



Oil and Food Prices for a Net Oil Importing-country: How Are Related in Indonesia?

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ABSTRACT

Our study examines the asymmetric responses of food prices to oil prices in Indonesia as a net oil and food-importing country. We apply non-linear autoregressive distributed lag to investigate the responses of food prices to oil prices. Due to the different impacts of oil price on sub-component of the food price index, this study decomposes the general food prices index into 11 sub-components food price indices. The oil prices asymmetrically affect food prices but incomplete pass-through except the preserved fish prices. The highest impact of oil price is on beans and nuts prices, followed by cereals, roots, and their product prices. More interestingly, the response of food price to an increase in oil price is higher than the response of food price to a decrease in oil price known as rockets and feathers phenomenon for general food prices, cereals, roots, and their product prices, meat and its product prices, eggs, milk, and their product prices, bean and nuts prices, fruit prices, and fats and oil prices.

Keywords: Food Prices, Oil Price, Non-Linear Autoregressive Distributed Lag, Net oil-Importing Country, Indonesia

JEL Classifications: C22; E31; Q11

1. INTRODUCTION

The world food crisis has been starting since 2004, marked by soaring food prices in the world. The world food price index increased sharply from 161.4 in 2007 to 201.4 in 2008. The world food price index declined in 2009 and 2010, but it experienced to reach a peak of 229.9 in 2011. Other foods such as meat, dairy, cereals, vegetable oil, and sugar also increased in line with rising world food prices since 2004. The meat price index reached the highest peak of 198.3 in 2014. The dairy price index experienced the highest price of 242.7 in 2013. Meanwhile, the cereals price index and vegetable price index experienced price crises much earlier in 2011 with 240.9 and 254.5. The sugar price index experienced the most severe crisis with a price index of 368.9 in 2011.

This increase in food prices concurred with an increase in world oil prices. The world oil price crisis began in 2000. The world oil price reached the highest price of US \$ 100.01 per barrel in 2008.

It then declined 3 years later and rose again to the US \$ 92.41 per barrel in 2013. It is not surprising that the oil price has been investigated as a plausible reason for food price crisis because the high food price crisis was co-movement with high oil price (e.g., Baffes, 2007; Chen et al., 2010; Avalos, 2014; Wang et al., 2014; Paris, 2018; Taghizadeh-Hesary et al., 2019). Rising world oil prices affect energy-based input prices such as fertilizer and fuel in which directly affect transportation costs. As a result, increases in oil prices affect the cost of food production and subsequently the food prices. In addition, the increase in global food prices also directly affects domestic food prices for food-importing countries.

Indonesia has also been experiencing a food price crisis, especially the price of meat since 2010. The price of beef has been increasing steadily since 2013. The average price of beef was approximately IDR 58,500/kg in 2010. However, the average price of beef increased roughly IDR 100,000/kg in 2014. It increased roughly by 70.94%. Similarly, broiler chicken has been increasing since 2011. The price of broiler chicken was IDR 19,500 in 2011 and

then experienced an increase of IDR 28,000 in 2014¹. Although its rise was not as high as beef, the increase in the price of broiler chicken was still quite high by 43.59%.

Indonesia is a net oil-importing country as well as a net food-importing country. The net food-importing country has occurred since 1990 when Indonesia has shifted from an agricultural economy to an industrial economy since 1980. Furthermore, this economic transformation has also led the country to rapid urbanization. As a result, land demand for non-agricultural activities such as housing, industry, and office building is very high. The agricultural land conversion (ALC) is 187,720 ha/year. Out of the total ALC, 48.96%, 35.50%, 14.55% of converted land is for housing, industry, and office building development respectively (Rondhi et al., 2018). The high ACL has caused the production of agricultural products to decline so that Indonesia has to fulfill domestic food consumption from imported food such as rice as a staple food, wheat, corn, beef, soybeans, peanuts, vegetables, and fruits.

This paper examines the asymmetric response of disaggregate food prices in Indonesia to the world oil price. The contribution of this study to the body of knowledge may come from the following ways. Some existing empirical studies investigated the asymmetric response of general food prices to oil prices (e.g., Ibrahim and Chanchaoenchai, 2014; Ibrahim, 2015; Abdalaziz et al. 2016; Widarjono and Hakim, 2019). However, applying general food prices may conceal for disaggregate food prices. Moreover, this study can provide an empirical link between oil prices and disaggregate food prices for net oil and food-importing country using asymmetric effects.

The rest of this paper is written as follows. The next section highlights the previous empirical studies on the response of food prices to oil prices. Section 3 discusses the method to examine the asymmetric effect of oil prices on food prices, including data using for this study. Section 4 presents and discusses the findings. A conclusion is reported in the last section.

2. LITERATURE REVIEW

The concurrent upswings of oil prices and food prices have stimulated an investigation about the relationship between oil prices and food prices. Crude oil price influences the food price through two channels, namely the supply and demand side. On the supply side, crude oil directly affects the input of agricultural commodities through energy-intensive input such as fertilizer (e.g., Mitchell, 2008; Nazlioglu and Soytaş, 2011). On the demand side, the crude oil price crisis has stimulated to find alternative inputs such as bioethanol and biodiesel as biofuels, which are mainly from crops of corn, oil palm, and soybean because of substitutability between fossil fuel and biofuels. The food prices increase because the demand for those crops increase (e.g., Serra and Zilberman, 2013; Myers et al., 2014; Fernandez-perez et al., 2016; Paris, 2018).

