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Dependency Model of the Exchange Rate with the Volume Export of Mining Products in Indonesia Using Copula

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ABSTRACT

This research aims to analyze the dependence of the IDR-USD exchange rate on the volume of mining exports in Indonesia using the copula approach. This dependence is important to understand considering that the exchange rate and mineral exports have a direct impact on the country's economy which depends on foreign exchange from this sector. Mineral exports are one of the country's main sources of foreign exchange, while the exchange rate influences the competitiveness of exports on the international market. The mining products taken are iron and steel, copper and nickel, which are Indonesia's leading commodities. The copula method was chosen because of its ability to capture and model non-linear dependencies between variables, without considering the distribution of each variable. Copula makes it possible to model the marginal distribution of exchange rates and export volumes separately from their dependency structures, which is in line with the complex and dynamic nature of the Indonesian mining sector economy. The results show that there is no significant dependence between the exchange rate and the volume of commodity exports taken. Therefore, this commodity export volume policy will not have a significant effect on fluctuations in the IDR-USD exchange rate and vice versa. This article can be a recommendation for exporters to understand that export volumes do not need to pay attention to exchange rate fluctuations.

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A. INTRODUCTION

Indonesia is a country rich in natural resources which includes land and sea areas in the form of mining mineral reserves. The United States government geological institute (U.S. Geological Survey) states that Indonesia is one of the world's mineral commodity centers. Indonesia has 1.7% of world iron emissions reserves of 2.9 billion tonnes (Kementerian ESDM, 2021). This could be an investment opportunity for Indonesia and is in line with the statement by the World Steel Association (World steel) where world demand for steel increases by more than 1% every year. Steel has quite high economic value and the government continues to encourage this opportunity considering the many positive impacts that can be obtained in Indonesia's economic and investment sectors.

Indonesia also has more than 40% of the world's nickel reserves and broke the record for nickel export volume in 2022 of 777.4 thousand tons (U.S. Geogolical Survey, 2023). Indonesia officially prohibits export activities of raw materials such as nickel ore and bauxite and focuses on exports of domestic processing and refining products. This aims to increase domestic economic value and state foreign exchange earnings (Dirjen Mineral dan Batubara, 2023).

Import-export activities depend on available foreign exchange reserves (Ratnaningtyas & Huda, 2023). The stability of the country's foreign exchange reserves must be considered to maintain smooth international transactions (Jeanne & Rancière, 2006). There is a link between foreign exchange and the exchange rate so that the country remains able to maintain foreign exchange reserves which will be used as a tool for international economic and financial transactions (Dani et al., 2020; Iancu et al., 2020). The exchange rate or foreign exchange rate is directly proportional to export volume (Ping, 2011). The weakening of the rupiah exchange rate has an impact on the value of national exports and investment (Ndoen et al., 2020). Looking at these considerations, one way to increase the country's foreign exchange is to carry out export activities (Frohm, 2021). This research focuses on discussing the volume of exports of mineral mining goods by paying attention to the relationship between exchange rates.

Some literature looks at the relationship in stock and commodity markets concentrates on the use of the copula method. The copula method does not require the assumption of normality in the data, so copula is a suitable method for analyzing the dependence between two or more random variables (Krouthén, 2015). To expand the use of copulas, a mixed copula model is used to model various types of dependency structures between exchange rates and export volumes of steel, copper, nickel, and aluminium in Indonesia.

Based on this introduction, this research examines the dependency between the exchange rate and the volume of exports of iron and steel, copper, and nickel in Indonesia. The sensitivity values obtained show the dependence between the variables tested by applying the single copula model. The results will show which export volume of mining products has the highest sensitivity to the exchange rate so that it can be taken into consideration in coming up with recommendations regarding export activities for these commodities.

B. METHODS

The data used in this research is data on monthly export volumes of iron and steel, copper and nickel as well as data on the exchange rate of the Rupiah against the US Dollar for the period January 2010 – August 2023. Data is obtained from the Indonesian export foreign trade statistics bulletin published by the Central Bureau of Statistics Indonesia (BPS Indonesia) every month. The first step taken was to check the autocorrelation effect on each data using the Ljung-Box test. If the data is free from autocorrelation effects, the best distribution can be immediately selected which is then used for copula modeling. However, if there is an autocorrelation effect in the data, time series analysis is carried out.

