On Prediction of Euro and Pound Sterling using Box-Jenkins Approach

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Abstract

The foreign exchange market is the largest financial market in the world, with over a trillion US dollars traded each day. In addition, the exchange rates are very sensitive to the surrounding factors. Thus, the international currency trading market provides high returns and motivates investors to enter the market. As a result, the ability to accurately forecast foreign exchange rates is an important factor for investing in the foreign exchange market. The purpose of the study is to determine ARIMA models proposed by Box-Jenkins (1976) for forecasting the euro and pound sterling exchange rates by using the secondary data of closed rates of euro and pound sterling in terms of the US. dollar at every 4-hour period from the 00:00 (GMT) of September 23, 2019, to the 20:00 (GMT) of November 29, 2019. The total number of observations of each exchange rate is 300. The first 270 observations of each exchange rate are used as a training data set to develop the forecasting models and the remaining 30 observations are used as a validation data set for model evaluation. With the graphical analysis of autocorrelation function (ACF) and partial autocorrelation function (PACF), the $ARIMA(p,d,q)$ where $p=1,\ 10, d=0, q=9$ and $ARIMA(p,d,q)$ where $p=0, d=1, q=9$ are proposed as the potential forecasting models for the euro exchange rate. For the pound sterling exchange rate, the $ARIMA(p,d,q)$ where $p=1,2, d=0, q=6$ and $ARIMA(p,d,q)$ where $p=0, d=1, q=6$ are proposed. Then, the likelihood estimation method is employed to estimate the parameters of the proposed models. The Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) are selectively used as the model selection criteria which both criteria provide the same results on determining the best model for exchange rate forecasting. The empirical results were found that the $ARIMA(p,d,q)$ where $p=1,10, d=0, q=9$ is outstandingly selected to be the forecasting model of the euro exchange rate. In addition, the $ARIMA(p,d,q)$ where $p=1,2, d=0, q=6$ is also determined as the forecasting model for the pound sterling exchange rate. We obviously found from the proposed models that if we keep using the same model to forecast the longer period, the forecasting error will become wider according to the time period as result these forecasting models will be able to perform well only in a short time forecasting horizon. To reduce the forecasting error for the longer period, the new observed foreign exchange rate needs to be recursively incorporated in the estimation of $ARIMA(p,d,q)$ parameters. Then, the newest parameters will be used to forecast value for the next period. Therefore, the investor always needs to modify the forecasting model with the incorporation of a newly observed data when they would like to perform the longer forecast horizon to increase the model's accuracy.

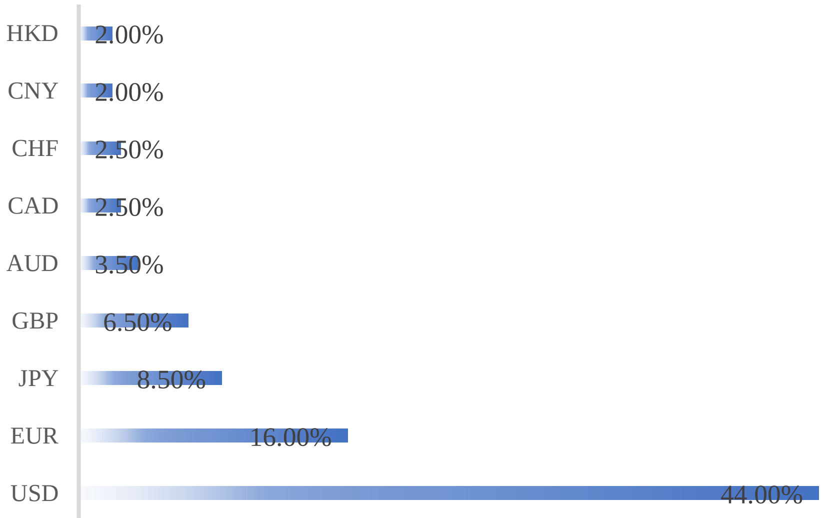
Keywords: Forecasting; Exchange Rate; Box-Jenkins ARIMA Model; Model Selection Criteria

1. Introduction

The foreign exchange market is the largest financial market in the world in which the daily trading volume is exceeding a trillion US dollars ("Foreign exchange market," n.d.). The amount of money traded each week is also larger than the US's full-year GDP.

