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ANALYSIS OF THE DEPENDENCIES COMMODITY PRICES AND STOCK MARKET INDEXES USING COPULA

Salsabilla Rahmah[1*], Retno Budiarti[2], I Gusti Putu Purnaba[3]

[1,2,3] *Applied Mathematics Study Program, Institut Pertanian Bogor*
Jl. Raya Dramaga, Jawa Barat 16680, Indonesia

Corresponding author's e-mail: ***2502salsabilla@apps.ipb.ac.id***

ABSTRACT

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Indonesia is rich in natural resources and occupies an important position in the global raw materials market. The country's rich resources such as oil, coal, nickel, and crude palm oil (CPO) have a significant impact on the economic situation. As one of the world's leading producers and exporters of these raw materials, Indonesia's economic fate is closely linked to price fluctuations. This study uses the copula method to model the dependence between stock and commodity returns and calculates the dependence between commodity prices (oil, coal, nickel, CPO) and Indonesian stock market index (IHSG) The data used for this analysis was sourced from Bloomberg.com, covering the period from 29 September 2021 to 29 September 2023. This study investigates the dynamic dependencies between commodity price returns and the Indonesian stock market index. The results show that the correlations between oil prices and the Indonesian stock index, and between CPO prices and the stock index are generally weak. However, there are exceptions to stock index returns, such as their relatively high dependence on coal and nickel. This diverse research provides valuable insight into the complex interdependencies in Indonesia's financial landscape. Understanding dependence between commodity prices and stock indexes is of great value to investors and policymakers, as it is the basis for making informed decisions to navigate the complex global economy.

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1. INTRODUCTION

Indonesia is a country rich in natural resources. One of Indonesia's riches lies in its products and commodity reserves. According to records from the U.S. government agency (U.S. Geological Survey), Indonesia is one of the world's producers and reserves of mining materials. In 2016, Indonesia was recorded as the third-ranked tin producer in the world. Indonesia contributed about 9.5% of world nickel, coal producers with a share of 2.2% of world production [1]. Besides that, Indonesia also produces crude oil, Indonesia ever reached peak oil production in 1977 and 1995, with an output of 1.6 million barrels per day. [2]. Indonesia also has become the world's largest exporter of palm oil [3]. Commodities have an essential role in people's lives. In 2021 Indonesia's Gross Domestic Product (GDP) growth rate increased to 5% compared to 5.02% in 2020. The mining industry contributed around 8.98% of GDP in 2021 [4]. Many things influence commodity prices in Indonesia. Severe events such as earthquakes and typhoons, even Indonesian government regulations, can affect commodity prices in Indonesia [5]. Commodities prices play a crucial role in stock market performance. Reducing oil prices reduces production costs and increases economic growth [6].

The wealth of commodities in Indonesia has quite influenced the stock market movement in Indonesia. Generally, stocks are considered to react to macroeconomic fundamentals and financial variables. Further study proves that perceived market risk and uncertainty influence stock market movements. Based on the U.S. Energy Information Administration (2021). The country’s petroleum share, although decreasing since 2018. In the same period, stock prices also experienced a decrease. This phenomenon means a positive influence exists between world oil prices and stock prices. This is because the capital market activity indicates a country's progress [7]. Stocks related to mining and oil and gas commodities have quite an influence on the ups and downs of the stock market index. Several studies have agreed that world oil prices have both positive and negative impacts on the stock market [8]. The factors influencing stock interdependence are an ongoing research problem. Sukcharoen, in 2014, studied the dependence between oil prices and stock market indices of various countries between 1982 and 2007. The results of this study showed a weak dependence between oil prices and stock indices for most cases, but for the stock indices of consuming and producing countries, major oil companies (the United States and Canada) have been shown to have a relatively strong dependence on the oil price series [9].

Existing literature states the substantial dependence between commodity prices and the stock market. There is a context in this literature that rising commodity prices increase stock prices in oil-importing countries mainly due to higher export income [10]. Other findings with similar results from importing countries include [10], [11], and [12]. However, several other studies, such as [13] and [14] did not find a dependence between commodity prices and stock returns. [10] Found that sources of variation in oil prices affect stock prices differently. In addition, supply-side variations in oil prices due to supply shocks reduce their impact on stock prices compared to demand-side shocks. [15] argue that in strong demand-side shocks, stock markets in oil-importing countries can react negatively to adverse oil price shocks.