¹ The exchange rate of USD against Indonesian Rupiah (IDR) was approximately IDR 11,850 in 2014.

Many empirical studies investigated the relationship between oil prices and food prices. The results, however, are unclear pictures. Some empirical studies documented that an increase in agricultural commodity prices is related to oil price such as Baffes (2007), Alghalith (2010), Chen et al. (2010), Nazlioglu (2011), Reboredo (2012), Wang et al. (2014), Avalos (2014), Paris (2018), among them. For example, Baffes (2007) indicated the highest impacts of the oil price are on cocoa (beverage group), Groundnut oil (food group), and Phosphate rock (raw materials and fertilizer group). Chen et al. (2010) found that the price of oil is responsible for an increase in grain price. Paris (2018) revealed that prices of soybean, wheat, sunflower, and rapeseed are associated with oil prices during the oil price crisis.

Instead of an individual agricultural commodity, some researchers such as Ibrahim and Chanchaoenchai (2014), Ibrahim and Said (2012), Ibrahim (2015), Abdalaziz et al. (2016), Lucotte (2016), Taghizadeh-Hesary et al. (2019), Liu et al. (2019), Widarjono and Hakim, 2019) among the others investigated the impact of oil on the food price index. The oil price affects asymmetrically on food prices in emerging markets such as Thailand (Ibrahim and Chanchaoenchai (2014), Malaysia (Ibrahim and Said, 2012; Ibrahim, 2015) and Indonesia (Abdalaziz et al., 2016; Widarjono and Hakim, 2019). Food price increases are related to oil price increases, but oil price decreases do not affect food prices. Taghizadeh-Hesary et al. (2019) also confirmed that food prices are linked to crude oil prices for some Asian countries. In addition, there is also a strong co-movement between crude oil price and cereal, dairy products, meat, sugar, vegetable oil, and food prices after post-boom price oil (Lucotte, 2016; Al-Maadid et al., 2017). Accordingly, future crude oil prices affect future agricultural commodities prices (Liu et al., 2019).

On the contrary, some previous empirical studies do not support the link between oil price and agricultural commodity prices such as Lambert and Miljkovic (2010), Zhang et al. (2010), Gilbert, (2010), Jongwanich and Park (2011), Nazlioglu and Soytaş (2011), Reboredo (2012), Byrne et al. (2013), among the others. Lambert and Miljkovic (2010) found that US food prices are influenced by farm and manufacturing wages instead of oil prices. Zhang et al. (2010) and Reboredo (2012) for global commodities agricultural prices and Nazlioglu and Soytaş (2011) for Turkey documented a no long-run co-movement between the world oil prices and prices of some agricultural commodities such as rice, wheat, maize, soybeans. Nazlioglu and Soytaş (2012) proved that oil prices indirectly influence food prices through the exchange rate.

Ibrahim (2015), Abdalaziz et al. (2016), Widarjono and Hakim (2019) examined the response of the aggregate food price index to the oil price. However, the effect of oil price on disaggregate food prices has a different magnitude (Gao et al., 2014; Lucotte, 2016). Using aggregate food price index to investigate the inflationary effect of oil prices on food prices may obscure results. Therefore, this study examines the inflationary effects of oil price on the disaggregate food price indices. Moreover, because the inflationary effect of oil prices on food prices is asymmetric (Ibrahim, 2015;

Abdlaziz et al., 2016; Widarjono and Hakim, 2019), this study examines the asymmetric response of all sub-components of the food price indices to oil prices.

3. METHODOLOGY AND DATA

This study follows the augmented Phillips curve model to investigate a long-run relationship between oil prices and food prices (Ibrahim, 2015; Abdlaziz et al., 2016). The relationship between oil price and food price can be written as follows:

$$LGF_t = \alpha_0 + \alpha_1 LOL_t + \alpha_2 LGP_t + e_t \tag{1}$$

Where LGF_t is the general food price index, LOL_t is the price of world oil, and LGP_t is the output gap. This study includes the output gap to capture the business cycle effect as an aggregate demand shock. The output gap measures a difference between the actual output and its potential output and is calculated by applying the Hodrick-Prescott filter procedure. The industrial production index (IPI) is employed to proxy for output due to the unavailability of monthly GDP data. All variables are expressed in logarithm natural.

The impact of oil price on the food prices is asymmetric instead of symmetric (e.g., Ibrahim and Chanchaoenchai, 2014; Ibrahim and Said, 2012; Ibrahim, 2015; Abdlaziz et al., 2016; Widarjono and Hakim, 2019). The equation (1) can be rewritten to consider the asymmetric impact of oil price on food prices as follows (Shin et al., 2014):

$$LGF_t = \delta_0 + \delta_1 LOL_t^+ + \delta_1 LOL_t^- + \delta_1 LGP_t + \varepsilon_t \tag{2}$$

Where δ_1 and δ_2 are partial sums of increase and decrease in oil price respectively. δ_1 and δ_2 are calculated as follows (Shin et al., 2014):

$$LOL_t^+ = \sum_{i=1}^p \Delta LOL_{t-i}^+ = \sum_{i=1}^p \max(LOL_t, 0) \tag{3}$$

$$LOL_t^- = \sum_{i=1}^p \Delta LOL_{t-i}^- = \sum_{i=1}^p \min(LOL_t, 0) \tag{4}$$