The currency exchange rate is very sensitive to the surrounding factors. The price of the exchange rate will normally fluctuate according to the demand and supply of each currency. However, they may possibly depend on many factors for example interest rates, inflation, oil prices, gold prices, economic conditions, political situations, domestic and international events as well as the announcement of important numbers of each country, such as unemployment and etc. Due to a large number of players and the fluctuation in price all the time, there will be trading in major currencies shown in Figure 1 such as US dollars (USD), Euro (EUR), Pound sterling (GBP), Yen (JPY) and etc. Therefore, these currencies will have very high liquidity for trading. There are many different traders in the international currency market, for example, the central bank, commercial bank, investment bank, brokers, dealers, pension fund, an insurance company, international organization, and the general public. The purposes for trading of each trader are vary depending on their purposes where some traders mainly focus on profit (Arbitrager) and some traders may focus on protecting against risk (Hedger). However, a large proportion of traders just would like to buy/sell foreign currency to pay for goods and services.

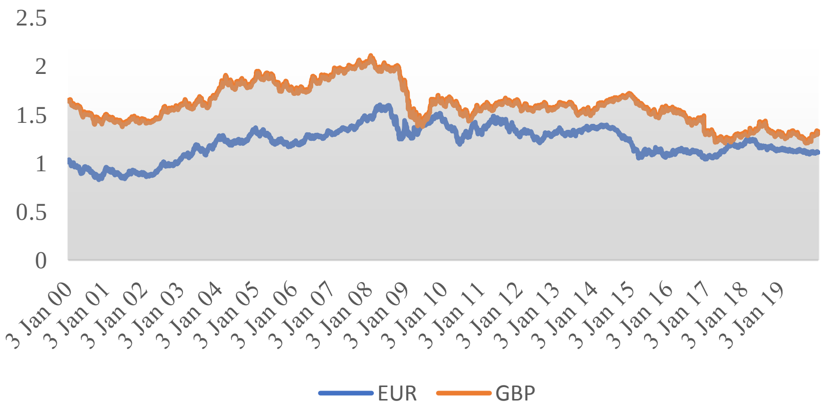
Figure 1: The most actively traded currencies in the world



Source: Remitr (2020, October 16)

Although the number of retail investors in the international currency trading market has not been officially collected yet, there is a large amount of money invested in the foreign exchange market. However, the nature of the currency market is highly volatile and requires a lot of money to trade in an international currency. Therefore, the international currency trading market is a market that provides high returns and motivates many investors to enter the market. Therefore, the ability to accurately forecast international exchange rates inevitably is an important factor for investing in foreign exchange trading among investors. We found a great development of time series analysis since the approach of Box and Jenkins (1976). Cheung (1993) then applied the generalized ARIMA included the Fractionally Integrated Autoregressive Moving Average (FARIMA) in examining the existent of long-term memorable characteristics of the Pound sterling (GBP), German mark (DEM), Swiss franc (CHF), France franc (FRF) and Japanese yen (JPY). In addition, Kamruzzaman & Sarker (2003) applied a computational intelligence-based technique (Artificial Neural Network) for forecasting six different currencies against Australian dollar which the ARIMA model was used to compare. We found the some of the variation of studies in Thailand, for example, Lion (1997) modified the time series data by applying the power transformation before estimating the parameters of the ARIMA model. For some studies that the ARIMA model was directly used to forecast the value of a variety of product, there are Fansiri (2004), which $ARIMA(p,d,q)$ where $p=1,19, d=1, q=0$ were used to forecast the export price of rice, Udomsombatchai (2004), which proposed two potential $ARIMA(p,d,q)$ models where $p=1, d=1, q=1$, and $p=2, d=1, q=0$ were used to forecast the price of broiler chickens, Chaiwan (2007), which proposed the combination of $ARIMA(p,d,q)$ models where $p=1,2,12, d=0, q=21$ were used to forecast the export value of jewelry and accessories, Rungsuprangsi (2007) which $ARIMA(p,d,q)$ where $p=2, d=1, q=2$ was used to forecast the euro rate, and Pingmueang (2012) which $ARIMA(p,d,q)$ where $p=1, d=1, q=2$ was used to forecast the futures gold price. Apart from the direct application of the ARIMA model, Siriphanich (2007) forecasted the time series of stock price with the mixed model of ARIMA and Artificial Neural Network. In addition, Khruachalee (2017) forecasted 4 major Asian currencies that were actively traded in the foreign exchange market including Japanese yen (JPY), Chinese yuan (CNH), Singapore dollar (SGD), and Malaysia ringgit (MYR) by the ARIMA with Explanatory Variable or "ARIMAX" model. The modification of the ARIMA model desirably improves the forecasting performance in serval aspects such as increasing accuracy, reducing time consume, reducing complexity and etc. Because of the development of an accurate model, it can be used to plan strategies to make profits or to reduce the risk.

