that petroleum and corn futures price returns do not have any correlation (Kanamura, 2009). In the studies of Ciaian and Kancs (2011a) and Ciaian and Kancs (2011b), it is found that the prices of agricultural commodities which included directly and indirectly used in bioenergy production are influenced by energy prices. Besides, the researchers found that the energy and food market are increasingly cointegrated over time (Ciaian & Kancs, 2011a; Ciaian & Kancs, 2011b).
Additionally, another group of the researchers have their interest on investigating the correlations between energy and agricultural commodities by concerning the food crisis in 2008. With the special use of wavelet coherence technique, it is observed that the weak

[74] The agricultural commodities in the study of Zhang et al. (2010) have included corn, rice, soybeans, sugar and wheat.
[75] These agricultural commodities consist of corn, wheat, sugar and soybeans (Algieri, 2014).
[76] Petroleum represents energy whereas soybean and soybean oil represent biofuels and agricultural commodities refer to sugar, wheat and corn (Kanamura, 2009).

e-ISBN 978-967-11473-2-0

connections from biofuels to almost all biofuels feedstock commodities in pre-crisis period have changed into a strong positive one after the crisis (Vacha, Janda, Kristoufek, & Zilberman, 2013) [77]. Similar changes have also been obtained by Kristoufek, Janda and Zilberman (2012) by employing different methods, which are minimal spanning trees and hierarchical trees.

Likewise, the issue of food security has motivated a few researchers to study on the impact of biofuels expansion on food prices through the allocation of land use. From the finding of Ge, Lei, and Tokunaga (2014), an increase in bioethanol production will lead food prices to rise, given that there is no potential land input. This result is consistent with what Bryngelsson and Lindgren (2013) has observed where food prices increase as the outcome of increased bioenergy demand. However, Monteiro, Altman and Lahiri (2012) argued that in US, ethanol area does not have impact on food price significantly and the researchers found that ethanol area has negative impact on food price in Brazil.

3. Data Description and Modeling Framework

This study covered period from January 2006 to March 2014 with monthly data frequency. We have collected the secondary data from Thailand for this study which includes the production of bioethanol, *ETH* as a fuel from Department of Alternative Energy Development and Efficiency (DEDE) of Thailand, farm gate price of sugarcane, *SGC* and farm gate price of cassava, *CAS* from Office of Agricultural Economics (OAE) of Thailand, as well as the export price of cane molasses, *MOL* from The Customs Department of Thailand.

Eq.1 and Eq.2 are the general model for this research. To avoid any model misspecification bias, we choose to employ a linear-logarithmic model for Eq.1 whereas a logarithmic-linear model is used for Eq.2[78].

$$ETH_t = \beta_0 + \beta_1 FS_t + \varepsilon_{1t} \quad (1)$$
$$FS_t = \alpha_0 + \alpha_1 ETH_t + \varepsilon_{2t} \quad (2)$$

where ETH_t represent as production of bioethanol (million liter per month), FS_t denotes as farm gate price of sugarcane (Baht per ton) ($\ln SGC_t$), export price of cane molasses (Baht per kilogram) ($\ln MOL_t$) and farm gate price of cassava (Baht per kilogram) ($\ln CAS_t$) respectively. Whereas, ε_{1t} and ε_{2t} are the residual of the models.

4. Empirical Results

4.1 Unit Root Results

Although ARDL does not require any unit root test on variables in initial, Duasa (2007) stated that these test could tell us whether the ARDL model is appropriate to be used. Table 1 shows the results of ADF and PP tests. Both results are consistent and suggested that there is a mixture of *I(0)* and *I(1)*. Hence, ARDL bounds testing approach is appropriate to be used to examine long-run relationship among variables.

[77] In the study of Vacha et al. (2013), biofuels refer to ethanol and biodiesel. The feedstock for ethanol includes corn, wheat, and sugarcane. Meanwhile, soybeans and rapeseed oil are the feedstock for biodiesel.

[78] Fanaei et al. (2008) had used a linear-logarithmic model for modelling the new acid hydrolysis step for bioethanol production from waste wood. Total amount of fermentable sugar produced (mg/100ml) in hydrolysis step using 2%, 5%, 10% and 20% acid concentrations is predicted by depending on the logarithm of process duration time (minute).

