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Global commodity price shocks and Indonesia's exchange rate dynamics during the Russia-Ukraine conflict: A VECM analysis

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ABSTRACT

The Russia–Ukraine conflict has disrupted global commodity markets, particularly crude oil, natural gas, wheat, and corn, leading to increased price volatility and affecting exchange rate dynamics. This study aims to analyze the Granger-causal relationship between global commodity prices and the USD/IDR exchange rate using the Vector Error Correction Model (VECM). Monthly data from November 2013 to September 2023 are employed to examine both short-run dynamics and long-run equilibrium relationships. The results show that, in the long run, crude oil prices have a negative relationship with the USD/IDR exchange rate, indicating an appreciation of the Indonesian Rupiah, while natural gas, wheat, and corn prices have positive effects, contributing to currency depreciation. In the short run, only crude oil prices significantly influence the exchange rate. The Granger causality test reveals a unidirectional relationship from crude oil prices to the exchange rate. Furthermore, the model demonstrates high predictive accuracy, with MAPE values of 1.54% (exchange rate), 6.91% (crude oil), 10.54% (natural gas), 6.92% (wheat), and 4.50% (corn). These findings highlight the dominant role of energy commodities and confirm that global commodity shocks significantly influence exchange rate movements, providing important insights for policymakers in managing economic stability.

1. Introduction

The conflict between Russia and Ukraine has become one of the most significant geopolitical events affecting global economic stability in recent years (Wang et al., 2023). Since 2013, this conflict has been triggered by the Ukrainian President's rejection of a monetary agreement with the European Union under pressure from Russia, which then retaliated by seizing the Crimean region (Rusydiana et al., 2019). Russia's actions triggered economic sanctions from Western countries, which had a widespread impact on global trade, particularly in commodity trading (Logayah et al., 2023). This conflict not only impacts political and security sectors but also disrupts global markets, particularly commodity markets (Wang et al., 2023). Ukraine and Russia are significant producers of global commodities, including crude oil, natural gas, wheat, and corn. Russia ranks second in natural gas exports and third in crude oil exports (Handayani & Purba, 2022). At the same time, Ukraine ranks fifth in wheat exports and fourth in corn exports, according to the European Commission (Krismawati & Fitriyani, 2022). This conflict has disrupted production and supply of the commodity, triggering shortages and price increases in international markets (Alam et al., 2022). The prices of crude oil, natural gas, wheat, and corn have increased from before the conflict (2010-2012) to the conflict period (2013-2023), with an average price increase of 1.06% for crude oil, 3.20% for natural gas, 3.51% for wheat, and 1.09% for corn (Investing, 2023a). These disruptions have intensified volatility in international commodity prices and created uncertainty in global trade dynamics (Logayah et al., 2023).

The rising volatility of global commodity prices has become a critical issue, as it directly affects macroeconomic stability, particularly in developing countries such as Indonesia. As a country that relies on energy imports while exporting certain commodities, Indonesia is highly vulnerable to global price fluctuations. Increasing commodity prices tend to elevate import costs, which may trigger inflation and lead to currency depreciation (Saragih, 2019). In addition, global uncertainty stemming from geopolitical conflicts often increases demand for safe-haven assets such as the U.S. dollar, further strengthening the USD against emerging-market currencies, including the Indonesian Rupiah (Danuwijaya et al., 2022). Currently, the average USD exchange rate has increased by 50.11% from before the conflict (2010-2012) to during the conflict (2013-2023) (Kurniawan & A'yun, 2022). Therefore, understanding the relationship between global commodity prices and exchange rates is essential for maintaining economic stability and formulating appropriate policy responses.

Performing causal analysis is essential for understanding the dynamic relationships among macroeconomic variables, particularly amid rising commodity prices, exchange rate fluctuations, supply uncertainty, and heightened global demand. Previous studies have extensively examined the interaction between commodity prices and exchange rates using various econometric approaches. For instance, Xu & Zhang (2021) identified a bidirectional causal relationship between commodity prices and exchange rates across countries, indicating mutual interdependence between these variables. Similarly, Nazlioglu & Soytas (2012) found that oil prices significantly influence exchange rates and agricultural commodity prices; however, they reported no causal relationship from exchange rates to certain commodity prices, suggesting asymmetric dynamics. These findings highlight that the relationship between commodity prices and exchange rates is complex and may vary by commodity type and economic conditions. Given this complexity, it is necessary to employ an analytical approach that is capable of capturing both causal interactions and dynamic adjustments among variables. One of the most appropriate methods for this purpose is the Vector Error Correction Model (VECM) captures both short-run dynamics and long-run equilibrium relationships.

