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DYNAMIC SHOCKS OF CRUDE OIL PRICE AND EXCHANGE RATE ON FOOD PRICES IN EMERGING COUNTRIES OF SOUTHEAST ASIA: A PANEL VECTOR AUTOREGRESSION MODEL

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ABSTRACT

This paper empirically analyzes food price responses to shocks from crude oil price and exchange rate volatility in five emerging Southeast Asian nations between 2000 and 2020 using impulse response functions and variance decomposition analysis of the dynamic panel Vector Autoregression approach. Based on the findings of the impulse response functions analysis, food prices respond positively to both oil price and exchange rate shocks. Meanwhile, the results of variance decomposition analysis show that food prices account for a significant portion of volatility in its own shock. The contribution of oil price shock to food price volatility is found to be greater than the contribution of exchange rate shock. Hence, the study recommends that policymakers in these nations should be vigilant about the impacts of oil price and exchange rate shocks on food prices since these factors may undermine price stability and exacerbate food security.

Contribution and originality: This research adds to prior research by examining how food prices in emerging Southeast Asian nations respond to oil price shocks and exchange rate volatility. The dynamic links between variables, together with the contributions of exchange rate shocks and oil price shocks in explaining food price behavior across the sample period, can be identified using impulse response and variance decomposition analysis.

1. INTRODUCTION

Over the last few decades, global civilization has faced a plethora of food security issues. Access to food is one of the most essential components of food security, and it is heavily impacted by economic variables. Food price and per capita income, for example, are two economic factors that have a large impact on people's economic access to food. Poor communities are particularly vulnerable since food accounts for a substantial portion of their household income. The sudden spike in food prices during the prevailing food price crisis had a significant impact on the livelihoods of many people (FAO, 2009), pushing millions into poverty and malnourishment. This was reinforced by Ivanic, Martin, and Zaman (2012), who discovered that the global food price increase in 2011 increased poverty by 44 million, corresponding to an average poverty increase of 1.1 percent and 0.7 percent in low and middle-income countries, respectively. Significantly, Hanif (2012) stressed that rising food prices were detrimental to the welfare of low-income households since their food consumption was enormous. In Malaysia, for instance, when food prices were high, lower-income quartile families bore a greater financial burden than higher-income quartile households (Ibrahim, 2015). According to FAO (2022), both the level and volatility of prices are important dimensions of food security, particularly regarding food accessibility and stability. Food stability is defined as the ability to sustain food security across time by ensuring supply stability and constant access to food resources. It is significantly impacted by economic, environmental, and political factors. Rising agricultural product prices have the potential to have a significant impact on socio-economic stability by affecting producer income, consumer purchasing power, the balance of payments, and the government budget. Thus, food price stability is a policy goal from the standpoint of impoverished people's welfare and monetary policymakers' credibility in stabilizing inflation expectations in an inflation-targeting environment (Iddrisu & Paul, 2020).

A variation in oil prices is one of the macroeconomic variables that will impact food prices, which will, in turn, have an impact on food security via food stability. In other words, an increase in oil prices has a positive effect on agricultural food prices. A spike in the price of oil may have an immediate impact on the cost of agricultural commodities and food items. Figure 1 depicts the relationship between the global food price index and crude oil price dynamics from January 1997 to January 2022. The monthly international food price index and crude oil price are represented on the vertical axis in USD. As illustrated, both the crude oil price and the international food price index experienced a considerable upward trend. From 2007 until mid-2008, the global financial crisis caused a surge in both crude oil and agricultural prices. In June 2008, oil and international food prices hit all-time highs, reaching $133.88 per barrel and $124.85, respectively. These prices then plummeted precipitously. In the first month of 2009, the price of crude oil was less than $50 per barrel. This fact led analysts to conclude that rising oil prices were to blame for the so-called food crisis. We may also infer from this trend that the volatility of the global crude oil price is positively related to the volatility of the global food price. Conversely, food price hikes in 2021 were mostly driven by both the recovery of food demand after the global COVID-19 pandemic and temporary logistical issues.

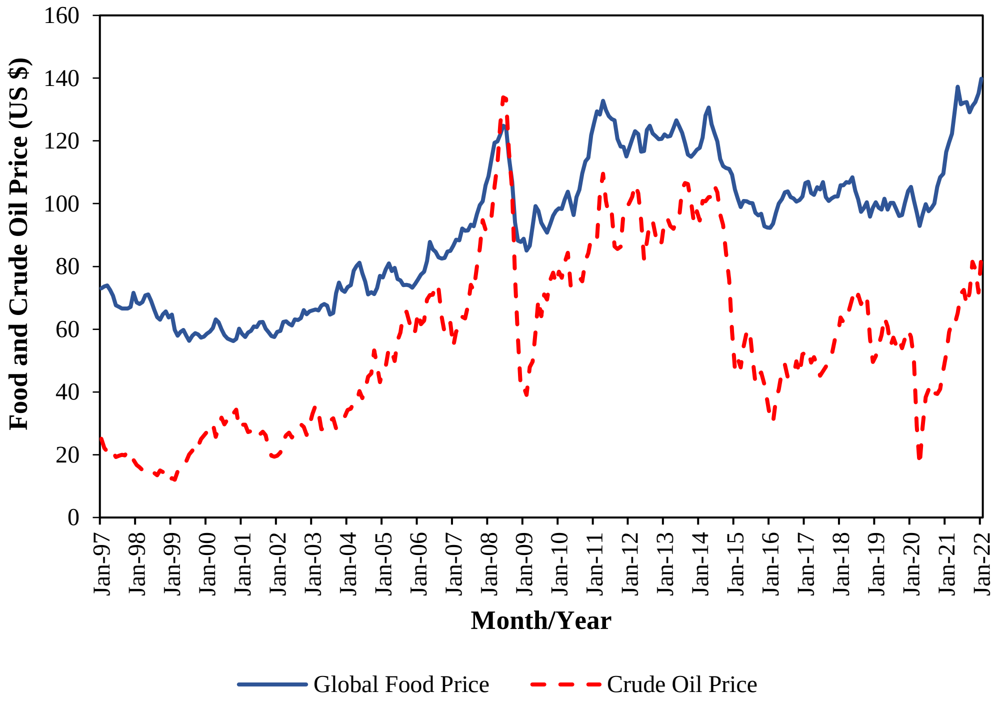

Figure 1. International food and crude oil prices from January 1997 to January 2022.
Source: Crude Oil Price (in dollars per barrel) and the Global Price of Food Index (in US dollars) are retrieved from the US Energy Information Administration Database and the FRED Federal Reserve Bank of St. Louis, respectively.

