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# THE IMPACT OF COMMODITY PRICES AND PORTFOLIO NET INFLOWS ON EXCHANGE RATES: A COMPARISON BEFORE AND AFTER COVID-19

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## ABSTRACT

The Indonesian Rupiah (IDR) exchange rate against the US Dollar (USD) has shown significant volatility, especially during the COVID-19 pandemic. This study examines how coal prices, commodity prices, and net inflows from stocks and government bonds (SBN) impact the IDR/USD exchange rate before and after the pandemic. Using Vector Autoregression (VAR) methodology, the research analyzes time-series data across both periods, employing Granger causality tests and impulse response function analysis to determine relationships between variables. Results reveal a fundamental shift in exchange rate determinants: pre-pandemic, coal prices predominantly influenced the rupiah, reflecting sensitivity to commodity markets; post-pandemic, government bond (SBN) net inflows became the primary factor affecting exchange rate movements. Granger causality tests confirm this transition, showing coal and commodity prices had causal relationships with the exchange rate before the pandemic, while government bond flows became more influential afterward. These findings have significant implications: Bank Indonesia should adjust monetary policy to account for bond market dynamics; financial institutions need to revise risk management strategies considering bond capital flows' increased influence; and the government should diversify Indonesia's economy to reduce commodity dependence while considering bond issuances' impact on the exchange rate, particularly when financing post-pandemic deficits.

**KEYWORDS** *exchange rates, commodity prices, portfolio flow, pandemic, vector autoregression*



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## INTRODUCTION

As understanding of the factors that affect exchange rate fluctuations develops, the focus shifts from internal structural factors to the importance of the influence of non-structural and external factors (Rogoff & Stavrakeva, 2008). In this context, Indonesia, a developing country with an open economy, offers interesting case studies to analyze exchange rate dynamics, especially regarding commodity prices and foreign capital flows.

Indonesia is known as one of the largest exporters of commodities in the world (Arifin et al., 2021; Firmansyah et al., 2017). Major commodities such as coal, palm oil, and minerals make up a significant portion of the country's gross domestic product (GDP) and export revenue (Admi et al., 2022; Sawyerr, 2020; Şen et al., 2024). For example, the coal mining sector accounted for around 6.6% of Indonesia's national GDP in 2022, with 70-75% of coal production exported abroad (Rezki, 2023). Indonesia's position as a major commodity exporter creates a close relationship between global commodity prices and the rupiah exchange rate (Dewi et al., 2025; Kurniasih et al., 2018; Rezki, 2023).

Several studies have shown a correlation between commodity prices and currency exchange rates in commodity-exporting countries. For example, studies of Australia and New Zealand show a strong relationship between commodity price indices and their currency exchange rates (Zou et al., 2017). Similarly, Latin American countries such as Brazil and Argentina also show a close correlation between the prices of their main export commodities and the strength of local currencies (Cashin et al., 2004). However, it is important to note that this relationship has not always been consistent across all countries and periods, underscoring the importance of specific analyses for each country (Kohlscheen et al., 2017).

On the other hand, foreign capital flows, especially in foreign portfolio investment (FPI), also play an important role in exchange rate dynamics. Generally, an increase in FPI tends to lead to an appreciation of the local currency due to the increasing demand for the currency (Combes et al., 2012). Portfolio flows to the market or government bond sector have the most significant impact on exchange rate changes (Ouedraogo, 2017). In Indonesia, significant FPI inflows into the government bond market have proven to strengthen the rupiah, although it also carries the risk of volatility in the event of a sudden withdrawal of funds (Soedarmono et al., 2022).

The COVID-19 pandemic has added a new dimension to this dynamic. High uncertainty during the pandemic increased volatility in global commodity and financial markets. For example, the price *of coal futures* contracts experienced a drastic decline at the beginning of the pandemic, from around $70.68 on March 27, 2020 to $51.62 on April 27, 2020 (Shaikh, 2022). This sudden change not only affects Indonesia's export revenue but also investor sentiment towards the rupiah. Given the complexity of the relationship between commodity prices, foreign portfolio flows, and the rupiah exchange rate, as well as the significant impact of global events such as the COVID-19 pandemic, this study aims to comprehensively analyze how these two factors – commodity prices and portfolio net inflows – affect the rupiah exchange rate. By comparing the relative influences of these two factors, this study is expected to provide valuable insights for policymakers, market participants, and academics in understanding and managing exchange rate dynamics in developing countries that depend on commodity exports, such as Indonesia.

This study will not only contribute to the literature on exchange rate determinants in developing countries, but will also highlight how external *shocks* such as pandemics can alter established inter-variable relationships. Thus, the results of this study are expected to be the basis for the development of more effective strategies in exchange rate management and macroeconomic policies in Indonesia.