The Vector Error Correction Model (VECM) has also been widely adopted to capture both short-run adjustments and long-run equilibrium relationships (Farida & Wulandari, 2020; Saputra & Sukmawati, 2021; Farida et al., 2023). For example, Kolo & Tzanova (2017) demonstrated that economic growth significantly affects import volumes alongside exchange rate dynamics, while Haqiq & Pharmasetiawan (2019) confirmed the effectiveness of VECM in modeling causal relationships between international tourism, price indices, and exchange rates. Despite these contributions, most prior studies focus on general macroeconomic conditions and do not explicitly incorporate geopolitical shocks as exogenous drivers. In particular, the impact of the Russia–Ukraine conflict on global commodity price volatility and its transmission to exchange rate movements remains underexplored. Therefore, integrating geopolitical factors into causality analysis is crucial to provide a more comprehensive understanding of how external shocks propagate through commodity markets and influence exchange rate dynamics in both the short and long run.

Given this gap, this study aims to provide a more comprehensive analysis by explicitly incorporating the Russia–Ukraine conflict as a contextual factor shaping global commodity prices and exchange rate dynamics. The novelty of this research lies in its integration of multiple key global commodities—crude oil, natural gas, wheat, and corn—within a single analytical framework, while simultaneously examining their causal relationship with the USD/IDR exchange rate within the context of heightened geopolitical uncertainty associated with the Russia–Ukraine conflict. In addition, this study utilizes the VECM approach to capture both short-run adjustments and long-run equilibrium relationships among variables. This approach provides a deeper understanding of how external shocks, such as geopolitical conflicts, propagate through commodity markets and affect exchange rates. The contribution of this study is twofold. First, it provides empirical evidence on the dynamic causal relationship between global commodity prices and the USD/IDR exchange rate amid geopolitical instability. Second, it offers policymakers practical insights for designing strategies to mitigate the impact of global shocks on domestic economic stability. By understanding the transmission mechanism between commodity prices and exchange rates, governments and stakeholders can develop more effective policies to manage inflation, stabilize currency movements, and anticipate future economic risks.

2. Method

This study used secondary monthly time series spanning from November 2013 to September 2023. The data sources used are crude oil prices (Oil), natural gas prices (Gas), wheat prices (WP), corn prices (CP), and the USD/IDR exchange rate (ER), obtained from the website Investing (2023b). This study used the Vector Error Correction model (VECM), an extension of the Vector Autoregressive (VAR) model designed for cointegrated, non-stationary time series, enabling simultaneous analysis of long-run equilibrium relationships and short-run dynamics. VECM offers several advantages, particularly its ability to incorporate the Error Correction Term (ECT), which captures the speed of adjustment toward long-run equilibrium following short-run deviations. In addition, VECM is well-suited for handling non-stationary but cointegrated data, making it more appropriate than conventional VAR models when stable long-run relationships exist (Liang & Schienle, 2019; Shao et al., 2021). The model also enables the identification of predictive relationships among variables through Granger causality analysis and supports dynamic analysis using Impulse Response Function (IRF) and Variance Decomposition (VD) to evaluate the impact of shocks over time (Thierry et al., 2016). Furthermore, VECM has demonstrated reliable forecasting performance in various empirical studies (Farida & Wulandari, 2020; Farida et al., 2023), making it a robust approach for analyzing the dynamic interaction between global commodity prices and exchange rates.

According to Chong et al (2026) the first step in VECM is assessing variable stationarity using the Augmented Dickey-Fuller (ADF) unit root test. The analysis proceeded in several stages. First, the ADF unit root test was conducted to assess the stationarity of each series. Second, the Johansen cointegration test was employed to determine whether a long-run equilibrium relationship existed among the variables. Third, the optimal lag length was selected using the Akaike Information Criterion (AIC) and Schwarz Criterion (SC). The VECM was then estimated, followed by Granger causality, impulse response function, and variance decomposition analyses. Finally, forecasting accuracy was evaluated using MAPE. The MAPE calculating predictions from the optimal VECM model using the MAPE value. This research is anticipated to provide valuable insights to the government for developing economic and financial strategies (Gorgi et al., 2024; Purna et al., 2016). Here is the general equation of Vector Autoregressive (VAR) based on Bruns & Lütkepohl (2024):

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + \cdots + \beta_p Y_{t-p} + \varepsilon_t \quad (1)$$

where Y_t is vector $\mathrm{n} \times 1$ with n time variables t; Y_{t-p} vector $\mathrm{n} \times 1$ with n time variables $\mathrm{t} - \mathrm{i}$; $\alpha =$ vector of constants $\mathrm{n} \times 1$; β_1 is the matrix of parameter coefficients $\mathrm{n} \times \mathrm{n}$; $\mathrm{p} =$ lag in the equation; $\mathrm{t} =$ time; $\varepsilon =$ vector of residuals $\mathrm{n} \times 1$. The concepts of cointegration and error correction were first presented by Engle and Granger in 1987 (Liang & Schienle, 2019). Subsequently, Johansen and Juselius introduced the Vector Error Correction Model (VECM) in 1990, which provides a straightforward method for separating short- and long-run components in data. VECM is a VAR model with additional restrictions (Shao et al., 2021). These restrictions are necessary because the data are non-stationary and cointegrated. The primary feature of the VECM model is the inclusion of the Error Correction Term (ECT), a crucial component (Thierry et al., 2016). The ECT is a metric that reflects the short-run adjustments of variables toward long-run equilibrium; thus, the general structure of the VECM model, based on Kuo (2016) as follows:

$$Y_t = \alpha_{ot-1} + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \beta_3 \Delta Y_{t-3} + \cdots + \beta_p \Delta Y_{t-p} + \varepsilon_t \quad (2)$$

