

Stock Price Short-term Forecasting Based On GARCH Model

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Keywords: Forecasting, Stock Price, GARCH.

Abstract. Using the stock price data to set up a sequence to explain the relationship of stock price data, the future stock price can be forecasted. This paper conducts the real modeling research on the shanghai composite index utilized the GARCH-class models. The results of this paper had indicated that stock price undulation in the Shanghai Stock market has the obvious GARCH effect. The condition variance sequence of returns rate is stationary, the GARCH model has the predictability. And GARCH (1, 1) model may well in the fitting and the forecast the shanghai stock price index. This simulation model may realize the short-term high accuracy to forecast well that. The forecast value of shanghai index was closer to actual value, indicating that the GARCH model in the paper was a certain accuracy. This paper was helpful to dodge the risk regarding, and develop the profit space for the investors.

1. Introduction

In the stock market, the researchers have tried to find an effective forecast method of stock index, to dodging the risks, seizing the initiative, making the investment profit maximization. So, the study of stock index fitting, simulation and forecasting is a great significance to the investors and the development of disciplines.

The practice was shown that the time series of returns in the capital market is non-normal and thick tail. And it has volatility aggregation and persistence. If the fluctuation of current period is great, the fluctuation of next period will be great too. And it will be strengthened or weakened as the current yield deviates from the mean. Conversely, if the fluctuation of the current period is small, the fluctuation of the next period will be small, unless the current rate of return is seriously deviated from the mean.

The GARCH model not only makes up for the shortage of computational efficiency and precision caused by too many model order under the finite sample, but also has a good handling capacity of thick tail. The GARCH model has become one of the most important tools to measure the volatility of the financial market. This paper collected the daily closing price data of the shanghai composite index during the period of 2017-01-03 to 2017-12-15 (233 working days) and uses GARCH model to solve the forecast problem of shanghai composite index.

2. The GARCH Model

2.1 The ARCH Model

Engle (1980) proposed a new stochastic process model, which is called the autoregressive conditional heteroskedasticity model (ARCH), which is used to capture the temporal and clustering characteristics of financial data. The formula of ARCH is as follow:

$$y_t = S(y_{t-1}, y_{t-2}, \dots) \varepsilon_t \equiv h_t^{1/2} \varepsilon_t \quad (1)$$

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2 + \alpha_2 y_{t-2}^2 + \dots + \alpha_p y_{t-p}^2 \quad (\alpha_0 > 0, \alpha_i \geq 0, i=1, 2, \dots, p) \quad (2)$$

The ε_t is the sequence of independent and identically distributed (i.i.d). $\varepsilon_t \sim N(0, 1)$.

It was called ARCH (p). The p is the order of model.

2.2 The GARCH Model

Bollerslev (1986) proposed an improved ARCH model, which is called the generalized autoregressive conditional heteroskedasticity model (GARCH). The GARCH model add the

autoregressive influence of heteroscedasticity itself into ARCH model. The GARCH model can describe most of the time series of financial returns. So it is widely used in the research of stock price's volatility. The formula of GARCH is as follow^[1,2]:

$$y_t = S(y_{t-1}, y_{t-2}, \dots) \varepsilon_t \equiv h_t^{1/2} \varepsilon_t \quad (3)$$

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2 + \alpha_2 y_{t-2}^2 + \dots + \alpha_p y_{t-p}^2 + \beta_1 h_{t-1} + \dots + \beta_q h_{t-q} \quad (\alpha_0 > 0, \alpha_i \geq 0, i=1, 2, \dots, p; \beta_j \geq 0, j=1, 2, \dots, q) \quad (4)$$

3. Data Description & Test

3.1 The Original Data

This paper collected the daily closing price data of the shanghai composite index during the period of 2017-01-03 to 2017-12-15 (233 working days) from the Chinese Finance & Business Magazine (http://app.finance.china.com.cn/stock/quote/history.php?code=sh000001&begin_day=2017-01-03&end_day=2017-12-15). The first order difference of the closing price logarithm was used to measure the stock returns. There is a large number of rounding errors in the calculation, so the multiplication of 100 can reduce the error.

$$R_t = (\ln(p_t) - \ln(p_{t-1})) * 100 \quad (5)$$

The R_t is the returns of t period. The p_t is the daily closing price of t period.