This research contributes novel insights by examining structural changes in exchange rate determinants before and during the COVID-19 pandemic, offering unique perspectives on how economic shocks transform financial relationships (Aloui et al., 2020; Narayan et al., 2020), while specifically highlighting the shift from coal prices to government bond (SBN) net inflows as key exchange rate determinants (Basri, 2017; Juhro & Iyke, 2019). It uniquely bridges the gap between commodity market dynamics and financial flows in determining exchange rates in emerging markets like Indonesia (Fratzscher et al., 2019; Reboredo et al., 2017), and, unlike previous studies conducted under normal economic conditions, provides specific policy recommendations for monetary authorities and market participants navigating the post-pandemic economic landscape (Iyke, 2020; Narayan, 2020).

## RESEARCH METHODS

This study uses daily data obtained from Bank Indonesia (2024) and Bloomberg Terminal. The dataset covers the periods before and after the COVID-19 pandemic, allowing for comparative analysis between the two periods. To capture the difference in impact before and after COVID-19, we divided the data into two sample periods:

a. Pre-COVID-19 Period: 1 January 2016 - 31 December 2019
b. Post-Covid-19 Period: 1 January 2020 - 29 December 2023

The variables used in this study are presented through diagram 1, including:

a. Rupiah Exchange Rate against the US Dollar (dexch): To describe exchange rate changes more accurately, we use a differentiated exchange rate. This rate reflects the daily change in the Rupiah's exchange rate against the US Dollar.
b. Coal (pcoal) price: Represents one of Indonesia's main export commodities.
c. Commodity Price Index (pcomm): Reflects the general movement of commodity prices.
d. Net Inflow of Government Securities (ni_sbn): Describes the flow of foreign capital in the government bond market.
e. Stock Net Inflow (ni_saham): Shows the flow of foreign capital in the stock market.

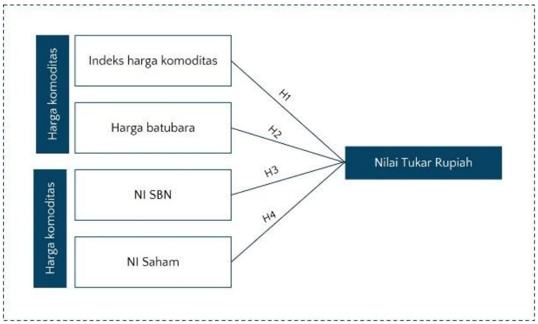



**Figure 1. Research Variables**

Table 1 presents a summary of descriptive statistics of these variables divided by the period before and after the COVID-19 pandemic to provide a preliminary overview of the characteristics of the data used.

**Table 1. Descriptive Statistics for Each Variable**

| Variable | Period | Observations | Mean | Maximum | Minimum | Std. Dev. |
|---|---|---|---|---|---|---|
| Dexch | Pre-Covid | 1042 | 0.07 | 212.00 | -215.00 | 42.93 |
| | Post-Covid | 1042 | 1.47 | 690.00 | -413.00 | 62.35 |
| pcoal | Pre-Covid | 1042 | 1171543.81 | 1751120.00 | 652785.75 | 294082.28 |
| | Post-Covid | 1042 | 2701966.84 | 6810690.00 | 716442.00 | 1836846.54 |
| pcomm | Pre-Covid | 1042 | 1147423.93 | 1329030.00 | 992544.05 | 59969.11 |
| | Post-Covid | 1042 | 1424403.69 | 1993270.00 | 899942.50 | 296057.70 |
| ini_sbn | Pre-Covid | 1042 | 607.88 | 10966.04 | -15260.38 | 2452.65 |
| | Post-Covid | 1042 | -171.68 | 7870.27 | -13339.69 | 2407.79 |
| ini_saham | Pre-Covid | 1042 | -35.24 | 52087.24 | -11539.26 | 1917.86 |
| | Post-Covid | 1042 | 117.85 | 19423.67 | -17922.72 | 1671.20 |

The volatility of the rupiah exchange rate against the US dollar (dexch) showed a significant increase in the post-COVID-19 period, reflected in the magnitude of the standard deviation, which increased from 42.93 in the pre-pandemic period to 62.35 in the post-pandemic period. Coal prices have experienced a drastic spike, both in terms of average and volatility, where the average coal price has more than doubled, from around 1.17 million in the pre-pandemic period to 2.70 million in the post-pandemic period, with a noticeable increase in volatility from the enlarged standard deviation from around 294 thousand to 1.84 million. The commodity price index (pcomm) also showed an upward trend, although not as dramatic as coal prices, with the average index increasing from about 1.15 million to 1.42 million, followed by increased volatility reflected in the magnitude of the standard deviation.

The pattern of foreign capital flows has undergone an interesting change, where the net inflow of Government Securities (ni_sbn) changed from a positive average (607.88) to negative (-171.68) in the post-pandemic period, indicating capital outflows from the government bond market. On the other hand, the net inflow of stocks (ni_saham) actually showed a change from a negative average (-35.24) to a positive (117.85) in the post-pandemic period, which may reflect the increased interest of foreign investors in the Indonesian stock market amid global uncertainty.