The Mean Absolute Percentage Error (MAPE) is employed to evaluate the forecasting model's accuracy in this investigation. MAPE represents the mean absolute deviation between forecasted and actual values, expressed as a percentage of the actual value (de Myttenaere et al., 2016). The advantage of using MAPE in this research is that it presents error rates as percentages, which facilitates interpretation (Suryatin et al., 2024). A lower MAPE value indicates lower error (Kim & Kim, 2016). Thus, the calculation of the MAPE value based on Choi et al (2023):

$$MAPE = \frac{1}{n} \sum_{i=t}^{n} \left| \frac{Y_t - \bar{Y}_t}{Y_t} \right| x100 \quad (3)$$

where: Y_t = actual value at time t; $\widehat{Y}_t$ = predicted value at time t; n = number of data.

3. Results and Discussion

A descriptive statistical analysis was performed to provide an overview of the data distribution and behavior before conducting a VAR/VECM analysis. The results of this analysis are the average (mean), median, maximum, minimum, and standard deviation values for each variable. Table 1 shows that all variables exhibit considerable variability and volatility throughout the observation period. Both global commodity prices and the USD/IDR exchange rate exhibit significant volatility, reflecting their sensitivity to external shocks and changing global economic conditions. The presence of noticeable dispersion suggests that the data are not evenly distributed and may contain extreme values at certain times, suggesting potential asymmetry in the distribution. This overall pattern highlights the dynamic nature of the variables and underscores the importance of employing a robust time-series approach, such as a VECM, to effectively capture both short-run movements and long-run relationships among them.

Table 1. Descriptive Statistics

Variables	Oil	Gas	WP	CP	ER
Mean	14051.41	68.73353	3.78675	359.5050	471.7479
Median	14217.50	63.81000	3.09800	312.2500	398.5000
Maximum	16640.00	130.5000	10.02800	811.0000	827.0000
Minimum	11662.50	29.13000	1.86400	180.0000	330.7500
Std. Dev.	10249.90	21.41629	1.77770	139.6128	137.9756
Observations	119	119	119	119	119

Source: data processed

The conventional technique for assessing data stationarity is the unit root test. The often employed unit root test is the Augmented Dickey-Fuller (ADF) test, which posits the following hypotheses: The null hypothesis (H_0) of the ADF test states that the series contains a unit root and is therefore non-stationary, whereas the alternative hypothesis (H_1) indicates that the series is stationary. H_0 is rejected when the p-value is less than 0.05. Table 2 show At level, all variables have p-values greater than 0.05; therefore, the null hypothesis cannot be rejected, indicating that the series are non-stationary.

Table 2. ADF Unit Root Test Results at Level

Variables	α	ADF statistic value	Level Mackinnon table value	P-value	Description
Exchange Rate USD/IDR	0.05	-1.805413	-2.886509	0.3763	Non-stationary
Crude Oil Prices	0.05	-1.698981	-2.886074	0.4292	Non-stationary
Natural Gas Prices	0.05	-2.101199	-2.886074	0.2447	Non-stationary
Wheat Prices	0.05	-1.859681	-2.886290	0.3503	Non-stationary
Corn Prices	0.05	-1.862241	-2.886290	0.3491	Non-stationary

Source: data processed

Table 2 shows the ADF statistic values (absolute) for the USD/IDR exchange rate, crude oil prices, natural gas prices, wheat prices, and corn prices are less than the absolute McKinnon critical values, with p-values exceeding 0.05. Fail to reject H_0, suggesting that the data is non-stationary. A stationarity assessment was conducted at the first-difference level, as the five variables are non-stationary in levels. Ensuring stationarity is crucial in time series analysis because non-stationary data can lead to spurious regression results, where relationships between variables appear significant but are actually misleading. Moreover, stationarity is a fundamental assumption in VAR/VECM modeling, as it ensures stable statistical properties over time, enabling more reliable estimation, valid inference, and accurate forecasting of the relationships among variables. Table 3 presents the Augmented Dickey-Fuller (ADF) test in first differences. The ADF statistic values (absolute) for the exchange rate of USD/IDR, crude oil prices, natural gas prices, wheat prices, and corn prices exceed the critical values of McKinnon (absolute) and have a p-value less than 0.05. At first difference, all p-values are below 0.05; therefore, the null hypothesis is rejected, indicating that all variables are stationary. The stationary variables means that all variables has mean near of zero and constant variance.

