PREDICTING THE JAPANESE YEN'S VOLATILITY IN RELATION TO THE INDONESIAN RUPIAH

[1]*Afied Akhmad*, [2]*Feza Raffa Arnanda*, [3]*Linda Monica Sari*, [4]*Rakaninda Indah Kuswardani*, [5]*Fitri Kartiasih**
[1,2,3,4]*Program Studi DIV Komputasi Statistik, Politeknik Statistika STIS*
[5]*Program Studi DIV Statistika, Politeknik Statistika STIS*
Jalan Otto Iskandardinata No.64C Jakarta 13330, Indonesia
[1]222111850@stis.ac.id, [2]222112058@stis.ac.id, [3]222112155@stis.ac.id,
[4]222112305@stis.ac.id, [5]fkartiasih@stis.ac.id
**Corresponding author*: fkartiasih@stis.ac.id

Abstract

Japan has experienced low inflation and continuous deflation since the economic bubble of the 1980s. Following the COVID-19 pandemic, the world was preoccupied with deflation in various countries, worsening Japan's financial condition. As a result, the Japanese currency's exchange rate could not compete with other currencies. This situation significantly affects the value of Indonesia's exports and imports, as Japan is one of the leading export destinations and a primary supplier of implications for Indonesia. The purpose of this study is to forecast the volatility of the exchange rate between the yen and the IDR for the future. The data used in this research is the buying rate variable from the yen to IDR exchange rate data from January 3, 2020, to November 27, 2023. The method used for the high-volatility data is the GARCH model. The best modeling obtained is GARCH(0,1). The forecast results provide an insight into the buying exchange rate of the yen against the IDR until the beginning of 2024.

Keywords: *COVID-19; exchange rate; GARCH; Russia-Ukraine War; volatility*

INTRODUCTION

COVID-19 has garnered extensive research attention due to its immense impact across various fields. Governments worldwide responded to the WHO's declaration of COVID-19 as a global pandemic on March 11, 2020, by implementing various policies. A crucial measure was area closure or lockdown, aimed at restricting people's movements and activities to mitigate the spread of the virus. Research by Cheval et.al in 2020 indicates that lockdowns, particularly when initiated early in an outbreak, have been effective in reducing virus transmission. This strategy is quite effective in controlling the disease, but it also has significant consequences (Chakraborty & Maity, 2020). Bonam and Smădu (2021) found long-term economic effects regarding the pandemic and inflation, showing that inflation trended significantly downward for over a decade after the global health crisis resulting from the COVID-19 pandemic. Crisis management during the Covid-19 pandemic has put the government in a difficult position.

Two years later, the world again experienced a crisis due to the Russian-Ukrainian invasion. The occurrence of economic and geopolitical instability due to a conflict will have a significant impact on investors and the financial stability of a country (Chortane & Pandey, 2022). These phenomena in the international economic system, especially in the monetary system, influence decisions, institutional practices, and domestic regulations, which will influence the exchange of national currency with global currency (Faris, 2022). Therefore, a monetary system controlled by domestic entities in

https://doi.org/10.35760/eb.2024.v29i3.10404

maintaining exchange rates, inflation, economic growth rates, and interest rates significantly impacts the results of a country's central bank policy (Faris, 2022). Research by the Swiss National Bank suggests that the war's effects are expected to be twice as significant within one to two years. In Germany, Britain, France, Italy, and Switzerland, inflation would have been 0.2 to 0.4 percent lower without the war, with Germany being the most affected, according to Swiss National Bank findings. Moreover, the repercussions of the Russia-Ukraine war extend beyond Europe, affecting countries like Japan. The conflict has influenced Japan's economy, resulting in increased commodity prices and inflation (Figure 1). Although Japanese inflation rose to 2.50% in 2022, a 2.73% increase from the previous year, it remained relatively low compared to other affected nations. Despite the impact of the conflict, Japan's inflation rates were still below those of countries most affected by the war, as illustrated in inflation graphs.

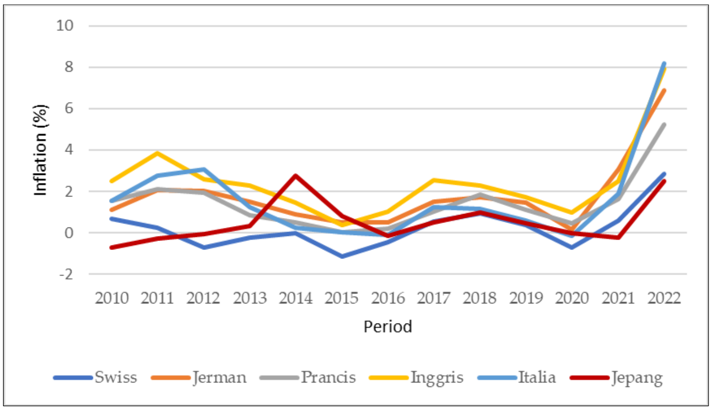
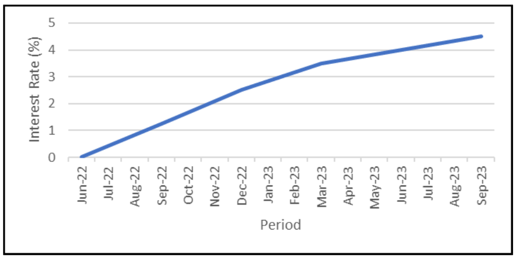


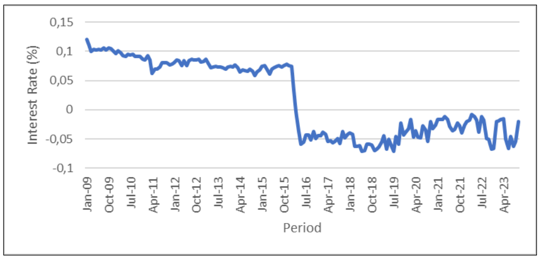
Figure 1. Inflation in Several European Countries and Japan.
Source : World Bank (2023)

The European Central Bank (ECB) estimates that inflation will continue to increase, especially in Europe. To combat this inflationary trend, the ECB began raising interest rates on July 21, 2022, by 0.5%, and on September 08, 2022, it increased by 1.25%. The upward trend occurs until September 2023, shown in Figure 2(a). Amid rising interest rates, Japan has adopted a policy of holding interest rates to maintain stable economic growth. This was caused by Japan's condition, which experienced low inflation and deflation before the Russian-Ukrainian war. Low-interest rates indicate tight monetary policy (Friedman, 1978). Regarding this, the BOJ issued a policy to maintain ultra-low interest rates.

Based on BOJ data in October 2023, Japanese interest rates are at –0.02%, as shown in Figure 2(b). Japan's decision to maintain low-interest rates has caused the spread between investment instruments denominated in yen and US dollars, which meant that the yen currency plummeted and could not compete with other countries (Botman et al., 2013). This exchange rate volatility can result in companies with weak balance sheets with high leverage facing the risk of significant losses and influencing shareholders to decide on new investments (Eklou, 2023a; Li et al., 2022). If the demand for a currency increases while the supply remains constant or decreases, then the exchange rate of that currency will increase, and vice versa. (Mankiw & Gregory, 2008).



(a)



(b)

Figure 2. Interest Rates.

Sources: (a) European Central Bank, 2022 - 2023; (b) (Bank of Japan, 2009 - 2023).