For time series analysis, the first step is to test the stationarity of the data regarding the variance and mean. Data stationarity testing for variance was carried out using the Box-Cox test. If it is not stationary then a Box-Cox transformation will be carried out. Test the stationarity of the data against the mean using the Dickey-Fuller test. If it is not stationary then differentiation will be carried out. After that, order identification and ARIMA model estimation were carried out. The selected ARIMA model was then tested for the white noise assumption against the model error. After that, the best distribution will be selected from the model using the Anderson-Darling test. The best distribution that has been obtained is then transformed into a uniform distribution. The uniform distribution obtained is then fitted using a copula. Estimating a joint distribution model for each pair of data using single Copula in Archimedean Copula (Frank, Clayton, and Gumbel). The copula model used is defined as follows,

$$C_\theta^{Fr}(u,v) = -\frac{1}{\theta}\ln\left(1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1}\right), \;\; \theta > 0 \tag{1}$$

$$C_\theta^{Cl}(u,v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-\frac{1}{\theta}}, \;\; 0 < \theta < \infty \tag{2}$$

$$C_\theta^{Gu}(u,v) = \exp\left(-\left[(-\ln u)^\theta + (-\ln v)^\theta\right]^{\frac{1}{\theta}}\right), \;\; 1 \leq \theta < \infty \tag{3}$$

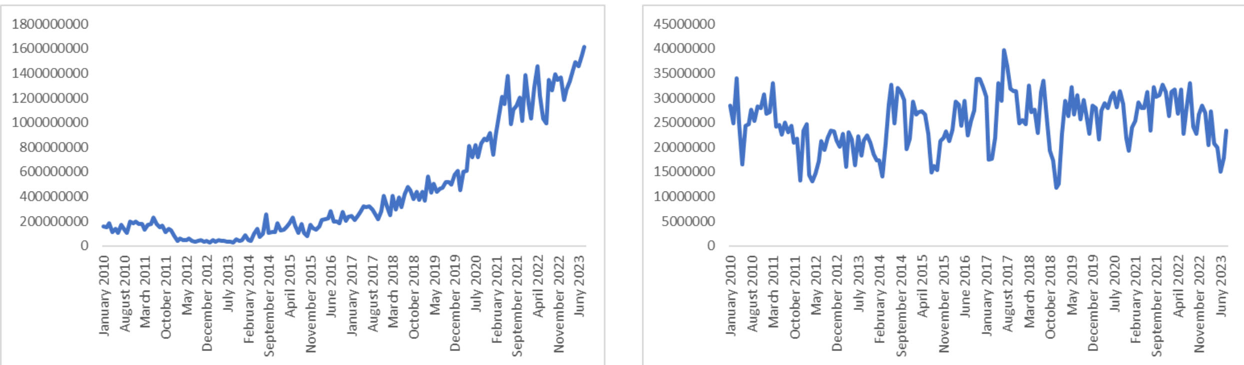
with θ is parameter function, while u and v is value of the marginal distribution of data.

Equation (1) defines the Frank copula, equation (2) defines the Clayton copula, while equation (3) defines the Gumbel copula (Jaworski et al., 2009; McNeil et al., 2005; Nelsen, 2006). Archimedean copula was chosen because it is most suitable for modeling the data used in this study. This copula is able to measure the dependencies of asymmetric models and capture dependencies on the tails of certain distributions (Haugh, 2016; Sutikno et al., 2014).

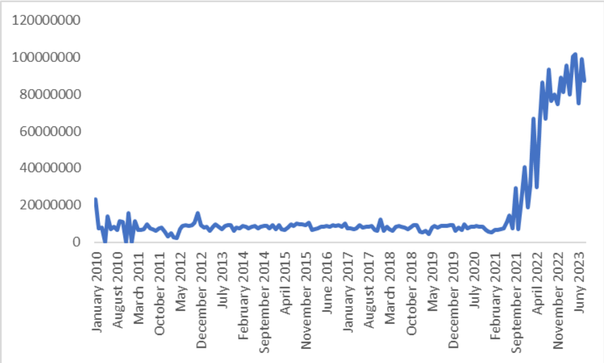
C. RESULT AND DISCUSSION

1. Data Description

The data graphic presentation is designed to provide a comprehensive overview of the characteristics of the data set used in this research. It also aims to provide a visual understanding of the data. The export volume graph for each commodity and the IDR-USD exchange rate is presented in Figure 1 below.