Table 3. ADF Unit Root Test Results at First Difference

Variables	α	First Difference			Description
		ADF Stat	MacKinnon	P-value	
Exchange Rate USD/IDR	0.05	-9.902333	-2.886509	0.0000	Stationary
Crude Oil Prices	0.05	-9.429437	-2.886290	0.0000	Stationary
Natural Gas Prices	0.05	-10.10770	-2.886290	0.0000	Stationary
Wheat Prices	0.05	-8.874648	-2.886290	0.0000	Stationary
Corn Prices	0.05	-8.387607	-2.886290	0.0000	Stationary

Source: data processed

The Johansen Cointegration Test is the most frequently used cointegration test in VAR/VECM methodologies. The Johansen cointegration test's testing requirements and assumptions are delineated below. If the trace statistics and max-eigen statistic values are less than the critical value of 5%, H_0 is considered acceptable (no cointegration). If the trace and max-eigenvalue statistics exceed the 5% critical value, the hypothesis H_1 is accepted (cointegration exists). Table 4 shows both the trace statistic and the maximum eigenvalue statistic exceed the 5% critical value. Consequently, H_0 is rejected, indicating the presence of five cointegrating correlations among the USD/IDR exchange rate variables, crude oil prices, natural gas prices, wheat prices, and corn prices. The Vector Error Correction Model is employed in VAR modeling to account for cointegration. Vector Error Correction Model (VECM).

Table 4. Johansen Cointegration Test Results

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized	Eigenvalue	Trace statistic	Critical Value of 0.05	Probability
None *	0.387339	208.1990	60.06141	0.0000
At most 1 *	0.375345	151.8554	40.17493	0.0000
At most 2 *	0.290000	97.74157	24.27596	0.0000
At most 3 *	0.237737	58.35514	12.32090	0.0000
At most 4 *	0.210198	27.13685	4.129906	0.0000
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized	Eigenvalue	Max-Eigen Statistic	Critical Value of 0.05	Probability
None *	0.387339	56.34353	30.43961	0.0000
At most 1 *	0.375345	54.11387	24.15921	0.0000
At most 2 *	0.290000	39.38642	17.79730	0.0000
At most 3 *	0.237737	31.21830	11.22480	0.0000
At most 4 *	0.210198	27.13685	4.129906	0.0000

Source: data processed

Identifying the optimal lag facilitates the examination of variable responses and mitigates autocorrelation within the VAR/VECM framework. This study employs the AIC and S.C. criteria to determine the optimal lag length. Table 5 shows the smallest values for the AIC and S.C. criterion with an asterisk. The minimum AIC and SC. values occur at lags 1 and 2, respectively.

Table 5. Optimal Lag Length Selection

Lag	LogL	AIC	SC	Lag	LogL	AIC	SC
0	-2381.882	43.39786	43.52061*	5	-2265.534	43.55516	46.74664
1	-2355.677	43.37595	44.11244	6	-2240.727	43.55868	47.36390
2	-2319.621	43.17493*	44.52517	7	-2213.267	43.51394	47.93291
3	-2297.413	43.22568	45.18967	8	-2185.146	43.45720	48.48992
4	-2274.827	43.26957	45.84731				

Source: data processed

Table 6 presents the short-run and long-run estimates of the VECM for the USD/IDR exchange rate, crude oil prices, natural gas prices, wheat prices, and corn prices. The VECM model's estimation results are not only statistically significant but also provide meaningful economic interpretations. In the long run, crude oil prices negatively affect the USD/IDR exchange rate, suggesting that higher global oil prices tend to strengthen the Indonesian Rupiah. This phenomenon can be explained by Indonesia's position in global commodity markets, where rising oil prices may boost export revenues and foreign exchange inflows, thereby supporting currency appreciation (Handayani & Purba, 2022). Conversely, natural gas, wheat, and corn prices show a positive relationship with the exchange rate, implying that increases in these commodity prices are associated with Rupiah depreciation. This can be linked to Indonesia's dependence on imports for essential commodities, where rising global prices increase import costs, deteriorate the trade balance, and exert downward pressure on the domestic currency (Saragih, 2019; Danuwijaya et al., 2022).