Chortane and Pandey's research highlights the impact of the Russia-Ukraine war on exchange rate volatility among the Russian rubble, the US dollar, and the Euro, demonstrating how global currencies were affected. International trade, crucial for national economies, operates on principles of absolute advantage, as noted by Dominick. Japan's significant role in international trade, emerging as both a primary exporter and importer in Indonesia over the past five years according to BPS (2023), underscores the importance of exchange rate stability. The weakening yen, as observed, can profoundly influence the value of exports and imports, aligning with Chaudhary's findings on the significant impact of exchange rates on trade. Subanti, Hakim, Riani, Hakim, and Nasir (2019) and Jabara (2009) further confirm the negative correlation between exchange rates and the value of exports and imports. In addition, Vo and Zhang (2019) revealed that exchange rate volatility was proven to influence trade activities between China and Japan. It is emphasized by the findings of Nishimura and Hirayama (2013), which confirm that the strategy of depreciating the Vietnamese currency by increasing manufacturing exports in the short term has a negative impact on exchange rate volatility in the long term.

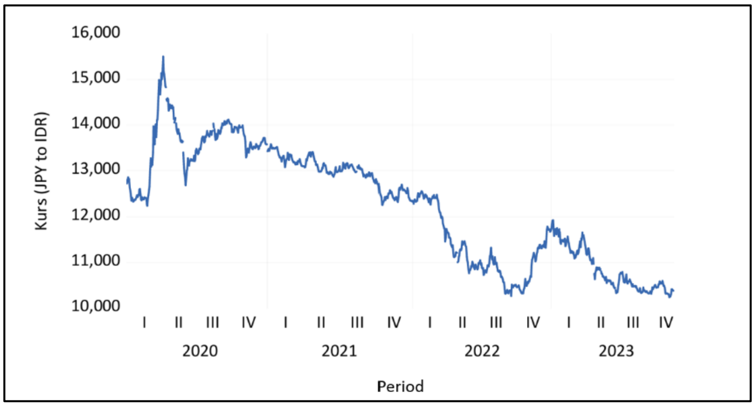


Figure 3. Japanese Yen exchange rate against the IDR.

Source : Bank Indonesia.

The Japanese yen's buying rate against the IDR exhibited significant volatility from January 2020 to November 2023, with a downward trend observed since January 2023. Ramoni-Perazzi and Romero (2022) emphasize that a competitive exchange rate facilitates efficient investment resource allocation and international transactions between countries. If Indonesia has debt in the Japanese currency, the weakening of the Yen will cause the amount of debt that must be paid in IDR to increase. This could increase the debt burden for the Indonesian government and companies that owe money in foreign currency. This study aims to predict future yen and IDR exchange rate volatility, focusing

https://doi.org/10.35760/eb.2024.v29i3.10404

on the period from January 2, 2020, to November 27, 2023, encompassing the early stages of the COVID-19 outbreak and the Russian-Ukrainian invasion. Previous research has analyzed the impact of these events on exchange rates but lacked future rate forecasting. Limitations include the necessity to analyze current exchange rate volatility and forecast yen rates against the IDR using the latest datasets. The study's findings can serve as a reference for understanding policy risks associated with domestic currency movements and their effects on economic activity.

LITERATURE REVIEW

Theoretical Concept

Covid-19 first appeared in the world in early December 2019, precisely in China. One of the most affected aspects is the economic condition of a country. Due to COVID-19, there are many restrictions on business activities and people's lives which have an impact reducing people's purchasing power (Sihaloho, 2020). Sihaloho (2020) stated that Japan, one of countries that became members of the G7, declared to have entered the brink of recession due to COVID-19. Previous research has also stated that COVID-19 will have an impact on the weakening of the Chinese economy and the threat of a recession in Japan (Rusiadi, Aprilia, Adianti & Verawati, 2020). The increase in COVID-19 cases is also comparable to the increase in exchange rate volatility, which initially increased at the beginning of 2020 (Feng, Yang, Gong, & Chang, 2021). Beckmann and Czudaj (2022) said that the IDR exchange rate became weak, which was IDR 16,575.00 on the 23rd of March 2020.

The war between Russia and Ukraine began with the initial conflict in 2013. Colonization, better known as the Russian invasion of Ukraine, had an impact on various aspects. However, what stands out is that this invasion has disrupted the world economic cycle for a long time, accompanied by the influence of the COVID-19 pandemic (Simanjuntak & Dermawan, 2023). Aspects of volatility can influence a country's economy. Therefore, it is essential to understand volatility for a country's future (Zhang, Raza, Wang, & Sui, 2023). The rise and fall of one country's currency exchange rate against another country's perspective is an understanding of volatility, where a country's economy becomes unstable both from a macro and micro if the country's currency exchange rate experiences extreme volatility (Mukhlis, 2011).

The exchange rate can be influenced by the balance between demand and supply, where the exchange rate is one of the things that significantly influences an open economy (Ginting & Kartiasih, 2019; Setiawan & Kartiasih, 2021). The central bank can control inflation and the exchange rate of a country's currency by changing interest rates. Low-interest rates will weaken the country's currency exchange rate due to declining demand for the currency and vice versa. The inflation rate also plays a vital role in calculating a country's exchange rate; a low inflation rate will increase a country's exports (Hanifah & Kartiasih, 2018; Kartiasih, Ramadhani, Fitri & Aselnino, 2022). This will impact the increasing demand for purchasing the country's currency so that the exchange rate will increase (Patel, 2014). Countries with surplus finances will get more benefits than countries with deficits. This will attract other countries who are ready to provide capital and can see the appreciation value of the currency relative to other countries. Another factor that influences a country's exchange rate is the amount of debt. A country will not attract foreign investors if the country has a large amount of debt. Other countries will be attracted to a country with a high gross domestic product and a stable government.

In the last 25 years (1995 – 2019), a questionable phenomenon emerged, where the IDR experienced depreciation against the Japanese yen (Laksono & Edison, 2020). The depreciation phenomenon impacts the price of goods being more expensive domestically compared to abroad. In this period there was a trade balance surplus because the value of exports continued to increase, and the value of imports continued to decline. This raises the question of whether the performance of export and import activities between Indonesia and Japan will affect the trade balance which will be used to estimate fluctuations in the IDR exchange rate against the Japanese yen.

Related Research

Modeling and forecasting exchange rate volatility is significant because it can guide policymakers' decisions. Abdullah, Siddiqua, Siddiquee, & Hossain (2017) modeled and predicted the Bangladeshi currency (Taka) or BDT with the United States USD. This research uses daily time series data for 7 years from the 1st of January 2008 to the 30th of April 2015, using the GARCH Family method (GARCH, EGARCH, TGARCH, IGARCH) and using standard assumptions and the Student's T distribution on the residual error and using the Student's T distribution to produce better results. The use of the EGARCH(1,1) and GARCH(1,1) models in research by Ma et al. (2014) shows that the overall volatility of the Chinese Yuan can be said to be consistent, but the model can still forecast well.

Another research shows that the GARCH model is the best model for data with high volatility based on statistical values of model goodness of fit tests such as RMSE and MAE. This conclusion is supported by various studies (Gabriel, 2012; Kannan & Balamurugan, 2022; Mamilla, Kathiravan, Salamzadeh, Dana, & Elheddad, 2023). The GARCH-based volatility model is the most appropriate because it provides consistent and significant estimates. In contrast, entropy-based predictions show higher acceptance but are less consistent and unreliable (Islam, 2013; Krishnaprabha & Vijayakumar, 2015; Mamilla et al., 2023; Pele et al., 2017). Research conducted by Satriana and Priyarsono, (2019) shows that assessing exchange rate volatility generally uses conditional standard deviations from annual, quarterly, or monthly exchange rates. This approach is supported by various researchers, such as Aftab, Syed, and Katper (2017), Asteriou, Masatci, & Pilbeam (2016), Chit et al. (2011); Kafle (2011), and Senadza and Diaba (2018). The measure of volatility is crucial because it influences the private sector's expectations of inflation, a critical variable in exchange rate dynamics, as noted by the IMF in 2023 (Eklou, 2023). Several references also say that the GARCH model produces accurate predictions for volatility data, especially the GARCH(1,1) model in the short term. Charfi and Mselmi (2022) show that GARCH(1,1) has predictive power in modeling daily exchange rates in Tanzania. Another research conducted by Huq, Rahman, Rahman, Shahin and Ali (2013) found that ARMA(1,1) with GARCH(1,1) and GARCH(2,1) can be applied to the Dhaka Stock Exchange, where the data also has high volatility.