(a) (b)



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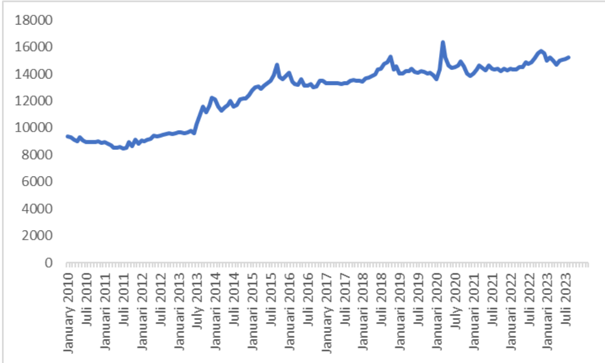


(d)

Figure 1. Export Volume Graph of (a) Iron and Steel; (b) Copper; (c) Nickel; and (d) Exchange Rate

This section only provides a general overview of the data used. Descriptive statistics of the data are presented in Table 1 below.

Table 1. Descriptive Statistics

Data	Mean	St. Deviation	Skewness	Kurtosis	Exchange Rate Correlation
Iron and Steel	440999600	442688646	1,16	0,01	0,67
Copper	25098439	5450903	-0,24	-0,36	0,24
Nickel	16098552	22637965	2,67	5,73	0,39
Exchange Rate	12583	2249	-0,63	-1,11	1,00

The skewness value in statistics is used to measure the asymmetry of data distribution. Skewness shows the extent to which the data distribution is skewed to the left or right from the mean. The kurtosis value is used to see the tendency for data normality (Kim, 2013; MacGillivray, 1986). Based on Table 2, the skewness value ranges far from 0, so it supports that the data tends to be asymmetrical. The kurtosis value also stretches far from 3, so the data tends to be non-normal.

2. Autocorrelation Effect

Data freedom is needed to anticipate errors in parameter estimation and errors in decision making (Birnbaum & Wan, 2020). The existence of autocorrelation effects was checked using the Ljung-Box test with the hypothesis,

H_0 : There is no autocorrelation effect
H_1 : There in an autocorrelation effect

and H_0 is rejected if $p\text{-}value < \alpha = 0.05$.

Table 2. Ljung-Box Test Results for Each Data

Data	χ^2	*p-value*
Iron and Steel	1471,80	2,2e-16
Copper	131,29	2,2e-16
Nickel	824,73	2,2e-16
Exchange Rate	298,35	2,2e-16

Based on the results of the Ljung-Box test, the $p\text{-}value$ for the five data is < 0.05. H_0 is rejected, there is autocorrelation in the data, so it is necessary to do time series analysis. Time series analysis requires stationarity assumptions regarding variance and mean (Chatterjee & Simonoff, 2020; Ludlow & Perez, 2018). Therefore, the next step was to test the stationarity of the data.

3. Stationarity of Variability

Data stationarity testing for variance was carried out using the Box-Cox test by finding the optimal lambda value. Data is said to be stationary when lambda approaches 1 or the confidence interval contains the value 1.

Table 3. Box-Cox Test Results

Data	Lambda (λ_1)	Confidence Interval
Iron and Steel	0,00	0,00 – 0,14
Copper	1,37	0,81 – 1,94
Nickel	0,00	0,00 – 0,02
Exchange Rate	2,00	1,88 – 2,00

Based on the Box-Cox test in Table 3, data on the export volume of copper and aluminum has been stationary with respect to variance, while the export volume of steel, nickel and the exchange rate has not been stationary with respect to variance. Box-Cox transformation (2014) is carried out on data that is not stationary with respect to variance with the formula:

$$y^{\lambda} = \begin{cases} \dfrac{y^{\lambda} - 1}{\lambda}, & \lambda \neq 0 \\ \log y\ , & \lambda = 0 \end{cases} \tag{4}$$

where y is the data distribution. The data is transformed $n - 1$ times until it reaches the stationarity requirement for variance. Table 4 shows that the transformation data is stationary regarding variance.