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Crude oil is essential to socio-economic development and sustainability because it is the world's most significant raw commodity and source of basic energy. As most industries rely on oil as raw material, higher oil prices will eventually raise production costs. Consequently, an increase in the pass-through price of crude oil reduces the supply of food and agricultural commodities due to rising fertilizer, transportation, and capital costs. Because oil is a fundamental component of fertilizer, a spike in energy prices puts agricultural commodities and food prices at risk. Furthermore, the cost of processing and shipping agricultural commodities is affected by energy prices in global agricultural markets. Distributing geographically diversified agricultural products to consumers in other countries and who are concentrated in urban areas, for example, invariably entails transportation costs that are heavily impacted by energy prices (Chevroulet, 2008). Oil prices have been found to be linked to food prices via demand and supply mechanisms. However, the impact of oil prices on food prices suggests that demand pressures and financialization dynamics are far more relevant in explaining price increases than supply considerations (Tadasse, Algieri, Kalkuhl, & Braun, 2014).

Furthermore, another primary driver of food price rises underlined in the recent food crisis is the depreciation of the US dollar, which is the preferred currency for most international commodity transactions. In theory, as the US dollar appreciates versus other currencies, the dollar price of products imported from other countries decreases, while a stronger dollar makes commodities that the United States exports more expensive in terms of foreign currency. In contrast, when the US dollar depreciates, consumers in a dollar-pegged country pay much higher local costs for imported food goods than consumers in a flexible exchange rate economy, assuming all else is equal. As a result of exchange rate fluctuations, changes in the prices of imported finished goods and imported inputs can cause changes in domestic prices. Besides that, because most goods are traded on global markets, currency exchange rates have a considerable influence on food prices. Figure 2 illustrates an inverse relationship between the worldwide food price index and the nominal broad US dollar index, also known as the Trade-Weighted US Dollar Index, which gauges the value of the US dollar against other currencies. The annual international food price index is plotted on the left axis, while the nominal broad US dollar index is plotted on the right axis. As shown, in 2021, the recent global COVID-19 pandemic had already curtailed demand for exports, resulting in exchange rate depreciation, which increased the domestic prices of imported food. To achieve price stability, governments must consider the exchange rate as a factor influencing food prices.

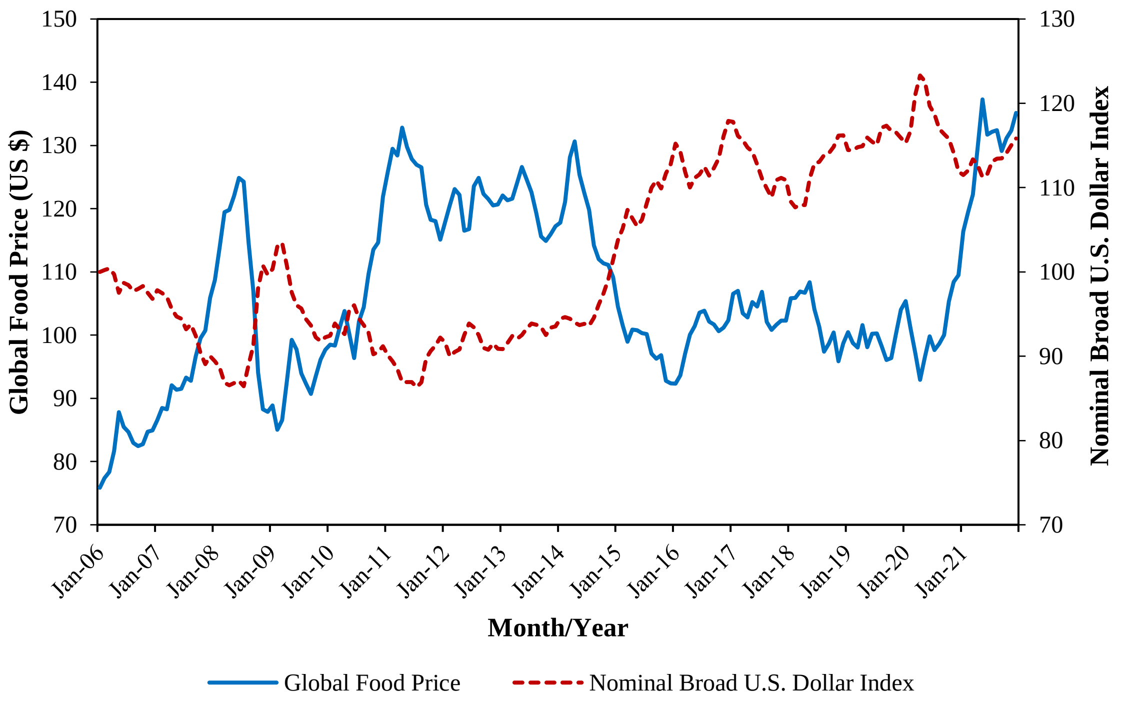

Figure 2. Food price and nominal broad U.S dollar index from January 2006 to December 2021.
Source: Global Price of Food Index (in US dollars) and Nominal Broad U.S Dollar Index are retrieved from the FRED Federal Reserve Bank of St. Louis, respectively.

Most significantly, energy prices and exchange rates influence global agricultural markets through what are known as macroeconomic repercussions. Because agriculture is critical to addressing hunger, poverty, and food security issues, it is becoming increasingly important to examine the factors that influence food prices. Rising global food and oil prices, along with the growing dependency of the Asian region on imported energy and food, were projected to increase domestic consumer prices (Jongwanich & Park, 2011). Accordingly, this paper attempts to empirically investigate the impact of oil price and exchange rate fluctuations on food price volatility in five emerging Southeast Asian nations. The aim of the study is to attempt to answer the following research questions: (i) How do food prices respond to macroeconomic shocks like crude oil prices and exchange rates, and how do these macroeconomic forces respond to the food price impulse? (ii) How much variation in food prices can be explained by fluctuations in oil prices and exchange rates? The impulse response functions and variance decomposition analysis of the panel VAR technique are applied to annual data from 2000 to 2020 in five emerging Southeast Asian countries.