Table1: Unit Root Test Result for Thailand

Variables	ADF Test		PP Test	
	Level	First Difference	Level	First Difference
ETH	-4.8494*	-	-4.8438*	-
$\ln SGC$	-2.4888	-11.669*	-2.4888	-11.815*
$\ln MOL$	-5.8024*	-	-5.7850*	-
$\ln CAS$	-2.6213	-6.6859*	-2.1931	-6.4281*

Notes: All variables had been transformed to natural logs except bioethanol production. Asterisks (*) indicate statistical significant at 1% levels.

4.2 ARDL Bounds Testing Approach Results

ARDL bound testing approach was developed by Pesaran, Shin and Smith (2001) to examine the long-run relationship among the variables. It is a general dynamic specification model which includes the lags of the endogenous variable and the lagged of exogenous variables to estimate the short-run effects directly and the long-run equilibrium relationship indirectly (Royfaizal, 2009).

As compared to other conventional cointegration tests, several advantages of ARDL bound testing approach have been highlighted in the studies of Sari and Soytas (2009), and Duasa (2007). ARDL is able to solve the problems aroused from the non-stationary series. Therefore, the pretesting for unit root on series is not necessary at all. The underlying series can be in different order of integration, either purely I(0) or purely I(1) or both. Besides, even though the sample size is small, cointegrating relationship can be determined efficiently[79]. The ARDL model for this research is shown as follow:

$$\Delta ETH_t = \alpha_0 + \sum_{i=1}^{k} \alpha_1 \Delta ETH_{t-i} + \sum_{i=0}^{k} \alpha_2 \Delta \ln FS_{t-i} + \delta_1 ETH_{t-1} + \delta_2 \ln FS_{t-1} + \varepsilon_{1t} \qquad (3a)$$

$$\Delta \ln FS_t = \gamma_0 + \sum_{i=1}^{k} \gamma_1 \Delta \ln FS_{t-i} + \sum_{i=0}^{k} \gamma_2 \Delta ETH_{t-i} + \eta_1 ETH_{t-1} + \eta_2 \ln FS_{t-1} + \varepsilon_{2t} \qquad (3b)$$

The short-run parameters are represented by α and γ. The long-run parameters are denoted as δ and η. To examine the cointegrating relationship, the Wald test (F statistic) is conducted such that restrictions are imposed on the estimated long-run coefficients of bioethanol production and FS (sugarcane farm gate prices, cane molasses export price and cassava farm gate price respectively). Since our sample size contains of 99 observations, we prefer to use the sets of critical values created by Pesaran et al. (2001). If the F-statistic exceeds the upper bound critical value, we should reject the null hypothesis and conclude that there is a long-run relationship between the variables. However, the null hypothesis will not be rejected when the F-statistic is smaller than the lower bound critical value, thus a long-run relationship does not exist. However, if the F-statistic falls within the critical bound values, the result will be inconclusive unless we carry out the unit root tests to know the order of integration of the underlying variables before continuing with the ARDL approach.

[79] Narayan (2005) had tabulated the critical values for the sample size of 30 to 80 based on his own argument that the two existing sets of critical values developed by Pesaran et al. (2001) can only be applied on large sample size ranging from 500 to 1,000 observations and 20,000 to 40,000 replications respectively.

Table 2: ARDL Long-run Relationship for Thailand

ARDL Model		Optimal lag	F-test [Prob]	Serial Correlation[a] [Prob]	Functional Form[b] [Prob]	Normality[c] [Prob]	Heteroscedasticity[d] [Prob]
Dependent variable	Independent variable						
DETH	DlnSGC	11	4.1827 [0.020]	9.8428 [0.630]	2.2494 [0.134]	1.9333 [0.380]	0.069232 [0.792]
DlnSGC	DETH	4	1.0569 [0.352]	16.5700 [0.167]	3.0712 [0.080]	380.3548 [0.000]	0.30281 [0.582]
DETH	DlnMOL	12	2.7661 [0.071]	9.5057 [0.659]	0.74820 [0.387]	1.1440 [0.564]	3.6371 [0.057]
DlnMOL	DETH	2	5.5655*** [0.005]	19.1004 [0.086]	31.8897 [0.000]	306.6749 [0.000]	12.0290 [0.001]
DETH	DlnCAS	12	2.1758 [0.123]	14.0993 [0.294]	1.3658 [0.243]	1.5871 [0.452]	1.4911 [0.222]
DlnCAS	DETH	10	5.6048*** [0.006]	19.9047 [0.069]	0.11768 [0.732]	29.5817 [0.000]	0.26536 [0.606]