Table 4. Box-Cox Transformation Results

Data	Data Transformation	Lambda (λ_n)	Confidence Interval
Iron and Steel	s^{λ}	$\lambda_5 = 1{,}01$	0,68 – 1,31
Nickel	n^{λ}	$\lambda_4 = 1{,}05$	0,64 – 1,45
Exchange Rate	z^{λ}	$\lambda_4 = 0{,}97$	0,78 – 1,51

4. Stationarity of Mean

Next, the volume of copper exports is symbolized C_t. Testing data stationarity against the mean uses the Dickey-Fuller test with a hypothesis (Afriyie et al., 2020):

H_0 : Data is not stationary with respect to the mean
H_1 : Data is stationary with respect to the mean

and H_0 is rejected if $p\text{-}value < 0.05$. The dickey-fuller test result can be seen in Table 5.

Table 5. Dickey-Fuller Test Result

Data	*p-value*
s^{λ}	0,5848
C_t	0,0125
n^{λ}	0,7958
Z_t	0,3741

Based on the Dickey-Fuller test results in Table 5, the C_t have a $p\text{-}value < 0.05$, so the data is stationary with respect to the mean. Meanwhile s^{λ}, n^{λ} and z^{λ} have a $p\text{-}value > 0.05$, which means the data is not stationary with respect to the mean, so it is necessary to differencing using a formula:

$$S_t = s_t^{\lambda} - s_{t-1}^{\lambda} \tag{5}$$

$$N_t = n_t^{\lambda} - n_{t-1}^{\lambda} \tag{6}$$

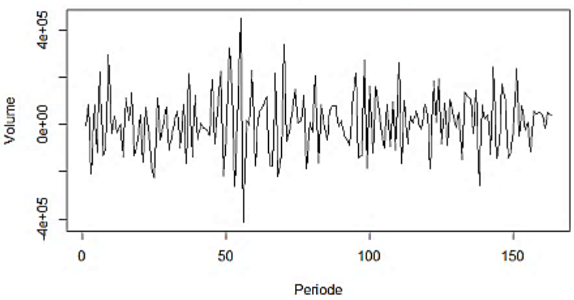
$$Z_t = z_t^{\lambda} - z_{t-1}^{\lambda} \tag{7}$$

and the Dickey-Fuller test was carried out again on the differencing data, as shown in Table 6.

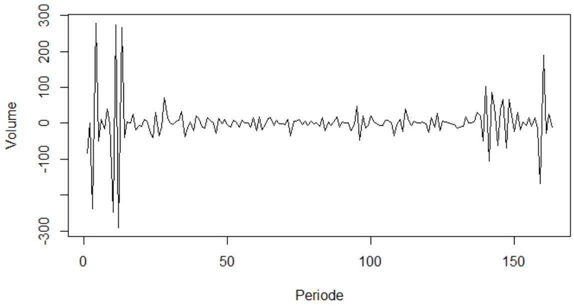
Table 6. Dickey-Fuller Test Result After Differencing

Differencing Data	*p-value*
S_t	0,01
N_t	0,01
Z_t	0,01

Table 6 shows that differencing data has a $p\text{-}value < 0.05$, meaning that the data is stationary with respect to the mean. Figure 2 below shows a plot of S_t, N_t and Z_t data which is stationary towards the mean.



(a)



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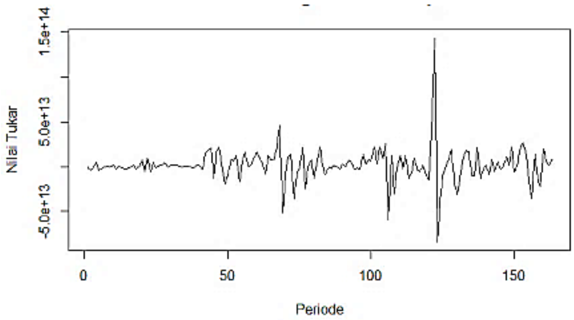

(c)

Figure 2. Plot of (a) S_t; (b) N_t; (c) Z_t

5. Order Identification and ARIMA Model Estimation

The ARIMA model (p,d,q) with initial estimates of p and q is obtained from the autocorrelation function (ACF) plot and partial autocorrelation function (PACF) plot for each data and d is differencing order (Yakubu & Saputra, 2022). ARMA model selection is carried out based on the AIC value of each model. The lowest AIC indicates the best model to choose. The initial estimation of the plot is then overfitted to ensure the best model estimate. Overfitting is done by adding one order at a time. The resulting model is as shown in Table 7.