This study employs non-linear autoregressive distributed lag (NARDL) models proposed by Shin et al. (2014) to investigate the asymmetric effects of oil prices on food prices. The NARDL model of equation (2) is written as follows.

$$\begin{aligned} \Delta LGF_t = & \rho_0 + \rho_1 LGF_{t-1} + \rho_2 LOL_{t-1}^+ + \rho_3 LOL_{t-1}^- \\ & + \rho_4 LGP_{t-1} + \sum_{i=1}^l \sigma_{1i} \Delta LGF_{t-i} + \sum_{i=0}^m \sigma_{2i} \Delta LOL_{t-i}^+ \\ & + \sum_{i=0}^p \sigma_{3i} \Delta LOL_{t-i}^- + \sum_{i=1}^q \sigma_{4i} \Delta LGP_{t-i} + \mu_t \end{aligned} \tag{5}$$

As the dynamic regression model, the NARDL can capture the asymmetric responses of the disaggregate food prices to oil prices both in the short-run as well as long-run. The short-run asymmetric effects of increase and decrease in oil price on food price are

$$\pi_1 = \sum_{i=0}^m \sigma_{2i} \Delta LOL_{t-i}^+ \text{ and } \pi_2 = \sum_{i=0}^p \sigma_{3i} \Delta LOL_{t-i}^-$$

Accordingly, the long-run asymmetric effects of increase and reduction in oil price on food price are measured by $\vartheta_1 = -\frac{\rho_2}{\rho_1}$ and $\vartheta_2 = -\frac{\rho_3}{\rho_1}$.

This study takes the following four steps to estimate equation (5) following Shin et al. (2014). In the first step, equation (5) is estimated by employing the OLS method. The general-to-specific method is adopted to find the final specification of equation (5) by sequentially dropping lag, which is statistically insignificant. In the second step, this study conducts a cointegration test to check the relationship between the dependent and independent variables in the long-run. The cointegration test involves the bounds testing approach proposed by Pesaran et al. (2001), which follows the Wald F test. The null hypotheses of no long-run relationship or no cointegration are $\rho_1 = \rho_2 = \rho_3 = \rho_4 = 0$. In the third step, our study carries out the long-run asymmetric impact of oil prices on food prices. The null hypothesis of the long-run asymmetric response of food prices to oil prices is $\vartheta_1 = \vartheta_2$. As the null hypothesis of no asymmetric effect is rejected, a rise (reduction) in oil price affects asymmetrically on food prices for the long-run. In the final step, this study calculates the long-run asymmetric coefficient of positive oil price (ϑ_1) and negative oil price (ϑ_2) on food prices.

Table 1: Descriptive statistics

Food price index	Mean	Std. Dev.	Maximum	Minimum	Skewness
ΔGF	0.493	1.237	6.000	-3.400	0.800
ΔCR	0.494	1.295	4.810	-5.350	0.538
ΔMT	0.417	2.502	10.170	-6.930	0.188
ΔFF	0.485	1.304	4.560	-2.070	0.882
ΔPF	0.525	1.875	12.740	-12.740	-0.460
ΔEG	0.363	1.742	4.770	-5.330	-0.046
ΔVE	0.621	2.372	9.750	-6.330	0.423
ΔBN	0.464	1.334	13.100	-1.820	5.815
ΔFR	0.532	1.179	6.060	-2.960	0.901
ΔSP	0.644	8.859	39.720	-40.630	0.407
ΔFO	0.377	1.233	7.080	-3.430	1.247
ΔOF	0.374	0.751	2.760	-1.950	0.444
ΔOL	0.142	5.516	14.280	-27.500	-1.131

This study uses a monthly time series data, covering from 2000: M1 to 2017: M12. Due to different impact of oil price to sub-

component of the general food price index, this study decomposes the general food price index (GF) into 11 sub-components food

Table 2: Unit root test

Food price index	Level		First difference	
	ADF	PP	ADF	PP
General food	-1.518	-2.335	-3.376*	-10.639***
Cereals, roots, and their products	-1.587	-1.586	-10.358***	-9.547***
Meat and its products	-1.838	-5.079***	-4.118***	-15.797***
Fresh fish	-4.235***	-3.163	-4.235***	-15.033***
Preserved fish	-3.298*	-9.965***	-9.624***	-45.976***
Eggs, milk and their products	-2.660	-4.205***	-3.613**	-17.383***
Vegetables	-5.911***	-4.301***	-9.091***	-15.059***
Beans and nuts	-1.223	-1.405	-10.964***	-10.917***
Fruits	-2.130	-1.935	-12.396***	-12.268***
Spices	-5.490***	-4.934***	-12.148***	-15.120***
Fats and oils	-1.913	-1.610	-5.634***	-10.148***
Other food items	-4.350***	-3.906**	-3.574***	-11.284***