The next sections of this work are arranged thus. Section 2 is a review of the literature, including existing and recent studies on the link between food prices, oil prices, and exchange rates. The paper next delves into the data and methods used in this study in Section 3. Section 4 presents empirical findings and discusses them, while Section 5 concludes with some recommendations and limitations to be addressed.

2. REVIEW OF LITERATURE

The global food crisis that occurred during the previous decade piqued academics' interest and has been the topic of much scholarly and public discussion due to the negative impact of growing food prices on people's well-being in both wealthy and poor nations. From an empirical approach, studies focusing on the influence of oil prices on agricultural commodity prices have employed a variety of methodologies. Saghaian (2010) used Granger causality to identify the possible simultaneous causal mechanisms between energy and commodity variables. While there was a significant connection between oil and commodity prices, the evidence for a causal relationship between oil and commodity prices was inconclusive, according to the findings. Gohin and Chantret (2010) utilized a world computable general equilibrium model to examine the long-run effects of energy prices on global agriculture markets while accounting for macroeconomic indicators. Their study sought to determine if the hitherto overlooked macroeconomic repercussions of energy prices outweighed the other effects on global food prices. The analysis revealed that incorporating the real income effect may potentially suggest a negative association between global food and energy prices. Esmaeili and Shokoohi (2011) employed principal component analysis to investigate the co-movement of seven key commodities' food prices: eggs, beef, milk, oilseeds, rice, sugar, and wheat. They observed that the price of crude oil had an indirect influence on food prices and global GDP. Ibrahim (2015) used a nonlinear autoregression distributed lag (NARDL) model to study the long- and short-run cointegration of oil price variations and food prices in Malaysia. The findings indicated that long-run oil price increases had a positive long-run influence on food prices, but there was no significant association between long-run oil price drops and food prices. Likewise, Wong and Shamsudin (2017) used the NARDL model to investigate the impact of crude oil price volatility, real GDP, and exchange rates on Malaysian food price volatility. Using quarterly data from the first quarter of 2000 to the second quarter of 2016, the bounds test for cointegration found a significant long-run link between the underlying variables and food prices, while only the price of crude oil had a symmetric long-run influence on the volatility of food prices. Conversely, real GDP and exchange rates had an asymmetric long-run influence on food price changes. Lucotte (2016) explored the co-movement of crude oil and food prices using the VAR prediction errors model. The results demonstrated a statistically significant relationship between the two variables in the post-commodity-boom era but none in the pre-commodity-boom period. Nwoko, Aye, and Asogwa (2016) used the Johansen and Jesulius cointegration test to analyze the long- and short-term relationships between oil price changes and food price variations along with the causal linkage between them. The results indicated that there was a long-run relationship between oil price volatility and domestic food prices. The vector error correction model demonstrated a positive and significant short-run relationship between oil price volatility and food price volatility. The Granger causality test revealed unidirectional causality with causality running from oil price volatility to food price volatility, but not vice versa. Pal and Mitra (2017) employed wavelet-based analysis on monthly pricing data from January 1990 to February 2016 to study the association between crude oil prices and food price indices. The study identified a short-term association between various food prices and crude oil prices. Because there was a close link between crude oil and food prices, global food prices were extremely vulnerable to swings in oil prices. Using the linear ARDL technique, Zmami and Ben-Salha (2019) empirically studied the linear and nonlinear impacts of the world food price index on global food prices and the price indices of five major agricultural commodities between January 1990 and October 2017. Taghizadeh-Hesary, Rasoulinezhad, and Yoshino (2019) used a panel vector autoregressive model with other economic variables to capture the reaction of food prices to energy price shocks. They discovered that agricultural food prices respond positively to oil price fluctuations.

As previously stated, research on the relationship between crude oil prices and agricultural food prices, both global and national, is vast but with inconclusive results. A corpus of empirical research reveals that major volatility in agricultural commodity prices is a dynamic process generated by oil prices with varying impact directions (Avalos, 2014; Chen, Kuo, & Chen, 2010; Esmaeili & Shokoohi, 2011; Gohin & Chantret, 2010; Ibrahim, 2015; Nwoko et al., 2016; Olayungbo, 2021; Pal & Mitra, 2017; Saghaian, 2010; Tadasse et al., 2014; Taghizadeh-Hesary et al., 2019; Wong & Shamsudin, 2017). Avalos (2014), for example, discovered that oil price shocks had a positive and significant impact on corn prices. In contrast, Olayungbo (2021) revealed a short-run negative relationship between oil prices and food prices in twenty-one emerging oil-exporting and food-importing nations. This is corroborated by Rafiq and Bloch (2016), who proved that increased oil prices had long-term favorable impacts on twenty commodities while having short-term negative effects on just thirteen commodities. Hameed and Arshad (2008) discovered a long-run causal link between petroleum and grain prices, while other research found no evidence to substantiate the association between variables. Yu and Bessler (2006) examined the cointegration and causality relationship between global vegetable oil prices and crude oil prices. However, there was no evidence to back up the hypothesis. Similarly, Zhang and Reed (2008) found no evidence to support the hypothesis that crude oil prices are related to Chinese maize, soy meal, and hog prices. According to a linear causality analysis, oil and agricultural commodity prices had no influence on one another. Fowowe (2016) proved that there was no long-term relationship between South African oil and food prices. Mutuc, Pan, and Hudson (2010) evaluated the impact of oil price shocks on US cotton prices and found no evidence to support cotton prices' responsiveness to petroleum price fluctuations. Reboredo (2012) also showed that food prices had not adjusted to the oil price shock.

