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# Forecasting Of IQD/USD Exchange Rate By Using Some Machine Leaening Methods With Time-Varying Volatility

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***Abstract :*** *Abstract: The machine learning technique such as random forests and regression trees, are nonparametric methods that it recently used for regression estimation. In these methods, the variance of random errors needs to be constant, but that's not true always, especially, in the financial data. Unfortunately, the financial time series suffer from the volatility that happens during different periods where the researchers were an effort to solve this problem by combining the random forest and the regression trees with the GARCH model. In this paper, we use these methods to estimate the conditional variance of the GARCH model to forecast the exchange rate of IQD/USD.* *KEYWORDS :Machine learning; random forests; regression trees; exchange rate; GARCH model.*

**INTRODUCTION:** In the financial market, modelling and forecasting volatility become a very active research area over last decades because of a volatility that it is considered as important concept in many economic and financial fields. The essential feature of this volatility that it cannot be seen directly, so financial analysts are interested to get accurate estimate of the conditional volatility. Therefore, there are many models developed for estimation the conditional volatility of financial time series, where the most well-known models are the conditional heteroscedastic models such as the Autoregressive Conditional Heteroscedasticity model (ARCH) and General Autoregressive Conditional Heteroscedasticity model (GARCH). ARCH model suggested by Engle (1982), where it can be written as follows (Engle, 2001):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 \quad (1)$$

where $\alpha_0, \alpha_1, \alpha_2, \ldots.., \alpha_i$ is parameters of model , $\alpha \geq 0, e_t$ is the random error, $p$ is the order of model and $\sigma_t^2$ represents the Conditional variance and this model was developed into GARCH model by Bollerslev (1986) that can be defined as follows (Bollerslev, 1986)( Bollerslev and et al, 1992):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_j^q \beta_j \, \sigma_{t-j}^2 \quad (2)$$

where $\beta_1, \beta_2, \ldots \beta_j$ is the new parameters and $\beta_j \geq 0$ ,$p$ $and$ $q$ is the order of the GARCH model . They were found this model to become the first models that were introduced into the literature and it's very popular where they enable the researchers to estimate the conditional variance of series. Moreover, there are many empirical applications for modelling and predictions time-varying conditional of a financial time series such as Nelson 1991, Bollerslev et al. 1992, Engle and Patton 2001, Alberg et al. 2008 and etc.

The main feature of these models is to give a good forecast of future volatility, so it will be helpful for obtaining a more efficient portfolio allocation. This types of models were designed for modeling and forecast the conditional variance that is second order moment of a series by using past unpredictable changes of the returns series, where it more applied successfully in economics and finance, specifically in the financial market research.

## 1. ESTIMATION METHODS

### 1.1 REGRESSION TREES

Regression trees suggested by L. Breiman (1984), it is one of the machine learning methods that can be represented as decision tree. Decision tree is a visual representation, where it includes internal nodes that represent a test for one of input variables and terminal nodes are called leafs that represent the decision or prediction, where this prediction is the mean of all response value (Garg, 2012). In the linear regression analysis, the relation between the response variable and one or more than one explanatory variable is linear. It well-known the performance predictive of the linear regression degrades if there are nonlinear relationship or interaction between the variables. Regression tree is a predictive model, where it is better deal with non-linarites and interaction in dataset. However, it is grown as binary tree that means each node in the tree has two nodes. The goal of regression tree is to obtain better split of the variable and reduce the sum of square error (SSE), where it used the classification and regression tree (CART) algorithms that is one of the machine learning algorithms (Onur, 2014).

Furtherer, the regression tree algorithm start with the root node, then each node in tree split into left or right sub-branch, this depend on the conditions that must be satisfied and then access the leaves (terminal nodes) that is making the prediction or decision. The prediction at leaves $b$ is computed by (Garge, 2012):

$$m_b = \frac{1}{n_b}\sum_{i \in b} y_i \qquad (3)$$

Where $n_b$represents the number of the observation in terminal nodes and $y_i$ represents the response variables. For we have split the sample space into b regions$R_1, R_2, \ldots, R_b$, the response is modeled as follows:

$$g(x) = \sum_{i=1}^{b} m_b\, I(x \in R_b) \qquad (4)$$

Where $I(.)$ is indicator
and SSE is:

$$SEE = \sum_{a \in leaves(T)} \sum_{i \in b} (y_i - m_i)^2 \qquad (5)$$

## 1.2 RANDOM FOREST

L. Breiman (2001) suggested the random forests method, which are combination of decision tree. It used for regression and classification to select the variables automatically، when large sample sizes with large number of variables. It is one of the machine learning techniques, which used to generate accurate predictive models (Garge, 2012). Researchers face great difficulty for determining the best variables to be included in the model, so the CART algorithm is used to build each tree (Onur, 2014). It is a technique that includes a number of separate decision trees to generate a robust and accurate model.