The critical values are 1% (6.84 - 7.84), 5% (4.94 - 5.73) and 10% (4.04 - 4.78) significant level. Asterisks (*), (**) and (***) indicate statistical significant at 1%, 5% and 10% levels, respectively. The critical values were obtained from Pesaran et al., (2001), Case III: Unrestricted intercept and no trend. Notes: The optimum lag was selected using SBC. The maximum lag was fixed at 12. [a]Lagrange multipier test of residual serial correlation. [b]Ramsey's RESET test using the square of the fitted values. [c]Based on a test of skewness and kurtosis of residuals. [d]Based on the regression of squared residuals on squared fitted values.

According to Ibarra (2011), the optimal lag of the model is traditionally determined by the information criterion but at the same time, the suggested lag has to pass all the diagnostic tests before proceeding to the next step. In this study, optimal lags for each model selected based on minimum SBC value. However, if the suggested optimal lag based on SBC does not pass all the diagnostic tests, then, the lag length will be reselected based on another lowest SBC value until the model does not suffer any statistical problems. In the second step, bounds test will be used to detect the existence of cointegration among variables based on the selected optimum lag.

Table 2 presents the results of bounds test and diagnostic tests for all combinations of variables. From Table 2, the F-test statistic (5.5655) for 4th model is more than the upper bound critical value (4.78) at 10% significance level. The null hypothesis is rejected and this shows that cointegration exists between bioethanol production and cane molasses export price. Meanwhile, the F-test statistic (5.6048) for the last model also exceeds the upper bound critical value (4.78) at 10% significance level. Again, the null hypothesis has been rejected. This means that the cassava farm gate price and bioethanol production have a long-run relationship. Whereas, the rest of the models shown in Table 2 indicate that there is no long-run relationship exist among the variables because their F-test statistic are lower than the lower bound critical values at 1%, 5% and 10% significance levels.

To double confirm the results, all models have been re-estimated by including the Error Correction Representation (ECT) and the results are shown in Table 3. The significance of the ECT will refer to the probability value. For the 2nd model, the coefficient value of ECT (-0.0910) is negative and significant at 5% significance level. This shows that the deviation from the long-term sugarcane farm gate price is corrected by 9.10% over each month. Surprisingly, this significant ECT has suggested that the sugarcane farm gate price and bioethanol production actually have a long-run relationship. Although this result is not consistent with the bounds test result (Table 2), this result is more accurate to confirm that there is a long-run relationship.

Table 3: Results of Estimated Error Correction Representation for the Selected ARDL Model

ARDL Model	Optimal lag	Error Correction Term (ECT)

Dependent	Independent		Coefficient	T-ratio [Prob]
DETH	DlnSGC	11	-0.0682	-1.1165 [0.267]
DlnSGC	DETH	4	-0.0910	-2.3213 [0.022]**
DETH	DlnMOL	12	-0.0292	-0.6498 [0.518]
DlnMOL	DETH	2	-0.5105	-5.6755 [0.000]*
DETH	DlnCAS	12	-0.0607	-1.2220 [0.225]
DlnCAS	DETH	10	-0.0785	-2.5355 [0.013]**

Notes: Asterisks (*), (**) and (***) indicate statistical significant at 1%, 5% and 10% levels, respectively.

In addition, it's found that the ECT coefficient value for 4th model (-0.5105) and 6th model (-0.0785) are negative and significant at 1% and 5% significance levels respectively. For 4th model, the deviation from the long-term export price of cane molasses is corrected by 51.05% over each month. For 6th model, the deviation from the long-term cassava farm gate price is corrected by 7.85% over each month. These results are consistent with bounds test results as shown in Table 2. Thus, there are long-run relationships between cane molasses export price and bioethanol production as well as between cassava farm gate price and bioethanol production.