Figure 2: EUR and GBP Historical Data (January 2000 – January 2019)



Source: Fusion Media (n.d.)

As shown in Figure 2, the volatility of both euro and pound sterling is moderately high. However, the recent trend of both currencies is slightly slow down due to the economic instability and US-China trade war. Due to the most actively traded and largely fluctuated currencies over the past 20 years, euro and pound sterling will be selectively used as sample. This study aims to construct the forecasting model for the euro and pound sterling by Box and Jenkins (1976) approach in order to support the policymaker in economic policy decisions to manage the key economic indicators. In addition, we expect that the forecasting model can be used as a vital tool for investment decisions in the international currency market as well as the information for investors who would like to convert foreign currencies, such as importers, exporters etc.

2. Research objective

The objective of this research is to construct a forecasting model for the exchange rate of the euro and pound sterling based on the Box and Jenkins approach.

3. Methodology

3.1. Data

The 4-hour closing price of 300 observable values for the exchange rates of both the euro (EUR) and the pound sterling (GBP), both of which are valued in US dollars. The exchange rates of both currencies are collected from 23 September 2019 at 00:00 (GMT) until 29 November 2019 at 20:00 (GMT). However, the data is divided into 2 parts, where the first part is collected from 23 September 2019 at 00:00 hrs until 22 November 2019 at 20:00 hrs. This part consists of 270 observable values of both the euro (EUR) and the pound sterling (GBP). The first part will be used to construct the forecasting models based on the Box and Jenkins (1976) approach. The second part will be collected from November 25, 2019, at 00:00 hrs until November 29, 2019, at 20:00 hrs. This part will be used to validate the forecasting models constructed from the first part which consists of 30 observation values of the euro (EUR) and the pound sterling (GBP).

3.2. Box and Jenkins Time Series Models

The concept of Box-Jenkins (1976) is to bridge the relationship between past information and construct the forecasting model that extracts the behavior of time series data. The approach assumes that the current observation data is a linear function of the observed data and the value of past random errors which are generally illustrated as the following equation:

$$Y_t = \delta - \varphi_1 u_{t-1} - \ldots - \varphi_p u_{t-p} + u_t + \theta_1 Y_{t-1} + \ldots + \theta_p Y_{t-p}$$

Where;

Y_t denotes the observable value of the time series at time t

δ denotes a constant in the model

u_t denotes a random discrepancy at an independent time with a mean of 0 and variance σ^2

θ_p and φ_q denote parameters in the model

$p = 1, 2, ..., m$ and $q = 1, 2, ..., n$ denote the integer which represents the rank of the model