Table 7. Selected ARIMA Model

Data	ARIMA Model	Parameter	Coefficient	AIC
S_t	ARIMA(0,1,2)	MA(1)	-1,5376	4250,25
		MA(2)	0,5563	
C_t	ARIMA(1,0,0)	Intercept	25114657,8	5481,48
		AR(1)	0,6034	
N_t	ARIMA(1,1,2)	AR(1)	-0,3803	1691,00
		MA(1)	-1,5443	
		MA(2)	0,5521	
Z_t	ARIMA(1,1,2)	AR(1)	0,6232	9974,79
		MA(1)	-1,8577	
		MA(2)	0,8576	

Based on Table 7, the ARIMA model for each data is obtained as follows:

$$B_t \quad = -1{,}5376\varepsilon_{t-1} + 0{,}5563\varepsilon_{t-2} + \varepsilon_t \tag{8}$$

$$T_t \quad = 25114657{,}8 + 0{,}6034T_{t-1} + \varepsilon_t \tag{9}$$

$$N_t = -0{,}3803N_{t-1} - 1{,}5443\varepsilon_{t-1} + 0{,}5521\varepsilon_{t-2} + \varepsilon_t \quad (10)$$

$$A_t = 20839970 + 0{,}8780A_{t-1} - 0{,}6990\varepsilon_{t-1} + \varepsilon_t \quad (11)$$

$$Z_t = 0{,}6232Z_{t-1} - 1{,}8577\varepsilon_{t-1} + 0{,}8576\varepsilon_{t-2} + \varepsilon_t \quad (12)$$

6. White Noise Error Assumption

The white noise error assumption is an error autocorrelation check carried out on the model (Moffat & Akpan, 2019; Sudipa et al., 2023). This assumption uses the Ljung-Box test with a hypothesis:

H_0 : Independent errors
H_1 : Dependent errors

and H_0 is rejected if $p\text{-}value < 0.05$. The following is the ljung-box test result white noise error assumption as shown in Table 8.

Table 8. Ljung-Box Test Result White Noise Error Assumption

Data Error	Model ARIMA	χ^2	$p - value$
S_t	ARIMA (0,1,2)	0,0966	0,7559
C_t	ARIMA (1,0,0)	0,2034	0,6520
N_t	ARIMA (1,1,2)	0,5541	0,4566
Z_t	ARIMA (1,1,2)	0,4476	0,5034

Based on Table 8, all data has a $p\text{-}value > 0.05$, meaning that the data errors are independent of each other. Next, the best distribution is selected which most closely matches the empirical distribution to be used in the copula model later.

7. Selection of the Best Distribution

Estimating the distribution of data errors through histogram plots and comparing them with empirical scatter plots. Selection of the best distribution using the Anderson-Darling test (Ruslau & Silubun, 2018). The best fit error distribution will be used in the copula analysis. Selection of the best distribution is done with a hypothesis:

H_0 : The distribution fits empirical distribution
H_1 : The distribution doesn't fit the empirical distribution

and H_0 is rejected if $p\text{-}value < 0.05$. The following is the appropriate distribution as shown in Table 9.

Table 9. Appropriate Distribution

Data Error	Distribution	Parameter	*p-value*
Iron and Steel (S_t)	Normal	μ_1 = 6944	0,7807
		σ_1 =116787	
Copper (C_t)	Normal	μ_2 = -33703	0,9725
		σ_2 = 4330175	
Nickel (N_t)	Laplace	θ_1 = 3,9370	0,0719
		s_1 = 23,6332	
Exchange Rate (Z_t)	Laplace	θ_2 = 279273833355	0,7486
		s_2 = 3,2649e+12	

Table 9 shows that the distribution of steel, copper and aluminum errors best fits the normal distribution, while nickel and exchange rates match the Laplace distribution. Next, the joint distribution function (copula) uses this distribution.