After that, the models have been used to estimate the long-run coefficients under ARDL approach. Table 4 displays the models consist of variables that have long-run relationships. The significance of independent variable in explaining the dependent variable for every model is interpreted by using probability value. All the three models appeared to be significant at 5% and 10% significance level. The sugarcane farm gate price, cane molasses export price and cassava farm gate price will increased by 0.63%, 0.02% and 0.01% for every one million liter increase in bioethanol production, respectively.

Table 4: Results of Estimated Long-Run Coefficients Using ARDL Approach

ARDL Model		Coefficient	Standard Error	T-ratio[Prob]
Dependent	Independent			
lnSGC	ETH	0.0063	0.0027	2.3106 [0.023]**
lnMOL	ETH	0.0002	0.0045	2.0373 [0.070]***
lnCAS	ETH	0.0001	0.0053	2.0129 [0.090]***

Notes: Asterisks (*), (**) and (***) indicate statistical significant at 1%, 5% and 10% levels, respectively.

Lastly, cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMSQ) tests are the stability tests that used to detect structural breaks and to check whether the estimated long-run and short-run parameters in Eq. 3a and 3b are stable over the data period. From Figure 1, all plots of CUSUM and CUSUMSQ are within the critical 5% bounds. This indicates the stability of coefficients, thus confirming the long-run relationships among the variables.