3.3 Stationary Test or Unit Root Test

In order to avoid the inconstant mean and variances of data at different time, the unit root testing is used to check if the data is stationary [$I(0)$; integrated of order 0] or non-stationary [$I(d); d > 0$, integrated of ordered] by considering the Augmented Dickey – Fuller test statistics at the 1%, 5%, and 10% level of significance respectively. The Augmented Dickey-Fuller test will examine whether the appropriate model consists of intersection and time trend by using the model without trend and intercept, with the trend and intercept, and with intercept but without trend respectively. The Augmented Dickey-Fuller test will select automatically the suitable lag lengths. In this research, we will determine the maximum value of lag lengths at 12. For the consideration of the stationary of data, we will analyze by comparing the Augmented Dickey-Fuller test statistic with the MacKinnon critical statistic at the significance level of 1%, 5%, and 10% respectively. If the Augmented Dickey-Fuller test statistic is greater than the MacKinnon critical value, then the null hypothesis (H_0) is accepted and the alternative hypothesis (H_1) is rejected. Therefore, the time series data is non-stationary. With this anomaly, we will transform the non-stationary time series data by applying 1st differencing or next order of differencing until the Augmented Dickey-Fuller test statistic is less than the MacKinnon critical value which will reject the null hypothesis (H_0) and accept the alternative hypothesis (H_1), indicating that the time series data is stationary.

3.4 Determining the Order of ARIMA Model

By comparing the characteristics of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of time series data to the theoretical ACF and PACF, we can determine the order p , d , and q of the ARIMA model.

3.5 Parameters Estimation Method of the ARIMA model (p, d, q)

With the maximum likelihood estimation method, the parameters of the $ARIMA(p,d,q)$ are determined. Since the current observation data is a linear function of the observed data and the value of past random errors, we can illustrate as

$$Y_t = X^{'}\beta + \varepsilon_t$$

Where; $t = 1, 2, ..., T$ is the time period.

($Y_t, X_t^{'}$) are independent identically distributed random variable (i.i.d.)

$x_t^{'}$ is the t^{th} -row of the X matrix.

$\varepsilon_t \mid x_t \sim$ i.i.d. $N(0, \sigma_\varepsilon^2)$

Therefore, $Y_t \mid x_t \sim$ i.i.d. $N(X^{'}\beta, \sigma_\varepsilon^2)$ and

$$L(y, x; \zeta) = \prod_{t=1}^{T} L_t(y_t, x_t; \zeta)$$

Where; L_t is the (exact) likelihood function for observation t

$$L_t(y_t, x_t; \zeta) = f_{Y_t|X_t}(y_t \mid x_t; \zeta) \times f_{X_t}(x_t)$$

Accordingly, the exact likelihood function is given by

$$L(y, x; \zeta) = \prod_{t=1}^{T} f_{Y_t|X_t}(y_t \mid x_t; \zeta) \prod_{t=1}^{T} f_{X_t}(x_t)$$

The conditional log-likelihood function is then given by

$$l(y \mid x; \zeta) = -\frac{T}{2}\log(\sigma_\varepsilon^2) - \frac{T}{2}\log(2\pi) \ - \frac{1}{2\sigma_\varepsilon^2}\sum_{t=1}^{T}(y_t - x_t^{'}\beta)^2$$

3.6. Suitability Analysis of the ARIMA model

By testing the estimated parameters of the forecasted model with t statistic, if there is a difference from 0 at the significant level of 0.05, we can assume that the estimated parameter is suitable for forecasting purposes. In addition, we also perform the autocorrelation test of the estimated error with the Box-Pierce Chi-Square statistic by considering whether there is no difference from 0 at the significant level 0.05 from Lag 1 to 48.

3.7 Model selection criteria for the predictive capability of ARIMA models (*p, d, q*)

In order to determine the performance of the predictive model, we will consider the lowest values of the Mean Squares Error (MSE) and Mean Absolute Percentage Error (MAPE) as suggested by Lorchirachoonkul & Jitthavech (2005).

Mean Square Error (MSE) is the forecasting accuracy measured by the size of the tolerances of forecasting from squares of error values. This value is the unit of measurement of squared units of observation value.

$$MSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}$$

Mean Absolute Percentage Error (MAPE) is a measure of the accuracy of the predictive model measured by the magnitude of the predictions compared with the actual value. This measure of accuracy is unitless.

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|}{n} \times 100$$

Where; A_t is the actual value.