***, **, * show significant at $\alpha=1\%$, 5% and 10% respectively

Table 3: NARDL estimation

Variable	GF Coeff.	s.e	CR Coeff.	s.e	MT Coeff.	s.e	FF Coeff.	s.e
C	0.127**	0.058	0.257***	0.051	0.402***	0.108	0.050	0.067
lp_{t-1}	-0.035**	0.017	-0.081***	0.016	-0.108***	0.029	-0.014	0.018
lot_{t-1}^+	0.008**	0.003	0.025***	0.005	0.017***	0.005	0.007***	0.002
lot_{t-1}^-	0.002	0.002	0.006*	0.003	-0.001	0.005	0.005*	0.003
lgp_{t-1}	0.182***	0.040	-0.095***	0.028	0.090**	0.035	0.230***	0.066
Δlp_{t-1}	0.325***	0.063	0.309***	0.062	0.341***	0.059	0.200***	0.068
Δlp_{t-2}	-0.245***	0.066	-0.128**	0.062	-0.254***	0.061		
Δlp_{t-3}							-0.163**	0.064
Δlp_{t-6}	0.194***	0.058						
Δlp_{t-10}							-0.206***	0.059
Δlp_{t-11}			0.242***	0.058			0.263***	0.060
Δlp_{t-12}	0.220***	0.055	0.248***	0.062	0.304***	0.052	0.228***	0.060
Δlot_{t-7}^+					-0.088**	0.034		
Δlot_{t-9}^+	-0.037**	0.018	-0.063**	0.027				
Δlot_{t-12}^+							0.041**	0.018
Δlot_t^-					-0.058**	0.027		
Δlot_{t-2}^-			-0.079***	0.021				
Δlgp_{t-1}	-0.143***	0.036					-0.192***	0.066
Δlgp_{t-2}	-0.196***	0.032			-0.142***	0.030	-0.222***	0.063
Δlgp_{t-3}	-0.085***	0.028					-0.187***	0.059
Δlgp_{t-4}	-0.077***	0.024					-0.153***	0.052
Δlgp_{t-5}	-0.051***	0.018					-0.169***	0.046
Δlgp_{t-6}							-0.117***	0.041
Δlgp_{t-7}							-0.100***	0.037
Δlgp_{t-8}							-0.110***	0.034
Δlgp_{t-9}							-0.075**	0.031
Δlgp_{t-10}							-0.069**	0.030
Δlgp_{t-11}	-0.062***	0.015	-0.059***	0.022	-0.090***	0.028	-0.102***	0.026
Δlgp_{t-12}							-0.084***	0.019
R ²	0.529		0.456		0.512		0.586	
J-B	15.258	0.000	142.156	0.000	0.866	0.649	0.689	0.709
ARCH1	0.061	0.805	1.358	0.244	0.043	0.835	2.186	0.139
ARCH2	0.107	0.948	4.624	0.099	0.921	0.631	4.090	0.129
LM1	1.723	0.189	0.385	0.535	0.177	0.674	0.000	0.993
LM2	2.509	0.285	1.058	0.589	0.393	0.822	0.224	0.894

***, **, * reject the null hypothesis at $\alpha=1\%$, 5% and 10% respectively. JB, ARCH, and LM stand for normality, heteroskedasticity, and autocorrelation test. NARDL: Non-linear autoregressive distributed lag

price indices consisting of (1) Cereals, roots, and their products (CR); (2) Meat and its products (MT); (3) Fresh fish (FF); (4) Preserved fish (PF); (5) Eggs, milk and their products (EG); (6) Vegetables (VE); (7) Beans and nuts (BN); (8) Fruits (FR); (9) Spices (SP); (10) Fats and oils (FO); and (11) Other food Items (OF). The data for the general food price index and its sub-components were collected from the Indonesian Central Bureau of Statistics. The price of West Texas Crude oil is proxy the price of world crude oil and was obtained from the Federal Reserve Bank of St. Louis, USA. The IPI was collected from International Financial Statistics.

4. RESULTS AND DISCUSSION

Table 1 exhibits the growth rate of the general food price index as well as each component of the general food price index. The

highest rate of price growth is spice prices (0.644), followed by vegetable prices (0.621) per month. Spice prices are very volatile with the highest standard deviation of 8.859. The lowest rate of growth is eggs, milk, and their product as the dairy product (0.363) with a standard deviation of 1.742. Food groups that rely on natural conditions such as the weather are relatively high with an average above 0.5 such as vegetables, fruit, and preserved fish. With the exception of PF and EG, all variables are positively skewed, meaning that most prices of all sub-component of GF exceed the average prices. Meanwhile, the oil price is relatively stable with the growth rate of 0.142 per month but with a high standard deviation (5.516).

NARDL is applicable if none of the variables is integrated into the second difference data. This study initially performs unit root to check the stationary data. This study applies ADF and PP tests