Table 6. VECM Estimation Results

Variables	ER	Oil	Gas	WP	CP
Short-Run Estimation					
	Dependent Variable				
CointEq1	-0.383462 [-5.17024]	0.003314 [2.42006]	-0.000528 [-3.75130]	-0.007472 [-0.94416]	-0.005589 [-0.68606]
ER(-1)	-0.218548 [-2.60613]*	-0.004250 [-2.74460]*	0.000357 [2.24573]*	0.017818 [1.99123]*	0.000343 [0.03729]
ER(-2)	-0.368251 [-4.47831]*	-0.002969 [-1.95552]	0.000356 [2.28572]*	0.005685 [0.64795]	-0.011034 [-1.22178]
Oil(-1)	-33.20346 [-4.29508]*	-0.271439 [-1.90166]	-0.049120 [-3.35100]*	1.146644 [1.39006]	0.191436 [0.22547]
Oil(-2)	-17.11602 [-2.68302]*	-0.107217 [-0.91025]	-0.007754 [-0.64103]	-1.518640 [-2.23097]*	0.044936 [0.06413]
Gas(-1)	119.9862 [2.42598]*	-1.691898 [-1.85269]	-0.461889 [-4.92514]*	17.36804 [3.29097]*	0.550756 [0.10139]
Gas(-2)	48.74504 [1.02868]	1.693242 [1.93527]	-0.333957 [-3.71677]*	3.531657 [0.69847]	1.620880 [0.31144]
WP(-1)	1.962963 [1.94858]	-0.006427 [-0.34552]	0.000294 [0.15412]	-0.329677 [-3.06699]*	0.123995 [1.12069]
WP(-2)	-0.603054 [-0.74773]	-0.018829 [-1.26445]	0.000115 [0.07514]	-0.184598 [-2.14505]*	-0.057759 [-0.65205]
CP(-1)	1.444866 [1.56590]	-0.019254 [-1.13014]	-4.64E-05 [-0.02651]	-0.004313 [-0.04381]	-0.509856 [-5.03103]*
CP(-2)	1.169488 [1.33047]	-0.014562 [-0.89722]	0.001863 [1.11768]	-0.078957 [-0.84182]	-0.274248 [-2.84070]*
C	6.154353 [0.17751]	0.041499 [0.06483]	-0.009728 [-0.14797]	-1.031041 [-0.27870]	-1.023944 [-0.26890]
R-squared	0.529037	0.440028	0.507492	0.486296	0.285710
Long-Run Estimation					
ER(-1)			1.0000		
Oil(-1)			-110.0932 [-6.07329]		
Gas(-1)			657.5578 [4.13961]		
WP(-1)			6.960168 [2.88908]		
CP(-1)			6.824518 [2.52168]		

Source: data processed

Table 6 shows that, in the short run, only crude oil prices have a statistically significant relationship with the USD/IDR exchange rate, suggesting that oil price fluctuations are more rapidly transmitted to exchange rates than those of other commodities. Economically, this is reasonable given that oil is a strategic commodity that directly influences production costs, inflation, and global market sentiment. Meanwhile, other commodities such as natural gas, wheat, and corn may require a longer transmission mechanism through trade channels before affecting exchange rate dynamics. From an economic perspective, each variable plays a distinct role in the system: crude oil acts as a key driver of global energy markets and macroeconomic stability; natural gas influences industrial production costs and energy demand; wheat and corn represent essential agricultural commodities affecting food security and inflation; and the USD/IDR exchange rate reflects overall macroeconomic conditions, including trade balance and external shocks. These findings are consistent with previous studies that highlight the interconnectedness between commodity prices and exchange rate dynamics (Nazlioglu & Soytas, 2012; Xu & Zhang, 2021), reinforcing the importance of incorporating multiple commodities into analyses of exchange rate behavior. The Granger Causality Test assesses whether a relationship between variables is reciprocal.