Moreover, various research on the link between the exchange rate and food prices have been undertaken in both developed and developing nations (Burakov, 2016; Capehart & Richardson, 2008; Harri, Nalley, & Hudson, 2009; Mitchell, 2008; Nazlioglu & Soytas, 2012; Rezitis, 2015; Saman & Alexandri, 2018; Sasmal, 2015). For example, Capehart and Richardson (2008) claimed that exchange rate movements, particularly a weakening US dollar, were a key factor in the 2007–2008 food crisis. According to Hyder and Shah (2004), when a country's currency depreciates, it leads to higher import prices due to growing marginal costs, as well as increased domestic demand, which indirectly influences the price of domestically produced goods. Harri et al. (2009) investigated the influence of exchange rates on food commodity prices and discovered that exchange rates played an important role in the relationship between oil and agricultural commodity prices. Rezitis (2015) explored the long-run relationship between crude oil prices, US dollar exchange rates, and the prices of thirty selected international agriculture prices and five international fertilizer prices using panel econometric techniques. The study discovered that variations in the value of the US dollar had a negative and statistically significant impact on agricultural commodity prices. Fluctuations in the value of the US dollar had a greater influence on commodity prices than changes in crude oil prices. The dynamic relationship between global oil prices and twenty-four global agricultural commodity prices was investigated by Nazlioglu and Soytas (2012), taking into account changes in the relative value of the US dollar. They acknowledged that a weak dollar had a positive impact on agricultural prices. Conversely, Burakov (2016) discovered that currency exchange rates had no effect on agricultural commodity prices in Russia when examining the long-term and short-term effects of changes in oil prices and the exchange rate on the prices of seven different categories of agricultural commodities. Mitchell (2008) discovered that adverse foreign exchange rates had a long-run effect on agricultural prices; however, the results were not robust.

Based on the preceding explanation, the extant empirical literature argues that there is no consensus on the link between food prices, oil prices, and exchange rates, and results vary among nations, data, and empirical methodologies. Such studies showed that when macroeconomic links are thoroughly investigated, energy and food prices may even move in the other direction. This study differs from past literature analyses in several key areas. First, the study examines the effects of oil price and exchange rate shocks on food prices on a regional rather than global or individual scale.

Therefore, we can see how changes in energy prices and exchange rates affect agricultural commodity prices in a specific region of Southeast Asia. The IEA (2019) affirmed that an analysis of the energy outlook must take into account Southeast Asia's growing weight which is home to roughly one-tenth of the world's population and whose rapidly growing economies shape many aspects of the global economic and energy landscapes. Rising fuel demand, particularly for oil, has considerably outstripped regional supply.

With overall energy consumption expected to rise by 60% by 2040, the region as a whole is on the verge of becoming a net importer of fossil fuels. Second, following the Asian financial crisis of 1997, the monetary authorities of the Association of Southeast Asian Nations (ASEAN) countries in Southeast Asia have made significant exchange rate regime reforms. Since then, large fluctuations in currency values have increased the risk of foreign business transactions.

Third, the dependence of Southeast Asia on agricultural commodities and food imports from the United States represents a large market for agricultural goods. According to the United States Department of Agriculture (2018), agricultural and food exports from the United States to Southeast Asia expanded quickly over the preceding decade with sales of agricultural and food commodities reaching nearly $11.8 billion in 2017, when the region was recognized as the third-largest regional market, trailing behind only East Asia and North America. With a population of over 641 million and agricultural imports amounting to a cost of more than $91 billion per year, the region is expected to remain a key market for US agricultural exports. Lastly, emerging Southeast Asian countries have received less attention in the literature, even though economic growth in these nations is strongly reliant on energy expansion and trade liberalization, indicating that these economies are more vulnerable to oil and exchange rate shocks. Hence, the purpose of this paper is to fill a research gap by applying the panel VAR approach to investigate the dynamic shocks of oil price and exchange rate on food prices in emerging Southeast Asian countries.

3. DATA AND METHODOLOGY

3.1. Variable Definitions, Measurement, and Sources

The current dataset spans 2000 to 2020 for five emerging Southeast Asian countries: Indonesia, Malaysia, the Philippines, Thailand, and Vietnam. As shown in Table 1, the data for this study are obtained from the United Nations Food and Agriculture Organization (FAO) and the United States Energy Information Administration (EIA). The period is determined by the availability of food price data[1], as the FAO dataset for the food price index begins in 2000. The entire food price index is taken into account in the study. Table 1 lists the variables used in this investigation.

[1] The food price index is the average of several commodity price indices, and it is based on 73 international food commodity prices divided into five primary groups: meat, vegetable oils, sugar, cereals, and dairy. The index is developed to monitor changes in food prices on the worldwide market.

Table 1. Description of variables.

Variables	Description	Sources
Food price	Consumer price index for food (USD)	Food and Agriculture Organization (FAO) of the United Nations
Oil price	Average of WTI benchmark (USD/ bbl.)	US Energy Information Administration
Exchange rate[2]	Standard local currency units per USD	Food and Agriculture Organization (FAO) of the United Nations

Note: bbl. stands for barrel, WTI refers to West Texas Intermediate and USD is United States dollar.

3.2. Panel Vector Autoregressive (Panel VAR) Model[3]

The study employs a panel VAR model, which is a multiple time series analysis model, to evaluate the relationship between the selected variables over time. The vector autoregression (VAR) model is a natural extension of the autoregressive model in which a vector of variables is treated as depending on their own lags and the lags of every other variable in the vector. The panel VAR model generates an endogenous system and considers all variables in an unrestricted way, which is more appropriate when the variables are heavily related and interact with one another. Thus, we may study the endogenous relationship between food price, oil price, and exchange rate, i.e., it allows us to highlight the lag effects of crude oil prices and exchange rates on food prices and determine whether the feedbacks from food prices to oil prices and exchange rates are achieved. As it is derived from the panel-data framework, it allows for unobserved individual heterogeneity for all variables by integrating fixed effects, which optimizes estimate consistency. This is relevant for the purposes of this study since there is variance between countries. Therefore, the dynamic variability among nations may be identified. Finally, the panel VAR technique can also simply capture time variability in shock coefficients and variance. This method can address omitted variable bias and heterogeneity problems that are common in cross-sectional studies. A generic panel VAR model is represented succinctly below:

$$Y_{i,t} = \rho_0 + \rho\,(L) Y_{\,i,t-j} + \mu_i + e_{it} \qquad (1)$$

Where $Y_{i,t}$ is $M \times 1$ dimension vectors, i represents the sample country ($i = 5$), t represents the time period, year ($t = 21$), j represents the lag order, ρ_0 represents the constant term vector, $\rho\,(L) = \rho_1 L^1 + \rho_2 L^2 + \cdots \rho_j L^j$ represents the parameter matrix of the delay operator, μ_i represents the individual fixed effects, and e_{it} represents the error term. Based on model (1), the following time stationary panel VAR model is provided to investigate the possible dynamic relationship between crude oil price, exchange rate, and food price:

$$FP_{i,t} = \alpha_0 + \sum_{j=1}^{m} \alpha_{1,j}\, FP_{\,i,t-j} + \sum_{j=1}^{m} \alpha_{2,j}\, OP_{i,t-j} + \sum_{j=1}^{m} \alpha_{3,j}\, ER_{\,i,t-j} + \varphi_i + u_{it} \qquad (2)$$

$$OP_{i,t} = \beta_0 + \sum_{j=1}^{m} \beta_{1,j}\, OP_{\,i,t-j} + \sum_{j=1}^{m} \beta_{2,j}\, FP_{i,t-j} + \sum_{j=1}^{m} \beta_{3,j}\, ER_{\,i,t-j} + \eta_i + v_{it} \qquad (3)$$

$$ER_{i,t} = \vartheta_0 + \sum_{j=1}^{m} \vartheta_{1,j}\, ER_{\,i,t-j} + \sum_{j=1}^{m} \vartheta_{2,j}\, FP_{i,t-j} + \sum_{j=1}^{m} \vartheta_{3,j}\, OP_{\,i,t-j} + \gamma_i + \omega_{it} \qquad (4)$$

[2] Exchange rate is described as national currency per US dollar, meaning the US dollar appreciates (depreciates) when the exchange rate appreciates (depreciates).

[3] The panel VAR technique inherits the features of the traditional VAR model which regards all system variables as endogenous. It was initially presented by Holtz-Eakin, Newey, and Rosen (1988).

Where, $FP_{i,t}$, $OP_{i,t}$, and $ER_{i,t}$ denote food price, oil price, and exchange rate, respectively. *m* refers to the lag number, u_{it}, v_{it}, ω_{it} are white noise errors or stochastic error terms often called shocks or impulses or innovations, and φ_i, η_i, and γ_i are individual fixed effects for the panel member *i*. Models (2) to (4) show each dependent variable ($FP_{i,t}$, $OP_{i,t}$, and $ER_{i,t}$) is a function of its lagged values and the lagged values of other variables in the model.

Prior to undertaking panel VAR analysis, unit root checking of variables is a necessary procedure in time series analysis that confirms all variables are stationary at order one, I (1). The stationarity of the data should be evaluated to verify the accuracy of parameter estimation and to prevent the possibility of "pseudo regression." The cointegration test can only be performed when the variables are single integrals of the same order. To investigate the stationarity and determine the integration level of the selected variables, the study utilizes four different, recently developed panel unit root tests, namely IPS test by Im, Shin, & Pesaran (2003), LLC test by Levin, Lin, & Chu (2002), the Augmented Dickey-Fuller (ADF) Fisher Chi-square test created by Dickey and Fuller (1981), and the Phillips Perron (PP) Fisher Chi-square test developed by Phillips and Perron (1988). The null hypotheses (H_0) of all unit root tests states that the series has a unit root or nonstationarity, whereas the alternative hypotheses (H_1) states that the series does not have a unit root. If we reject the null hypotheses, we conclude that the series is stationary, or the series does not contain a unit root. Panel data's cointegration test is necessary to determine whether there is cointegration between variables. This study employs three types of panel cointegration tests, including the Pedroni residual cointegration test developed by Pedroni (1999); Pedroni (2004) and the Kao residual cointegration test developed by Kao (1999). Pedroni (1999); Pedroni (2004) developed seven different tests to determine the existence of panel cointegration that allow considerable heterogeneity. The null and alternative hypotheses in the test for cointegration are "series are not cointegrated" and "series are cointegrated," respectively.

Table 2. Summary statistics for level series.

Statistics/ variables	Food price	Oil price	Exchange rate
Mean	77. 51	60.73	5921.05
Maximum	121.62	99.67	23208.37
Minimum	25.70	25.93	3.06
Std. Dev.	26.29	24.41	7863.26
Observations	105	105	105

4. EMPIRICAL RESULTS AND DISCUSSION

The descriptive statistics for the series are shown in Table 2. The yearly average food price in the nations studied is \$77.51, with a maximum of \$121.62 and a minimum of \$25.70. The average oil price during the study period is \$60.73/ bbl, while the exchange rate has an average of 5,921.05 with a maximum and minimum of 23,208.37 and 3.06, respectively.

For the unit root test, the study utilizes EViews software's Automatic Selection: Schwarz Information Criterion to determine the lag length. Table 3 displays the results of the unit root testing of LLC, IPS, ADF-Fisher, and PP-Fisher for food price, oil price, and exchange rate. Each test is run for the level and first difference of the variables. We can clearly see that none of the series can reject the null hypothesis at levels, indicating that the series has a unit root and is nonstationary. Because the variables are not stationary at levels, the data are first differenced before proceeding with the analysis. The first-order difference of the series shows that all reject the null hypothesis at the 1% significance level. In other words, at first-order single integral sequences, I (1), the food price index, world crude oil price, and exchange rate are stationary. Thus, there is no pseudo regression problem, and we may use panel cointegration tests to detect the presence of a long-run relationship. If the two series have different integration orders, they cannot create a cointegrated series.

Table 3. The results of the panel data unit root tests for the series.

Variables	LLC	IPS	ADF-Fisher Chi-square	PP- Fisher Chi Square
Level				
Food Price	1.10 [0.86]	4.36 [1.00]	1.51 [0.99]	0.38 [1.00]
Oil Price	-0.57 [0.28]	-0.55 [0.29]	9.33 [0.50]	9.45 [0.49]
Exchange rate	-0.04 [0.48]	1.32 [0.91]	4.53 [0.92]	4.10 [0.94]
First Difference				
ΔFood Price	-3.69 [0.00]	-3.71 [0.00]	31.27 [0.00]	30.65 [0.00]
ΔOil Price	-8.66 [0.00]	-6.60 [0.00]	55.07 [0.00]	54.96 [0.00]
ΔExchange rate	-4.97 [0.00]	-4.81 [0.00]	40.29 [0.00]	40.73 [0.00]

Note: LLC = Levin, Lin & Chu t, IPS = Im, Pesaran and Shin W-stat, ADF = Augmented-Dickey Fuller, PP = Philips-Perron, Δ denotes the first-order difference, values in [ ] denote probability of significance.

Table 4. Kao residual cointegration test.

Test	t-statistic	Probability
ADF	-0.29	0.39

Note: ADF = Augmented-Dickey Fuller.

