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Forecasting the Exchange Rate of the Jordanian Dinar versus the US Dollar Using a Box-Jenkins Seasonal ARIMA Model

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Abstract

Seasonal Autoregressive Integrated Moving Average (SARIMA) model was fitted for the time series data either to better understand the data or to predict the future points in the series (forecasting). Using the forecasting for the exchange rate is very important at the national, regional and international levels. It can help investors minimize financial risk as well maximize earnings in the volatility of the global economy. The aim of this study was to use the time series model to forecast the exchange rate of Jordan dinar based on the monthly data collected for Jordanian dinar vs US dollar. Exchange rate prediction is performed using two methods; Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) time series. After comparing the forecasting method using ARIMA $(1, 0, 1)$ and SARIMA $(1, 0, 1)(1, 0, 0)_{12}$ models, we find that the second model shows a smaller mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error

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(MAE) and mean absolute square error (MASE) as compared to the first; That is, SARIMA $(1,0,1)(1,0,0)_{12}$ model is the most appropriate method to forecast the exchange rate of the Jordanian dinar vs US dollar.

1 Introduction

The exchange rate of foreign currencies is very important at the macroeconomic level of any country. It is one of the things that the board of directors is interested in [13] in view of the diversity of the positive and negative effects of raising or reducing it in terms of investments such as exports, imports and demand for securities such as stocks and bonds. On the other hand, the exchange rate affects study, treatment and foreign tourism.

The exchange rate of the Jordanian dinar has started since the establishment of the Jordanian Monetary Council in 1950. At the same time, the Jordanian dinar was considered the currency of the Hashemite Kingdom of Jordan. As for the exchange rate of the dinar to the dollar, many Jordanian economists have agreed that this correlation has implications for monetary and economic stability. Therefore, investors had to pay attention to the exchange rate by knowing expectations and forecasts on the subject. In other words, the exchange rate forecasts help investors to increase incomes and decrease financial risk, due to the volatility in the global economy that is affecting the local economy.

Therefore, the aim of the present study is to obtain the best forecasting model for the exchange rate from JOD to US dollar with the lowest error rate. In addition, test the accuracy of the performance of the test data for the specific model using several criteria such as (MAPE), (RMSE) and (MASE).

The remainder of this study consists of four sections. Section 2 shows literature reviews while Section 3 supplies the information for the methodology. Section 4 provides analysis and results. Finally, the results for this study are in Section 5.

2 Summary of Previous Studies

For centuries many studies have been published that relate to the exchange rate. One of the old studies by Meese and Rogoff [9] supported that out-of-sample appropriate is an essential measure to consider when evaluating empirical exchange rate models. In 2016, Etuk [2] stressed that the foreign exchange is a main case in the discussion of the world economy. In the mean time, he proposed the daily UGX-NGN exchange rates track an additive Seasonal ARIMA $(1,1,0)\times(1,1,0)_7$ model. Meanwhile, in [13], Ngan showed that ARIMA model is appropriate for estimating foreign exchange rate in Vietnam for short-term.

Later in [17], Yıldıran and Fettahoğlu used 3,069 daily observations from January 3, 2005 until March 8, 2017. They observed that the ARIMA $(2,1,0)$ for short-term outperforms ARIMA $(0,1,1)$ for long-term. In contrast, Mustafa et al. [12] used the performances of hybrid ARIMA-GARCH and hybrid ARIMA-EGARCH in modelling and forecasting exchange rate for (USD/MYR) and they found that ARIMA-EGARCH model is suitable and the best performance based on the value of AIC.

Then, Ismail et al. [7] found that feed forward neural network showed a smaller MSE and RMSE when they compared the model with ARIMA $(0,1,1)$ while Masarweh and Wadi [8] used daily data from Amman stock market in Jordan from 1993 to 2017 to exhibit the predictability for short-term prediction of the ARIMA $(1,1,2)$ model based on Root Mean Squared Error. On the other hand, Ismail et al. [7] reported that the rate of transformation increases or decreases from time to time according to many factors such as the status of the global economy.