Table 7. Granger Causality Test Results

Null Hypothesis:	Obs	F-Statistic	Prob.	Description
Crude Oil Prices Do Not Granger-Cause The Exchange Rate	117	0.45175	0.0477*	A one-way causal relationship exists between the USD/IDR exchange rate and crude oil prices.
Exchange Rate Does Not Granger-Cause Crude Oil Prices		2.62074	0.4722	
Natural Gas Prices Do Not Granger-Cause the Exchange Rate	117	0.17643	0.08385	There is no causal relationship between natural gas prices and the USD/IDR exchange rate.
Exchange Rate Does Not Granger-cause Natural Gas Prices		0.36839	0.6927	
Wheat Prices Do Not Granger-Cause Exchange Rate	117	0.74686	0.4762	There is no causal relationship between wheat prices and the USD/IDR exchange rate.
Exchange Rate Does Not Granger Cause Wheat Prices		1.27748	0.2828	
Corn Prices Do Not Granger-Cause Exchange Rate	117	0.98595	0.3763	There is no causal relationship between corn prices and the USD/IDR exchange rate.
Exchange Rate Does Granger-Cause Corn Prices		0.55119	0.5778	
Natural Gas Prices Do Not Granger-Cause Crude Oil Prices.	117	0.38400	0.6820	A one-way causal relationship exists between crude oil prices and natural gas prices.
Crude Oil Prices Do Not Granger-Cause Natural Gas Prices		5.48035	0.0054*	
Wheat Prices Do Not Granger-Cause Crude Oil Prices.	117	9.60471	0.0001*	There is a bidirectional causal relationship between wheat prices and crude oil prices.
Crude Oil Prices Do Not Granger-Cause Wheat Prices		5.44822	0.0055*	
Corn Prices Do Not Granger-Cause Crude Oil Prices.	117	2.42987	0.0927	There is no causal relationship between corn prices and crude oil prices.
Crude Oil Prices Do Not Granger-Cause Corn Prices		1.59734	0.2070	
Wheat Prices Do Not Granger-Cause Natural Gas Prices	117	10.9533	5.E-05	There is a one-way causal relationship between natural gas prices and wheat prices.
Natural Gas Prices Do Not Granger-Cause Wheat Prices		6.73063	0.0017*	
Corn Prices Do Not Granger-Cause Natural Gas Prices	117	3.47492	0.0343*	There is a one-way causal relationship between corn prices and natural gas prices.
Natural Gas Prices Do Not Granger-Cause Corn Prices		1.20712	0.3029	
Corn Prices Do Not Granger-Cause Wheat Prices	117	0.98497	0.3767	There is a one-way causal relationship between wheat prices and corn prices.
Wheat Prices Do Not Granger-Cause Corn Prices		4.16239	0.0180*	

Source: data processed

Table 7 shows a unidirectional granger-causal relationship between crude oil prices and the USD/IDR exchange rate. This study's results align with those of Nazlioglu & Soytas (2012), who found that crude oil prices significantly affect the USD/IDR exchange rate but not vice versa. The VAR results indicate that the USD/IDR exchange rate may rise in the near future as crude oil prices rise. Additionally, there is a unidirectional granger-causal relationship between crude oil and natural gas prices. This finding is consistent with the research by Butt et al (2020), which indicated that natural gas prices have a significant positive impact on the USD/IDR exchange rate in the short term. This suggests that currency appreciation may diminish as natural gas prices rise. Consequently, it is essential for the government to promptly regulate the foreign exchange market to reduce exchange rate volatility amid rising natural gas prices. A one-way granger-causal relationship exists between the prices of natural gas and wheat, between the prices of maize and natural gas, and between the prices of wheat and corn. These findings align with the research by Ramoroka & Muchopa (2022), who found that wheat and corn prices tend to rise despite fluctuations during specific periods, and that there is a one-way granger-causal relationship between their prices. Therefore, the producer's price of wheat can serve as an indicator for predicting the producer price of corn. Meanwhile, a two-way granger-causal relationship exists between wheat prices and crude oil prices. The Impulse Response Function (IRF) measures how a sudden change in one variable affects another over a set period of time. The IRF results for crude oil commodity prices are illustrated in Figure 1 that crude oil prices respond positively to shocks in crude oil, natural gas, wheat, and corn prices. In contrast, the reaction of crude oil prices to USD/IDR exchange-rate shocks fluctuates around the horizontal line, indicating inconsistency.