RESEARCH METHOD

The data used in this study are secondary data obtained from Bank Indonesia (www.bi.go.id). The variable employed is the buying rate of the Japanese yen against the Indonesian IDR daily (five working days) from January 3, 2020, to November 27, 2023, resulting in 968 observations. The research method applied is descriptive analysis, using

R-Studio and Microsoft Excel software to predict the yen's volatility against the Indonesian IDR.

Descriptive analysis is a process that summarizes and explains the significant characteristics of a data set (Fulk, 2023). Descriptive statistics can be used to encapsulate relationships between variables using visualization techniques. In executing this research, descriptive analysis summarizes statistics, such as the mean, median, standard deviation, minimum, and maximum values. Additionally, data visualization is employed to understand data patterns, including trends and fluctuations (volatility), using line graphs.

Model Development

There are three types of models for time series data: the Autoregressive Moving Average (ARMA) model, the Autoregressive Conditional Heteroscedasticity (ARCH) model, and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. In 1976, Box and Jenkins developed the ARIMA(m,D,n) model, where 'm' indicates the number of autocorrelations, 'D' represents the number of differencing elements, and 'n' signifies the number of moving averages (Box G E P & Jenkins G M, 1976). The "I" in ARIMA is used to differentiate a non-stationary series. However, when the time series data is stationary, three existing process classes can be used: autoregressive (AR), moving-average (MA), and mixed autoregressive and moving average (ARMA). The autoregressive model of order m, denoted as AR(m), can be expressed as

$$\gamma_t = \mu + \phi_1\gamma_{t-1} + \phi_2\gamma_{t-2} + \cdots + \phi_m\gamma_{t-m} + u_t \tag{1}$$

The Moving Average of order n, denoted as MA(n), can be expressed as follows:

$$\gamma_t = \mu + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_n u_{t-n} \tag{2}$$

Where $u_t (t = 1,2,..)$ is the error white noise with $E(u_t) = 0$ and $var(u_t) = \sigma^2$.

The combination of the AR(m) model and the MA(n) model forms the ARMA(m,n) model, which is expressed as :

$$\gamma_t = \mu + \phi_1\gamma_{t-1} + \phi_2\gamma_{t-2} + \cdots + \phi_m\gamma_{t-m} + \theta_1 u_{t-1} + \cdots + \theta_n u_{t-n} + u_t \tag{3}$$

Or in a sigma notation:

$$y_t = C + \sum_{i=1}^{m} \phi_i\gamma_{t-i} + \sum_{i=1}^{n} \theta_j\varepsilon_{t-j} \tag{4}$$

Where y_t is the daily exchange rate of the Japanese yen for the years 2022-2023, C is a constant value, ϕ_i represents parameters of the autoregressive component of order m, θ_j are parameters for the moving average component of order n and ε_t is the error at the time t. Here, m and n are non-negative integers.

There are two popular time-varying volatility models among researchers: the ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models. The ARCH model, developed by Engle R F in 1982, aims to predict the conditional variance of time series data.

$$y_t = C + \varepsilon_t \tag{5}$$

Where y_t is the observed value of the time series data, C is a constant value, ε_t represents the residual, z_t s the standardized residual which is independent and identically distributed, following a normal distribution with a mean of zero and a variance of one, and σ_t s the square root of the non-negative conditional variance. Generally, the formula for the ARCH(q) model can be expressed as follows:

$$\sigma_t^2 = \eta + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \quad (6)$$

The parameter constraint used are $\eta > 0$ dan $\alpha_j \geq 0$ ($j = 1, \ldots, q$) to ensure that conditional variance σ_t^2 is a non-negatif integer. Although the ARCH model is simple and frequently used among researchers, it also has its drawbacks. When modeling volatility using ARCH, a large lag value of q is required, resulting in many parameters that need to be estimated. This can make the estimation of parameters challenging.

Four years later, in 1986, Bollerslev developed a new version of the ARCH model, known as the GARCH model. The GARCH model uses fewer parameters compared to the ARCH model (Poon & Granger, 2003). The GARCH model comprises two parts: the mean equation, y_t and the variance equation, σ_t^2. The general form of the GARCH(p,q) model can be written as follows:

$$\sigma_t^2 = \eta + \sum_{j=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \quad (7)$$

Where η epresents long-term volatility with the condition $\eta > 0$, $\beta_i \geq 0$; $i = 1, \ldots p$ dan $\alpha_j \geq 0$; $j = 1, \ldots, q$. If $\beta_i + \alpha_j < 1$, then the GARCH(p, q) model is covariance stationary. The unconditional variance of the error is as follows:

$$var(\varepsilon_t) = \frac{\eta}{1-\beta-\alpha} \quad (8)$$

From the general formula of the GARCH(p,q) model, the GARCH(1,1) model can be defined as:

$$\sigma_t^2 = \eta + \beta \sigma_{t-1}^2 + \alpha \varepsilon_{t-1}^2 \quad (9)$$

Model Selection

After comparing various specifications of ARMA-GARCH models, the appropriate model can be selected based on the Akaike Information Criteria (AIC), and the Schwarz's Bayesian Information Criterion (SBC). The AIC, AICC, and SBC can be calculated as follows:

$$AIC = -2\,ln(L) + 2k \quad (10)$$

$$SBC = -2\,ln(L) + ln(N)\,k \quad (11)$$

Testing of Classical Assumptions

After selecting the model to be used, it's necessary to perform tests to ensure that the model is adequately fit for forecasting, commonly referred to as diagnostic testing or classical assumption testing. There are three tests :

Residual Normality Test

This normality test is conducted to determine whether the distribution of the residual values is normal or not. The testing criteria are based on the probability value or p-value obtained from the software output, with the following conditions:

- If the p-value > α, then the data are normally distributed.
- If the p-value < α, then the data are not normally distributed.

Non-autocorrelation Test

A good model is one that does not exhibit autocorrelation, i.e., correlation between residuals at period t and the previous period (t-1). Autocorrelation testing can be conducted using the Durbin Watson (DW) test or the probability value or p-value obtained from the software output. The testing criteria are:

- If the p-value > α, then the residuals are non-autocorrelated.
- If the p-value < α, then the residuals are autocorrelated.

Homoscedasticity Test

This test aims to ensure that the residuals have a constant variance for all observations in the model. The testing criteria are based on the probability value or p-value obtained from the software output, with the following conditions

- If the p-value > α, then the residuals are constant (homoscedastic).
- If the p-value < α, then the residuals are not constant (heteroscedastic).

Verification and Control of Forecasting

An important step after creating a forecast is to conduct verification to ensure that the forecast accurately reflects past data. To perform verification and test the stability of data patterns, a forecasting control chart or Moving range control chart can be used. These are designed to compare actual data with forecasted values.

In creating this control chart, the determination of upper and lower control limits on the Moving range chart or individual graph is done using 3-sigma. Derived from the 3-Sigma Control Limit Table with n=2, the value of $E_2 = 2.66$, leading to the formulation :

$$UCL = \bar{a} + E_2\overline{MR} = \bar{a} + 2.66\overline{MR} \tag{12}$$

$$LCL = \bar{a} - E_2\overline{MR} = \bar{a} - 2.66\overline{MR} \tag{13}$$

For its interpretation, from the forecast results depicted in the figure, if all points lie within the control limit area, it can be concluded that the forecasted data are sufficiently accurate.

