Comparative Analysis of forecasting exchange rate using ARCH and GARCH Models: A Case Study of China

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Abstract. This paper is focused on two different models, which are the Auto-Regressive Conditional Heteroskedasticity Model (ARCH) and the Generalized Autoregressive Conditional Heteroskedasticity model (GARCH). Furthermore, first, this work will explain what the ARCH Model is and what the GARCH Model is. Secondly, comparing the ARCH Model to the GARCH Model to show which key benefits can help people forecast the exchange rate. After that based on some cases in China to illustrate how these two models work. Then proving the GARCH Model is more useful than the ARCH model when the GARCH Model connects with another model.

Keywords: GARCH Model, ARCH Model, China, exchange rate.

1 Introduction

In the financial market, one of the significant keys to connecting international economic and trade activities is the exchange rate [1]. The exchange rate is the price of one country's currency against another country's currency and also has a great impact on foreign trade as well as investment. In the last decade, exchange rate volatility has increased and caused a loss of economic welfare [2]. For example, Kwofie and Ansah described how the exchange rate can influence stock returns and the macroeconomy. It can also affect the analysis of investments, risk management, and derivatives pricing [3].

In order to avoid exchange rates having a huge impact on the financial market, countries have their own ways to solve this problem. There are some special elements and situations that will lead to a more volatile exchange rate. For instance, due to the pandemic, the exchange rate went from 1 pound to 8.2 RMB and then from 1 pound to 7.6 RMB. However, the recent price of 1 pound is 9.14 RMB. It may put a lot of stress on certain fields of industry. Moreover, in another case, COVID-19 has had a huge impact on the exchange rate of the stock market in several countries, such as Pakistan, China, and America. Consequently, people try to forecast the trend of exchange rates, which can help reduce risks and uncertainty [4].

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Therefore, numerous professional analysts have used variable quantitative analytics skills and tools and set up some models to forecast for various countries. There are three famous models. Firstly, the autoregressive conditional heteroskedasticity (ARCH) model The ARCH process, created by Engle in 1982, allows the fluctuation of a variable's value to change over time as a function of past errors while keeping the overall average fluctuation constant [5]. Secondly, the Generalized ARCH (GARCH) model is the extension of ARCH processes to GARCH processes and is very similar to the extension of standard time series AR processes to general ARMA processes, which allows for more flexible hysteresis structures and more general processes [5].

In one case, the data was used to test and prove that for within-sample modeling, the GARCH model can be the best [6]. Mohsin described using GARCH models to test exchange rate fluctuations against the US dollar to confirm that the GARCH model is helpful in Pakistan [7]. In this article, it is stated that Pakistan is a developing country, which is the same as China. Furthermore, comparing the GARCH model to the other two models to forecast the exchange rate in China is a keen and interesting research topic.

In this work, Firstly, it will describe the definition of the Autoregressive Conditional Heteroskedasticity (ARCH) model. Moreover, the explanation of the mechanism of the ARCH model in forecasting the exchange rate for China Furthermore, the interpretation of the advantages and drawbacks of the ARCH model Secondly, the same steps in the generalized autoregressive conditional heteroskedasticity model and the longer short-term model. Finally, analyze and compare the three models to discuss which model has a higher percentage of predicting the exchange rate in China.

2 Autoregressive Conditional Heteroskedasticity Model

2.1 Definition

The Auto-Regressive Conditional Heteroskedasticity (ARCH) model was designed by Robert Engle in 1982 to address econometricians' concerns about the degree of inaccuracy of analytical models that would create volatility problems [8]. The ARCH model is a statistical model that has two fundamental properties derived from its name: autoregressiveness and heteroskedasticity. ‘Autoregressive’ denotes the model's utilization of past volatility data to forecast future volatility patterns [9]; this indicates that the model is able to predict economic variables as well as the size of the error in those predictions [10]. Meanwhile, the term ‘heteroskedasticity’ refers to the acknowledgment that the variance exhibited by the time series is non-constant [9].

2.2 Mechanism

Conditional variances and covariances usually depend very much on the past state. In general, time series are defined by random recursive equations that set the relationship between past and future observations [11]. Understanding the nature of this temporal dependence is critical to many issues in finance [12]. Because the ARCH model has considerable flexibility and completeness in mathematics and statistics, it is used in the modelling and prediction of continuous-time randomized experiments in practice [11]. ARCH can be used for time-varying confidence intervals for the prediction of exchange rate change points, so it is naturally suitable for modelling time-varying risk premiums [12].