In the construction of random forests, the bootstrap sample of the training data is used to build all trees at random (Breiman, 2001). To choose the best splitting for each node is based on comparing the error rate between the features, which the error convergence with increasing the number of trees, because the error depends on the strength of the separate trees and the correlation among the trees. Random Forest is a powerful model against overfitting and is good with high noise in the training data. One of the characteristics of random forest is self-estimation to monitor the strength of correlation and error. After the ensemble of trees $\{T_b\}_1^B$ to make predictive at all the new point as:

$$\widehat{f_{rf}^{B}} = 1/B \sum_{b=1}^{B} T_b(X) \qquad (6)$$

Where $B$ represents the number of trees.

## 2 RESEARCH AND METHOD

It can be written the algorithm of this paper for predicting of return series as steps follows:
We let

$$\widehat{y_t} = f(\odot, x_t) \qquad (7)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 \qquad (8)$$

Where $e_t = y_t - \widehat{y_t}$

1. The data set is split into training and test sets
2. Estimate the model in equ (7) by using of machine learning models and then calculate its residuals.
3. Estimate the conditional variance of GARCH model and standard error of conditional variance $\sqrt{\sigma_t^2}$ by using the residuals in step 2.
4. the transformation of $y_t$ parried out by using $\sqrt{\sigma_t^2}$ from previous step to reduce the volatility clustering that it effect on $y_t$ as follows:

$$y_t^* = y_t / \sqrt{\sigma_t^2}$$

5. Again, it used the transformed $y_t^*$ with machine learning model

**3. RESULT AND DISCUSSION**

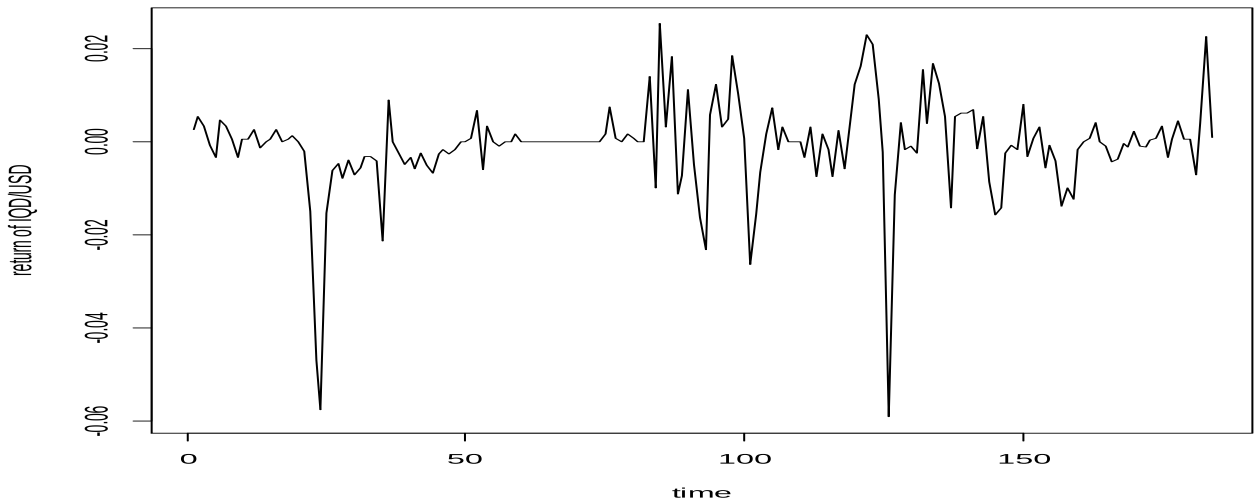
In this paper, we used the monthly exchange rate data of IQD/USD covering the period from Jan, 2005 to May, 2020, where it has collected from the Center Bank of Iraq. We selected this period because of instability of country and then it calculated the monthly return $y_t$ at time t as follows:

$$y_t = \ln(p_t) - \ln(p_{t-1}) \qquad (10)$$

Where $p_t$the exchange is rate at time$t$ and $p_{t-1}$ is the exchange rate at time$t-1$.

Observations have been divided into 128 as training set and 56 as test set. The monthly return series (IQD/USD) can be depicted in Figure 1. Figure 1 display the return series is stationary in mean, but it is non-stationary in variance due to the volatility clustering phenomena during different period.

**Figure 1 IQD/USD index: Jan, 2005- May, 2020**




**Source:** own elaboration based on IQD/USD

Figure 2 (a) display the Autocorrelation Function (ACF) of the return series where we noted that insignificant correlation in lag 1, 2, 6 and lag 10 that means just the lag 1, 2, 6 and lag 10 affected that by fluencies clustering phenomena, whilst in (b) shows that the Partial Autocorrelation Function (PACF) of return series where we noted that the almost lags within boundary. In figure 2 (c) and (d) show that the autocorrelation function (ACF) and Partial Autocorrelation Function (PACF) of the squared return series where almost the almost lags within the boundary. In figure 3 shows that the normal Q-Q plot where it display the return series of IQD/USD non-normal distribution.