This study uses the standard Vector Autoregression (VAR) model to analyze the dynamic relationship between net inflows, the exchange rate of the Rupiah against the US dollar, and commodity prices before and after COVID-19. The VAR model was chosen because it captures dynamic relationships between variables in a time series that allows for a two-way relationship between these variables. Several studies use the VAR method to research the influence of volatility, specifically, the influence of commodity price volatility on exchange rates. Doojav et al (2024) examined the effect of commodity price influences on changes in the value of the tuakr using structural Bayesian vector autoregression, Nia et al (2023) examined the influence of market volatility in *the cryptocurrencies* and gold markets using VAR, Alsadiq et al (2021) examined the effect of shocks in the commodity market on exchange rates in Caribbean countries using a *vector autoregression* panel, Ji et al (2024) The influence of oil price changes on output, exchange rate, and inflation in BRICS countries was examined using structural vector autoregression.

The standard VAR model used involves three endogenous variables: net inflows (ni), exchange rate (dexch), and commodity prices (commi). The equation of the standard VAR model is as follows:

$$\begin{aligned}
\mathrm{ni}_t &= \alpha_1 + \sum_{j=1}^{k} \beta_{1j}\mathrm{ni}_{t-j} + \sum_{j=1}^{k} \gamma_{1j}\mathrm{dexch}_{t-j} + \sum_{j=1}^{k} \theta_{1j}\mathrm{commi}_{t-j} + \epsilon_{1t} \\
\mathrm{dexch}_t &= \alpha_2 + \sum_{j=1}^{k} \beta_{2j}\mathrm{ni}_{t-j} + \sum_{j=1}^{k} \gamma_{2j}\mathrm{dexch}_{t-j} + \sum_{j=1}^{k} \theta_{2j}\mathrm{commi}_{t-j} + \epsilon_{2t} \\
\mathrm{commi}_t &= \alpha_3 + \sum_{j=1}^{k} \beta_{3j}\mathrm{ni}_{t-j} + \sum_{j=1}^{k} \gamma_{3j}\mathrm{dexch}_{t-j} + \sum_{j=1}^{k} \theta_{3j}\mathrm{commi}_{t-j} + \epsilon_{3t}
\end{aligned}$$

where:

a. $\mathrm{ni}_t$: represents net inflows, which can be in the form of net inflows in the stock market or bond market (SBN only)
b. $\mathrm{dexch}_t$: is the exchange rate (IDR/USD) on the tth day.
c. $\mathrm{commi}_t$: represents the price of commodities, which can be a commodity index or coal on the tth day.
d. $\alpha_{1,}\alpha_{2,}\alpha_{3,}$: is an *intercept.*

e. $\beta_{ij}, \gamma_{ij}, \theta_{ij}$: is the coefficient of the lag value.

Before estimating the VAR model, a Root Unit Test was carried out using Augmented Dickey-Fuller (ADF) for each variable (dexch, commi, ni_saham, ni_sbn) at the level and first difference. The null hypothesis in this test is that the data contains root (not stationary) units. If the variable is not stationary, *the time series* data of that variable will be differentiated to achieve stationarity.

After that, the author determines the optimal amount of lag (k) using several criteria: (1) Akaike Information Criterion (AIC); (2) Schwarz Criterion (SC); and (3) Hannan-Quinn Criterion (HQ). The optimal amount of lag is selected based on the minimum values of these criteria to ensure the model captures the dynamics of relationships between variables without *overfitting*. After determining the optimal lag, the standard VAR model will be estimated. The Granger Causality test is carried out to determine whether one variable can predict another variable. The null hypothesis is that the lag of one variable does not help predict other variables. The rejection of the null hypothesis indicates the existence of Granger Causality. The next *impulse response function* (IRF) is used to track the impact of a one-unit shock on one endogenous variable on the value of another variable at subsequent times. The IRF visualizes how the dexch, commi, and ni variables respond to a shock in one of the endogenous variables in the VAR system.

The stability of the VAR model will be tested by examining the Inverse Roots of the AR Characteristic Polynomial. A model is considered stable if all the roots of the characteristic equation are within a unit circle. Finally, Variance Decomposition is carried out to determine the contribution of each variable to the *forecast error variance* of other variables. This analysis helps to understand the proportion of predicted variance of each variable caused by the variable compared to surprises from other variables.

All stages of the above analysis were carried out separately for the period before and after COVID-19. The results of these two periods were then compared to identify changes in the dynamics of the relationship between net inflows, exchange rates, and commodity prices as a result of the COVID-19 pandemic. A summary of the entire stages of the above analysis is presented in Diagram 2 below.