Model Evaluation

The outcomes of the development and selection of the forecasting model are evaluated using three measures: Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

$$MSE = \frac{1}{T}\sum_{t=T_1}^{T}(\sigma_t^2 - \hat{\sigma}_t^2)^2 \tag{14}$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=T_1}^{T}(\sigma_t^2 - \hat{\sigma}_t^2)^2} \tag{15}$$

$$MAPE = \frac{1}{T}\sum_{t=T_1}^{T}\left|\left(\frac{\sigma_t^2 - \hat{\sigma}_t^2}{\sigma_t^2}\right) \times 100\right| \tag{16}$$

Where T is the total number of observations, and T_1 is the first observation outside the sample. Then, for σ_t^2 and $\hat{\sigma}_t^2$ they are the actual and predicted values of conditional variance at time t, respectively. When comparing ARMA-GARCH models, the model with the smallest MSE, RMSE, and MAPE values is selected as the forecasting model with the best accuracy.

Forecasting

After verification and evaluation, the best model can be used for forecasting several upcoming periods (by the research objectives) based on the currently available information and data. The forecast results from the model must be within acceptable limits to be usable. This forecasting can assist in decision-making with reasonable estimates of what will happen in the future.

RESULTS AND DISCUSSION

Descriptive Analysis

Table 1 describes the data of the purchase rate of the yen against the IDR from January 2, 2020, to November 27, 2023. The amount of data observed is as much as 968 with five-day data (five working days), which covers a specific period. The lowest exchange rate of these two countries is Rs.10,238.00 on the foreign exchange market, which means to get 100 Japanese yen, it is necessary to exchange Rs.10,238.00. The higher or more expensive purchase rate implies that the Indonesian IDR currency has a lower value compared to the money of the Japanese yen. In other words, it is necessary to exchange more IDR to buy one unit of Japanese Yen (in this case, 100 yen).

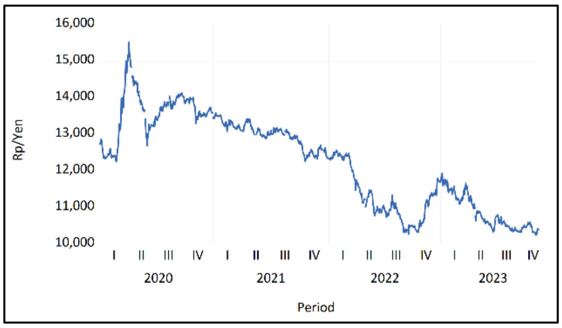
Table 1. Descriptive analysis of Indonesian IDR purchasing rate data against Japanese yen Period 02 January 2020 to 27 November 2023.

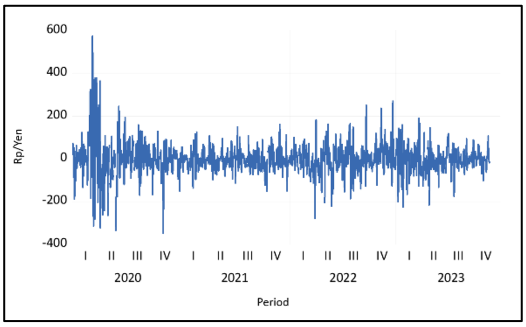
Volume of Data	Minimum Value	First Quarter	Second Quarter (Median)	Mean	Third Quarter	Maximum Value
968	10238	10982	12406	12222	13238	15508

Source: Bank Indonesia (http://www.bi.go.id/)

Based on Table 1, course movements can be seen from minimum to maximum, while central trend measurements such as the first quarter, median, and third quarter provide information about the data distribution and where most observations are concentrated.

The second quarter or median of the exchange rate, which divides the data into two equal parts, is at the value of IDR 12,406.00. At the same time, the average speed during the period was IDR 12,222.00. The lowest value of 75% of the data, commonly referred to as the third quarter, reaches IDR 13,238.00, indicating that there is an increase in the rate at the top of the distribution.





(a) **(b)**

Figure 4. Exchange value of yen against IDR: : (a) *Level;* (b) *First Difference.*

Source: Bank Indonesia (http://www.bi.go.id/)

Based on Figure 4, both (a) and (b) show the time and exchange rate relationship of the Japanese Yen against the Indonesian IDR. The difference lies in the data of the exchange value, which is the differentiating result of Figure 4(b). From Fig. 4(a), there is a volatile pattern, which is more clearly shown in the different results. This means that the purchase rate of the Japanese yen against the Indonesian IDR tends to fluctuate or be unstable. These unstable exchange rate fluctuations can be caused by several factors, including economic, political, and market. From a financial point of view, for example, if the demand for a currency rises or the supply decreases, the exchange rate can increase. Then, in macroeconomic terms, such as economic growth, inflation, and interest rates, a country can influence the exchange rate of its currency. Countries with solid growth, low inflation, and high interest rates tend to have more robust exchange rates. Political instability, policy, or unexpected political events like the Russian-Ukrainian invasion and the COVID-19 pandemic can trigger exchange rate fluctuations. Usually, because of this, investors are not sure to make investments, affecting the currency's exchange rate. In addition, exports and imports also affect the rate of exchange. Market sentiment and perceptions of actors relating to investors' and speculators' decisions also play an essential role.

Formation and Selection of ARIMA Models

Data Identification

Before performing the purchase rate modeling, the time frame analysis requires the assumption that the data is stationary to avoid spurious regression. Data stationarity is formally tested over time using visualization and formal testing. To use visualization, it can be seen from Figure 5(a) that the data is not stationary on mean and variance, so it requires further processing to station. However, the graph is still subjective and requires more rigorous statistical testing. A formal statistical test or root unit test that can be performed is the Augmented Dicky-Fuller Test.

At the level, the formal test results with the root test unit showed that the p-value obtained was 0.8518, more significant than the 5% significance rate. (0.05). Thus, the decision cannot reject the zero hypothesis H0 and state that the purchasing rate variable data still contains root units or is not stationary at the level. Since the purchasing rate variable data used is not stationary at the level, the first differentiation is done on the data, and the root test unit is returned to see its castration. The result shows that the p-value is 0.0000, smaller than the 5% significance rate. (0.05). Therefore, the decision can reject H0 and state that the variable does not contain root units or has been stationary at the first difference.

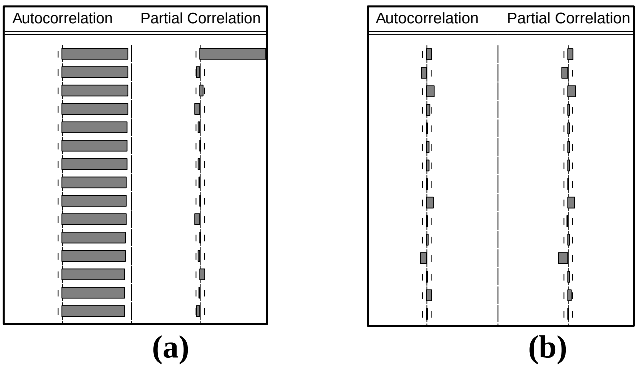


Figure 5. The buying rate of the Japanese Yen against the Indonesian IDR in: (a) level; (b) first difference.

Source: Bank Indonesia (http://www.bi.go.id/)

The stationary or non-stationary data can also be seen from the ACF and PACF patterns on the choreogram. The test was based on the autocorrelation function. (ACF). The correlogram decreases rapidly for stationary data as k (lag) increases. For non-stationary data, the correlogram tends not to go to zero (slow down).

Based on Figure 5(a) above, it can be seen that on the autocorrelation function correlogram or ACF of the rate variable, there is a slight decrease in autocorrelation from the first lag, so it is non-stationary data. Since the data is non-stationary, it is necessary to differentiate first to become stationary data. The first difference chart, including the ACF correlogram, is shown in Figure 5(b).