Recently, many authors have been interested in the exchange rate issue in terms of selecting the best predictive model. Among those, He and Jin [5] used the inverse ARIMA-GM model to predict the exchange rate for (US Dollar/Japanese Yen). They inferred that the combined model has higher forecasting accuracy for exchange rate. In contrast, V. Thuy and D. Thuy [16] applied the autoregressive distributed lag (ARDL) bounds testing approach to the analyses of magnitude relationships among active exchange rate volatility and exports. Their results showed that the exchange rate volatility will have a reverse effect for the export magnitude in the long-term.

As a summary, previous studies have shown that there are mixed results in terms of selecting the appropriate model for forecasting the exchange rate. So, the current study focuses on constructing time series model to forecast the monthly exchange rate by using Box-Jenkins approach. Moreover, because of the paucity of studies in which the prediction of the exchange rate of the Jordanian dinar against the US dollar was stated by constructing a forecasting model. Also, the studies did not focus on the accuracy of the performance of the test data for the specific model. Hence, this is a different point of view that this study will highlight.

3 Materials and Methods

3.1 Collection Of Data

Monthly data of the Jordanian Dinar exchange rate vs US Dollar from March 2008 to July 2019 published in the website www.investing.com/currencies/jod-usd-historical-data were used in this study. The data were divided into two parts: the first included data from March 2008 to March 2018 consisting of 121 observations which were used to fit the forecasting model; the second has data from April 2018 to July 2019 consisting of 16 observations which were used to test the accuracy of in-sample forecast. Forecasts were then created out-of-sample data consisting of 12 months having significant economic importance for the exchange rate where the statistical analysis was implemented by using R software [3].

3.2 ARIMA and SARIMA Models

The definitions of ARIMA and SARIMA model were proposed by Box and Jenkins [1] as follows. A stationary time series $\{x_t\}$ is called an autoregressive integrated moving average model of order p, d, q, designated $ARIMA(p, d, q)$, if

$$\phi_p(B)\nabla^d x_t = \theta_q(B)\varepsilon_t \tag{1}$$

whereas,

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \tag{2}$$

$$\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q \tag{3}$$

$$\nabla^d = (1 - B)^d \tag{4}$$

where $\phi_p(B)$ is a polynomial of autoregressive with order p is denoted by $AR(p)$; $\theta_q(B)$ is a polynomial of moving average with order q is denoted by $MA(q)$. The number d is the non-seasonal differencing orders. B is the backward shift operator defined by $B^k X_t = X_{t-k}$.$\nabla$is the non-seasonal differencing operators. Moreover, $\{\varepsilon_t\}$ is a white noise process.

In contrast, when the data have a phenomenon that repeated the pattern in time series data, the series is denoted by Seasonal $ARIMA(p, d, q)(P, D, Q)_S$. The generalized form of SARIMA model can be written [1] as:

$$\phi_p(B)\Phi_P(B^S)\nabla^d\nabla_S^D x_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t, \tag{5}$$

whereas,

$$\Phi_P(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdots - \Phi_P B^{PS} \tag{6}$$

$$\Theta_Q(B^S) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS} \tag{7}$$

$$\nabla_S^D = (1 - B^S)^D \tag{8}$$

where $\Phi_P(B^S)$ is a polynomial of seasonal autoregressive with order P and seasonal period S is denoted by $SAR(P)$; $\Theta_Q(B^S)$ is a polynomial of seasonal moving average with order Q and seasonal period S is denoted by $SMA(Q)$. ∇_S^D are the seasonal differencing operators.

3.3 Testing For White Noise

In [10], Montgomery et al. pointed out that if the time series consisting of uncorrelated observations and has a constant variation, then it is called white noise. In other words

$$\varepsilon_t \overset{\text{iid}}{\sim} (0, \sigma^2),$$

where the plot for Autocorrelation Function (ACF) and Partial Autocorrelation Functions (PACF) were used to test the time series whether it is white noise or not.