8. Copula

Probability transformation before using copula is needed to change the distribution to be uniform. This is done because the copula definition area is a uniform distribution. Opportunity transformation is carried out by:

$$S \sim \mathcal{N}(\mu_1, \sigma_1^2) \ \rightarrow U_1 = F_S(s) \sim U(0,1) \tag{13}$$

$$C \sim \mathcal{N}(\mu_2, \sigma_2^2) \rightarrow U_2 = F_C(c) \sim U(0,1) \tag{14}$$

$$N \sim Laplace(\theta_1, s_1) \rightarrow U_3 = F_N(n) \sim U(0,1) \tag{15}$$

$$Z \sim Laplace(\theta_2, s_2) \rightarrow V = F_Z(z) \sim U(0,1) \tag{16}$$

This transformation proves that the distribution is uniform and the data fits theoretically and empirically. Copula is used to determine the joint distribution function between two data. Before creating a joint distribution function, a goodness-of-fit test for copula is carried out to see which copula is suitable for use in each pair of data (Okhrin et al., 2021). Data dependency modeling is carried out using single copula fitting. The copulas used are the Frank, Clayton, and Gumbel copulas. Clayton's copula can capture the dependence effect on the lower tail, while Gumbel's copula can capture the dependence effect on the upper tail. Frank's copula alone cannot capture the effects of dependence on any tail. Single copula parameter estimation uses the maximum likelihood method. The selection of the most appropriate copula model is based on the lowest AIC value. In copula modeling, dependency is measured by the Kendall's Tau (τ) correlation parameter. The following is the single copula fitting model as shown in Table 10.

Table 10. Single Copula Fitting Model

Data	Copula	Parameter	Loglikehood	AIC	τ
Iron and Steel – Exchange Rate	Frank	-0,4199	0,2359	1,5282	-0,0465
Copper – Exchange Rate	Frank	-0,7418	0,8234	0,3532	-0,0819
Nickel – Exchange Rate	Clayton	0,0456	0,3836	1,2327	0,0222

The best copula model is written as follows:

$$(S_t, Z_t) \sim C^{Fr}_{-0,4199}(u_1, v) = \frac{1}{0,4199}\ln\left(1 + \frac{(e^{0,4199u_1} - 1)(e^{0,4199v} - 1)}{e^{0,4199} - 1}\right) \quad (17)$$

$$(C_t, Z_t) \sim C^{Fr}_{-0,7418}(u_2, v) = \frac{1}{0,7418}\ln\left(1 + \frac{(e^{0,7418u_2} - 1)(e^{0,7418v} - 1)}{e^{0,7418} - 1}\right) \quad (18)$$

$$(N_t, Z_t) \sim C^{Cl}_{0,0456}(u_3, v) = \left(u_3^{-0,0456} + v^{-0,0456} - 1\right)^{-\frac{1}{0,0456}} \quad (19)$$

where the (S_t, Z_t) model is the Iron and Steel – Exchange Rate model, the (C_t, Z_t) model is the Copper – Exchange Rate model, and the (N_t, Z_t) model being the Nickel – Exchange Rate model. A positive τ value interprets that when the IDR-USD exchange rate increases (the rupiah weakens) then the export volume also tends to increase and if a negative τ value interprets that when the IDR-USD exchange rate decreases (the rupiah weakens) then the export volume tends to decrease. The Frank Copula best models the dependence of the exchange rate on the volume of steel and copper exports. The dependence of the exchange rate on nickel export volume is best modeled by the Clayton copula.

Based on Table 10, a low value of τ indicates a very weak dependency of each pair of data. The exchange rate is positively correlated with the volume of nickel exports with the correlation τ is 0,0222, but negatively correlated with the volume of exports of copper and steel with the τ value of -0,0465. Even though the correlation is negative and relatively weak, the τ value of -0.0819 between the volume of copper exports and the exchange rate indicates a stronger dependency than other commodities. The interpretation of this negative τ value is that when the export volume of copper and iron and steel tends to fall, the exchange rate tends to increase (the rupiah weakens). Meanwhile, for positive tau, when the volume of nickel exports increases, the exchange rate tends to decrease (the rupiah strengthens). This also applies to events of decrease or increase in the opposite variable.