Models

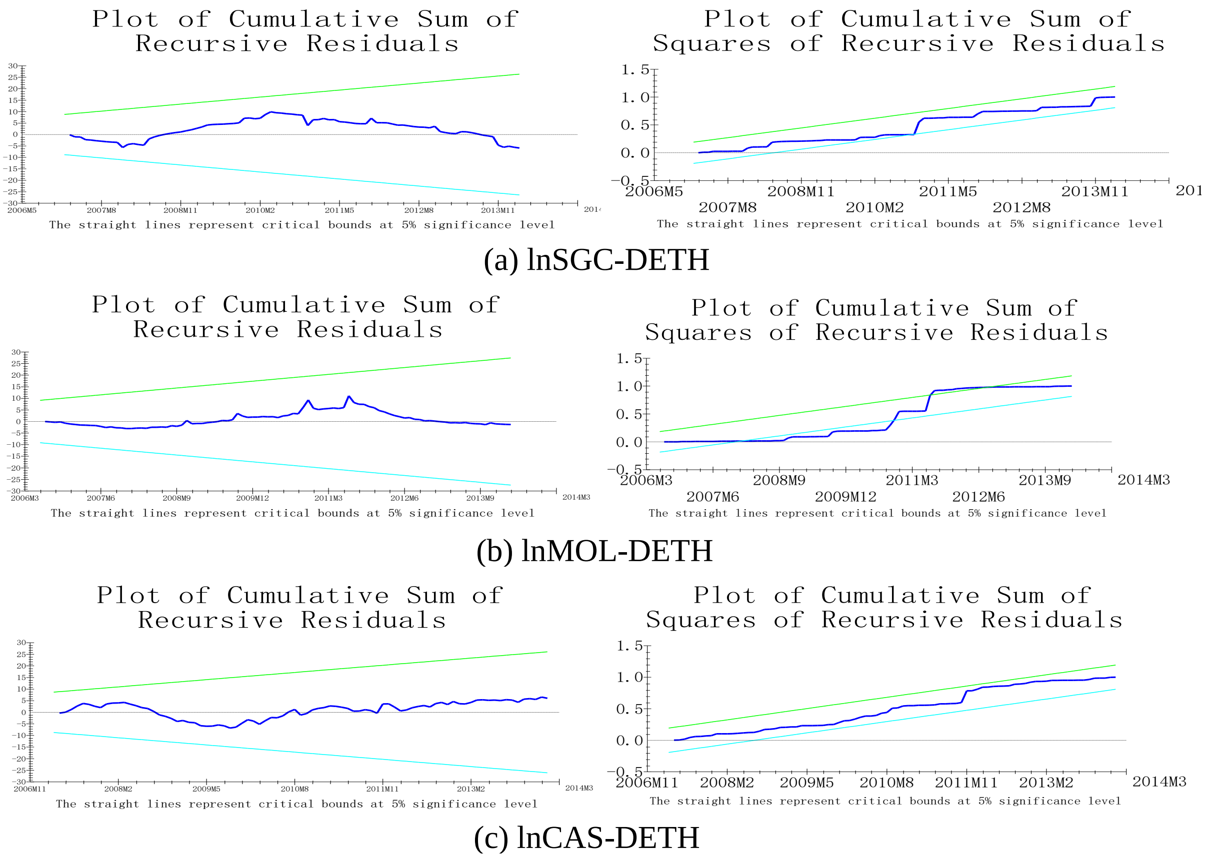

Figure 1: Plot of CUSUM and CUSUMSQ Tests for the Parameter Stability from ARDL

5.3 Granger Causality Test (Wald Test)

Granger causality test (Wald test) under ARDL framework also known as short-run causality test (Nathan & Liew, 2013). This causality test is used to determine the directions of causality among variables in a model once the ARDL cointegration test had identified the variables are having a long-run relationship (Ozturk & Acaravci, 2010). Furthermore, when cointegration among variables exists in a model, the standard Granger-type causality test is augmented with lagged error correction term (ECT) (Narayan & Smyth, 2004). The following equations are the causality test model for this research:

$$\Delta \ln ETH_t = \alpha_0 + \sum_{i=1}^{m} \beta_{1i} \Delta \ln ETH_{t-i} + \sum_{i=1}^{k} \beta_{2i} \Delta \ln FS_{t-i} + \mu_1 EC_t + \varepsilon_{1t} \qquad (4a)$$

$$\Delta \ln FS_t = \theta_0 + \sum_{i=1}^{k} \varphi_{1i} \Delta \ln FS_{t-i} + \sum_{i=1}^{m} \varphi_{2i} \Delta \ln ETH_{t-i} + \mu_2 EC_t + \varepsilon_{2t} \qquad (4b)$$

where lag operator denoted as Δ. The estimated coefficients are represented as α_0, β, θ_0 and φ. m and k are the optimal lag of the series. ε_{1t} and ε_{2t} are the error term for each model. μ is the speed of the adjustment for each model and the EC_t is the ECT. The null hypothesis of Granger causality is X_t does not Granger cause Y_t and vice versa. If β_{2i} and φ_{2i} are jointly significant, the null hypothesis should be rejected (Nathan & Liew, 2013). Otherwise, null hypothesis will be rejected.

e-ISBN 978-967-11473-2-0

Table 5: Result of Granger Causality Test (Wald Test F-statistic)

Null Hypothesis	Wald Test		Direction
	Chi-square	Prob	
lnSGC does not Granger cause ETH	0.4778	0.489	
ETH does not Granger cause lnSGC	5.3829	0.020**	ETH → lnSGC
lnMOL does not Granger cause ETH	3.0528	0.081***	lnMOL → ETH
ETH does not Granger cause lnMOL	32.185	0.000*	ETH → lnMOL
lnCAS does not Granger cause ETH	1.5662	0.211	
ETH does not Granger cause lnCAS	8.7588	0.003*	ETH → lnCAS

Note: Asterisks (*), (**) and (***) denote the rejection of the null hypothesis at 1%, 5% and 10% significance levels, respectively.

Table 5 shows the Granger causality test result obtained through Wald test. The significance of causal effect is determined by using the probability value in Wald test. The results shows that there is only one way causal effect found in the model of sugarcane farm gate price and bioethanol production as well as cassava farm gate price and bioethanol production. The result shows that the bioethanol production does Granger cause sugarcane farm gate price at 5% significance level. This means that the changes of bioethanol production in the past can be used to predict the occurrence of event of the sugarcane farm gate price. Whereas, the result shows that bioethanol production does Granger cause cassava farm gate price at 1% significance level. This means that the change in bioethanol production in the past can used to predict the occurrence of event of cassava farm gate price. These findings are consistent with the theory discussed in the earlier part.