3.4 Testing For Stationary

The stationary of ARMA process is related to the AR component in the model [10]. A time series is said to be stationary if the statistical properties have a constant that does not change over time. In other words, the mean and the variance are constant with time. For this reason, Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were used in [10] and [11] respectively.

3.5 Checking For Diagnostic

At this stage, the residual is evaluated through several measures such as the p-value for Ljung-Box test statistic and Autocorrelation Function (ACF) of the residuals [10]. The Kolmogorov-Smirnov normality test was used according to [10]. Thus, the rejection or acceptance of the null hypothesis is determined.

3.6 Criteria For Choosing The Best Model

When selecting the fit model among several models, there are many criteria that can be used for choosing the best [10]. Two important criteria are the Akaike Information Criterion (AIC) and Schwartz Bayesian Information Criterion (BIC).

$$AIC = -2\ln(l) + 2k. \tag{9}$$

$$BIC = -2\ln(l) + k\ln(n). \tag{10}$$

where l is a likelihood for the model, k is the order for the autoregressive (AR) plus the order for the moving average (MA) (meaning $k = p + q$), n is the number of observations. Therefore, it is the best model which gives the least value to both AIC and BIC [10].

3.7 Forecast Accuracy Measures

Evaluation of the prediction model is determined by the accuracy of the forecast. Therefore, there are measures for this purpose. They are as follows:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \tag{11}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100 \tag{12}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \tag{13}$$

$$MASE = \frac{\frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right|}{\frac{1}{n-1}\sum_{t=2}^{n}\left|Y_t - Y_{t-1}\right|}, \tag{14}$$

where Y_t is the actual value, $\hat{Y}_t$ is the forecasted value, and n is the number of predictions. In [4], Haw et al. mentioned that the model that gives the smallest value in all criteria is a fit model to forecasting.

4 Results And Discussion

Generally, this study is different from the other related studies in the application of the ARIMA and Seasonal ARIMA (SARIMA) model for exchange rate data will be implemented for forecasting. Previous studies related to the ARIMA and SARIMA model did not focus on the accuracy of the performance of test data for the specific model. Hence, this is a different point of view that this study will highlight.

In this section, we briefly discuss the behavior of the time series data through using time series plot prior to constructing the model, where the x-axis represents the time of observations while the y-axis represents the price. After that, we construct the model as defined by Box-Jenkins approach.

In this case, the analysis of the time series was used to analyze the monthly data of the Jordanian dinar vs the US dollar from March 2008 to July 2019. Figure 1 displays the time series plot for the exchange rate JOD-USD. The series displays great fluctuations over time, especially in 2010 and 2014. The higher values show extremely more variation than the lower values [14]. Using R-software implementation, it was shown that the arithmetic mean=1.411336 for the monthly data of JOD-USD. Moreover, Table 1 showed the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for the same data is not stationary based on the p-value< 0.05 (95% confidence interval) for KPSS.

As a result, the time series is not stationary so data transformation must be done by taking the difference after calculating the natural logarithm to stabilize the series. See Figure 2. The Autocorrelation Function (ACF)