D. CONCLUSION AND SUGGESTIONS

Based on the results of this research, it can be concluded that there is no significant relationship between the IDR-USD exchange rate and the export volume of steel, copper and nickel. The strongest dependency is on the volume of copper exports and the exchange rate, followed by iron and steel and the exchange rate which both have a negative correlation of -0,0819 and -0,0465. Nickel export volume and the exchange rate have a positive correlation of 0,0222, and nickel export volume has the weakest dependence on the exchange rate compared to others.

The results of this copula model can be used as recommendations regarding considerations for Indonesia's export activities, especially for the commodities steel, copper and nickel. The exchange rate is not an important indicator in decision making when considering export volume. On the other hand, fluctuations in the export volume of related commodities do not have a significant effect on the strengthening/weakening of the exchange rate. Further research is recommended to add other variables such as commodity prices, suitability of exchange rates based on commodity type and macroeconomic factors. The addition of variables is considered to assess stronger dependencies in a more comprehensive use of the copula model.

REFERENCES

Afriyie, J. K., Twumasi-Ankrah, S., Gyamfi, K. B., Arthur, D., & Pels, W. A. (2020). Evaluating the performance of unit root tests in single time series processes. *Mathematics and Statistics*, *8*(6), 656–664. https://doi.org/10.13189/ms.2020.080605

Birnbaum, M. H., & Wan, L. (2020). Marter: Markov true and error model of drifting parameters. *Judgment and Decision Making*, *15*(1), 47–73. https://doi.org/10.1017/s1930297500006902

Chatterjee, S., & Simonoff, J. S. (2020). Time Series Data and Autocorrelation. In *Handbook of Regression Analysis* (pp. 81–109). John Wiley & Sons, Inc. https://doi.org/10.1002/9781118532843.ch5

Dani, S. C. R., Ismanto, B., & Sambara Sitorus, D. (2020). Pengaruh Ekspor Impor Dan Nilai Tukar Rupiah Terhadap Cadangan Devisa Indonesia Tahun2000-2019. *Jurnal Ecodunamika*, *3*(2), 791–792.

Dirjen Mineral dan Batubara. (2023). Booklet Promosi Investasi Mineral tahun 2023 "Hilirisasi Bauksit." In *Direktorat Pembinaan Program Mineral dan Batubara, Kementerian ESDM RI*. Kementerian ESDM. https://www.minerba.esdm.go.id/upload/ebook/20231113143857.pdf

Frohm, E. (2021). Dominant Currencies and the Export Supply Channel. In *SSRN Electronic Journal* (Issue 2580). https://doi.org/10.2139/ssrn.3898299

Haugh, M. (2016). An Introduction to Copulas. *Quantitative Risk Management*, *1*.

Iancu, A., Anderson, G., Ando, S., Boswell, E., Gamba, A., Hakobyan, S., Lusinyan, L., Meads, N., & Wu, Y. (2020). Reserve Currencies in an Evolving International Monetary System. In *Departmental Papers*. International Monetary Fund. https://doi.org/10.5089/9781513560298.087

Jaworski, P., Hardle, W., Durante, F., & Rychlik, T. (2009). Copula theory and its applications. *Lecture Notes in Statistics*, 198. https://doi.org/10.1007/978-3-642-12465-5

Jeanne, O., & Rancière, R. (2006). *The Optimal Level of International Reserves for Emerging Market Countries: Formulas and Applications* (No. 229; 06). https://www.imf.org/external/pubs/ft/wp/2006/wp06229.pdf

Kementerian ESDM. (2021). *Peluang Investasi Besi Indonesia*. Direktorat Jenderal Mineral dan Batubara, Kementerian ESDM. https://www.esdm.go.id/assets/media/content/content-peluang-investasi-besi-indonesia.pdf