Fig.1 the graph of p_t

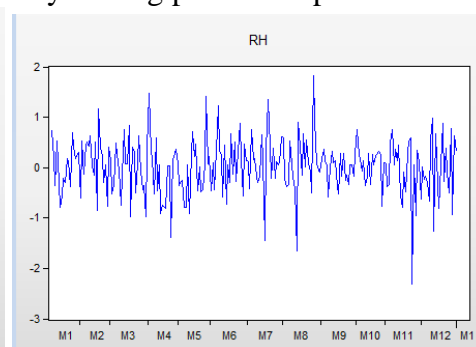


Fig.2 the graph of R_t

From Fig. 1, the p_t is a non-stationary time series. The sequence of R_t may be stationary (Fig. 2).

3.2 The Stationarity Test

The ADF test is a commonly used unit root test method to test stationarity. A sequence which has a unit root is non-stationary. For a stationary time series data, it is necessary to reject the null hypothesis at a given confidence level. The formulas of ADF are as follows:

$$\Delta u_t = c + \delta u_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta u_{t-i} + \varepsilon_t \quad (6)$$

The Formula (4) was be used to construct ADF test statistics.

$$ADF = \frac{\hat{\delta}}{S(\hat{\delta})} \quad (7)$$

The $S(\hat{\delta})$ is the sample standard deviation of δ .

Null Hypothesis: CLOSE has a unit root Exogenous: Constant Lag Length: 0 (Automatic - based on SIC, maxlag=14)			Null Hypothesis: RH has a unit root Exogenous: None Lag Length: 0 (Automatic - based on SIC, maxlag=14)		
	t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.590058	0.4861	Augmented Dickey-Fuller test statistic	-15.98725	0.0000
Test critical values: 1% level	-3.457286		Test critical values: 1% level	-2.574593	
5% level	-2.873289		5% level	-1.942147	
10% level	-2.573106		10% level	-1.615821	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		

Fig.3 the ADF test of p_t Fig.4 the ADF test of R_t

From Fig.3, it was shown that the p_t has a unit root. The original hypothesis ($\delta=0$) is accepted. And the p_t sequence is non-stationary. From Fig.4, the ADF statistic absolute value (15.98725) was more than 1% level critical absolute value (2.574593). And the p -value (0.0000) of the R_t sequence is less than 0.05. The sequence of R_t is stationary.

3.3 The Correlation Test

From Fig.5, the autocorrelation and partial autocorrelation coefficients fall into the double estimated standard deviation. And the corresponding p-values are more than confidence level 0.05. So there is no significant correlation in the significant level of the sequence at 5%.

Date: 01/21/18 Time: 21:07
Sample: 1/03/2017 1/09/2018
Included observations: 242

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.030	-0.030	0.2180	0.641
		2 -0.043	-0.044	0.6696	0.715
		3 -0.030	-0.033	0.8912	0.828
		4 -0.036	-0.040	1.2121	0.876
		5 -0.015	-0.020	1.2655	0.938
		6 0.102	0.097	3.8623	0.695
		7 -0.031	-0.029	4.1094	0.767
		8 0.031	0.036	4.3509	0.824
		9 0.088	0.094	6.3105	0.708
		10 -0.036	-0.023	6.6348	0.759
		11 0.011	0.021	6.6655	0.825
		12 -0.067	-0.073	7.8308	0.798

Fig.5 The autocorrelation diagram and partial autocorrelation diagram of R_t

There is no significant correlation in the sequence. the sequence of R_t is a white noise sequence. The following model was established[3].

$$R_t = \pi_t + \varepsilon_t \quad (8)$$

Subtracting the average value of R_t , the sequence of W_t established.

$$W_t = R_t - 0.021971 \quad (9)$$

0.021971 is the average value of R_t .

3.4 The Heteroscedasticity Test

From Fig.2, the distribution of R_t has the characteristics of clustering. The fluctuation of R_t was small in some time periods, and was very great in other time periods. It was shown that the sequence of R_t had obvious heteroscedasticity. So, the ARCH test needs to be used to test the heteroscedasticity of R_t . The sequence of Z_t ($Z_t = W_t^2$) was established.