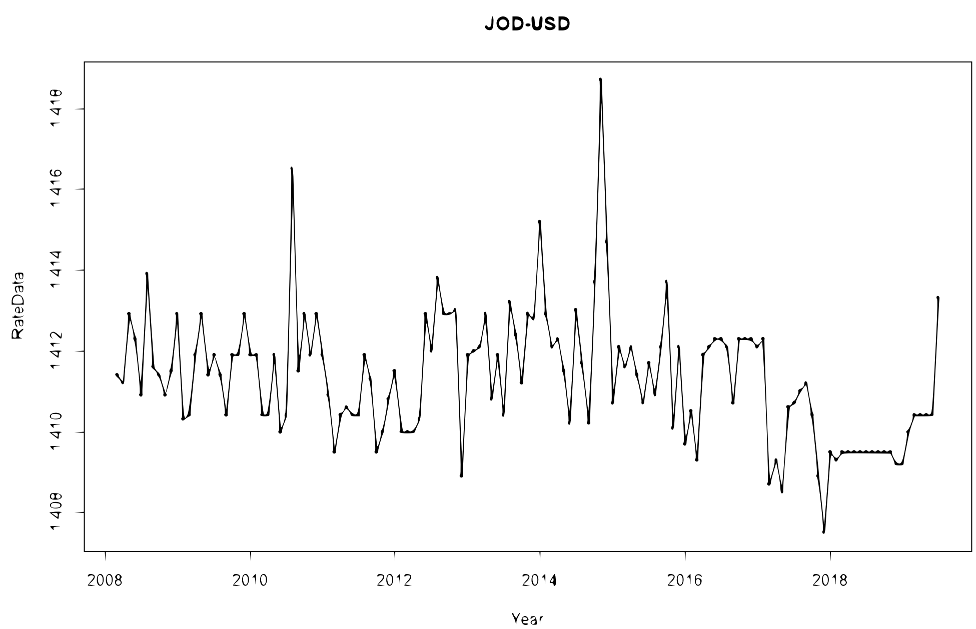

Figure 1: Monthly data of the Jordanian Dinar exchange rate vs US Dollar from March 2008 to July 2019

and Partial Autocorrelation Functions (PACF) for the last data is exhibited in Figure 3. Montgomery et al., [10] pointed that ACF is an excellent tool

Table 1: KPSS test for monthly JOD-USD

Test Type	The value for the test	p-value
KPSS for Level	0.6631	0.0169
KPSS for Trend	0.25921	0.01

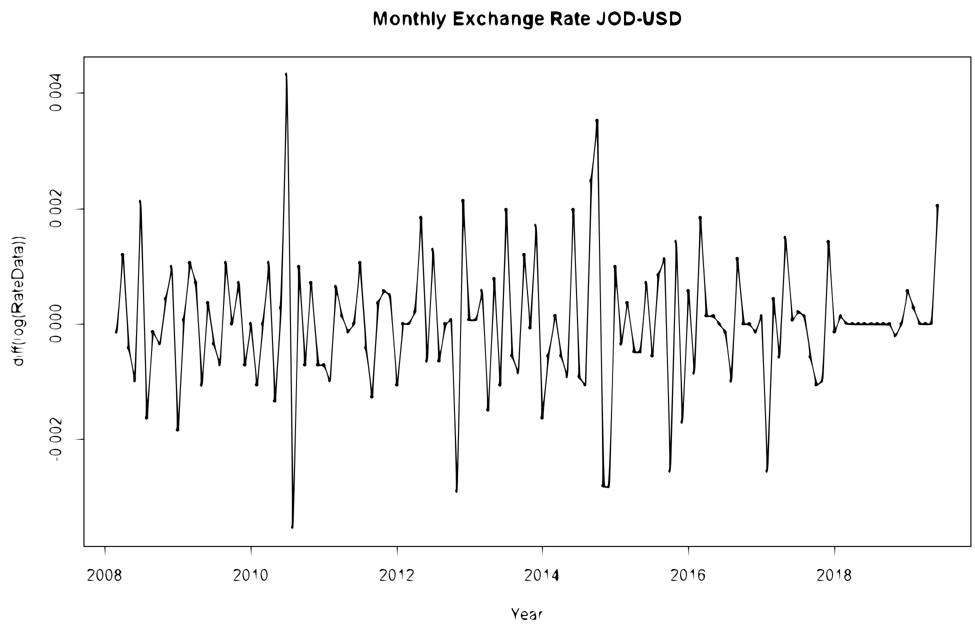

Figure 2: Monthly data after taking the natural logarithm then the difference

in identifying the order of $MA(q)$ process, because it is expected to "cut off after lag q. These figures showed that the series is not white noise.