Table 3: Continue

Variable	PF Coeff.	s.e	EG Coeff.	s.e	VE Coeff.	s.e	BN Coeff.	s.e
C	0.635***	0.230	0.111	0.085	0.427***	0.101	0.086*	0.045
lp_{t-1}	-0.172***	0.064	-0.027	0.022	-0.122***	0.030	-0.025*	0.014
lol_{t-1}^+	0.019**	0.008	0.008**	0.003	0.018***	0.005	0.013***	0.004
lol_{t-1}^-	-0.014*	0.009	0.005*	0.003	-0.012**	0.006	0.009***	0.003
lgp_{t-1}	-0.111**	0.047	0.225***	0.044	-0.007	0.041	0.057**	0.025
Δlp_{t-1}	-0.625***	0.080			0.220***	0.066	0.308***	0.068
Δlp_{t-2}	0.290***	0.083	-0.210***	0.064			-0.177**	0.070
Δlp_{t-3}	0.220**	0.090	-0.138**	0.058			0.136**	0.069
Δlp_{t-4}	-0.328***	0.089						
Δlp_{t-5}	-0.292*	0.078			-0.143**	0.061		
Δlp_{t-6}			0.125**	0.059	0.195***	0.061		
Δlp_{t-1}	0.093*	0.054						
Δlp_{t-10}			-0.224***	0.057				
Δlp_{t-12}			0.244***	0.059	0.123**	0.060		
Δlol_{t-4}^+					-0.085**	0.038		
Δlol_{t-6}^+	-0.087*	0.050						
Δlol_{t-11}^+			-0.058**	0.024	-0.093**	0.037		
Δlol_t^-	-0.112***	0.036						
Δlol_{t-6}^-	0.156***	0.041			0.094***	0.031		
Δlol_{t-7}^-	-0.090**	0.038			-0.068**	0.032		
Δlol_{t-12}^-							-0.039**	0.019
Δlgp_t			0.077***	0.026				
Δlgp_{t-1}			-0.121***	0.037	-0.128***	0.031		
Δlgp_{t-2}			-0.131***	0.035				
Δlgp_{t-3}			-0.107***	0.027				
Δlgp_{t-5}			-0.066***	0.024				
Δlgp_{t-6}			-0.066***	0.024				
Δlgp_{t-8}					0.098***	0.034		
Δlgp_{t-9}					0.087***	0.033		
Δlgp_{t-10}							0.053***	0.020
Δlgp_{t-11}					-0.133***	0.034		
Δlgp_{t-12}					-0.117***	0.035		
R-squared	0.654		0.525		0.438		0.227	
J-B	21137	0.000	1.574	0.455	4.178	0.124	25958	0.000
ARCH1	0.464	0.496	0.320	0.572	0.143	0.706	0.010	0.920
ARCH2	0.460	0.795	1.413	0.493	0.695	0.707	0.033	0.984
LM1	0.086	0.769	1.317	0.251	0.072	0.788	0.091	0.763
LM2	0.177	0.915	4.050	0.132	0.072	0.965	0.815	0.665

***, **, * reject the null hypothesis at $\alpha=1\%$, 5% and 10% respectively. JB, ARCH, and LM stand for normality, heteroskedasticity, and autocorrelation test

Table 3: Continue

Variable	PF Coeff.	s.e	SP Coeff.	s.e	FO Coeff.	s.e	OF Coeff.	s.e
C	0.099**	0.047	0.812***	0.147	0.244***	0.059	0.196***	0.068
lp_{t-1}	-0.026*	0.013	-0.226***	0.041	-0.067***	0.017	-0.048***	0.017
lol_{t-1}^+	0.006***	0.002	0.023*	0.013	0.016***	0.005	0.004**	0.001
lol_{t-1}^-	0.002	0.003	-0.033**	0.014	0.005*	0.003	-0.003	0.002
lgp_{t-1}	0.042**	0.017	0.181	0.110	0.109***	0.032	0.017	0.013
Δlp_{t-1}	0.203***	0.061	0.249***	0.067	0.442***	0.064	0.131**	0.060
Δlp_{t-2}					-0.241***	0.072		
Δlp_{t-3}					0.135*	0.072		
Δlp_{t-4}	-0.129**	0.057			0.206***	0.063		
Δlp_{t-7}					0.180***	0.061	-0.112**	0.049
Δlp_{t-9}					0.149**	0.065	-0.109**	0.047
Δlp_{t-12}	0.244***	0.059					0.280***	0.052
Δlol_{t-1}^+			-0.298**	0.125				
Δlol_{t-5}^+	-0.068***	0.017						
Δlol_{t-7}^+							-0.034***	
Δlil_{t-8}^+			0.252**	0.113				
Δlol_{t-11}^+	-0.036**	0.017					-0.022*	0.011
Δlol_t^-							-0.023**	0.009
Δlol_{t-1}^-			0.218**	0.097				
Δlol_{t-7}^-					-0.064***	0.019		
Δlol_{t-8}^-	-0.027**	0.013						
Δlol_{t-12}^-							0.023**	0.009
Δlgp_t					-0.076***	0.025		
Δlgp_{t-1}							-0.028***	0.009
Δlgp_{t-2}			-0.350***	0.092			-0.058***	0.010
Δlgp_{t-3}							-0.044***	0.011
Δlgp_{t-4}					0.040*	0.021		
Δlgp_{t-8}					0.088***	0.022		
Δlgp_{t-9}					0.128***	0.025		
Δlgp_{t-10}					0.108***	0.021		
Δlgp_{t-11}	-0.071***	0.014						
R-squared	0.393		0.245	0.008	0.453		0.516	
J-B	14.206	0.001	18.104	0.000	85.911	0.000	30.659	0.000
ARCH1	0.688	0.407	0.008	0.930	12.537	0.000	2.546	0.111
ARCH2	4.028	0.134	0.506	0.776	26.909	0.000	5.491	0.064
LM1	3.252	0.071	2.920	0.088	2.069	0.150	7.166	0.007
LM2	3.470	0.176	5.640	0.060	2.461	0.292	10.382	0.006

***: ***: * reject the null hypothesis at $\alpha=1\%$, 5% and 10% respectively. JB, ARCH, and LM stand for normality, heteroskedasticity, and autocorrelation test.

with constant and trend to specify the order of integration of the variables. Table 2 exhibits the results of both stationary. FF, preserved fish, vegetables, spices, and other foods are stationary in level and the rest of the variables are not stationary in level, but they become stationary after the first differencing. Because none of all variables becomes stationary in the second differenced data, then this study can proceed to estimate equation (5).