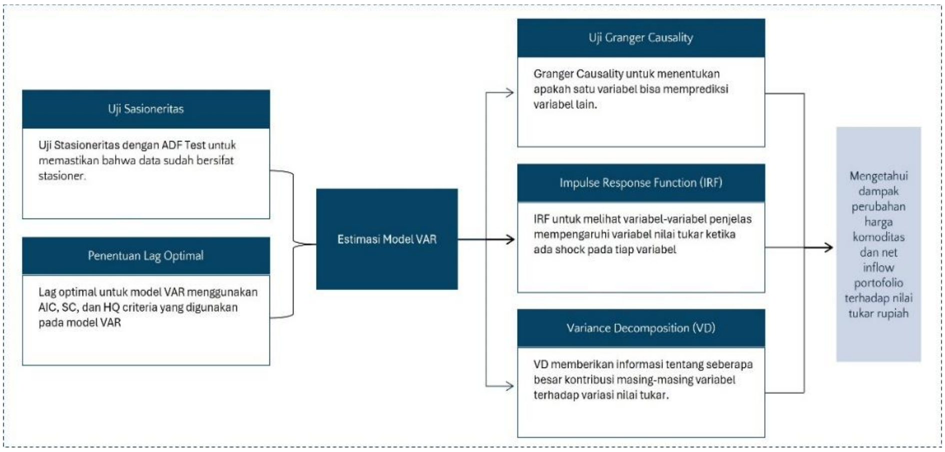



**Figure 2. Analysis Stages**

## RESULTS AND DISCUSSION

### Test Root Unit

Before proceeding with the estimation using the standard-VAR method to assess the impact of commodity prices, especially coal prices, and net inflows from stocks and government securities on the exchange rate, it is important to ensure that the variables used are stationary. Ensuring stationarity in time series data is essential to avoid biased regression and invalid outcomes.

**Table 2. Result Unit Root Test Augmented Dickey-Fuller (ADF)**

| Variable | | Pre-Covid | | | Post-Covid | | |
|---|---|---|---|---|---|---|---|
| | | **Level** | **First-diff.** | **Stationary** | **Level** | **First-diff.** | **Stationary** |
| Dexch | t-Stat | -28.629 | -19.463 | I(0) | -13.292 | -14.629 | I(0) |
| | Prob. | 0.000 | 0.000 | | 0.000 | 0.000 | |
| pcoal | t-Stat | -1.589 | -26.751 | I(1) | -1.278 | -20.963 | I(1) |
| | Prob. | 0.488 | 0.000 | | 0.642 | 0.000 | |
| pcomm | t-Stat | -2.332 | -33.500 | I(1) | -1.143 | -30.072 | I(1) |
| | Prob. | 0.162 | 0.000 | | 0.701 | 0.000 | |
| ni_sbn | t-Stat | -19.519 | -19.445 | I(0) | -13.104 | -17.116 | I(0) |
| | Prob. | 0.000 | 0.000 | | 0.000 | 0.000 | |
| ni_saham | t-Stat | -30.978 | -18.866 | I(0) | -15.636 | -19.960 | I(0) |
| | Prob. | 0.000 | 0.000 | | 0.000 | 0.000 | |

To check the stationarity of the data, the authors conducted the Augmented Dickey-Fuller (ADF) test. Based on Gujarati (2004), the data is considered stationary if the probability of the statistical test shows a significance level of 1%, which means that the p-value is less than 0.01. The results of the ADF test in Table 2 show that some variables are stationary at the level or I(0) and some other variables are stationary at *the first difference,* I(1).

For the variables that are stationary in the first difference I(1), the author will use the first difference version of the data series in the VAR estimation. With the results showing that all variables have met the stationery requirements, we can proceed to the advanced standard-VAR estimation stage of selecting the appropriate amount of *lag* for the estimation model.

**Determining the Recommended Amount of Lag**

One of the important steps in estimating a VAR model is determining the optimal amount of lag. The selection of the right amount of lag aims to capture the dynamics of the relationships between variables without adding unnecessary complexity to the model. In this study, the authors used several information criteria such as the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ) to help determine the optimal amount of lag.

Table 3 shows the different lag amount recommendations based on each criterion. For the pre-COVID period, the AIC and HQ criteria recommend using lag 2, while the SC criteria recommend lag 1. In the post-COVID period, AIC and HQ also recommend lag 2, while SC recommends lag 1.

**Table 3. Hasil VAR-Team Selection Criteria**

| Was | Pre-Covid | | | Post-Covid | | |
|---|---|---|---|---|---|---|
| | AIC | SC | HQ | AIC | SC | HQ |
| 1 | 89.72 | 89.85* | 89.77 | 94.80 | 94.93* | 94.85 |
| 2 | 89.63* | 89.88 | 89.73* | 94.71* | 94.95 | 94.80* |
| 3 | 89.65 | 90.03 | 89.80 | 94.71 | 95.08 | 94.85 |
| 4 | 89.68 | 90.18 | 89.87 | 94.71 | 95.21 | 94.90 |
| 5 | 89.71 | 90.34 | 89.95 | 94.74 | 95.36 | 94.98 |
| 6 | 89.73 | 90.48 | 90.02 | 94.76 | 95.51 | 95.04 |
| 7 | 89.76 | 90.63 | 90.09 | 94.77 | 95.65 | 95.11 |
| 8 | 89.80 | 90.79 | 90.17 | 94.80 | 95.79 | 95.18 |
| 9 | 89.82 | 90.94 | 90.24 | 94.82 | 95.94 | 95.25 |
| 10 | 89.76 | 91.00 | 90.23 | 94.84 | 96.09 | 95.31 |

* Recommended lag amount

Referring to these results, the authors chose to use lag 2 in estimating the VAR model. This selection is based on the consistency of the recommendations of the AIC and HQ criteria, which are often considered to be more sensitive in identifying long-term dynamics between variables, especially in time series data with daily frequency.