From the results, there is bidirectional causal effect for bioethanol production and cane molasses export price. Cane molasses export price does Granger cause bioethanol production at 10% significance level. Meanwhile, bioethanol production does Granger cause cane molasses export price at 1% significance level. This finding indicates that when bioethanol production increase, demand for cane molasses will also increase and hence cause the price of cane molasses increase. Export price of cane molasses will also increase due to the shortage in supply of cane molasses to international market.

6. Conclusion and policy recommendations

From the result of this study, it is found that when bioethanol production act as independent variable, long-run equilibrium exist between bioethanol production and sugarcane farm gate price, cane molasses export price and cassava farm gate price, respectively. Besides that, it is also found that Granger causality exists among the variables. Sugarcane farm gate price and bioethanol production as well as cassava farm gate price and bioethanol production are found to be having unidirectional Granger causality effect. Meanwhile, bidirectional Granger causality effect is found between cane molasses export price and bioethanol production. In terms of policy implication, the Thai government should ensure the supply of agricultural commodities is adequate to meet demands from bioethanol production and other purposes as well as to stabilize their prices.

Acknowledgement

Research grant (6200/T92) funded by the Universiti Tunku Abdul Rahman, Malaysia is gratefully acknowledged. Thanks to Chiew Feng Theng and Loy Heng Ying who served as research assistant under this project.

References

Algieri, B. (2014). The influence of biofuels, economic and financial factors on daily returns of commodity futures prices. *Energy Policy*, *69*, 227-247.

Business-in-Asia.com. (2007). *Opportunities for ethanol industry in Thailand*. Retrieved from http://www.business-in-asia.com/thailand/ethanol_cassava.html

Bryngelssonn, D. K., & Lindgren, K. (2013). Why large-scale bioenergy production on marginal land is unfeasible: a conceptual partial equilibrium analysis. *Energy Policy*, *55*, 454–466.

Cane and Sugar Industry Policy Bureau. (2006). *Sugarcane and sugar industry and renewable energy production.*

Cha, K. S., & Bae, J. H. (2011). Dynamic impacts of high oil prices on the bioethanol and feedstock markets. *Energy Policy*, *39*, 753–760.

Chin, K. L., & H'ng, P. S. (2013). A real story of bioethanol from biomass: Malaysia perspective. *Biomass Now – Sustainable Growth and Use*, 329-346.

Ciaian, P., & Kancs, D. (2011). Food, energy and environment: Is bioenergy the missing link? *Food Policy*, *36*, 571-580. doi: 10.1016/j.foodpol.2011.06.008

Ciaian, P., & Kancs, D. (2011). Interdependencies in the energy-bioenergy-food price systems: A cointegration analysis. *Resource and Energy Economics*, *33*, 326-348. Disappointing molasses yields and an early finish: (-500,000 mt). (2014, May). *UM Trading*.

Du, X., & McPhail, L. L. (2012). Inside the Black Box: the Price Linkage and Transmission between Energy Agricultural Markets. *Energy Journal*,*33*(2), 171-194.

Duasa, J. (2007). Determinants of Malaysian trade balance: An ARDL bound testing approach. *Global Economic Review*, *36*(1), 89-102.

Fanaei, M. A., Khansari, Z., & Maskooki, A. (2008). New method for bioethanol production from waste wood. *5th International Chemical Engineering Congress and Exhibition*.

Gardebroek, C., & Hernandez, M. A. (2013). Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. *Energy Economics*, *40*, 119–129.

Ge, J., Lei, Y., & Tokunaga, S. (2014). Non-grain fuel ethanol expansion and its effects on food security: a computable general equilibrium analysis for China. *Energy*, *65*, 346-356.

Hirshleifer, J., Glazer, A., & Hirshleifer, D. (2005). The supply function. *Price theory and applications: Decisions, markets, and information* (7^{th} ed.) (pp. 192-199). New York, United States: Cambridge University Press.

Ibarra, C. A. (2011). Import elasticities and the external constraint in Mexico. *Economic Systems, 35*, 363-377.

Kanamura, T. (2009). Monitoring the Upsurge of Biofuels in Commodity Futures Markets. *ICFAI Journal of Derivatives Markets,6*(1), 29-48.