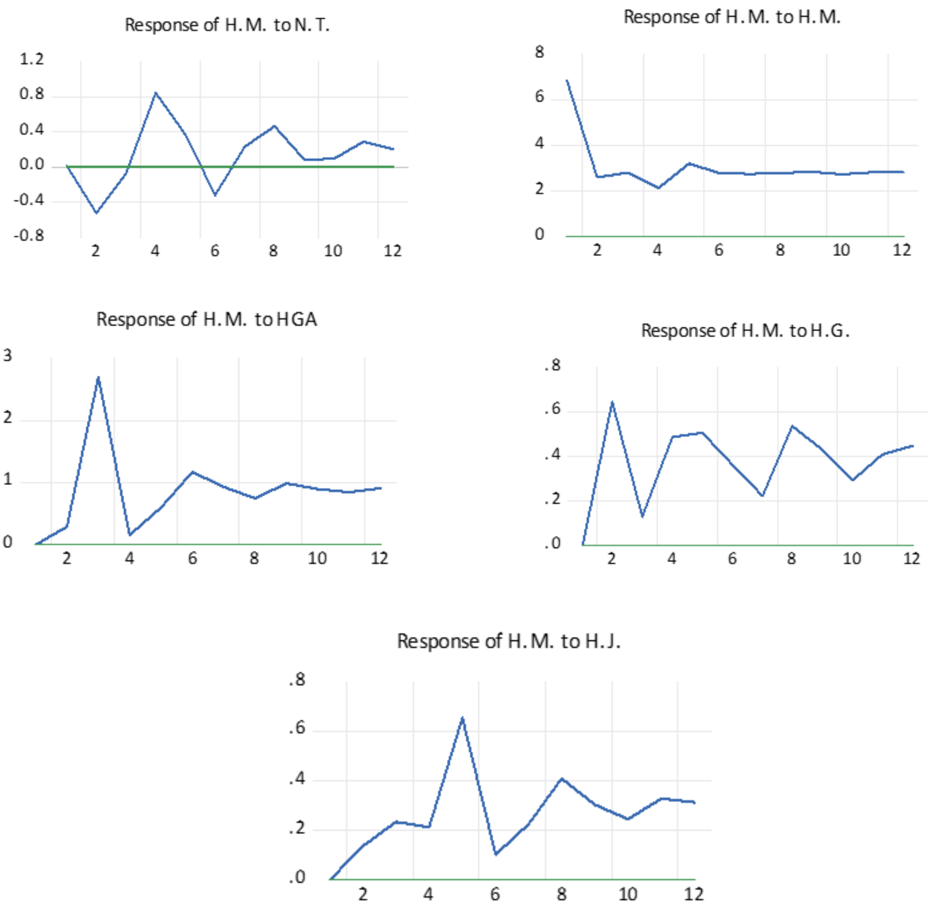

Figure 1. The Impulse Response Function of VECM

Figure 1 shows that the IRF analysis provides important insights into how the USD/IDR exchange rate responds dynamically to shocks in each commodity price variable. A positive shock to crude oil prices generally leads to a gradual appreciation of the Rupiah, reflecting improved external balances and foreign exchange inflows, consistent with the role of commodity prices in exchange rate dynamics (Nazlioglu & Soytas, 2012). In contrast, shocks to natural gas prices tend to depreciate the Rupiah, as higher energy prices increase production costs and import expenditures, thereby putting pressure on the exchange rate (Butt et al., 2020). Similarly, shocks in wheat and corn prices elicit a depreciating response, which can be explained by increased food import dependence and inflationary pressures, consistent with inter-commodity price transmission mechanisms (Ramoroka & Muchopa, 2022). The IRF results also show that responses evolve over several periods, indicating that shocks are transmitted gradually rather than instantaneously and reflecting the dynamic adjustments captured by the VECM framework (Purna et al., 2016; Thierry et al., 2016). Overall, these findings confirm that each variable contributes differently to exchange rate movements, where energy commodities influence macroeconomic stability and external balances. In contrast, agricultural commodities primarily affect inflation and import dynamics.

Table 8. Variance Decomposition Results

Period	S.E.	ER	Oil	Gas	WP	CP
1	6.858101	0.000333	99.99967	0.000000	0.000000	0.000000
2	7.386514	0.491813	98.55732	0.151469	0.766258	0.033141
3	8.351523	0.392208	88.40073	10.47983	0.623267	0.103966
4	8.676626	1.302404	87.90893	9.738738	0.893520	0.156411
5	9.310566	1.287228	88.14666	8.864439	1.070936	0.630732
6	9.803713	1.263351	87.64947	9.404897	1.102590	0.579696
7	10.23123	1.211716	87.69501	9.452481	1.059649	0.581146
8	10.66050	1.306899	87.59125	9.189589	1.229453	0.682812
9	11.09250	1.213001	87.52511	9.270659	1.285389	0.705839
10	11.46361	1.142638	87.60310	9.279716	1.268183	0.706368
11	11.85168	1.128008	87.64842	9.180640	1.305577	0.737359
12	12.23174	1.086776	87.63013	9.165827	1.359320	0.757947

Source: data processed

Table 8 shows the impact of shocks from each variable on crude oil prices. The VD analysis for crude oil prices, the most significant contribution comes from wheat prices, which reach 0.76% in the second period and increase to 1.35% in the twelfth period. The following contributions come from the USD/IDR exchange rate, natural gas, and corn prices. In the short term (the second period), the contributions from the USD/IDR exchange rate, natural gas prices, and corn prices are 0.49%, 0.15%, and 0.03%, respectively. Meanwhile, in the long term (the twelfth period), the contribution from the USD/IDR exchange rate increases to 1.08%, natural gas prices to 9.16%, and corn prices to 0.75%. The VD results provide important economic insights into how shocks from each variable contribute to the variability of crude oil prices over time. The findings show that crude oil prices are primarily driven by their own dynamics, reflecting the strong internal dynamics of global oil markets; however, over time, the influence of other variables, such as natural gas prices and the USD/IDR exchange rate, becomes more significant. The rising contribution of natural gas prices indicates a strong linkage among energy commodities, in which shocks in one energy market can spill over to others through substitution effects and integrated global demand (Butt et al., 2020). Meanwhile, the contribution of the USD/IDR exchange rate highlights the role of exchange rate movements in affecting commodity price dynamics through trade competitiveness and international pricing mechanisms (Purna et al., 2016; Gunawan et al., 2025). In addition, the contributions of wheat and corn prices, although relatively small, suggest interdependence between agricultural and energy commodities, which may arise from shared supply chains and global market disruptions (Ramoroka & Muchopa, 2022), indicating that the effects of shocks are transmitted through economic channels such as inflation, trade balance, and market expectations, confirming the interconnected nature of commodity markets and exchange rate dynamics within the VECM framework (Thierry et al., 2016).