Table 5. Pedroni residual cointegration test.

Tests	Statistic	Weighted Statistic
Panel v-statistic	0.51 [0.30]	-0.13 [0.55]
Panel rho-statistic	-0.92 [0.18]	-0.28 [0.39]
Panel pp-statistic	-2.11 [0.02]*	-1.54 [0.06]
Panel ADF-statistic	-0.17 [0.43]	0.07 [0.53]
Group rho-statistic	0.48 [0.69]	-
Group pp-statistic	-1.39 [0.08]	-
Group ADF-statistic	0.61 [0.72]	-

Note: Values in [ ] denote probability of significance. * denotes 5% significant level.

Table 4 shows the result of the Kao Residual Cointegration test, which is used to test the null hypothesis that there is no cointegration relationship. Because the probability value is more than 5%, the test result cannot reject the null hypothesis. We can clearly infer that there is no cointegration or long-run relationship between the variables. Furthermore, as indicated in Table 5, the Pedroni cointegration test is employed to assess the robustness of the cointegration test. Thus, we may also infer that there is no cointegration in six of the seven Pedroni tests since the null hypothesis cannot be rejected because the p-value is larger than the 5% level of significance. The variables are not cointegrated, so we have omitted long-term causality from our study and focused on short-term causality, which is the next step to estimating panel VAR.

When estimating the panel VAR model, it is also necessary to select the optimal lag order and evaluate the serial correlation among the variables included in the model. After verifying for cointegration, the panel VAR model is estimated with two lag periods using Akaike's information criteria (AIC), which is then used for the rest of the modeling procedure.

The Lagrange Multiplier (LM) diagnostic test is given in Table 6 as a technique for validating the serial correlation of the residuals. The test yielded a probability larger than 0.05 percent, so H_0 cannot be rejected, and there is no autocorrelation in the model at lag order 2 based on AIC. Besides that, it is important to evaluate whether the panel VAR model is stable.

When all inverse roots of the AR polynomial have modulus less than one and all eigenvalues fall inside the unit circle, the model is said to be stable. Otherwise, it seems that the model does not fulfill the stability condition. If the panel VAR model is not stable, several analyses on it may be invalid. Figure 3 depicts the polynomial roots of the autoregressive process, suggesting that the model is stable and the estimation results may be assessed. Figure 3 and Table 7 both indicate that the panel VAR is invertible and has an infinite-order vector moving average (VMA) representation when the moduli of the companion matrix are all less than one.

Table 6. VAR residual serial correlation LM tests.

Lag	Rao F-stat
1	1. 19 [0.30]
2	1.10 [0.36]

Note: Lagrange Multiplier (LM). Values in [ ] denote probability of significance.

Table 7. Roots of characteristic polynomial.

Endogenous variables: D(FP) D(COP) D(ER)	
Root	**Modulus**
0.64	0.64
0.02 – 0.53i	0.53
0.02 + 0.53i	0.53
0.12 – 0.28i	0.31
0.12 + 0.28i	0.31
-0.22	0.22

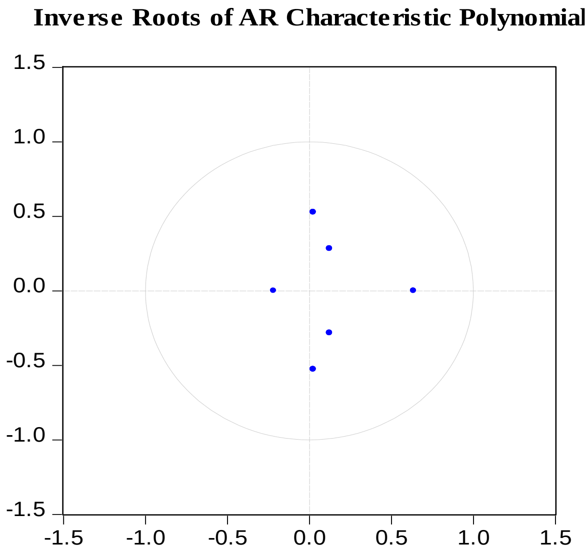

Figure 3. Panel VAR stability test.

Impulse response functions (IRFs) for the corresponding panel VAR models are generated for further investigation. The IRF test is used to explore the temporal trend of food prices in emerging Southeast Asian countries in response to a one standard deviation variation in the oil price and exchange rate. In this study, the confidence bands for the impulse response function are produced by Monte Carlo simulation methods based on 100 draws. Figure 4 illustrates an analysis of impulse response functions, which demonstrate how food prices respond to changes in oil prices and exchange rates. The horizontal axis for each graph is in time units, years in this context; therefore, the response function is given over a ten-year period. The units of the variables are shown on the vertical axis. The left panel of Figure 4 demonstrates that the response of food prices to an increase in the price of oil is positive from the first period and continues to be positive until period ten, i.e., when the price of oil rises by one standard deviation, the price of food rises as well. When the price of crude oil rises, so does the cost of agricultural and food production, and suppliers will immediately raise food prices to compensate for the loss of profit. The findings of Baffes (2007); Harri et al. (2009); Chen et al. (2010); Baffes and Dennis (2013); Ibrahim (2015), and Taghizadeh-Hesary et al. (2019) all corroborate the strong influence of oil prices on agricultural food prices. Similarly, the right panel of Figure 4 shows that food prices respond positively to exchange rate shocks, which is consistent with the findings of Huh and Park (2013), who discovered that most domestic food prices in eleven developing Asian countries increased as a result of a positive exchange rate shock. This means that any significant increase in the value of the currency leads to an increase in food prices.