F_t is the forecasted value.

n is the total time period.

4 Empirical Results

4.1. The Forecasting model of Euro Exchange Rate

Based on the forecasting approach of Box-Jenkins (1976), there are 2 possible models that are suitable for predicting the closing price of the euro currency exchange rate.

Model 1: $ARIMA(p,d,q)$ where $p=1,10,\ d=0$ and $q=9$

$$(1-\theta_1 B-\theta_2 B^{10})Y_t=\delta+(1-\varphi_1 B^9)u_t$$

Where; Y_t denotes the closed price at time t.

$\delta=(1-\theta_1-\theta_2)\mu$ denotes a constant in the model.

u_t denotes an error term at time t.

φ_1 denote parameters of moving average for lag length 9.

θ_1 denote parameters of autoregressive for lag length 1.

θ_2 denote parameters of autoregressive for lag length 10.

B denotes the backshift operator which $B^k Y_t = Y_{t-k}$

We can formulate this expression as follows

$$\hat{Y}_t = 0.06501+1.10014Y_{t-1}-0.05907Y_{t-10}-0.16261u_{t-9}$$

(<0.001) (<0.001) (0.0054) (0.0135)

Noted: number in the parenesis is the p-value

Even though the time series of the euro closing price is stationary at a different level of the stationary test / unit root test (without the trend and intercept, with the trend and intercept, and with the intercept but without trend respectively), we as well as consider the alternative analysis of the first difference of the euro closing price by taking the first difference to the time series of the euro closing price. We then consider the characteristics of ACF and PACF with the theoretical ACF and PACF to gather the order p , d and q of the model with the first difference on the time series of the euro closing price as follow.

Model 2: $ARIMA(p,d,q)$ where $p=0,\ d=1$ and $q=9$

$$Y_t - Y_{t-1} = \mu + (1-\varphi_1 B^9)u_t$$

Where; Y_t denotes the closed price at time t.

Y_{t-1} denotes the closed price at time $t-1$.

μ denotes the mean of the closed price.

φ_1 denote parameters of moving average for lag length 9.

B denotes the Backshift Operator which $B^k Y_t = Y_{t-k}$

u_t denotes an error term at time t.

We can then formulate this expression as follows

$$\hat{Y}_t - \hat{Y}_{t-1} = -0.00013 - 0.14319 u_{t-9}$$

(0.4404) (0.0250)

Noted: number in the parenesis is the p-value

For further illustration, we provide the plots of each model as shown in Figures 3 and Figure 4. The forecasting period is started from November 25, 2019, at 00:00 hrs until November 29, 2019, at 20:00 hrs. It is obviously seen from these figures that the ARIMA model with $p=1,10,\ d=0$ and $q=9$ provides a reasonably good tracking on the actual data. On the other hands, the ARIMA model with $p=0,\ d=1$ and $q=9$ provide a large deviation from actual data during the last period of the forecasting, started from period 15 until period 30 which we can obviously see that the forecasting performance of the $ARIMA(p,d,q)$ where $p=1,10,\ d=0$ and $q=9$ is better off.

Figure 3: The plot of forecasted euro currency value from the $ARIMA(p,d,q)$ where $p=1,10,\ d=0$ and $q=9$.

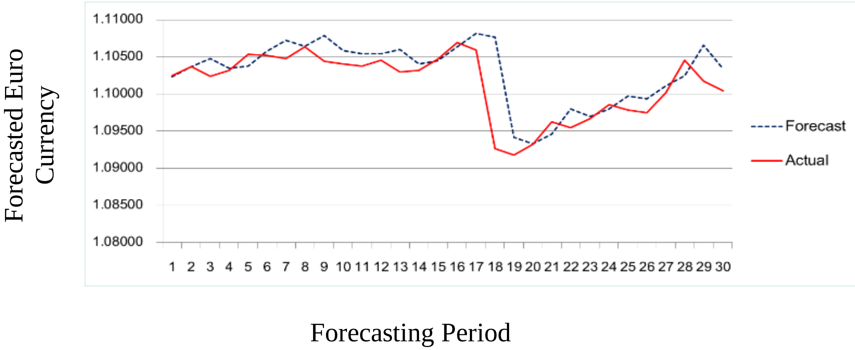


Figure 4: The plot of forecasted euro currency value from the $ARIMA(p,d,q)$ where $p=0,\ d=1$ and $q=9$

