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The Analysis of ICBC Stock Based on ARMA-GARCH Model

Si-qin LIU[1] Hong-guo SUN[1*]

[1] （Department of Mathematics and Finance
Hunan University of Humanities Science and Technology, Loudi , China)

Abstract: This paper uses the time series analysis method and establishes the ARMA-GARCH model to analyze and predict the ICBC stock price, roughly determine the rationality of ICBC investment, and put forward the corresponding investment advice.

Keywords: ICBC；ARMA；GARCH；Volatility

I. Introduction

ICBC is one of the four largest state-owned banks in China, According to The Banker's 2017 Global Bank 1000 Ranking,ICBC of China won the first in the world.Research on ICBC of China's stock will help ICBC to better understand its own development and help investors make the right investment decisions.

II. Literature Review

In 1970s, American statisticians Box and Jenkins proposed an autoregressive moving average model; In 1992, Nelson proposed an exponential GARCH model to solve the problem of heteroskedasticity. Chinese scholars extensive use of these models to China's stock issue has been studied. ZhangZhi Qin and Jiang Wei(2012)used the GARCH model to analyze China’s commercial bank stocks and compared them with the Shanghai Stock Exchange’s final index, It is concluded that China’s commercial bank stocks are characterized by high volatility; Xu Hao(2013) used ICBC as an example to analyze the volatility of the same stock price listed in the two cities. Yang Qi(2016)used time series model to analyze and predict the price of a certain stock, It is proved that establishing the ARMA-GARCH model can effectively predict the short-term stock price, which is of positive significance for guiding investment. Fan Chuanzhi(2012) selected the commercial bank to start the process, using time series methods to perform basic descriptive statistics on stock price fluctuations and yields of 14 commercial banks and analyze the characteristics of their stock fluctuations. Meng Kun and Li Li(2016) forecasts the future trend of the stock price by studying the short-term movement of the daily closing price of the Shanghai Composite Index and formulating a corresponding stock investment strategy;Li Dan(2014) and others modeled the Shanghai-Shenzhen 300 index and obtained that the volatility of the stock index futures market has the characteristics of ARCH effect and long memory. The behavior of market traders has the possibility of increasing market risk; Wu Yu Xia and Wen Xin (2016)found the patterns and trends in the stock price changes by establishing a stock ARMA model, emphasizing that short-term forecasting is effective and can provide reference for investors' investment; Li Xiu Qin and Liang Man Fa(2013)verified that the test results of the ARMA model are significant and the prediction accuracy is ideal. Therefore, the time series model is feasible for predicting the stock market and can provide suggestions for analysis of securities investment; According to Chen Qiaoyu(2012), the daily fluctuation of ICBC's stock daily return rate is low, and its daily rate of return is not closely related to its fluctuations; Yang Hao(2017)has a fluctuating cluster effect, heteroskedasticity, and "leverage effect" by establishing a daily return rate of stocks.

III. Model Introduction

ARMA, the Auto Regressive Moving Average process. ARMA (p,q) process can be written as follows,

$$y_t = c + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$$

Among them, ε_t is defined as a white noise process with variance, c is a constant term, α_i and θ_j are auto-regressive coefficients and moving average coefficients, respectively.

Lag operator form:

$$(1 - \alpha_1 L - \alpha_2 L^2 - \cdots - \alpha_p L^p) y_t = c + (1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q)\varepsilon_t$$

GARCH, the conditional mean regression model. The basic expression of GARCH(1,1) is:

$$\begin{cases} y_t = x_t'\emptyset + u_t, \quad u_t \sim (0, \sigma_t^2) \\ \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{cases}$$

Among them, y_t and x_t represent the dependent variable and the independent variable respectively, and u_t represents the random disturbance term without sequence correlation.

Modeling steps:

1) Test the stationarity of the original data. If the data is not stationary, the data can be differentiated to obtain a stationarity sequence.
2) Determine the order of the model p and q according to the AIC test by calculating statistics that describe the characteristics of the sequence, such as autocorrelation coefficients and partial autocorrelation data.
3) Estimate the model parameters by using least square method and verify the rationality of the model.
4) Determine the match between the model and observed data by determining whether the residual is white noise data.
5) If there is heteroscedasticity in the residual sequence, perform ARCH test and establish a GARCH model.
6) Future data prediction using the finally established model.

IV. Empirical Analysis

4.1 Selection of data

Download the daily closing price data of ICBC (601398) from 2015/6/15 to 2018/6/15 from Great Wisdom Software, totaling 490 samples.