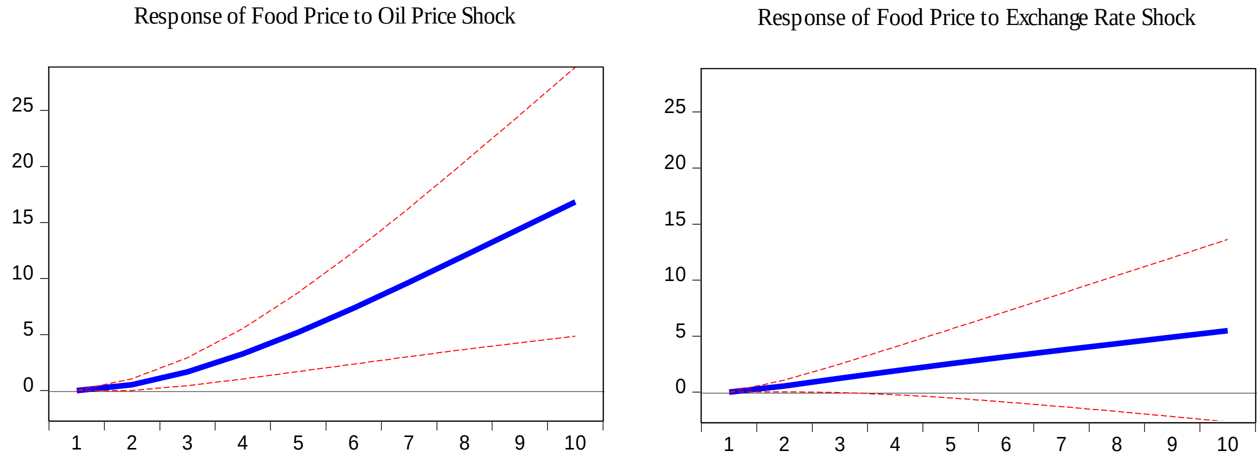

Figure 4. Accumulated response of food price to WTI oil price and exchange rate shocks.

Note: Upper and lower red dashed lines represent the confidence intervals. Decomposition method is Cholesky adjusted of one standard shock with two standard error bands.

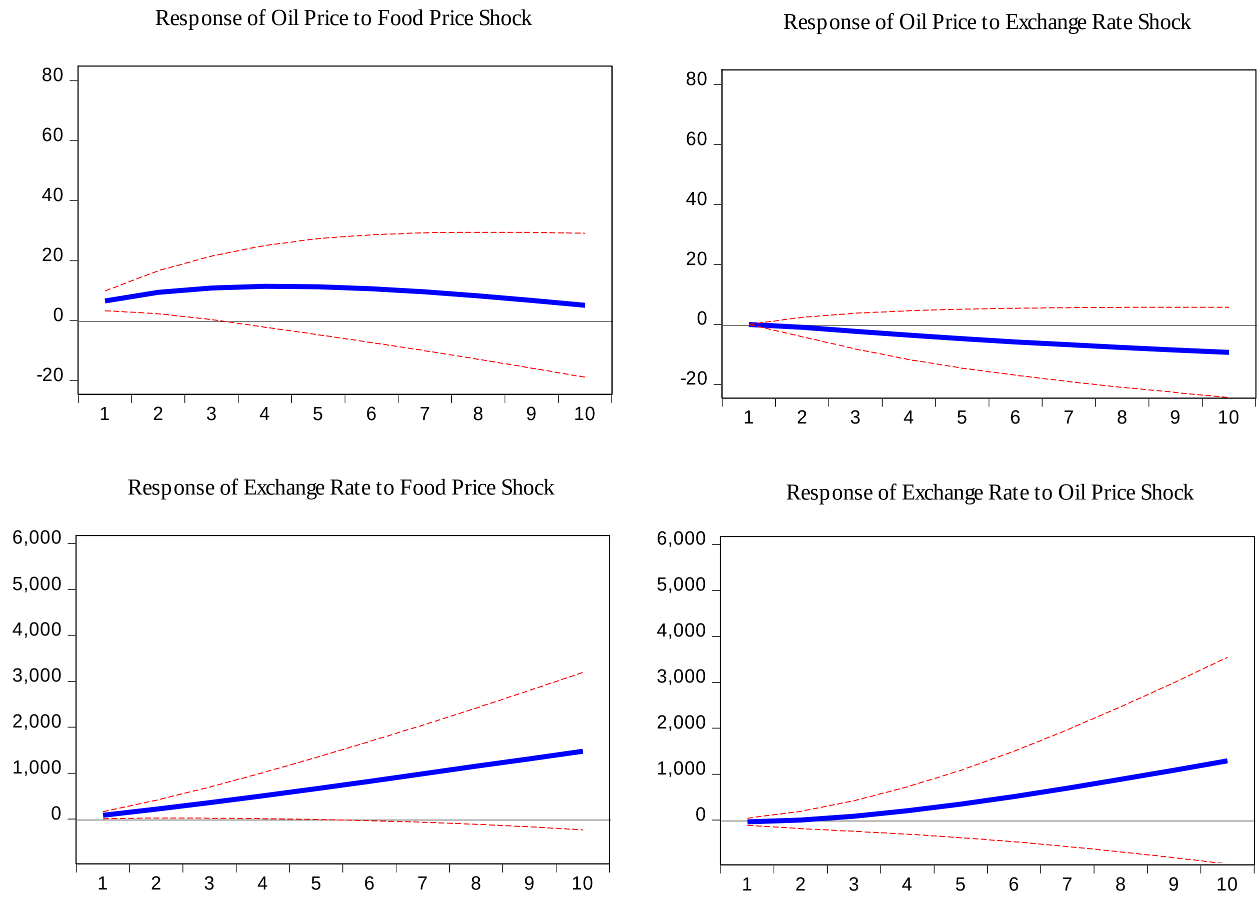

Figure 5. Accumulated response of WTI crude oil price and exchange rate to different shocks.

Note: Upper and lower red dashed lines represent the confidence intervals. Decomposition method is Cholesky adjusted of one standard shock with two standard error bands.

Furthermore, as shown in Figure 5, the study includes further analysis on the accumulated response of macroeconomic variables (oil price and exchange rate) to the impulses of other variables. The graphs on the upper left and right sides show how oil prices react to food price and exchange rate shocks, respectively. From the first through the sixth period, the oil price rises in response to an increase in food prices and then begins to fall gradually beginning with the seventh period. Conversely, the oil price shows a negative response to the exchange rate impulse. Oil prices fall precipitously in response to a one standard deviation rise in exchange rate shocks. This discovery is identical to the findings of Akram (2004) and Zhang, Fan, Tsai, and Wei (2008), who discovered a negative response of oil prices to exchange rate shocks, indicating that as the value of the US dollar falls, crude oil prices rise. The accumulated response of the exchange rate to shocks of different impulses (food and oil prices) is illustrated on the bottom left and right sides of Figure 5. Both plots demonstrate positive exchange rate responses to both food and oil price shocks. The positive reaction of the exchange rate to any oil price shock is in tandem with the findings of Amano and Van Norden (1998), Bénassy-Quéré, Mignon, and Penot (2007) and Huang and Feng (2007). As the price of oil rises, so do food prices, which in turn increases the exchange rate. Kisswani, Harraf, and Kisswani (2019) estimated NARDL analysis of positive and negative shocks found that an increase in oil prices leads the US dollar to appreciate (depreciate in the national currency), whereas a decline in oil prices causes the US dollar to depreciate (appreciation in the national currency).