**Graanger Causality Test Results**

To test the causality relationship between independent variables and exchange rate variables (**dexch**), the author conducted a Granger Causality test, whose results are presented in Table 4 below. The null hypothesis of this test states that a variable is not "Granger-Caused" by the dependent variable. Suppose the probability value (p-value) is less than 0.1. In that case, the null hypothesis can be rejected, which means a Granger causal relationship exists between the independent variable and the dependent variable.

**Table 4. Granger Causality Test Results**

*Dependent variable: dexch

| Variable | Pre-Covid | | Post-Covid | |
|---|---|---|---|---|
| | Chi-sq | Prob. | Chi-sq | Prob. |
| dpcoal | 10.703 | 0.005 | 0.582 | 0.900 |
| dpcomm | 4.994 | 0.082 | 4.207 | 0.240 |
| ni_saham | 1.669 | 0.434 | 0.702 | 0.873 |
| ni_sbn | 0.012 | 0.994 | 21.997 | 0.000 |

In the pre-COVID period, the test results showed that the dpcoal variable (coal price) had a Granger Cause against dexch (exchange rate) with a p-value of 0.005, or statistically significant at 1%. On the other hand, the dpcomm variable (commodity price) also has a Granger cause for the exchange rate, even though it is at a significance level of 10%. Meanwhile, the variables ni_saham (net inflow of stocks) and ni_sbn (net inflow of government securities) did not show a significant causal relationship with the exchange rate, with p-values of 0.434 and 0.994, respectively.

In the post-COVID period, there was a significant change where the variable ni_sbn (net inflow of government securities) showed a strong Granger-Cause against the exchange rate with a p-value of 0.000. This indicates that after the pandemic, net capital inflows from government securities significantly influenced the exchange rate. In contrast, the variables dpcoal, dpcomm, and ni_saham did not show a significant causal relationship in this period. Overall, these results show that before the pandemic, coal prices affected the exchange rate, while after the pandemic, the net inflow of government securities became a more significant factor in influencing exchange rate movements. These findings are in line with the results of previous research (Ouedraogo, 2017; Soedarmono et al., 2022).

**IRF Visualization Results**

The *Impulse Response Function* (IRF) analysis provides further insight into the dynamics of the short-term relationship between exchange rates (dexch) when there is *a shock* in the variables of coal prices (dpcoal), general commodity prices (dpcomm), net inflows from government securities (ni_sbn), and net inflows of stocks (ni_saham). As seen in Figure 1, the results show a significant positive response to positive shocks in coal and commodity prices in the pre-COVID period. This indicates that the increase in coal and commodity prices may increase the nominal or depreciate the Rp/USD exchange rate. Meanwhile, the interpretation of *the shock* of *SBN net inflows* and stocks refers to the results of the Granger Causality test in the previous sub-chapter.

In the post-COVID period shown by Figure 2, positive shocks in SBN gave negative responses that tended to be deeper and more significant at the Rp/USD exchange rate compared to shocks from other variables. These findings are consistent with the results of the previous Granger Causality test, which showed that SBN significantly influenced the exchange rate after the pandemic.