Correlogram of ZH

Date: 01/21/18 Time: 20:53
Sample: 1/03/2017 1/09/2018
Included observations: 242

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.094	0.094	4.1885	0.041
		2 0.130	0.122	12.233	0.002
		3 0.107	0.086	17.678	0.001
		4 0.033	0.003	18.214	0.001
		5 0.086	0.062	21.759	0.001
		6 0.015	-0.009	21.868	0.001
		7 0.075	0.057	24.608	0.001
		8 0.027	0.003	24.950	0.002
		9 0.029	0.010	25.348	0.003
		10 0.059	0.038	27.042	0.003
		11 0.017	0.003	27.186	0.004
		12 0.036	0.013	27.818	0.006

Fig.6 The autocorrelation diagram and partial autocorrelation diagram of Z_t

Fig.6 was shown that the sequence has autocorrelation, which means that the original hypothesis is rejected. The sample has obvious heteroscedasticity. And there was ARCH effect.

4. Forecasting by GARCH Model

4.1 The Determination Of Order

It was necessary to determine the order, before the coefficient of GARCH was estimated. The AIC information criterion and the SC criterion were used to determine the order of model. The commonly used GARCH models include: GARCH(1,1), GARCH(1,2), GARCH(2,1). The results of each model were as follows:

Dependent Variable: WH
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/21/18 Time: 21:38
Sample (adjusted): 1042017 12/29/2017
Included observations: 242 after adjustments
Convergence achieved after 8 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*GARCH(-1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Variance Equation				
C	0.155635	0.059720	2.606078	0.0092
RESID(-1)^2	-0.055763	0.007748	-7.196749	0.0000
GARCH(-1)	0.516824	0.202958	2.542519	0.0110
R-squared	-0.000000	Mean dependent var	1.76E-07	
Adjusted R-squared	0.004132	S.D. dependent var	0.544277	
S.E. of regression	0.543151	Akaike info criterion	1.945072	
Sum squared resid	71.39320	Schwarz criterion	1.688323	
Log likelihood	-195.0537	Hannan-Quinn criter.	1.652495	
Durbin-Watson stat	2.051397			

Fig.7 GARCH(1,1)

Dependent Variable: WH
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/21/18 Time: 21:38
Sample (adjusted): 1042017 12/29/2017
Included observations: 242 after adjustments
Convergence achieved after 24 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*GARCH(-1) + C(4)*GARCH(-2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Variance Equation				
C	-0.001717	0.017829	-0.099317	0.9233
RESID(-1)^2	-0.055965	0.015664	-3.636659	0.0003
GARCH(-1)	0.295453	0.234890	0.913568	0.3609
GARCH(-2)	0.855226	0.229504	3.725417	0.0002
R-squared	-0.000000	Mean dependent var	1.76E-07	
Adjusted R-squared	0.004132	S.D. dependent var	0.544277	
S.E. of regression	0.543151	Akaike info criterion	1.586000	
Sum squared resid	71.39320	Schwarz criterion	1.653669	
Log likelihood	-189.1160	Hannan-Quinn criter.	1.619231	
Durbin-Watson stat	2.051397			

Fig.8 GARCH(1,2)

Dependent Variable: WH
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/21/18 Time: 21:38
Sample (adjusted): 1042017 12/29/2017
Included observations: 242 after adjustments
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*RESID(-2)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Variance Equation				
C	0.005819	0.008731	0.666548	0.5051
RESID(-1)^2	-0.021471	0.047429	-0.452691	0.6508
RESID(-2)^2	-0.025470	0.050538	-0.523752	0.6005
GARCH(-1)	1.025286	0.024043	42.54416	0.0000
R-squared	-0.000000	Mean dependent var	1.76E-07	
Adjusted R-squared	0.004132	S.D. dependent var	0.544277	
S.E. of regression	0.543151	Akaike info criterion	1.579998	
Sum squared resid	71.39320	Schwarz criterion	1.636577	
Log likelihood	-187.0479	Hannan-Quinn criter.	1.602139	
Durbin-Watson stat	2.051397			

Fig.9 GARCH(2,1)

GARCH (2,1) has the least value of AIC and the least value of SC. But some of GARCH(2,1) coefficients were not passed by T test. Same as GARCH(1,2) model. So GARCH(1,1) model was selected.