Table 2 showed the Kolmogorov-Smirnov, Augmented Dickey-Fuller (ADF), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests for these data. Based on the p-value =0.05, it was revealed that the data is stationary, normality and does not have a unit root.

Table 2: Statistical tests for diff(log(RateData))

Test Type	The value for the test	p-value	Level of Significance	State
Kolmogorov-Smirnov	0.10927	0.07773	0.05	Normal
ADF	-7.5947	0.01		Stationary
KPSS for Level	0.037527	0.1		Stationary
KPSS for Trend	0.033863	0.1		Stationary

To choose the best model among several models, Akaike Information Cri-

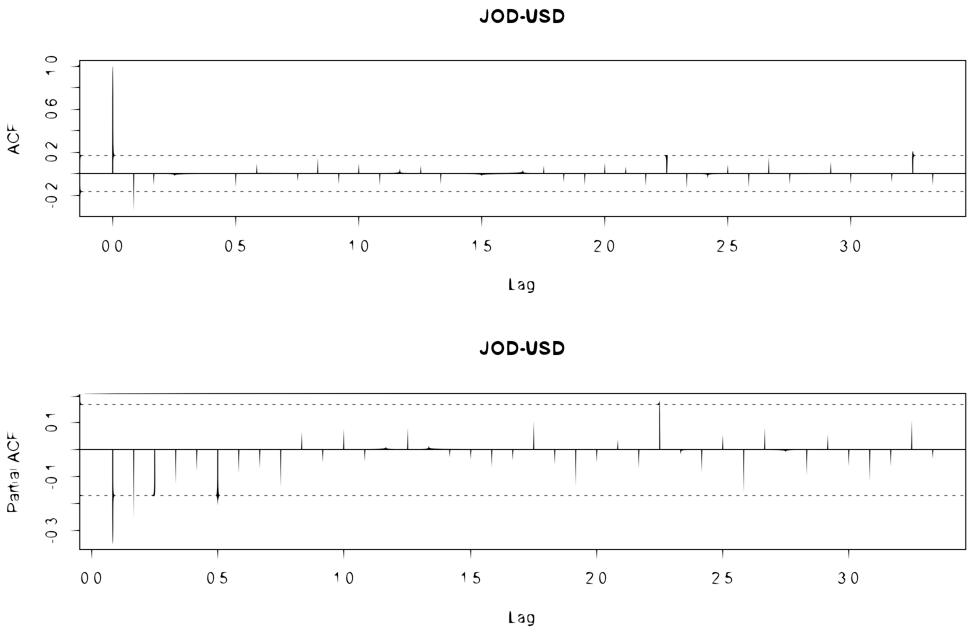

Figure 3: ACF and PACF for diff(log(RateData))

terion (AIC) and Schwartz Bayesian Information Criterion (BIC) were used. ARIMA(1,0,1) model were the best because they had the lowest value (-1491.853 and -1483.115) for both AIC and BIC, respectively as shown in Table 3, which indicates a good model. This result was confirmed by Montgomery et al., [10], who reported that the models which have small values of the AIC or BIC are considered good models. The next model is SARIMA $(1, 0, 1)(1, 0, 0)_{12}$, in terms of AIC and BIC. Therefore, the two models will be taken and compared through forecast accuracy measures. Best fitted model residuals in the Box-Jenkins methodology should be independently identically normally distributed (iid) [6]. By looking at Table 4, the two models have the property of the unit root for the residuals, and they do not contain heteroscedasticity for the square residuals by using the p-value for the Ljung-Box test statistic [10]. In other words, there does not exist an Autoregressive Conditional Heteroscedasticity (ARCH) model. We note that the p-value for the residuals of the second model is larger than the first. This is one of the indicators that gives the conclusion that the SARIMA $(1, 0, 1)(1, 0, 0)_{12}$ model is the best. Figure 4 displays the time series plots of the residuals for the SARIMA $(1, 0, 1)(1, 0, 0)_{12}$ model. From the plot ACF of the residuals, all residuals values within tolerance interval and very small with nonsignificant correlation between them. As a result, the errors yield

