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Kweichow Moutai Stock Daily Return Forecast Analysis

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ABSTRACT. *This paper obtained all the data of Kweichow Moutai stock from its listing date to July 2,2020 from Yahoo Finance, took the logarithm of the daily closing price and then differentiated to obtain the daily logarithm return rate to approximately replace the daily return rate, and modeled the time series of the daily logarithm return rate of Kweichow Moutai stock.The ARMA (0,(2)) sparse coefficient model of the daily log return rate is established by combining the ACF and BIC graphs of the daily log return rate. The residual square test of the model results shows that there is a strong autocorrelation. Therefore,based on this, the ARMA(0,2)+GARCH(1,1) model is improved according to the experience.By residuals and residuals squared tests of the model results, it is found that all of them are stationary white noise sequences. Therefore, it is believed that the improved model has a high degree of extraction of the original sequence information and a good fitting effect. Moreover, this model is used to predict the daily logarithm return rate in the next 6 days.*

KEYWORDS: *time series analysis, ARMA model, GARCH model, Kweichow Moutai Stock, Daily log rate of return*

1. Introduction

Many stock or fund earnings forecasts is done through the analysis of time series model, in order to verify this method, this article will choose guizhou maotai shares, with the logarithm yield of approximate alternative day yield of stocks, the first day logarithm yield of guizhou maotai shares of stationary time series modeling, and the result of the model of residual error and residual square test to see whether there is a strong correlation.If there is, GARCH model is added and ARMA+GARCH model is established until the residual and residual square of model results are stationary white noise sequences.At this time, the model has a high degree of extraction of the original sequence information and good fitting effect. Therefore, the model can be used to predict and analyze the daily logarithm return rate in the next few days.

2. Acquisition and analysis of Kweichow Moutai's stock and closing price data

2.1 Acquisition and analysis of Kweichow Moutai stock data

In order to understand the trend of Kweichow Moutai stock, we downloaded all the stock data of Kweichow Moutai from Yahoo Finance through R software until July 2, 2020, and obtained the stock data as shown in Figure 1:

Figure. 1 Stock data chart of Kweichow Moutai

As can be seen from the trend chart of the data, the stock of Kweichow Moutai shows a trend of steady growth on the whole, which has increased sharply since 2018, while there is no obvious cyclical trend. It can be seen that the overall development of Kweichow Moutai has made steady progress, and it has made rapid progress in recent years.

2.2 Acquisition and analysis of the closing price data of Kweichow Moutai Stock

We used the closing price function built in R software to obtain the daily closing price of Kweichow Moutai stock, and drew the time series diagram of the daily closing price, as follows:

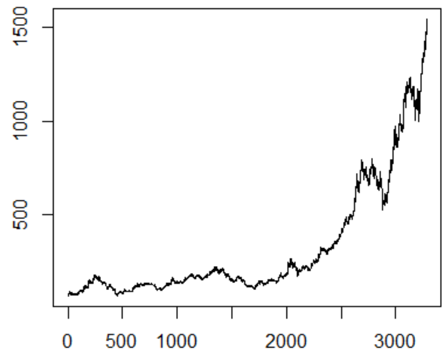

Figure 2 Sequence chart of daily closing price of Kweichow Moutai stock

It can be seen from the time sequence chart of daily closing price that the trend presented is basically consistent with the trend chart of real-time stock data and has an obvious long-term trend.In order to eliminate the influence of long-term trend on return rate analysis, and in order to facilitate the calculation and acquisition of return rate data, logarithmic return rate is adopted for analysis.

3. Acquisition and analysis of logarithmic return rate of Kweichow Moutai Stock

3.1 Daily stock return rate and daily logarithmic return rate

The rate of return on stocks refers to the ratio between the total amount of return obtained by investing in stocks and the original amount of investment. The data we obtained here are daily data, so the rate of return on stocks here refers to the daily return on stocks. The daily return on stocks can be understood as:

$$p_t = \frac{X_t}{X_{t-1}}$$

And logarithmic return rate, as the name implies, refers to the logarithm of return rate, which can be simplified as:

$$Y_t = \ln(\frac{X_t}{X_{t-1}}) = \ln(X_t) - \ln(X_{t-1})$$

As the original time series usually has a certain long-term trend, it is generally necessary to carry out difference processing on the original series, which can be well expressed by the logarithmic return rate, which is approximately equal to the return rate[1].To sum up, we choose logarithmic return rate instead of return rate for analysis.