This study set the lag order of 12 as a maximum lag to estimate the NARDL model in equation (5). The upper part of Table 3 presents the NARDL estimation for GF and all sub-component of GF, including the coefficient of determination (R^2) for measuring the goodness of fit. Before drawing inferences, this study has to

check the specification adequacy of the NARDL model stemmed from the various diagnostic statistics. These diagnostic statistic tests consist of the Jarque-Bera (J-B) for the error normality, Autocorrelation Conditional Heteroskedasticity (ARCH) up to order 2 for heteroskedasticity and Langrage Multiplier (LM) up to order 2 for autocorrelation. The bottom part of Table 3 presents those diagnostic statistic tests. MT, FF, EG, VE model pass error normality test. With the exception of the FO model, all models fulfill homoskedasticity tests. Likewise, all models are the absence of autocorrelation except for the OF model.

From the estimated coefficient in Table 3, then this study tests cointegration applying the bound testing approach following the

F_{PSS} test statistics. These cointegration test results are shown in Table 4. The computed F values of general food prices index (GF), cereals, roots, and their products (CR), meat and its products (MT), fresh fish (FF), eggs, milk, and their products (EG), vegetables (VE), beans and nuts (BN), fruits (FR), spices (SP), and fats and oils (FO) are higher the critical upper bound at $\alpha=10\%$ or lower level. On the other hand, the computed F values of preserved fish (PF) and Other food items (OF) lay between lower and upper bound at $\alpha=10\%$. Based on the bounds test, this study finds that general food prices and its sub-component, oil price, and output gap co-move in the long-run.

Accordingly, with this bound F test, this study can perform the asymmetric effect of oil price on food prices and its sub-component to check whether food prices respond asymmetrically to an increase and decrease in oil price. The asymmetric tests of oil price on disaggregate food prices following the Wald F test are presented in Table 5. The null hypothesis of no long-run asymmetry impact of oil price on GF and all sub-components of GF is rejected for all food prices. This study concludes that responses of food prices and its sub-component to oil price change have a different magnitude as oil prices increase and decrease. These findings are line with the existing empirical studies for developing countries (e.g., Ibrahim and Chanchaoenchai, 2014 for Thailand; Ibrahim and Said, 2012; Ibrahim, 2015 for Malaysia; Abdalaziz et al. 2016 for Indonesia).

Finally, this study calculates the long-run coefficient of oil price from the estimated coefficient of NARDL to measure the asymmetric effect of oil prices on food prices and its sub-component, including the long-run coefficient of the output gap. Table 6 presents the coefficient of positive and negative oil price and the output gap in the long-run. With the exception of FF, the null hypothesis of the positive coefficient of the oil price is rejected at $\alpha = 10\%$ or lower level. Meanwhile, the null hypothesis of the negative coefficient of the oil price is rejected for cereals, roots, and their products (CR), preserved fish (PF), vegetables (VE), beans and nuts (BN), spices (SP), fats and oils (FO), and other food items (OF) at $\alpha = 10\%$ or lower level. The null hypothesis of output gap coefficients is rejected for all sub-component of food prices except for FF, eggs, milk, and their products (EG), Vegetables (VE), and other food (OF) at $\alpha = 10\%$ or lower level.

The long-run coefficient of positive oil price for general food prices (GF) is 0.2403. This coefficient is higher than that of Malaysia by 0.0605 (Ibrahim, 2015) but it is lower than the existing empirical study in Indonesia by 0.6420 using quarterly data (Abdalaziz et al., 2016). This result predicts that an increase in oil price by 1% leads to a rise in general food prices roughly by 0.2403%. By contrast, a reduction in oil price has no effect on general food prices. Our finding confirms the other empirical study such as Ibrahim (2015) and Abdalaziz et al. (2016). The long-run coefficients of positive oil price for each sub-component of FG are from 0.0744 for other food items to 0.5250 for beans and nut. On the other hand, the long-run coefficients of negative oil price for each food price index range from -0.0772 for cereals, roots, and their products (CR) to -0.3634 for beans and nuts. Some of

Table 4: Cointegration test

Food price index	F_{PSS} statistic	Critical Value		
		α	Lower	Upper
General food	8.208	1%	5.15	6.36
Cereals, roots, and their products	8.820	5%	3.79	4.85
Meat and its products	6.404	10%	3.17	4.14
Fresh fish	5.795			
Preserved fish	3.270			
Eggs, milk and their products	9.211			
Vegetables	4.540			
Beans and nuts	4.852			
Fruits	4.725			
Spices	9.509			
Fats and oils	7.586			
Other food items	3.362			

The critical values come from Pesaran et al., (2001)

Table 5: Long-run asymmetric test

Food price index	W_{LR}	Prob.
General food	109.076	0.000
Cereals, roots, and their products	554.503	0.000
Meat and its products	379.207	0.000
Fresh fish	3.470	0.064
Preserved fish	770.162	0.000
Eggs, milk and their products	4.307	0.039
Vegetables	875.007	0.000
Beans and nuts	11.258	0.001
Fruits	50.759	0.000
Spices	350.471	0.000
Fats and oils	227.269	0.000
Other food items	385.991	0.000