Overall, there is a complex dependence between commodity prices and stock market performance, and the impact of commodity prices on stock market indices varies depending on the particular commodity, country, and other factors. However, a more realistic modelling of the distribution of random variables is needed to understand better the dependence between commodity prices and stock market performance. Many methods can be used to determine the structure of the dependence between financial assets and commodities. One common way that can be used to measure dependencies between financial support is the Pearson correlation. However, this measure only measures linear dependence between random variables, which are assumed to have a normal distribution, so it does not work well. Therefore, Copula is more suitable for analyzing dependencies between assets because it is not limited by normality assumptions [16]. The copula method is an appropriate solution for analyzing dependency patterns between two or more random variables that do not require normality assumptions. Copula is a function that can combine several marginal distributions into a typical distribution [17]. In 2014, using the copula method, Sukcharoen studied the relationship between oil prices and stock market indices in various countries between 1982 and 2007. In most cases, Sukcharoen's research shows a weak dependence between oil prices and stock indices. Still, the stock indices of large oil-consuming and producing countries (the United States and Canada) prove they have a relatively strong dependence on oil prices. It is known that Indonesia is a country that produces oil, nickel, coal, and CPO. The difference between this and previous research is that previous research studied the relationship between one commodity and many stock market indices in various countries. However, in this research, the researcher wants to look for the relationship between many commodities and one stock market index in Indonesia.

Based on the description above, researchers are examining the critical dependence between commodity prices and the stock market index in Indonesia. This research is of paramount importance as it can significantly enhance our understanding of how fluctuations in commodity prices impact stock market performance. Such insights are crucial for investors and policymakers, who rely on accurate data to make informed decisions regarding investments and economic policies. For investors, understanding this relationship is vital. If commodity prices are expected to rise, they might consider increasing their investments in companies that produce or use these commodities. Conversely, if commodity prices are predicted to fall, they might seek alternative investments to safeguard their portfolios. For policymakers, this research is equally essential. By understanding the link between commodity prices and the stock market, they can implement measures to stabilize prices or boost production, thereby maintaining economic stability. This is especially urgent in a volatile market environment where unexpected changes in commodity prices can lead to significant economic disruptions. By thoroughly examining the dependence between commodity prices and stock market indices, researchers and analysts can provide critical insights into market trends. This in turn will help investors make more strategic decisions and enable policymakers to craft effective economic strategies. The urgency of this research cannot be overstated, as it holds the potential to influence investment strategies and economic policies, ultimately contributing to the stability and growth of Indonesia's economy.

2. RESEARCH METHODS

This research used data from September 29, 2020, to September 29, 2022, including daily return data for commodities like oil, nickel, coal, and CPO, along with the Indonesian daily stock index return data, IHSG. The research was meticulously structured into a series of well-defined steps. First, the initial analysis involved plotting the data distribution through histogram plots and calculating descriptive statistics. This step provided an essential overview of the dataset's characteristics.

The next phase of the research focused on assessing the independence of each financial asset. The Ljung-Box test was employed to identify any autocorrelation effects. If the assets were found to be independent, the analysis progressed to the following stage to distribution estimation. However, if autocorrelation was detected, the research delved into ARMA modeling to address this issue effectively. This step was crucial in ensuring the validity of subsequent analyses.

Once the data's independence was confirmed, the research moved on to assess the stationarity of the data concerning its mean, employing the Augmented Dickey-Fuller (ADF) test. In cases of non-stationarity, differencing was applied, and the stationarity test was repeated. Upon achieving stationarity, the study continued by examining the variance's stationarity using the Box-Cox test. If non-stationarity was observed, the Box-Cox transformation was implemented. The order of the ARMA model was determined and estimated before proceeding with the subsequent steps, ensuring that the data was prepared for in-depth statistical analysis.

Following these preparatory steps, the research ventured into statistical modeling and distribution estimation. The distribution of commodity price returns was estimated and compared to an empirical scatter plot. The best-fitting distribution was selected based on the Anderson-Darling test results. Subsequently, the data distribution or error of the ARMA model was estimated and contrasted with an empirical scatter plot using the Anderson-Darling test. This comprehensive analysis approach ensured that the researchers thoroughly explored financial and commodity data, combining statistical tests, modelling techniques, and distribution estimation to gain valuable insights into the dataset's behaviour and dependences, thereby contributing to the depth of the research findings.