4.2 The establishment of a model

1) Check the smoothness of the original data sequence

Figure 1: Diagram of raw data

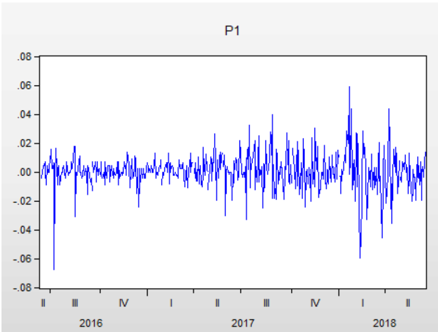


Figure 2: Diagram after raw data processing

From Figure 1, we can see that the stock price of ICBC's original stock is not stable during this period.The ADF unit root test its smoothness as shown in Table3 .The P value is 0.5860, which is much greater than the significance level α. The original hypothesis is accepted and the original data is considered to have a unit root. The logarithmic difference processing of the original data is needed to eliminate the unit roots, and then the ADF test is performed. It is found that the data after one difference is already stable (Table 2), basically fluctuate around a certain number, and the model can be established.

Table 1Original data unit root test results

Null Hypothesis: P has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.394030	0.5860
Test critical values:	1% level	-3.443524	
	5% level	-2.867243	
	10% level	-2.569870	

Table 2Unit Root Test Results after Data Processing

Null Hypothesis: P1 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.90133	0.0000
Test critical values:	1% level	-3.443524	
	5% level	-2.867243	
	10% level	-2.569870	

From the basic statistics of stock returns (Figure 3), we can see that the average is greater than 0, indicating that the overall rate of return is positive.In the sample interval, it can be seen that the kurtosis is 8.260944, which is greater than 3, indicating that the yield is a spike. In addition, the skewness is -0.417745, which is a negative value, that is, the yield is left-biased; JB is 578.1524, and the P value is 0. It can be considered that under the 1% significance level, the ICBC stock yield does not obey the normal distribution.

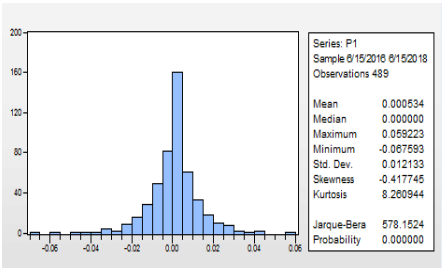
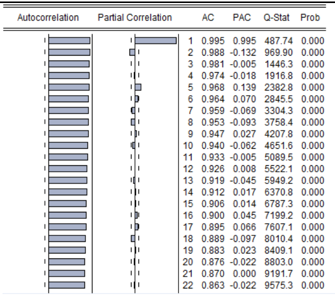


Figure 3： basic statistics of stock returns

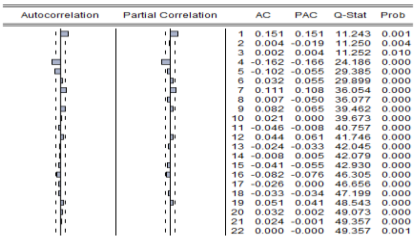
2) The choice of model

Autocorrelation coefficient and partial autocorrelation coefficient as follows:



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.995	0.995	487.74	0.000
		2	0.988	-0.132	969.90	0.000
		3	0.981	-0.005	1446.3	0.000
		4	0.974	-0.018	1916.8	0.000
		5	0.968	0.139	2382.8	0.000
		6	0.964	0.070	2845.5	0.000
		7	0.959	-0.069	3304.3	0.000
		8	0.953	-0.093	3758.4	0.000
		9	0.947	0.027	4207.8	0.000
		10	0.940	-0.062	4651.6	0.000
		11	0.933	-0.005	5089.5	0.000
		12	0.926	0.008	5522.1	0.000
		13	0.919	-0.045	5949.2	0.000
		14	0.912	0.017	6370.8	0.000
		15	0.906	0.014	6787.3	0.000
		16	0.900	0.045	7199.2	0.000
		17	0.895	0.066	7607.1	0.000
		18	0.889	-0.097	8010.4	0.000
		19	0.883	0.023	8409.1	0.000
		20	0.876	-0.022	8803.0	0.000
		21	0.870	0.000	9191.7	0.000
		22	0.863	-0.022	9575.3	0.000

Figure 4:Original data autocorrelation test



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.151	0.151	11.243	0.001
		2	0.004	-0.019	11.250	0.004
		3	0.002	0.004	11.252	0.010
		4	-0.162	-0.166	24.186	0.000
		5	-0.102	-0.055	29.385	0.000
		6	0.032	0.055	29.899	0.000
		7	0.111	0.108	36.054	0.000
		8	0.007	-0.050	36.077	0.000
		9	0.082	0.065	39.462	0.000
		10	0.021	0.000	39.673	0.000
		11	-0.046	-0.008	40.757	0.000
		12	0.044	0.061	41.746	0.000
		13	-0.024	-0.033	42.045	0.000
		14	-0.008	0.005	42.079	0.000
		15	-0.041	-0.055	42.930	0.000
		16	-0.082	-0.076	46.305	0.000
		17	-0.026	0.000	46.656	0.000
		18	-0.033	-0.034	47.199	0.000
		19	0.051	0.041	48.543	0.000
		20	0.032	0.002	49.073	0.000
		21	0.024	-0.001	49.357	0.000
		22	0.000	-0.000	49.357	0.001

Figure 5: log-differential data

Figure 4 shows the autocorrelation and partial autocorrelation plots of the original data. It can be seen that the autocorrelation is trailing, while the partial autocorrelation is the first-order truncation; Figure 5 is the autocorrelation and partial autocorrelation plot of the log-differential data. It can be seen that the autocorrelation coefficients and partial autocorrelation coefficients are significant at the 1st and 4th order, and there is no obvious truncation in the autocorrelation map and the partial autocorrelation map. The model cannot be defined as only the AR model or the MA model, so we are considering establishing an ARMA model.