W_{LR} is the Wald test for the long-run asymmetric effect

Table 6: Long-run relationship

Food price index	lol_t^+	lol_t^-	lgp_t
General food	0.2403*** (0.0668)	-0.0521 (0.0797)	5.2214** (2.8576)
Cereals, roots, and their products	0.3079*** (0.0366)	-0.0772** (0.0419)	-1.1751*** (0.3896)
Meat and its products	0.1597*** (0.0359)	0.0112 (0.0408)	0.8304** (0.4052)
Fresh fish	0.5347 (0.6173)	-0.3919 (0.6885)	16.9347 (23.6876)
Preserved fish	0.1110*** (0.0289)	0.0834** (0.0328)	-0.6442** (0.3655)
Eggs, milk and their products	0.2993* (0.1962)	-0.1977 (0.2400)	8.3907 (7.3056)
Vegetables	0.1469*** (0.0329)	0.0964** (0.0374)	-0.0578 (0.3321)
Beans and nuts	0.5250** (0.2032)	-0.3634* (0.2443)	2.2827* (1.6467)
Fruits	0.2511** (0.1090)	-0.0674 (0.1297)	1.6110* (1.0820)
Spices	0.1020*** (0.0536)	0.1443** (0.0605)	0.8011* (0.5387)
Fats and oils	0.2309*** (0.0386)	-0.0793** (0.0438)	1.6232*** (0.6190)
Other food items	0.0744*** (0.0255)	0.0587** (0.0294)	0.3423 (0.3038)

***, **, * reject the null hypothesis at $\alpha=1\%$, 5% and 10% respectively. The parentheses show the standard error

the long-run coefficients of negative oil prices have a positive sign as not expected in economic theory such as preserved fish (PF), vegetables (VE), species (SP), and other food items (OF). More interestingly, the impact of oil price increase is higher than that of oil price reduction on food prices. These findings support a rocket and feather phenomenon where the speed of cost increase is faster than cost decrease because of downward sticky-price (Tappata, 2009). The long-run coefficients of the output gap are mixed either positive signs as expected in economic theory and negative sign. The lowest and highest coefficients of the output gap are spices (0.8011) and fats and oil (1.642) respectively. More interestingly, the impact of the output gap on the general food price index is relatively high (5.2214). It roughly predicts that food prices increase by 5.22% as the output gap rises by 1%.

From the above results, rising oil price asymmetrically affects disaggregate food prices. There are two reasons. First, the increase in world oil price increases transportation costs so food prices become expensive. A number of studies document that the biggest impact of oil prices on disaggregated consumer price index is transportation prices such as Ibrahim and Chanchaoenchai (2014) for Thailand, Ibrahim (2015) for Malaysia and Widarjono and Hakim (2019) for Indonesia. Second, the increase in world oil prices has raised world food prices, thus affects the price of imported food (see e.g., Baffes, 2007; Ciaian and d'Artis, 2011; Paris, 2018). As a food net-importing country, increasing world food prices raise domestic food prices because of the high prices of imported food. The effect of oil price on beans and nuts prices (BN) and cereals and roots and their product prices (CR) is high because Indonesia is a large importer of foodstuffs from the two food groups. The amount of wheat, soybeans, rice, peanuts, and corn imports from total food imports was 47.12%, 33.63%, 8.18%, 1.51%, and 5.22% respectively in 2018. The increase in food prices is strongly influenced by aggregate demand shock, coupled with the high cost of transportation as aggregate shock hits due to the island country.

5. CONCLUDING REMARKS

It is interesting to analyze the relationship between world oil prices and domestic food prices in both net oil and food-importing countries such as Indonesia as an emerging market. Our empirical study examines the asymmetric impact of oil price on disaggregate food prices applying the non-linear distributed lag model. This study finds some important findings of the relationship between oil prices and food prices. First, the co-movement between oil prices and disaggregate food prices is a presence in the long-run. Second, aside from the FF group, the world oil price influences food prices and its sub-components. The impact of oil prices on food prices is varied across food groups but incomplete pass-through. The highest impact of oil price is for beans and nuts group, followed by cereals and roots, and their products group. However, the impact of oil prices on other food groups is low. Third, oil price asymmetrically affects food prices. The food price rises faster to oil price increase than an oil price decrease.

This study hints on some aspects that need further attention. The world oil price asymmetrically affects domestic food prices due to

high transportation costs and high food import prices. Therefore, monitoring and controlling food prices during the oil price hike can help policy-maker to achieve the inflation target for Indonesia, which adopts an inflating targeting. Furthermore, there needs to be a look out on the increase in food prices since it affects the amount of food consumption as well as nutritional intake. The Indonesian government has set a minimum consumption of calories and protein by 2000 kcal and 52 grams. The average calorie and protein consumptions were 1,992.69 kcal and 55.11 g/day in 2015. The average calorie and protein consumptions fulfilled the minimum requirement of 2,147.09 kcal and 62.19 g in 2018. However, there are eight out of 34 provinces with average calorie consumption under 2000 kcal per day and three provinces with average protein consumption under 52 grams per day. Stabilizing food prices such as rice, wheat, corn, and soybeans during the oil price crisis is very important. Stabilizing those food prices may maintain the minimum calorie and protein consumption in Indonesia during oil price shock because the consumption of calories is barely a minimum standard of calorie intake as a main source of energy.