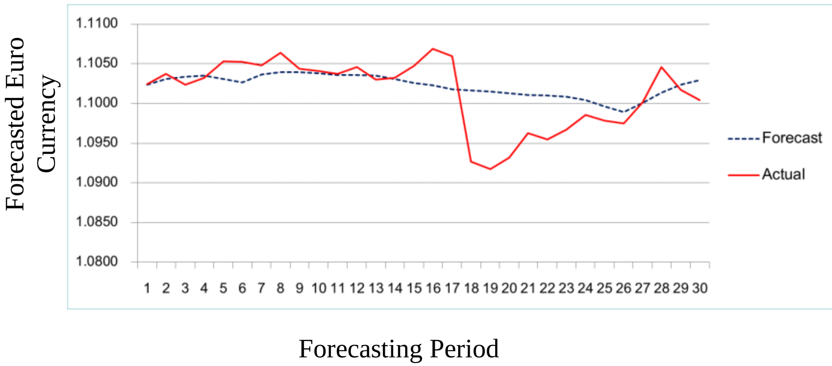


Table 1: The estimated value of MSE and MAPE of predictive models in forecasting the closing price of the euro currency exchange rate.

Model	Model Efficiency	MSE	MAPE
$ARIMA(1,10,0,9)$	1 or 2 period ahead	1.114×10^{-5}	0.180%
$ARIMA(0,1,9)$	9 period ahead	1.341×10^{-5}	0.232%

Since the estimated values of MSE and MAPE of the $ARIMA(p,d,q)$ where $p=1,10$, $d=0$ and $q=9$ provides the lower value, we can surely conclude that the $ARIMA(p,d,q)$ where $p=1,10$, $d=0$ and $q=9$ is more suitable for forecasting the euro currency exchange rate.

4.2. The Forecasting Model of Pound Sterling Exchange Rate

We perform the same procedure of Box-Jenkins (1976) applied to the forecasting of the euro currency exchange rate and found that there are 2 possible models that are suitable for forecasting the pound sterling currency exchange rate.

Model 1: $ARIMA(p,d,q)$ where $p=1,2$, $d=0$ and $q=6$

$$(1-\theta_1 B-\theta_2 B^2)Y_t=\delta+(1-\varphi_1 B^6)u_t$$

Where; Y_t denotes the closed price at time t.

$\delta=(1-\theta_1-\theta_2)\mu$ denotes a constant in the model.

u_t denotes an error term at time t.

φ_1 denote parameters of moving average for lag length 6.

θ_1 denote parameters of autoregressive for lag length 1.

θ_2 denote parameters of autoregressive for lag length 2.

B denotes the Backshift Operator which $B^k Y_t=Y_{t-k}$

We can formulate this expression as follows

$$\hat{Y}_t=1.53896+1.10723Y_{t-1}-0.13056Y_{t-2}-0.14853u_{t-6}$$

(<0.001) (<0.001) (<0.001) (<0.001)

Noted: number in the parenesis is the p-value

In this section, we also consider the first difference of the pound sterling closing price by taking the first difference to the time series of pound sterling closing price, even though the time series of the pound sterling is stationary at a different level of the stationary test (without the trend and intercept, with the trend and intercept, and with the intercept but without trend respectively). Then, we consequently consider the characteristics of ACF and PACF with the theoretical ACF and PACF to gather the order p , d and q of the first difference on the time series of the pound sterling closing price.

Model 2: $ARIMA(p,d,q)$ where $p=0,\ d=1$ and $q=6$

$$Y_t - Y_{t-1} = \mu + (1-\varphi_1 B^6)u_t$$

Where; Y_t denotes the closed price at time t.