Model Parameter Estimation

Once the stationarity assumption is met, the next stage is the determination or estimation of the model parameters. From the correlogram in Figure 5(b) above, it is seen that there is a bar passing through the Bartlet line, so the model formed is ARIMA (3,1,4). To ensure the subjective result based on the vision on the correlogram, a determination is made using the feature Automatic ARIMA Forecasting. Using auto-ARIMA, ARMA (3,4) (0,0) is obtained as an estimate of the model with the lowest AIC and BIC values compared to other candidate models. The estimated results can be shown in Table 2.

Table 2. Model Parameter Estimation of ARCH.

Model	AIC*	BIC	Model	AIC*	BIC
(3,4)(0,0)	-7.26392	-7.21856	(1,4)(0,0)	-7.26280	-7.22752
(1,3)(0,0)	-7.26384	-7.23360	(4,1)(0,0)	-7.26274	-7.22746
(3,0)(0,0)	-7.26345	-7.23825	(2,3)(0,0)	-7.26273	-7.22744
(4,2)(0,0)	-7.26345	-7.22313	(0,3)(0,0)	-7.26269	-7.23748
(2,4)(0,0)	-7.26316	-7.22283	(1,1)(0,0)	-7.26228	-7.24212
(3,1)(0,0)	-7.26312	-7.23288	(2,2)(0,0)	-7.26193	-7.23169
(3,2)(0,0)	-7.26285	-7.22756	(4,0)(0,0)	-7.26187	-7.23163

The dependent variables are the result of the first differentiation, so the model used in this study is ARIMA (3,1,4). Research conducted by (Anjuita, Rahayu, & Siregar, 2023), analyzes interventions from time series data between the yen and the IDR and conducts modeling and forecasting too. The best model obtained is ARIMA (4,2,0), but this research does not analyze volatility in the movement of the yen exchange rate with the IDR.

Forecast Verification Using Moving Range Control Maps

From the results of the verification process on the ARIMA (3,1,4) obtained UCL and LCL values for the first data as follows:

$$UCL = \bar{a} + E_2\overline{MR} = -6.6947 + 2.66(80.0974) = 153.4641$$

$$LCL = \bar{a} - E_2\overline{MR} = -6.6947 - 2.66(80.0974) = -166.8385$$

These calculations continue to be done until the last data. Then, visualize it by combining it with the results of the prediction using the ARIMA (3,1,4), as in Figure 6 below.

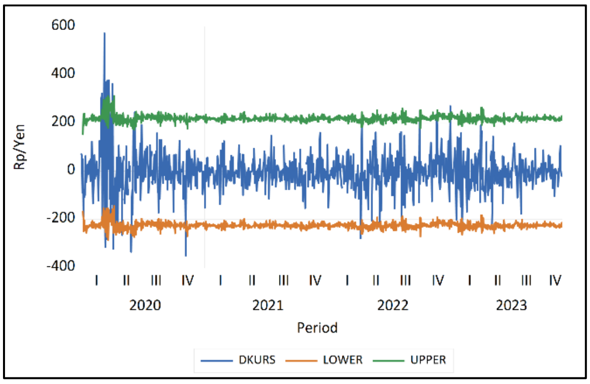


Figure 6. Moving Range Control Map from ARIMA (3,1,4).

Based on Figure 6, it can be seen that in the ARIMA model, information is captured and not captured. The information captured is characterized by residuals randomly distributed in the 2020 period, while data is not charged when the residuals show a pattern around the end of 2020 to the beginning of 2022. The standard and homoscedasticity assumptions are not met from the classical assumption tests, thus indicating that the model cannot capture all the information. As for the upper and lower bounds, neither bound cover the actual values well and has inconsistent widths, indicating that the model could more effectively capture uncertainty and variation in the data. Therefore, modelling will be carried out using ARCH/GARCH, which will capture all the information. Also, variations in ARIMA forecast results appear more stable than variations in actual data (actual data is more volatile than ARIMA forecast results). In that case, the ARIMA model cannot fully capture high-volatility information and inaccurate data. In other words, a simple ARIMA model cannot do this, so a more complex model such as GARCH is considered to be used to handle varying volatility in this time series data.

Formation and Selection of ARCH/GARCH Models

Model Parameter Estimation

The data used remains the same, so you can skip the data identification step to estimate model parameters. The ARCH/GARCH model can be selected from all possible combinations by choosing the most straightforward order possible or can be seen from the ACF PACF results. After carrying out several varieties and calculating the AIC value, the results in Table 3 below were obtained.

Table 3. All Possible Combinations from the GARCH Model along with AIC values.

Model	AIC-value
GARCH (0,1)	11.4704
GARCH (1,0)	11.5138
GARCH (1,1)	11.7233
GARCH (1,2)	11.7285
GARCH (2,1)	11.6329
GARCH (2,2)	11.6707

In several related studies, especially in the context of modeling and estimating the volatility of Malaysian natural rubber prices studied by Ghani and Rahim (2019), where the GARCH (1,1) model is considered popular because it is simple and effective in capturing group volatility. This agrees with research by Brooks C (2014) on various time series data (Hill, Griffiths & Lim, 2011).

From the estimation results of the GARCH model above, we obtained GARCH (0.1) or ARCH (1) with the smallest or lowest AIC to use this model for this research and simpler than models in other studies.

Classical Assumption Testing

The following are the results of the classical assumption test, (a) Normality Assumption. The results of testing the normality assumption show that the p-value obtained is 0.0000..., which is smaller than the significance level of 5% (0.05). Thus, the decision taken can be rejected H0 and states that the residuals along the observed values do not follow an average probability theoretical distribution, which means the GARCH (0,1) model does not meet the normality assumption. The calculation results for skewness were -0.1213, and kurtosis was 5.9724; (b) Non-Autocorrelation Assumption. Based on the autocorrelation test results, several p-values exceeded the significance level of 0.05 (with p-value of 0.954 at lag 1). This means the decision cannot reject H0 and states that the residual is white noise or random. White noise residuals indicate that the model has succeeded in capturing patterns that can be explained, and no residual marks remain. Thus, the GARCH (0,1) model meets the non-autocorrelation assumption; (c) Homoscedasticity Assumption. Based on the results of the homoscedasticity assumption test, it was obtained that all p-values from lag 1 to 36 were more than 0.05; this means that the decision taken can reject H0. From these results, it can be seen that the variance of the error along the observed values is constant (homoscedasticity). In other words, the GARCH (0,1) model meets the homoscedasticity assumption.

Forecast Verification Using Moving Range Control Maps

From the results of the verification process in the GARCH (0.1) model, the UCL and LCL values for the first data are obtained as follows:

$$UCL = \bar{a} + E_2\overline{MR} = -35.5347 + 2.66(69.0897) = 102.6448$$

$$LCL = \bar{a} - E_2\overline{MR} = -6.6947 - 2.66(69.0897) = -173.7142$$

This calculation continues until the last data. Then, it is visualized by combining it with the forecasting results using the GARCH (0,1) model as in Figure 7.

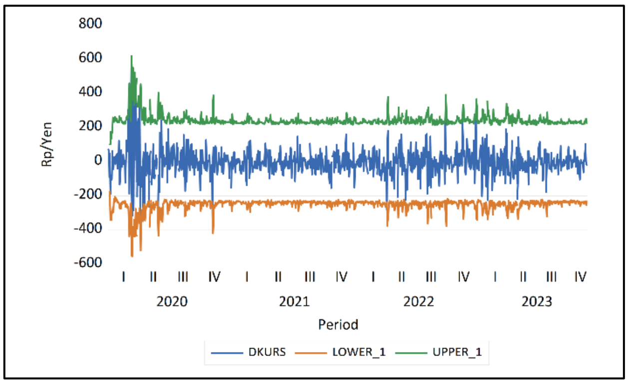


Figure 7. Moving Range Control Map from GARCH model (0,1).