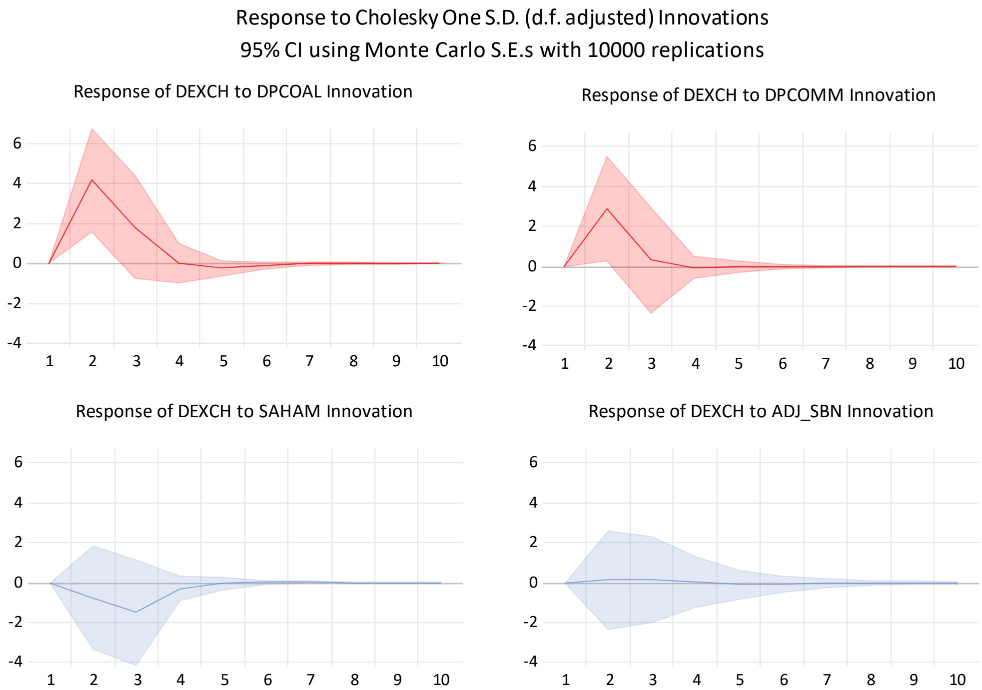



**Figure 3. IRF Pre-COVID Results**

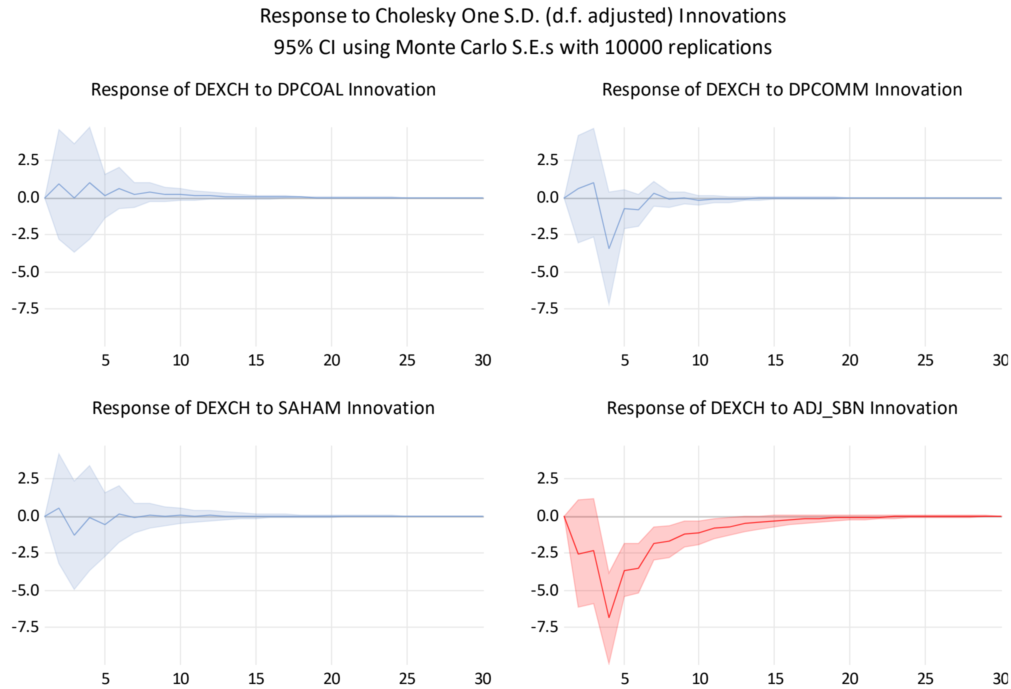



**Figure 4. IRF Post-COVID Results**

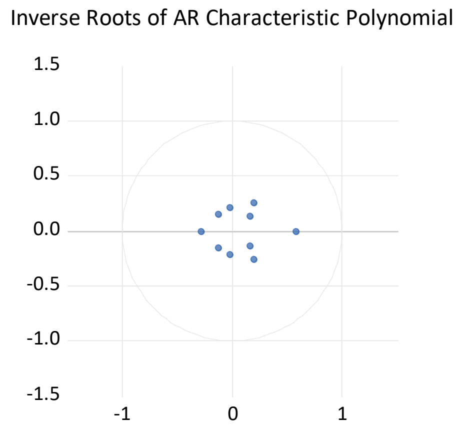
**Stability Test and Variance Decomposition Results**

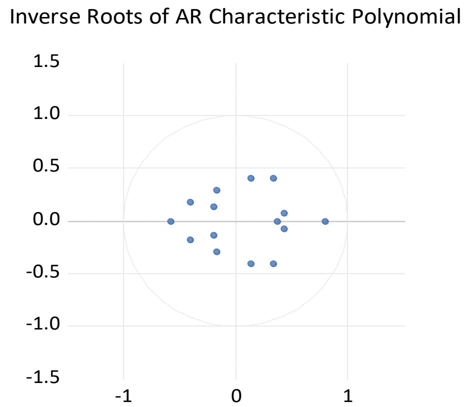
To ensure the stability of the VAR model, the authors conducted a stability test by observing *the inverse roots* of the *autoregressive polynomial* (AR) characteristics. This test aims to see if the estimated VAR model is stable. A model is considered stable if all modulus values of the *root* are less than 1 and all *inverse points of the root* are located within the circle of units.