Table 8. Forecast error variance decomposition of food price to shocks.

Period	Food price	Oil price	Exchange rate
1	100.00	0.00	0.00
2	96.36	1.73	1.91
3	91.58	5.69	2.77
4	87.02	10.05	2.93
5	83.00	14.10	2.90
6	79.56	17.63	2.81
7	76.66	20.61	2.73
8	74.21	23.12	2.66
9	72.15	25.23	2.62
10	70.41	27.00	2.59

Note: Standard errors is Monte Carlo (100 repetitions).

To generate more dynamic findings, the forecast error variance decomposition approach is used to analyze the contributions of each shock source to the forecast error variance of each endogenous variable over a certain time horizon. The variation of forecast error increases when the forecast horizon is extended. Table 8 shows the food price variance decomposition analysis over a ten-year time horizon, indicating how much the price of food in five Southeast Asian nations is explained by innovation from both oil prices and exchange rates. In period 1, there is just one shock that generates a forecast error. The forecast error variance of food prices is 100 percent because of its own shock, i.e., the volatility of both the oil price and exchange rate have no contemporaneous effect on food prices in the first period, clearly indicated by the 0 percent. In the short-term, say in year three, the food price fluctuation has a substantial and major share in food price volatilities (own shock) and accounts for 91.58 percent, the shock to oil price explains 5.69 percent, and 2.77 percent of the shocks are from exchange rates, i.e., prior accumulated inflation in food prices causes future inflation in food prices. The short-run fluctuation in domestic food prices is primarily explained by its own shock across nations, corroborating the findings of Huh and Park (2013), while in the long-term, in year ten, the shock to food prices can contribute 70.41 percent of its own shock, the shock to oil prices explains 27 percent, and the exchange rate explains just 2.59 percent. The findings assume that this is due to government initiatives aimed at mitigating the impact of global food price fluctuations on domestic markets. For example, Indonesia and Vietnam have imposed restrictions on rice exports or raised export duties. In a nutshell, one of the most significant shocks to food prices is the rise in food prices themselves. However, the proportionate contribution of its own shocks declines with time in parallel with the diminishing and increasing effect of the exchange rate and the oil price shocks in explaining the variation of food prices, respectively.

5. CONCLUSION AND SUGGESTION

Crude oil prices and currency fluctuations influence both imported and domestically produced food prices. Many governments, politicians, and economists are particularly interested in assessing the food price increase in light of the recent volatility in global oil prices and exchange rates as a result of the COVID-19 pandemic and the Ukraine war crisis. Using a panel vector autoregression approach, this paper empirically examines the response of food price fluctuations to crude oil prices and exchange rate volatility in five emerging Southeast Asian countries, namely Indonesia, Malaysia, the Philippines, Thailand, and Vietnam, from 2000 to 2020. The study uses impulse response function and variance decomposition techniques of the panel VAR model to answer the study's research questions. Based on the findings of the impulse response analysis, the study finds that the response of food prices to oil price shocks is positive. Food prices rise dramatically in response to a one-standard-deviation shock to the global oil price. In addition to global oil prices, the study analyses the exchange rate as a key economic shock impacting agricultural commodity prices. Changes in the prices of imported commodities, including both finished goods and raw resources, can have a direct influence on local prices. As certain Southeast Asian food items are imported, exchange rate volatility is likely to have an effect on food prices. The finding of the impulse response function reveals that any exchange rate shocks cause the consumer price of food index to respond positively. This means that if the exchange rate rises, so will the cost of imports, putting upward pressure on food prices.

The contribution and relative importance of oil prices and exchange rates on food prices may be discovered using variance decomposition. The research subsequently examines the variance decomposition of the VAR model in identifying the impact of exchange rate and oil price shocks in explaining the behavior of food prices across the sample period. The variance in food prices is mostly explained by its own shocks. In the short-term, for instance, in the third period, the food price variation is explained by its own shocks of approximately 91.58 percent, exchange rate shocks of approximately 2.77 percent, and oil price shocks of approximately 5.69 percent. Overall, we can observe that the influence of WTI crude oil price on food price increases with time, but the effect of exchange rate on food price slightly declines. The contribution of oil price shocks to food price variations is found to be higher than exchange rate shocks on food prices. Hence, the findings of the impulse response function and variance decomposition analysis would provide hints for better understanding the current dynamics of food prices, as well as implications for local and global policymakers for the development of national and international policies to improve food security in the region and other developing economies through food price stability and accessibility. Because of the rising trend of trade openness and the high reliance on food imports, emerging Southeast Asian economies may be more vulnerable to oil and global food crises. Understanding the oil price and exchange rate factors that lead to rising food prices in emerging markets is therefore crucial, not only for developing social welfare policies but also for emerging Southeast Asia's food trade policies. The study thus proposes that policymakers in the five nations discussed be concerned about the impact of rising oil prices and exchange rates on food prices, as these are crucial variables that may undermine price stability and exacerbate food security. Governments should also minimize their reliance on food imports, as exchange rate fluctuations have a substantial impact on the prices of both imported and domestic commodities. This study also suggests the following next research directions. Despite the hopeful results of this study, it is only the first step toward developing a more comprehensive empirical research that might possibly include more factors, data, and empirical approaches characteristic of robust findings on the drivers of food price volatility. This means further research on the interaction of food prices with supply-side and other macroeconomic shock factors is needed. Climate change, biofuels policy, agricultural market speculation, and food derivatives, for example, would raise food production costs because of high energy prices and currency volatility. Higher oil prices encourage the use of agricultural products for biofuel energy production, but they also increase the costs of food production and, as a result, world food prices. Tirado, Cohen, Aberman, Meerman, and Thompson (2010) emphasized the impact of climate change and biofuel production on food and nutritional security. Furthermore, an extension of this paper can also be enacted by adding exports and imports to the model, since these variables may also affect the exchange rate.

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