**Figure 2 a. ACF of the return series, b. PACF of the return series, c. ACF of the squared return series and d. PACF of the squared return series.**

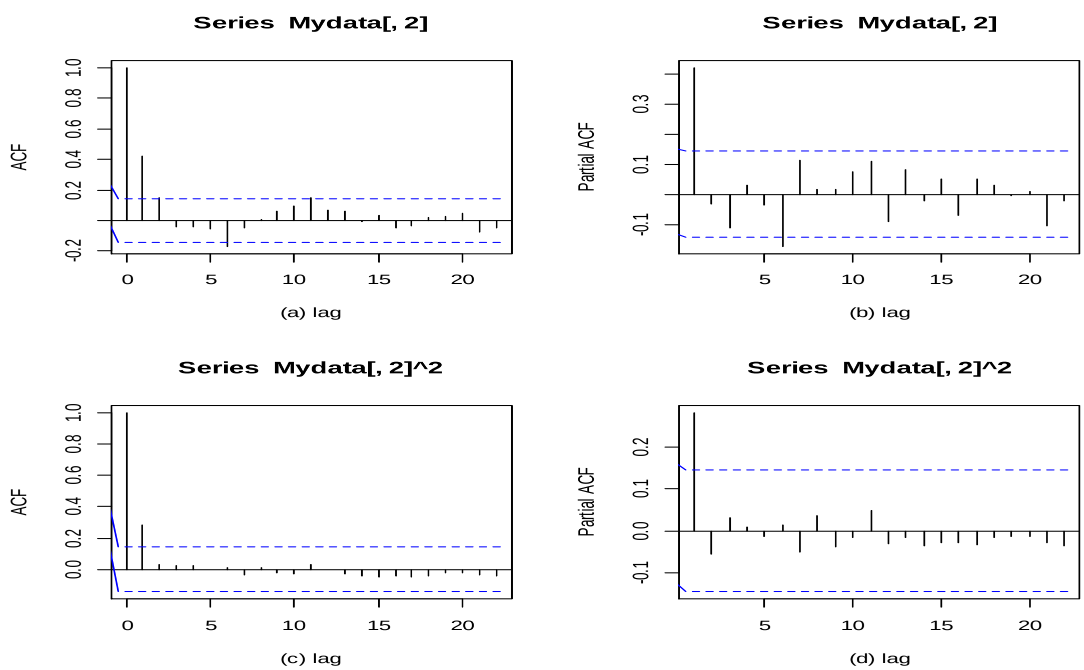


**Figure 3 Normal Q-Q plot for the squared return of $IQD/USD$.**

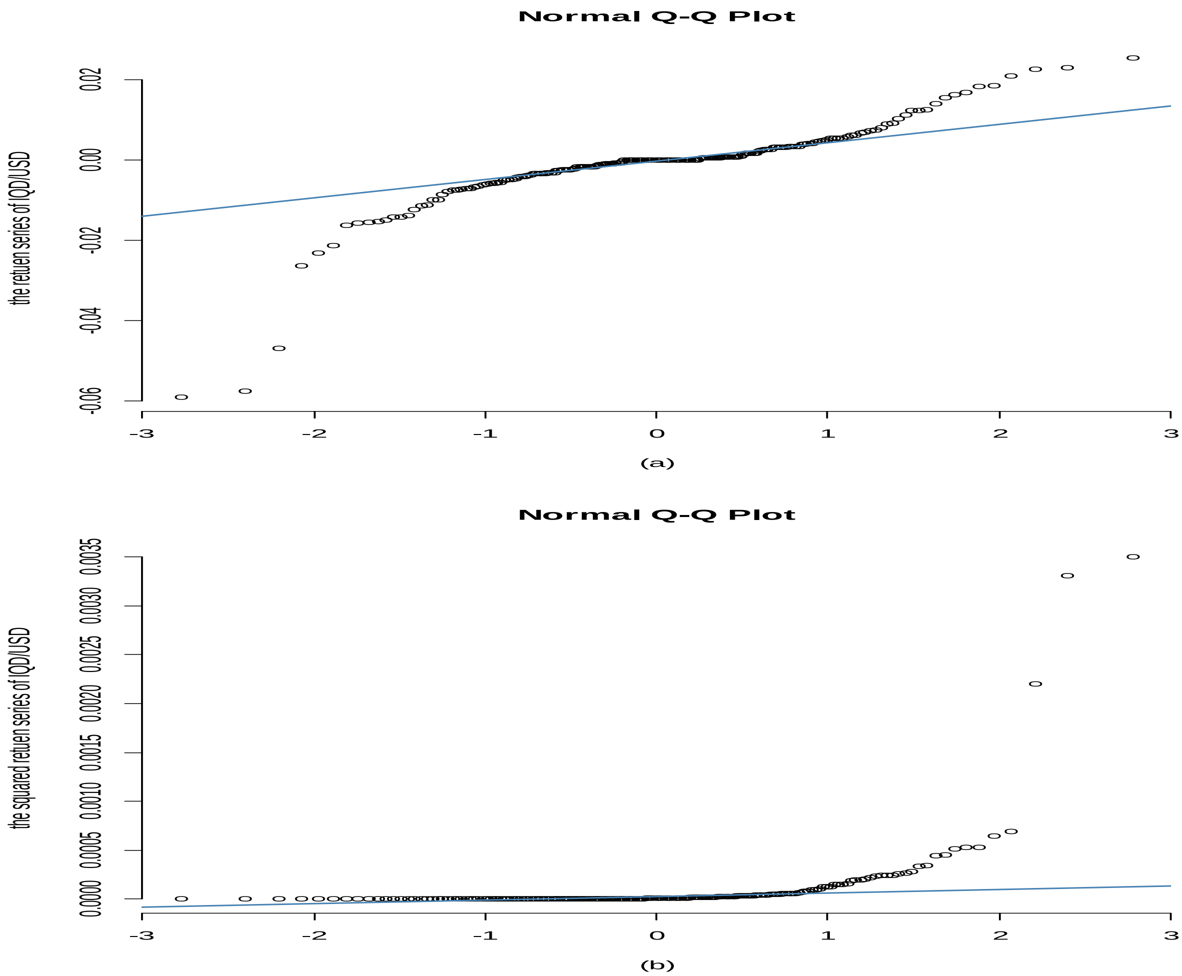



**Table 1 Descriptive statistic for the returns of $IQD/USD$.**

| Return | Mean | Stander Division | Median | Maximum | Minimum | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| IQD/USD | -0.0011 | 0.0106 | 0 | 0.0254 | -0.0591 | -2.1835 | 13.7359 |

**Recourse:** own elaboration based on IQD/USD

**Table 2 Tests of GARCH models for the returns of$IQD/USD$.**

| Return | Jargue-Bera test | Ljung-box test Q (10) | Ljung-box test Q (15) | Ljung-box test Q (20) | Ljung-box test Q (10) * | Ljung-box test Q (15) * | Ljung-box test Q (20) * | LM Arch Test |
|---|---|---|---|---|---|---|---|---|
| IQD/USD | 237.9615 [0.0000] | 25.6767 [0.0042] | 38.677 [0.0007] | 41.6976 [0.0030] | 2.8029 [0.9856] | 6.7362 [0.9645] | 8.6744 [0.9863] | 3.0389 [0.9952] |

Note: p-values are in brackets.

From the table, we noted the mean is not far from zero. It is characterized of this returns by high kurtosis and asymmetric. In table 2 ,the Jargue-Bera test is rejected the normality hypothesis for the returns because of the p-value of this test smallest than 5%, whilst the Ljung-box test refer no significant correlation at 0.005 for the returns of IQD/USD. LM Arch test rejected the null hypothesis due to the p-value of LM Arch test smallest than 0.005 where it means there are effect of GARCH model.