In this section, the mechanism of the univariate ARCH model will be explained.

$$\mathrm{Var}(y_t|y_{t-1}) = \sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 \tag{1)[13}$$

Equation 1 is a simplified equation calculating conditional variance, where represents the conditional variance of y_t given y_{t-1} and σ_t^2 represents the conditional variance. In addition, α_0 and α_1 are coefficients that suggest how past information can influence conditional variance. y_{t-1} represents the squared value of the variable at t-1.

$$y_t = \sigma_t \epsilon_t \quad (2)[13]$$

$$\sigma_t = \sqrt{\alpha_0 + \alpha_1 y_{t-1}^2} \quad (3)[13]$$

$$\epsilon_t \backsim (\mu = 0, \sigma^2 = 1) \quad (4)[13]$$

In Equation 2, σ_t is the conditional standard deviation of the variable at t. yt is the observed value of the variable at time t. ϵ_t is the error at time t. Equation 3 calculates the conditional standard deviation which is the root of Equation 1 that measures conditional variance. In part 4, the error term (ϵ_t) is assumed to follow a standard normal distribution, this means the mean (μ) is 0 and the variance (σ^2) is 1.

2.3 Case of Application

In Malik's paper published in 2011, he applied the univariate ARCH model in measuring the exchange rate in Pakistan. To conduct an estimation of this model, solely the exchange rate data is needed. Exchange rate data is collected from International Financial Statistics, the US Bureau of Labor Statistics, and the State Bank of Pakistan. In the process of estimation, data consistency is firstly verified through a graph with abnormal points identified and represented using dummy variables. Next, stationarity and unit root are checked using the Augmented Dickey-Fuller test. Then first difference (D(s)) is used to ensure stationarity in the data. After the model is estimated, predictions will be produced and evaluated by comparing them with the actual value to give performance measures [14].

In Figure 1 where non-stationary data is used in the model, it can be observed that the model mostly matches with the actual data. However, there is a certain delay though the model captured every turning point [14].

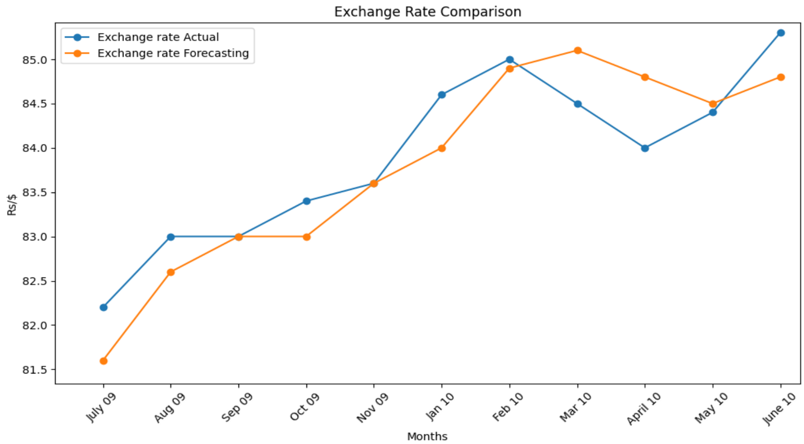

Fig. 1. ARCH Model with non-stationary data [14]

3 Generalized Autoregressive Conditional Heteroskedasticity model

3.1 Definition

The ARCH model is too simple to predict the exchange rate more accurately, and the extension of the ARCH process to the GARCH process is very similar to the extension of the standard time series AR process to the general ARMA process. In addition, GARCH (generalized autoregressive conditional heteroscedasticity) allows a more flexible lag structure and a more general process [15,16]. It was developed by Bollerslev in 1986 [17,18].

Generalized Auto-Regressive Conditional Heteroskedasticity, GARCH is an econometrics term proposed in 1982 by Robert F. Engle, winner of the 2003 Nobel Prize in Economics [19]. The GARCH model is a method to estimate the volatility of financial markets [19]. As a statistical model, the GARCH model can be used to analyze different types of financial data, such as macroeconomic data [19]. In addition, the model is commonly used by financial institutions to estimate the return volatility of stocks, bonds, and market indexes. They use this information to determine prices and identify assets that may offer higher returns to help them with asset management and good investment decisions. The GARCH model also comes in several forms. Financial professionals generally prefer the GARCH process because it provides a more realistic context than other models when trying to predict the prices and interest rates of financial instruments.

Because GARCH will cause more volatility, some companies with natural leverage will have more negative impact as a result, and the Ordinary Least Squares (OLS) model can minimize the deviation between data points and regression line to fit these points, so we choose to combine the two models [19,20].

3.2 Mechanism

This paper cites the OLS model and GARCH model of an article in which the OLS model and GARCH model study the unpredictability of swap size and its effect on securities trading returns. It uses nine formulas:

$$Pr(y_{t+m}|\psi_t = \Pr(y_{t+m}|\Omega_t) \quad (5)[20]$$

The dynamic relationship between stock file cost and transaction size is determined by Granger's Causality officially. If x_t Grangerl leads to some other time arrangement y_t if the arrangement y_t useful past estimates to make predictions (x_t, y_t) than using real estimates y_t. Therefore, x_t ignores all m > 0 gives the probable transfer y_{t+m} give (y_t, y_{t-1},...). The restrictive likelihood cycle given equivalent to y_{t+m}give both (y_t, y_{t-1}, ...) and (x_t, x_{t-1}, ...). In other words, x_t cannot produce a Granger-cause y_t. $Pr(.)$ indicates restrictive likelihood, ψ_t is the dataset for time t is in the last several years'estimates of y_t and Ω_t is a dataset containing estimates from x_t and y_t to the time points t.

