ICIC Express Letters
Part B: Applications
Volume **7**, Number **9**, September **2016**

ICIC International ©2016 ISSN 2185-2766
pp. 1925–1932

AN ACCURACY COMPARISON BETWEEN THE TIME-SERIES AND THE COMPUTATIONAL INTELLIGENCE MODELS ON THE TAIWAN-CENTRAL AMERICA FREE TRADE AGREEMENTS

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Received February 2016; accepted May 2016

Abstract. *Starting from the mid-20th century, Taiwanese economy is extremely export-oriented due to the lack of natural resources. To ensure the growing of the economy, Taiwan government keeps actively looking for opportunities for participation in the world economic system to avoid the slowdown of multinational liberalization. As one example, Taiwan vigorously participates in FTAs with countries of Central America. International economic conditions are significantly important to international trade and the export/import volume will be affected by the foreign exchange rate. If the impact level of an incident or an event occurrence is analyzed along with the foreign exchange rate forecasting, there is a chance to maximize the trade surplus, thus boosting the economic growth. Based on the event study methodology, the selected agreements include four Taiwan signed FTAs with countries in Central America. The observation period setting is 70 days of pre-event period and 70 days of post-event period. In this paper, we use two commonly used time-series models including the GARCH and the EGARCH and a Computational Intelligence (CI) model established by the Interactive Artificial Bee Colony (IABC) method for finding the impact on the foreign exchange rate forecasting. The Mean Absolute Percentage Error (MAPE) is adopted to compare the accuracy of exchange rate prediction. The experimental results indicate that the IABC based foreign exchange rate forecasting model presents higher forecasting accuracy than the conventional time-series models and is able to resist the impact caused by the FTAs.*
Keywords: Event study, Free trade agreement, GARCH, EGARCH, IABC, Computational intelligence

1. **Introduction.** Taiwan has a very small territory with limited natural resources. For this reason, Taiwanese economy is extremely export-oriented. In international trade, foreign exchange rates are one of the most important adjustment levers. If corporations in Taiwan are able to take full advantage of the foreign exchange rate trends, the corporations in Taiwan are able to maximize their trade surplus, thus boosting the economic growth of the country. Given the importance of the international trade to Taiwanese economy, this study investigated the respective impact of signing free trade agreements between Taiwan and four Central American countries such as Guatemala, Nicaragua, El Salvador, and Honduras, on the results produced by foreign exchange rate forecasting models. The

analytic results can offer some insight to central banks and investors in foreign exchange markets (forex, FX, or currency market).

Although the event study methodology has been widely used in many financial and management fields, only few researches are related to concern the signing of free trade agreements as a factor in the foreign exchange rate forecasting. After 1990, scholars (Kwok and LeRoy) [1] starts to apply event studies to the foreign exchange market in the research. The event study methodology is able to provide a null hypothesis and to investigate whether the occurrence of a certain event will cause the fluctuation of foreign exchange rates and abnormal returns. Furthermore, Bajo and Petracci (2006) [2] define the event study methodology as the basic method to test for "semi-strong form efficiency". The semi-strong form efficiency of the EMH states that stock prices reflect all publicly available information. For this reason, abnormal trading volume is seen as a signal of upcoming announcements by investors. The event study methodology aims to find out whether there will be unusual changes in stock prices and abnormal returns after an event takes place.

There are many exchange rate forecasting models and the most frequently used models maybe the time-series. Time-series modeling is a classic analysis tool in economics and finance fields. The spirit of such modeling lies in its assumption that all current data is somehow connected with historical data. One of the most famous ones is Autoregressive Conditional Heteroskedasticity (ARCH) model which is proposed by Engle (1982) [3]. Engle claims that the ARCH model can be used to solve the problem with the volatility of time series. Thereafter, the ARCH model is developed very fast in quantitative economics. Few years later, Bollerslev (1986) improves the ARCH model and develops a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model [4]. The GARCH model is an extension of the ARCH model. The GARCH model assumes that the current conditional variances are a function of both the preceding period's conditional variances and the squares of the error terms, and the plus or minus sign of the error terms does not affect these conditional variances. Hence, GARCH model is not able to depict the asymmetric feature shown by the volatility of the conditional variances of returns. Nevertheless, many distributions of returns have the leptokurtic feature. Residuals of stock market returns affect returns asymmetrically. That is to say, GARCH model is not able to explain the negative correlation between stock returns and changes in volatility. To improve the GARCH model, Nelson (1991) proposes the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model [5].