Kim, H. (2013). Statistical notes for clinical researchers : assessing normal distribution (2) using skewness and kurtosis. *Restorative Dentistry & Endodontics*, *7658*(2), 52–54. https://doi.org/http://dx.doi.org/10.5395/rde.2013.38.1.52

Krouthén, J. (2015). Extreme joint dependencies with copulas A new approach for the structure of C-Vines. In *U.U.D.M. Project Report* (Vol. 24). https://www.diva-portal.org/smash/get/diva2:827739/FULLTEXT01.pdf

Ljung, G. M., & Box, G. E. P. (2014). On a measure of lack of fit in time series models. *Biometrika*, *65*(2), 297–303. https://doi.org/10.2307/2335207

Ludlow, L., & Perez, S. (2018). Addressing Autocorrelation in Time Series Data: A Comparison of Four Analytic Methods Using Data from College Course Evaluations. *General Linear Model Journal*, *44*(1), 11–23. https://doi.org/10.31523/glmj.044001.002

MacGillivray, H. . (1986). Skewness and Asymmetry: Measures and Orderings. *The Annals of Statistics*, *14*(3), 994–1011. https://doi.org/10.1214/aos/1176350046

McNeil, A. J., Frey, R., & Embrechts, P. (2005). *Quantitative Risk Management: Concepts, Techniques and Tools*. Princeton University Press. https://press.princeton.edu/books/hardcover/9780691166278/quantitative-risk-management

Moffat, I. U., & Akpan, E. A. (2019). White Noise Analysis: A Measure of Time Series Model Adequacy. *Applied Mathematics*, *10*(11), 989–1003. https://doi.org/10.4236/am.2019.1011069

Ndoen, W. M., Amtiran, P. Y., & Minggu, M. (2020). The Effect of Exports on Economic Growth in Indonesia With the Exchange Rate of Rupiah as A Moderated Variables. *Advances in Economics, Business and Management Research*, *158*, 520–524. https://doi.org/10.2991/aebmr.k.201212.073

Nelsen, R. B. (2006). *An Introduction to Copulas* (2nd Ed). Springer Science Business Media. https://link.springer.com/book/10.1007/0-387-28678-0

Okhrin, O., Trimborn, S., & Waltz, M. (2021). gofCopula: Goodness-of-Fit Tests for Copulae. *R Journal*, *13*(1), 467–498. https://doi.org/10.32614/rj-2021-060

Ping, H. (2011). The economic and social effects of real exchange rate— Evidence from the Chinese provinces. In *International Conference on Social Cohesion and Development*. http://www1.oecd.org/development/pgd/46838088.pdf

Ratnaningtyas, A. H., & Huda, S. (2023). *The Influence of Interest Rates , Inflation , Exchange Rates and Exports on Indonesia's Foreign Exchange Reserves*. *3*(6), 2039–2054. https://doi.org/10.55927/ijba.v3i6.5727

Ruslau, M. F. V., & Silubun, H. C. A. (2018). Analysis of Wind Speed Distribution at the Mopah Airport in Merauke. *Atlantis Highlights in Engineering*, *1*(1), 958–963. https://doi.org/10.2991/icst-18.2018.193

Sudipa, I. G. I., Riana, R., Putra, I. N. T. A., Yanti, C. P., & Aristana, M. D. W. (2023). Trend Forecasting of the Top 3 Indonesian Bank Stocks Using the ARIMA Method. *SinkrOn*, *7*(3), 1883–1893. https://doi.org/10.33395/sinkron.v8i3.12773

Sutikno, Kuswanto, H., & Ratih, I. D. (2014). Gaussian copula marginal regression for modeling extreme data with application. *Journal of Mathematics and Statistics*, *10*(2), 192–200. https://doi.org/10.3844/jmssp.2014.192.200

U.S. Geogolical Survey. (2023). *Mineral Comodity Summaries 2023*. U.S. Geological Survey. https://doi.org/https://doi.org/10.3133/mcs2023.

Yakubu, U. A., & Saputra, M. P. A. (2022). Time Series Model Analysis Using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for E-wallet Transactions during a Pandemic. *International Journal of Global Operations Research*, *3*(3), 80–85. https://doi.org/10.47194/ijgor.v3i3.168