Kristoufek, L., Janda, K., & Zilberman, D. (2012). Correlations between biofuels and relates commodities before and during the food crisis: A taxonomy perspective. *Energy Economics, 34*, 1380-1391.

Monteiro, N., Altman, I., & Lahiri, S. (2012). The impact of ethanol production on food prices: The role of interplay between the U.S. and Brazil. *Energy Policy, 41*, 193-199.

Morgera, E., Kulovesi, K., & Gobena, A.(2009). Case studies on bioenergy policy and law: options for sustainability. *FAO Legislative Study.*

Mudiyanselage, N. H., Lin, C. Y. C., & Yi, F. (2013). An analysis of ethanol investment decisions in Thailand. *Theoretical Economics Letters, 3*, 14-20.

Narayan, P. K., & Smyth, R. (2004). Temporal causality and the dynamics of exports, human capital and real income in China. *International Journal of Applied Economics, 1*(1), 24-45.

Narayan, P. K. (2005). The saving and investment nexus for China: evidence from cointegration tests. *Applied Economics, 37,* 1979-1990.

Natanelov, V., McKenzie, A. M., & Huylenbroeck, G. V. (2013). Crude oil-corn- ethanol- nexus: A contextual approach. *Energy Policy, 63,* 504-513.

Nathan, T. M., & Liew, V. K. (2013). Does electricity consumption have significant impact towards the sectoral growth of Cambodia? Evidence from Wald test causality relationship. *Journal of Empirical Economics, 1*(2), 59-66.

Ozturk, I., & Acaravci, A. (2010). The causal relationship between energy consumption and GDP in Albania, Bulgaria, Hungary and Romania: evidence from ARDL bound testing approach. *Applied Energy, 87*, 1938-1943.

Patumsawad, S. (2011). 2nd generation biofuels: technical challenge and R&D opportunity in Thailand. *Journal of Sustainable Energy & Environment Special Issue*, 47-50.

Perloff, J. M. (2011). Supply. *Microeconomics* (6^{th} ed.)(pp. 17-21). Boston, United States: Pearson Addison Wesley.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Exonometrics, 16*, 289-326.

Preechajarn, S., & Prasertsri, P. (2010). *Biofuels annual*. United States: Global Agricultural Information Network.

e-ISBN 978-967-11473-2-0

Preechajarn, S., & Prasertsri, P. (2012). *Biofuels Annual 2012.*United States: Global Agricultural Information Network.

Preechajarn, S., & Prasertsri, P. (2013). *Biofuels annual.* United States: Global Agricultural Information Network.

Royfaizal, R. C. (2009). Crude oil consumption and economic growth: empirical evidence from Japan. *Integration & Dissemination, 4,* 87-93.

Russell, T. H., & Frymier, P. (2012). Bioethanol production in Thailand: a teaching casestudy comparing cassava and sugar cane molasses. *The Journal of Sustainability Education.* Retrieved from http://www.jsedimensions.org/wordpress/content/ bioethanol-production-inthailand-a-teaching-case-study-comparing-cassava-and- sugar-cane-molasses_2012_03/

Sari, R., & Soytas, U. (2009). Are global warming and economic growth compatible? Evidence from five OPEC countries? *Applied Energy, 86,* 1887-1893.

Silalertruksa, T., & Gheewala, S. H. (2010). Security of feedstocks supply for future bio-ethanol production in Thailand. *Energy Policy, 38*(11), 7476-7486.

Vacha, L., Janda, K., Kristoufek, L., & Zilberman, D. (2013). Time–frequency dynamics of biofuel–fuel–food system. *Energy Economics, 40,* 233–241.

Wu, H., & Li, S. (2013). Volatility spillovers in China's crude oil, corn and fuel ethanolmarkets. *Energy Policy, 62,* 878–886.

Zhang, Z., Lohr, L., Escalante, C., & Wetzstein, M. (2010). Food versus fuel: what do prices tell us? *Energy Policy, 38,* 445–451.

Zhou, A., & Thomson, E. (2009). The development of biofuels in Asia. *Applied Energy, 86*(1), S11-S20.