Compared to other foreign exchange rate forecasting models, computational intelligence methodologies also have been gradually adopted in the finance field for many years. The Interactive Artificial Bee Colony (IABC) algorithm proposed by Tsai et al. [6] is originally used to optimize numerical problems. The IABC is an improved version of the original ABC algorithm proposed by Karaboga in 2005 [7]. Bao and Zeng (2009) [8] point out that the advantages of such an algorithm include its simple concept, good usability, and low requirement on the number of parameters. Tsai et al. (2015) analyze the impact caused by the trade agreements to the stock market in Taiwan [10]. The similar analysis on foreign exchange rates with psychological factors is also given in the same year [11, 12]. In this paper, the IABC method is utilized to build the foreign exchange rate forecasting model. This study intends to investigate how the exchange rate prediction accuracy is under the impacts of four Free Trade Agreements (FTAs) with these three models conducted by the GARCH, the EGARCH, and the IABC in order to provide some insights to central banks and investors in foreign exchange markets. According to the experimental results, we conclude that utilizing the computational intelligence tool like IABC is an efficient way to get more accurate results in the foreign exchange rate forecasting than the conventional methods. The rest of the paper is assembled as follows: the related works are discussed in Section 2; the experiments and the experimental results are revealed in Section 3; and the conclusion is made in the last section.

2. **Related Works.**

2.1. **Time series models.** To find out which foreign exchange rate forecasting model has the best predictive ability in the FTA events, this paper examines and compares the accuracy of the foreign exchange rate forecasting models adopted in this study under the effect of four FTAs. First, the time series data are tested to see whether they are stationary using two unit root tests, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Next, the Box-Jenkins approach is used to build an ARIMA model. The Akaike Information Criterion (AIC) value and the Schwarz Criterion (SC) value are the criteria for choosing lag periods. The Jarque-Bera (J-B) test is a goodness-of-fit test to see whether sample data have the skewness and the kurtosis that match a normal distribution. Assume that the number of estimated parameters is n, and the total number of sample residuals is denoted by T. The J-B test result can be obtained by Equation (1):

$$JB = \frac{T-n}{6}\left[S^2 + \frac{1}{4}(u-3)^2\right] \tag{1}$$

where S stands for the skewness and u denotes the kurtosis.

After passing the J-B test, the data is ready for input to the GARCH and EGARCH models. The GARCH model can be defined by Equations (2) and (3):

$$\varepsilon_t = Y_t - X_t\alpha, \text{ where } Y_t|\Omega_t \sim N\left(X_t\alpha, \sigma^2\right) \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2, \text{ where } \alpha_0 > 0, \alpha_1 \geq 0, \text{ and } \beta_1 \geq 0 \tag{3}$$

where Y_t is a function of exogenous variable X_t, α_0, α_1, and β_1 are constant coefficient parameters, respectively, ε_t denotes the residual, σ_t^2 is the past squared residual of the past function, and σ_{t-1}^2 is a condition of the variation in the past on a number j.

On the other hand, the EGARCH model can be depicted by Equations (4) and (5):

$$Y_T = X_TB + \varepsilon_T, \text{ where } \varepsilon_T|\Omega_{T-1} \sim N(0, \sigma^2) \tag{4}$$

$$\ln\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\left[\alpha_i\left(\left|\frac{\varepsilon_t - i}{\sigma_t - i}\right| + E\left|\frac{\varepsilon_t - i}{\sigma_t - i}\right| + \Upsilon\left|\frac{\varepsilon_t - i}{\sigma_t - i}\right|\right)\right] + \sum_{j=1}^{p}\beta_j\ln\sigma_{t-j}^2 \tag{5}$$

where σ_t^2 is a function of both the previous p period's conditional variance and the previous q period's squares of error terms. Moreover, σ_{t-j}^2 is the conditional variance of previous j periods. In other words, p and q are the orders of the GARCH model.