Based on Figure 7, it can be seen that, in general, volatile data information can be captured by the model as seen in the confidence interval, which almost captures all the data. This is better than the previous ARIMA (3,1,4) model, which could not capture all the information. So, it can be concluded that the GARCH (0.1) or ARCH (1) model can handle varying volatility in the time series data of the buying rate of the Indonesian IDR currency against the Japanese yen and is quite suitable for forecasting.

Model Evaluation

After estimating the model, ARIMA (3,1,4) and GARCH (0,1) or ARCH (1) are obtained. These two models need to be evaluated to see which model has the best accuracy in forecasting. The measures used are Root Mean Squared Error (RMSE), Means Absolute Error (MAE) and Means Absolute Percentage Error (MAPE) with the lowest value being the best model. Below is a comparison of the two models in these three sizes.

Table 4. Comparison of ARIMA and ARCH/GARCH Model Evaluation Results.

Evaluation	Value	
	ARIMA (3,1,4)	GARCH (0,1)
RMSE	79.5557	78.3981
MAE	54.5280	52.3696
MAPE	NA	0.4264

Table 4 shows the model evaluation values in the three sizes, with the lowest value being the GARCH (0.1) or ARCH (1) model. Therefore, the model has better accuracy in forecasting than the ARIMA model (3,1,4).

Forecasting

After getting the best model, namely GARCH (0.1) or ARCH (1), this model can be used to forecast the value of the Indonesian IDR buying rate against the Japanese yen in the future. In this research, 5 daily data forecasts were carried out with the addition of 24 exchange rate data, starting from 28 November 2023 to 17 January 2024. This data can be seen in Table 5.

Meanwhile, the graph of forecasting results can be seen in Figure 8 below.

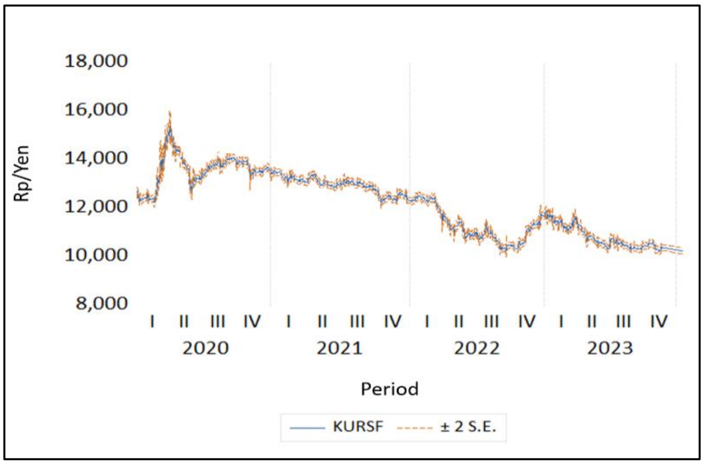


Figure 8. Comparison of actual data and GARCH (0.1) or ARCH (1) Forecasting Model Results.

Table 5. Results of Forecasting of the Indonesian IDR Exchange Rate against the Japanese Yen for the Period 28 November 2023 – 17 January 2024.

Period (MMM/DDD/YYY)	Exchange Rate (IDR)	Period (MMM/DDD/YYY)	Exchange Rate
11/28/2023	10373.8639	12/25/2023	10314.1973
11/29/2023	10372.1059	12/26/2023	10310.5954
11/30/2023	10372.9729	12/27/2023	10307.1069
12/01/2023	10371.5860	12/28/2023	10303.5281
12/04/2023	10369.5905	12/29/2023	10300.0006
12/05/2023	10367.6697	01/01/2024	10296.3654
12/06/2023	10364.9184	01/02/2024	10292.7513
12/07/2023	10362.0326	01/03/2024	10289.0380
12/08/2023	10358.3845	01/04/2024	10285.3418
12/11/2023	10354.6537	01/05/2024	10281.5707
12/12/2023	10350.3958	01/08/2024	10277.8261
12/13/2023	10346.2196	01/09/2024	10274.0340
12/14/2023	10341.7743	01/10/2024	10270.2787
12/15/2023	10337.5585	01/11/2024	10266.4973
12/18/2023	10333.2578	01/12/2024	10262.7566
12/19/2023	10329.2509	01/15/2024	10259.0012
12/20/2023	10325.2389	01/16/2024	10255.2832
12/21/2023	10321.4982	01/17/2024	10251.5536

From Figure 8 shows the difference or lag between the actual data and the forecast data is minimal, so this model is good enough for forecasting exchange rate data or the exchange rate of the Indonesian IDR against the Japanese yen. Based on calculations from forecasting results, it was found that the buying rate of the Japanese yen against the Indonesian IDR would decrease by 19.41% from the period 02 January 2020. When compared from the beginning of 2021, 2022, and the end of 2023, there was a decrease of 23.65%, 16.93%, and 0.02%. The estimated cause of the decline in the value of the Japanese yen buying rate against the Indonesian IDR is that the policy of the Central Bank of Japan has stayed the same regarding interest rates, which remain low (there has been no change in approach to increase them). Based on the results of the evaluation metrics that show the performance of GARC model, it is comparable to the results of the research that Charfi and Mselmi (2022) do that GARCH(1,1) has predictive power in modeling daily exchange rates in Tanzania. Another research conducted by Huq, Rahman, Rahman, Shahin, and Ali (2013) found that ARMA (1,1) with GARCH (1,1) and GARCH (2,1) can be applied to the Dhaka Stock Exchange, where the data also has high volatility. From those previouse studies, we can conclude that the GARCH model can take into account the volatility of exchange rate.

CONCLUSION AND SUGGESTION

The data used in this research is secondary data originating from Bank Indonesia. The variable used is the purchase rate of the Japanese Yen against the IDR in the period January 04, 2020, to November 27, 2023, with five daily data (five working days). We took data from 2020 to consider the impact of Covid-19 and the Russian-Ukrainian war.

At first, we only wanted to take the effects of the Russian-Ukrainian war and data from 2022. However, the resulting forecast could be better (it only gives results that tend to be constant). Then, after trying with data from 2020, it turned out that the forecast results looked better, and future volatility was visible.

The modeling obtained is GARCH (0,1) or ARCH (1). Volatility resulting from the COVID-19 pandemic and the Russia-Ukraine war influenced the Japanese Yen exchange rate against the IDR. The forecast results provide an overview of the exchange rate, especially the purchasing value of the Japanese Yen against the IDR until January 17, 2024. The volatility formed also has a downward trend, which means that the Japanese Yen exchange rate against the IDR will tend to decrease from the previous period until the beginning of 2024. The model obtained can explain forecasting until the beginning of 2024 well if seen from the model evaluation, and it can be seen that the difference or lag between the original data and the forecast data is tiny, so the model is good enough for forecasting.

This forecast shows that the Yen buying rate against the IDR is significantly likely to decline. This indicates that the appreciation of the IDR exchange rate against the Yen will continue. This condition will impact the prices of export products designated for Japan and the prices of imported products from Japan. Appreciation will cause the amount of goods exported from Indonesia to decrease and the amount of imported goods from Japan to increase because the price of goods in Indonesia is more expensive than the price of goods in Japan. This will cause the trade balance to decline and ultimately there will be a deficit in Indonesia because of the large amount of money flowing out. If the trade balances experience a prolonged deficit, it will drain the country’s foreign exchange reserves and result in Indonesia being unable to meet its foreign payment obligations. The government is expected to be able to design and establish appropriate policies to maximize phenomena that may occur. This research still needs to cover the convergence of the volatility of the Japanese Yen and IDR exchange rates. This research can be a reference for further research so that new insights can be obtained and have a tangible impact on policymakers.

REFERENCES

Abdullah, S. M., Siddiqua, S., Siddiquee, M. S. H., & Hossain, N. (2017). Modeling and forecasting exchange rate volatility in Bangladesh using GARCH models: a comparison based on normal and Student’s t-error distribution. *Financial Innovation, 3*(18), 1-19. doi.org:10.1186/s40854-017-0071-z.