**Table 3 shows AIC, BIC and H-Q value to select the order of GARCH models.**

| The model | AIC | BIC | H-Q |
|---|---|---|---|
| GARCH (1,0) | -1.4022 | -1.3500 | -1.3811 |

| | | | |
|---|---|---|---|
| GARCH (1,1) | -1.3858 | -1.3162 | -1.3576 |
| GARCH (1,2) | -1.4007 | -1.3216 | -1.3734 |

In the table 3 display that the AIC, BIC and H-Q value at the different order of GARCH models, where we found GARCH (1, 0) model is very suitable to predict for the returns series because it has lowest value of AIC, BIC and H-Q.

**Table 4 Show the $RMSE$ values for monthly returns of $IQD/USD$**

| Methods | $RMSE$ |
|---|---|
| Regression trees | 0.8990 |
| Random forests | 0.6290 |

Table 4 display the predictive performance for monthly return that it is obtained by$RMSE$, where it shown that the random forests outperform better than the regression trees.

## CONCLUSION

To measure the performance of the machine learning methods, we applied the random forests and the regression trees methods with GARCH model to predict the monthly returns, where this models are evaluated by using $RMSE$ criterion. The results shows that the GARCH $(1,0)$ is appropriate model to predict the monthly return series, the Q-Q normal plot, where it proved that the return series is non-normal distribution and the random forests methods gave that the best result comparison of the regression trees method to improve the performance predictive of the volatility of $IQD/USD$.

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