After the creation of volatility models, a diagnostic test is conducted on these models to check whether the standardized residuals already meet the requirement to be white noise. Finally, the Mean Absolute Percentage Error (MAPE) is adopted to analyze and compare the predictive ability of the exchange rate forecasting models. Also, the Ljung-Box Q statistic is used to see whether these models are white noise:

$$Q(P) = n(n+2)\sum_{k=1}^{p}\frac{1}{n-k^{p_k^2}} \sim \chi^2(P) \tag{6}$$

where n is the sample size and k denotes the lag periods. The statistic result is a chi-square distribution with p Degrees of Freedom (DOF).

The impact on the forecasting results are measured by the MAPE, which is proposed by Lewis (1982) [9]. The MAPE can be calculated by Equation (7):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|\hat{S}_t - S_t\right|}{S_t} \times 100\% \tag{7}$$

where n is the sample size, $\hat{S}_t$ is the expected exchange rate of period t, and S_t is the actual exchange rate of such a period.

2.2. **Interactive artificial bee colony.** In this paper, the IABC method [6] is adopted to build the foreign exchange rate forecasting model. This experiment examines and analyzes the accuracy of the foreign exchange rate forecasting results between the New Taiwan dollar and the U.S. dollar under the impact of 4 FTAs between Taiwan and four Central American countries. Before constructing the IABC model, we need to conduct the unit root test, the autocorrelation test, and the normality test on the input data. The IABC method can be depicted in 5 steps.

Step 1. Initialization: Assume we have i agents in a j dimensional space, and the solution matrix is denoted by X. The initialization is achieved by randomly spreading the agents into the solution space by Equation (8):

$$X = \min(X) + r[\max(X) - \min(X)] \tag{8}$$

where X is an i by j matrix, $\min(\cdot)$ and $\max(\cdot)$ denote the function extracting the minimum and the maximum value of X in all i rows, respectively, and r is a random number in the range of $[0, 1]$.

Step 2. Move the onlookers: Calculate the probability of food sources, which are provided by the employed bees, by Equation (9).

$$P_i = \frac{F(\theta_i)}{\sum_{k=1}^{S} F(\theta_k)} \tag{9}$$

where θ_i presents the position of the ith employed bee, S stands for the total number of employed bees, and P_i indicates the probability for the onlookers to choose the ith employed bee to follow.

Let N be a constant indicating the number of employed bees for an onlooker to refer to in the movement. Thus, the movement of the onlooker is calculated by Equation (10):

$$\theta_q(t+1) = \theta_q(t) + \sum_{p=1}^{N} \tilde{F}_{qp} \left[\theta_q(t) - \theta_p(t)\right] \tag{10}$$

where θ_q is the position of the onlooker, t denotes the iteration number, $\tilde{F}_{qp}$ means the normalized gravitation force, which is simply adopted from the probability of the food source, of the employed bee to the onlooker.

Step 3. Move the scouts: If an employed bee continuously has no follower onlookers in a predefined number of iteration, the employed bee becomes a scout and is moved by Equation (11):

$$\theta_k(t+1) = \theta_{k_{\min}}(t) + r \cdot [\theta_{k_{\max}}(t) - \theta_{k_{\min}}(t)] \tag{11}$$

where θ_k is the position of the scout, r denotes a random number in the range of $[0, 1]$, and the max and the min indicate the maximum and the minimum value occurring in all dimensions of θ_k, respectively.

Step 4. Update the near best solution: If the newly found solution presents better fitness value than the original stored solution, update the near best solution.

Step 5. Termination checking: Check whether the termination condition is satisfied. If so, output the near best solution and terminate the program; otherwise, go back to Step 2 and repeat the process.