Aftab, M., Syed, K. B. S., & Katper, N. A. (2017). Exchange-rate volatility and Malaysian-Thai bilateral industry trade flows. *Journal of Economic Studies, 44*(1), 99–114. doi.org:10.1108/JES-05-2015-0091.

Anjuita, A., Rahayu, W., & Siregar, D. (2023). Intervention analysis for modeling and forecasting exchange rates rupiah against yen. *Sainmatika: Jurnal Ilmiah Matematika dan Ilmu Pengetahuan Alam, 20*(1), 47–57. doi.org:10.31851/sainmatika.v20i1.9209

Asteriou, D., Masatci, K., & Pilbeam, K. (2016). Exchange rate volatility and international trade: International evidence from the MINT countries. *Economic Modelling, 58*, 133–140. doi.org:10.1016/j.econmod.2016.05.006.

Atalan, A. (2020). Is the lockdown important to prevent the COVID-19 pandemic? Effects on psychology, environment and economy-perspective. *Annals of Medicine and Surgery*, *56*, 38–42. doi.org:10.1016/j.amsu.2020.06.010

Bank Indonesia. (2023). *Kurs transaksi yen Jepang terhadap rupiah*. Retrieved from: https://www.bi.go.id/id/statistik/informasi-kurs/transaksi-bi/default.aspx

Bank of Japan. (2023). *Bank of Japan interest rates*. Retrieved from: https://www.stat-search.boj.or.jp/index_en.html#

Beckmann, J., & Czudaj, R. L. (2022). Exchange rate expectation, abnormal returns, and the COVID-19 pandemic. *Journal of Economic Behavior and Organization*, *196*, 1–25. doi.org:10.1016/j.jebo.2022.02.002.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. doi.org:10.1016/0304-4076(86)90063-1.

Bonam, D., & Smădu, A. (2021). The long-run effects of pandemics on inflation: Will this time be different? *Economics Letters*, *208*(2021), 1-4. doi.org:10.1016/j.econlet.2021.110065.

Botman, D., De, I., Filho, C., Lam, W. R., We, I. Q., Danninger, S., Blanchard, O., Schiff, J., & Philips, S. (2013). The curious case of the yen as a safe haven currency: A forensic analysis. *IMF Working Paper 13/228*.

Box, G. E. P., & Jenkins, G. M. (1976). Time series analysis: Forecasting and control (2nd ed). San Fransisco: Holden-Day.

BPS. (2023). Volume ekspor menurut negara tujuan utama (Berat bersih: ribu ton), 2000-2022.

Brooks C. (2014). Introductory econometrics for finance (3rd ed., Vol. 9). New York: Cambridge University Press.

Chakraborty, I., & Maity, P. (2020). COVID-19 outbreak: Migration, effects on society, global environment and prevention. *Science of The Total Environment*, 728, 138882. doi.org:10.1016/j.scitotenv.2020.138882.

Charfi, S., & Mselmi, F. (2022). Modeling exchange rate volatility: application of GARCH models with a normal tempered stable distribution. *Quantitative Finance and Economics*, *6*(2), 206–222. doi.org:10.3934/qfe.2022009.

Chaudhary, G., Hashmi, S., & Khan. Muhammad. (2016). Exchange rate and foreign trade: A comparative study of major South Asian and South-East Asian Countries. *3rd International Conference on New Challenges in Management and Organization: Organization and Leadership*, 85–93. doi.org:10.1016/j.sbspro.2016.09.011.

Cheval, S., Adamescu, C. M., Georgiadis, T., Herrnegger, M., Piticar, A., & Legates, D. R. (2020). Observed and potential impacts of the Covid-19 pandemic on the environment. In *International Journal of Environmental Research and Public Health*, *17*(11), 1–25. doi.org:10.3390/ijerph17114140.

Chit, M. M. M., Rizov, M., & Willenbockel, D. (2008). Exchange rate volatility and exports: New empirical evidence from the emerging East Asian Economies. *The World Economy*, *33*(2), 239-263. doi.org:10.1111/j.1467-9701.2009.01230.x.

Chortane, S. G., & Pandey, D. K. (2022). Does the Russia-Ukraine war lead to currency asymmetries? A US dollar tale. *The Journal of Economic Asymmetries* 26, e00265. doi.org:10.1016/j.jeca.2022.e00265.

Salvatore. (2013). *Ekonomi internasional 11E* . Nashville, TN: John Wiley & Sons.

Eklou, K. (2023). Dollar exchange rate volatility and productivity growth in emerging markets: Evidence from firm level data. *IMF Working paper*, WP/23/111. doi.org:10.2139/ssrn.4484773.

Engle R F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50,* 987–1007.

European Central Bank. (2023). *European Central Bank interest rate*. Retrieved from: https://id.investing.com/economic-calendar/interest-rate-decision-164

Faris, M. (2023). Analyzing volatility jumps in the international monetary system: Impact of Russia-Ukraine conflict on currency exchange rates. *SSRN Electronic Journal*. Retrieved from: https://ssrn.com/abstract=4509577. doi.org:10.2139/ssrn.4509577.

Feng, G. F., Yang, H. C., Gong, Q., & Chang, C. P. (2021). What is the exchange rate volatility response to COVID-19 and government interventions? *Economic Analysis and Policy, 69,* 705–719. doi.org:10.1016/j.eap.2021.01.018.

Friedman, M. (1970). A theoretical framework for monetary analysis. *Journal of Political Economy*, *78*(2), 193–238. Retrieved from: http://www.jstor.org/stable/1830684.

Fulk, G. (2023). Descriptive statistics, an important first step. *Journal of Neurologic Physical Therapy*, *47*(2), 63–63. Ovid Technologies (Wolters Kluwer Health). doi.org:10.1097/npt.0000000000000434.

Gabriel, A. S. (2012). Evaluating the forecasting performance of GARCH models: Evidence from Romania. *Procedia - Social and Behavioral Sciences*, *62*, 1006–1010. doi.org:10.1016/j.sbspro.2012.09.171

Ghani, I. M. M., & Rahim, H. A. (2019). Modeling and forecasting of volatility using ARMA-GARCH: Case study on Malaysia natural rubber prices. *IOP Conference Series: Materials Science and Engineering*, *48*(1), 012023. doi.org/10.1088/1757-899x/548/1/012023.

Ginting, C. P., & Kartiasih, F. (2019). Analisis ekspor kopi Indonesia ke negara-negara Asean. *Jurnal Ilmiah Ekonomi dan Bisnis, 16*(2), 143–157. doi.org:10.31849/jieb.v16i2.2922.

Hanifah, N., & Kartiasih, F. (2018). Determinan impor serat kapas di Indonesia tahun 1975-2014 (Pendekatan Error Correction Mechanism). *Media Statistika, 11*(2), 119–134. doi.org:10.14710/medstat.11.2.119-134.

Hill, R.C., Griffiths, W. E., & Lim, G.C.(2011). *Principles of Econometrics* (4th ed., Vol. 14). New Jersey: John Wiley & Sons, Inc.

Huq, M.M., Rahman, M.M., Rahman, M.S., Shahin, Md. A., & Ali, Md, A. (2013). Analysis of volatility and forecasting general index of Dhaka Stock Exchange. *American Journal of Economics,* *3*(5), 229–242. doi.org:10.5923/j.economics.20130305.04

Indriyani, S. (2016). Analisis pengaruh inflasi dan suku bunga terhadap pertumbuhan ekonomi di Indonesia tahun 2005 – 2015. *Jurnal Manajemen Bisnis Krisnadwipayana*, *4*(2), 1-11.