Table 3: Models with its AIC and BIC

Model with zero mean	AIC	BIC
ARIMA(1,0,1)	**-1491.853**	**-1483.115**
ARIMA(2,0,1)	-1489.855	-1478.204
ARIMA(1,0,2)	-1489.855	-1478.204
ARIMA(2,0,2)	-1487.864	-1473.3
ARIMA(2,0,0)	-1473.47	-1464.732
SARIMA(1,0,1)(1,0,0)$_{12}$	**-1490.49**	**-1478.84**
SARIMA(1,0,1)(0,0,1)$_{12}$	-1490.389	-1478.738

Table 4: Ljung-Box test statistic for the residuals

Model	p-value for the residuals	p-value for the square residuals
ARIMA(1,0,1)	0.9755	0.9893
SARIMA(1,0,1)(1,0,0)$_{12}$	0.9896	0.9875

from the model were white noise or independent [15]. The p-value for Ljung-Box test statistic is an important measure to look at residual correlations (Figure 4) where p-value $= 0.9896 > 0.05$ for this test, so the null hypothesis (H_0) of Ljung-Box would not be rejected for those lags. In other words, (H_0) of the Ljung-Box test is independence of the residuals. It is observed through Figure 4, all the Ljung-Box p-values lie above the dashed line. Based on the results, the above two models will be taken and predicted during from April 2018 to July 2019, previously identified as a test part. After obtaining 16-months forecasting in-sample, we need to compute the forecasting errors by using forecast accuracy measures such as MAE, MAPE, RMSE and MASE to evaluate the performance of these models and comparison between them. The results are reported in Table 5. small When accuracy measures used to evaluate the performance for the two models, it was observed that the test data for SARIMA$(1, 0, 1)(1, 0, 0)_{12}$ had the lowest values, which means that the model is more accurate. While the coefficient of variance (C.V.) for the