Table 5 shows that in the pre-COVID results, the highest modulus value was 0.5822, with other values ranging from 0.2830 to 0.3257, all of which were less than 1. In graph 1 of the inverse roots for the pre-COVID period, all *roots* are located within the unit circle, indicating that the VAR model for the period is stable.

For the post-COVID results, the highest modulus value is 0.7936, with other values between 0.5231 and 0.5790. Like the previous period, all of these modules are below 1. On the inverse roots chart for the post-COVID period, all inverse root points are also inside the unit circle, confirming the VAR model's stability after the pandemic.

Thus, based on the modulus results and inverse roots graphs, the estimated VAR model for both the Pre-COVID and Post-COVID periods meets the stability test, so the results of the previous IRF and Granger Causality analyses are reliable.




**Gambar 5. Pre-Covid and Post-Covid *Inverse Roots of AR Characteristic Polynomial***

The results of variance decomposition for the dexch variable (exchange rate) in the pre-COVID period show that in the first period (lag=1), 100% of the exchange rate changes are explained by that variable (dexch). That is, the inability to predict the change in the exchange rate in the first period is entirely due to the internal dynamics of the exchange rate itself.

Table 5 shows that, over time, the contribution of other variables began to be seen, although the most significant contribution still came from the dexch variable itself. For example, in the second period, 98.57% of the exchange rate changes were still explained by the exchange variable, while dpcoal (coal prices) began to contribute by 0.94%, and dpcomm (general commodity prices) contributed by 0.46%. The variables ni_saham (net inflow of stocks) and ni_sbn (net inflow of government securities) contributed very little, with 0.03% and 0.00%, respectively. The same pattern continues into later periods.

Meanwhile, a similar pattern can be seen in the post-COVID period where the dollar remains the most significant factor influencing exchange rate changes. However, over time, the contribution from ni_sbn began to increase significantly. In the first period, 0.18% of the exchange rate variation was explained by ni_sbn, and this contribution increased to 2.38% in the tenth period. This shows that capital flows from government securities have a greater impact than coal prices, commodity prices, and stock capital flows after the pandemic. These results are consistent with the findings of the previous section's Granger Causality and IRF tests.

**Table 5. Results of *Inverse Roots of AR Characteristic Polynomial* Stability Test (Left) and Variance Decomposition Results (Right)**

Hasil Uji Stabilitas *Inverse Roots of AR Characteristic Polynomial*

| Pre-Covid | Post-Covid |
|---|---|
| Modulus | Modulus |
| 0.5822 | 0.7936 |
| 0.3257 | 0.5790 |
| 0.3257 | 0.5231 |
| 0.2830 | 0.5231 |

Hasil Variance Decomposition

| Period | Pre-Covid | | | | | Post-Covid | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | dexch | dpcoal | dpcomm | ni_saham | ni_sbn | dexch | dpcoal | dpcomm | ni_saham | r |
| 1 | 100.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | 0.00 | 0.00 | 0.00 | |
| 2 | 98.57 | 0.94 | 0.46 | 0.03 | 0.00 | 99.78 | 0.02 | 0.01 | 0.01 | |
| 3 | 98.27 | 1.12 | 0.46 | 0.15 | 0.00 | 99.58 | 0.02 | 0.03 | 0.05 | |
| 4 | 98.26 | 1.12 | 0.46 | 0.16 | 0.00 | 98.04 | 0.05 | 0.34 | 0.05 | |
| 5 | 98.26 | 1.12 | 0.46 | 0.16 | 0.00 | 97.69 | 0.05 | 0.35 | 0.06 | |
| 6 | 98.26 | 1.12 | 0.46 | 0.16 | 0.00 | 97.35 | 0.06 | 0.37 | 0.06 | |
| 7 | 98.26 | 1.12 | 0.46 | 0.16 | 0.00 | 97.27 | 0.06 | 0.37 | 0.06 | |
| 8 | 98.26 | 1.12 | 0.46 | 0.16 | 0.00 | 97.20 | 0.06 | 0.37 | 0.06 | |
| 9 | 98.26 | 1.12 | 0.46 | 0.16 | 0.00 | 97.16 | 0.06 | 0.37 | 0.06 | |
| 10 | 98.26 | 1.12 | 0.46 | 0.16 | 0.00 | 97.13 | 0.06 | 0.37 | 0.06 | |

## CONCLUSION

This study uses VAR methodology to investigate how coal, commodity, and net inflows from stocks and government bonds (SBN) affected the IDR/USD exchange rate before and after the COVID-19 pandemic. The findings reveal a significant shift in factors influencing the rupiah: before the pandemic, coal prices were the dominant factor, reflecting the currency's sensitivity to commodity market fluctuations, while after the pandemic, net inflows from government bonds became the primary influence, as confirmed by Granger causality tests. These results have important implications for various stakeholders: Bank Indonesia should adjust monetary policy to account for bond market dynamics, financial institutions need to revise risk management strategies considering bond capital flows, and the government should diversify Indonesia's economy to reduce commodity dependence while considering how bond issuances impact the exchange rate, particularly when financing post-pandemic budget deficits.