3) modeling

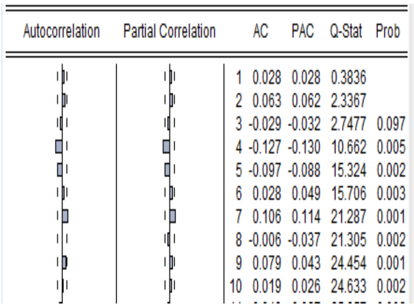
Table 3Data of Model Selection

	ARMA (1，1)	ARMA (1，2)	ARMA (2，1)
α_1	-0.548490	-0.966971	-0.82538
α_2			0.135934
θ_1	0.682662	1.133583	0.993191
θ_2		0.139689	
AIC	-6.001184	-6.00733	-6.00553

From the results of the model test in Table 3, the t-statistic significance and the AIC criterion are combined to see: AR(1), AR(2), and MA(1) for the ARMA(2,1) model. The coefficients are all significant and the AIC value is relatively small. Therefore, we can use the ARMA (2,1) Model City Industrial and Commercial Bank's daily closing price sequence modeling.

4) Model residual test

The residual sequence of the model should be a white noise sequence, so after the parameter estimation, the white noise test of the residual sequence of the model needs to be performed (see if the sample autocorrelation coefficients of the residual sequence all fall within the random interval). The residual sequence is not a white noise sequence, so there is still useful information in the residual sequence that has not been extracted and further improvement of the model is needed. Residual test results are shown in Figure 8.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.028	0.028	0.3836	
		2	0.063	0.062	2.3367	
		3	-0.029	-0.032	2.7477	0.097
		4	-0.127	-0.130	10.662	0.005
		5	-0.097	-0.088	15.324	0.002
		6	0.028	0.049	15.706	0.003
		7	0.106	0.114	21.287	0.001
		8	-0.006	-0.037	21.305	0.002
		9	0.079	0.043	24.454	0.001
		10	0.019	0.026	24.633	0.002

Figure 6: Autocorrelation Test

It can be seen from Figure 6 that the 4th and 7th order autocorrelation coefficients of the residual sequence samples do not fall within the random interval, and the residual sequence is not a white noise sequence. Considering that the distribution characteristics of the series of returns have strong volatility of residuals, and the residuals have heteroscedasticity, we need to use the GARCH model to analyze the fluctuation of stock returns.

Table4 GARCH modeltest results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.758480	0.111624	6.794939	0.0000
AR(2)	-0.137349	0.065566	-2.094813	0.0362
MA(1)	-0.742728	0.105410	-7.046111	0.0000
Variance Equation				
C	9.86E-06	2.74E-06	3.598823	0.0003
RESID(-1)^2	0.244118	0.038663	6.313994	0.0000
GARCH(-1)	0.724814	0.038663	18.74682	0.0000

The general GARCH model with GARCH(1,1) can explain most of the models, so we built the GARCH(1,1) model as shown in Table 4. From the figure, we can see that the correlation coefficient of the mean equation is significant at the level of 0.1 significance, and the GARCH equation fitting effect is also good, so we can use ARMA-GARCH model to fit the ICBC stock price.

Among them, $\alpha_1 + \beta_1 = 0.97 < 1$. It can be seen that the time series of ICBC's stock returns satisfies the stable condition. We can conclude that the impact of external shocks on ICBC’s stock price fluctuations is limited. The large value of β_1 indicates that ICBC has a long memory of external shocks, and the impact of external shocks on it is a slow process.

V. Conclusion

By establishing an ARMA-GARCH model, we can draw the following conclusions:

Firstly, ICBC's stock daily return price data is non-stationary;

Secondly, The kurtosis of the time-series data after the difference is greater than 3 in the normal distribution, which indicates that the daily return rate of ICBC shares has the characteristics of sharp peaks and thick tails;

Thirdly, ICBC shares have high volatility, high risk, and long memory of external shocks;

Finaly, ICBC's stock returns fluctuations have accumulation, that is, the historical rate of return will affect the current rate of return.

Investment advice: External information in the current period has a greater impact on ICBC's share price, and there is a continuous trend. Before investing, we should focus on more information so that we can make better decisions.

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