To further evaluate the predictive performance of the VECM model, a forecasting analysis is conducted for the period from October 2023 to September 2024. The results are visualized to compare the predicted values with the actual data, providing a clearer understanding of the model's accuracy and reliability. Figure 2 shows the predicted values for the USD/IDR exchange rate, crude oil, natural gas, wheat, and corn prices are close to the actual data. Furthermore, the accuracy of the predictions, measured by MAPE, is 1.54% for the USD/IDR exchange rate, 6.91% for crude oil prices, 10.54% for natural gas prices, 6.92% for wheat prices, and 4.5% for corn prices.

Figure 2. Forecasting Results for ER, Oil, Gas, WP, and CP

Table 9 shows that the USD/IDR exchange rate is forecast to follow an upward trend over the next 12 months, whereas crude oil, natural gas, wheat, and corn prices are expected to fluctuate, while the prices of wheat, crude oil, corn, and natural gas are expected to fluctuate due to several key factors related to the Russia–Ukraine conflict.

Table 9. Twelve-Month Forecast Results

Months	ER	Oil	Gas	WP	CP
October 2023	15428.81	90.21	3.308	499.721	479.86
November 2023	15423.72	90.83	3.204	492.455	484.25
December 2023	15495.50	89.83	2.544	494.455	475.62
January 2024	15585.45	86.29	3.342	490.237	473.50
February 2024	15590.42	86.70	2.268	495.323	465.23
March 2024	15647.30	89.85	2.018	392.621	470.75
April 2024	15653.79	88.96	2.395	385.322	474.26
May 2024	15682.04	88.80	2.542	387.634	465.72
June 2024	15710.30	89.73	3.371	490.925	469.62
July 2024	15738.56	90.25	3.975	495.763	475.13
August 2024	15766.81	90.32	3.855	495.562	477.93
September 2024	15795.07	91.50	3.832	512.213	479.64

Sources: data processed

The evaluation results demonstrate that the VECM model achieves high predictive accuracy, as indicated by relatively low MAPE values across all variables. The use of Mean Absolute Percentage Error (MAPE) as an evaluation metric is widely supported in the literature due to its ability to express forecast errors as percentages, making interpretation more intuitive and comparable across variables (de Myttenaere et al., 2016; Kim & Kim, 2016; Chong et al., 2026). A lower MAPE value indicates better forecasting performance, suggesting that the estimated model effectively captures the underlying data patterns. Furthermore, previous studies have shown that VECM-based models are reliable for forecasting macroeconomic and time series data, particularly when variables exhibit long-run equilibrium relationships (Kuo, 2016; Farida et al., 2023). The relatively accurate prediction results in this study also reflect VECM's ability to incorporate both short-run dynamics and long-run adjustments, which are essential for modeling complex interactions between commodity prices and exchange rates. These findings are consistent with prior research indicating that models that account for cointegration structures tend to produce more stable and accurate forecasts than models that ignore long-run relationships (Liang & Schienle, 2019; Shao et al., 2021).

4. Conclusion

This study finds that global commodity prices significantly influence the USD/IDR exchange rate in both the short and long run. In the long term, crude oil prices are negatively related to the exchange rate, indicating that increases in global oil prices tend to strengthen the Indonesian Rupiah. In contrast, natural gas, wheat, and corn prices show a positive relationship, suggesting that rising prices of these commodities contribute to the depreciation of the Rupiah due to increased import costs and external pressures. In the short term, only crude oil prices have a statistically significant impact on the exchange rate, highlighting the dominant and immediate role of energy commodities in transmitting global shocks to the domestic currency.

The results indicate that of the Granger causality test further reveal a unidirectional granger-causal relationship from crude oil prices to the USD/IDR exchange rate, as well as interdependencies among commodity prices, particularly between energy and agricultural commodities. In addition, the IRF and variance decomposition analyses demonstrate that shocks in commodity markets are gradually transmitted over time and that crude oil prices remain the primary driver, while other variables contribute through indirect channels, such as inflation, the trade balance, and market expectations. The VECM model also shows high predictive accuracy, as indicated by low MAPE values across all variables, suggesting it is reliable for forecasting exchange-rate and commodity-price movements.

Overall, these findings highlight the importance of global commodity price dynamics and geopolitical factors, such as the Russia–Ukraine conflict, in shaping exchange rate behavior in Indonesia. This study provides practical implications for policymakers: anticipate external shocks more effectively, manage exchange rate volatility, and design effective economic stabilization strategies. Future research is recommended to incorporate additional macroeconomic variables and alternative modeling approaches to further enhance the model's robustness and predictive performance.

Declarations

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