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REFERENCES

- Abdlaziz, R., Rahim, K., Adamu, P. (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.
- Alghalith, M. (2010), The interaction between food prices and oil prices. *Energy Economics*, 32(6), 1520-1522.
- Al-Maadid, A., Caporale, G.M., Spagnolo, F., Spagnolo, N. (2017), Spillovers between food and energy prices and structural breaks. *International Economics*, 150, 1-18.
- Avalos, F. (2014), Do oil prices drive food prices? The tale of a structural break. *Journal of International Money and Finance*, 42, 253-271.
- Baffes, J. (2007), Oil spills on other commodities. *Resources Policy*, 32(3), 126-134.
- Byrne, J.P., Fazio, G., Fiess, N. (2013), Primary commodity prices: Co-movements, common factors and fundamentals. *Journal of Development Economics*, 101(1), 16-26.
- Chen, S.T., Kuo, H.I., Chen, C.C. (2010), Modeling the relationship between the oil price and global food prices. *Applied Energy*, 87(8), 2517-2525.
- Ciaian, P., d'Artis, K. (2011), Interdependencies in the energy-bioenergy-food price systems: A cointegration analysis. *Resource and Energy Economics*, 33(1), 326-348.
- Fernandez-perez, A., Frijns, B., Tourani-rad, A. (2016), Contemporaneous interactions among fuel, biofuel and agricultural commodities. *Energy Economics*, 58, 1-10.
- Gao, L., Kim, H., Saba, R. (2014), How do oil price shocks affect consumer prices? *Energy Economics*, 45, 313-323.
- Gilbert, C.L. (2010), How to understand high food prices. *Journal of Agricultural Economics*, 61(2), 398-425.
- 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., Chanchaoenchai, K. (2014), How inflationary are oil

- price hikes? A disaggregated look at Thailand using symmetric and asymmetric cointegration models. *Journal of the Asia Pacific Economy*, 19(3), 409-422.
- Ibrahim, M.H., Said, R. (2012), Disaggregated consumer prices and oil price pass-through: Evidence from Malaysia. *China Agricultural Economic Review*, 4(4), 514-529.
- Jongwanich, J., Park, D. (2011), Inflation in developing Asia: Pass-through from global food and oil price shocks. *Asian Pacific Economic Literature*, 25(1), 79-92.
- Lambert, D.K., Miljkovic, D. (2010), The sources of variability in U. S. Food prices. *Journal of Policy Modeling*, 32(2), 210-222.
- Liu, X., Pan, F., Yuan, L., Chen, Y. (2019), The dependence structure between crude oil futures prices and Chinese agricultural commodity futures prices : Measurement based on Markov-switching GRG copula. *Energy*, 182, 999-1012.
- Lucotte, Y. (2016), Co-movements between crude oil and food prices: A post-commodity boom perspective. *Economics Letters*, 147, 142-147.
- Mitchell, D. (2008), A Note on Rising Food Prices. World Bank Policy Research Working Paper No. 4682.
- Myers, R.J., Johnson, S.R., Helmar, M., Bumess, H. (2014), Long-run and short-run co-movements in energy prices and the prices of agricultural feedstocks for biofuel. *American Journal of Agricultural Economics*, 96(4), 991-1008.
- Nazlioglu, S. (2011), World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy Policy*, 39(5), 2935-2943.
- Nazlioglu, S., Soytas, U. (2011), World oil prices and agricultural commodity prices: Evidence from an emerging market. *Energy Economics*, 33(3), 488-496.
- Nazlioglu, S., Soytas, U. (2012), Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. *Energy Economics*, 34(4), 1098-1104.
- Paris, A. (2018), On the link between oil and agricultural commodity prices: Do biofuels matter? *International Economics*, 155, 48-60.
- Pesaran, M.H., Shin, Y., Smith, R.J. (2001), Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289-326.
- Reboredo, J.C. (2012), Do food and oil prices co-move? *Energy Policy*, 49, 456-467.
- Rondhi, M., Pratiwi, P.A., Handini, V.T., Sunartomo, A.F., Budiman, S.A. (2018), Agricultural land conversion, land economic value, and sustainable agriculture: A case study in East Java, Indonesia. *Land*, 7(4), 1-19.
- Serra, T., Zilberman, D. (2013), Biofuel-related price transmission literature: A review. *Energy Economics*, 37, 141-151.
- Shin, Y., Yu, B., Greenwood-Nimmo, M. (2014), Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: Sickels, R., Horrace, W., editors. *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*. New York: Springer. p281-314.
- Taghizadeh-Hesary, F., Rasoulinezhad, E., Yoshino, N. (2019), Energy and food security: Linkages through price volatility. *Energy Policy*, 128, 796-806.
- Tappata, M. (2009), Rockets and feathers: Understanding asymmetric pricing. *The Rand Journal of Economics*, 40(4), 673-687.
- Wang, Y., Wu, C., Yang, L. (2014), Oil price shocks and agricultural commodity prices. *Energy Economics*, 44, 22-35.
- Widarjono, A., Hakim, A. (2019), Asymmetric oil price pass-through to disaggregate consumer prices in emerging market: Evidence from Indonesia. *International Journal of Energy Economics and Policy*, 9(6), 310-317.
- Zhang, Z., Lohr, L., Escalante, C., Wetzstein, M. (2010), Food versus fuel: What do prices tell us? *Energy Policy*, 38(1), 445-451.