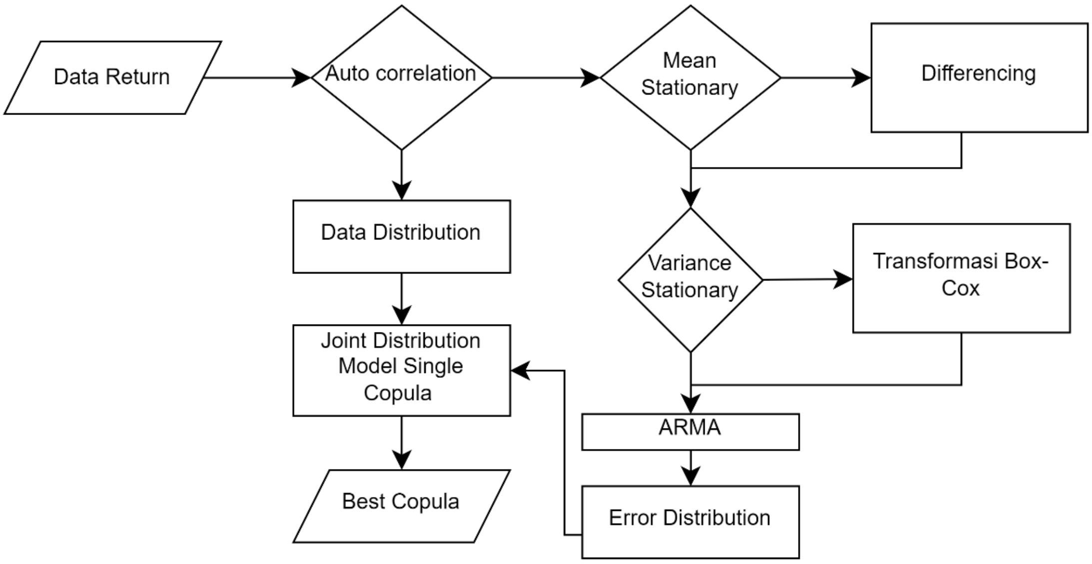

Figure 1. Research Framework

3. RESULTS AND DISCUSSION

Statistic descriptive of the returns for each asset along with the correlation to the IHSG in **Table 1**. From the skewness and kurtosis values for each data, the five asset returns are not normally distributed. Non-zero skewness (either positive or negative) indicates asymmetry.

Table 1. Descriptive Statistics

Data	Mean	Standard Deviation	Skewness	Kurtosis	Correlation IHSG
Oil	0.0014	0.0263	-0.7835	3.1805	0.039
Coal	0.0038	0.0365	-2.0614	57.2971	0.044
Nickel	0.0008	0.0339	6.1980	97.3252	0.068
CPO	0.0002	0.0255	-0.3209	2.7443	0.025
IHSG	0.0007	0.0086	-0.3146	2.4431	

Autocorrelation is a correlation that occurs between observations in one variable. According to [16], autocorrelation is one of the crucial things that needs to be considered when analyzing time series data. The existence of an autocorrelation effect on return data can be checked using the Ljung-Box test with a hypothesis.

H_0 : There is no autocorrelation effect.
H_1 : There is an autocorrelation effect.
H_0 rejection area based on p-value < 0.05.

The test results can be seen in **Table 2**. **Table 2** shows that only nickel commodity returns have a p-value < 0.05, which indicates an autocorrelation effect, so ARMA modeling is needed to eliminate this effect.

Table 2. Test of Autocorrelation Effects

Data	Test Statistics	p-value
Oil	0.0048	0.9446
Coal	0.5131	0.4738
Nickel	12.641	0.0003
CPO	0.7121	0.3987
IHSG	1.6126	0.2041

To eliminate the effect of autocorrelation on nickel commodity price returns, ARMA modelling will be carried out. First, several ARMA models are estimated to fit the data. Initial estimates of the order of p and q in the ARMA(p, q) model are obtained from the graph of the autocorrelation function (ACF) and graph of the partial autocorrelation function (PACF) of return data.