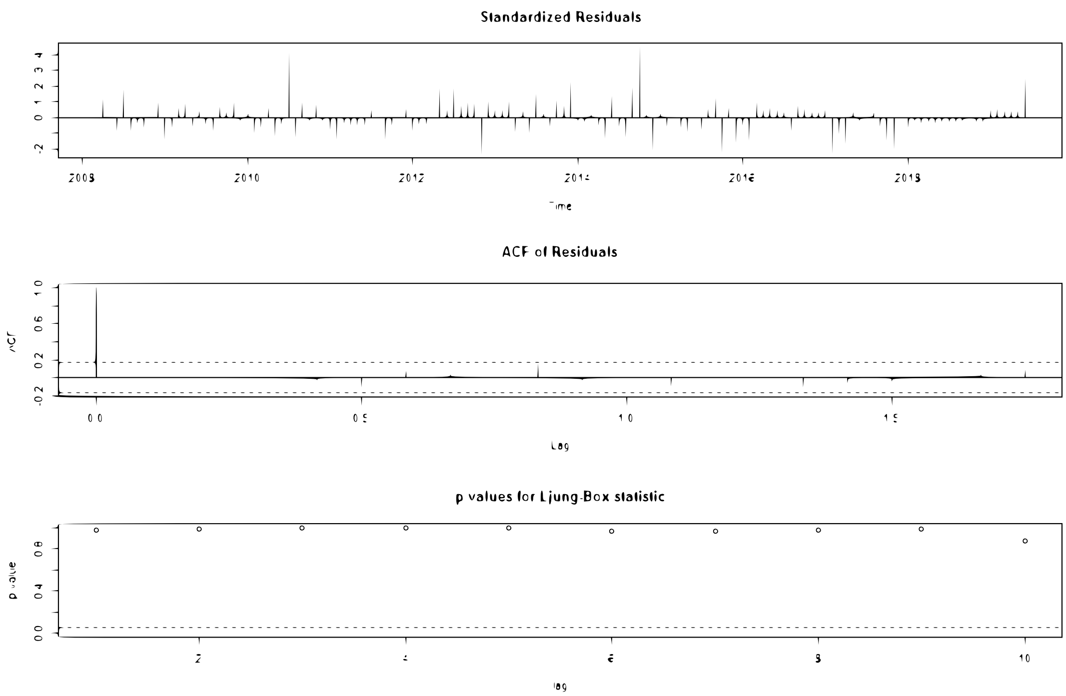

Figure 4: Plots of the residuals for the SARIMA $(1,0,1)(1,0,0)_{12}$ model

Table 5: Comparison the forecasting accuracy measures

Model	RMSE	MAE	MAPE	MASE
ARIMA(1,0,1)	0.00008025073	0.00004903276	0.004903276	0.000000006440179
SARIMA(1,0,1)(1,0,0)$_{12}$	0.00005739036	0.00004594878	0.004594878	0.000000003293653

test data in ARIMA(1,0,1) model and SARIMA$(1,0,1)(1,0,0)_{12}$ model were 827.971 and 1115.81 respectively. So, the SARIMA$(1,0,1)(1,0,0)_{12}$ model was more homogeneous. Based on the results obtained under this study, SARIMA$(1,0,1)(1,0,0)_{12}$ model is confirmed as an appropriate model for forecasting the exchange rate for monthly data from the Jordanian dinar to the US dollar. Due to its accuracy in the performance with the least predictive error, the forecast out-of-sample for the best model presented (Table 6) is from August 2019 to July 2020. The forecasting results of the model show that the exchange rate for the JOD-USD tends to decrease, increase and stabilize. Therefore, the managers of the banks in Jordan should care about

Table 6: Forecast out- of -sample for SARIMA$(1,0,1)(1,0,0)_{12}$model

Year	Month	Out - of - sample				
		Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2019	Aug	1.4112	1.4094	1.4130	1.4085	1.4139
	Sep	1.4106	1.4087	1.4125	1.4077	1.4135
	Oct	1.4104	1.4085	1.4124	1.4075	1.4134
	Nov	1.4104	1.4084	1.4123	1.4074	1.4134
	Dec	1.4103	1.4084	1.4123	1.4073	1.4134
2020	Jan	1.4103	1.4084	1.4123	1.4073	1.4134
	Feb	1.4104	1.4084	1.4124	1.4073	1.4135
	Mar	1.4104	1.4084	1.4124	1.4073	1.4135
	Apr	1.4104	1.4084	1.4125	1.4073	1.4135
	May	1.4104	1.4084	1.4125	1.4073	1.4136
	Jun	1.4104	1.4084	1.4125	1.4073	1.4136
	Jul	1.4106	1.4086	1.4127	1.4075	1.4138

this result. On the other hand, the Jordanian investors can use it in international and local business environments to help them maximize earnings and minimize financial risk. In addition, it is possible to conduct similar studies on exchange rate daily data using artificial neural networks and whether the exchange rate data has long memory.

5 Conclusion

Seasonal ARIMA method was more effective for JOD-USD rate in short-term prediction. In this application, a Box- Jenkins approach proved its suitability to modeling and forecasting the exchange rate data for the Jordanian Dinar vs US Dollar. This paper highlights the fact that an increase in tourism to Jordan contributes to the introduction of a difficult currency such as the dollar, which plays a prominent role in supporting the Jordanian dinar in the future. In this study, the best model was selected based on AIC and BIC. Diagnostic checking of the model has been done in several ways such as Ljung-Box test and Kolmogorov-Smirnov normality test. While in the analysis phase, the test data for SARIMA $(1,0,1)(1,0,0)_{12}$ model had the lowest value when accuracy measures such as MAE, MAPE, RMSE and MASE were used which means the model is more accurate whereas the test data for the ARIMA $(1,0,1)$ model were less homogeneous.

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