## REFERENCE

Admi, R., Saleh, S., & Fitrianto, G. (2022). The analysis of coal competitiveness and the factors affecting Indonesia's coal exports to the main destination countries (a case of 8 destination countries). *Journal of Developing Economies*, *7*(1), 15–28.

Alsadiq, A., Bejar, P., & Otker-Robe, I. (2021). *Commodity Shocks and Exchange Rate Regimes : Implications for the Caribbean Commodity Exporters* (Nomor 2021/104).

Arifin, Z., Suman, A., & Khusaini, M. (2021). Optimization of Selected Agricultural Export Commodities to Improve Indonesia's Weaponry Countertrade. *International Journal of Criminology and Sociology*, *10*(10), 579–588.

Bank Indonesia. (2024). *The impact of global capital flows on financial intermediation and monetary transmission in Indonesia*. https://www.bis.org/publ/bppdf/bispap148_k.pdf

Cashin, P., Céspedes, L. F., & Sahay, R. (2004). Commodity currencies and the real exchange rate. *Journal of Development Economics*, *75*(1), 239–268.

Combes, J. L., Kinda, T., & Plane, P. (2012). Capital flows, exchange rate flexibility, and the real exchange rate. *Journal of Macroeconomics*, *34*(4), 1034–1043.

Dewi, L. G. K., Widiasa, K. A. P., & Dewi, N. L. P. S. (2025). The Effect Of Foreign Exchange Rate Changes On Indonesia's Import-Export Values. *JUSTBEST Journal of Sustainable Business and Management*, *5*(1), 25–33.

Doojav, G., Purevdorj, M., & Batjargal, A. (2024). The Macroeconomic Effects of Exchange Rate Movements in A Commodity-Exporting Developing Economy. *International Economics*.

Firmansyah, F., Widodo, W., Karsinah, K., & Oktavilia, S. (2017). Export performance and competitiveness of Indonesian food commodities. *JEJAK: Jurnal Ekonomi dan Kebijakan*, *10*(2), 289–301.

Ji, Q., Liu, M., & Fan, Y. (2024). Effects of Structural Oil Shocks on Output, Exchange Rate, and Inflation in the BRICS Countries. *Emerging Markets Finance and Trade Journal*, *51*(6), 1129–1140.

Kohlscheen, E., Avalos, F. H., & Schrimpf, A. (2017). When the walk is not random: commodity prices and exchange rates. *International Journal of Central Banking*, *13*(2), 121–158.

Kurniasih, C. E., Hizir Nasir, M., Mahmud, M. S., Rashid, N., Ghazali, P. L., & Afthanorhan, A. (2018). Analysis of the relationship between world oil price and exchange rate on agricultural commodity prices in Indonesia. *International Journal of Academic Research in Business and Social Sciences*, *8*(12), 561–576.

Nia, V. M., Ferli, O., Novikri, I., Sembel, R., & Manurung, A. H. (2023). Identification of Market Volatility with Solid VAR Autoregression Validity in Indonesia Cryptocurrencies Or Gold. *Jurnal Ilmiah Manajemen Fakultas Ekonomi*, *9*(1), 45–46.

Ouedraogo, R. (2017). *Portfolio Inflows and Real Effective Exchange Rates : Does Sectorization Matter?* (Nomor WP/17/121).

Rezki, J. F. (2023). Understanding 'The Four Phase'of Coal Industries and its Economic Policy Implication in Indonesia: A Systematic Literature Review (SLR) Approach. *JURNAL EKBIS*, *24*(1), 389–430.

Rogoff, K. S., & Stavrakeva, V. (2008). *The continuing puzzle of short horizon exchange rate forecasting* (Nomor w14071).

Sawyerr, M. A. (2020). *Petroleum production affects natural resource reliance and economic growth in Ghana* 서울대학교 대학원.

Şen, A., Akpolat, A. G., & Balkan, İ. (2024). Commodity prices and economic growth: Empirical evidence from countries with different income groups. *Heliyon*, *10*(13).

Shaikh, I. (2022). Impact of COVID-19 pandemic on the energy markets. *Economic Change and Restructuring*, *55*(1), 433–484.

Soedarmono, W., Gunadi, I., Indawan, F., & Wulandari, C. S. (2022). *The Dynamics Of Foreign Capital Flows In Indonesia: Sources And Implications On Bond Market And Bank Stability* (Nomor WP/03/2022).

Zou, L., Zheng, B., & Li, X. (2017). The commodity price and exchange rate dynamics. *Theoretical Economics Letters*, *7*(6), 1770.