After estimating the initial model, proceed with checking the significance of the parameters of each estimated model. The ACF and PACF plots of nickel commodity price return data can be seen in **Figure 2**. The ARMA model selection was made based on each model's AIC value and the parameters' significance. According to **[18]**, the most appropriate model is the model with the smallest AIC value.

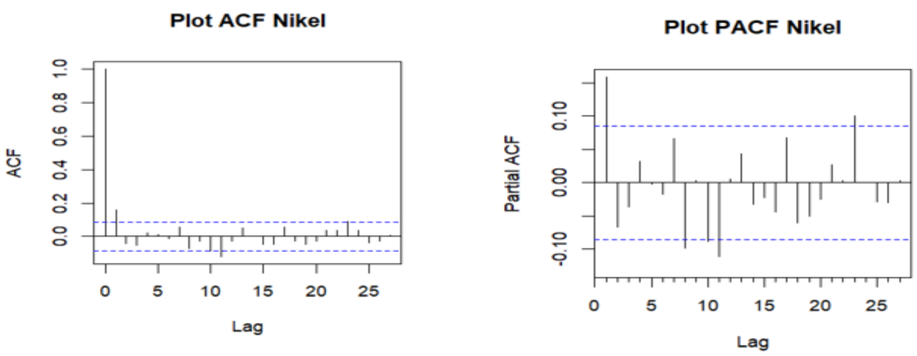

Figure 2. Plot of ACF and PACF Return Data for Nickel Commodity Prices

The ACF and PACF plots of nickel commodity price return data show a cut off at lag 1, so the initial guess model is AR(1), MA(1), or ARMA(1,1). The fitting results are shown in **Table 3.**

Table 3. ARMA Model Fitting Results for Nickel Commodity Price Return Data

Data	Model	Parameter	Coefficient	p-value	AIC
Nickel	AR(1)	AR(1)	0.1549	0.0003	2882.48
	MA(1)	MA(1)	0.1621	0.0002	2881.77
	ARMA(1,1)	AR(1)	-0.0250	0.9073	2883.76
		MA(1)	0.1858	0.3752	

From **Table 3**, it can be seen that the ARMA(0,1)/MA(1) model is suitable for nickel commodity price return data, as its parameters are significant (p-value $< \alpha = 0.05$) and it has the smallest AIC value. After obtaining the ARMA model, the existence of the autocorrelation effect was retested using the Ljung-Box test. The test results can be seen in **Table 4**. It can be seen that all p-values > 0.05, which indicates that the effect of autocorrelation on the return of each asset has been accommodated by the appropriate ARMA model.

Table 4. Autocorrelation Test (Ljung-Box) After ARMA Modeling

Data	ARMA Model	Lag	X^2	p-value
Oil	(0,0)	1	0.0049	0.9439
Coal	(0,0)	1	8.7015	0.7282
Nickel	(0,1)	1	18.421	0.1035
CPO	(0,0)	1	0.7183	0.3967
IHSG	(0,0)	1	1.4481	0.2288

Based on **Table 3**, the ARMA model equation of Nickel Return is as follows

$$r_t = 0.1408 + 0.1621\varepsilon_{t-1} + \varepsilon_t$$

Stationarity is one of the assumptions that must be met to analyze time series data. Data is said to be stationary if it does not have a long-term trend and has a constant mean and variance over time (stationary to the mean and variance). The return plot for each asset can be seen in **Figure 3**.

Figure 3 shows that the return on each asset is stationary (fluctuating around the value 0), so it can be assumed that the data is stationary with respect to the mean. To ensure that the return on each asset is stationary concerning the average, an ADF (Augmented Dickey-Fuller) test is carried out with the following hypothesis.

H_0: Data is not yet stationary
H_1: Data is stationary

with the rejection area H_0 is p-value < 0.05.

Table 5. Stationarity Test Results (ADF) on Return Data

Data	p-value
Oil	≤ 0.01
Coal	≤ 0.01
Nickel	≤ 0.01
CPO	≤ 0.01
IHSG	≤ 0.01

From Table 5, it can be seen that all assets have a p-value of less than 0.05, indicating that the assets are stationary with respect to the mean, so there is no need to differentiate the data.