To conduct the foreign exchange rate forecasting model with IABC, a fitness function for training the model is designed in Equation (12):

$$\min f(W) = \sum_{j=1}^{D} \left| \left(\sum_{m=1}^{M} w_m \cdot v_{d,m} \right) - R_{actual,d} \right| \tag{12}$$

where $f(\cdot)$ denotes the fitness function, D is the total number of the reference days in the historical data, M stands for the total number of factors referenced in our forecasting model, w_m and $v_{d,m}$ are the weighting and the value of the referenced factors, respectively, and $R_{actual,d}$ stands for the actual foreign exchange rate on the day d.

After the weight training, IABC model is able to produce the foreign exchange rate forecasting outcome by Equation (13):

$$R_{f,d} = \sum_{m=1}^{M} w_m \cdot v_{d-1,m} \tag{13}$$

where $R_{f,d}$ denotes the forecasting outcome on day d.

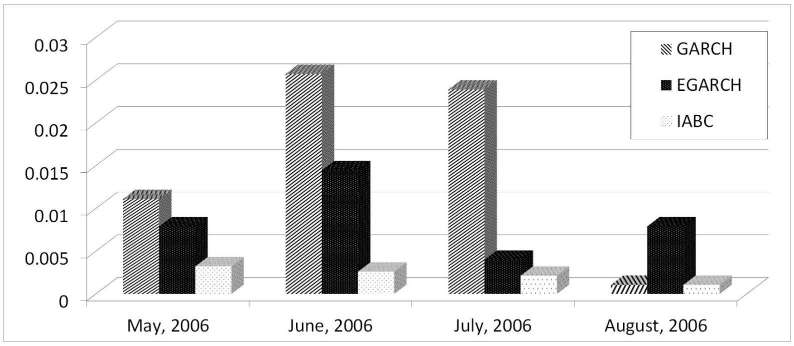
The MAPE values based on the forecasting outcomes produced by the GARCH$(1,1)$, the EGARCH, and the IABC models are calculated and are compared to find out which model is with the best capacity of resisting the impact caused by the FTA events.

3. **Experiments and Experimental Results.** The FTA events tested in this paper are the FTAs signed between Taiwan and Central American countries including Guatemala, Nicaragua, El Salvador, and Honduras. The interested period includes the pre-event period (70 days before the event) and the post-event period (70 days after the event). The foreign exchange rate forecasting models are built through the uses of GARCH, EGARCH, and the IABC methods, respectively. Finally, the MAPE values of the forecasting outcome are calculated in order to find out which foreign exchange rate forecasting model presents the best resistance to the FTAs' impact. Figure 1 presents the predictive ability of the forecasting models generated by GARCH, EGARCH, and IABC by MAPE. The vertical axis represents percentage changes in errors, and the horizontal axis denotes monthly averages.

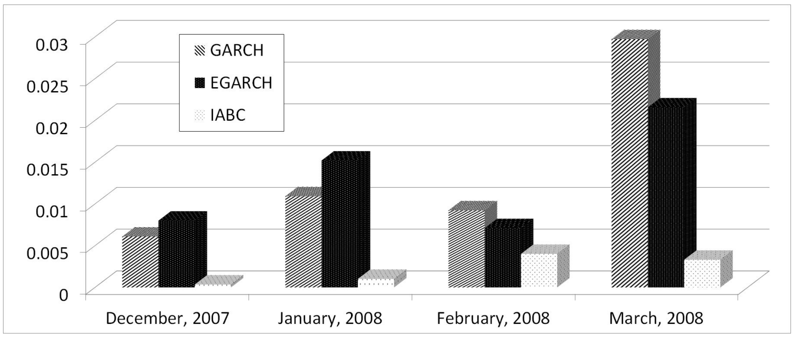
Since MAPE presents the differences (or can be said as the errors) between two signals, the smaller the MAPE value is, the similar the signals are. In the ideal case, the MAPE value should be equivalent to zero. A standard MAPE range is defined that its value is lower than 10% [9]. In Figure 1(a), both the GARCH and EGARCH models obviously fall within the standard range, suggesting that both two models have a pretty good predictive ability. The IABC model has the smallest MAPE values in all time intervals. This phenomenon implies that IABC model has an even better predictive ability than the time series models. The EGARCH model has smaller MAPE values than the GARCH model in May, June, and July, indicating that in these three months, the EGARCH model has better forecasting performance than the GARCH model. On the contrary, the GARCH model has a smaller MAPE value than the EGARCH model in August, suggesting that in this month, the GARCH model has better forecasting performance than the EGARCH model.