Y_{t-1} denotes the closed price at time $t-1$.

μ denotes the mean of the closed price.

φ_1 denote parameters of moving average for lag length 6.

B denotes the backshift operator which $B^k Y_t = Y_{t-k}$

u_t denotes an error term at time t.

We can formulate this expression as follows

$$\hat{Y}_t - \hat{Y}_{t-1} = -0.00013 - 0.14107 u_{t-6}$$

(0.4998) (0.0206)

Noted: number in the parenesis is the p-value

It also provides the plots of each model used to forecast the pound sterling closing price as shown in Figures 5 and Figure 6. The forecasting period is also started from November 25, 2019, at 00:00 hrs until November 29, 2019, at 20:00 hrs. It is also obviously seen that the ARIMA model with $p=1,2,\ d=0$ and $q=6$ provides a reasonably good tracking on the actual data. This result is consistent with the forecast of the euro currency exchange rate. On the other hands, the ARIMA model with $p=0,\ d=1$ and $q=6$ provide a large deviation from actual data along the period of forecasting, started from period 1 until period 30.

Table 2: The estimated value of MSE and MAPE of predictive models in forecasting the closing price of the pound sterling currency exchange rate.

Model	Model Efficiency	MSE	MAPE
$ARIMA(1,2,0,6)$	1 or 2 period ahead	6.026×10^{-6}	0.118%
$ARIMA(0,1,6)$	6 period ahead	3.307×10^{-5}	0.263%

According to the estimated values of MSE and MAPE of each model, we found that the $ARIMA(p,d,q)$ where $p=1,2,$ $d=0$ and $q=6$ provide the lower value. Therefore, we can confidently conclude that the $ARIMA(p,d,q)$ where $p=1,2,$ $d=0$ and $q=6$ is considered as a suitable model for forecasting the pound sterling exchange rate. In addition, the model performs the best in short-term forecasting (1 or 2 periods ahead).

From the analysis of the forecast results, we found that the model without differencing transformation is outstandingly outperformed in forecasting the foreign exchange rate which can be considered by the value of MSE and MAPE. However, the stationary property of time series data is mandatorily required for the ARIMA model. Therefore, the selection of transformation method will be the gap of each model in forecasting euro and pound sterling.

Figure 5: The plot of forecasted pound sterling currency value from the $ARIMA(p,d,q)$ where $p=1,2,$ $d=0$ and $q=6$.

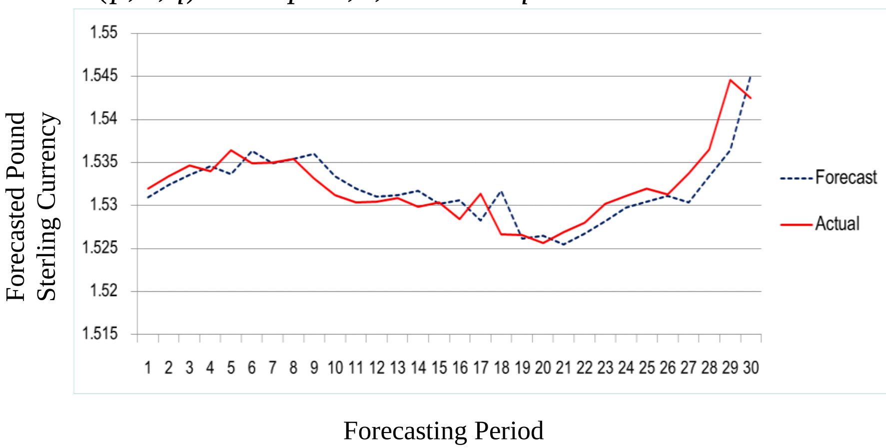
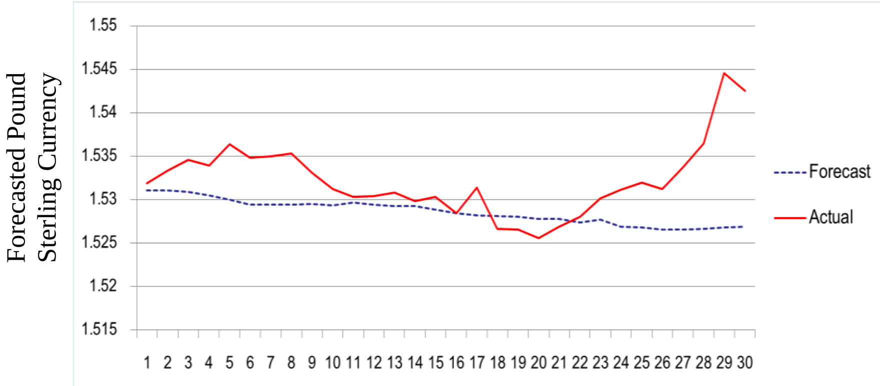