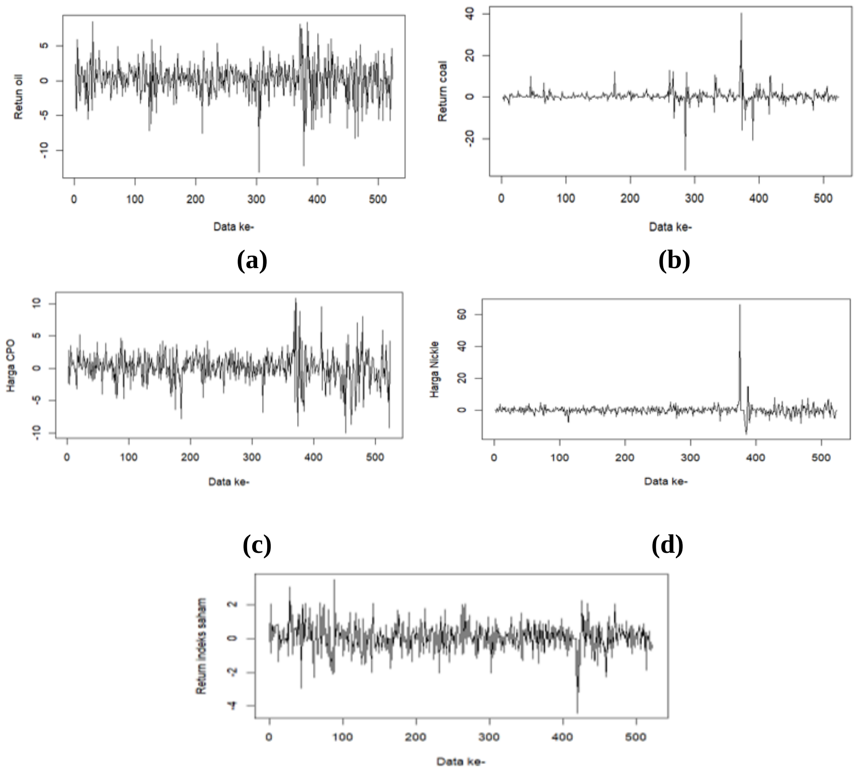

Figure 3. Time Series Plot of Asset Return Values for (a) Oil, (b) Coal, (c) Nickel Galat, (d) CPO, and (e) IHSG

Next, we will identify the marginal distribution by comparing the empirical distribution graph with the theoretical distribution of each asset. For nickel, error will be used as a value that measures the degree of agreement between the empirical distribution and the theoretical distribution

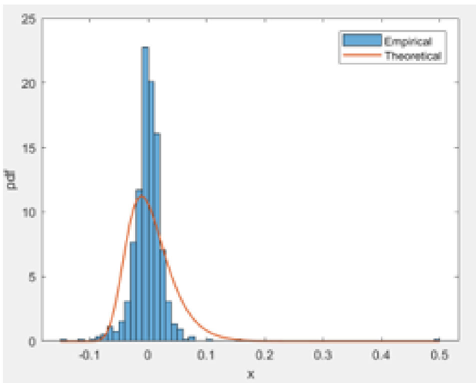

Figure 4. Histogram and Fitting of Nickel Error Distribution.

In Figure 4 you can see the distribution and fitting results for the nickel error distribution. From the fit results, the most suitable nickel error distribution is GEV. The results of identifying the marginal distribution of all assets are in Table 6.

Table 6. Corresponding Distribution for Each Variable

Data	Distribution
Oil	Logistic
Coal	Logistic
Nickel	GEV
CPO	Laplace
IHSG	Logistic

According to [19], copula can describe the dependence between assets better than rank correlation or linear correlation. Copula is used to determine the joint spread function between two assets. Here the fitting is carried out using a single Archimedean copula. In this study, the Archimedean copulas used to identify dependences between variables are the Clayton, Frank and Gumbel copulas. The Clayton copula can capture the dependency effect on the lower tail, while the Gumbel copula can capture the dependency effect on the upper tail. Frank copula itself cannot capture the effect of dependence on any tail. The fitting results using a single copula can be seen in Table 7. Parameter estimation for each copula uses the maximum likelihood method.