In Figure 1(b), both the GARCH and EGARCH models are within the standard range, indicating that both two models have a pretty good predictive ability. The IABC model has the smallest MAPE values in all time intervals. Such a phenomenon suggests that the IABC model has an even better predictive ability than the time series models. The GARCH model has smaller MAPE values than the EGARCH model in December and January, indicating that in these two months, the GARCH model has better forecasting performance than the EGARCH model. On the contrary, the EGARCH model has smaller MAPE values than the GARCH model in February and March, suggesting that in these two months, the EGARCH model has better forecasting performance than the GARCH model.

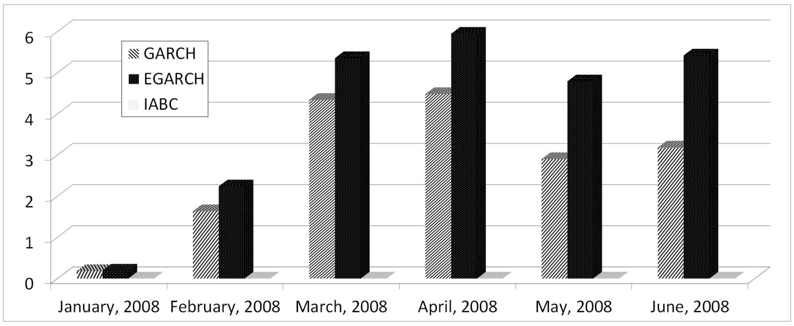
In Figure 1(c), excluding in January, both the GARCH and EGARCH models are 10% out of the standard range. This phenomenon indicates that the forecasting accuracy of both two models is lower than that of their counterparts in the other events. The IABC model not only falls within the standard range but also has smaller MAPE values in



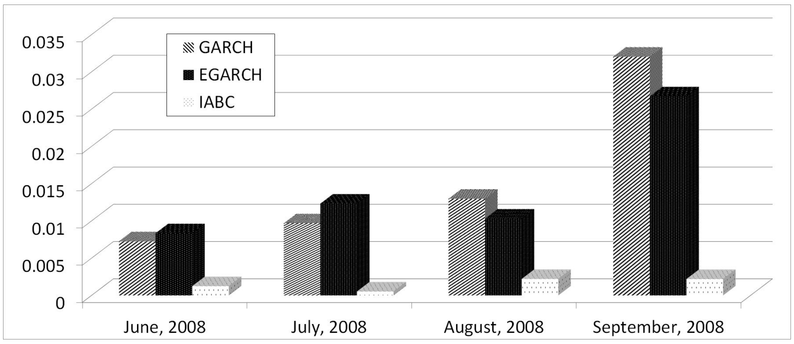
(a)



(b)



(c)



(d)

FIGURE 1. The MAPE values of GARCH, EGARCH, and IABC models in: (a) TW-GT FTA event, (b) TW-NI FTA event, (c) TW-SV FTA event, and (d) TW-HN FTA event

all time intervals, suggesting that it has a better predictive ability than the time series models.

In Figure 1(d), both the GARCH and EGARCH models are within the standard range, indicating that both two models have a pretty good predictive ability. The IABC model has smaller MAPE values in all time intervals. This phenomenon suggests that it has an even better predictive ability than the time series models. The GARCH model has smaller MAPE values than the EGARCH model in June and July, indicating that in these two months, the GARCH model has better forecasting performance than the EGARCH model. On the contrary, the EGARCH model has smaller MAPE values in August and September, suggesting that in these two months, the EGARCH model has better forecasting performance than the GARCH model.