4.2 The Residual Test

The residual of GARCH (1, 1) model was tested by the ARCH effect test. The number 1, 4, 8, 12 were selected as the lag orders.

Heteroskedasticity Test: ARCH

F-statistic	1.809970	Prob. F(1,239)	0.1798
Obs*R-squared	1.811398	Prob. Chi-Square(1)	0.1783

Fig.10 Residual Test : lag 1

Heteroskedasticity Test: ARCH

F-statistic	1.735762	Prob. F(4,233)	0.1429
Obs*R-squared	6.886823	Prob. Chi-Square(4)	0.1420

Fig.11 Residual Test : lag 4

Heteroskedasticity Test: ARCH

F-statistic	1.015902	Prob. F(8,225)	0.4248
Obs*R-squared	8.157644	Prob. Chi-Square(8)	0.4182

Fig.12 Residual Test : lag 8

Heteroskedasticity Test: ARCH

F-statistic	1.033020	Prob. F(12,217)	0.4195
Obs*R-squared	12.42887	Prob. Chi-Square(12)	0.4119

Fig.13 Residual Test : lag 12

Under the test of various lag values, the F statistics are not significant. It was shown that the residual of GARCH (1, 1) model does not have the ARCH effect^[4,5].

4.3 The Forecasting

The static forecast values were as Table 1.

Table 1 The static forecasting

Date	Actual	Forecast	Difference	Absolute-dif	Abs-dif-percent
12/18/2017	3307.17	3266.858	40.312	40.312	1.218927
12/19/2017	3296.39	3268.638	27.752	27.752	0.841891
12/20/2017	3275.78	3297.264	-21.484	21.484	0.655844
12/21/2017	3306.12	3288.332	17.788	17.788	0.538032
12/22/2017	3280.46	3300.785	-20.325	20.325	0.619578
12/25/2017	3297.06	3297.784	-0.724	0.724	0.021959
12/26/2017	3300.06	3281.181	18.879	18.879	0.572081
12/27/2017	3287.61	3306.846	-19.236	19.236	0.585106
12/28/2017	3296.54	3276.5	20.04	20.04	0.60791
12/29/2017	3267.92	3297.114	-29.194	29.194	0.893351

The results showed that the static forecast has a 0.655% of the average error rate. Considering the limit of the shanghai composite index, the maximum of error rate is 10%. However, from the actual effect, it is not satisfying. It shows that the static of dynamic forecast is not good.

The static forecast values were as Table 2.

Table 2 The dynamic forecasting

Date	Actual	Forecast	Difference	Absolute-dif	Abs-dif-percent
12/18/2017	3307.17	3300.635	6.534512	6.534512	0.197586
12/19/2017	3296.39	3301.361	-4.97075	4.97075	0.150794
12/20/2017	3275.78	3276.086	-0.30617	0.306172	0.009347
12/21/2017	3306.12	3302.812	3.308247	3.308247	0.100064
12/22/2017	3280.46	3274.537	5.922507	5.922507	0.180539
12/25/2017	3297.06	3304.263	-7.20339	7.203393	0.218479
12/26/2017	3300.06	3304.989	-4.92945	4.929453	0.149375
12/27/2017	3287.61	3283.716	3.894328	3.894328	0.118455
12/28/2017	3296.54	3293.442	3.09795	3.09795	0.093976
12/29/2017	3267.92	3272.169	-4.24859	4.248588	0.130009

The results showed that the dynamic forecast has a 0.135% of the average error rate. These results were very satisfactory, considering.

5. Conclusion

The GARCH model to the volatility of returns sequence can be well fitted, and all the coefficients are significant. After GARCH regression, the heteroscedasticity of the residual can be eliminated. It was shown that the GARCH model is more effective in estimating and forecasting the volatility of stock returns in Chinese stock market.

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