The selection of the most appropriate copula model is based on the AIC value. From Table 7 it can be seen that the most suitable copulas for petroleum-IHSG, coal-IHSG, nickel-IHSG and CPO-IHSG data are Clayton, Frank, Frank and Clayton respectively.

Table 7. Archimedean Copula Model Fitting Results

Data	Copula	Parameter	AIC
Oil	Clayton	0.1106	-7.944
Coal	Frank	0.5598	-0.977
Nickel	Frank	0.9163	-3.334
CPO	Clayton	0.0497	-0.025

Tail dependency in a copula model describes the size of the dependency between the extreme values of the random variables $X1$ and $X2$. This dependency can be illustrated through the coefficient of the tail dependency parameter which is obtained from the formation of a copula function from the bivariate distribution [20].

The coefficients of the lower tail λL and upper tail λU dependencies can be described in a bivariate copula with the following formula

The lower-tail dependence parameter λ_C^L

$$\lambda_C^L = \lim_{t\to 0^+} \Pr\left[Y \leq y(t) | X \leq x(t)\right]$$

the upper-tail dependence parameter λ_C^L

$$\lambda_C^U = \lim_{t\to 1^-} \Pr\left[Y > y(t) | X > x(t)\right]$$

Not all types of copula can capture the two types of tail dependencies, namely upper tail and lower tail dependencies. A copula with one parameter can only show one tail dependency [21].

Tabel 8. Lower-tail dan Upper-tail Dependencies

Data	Copula	Lower Tail	Upper Tail
Oil	Clayton	0.001893325	-
Coal	Frank	-	-
Nickel	Frank	-	-
CPO	Clayton	8.729431e-07	-

Based on the results above, it can be seen that oil and CPO have a dependence on the lower tail of the IHSG, and the Clayton component of petroleum-IHSG is greater, indicating that the return value of petroleum prices tends to have a dependence on the lower tail.

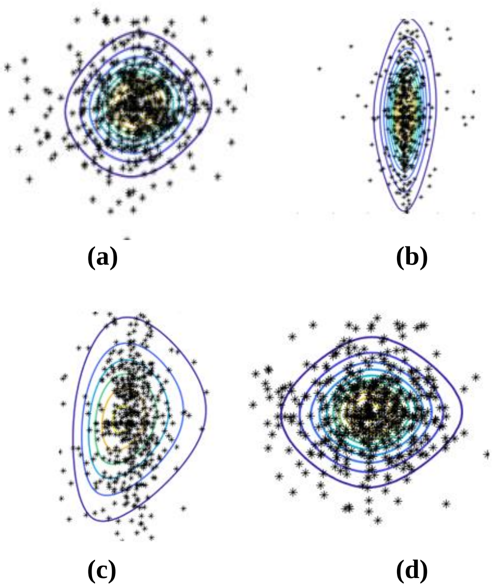

Figure 5. Copula Plot Results for Each Commodity with IHSG, (a) Oil, (b) Coal, (c) Nickel, (d) CPO

Furthermore, the characteristic of the Clayton copula is that it has a tail dependency at the bottom. Meanwhile, the Frank copula does not have tail dependencies with the interpretation of the dependencies explained based on the parameters. In copula modeling, measuring dependency with Kendall's Tau correlation with copula parameters is defined in **Table 6**, as follows:

Table 9. Dependencies with Kendall's Tau correlation with Copula Parameters

Data	Copula	τ
Oil	Clayton	0.0524
Coal	Frank	0.6200
Nickel	Frank	0.1010
CPO	Clayton	0.0242

Kendall's Tau is used to measure correlation or dependency between variables, while the copula parameter is used to describe the shape and strength of the dependencies in the conditional distribution which is used to connect the margin distribution of these variables.

4. CONCLUSIONS

From this research, it is concluded that nickel asset needs to be formed into a time series model using ARMA. Others, like oil, coal, and CPO without ARMA modelling

The analysis results show various dependences between commodity price returns and the IHSG (Composite Stock Price Index). Coal and nickel price returns have a significant dependence with the IHSG, while oil and CPO price returns show a weaker or insignificant dependence. Therefore, to maintain economic stability and manage risks related to commodity price returns, the government is considering more intensive monitoring of commodities that significantly influence the IHSG, namely coal and nickel.

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