Figure 2 shows the accumulated MAPE values obtained by different models over all FTA events between Taiwan and the Central American countries.

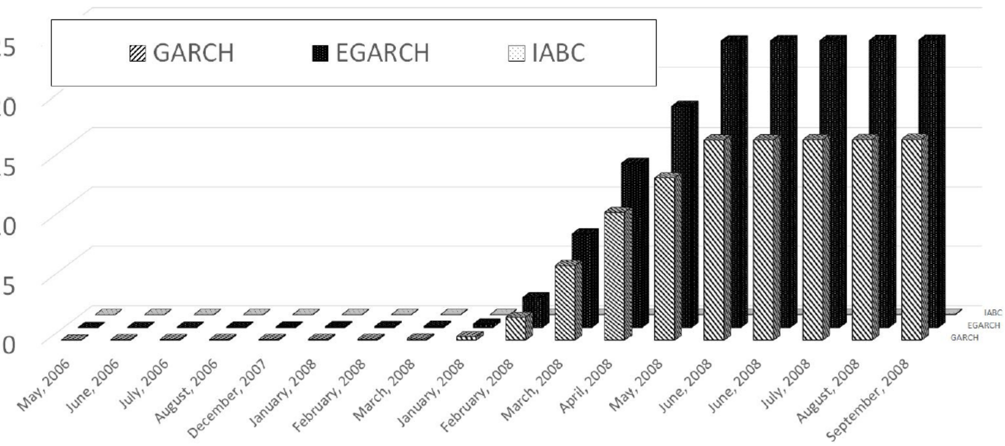


Figure 2. Accumulated MAPE values of GARCH, EGARCH, and IABC model

It is obvious that all forecasting models perform well in the first two events. The accumulated MAPE values produced by all models are relatively small. Nevertheless, the accumulated MAPE values produced by the time-series models are enlarged significantly in the third event. The differences between the conventional time-series models and the computational intelligence model are revealed.

The statistical analysis of the experimental results is given in Table 1.

Table 1. The statistical analysis of the MAPE values obtained by different models

	Mean	Maximum	Minimum	STD
GARCH	9.395×10^{-1}	4.484×10^{0}	1.072×10^{-3}	1.615×10^{0}
EGARCH	1.339×10^{0}	5.950×10^{0}	3.994×10^{-3}	2.291×10^{0}
IABC	1.901×10^{-3}	4.017×10^{-3}	3.462×10^{-4}	9.904×10^{-4}

According to Table 1, we find that IABC model and EGARCH model present the smallest and the largest average MAPE values, respectively. The time-series models present similar characteristics because their maximum and minimum MAPE values are all about 1000 times different; on the other hand, the IABC model shows relatively small difference between the maximum and the minimum MAPE values. Moreover, the STD of the IABC model is 9.904×10^{-4}, but the STD of the time-series models are both larger than 1. Thus, we can conclude that the prediction ability of the IABC model is much more stable than the conventional time-series models.

4. **Conclusion and Future Work.** In this paper, the GARCH, the EGARCH, and the IABC are utilized to construct the foreign exchange rate forecasting models. The MAPE value is used as the criterion for evaluating the forecasting accuracy of the models mentioned above. The interested analytic events include 4 FTAs signed between Taiwan and the Central American countries. The experimental results reveal that although the

forecasting accuracy of the time-series models is relatively low in the third event, the signing of the FTA between Taiwan and El Salvador, all exchange rate models show a good predictive ability. Even so, the IABC model has the best predictive ability among all the models. In the future work, we plan to use a wider diversity of exchange rate forecasting models to study which model has the best predictive ability.

Acknowledgment. This work is partially supported by the Key Project of Fujian Education Department Funds (JA15323), Fujian Provincial Science and Technology Project (2014J01218), Fujian Provincial Science and Technology Key Project (2013H0002), and the Key Project of Fujian Education Department Funds (JA13211). The authors also gratefully acknowledge the helpful comments and suggestions from the reviewers, which have improved the presentation.

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