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3.2 Analysis of daily log rate of return

The sequence diagram, ACF diagram and PACF diagram of daily logarithm return rate are as follows:

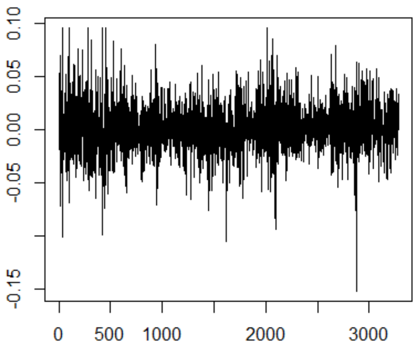

Figure. 3 Sequence diagram of daily logarithmic return rate

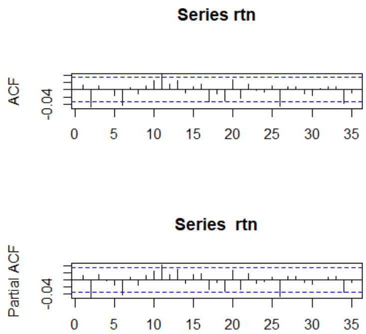

Figure. 4 ACF diagram and PACF diagram of daily logarithmic yield

By day logarithm yield sequence diagrams and ACF figure can be seen that basic near zero day logarithm yield fluctuation, the correlation coefficient is also quickly fall into two times the standard deviation of that day logarithm yield is more stable. At the same time, the randomness test of order 6 and order 12 of delay is carried out for daily logarithmic returns, tested the p values were 0.01683 and 0.01446 are < 0.05, rejecting the null hypothesis, indicating that the daily logarithm return rate is not a white noise sequence, and has fitting value.

4. Empirical analysis of daily logarithmic yield of Kweichow Moutai

Since the daily logarithm return sequence is a stationary series, we first construct ARMA model for the daily logarithm return sequence.

4.1 Establishment and solution based on ARMA model

4.1.1 Model order determination

We use R software to draw BIC graph of daily logarithmic return rate, as follows:

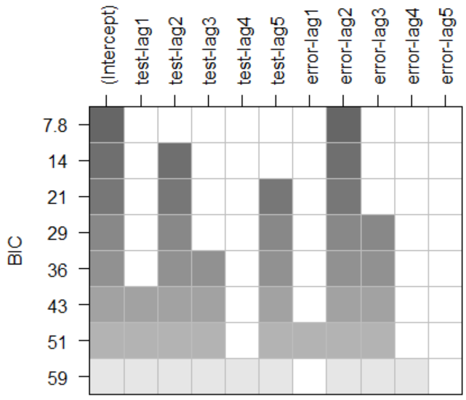

Figure. 5 BIC graph of daily logarithmic return

It can be found from BIC graph that when BIC is the smallest, AR part trailing and MA part second-order truncation, so we set the order of ARMA model as (0,2).

4.1.2 Model establishment and solution

According to the fixed-order results, we use the arima function of R software to establish the ARMA (0,2) model for the daily logarithm return sequence of kweichow moutai stock. However, we find that the p value of the significance t test of MA1 parameter θ_1 is equal to 0.17 > 0.05 means it is not significant. Therefore, parameters θ_1 are excluded before modeling. The modeling results are as follows:

```
Call:
arima(x = rtn, order = c(0, 0, 2), include.mean = FALSE, transform.pars = FALSE,
    fixed = c(0, NA))

Coefficients:
      ma1      ma2
        0  -0.0466
s.e.    0   0.0175

sigma^2 estimated as 0.0004524:  log likelihood = 7977.99,  aic = -15953.99
```