$$y_t = \alpha_0 + \Sigma_{k=1}^{p}\alpha_k y_{t-k} + \Sigma_{k=1}^{q}\beta_k x_{t-k} + u_t \quad (6)[20]$$

$$x_t = \Phi_0 + \Sigma_{k=1}^{p}\Phi_k y_{t-k} + \Sigma_{k=1}^{p}\Phi_k x_{t-k} + v_t \quad (7)[20]$$

In this equation p is a suitably selected positive figure; when k=0 in α_k and β_k, p is constant; besides, u_t and v_t regular influence terms have zero methods and limited changes. The dead speculation that x_t doesn't Granger-cause y_t is dismissed if the k of β_k is positive in condition (6) are in common essence not quite the same as zero utilizing a standard joint test. Also, y_t Granger-causes x_t if the Φ_k's, k is positive co-efficients in condition (7) are together not the same as zero. A bi-directional causality (or input) connection exists if the k of both β_k and Φ_k, k>0 is together not quite the same as zero. When the basic I(5) measures are cooperative, the resulting details must be changed by embedding a slack estimate like error-correction term of the joint as an additional information variable. Conditions (6) and (7) should therefore be replaced as:

$$\Delta y_t = \alpha_0 + \Sigma_{k=1}^{p}\alpha_k \Delta y_{t-k} + \Sigma_{k=1}^{p}\beta_k \Delta x_{t-k} + \delta ECT_{t-1} + u_t \quad (8)[20]$$

$$\Delta x_t = \Phi_0 + \Sigma_{k=1}^{p}\Phi_k \Delta y_{t-k} + \Sigma_{k=1}^{p}\Phi_k \Delta x_{t-k} + \eta ECT_{t-1} + v_t \quad (9)[20]$$

In this equation Δ is the distinction administrator with ECT_{t-1} represents the error adjustment term derived from the long-ago I(5) metric cointegration join between x_t and y_t .

$$x_t = a + \beta_t + \rho x_{t-1} + \Sigma_{k=1}^{p}\delta_k \Delta x_{t-k} + e_t \quad (10)[20]$$

In equation (10), (I) when β equal zero and |ρ| large than one, the arrangement x_t is fixed; (ii) β equal zero and ρ equal one then the arrangement is an I (5) measure; (iii) β ≠ 0 and |ρ| larger than one then this arrangement is pattern-based.

$$y_t = \beta_0 + \beta_1 USD + \beta_2 CNY + \beta_3 INR + u_t \quad (11)[20]$$

β_1~ β_3 are the boundary coefficients, and u_t is the polyphonic term. Then, use autoregressive conditional heteroscedasticity (ARCH) to test the rationality of the evaluated OLS model. At this point, the GARCH loop is used to evaluate the boundary determined by the GARCH (1,1) measure, as shown in the equation below.

$$r_t = \gamma_0 + \gamma_1 USD + \gamma_2 CNY + \gamma_3 INR + u_t \quad (12)[20]$$

$$\sigma_t^2 = \omega_0 + \alpha_1 \varepsilon_t^2 + \alpha_2 \sigma_t^2 \quad (13)[20]$$

Condition (12) is the average condition, and condition (13) is the change condition where the boundary characteristics are the same as in the past model;γ_0 is the capture; γ_1 to γ_3 are the boundary evaluation coefficient under average condition. σ_t^2 is the contingent difference where ω_0 is the average; $\alpha_1 \varepsilon_t^2$ is an instability report for a past period of time estimated as relaxation of the square from the mean, characterized by the ARCH term; $\alpha_2 \sigma_t^2$ is the scale change of the last time frame, which is characterized by the GARCH expression [20].

4 Conclusion

Less evidence exists to support the ARCH model's advantages. However, practically all asset price series were proposed by Bollerslev and French, Schwert, and Stambaugh based on the paper. It exhibits volatility clustering and is amenable to ARCH/GARCH modeling [15]. It is clear that the arch model has many different uses. The ARCH model's drawback is that it takes a long time to acquire data using it. It can be challenging to gauge how much hysteresis is included in the volatility, which results in a non-reduced model in which the non-negative requirements may not hold. In general, GARCH models are substantially easier. This is due to the fact that the GARCH model comprises larger ARCH models that contain a substantial amount of trailing information [16].

In addition, the GARCH model also has some shortcomings. The main disadvantage of the GARCH model is that it is not suitable for asymmetric effects of different instabilities. In asymmetric models, upward and downward trends in earnings are interpreted as bad news and good news, respectively. If a decline in returns is accompanied by an increase in instability, and the increased instability is greater than the instability caused by the increase in returns, then we say that it has a leverage effect. Since all terms in the GARCH model are squared, there will always be asymmetric answers in positive and negative periods. However, because of the natural leverage of most firms, weakness shocks are more disruptive than strength shocks because they produce greater volatility [21]. Of course, GARCH has its advantages, and the advantage of GARCH is that it has a more realistic context than other models when trying to predict the economy. This is why financial professionals prefer to use the GARCH process [22].

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