Islam, M. A. (2013). Estimating volatility of stock index returns by using symmetric Garch models. *Middle East Journal of Scientific Research*, *18*(7), 991–999. doi.org/10.5829/idosi.mejsr.2013.18.7.11806

Jabara, C. L. (2009). How do exchange rates affect import prices? Recent economic literature and data analysis. Retrieved from: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.usitc.gov/publications/332/ID-21.pdf

Kafle, K. R. (2011). *Exchange rate volatility and bilateral agricultural trade flows: the case of the United States and OECD countries* (Master's theses). Louisiana State University, 3713. Retrieved from https://repository.lsu.edu/gradschool_theses/3713

Kannan, K., & Balamurugan, S. (2022). Modelling and forecasting of stock price volatility of selected nifty 50 companies in India. *Open Access Repository*, *8*(7), 27–34. doi.org:10.17605/OSF.IO/VQ8FM.

Kartiasih, F. (2019). Inflasi dan siklus bisnis politik di Indonesia. *Media Trend*, *14*(2), 219–228. doi.org:10.21107/mediatrend.v14i2.4978.

Kartiasih, F., Ramadhani, A. R, Fitri, K.A. & Aselnino, P. (2022). Faktor-faktor yang mempengaruhi volume impor jagung Indonesia dari lima negara eksportir terbesar tahun 2009-2021. *INOVASI: Jurnal Ekonomi, Keuangan dan Manajemen*, *18*(4), 936–946.

Krishnaprabha, S., & Vijayakumar, M. M. (2015). A study on risk and return analysis of selected stocks in India. *International Journal of Engineering Technologies and Management Research*, *3*(4), 79-86.

Laksono, R., & Edison, A. (2020). Analysis of the effect of real exchange rate on trading balance case study of Indonesia-Japan bilateral trade relations (MLR and J-Curve conditions). *Solid State Technology*, *63*(3), 2735–2747. Retrieved from: www.solidstatetechnology.us.

Li, D., Magud, N. E., & Valencia, F. (2022). Financial shocks and corporate investment in emerging markets. *Journal of Money, Credit and Banking*, *52*, 613–644.

Ma, M., Du, J., & Lai, K. K. (2014). Modeling volatility of exchange rate of Chinese Yuan against US Dollar based on GARCH models. *Proceedings - 2013 6th International Conference on Business Intelligence and Financial Engineering, BIFE 2013*, 295–299. doi.org:10.1109/BIFE.2013.63

Mamilla, R., Kathiravan, C., Salamzadeh, A., Dana, L.-P., & Elheddad, M. (2023). COVID-19 pandemic and indices volatility: Evidence from GARCH Models. *Journal of Risk and Financial Management*, *16*(10), 447. doi.org:10.3390/jrfm16100447

Mankiw, & Gregory, N. (2008). *Makroekonomi* (6th ed.). Jakarta: Erlangga.

Maurya, P. K., Bansal, R., & Mishra, A. K. (2023). Russia–Ukraine conflict and its impact on global inflation: an event study-based approach. *Journal of Economic Studies*, *50*(8), 1824–1846). doi.org:10.1108/jes-01-2023-0003.

Muchlas, Z., Stie, D., Agus, A. M., Alamsyah, R., & Malang, A. (2015). Faktor-faktor yang mempengaruhi kurs rupiah terhadap dolar Amerika pasca krisis (2000-2010). *Jurnal JIBEKA*, *9*(1), 76–86.

Mukhlis, I. (2011). Analisis volatilitas nilai tukar mata uang rupiah terhadap dolar. *Journal of Indonesian Applied Economics*, *5*(2), 172–182.

Ningsih, Y. P., & Kartiasih, F. (2019). Dampak guncangan pertumbuhan ekonomi mitra dagang utama terhadap indikator makroekonomi Indonesia. *Jurnal Ilmiah Ekonomi dan Bisnis*, *16*(1), 78–92. doi.org:10.31849/jieb.v16i1.2307

Nishimura, Y., & Hirayama, K. (2013). Does exchange rate volatility deter Japan-China trade? Evidence from pre- and post-exchange rate reform in China. Japan and the World Economy, 25–26, 90–101. doi:10.1016/j.japwor.2013.03.002

Patel, P. (2014). Factors affecting currency exchange rate, economical formulas and prediction models. *International Journal of Application or Innovation in Engineering & Management*, *3*(3), 53–56.

Pele, D., Lazar, E., & Dufour, A. (2017). Information entropy and measures of market risk. *Entropy*, *19(*5), 1-19. doi.org:10.3390/e19050226.

Poon, S. H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. *Journal of Economic Literature*, *41*, 478–539.

Ramoni-Perazzi, J., & Romero, H. (2022). Exchange rate volatility, corruption, and economic growth. *Heliyon*, 8(12), 1-11. doi.org:10.1016/j.heliyon.2022.e12328.

Rusiadi, Aprilia, A., Adianti, V., & Verawati. (2020). Dampak Covid-19 terhadap stabilitas ekonomi dunia (Studi 14 negara berdampak paling parah). *Jurnal Kajian Ekonomi dan Kebijakan Publik*, *5*(2), 173-182.

Sihaloho, E., D. (2020). Dampak Covid-19 terhadap perekonomian Indonesia. OSF Preprints *Departemen Ilmu Ekonomi Universitas Padjadjaran*. Retrieved form: https://www.researchgate.net/publication/345682307_Dampak_Covid-19_Terhadap_Perekonomian_Indonesia. doi.org:10.13140/RG.2.2.14524.67205/1.

Satriana, E. D., Harianto, & Priyarsono, D. S. (2019). Pengaruh volatilitas nilai tukar terhadap kinerja ekspor utama pertanian Indonesia. *Buletin Ilmiah Litbang Perdagangan*, *13*(2), 163–186. National Research and Innovation Agency. doi.org:10.30908/bilp.v13i2.424.

Senadza, B., & Diaba, D. D. (2018). Effect of exchange rate volatility on trade in Sub-Saharan Africa. *Journal of African Trade*, *4*(1–2), 20-36. doi.org:10.1016/j.joat.2017.12.002

Setiawan, A., & Kartiasih, F. (2021). Contagion effect krisis Argentina dan Turki ke negara-negara Asia, benarkah terjadi? *Jurnal Ekonomi dan Pembangunan Indonesia*, *21*(Januari), 59–76. doi.org:10.21002/jepi.2021.05.

Simanjuntak, T. M., & Dermawan, D. (2023). Pengaruh perang Rusia dan Ukraina terhadap perekonomian di Negara Indonesia. *Jurnal Pendidikan Tambusai*, *7*(3), 24923–24930.

Subanti, S., Hakim, A. R., Riani, A. L., Hakim, I. M., & Nasir, M. S. (2019). Exchange rate volatility and exports: A panel data analysis for 5 ASEAN countries. *Journal of Physics*: *Conference Series*, 1217(1), 012089. doi.org:10.1088/1742-6596/1217/1/012089.

Vo, D., Vo, A., & Zhang, Z. (2019). Exchange rate volatility and disaggregated manufacturing exports: Evidence from an emerging country. *Journal of Risk and Financial Management*, *12*(1), 1-25. doi:10.3390/jrfm12010012.

World Bank. (2023). *Inflation, consumer prices (annual %)*. International Monetary Fund, International Financial Statistics and Data Files. Retrieved from: https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG

Xu, J., Khan, K., & Cao, Y. (2023). Conflict and exchange rate valuation: Evidence from the Russia-Ukraine conflict. *Heliyon,* *9*(6), 1-9. doi.org:10.1016/j.heliyon.2023.e16527.

Zhang, Z., Raza, M. Y., Wang, W., & Sui, L. (2023). Volatility predictability in crude oil futures: Evidence based on OVX, GARCH and stochastic volatility models. *Strategy Reviews*, *50*(2023), 1-12. doi.org:10.1016/j.esr.2023.101209.