Figure 6: The plot of forecasted pound sterling currency value from the $ARIMA(p,d,q)$ where $p=0$, $d=1$ and $q=6$



Forecasting Period

5. Conclusion

This research aims to construct a forecasting model for the exchange rate of the euro and pound sterling based on Box and Jenkins (1976) approach. The forecasting period is ranged from November 25, 2019, at 00:00 hrs to November 29, 2019, at 20:00 hrs. We found that the $ARIMA(p,d,q)$ where $p=1,10$, $d=0$ and $q=9$ is a suitable model for predicting the euro exchange rate. This model is effective in predicting only for 1 or 2 periods in advance. The predictions after 1or 2 periods ahead will incorporate the predicted values to continue forecasting in the predictive model. Then, the estimated error will be wider. For pound sterling, the $ARIMA(p,d,q)$ where $p=1,2$, $d=0$ and $q=6$ is a suitable model for predicting the pound sterling exchange rate. This model is also effective in predicting only for 1 or 2 periods in advance. The predictions after 1 or 2 periods ahead will also incorporate the predicted values to continue forecasting in the predictive model which will increase the forecasting error. According to the findings, these models are effective in performing a prediction only for a short time horizon because the predictive model will incorporate the prior predicted value as the new observable value to perform a further prediction. Therefore, predicting the value ahead, the newest actual observable value must always be placed into the forecasting model to protect the increasing of forecasted errors. However, this forecasting model should only be used with caution for a short-term forecasting horizon.

The accurate forecasting model can help traders in the international currency market and businesses to make better decisions. The traders can take advantage when the exchange rate does not match up. Because of the discrepancy between three foreign currencies, the traders, especially the arbitragers, will perform triangular arbitrage strategy to take profit without additional risk. In the case where we can accurately forecast the trend of the USD which will be depreciated against Euro (EUR) and Pound Sterling (GBP) in the next period, the traders can exchange an amount at one rate (EUR/USD). Then, the traders will convert again at the rate (EUR/GBP). Finally, the traders will convert it back to the original currency (USD/GBP) where USD is already depreciated. Assuming low transaction costs, employing this strategy, the traders will get a net profit without additional risk. However, traders who would like to take advantage of this strategy usually need to have advanced computer equipment and programs to automate the process because this opportunity has easily vanished if there are many traders who accurately speculate the future exchange rate.

In addition, the multinational corporations (MNCs) can manage their exposures on international transactions which are usually settled in the near future through the forecast exchange rate movements. The fluctuation of exchange rate mainly affects an MNC’s cash flow and value. Therefore, the accurate forecasting model will benefit MNCs to reduce their exchange rate exposure that may be able to stabilize their earnings and cash flows. In addition, it can also increase the MNC’s ability to repay its debt over the long run, thereby reducing the possibility of failure and allowing the MNC to borrow funds at a lower cost (Madura, 2018).

For further research, we can possibly include the explanatory variables to increase the forecasting performance which is known as the ARIMA with Explanatory Variable (ARIMAX). Khruachalee (2017) suggested that the ARIMAX model performed the best in forecasting the behavior of a foreign exchange rate with high volatility characteristic. Moreover, we can also apply a computational intelligence-based technique such as Artificial Neural Network with the ARIMA model as Siriphanich (2007) suggested.

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