Figure. 6 Modeling results of ARMA(0,(2)) of daily logarithmic return rate of

Kweichow Moutai stock

As can be seen from the results, the coefficient of MA2 θ_2=-0.0466, the variance of residuals σ^2=0.0004524, and the AIC index of the model is -15953.99. Therefore, the operator form of ARMA(0,(2)) is:

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$$Y_t = \log X_t - \log X_{t-1} = \frac{1+0.0466B^2}{1}\xi_t, \xi_t \sim WN（0,0.0004524）$$

4.1.3 Model test and analysis

(1) Residual test of daily log rate of return

In order to test the overall effect of the model, we first observed the ACF figure of the residual:

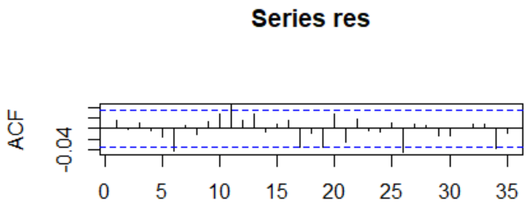

Figure. 7 ACF figure of daily logarithmic return residual

It can be found that the autocorrelation coefficient of the daily log rate of return residual fluctuated within two times of standard deviation, indicating that the daily log rate of return residual was stable. Then, we carried out the pure randomness test of order 6 and order 12, and the p value of the test was 0.2637 and 0.1172 both & GT, respectively.0.05, so the residual is considered to be a white noise sequence.

(2) Residual square test of daily logarithmic return rate

In order to better analyze the fitting effect of ARMA model, we also need to test the residual squared, and make the ACF figure of the residual squared, as follows:

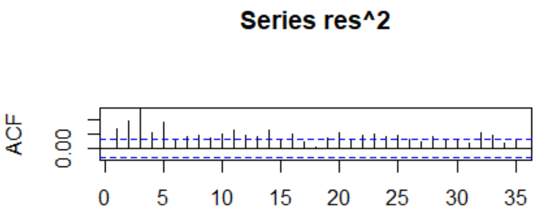

Figure. 8 ACF figure of the daily logarithmic return residual squared

It can be found that the autocorrelation coefficient of the residual square of the daily log rate of return always fluctuates beyond two standard deviations, indicating

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that the residual square of the daily log rate of return is not stable. At the same time, through the pure randomness test of order 6 and 12, it can be seen that the tested P values are both &lt.0.05 indicates that the square of the residual is not a pure random sequence. Therefore, the analysis from the Angle of the residual square shows that the original sequence information is not sufficiently extracted and the model needs to be further improved.

4.2 Improvement of ARMA model based on GARCH Model

In order to get better results, we added GARCH model on the basis of ARMA model.The order of GARCH model is generally set within order 1-3. If the order is too high, the result of the model will be complex and difficult to explain. In order to eliminate the autocorrelation of residual squared in financial time series, GARCH (1,1) model will be adopted.

Here, we add the original ARMA(0,2) and GARCH(1,1), and use the garchFit function in the fGarch package of R software for modeling [3]. The modeling results are shown in the following table:

Table 1 modeling results of ARMA(0,2)+GARCH(1,1)

Coefficient	μ	θ_1 (MA1)	θ_2 (MA2)	ω (omega)	α (alpha)	β (beta)
Result	0.0011589	0.011943	-0.039084	9.5421×10^{-6}	0.051718	0.92743
Amount of Information	AIC	BIC	SIC	SQIC		
Result	-4.942870	-4.931723	-4.942877	-4.938879		

According to the above modeling results, the model can be written as follows:

$$\begin{cases} r_t = 0.0011589 + 0.011943 r_{t-1} - 0.039084 r_{t-2} + \alpha_t \\ \alpha_t = \sigma_t \varepsilon_t, \varepsilon_t \sim N(0,1) \\ \sigma_t^2 = 9.5421\times10^{-6} + 0.051718\alpha_{t-1}^2 + 0.92743\sigma_{t-1}^2 \end{cases}$$

4.3 Model Test

In order to test the above improved model effect, we draw the timing diagram of the model result, as follows:

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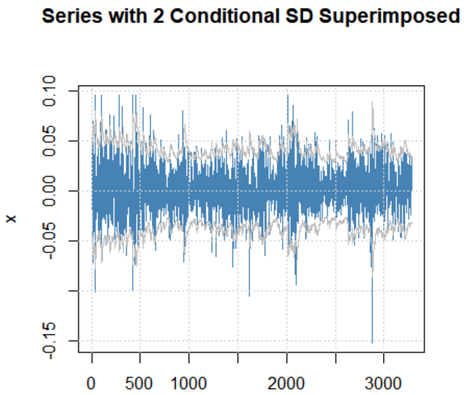

Figure. 9 Timing diagram of model fitting results

It can be seen from the timing diagram of the model fitting results that most of them are within two standard deviations, indicating that the fitted sequence is very stable. Meanwhile, the ACF diagram after the observation residue and the residue square are normalized:

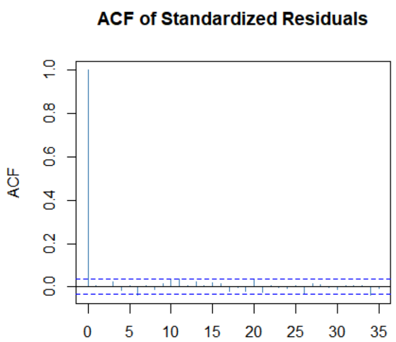

Figure.10 ACF figure of the residual of the fitting result

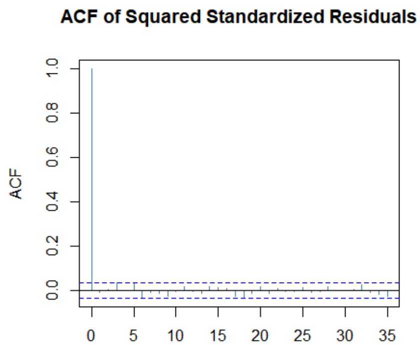

Figure. 11 ACF figure of the residual square of the fitting result

It can be seen from the ACF figure of residual and residual squared that the autocorrelation coefficients of both fall within two standard deviations immediately after order 0 and have a small fluctuation, which indicates that the residual and residual squared series after model fitting are stable.At the same time, lJung-box test for residuals and residuals squared shown in the modeling results can be used to obtain the following table:

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Table 2 LJung-Box test results of residuals and residuals squared

Object	Statistic	Result	p Value	Object	Statistic	Result	p Value
R	Q(10)	11.85219	0.2950707	R^2	Q(10)	15.08224	0.1290923
R	Q(15)	19.3566	0.1980269	R^2	Q(15)	18.0554	0.2597643
R	Q(20)	25.85187	0.17076	R^2	Q(20)	25.67606	0.176779

According to the p values corresponding to the test results in the table, the P values of residual and residual square are & GT;0.05, so the residual and the residual square are white noise sequences. In summary, the residual and the residual square after model fitting are both stationary white noise sequences, indicating that the model has a high degree of information extraction for the original sequence and a good fitting effect.

5. Model Prediction

The fitting of the model is to make a better prediction. For this reason, we use ARMA(0,2) model and GARCH(1,1) model to predict the daily logarithmic rate of return in the next 6 days. The results are as follows:

```
   meanForecast  meanError standardDeviation
1  7.437823e-04 0.01787366        0.01787366
2 -6.318938e-05 0.01795534        0.01795407
3  1.158852e-03 0.01804725        0.01803245
4  1.158852e-03 0.01812375        0.01810888
5  1.158852e-03 0.01819833        0.01818339
6  1.158852e-03 0.01827106        0.01825606
```

Figure. 12 Daily logarithmic yield forecast results for the next 6 days

Based on the above results, it can be concluded that the daily logarithmic returns of Kweichow Moutai stock in the next 6 days are respectively: 7.438×10^{-4}, -6.319×10^{-5}, 1.159×10^{-3}, 1.159×10^{-3}, 1.159×10^{-3}.

References

[1] https://www.jianshu.com/p/653d0f01531d?Clicktime = 1578736149
[2] https://max.book118.com/html/2016/0319/38071395.shtm
[3] R Language and Modern Statistical Methods, edited by Liu Qiang et al., Tsinghua University Press