Modeling Analysis of Vanke Enterprise Daily Profitability

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ABSTRACT
In this paper, the stock price and return rate of Vanke Group are modeled by GARCH model, and the fitting effects of GARCH model, EGARCH model and ARMA-EGARCH model are used and compared respectively. Through the comparison of AIC criteria, ARMA-EGARCH model is selected, and serves as the final model to explain the stock price of Vanke Group. After comparing the AIC criteria and selecting the model, the selected model was tested for the residual term and the residual square term, and the QQ plot of the standardized residual was drawn for comparison, and the model fitting was finally determined. Finally, after comparing the predicted value with the predicted confidence interval and the true value, it is concluded that ARMA-EGARCH model not only has a better interpretation effect, but also has a better prediction ability.

Keywords: *GARCH-like Model, Vanke Group, Model Fitting, Model Selection*

1. INTRODUCTION

No matter whether it is an index or an individual stock, yield research has always been the focus of relevant research on the secondary market, and Vanke Group, a leading real estate company, is no exception. The Vanke Group was established in May 1984 and successfully listed on the Shenzhen Stock Exchange in 1991. Although the share price of Vanke Group has fluctuated, its market value has grown significantly since its listing in 1991. Benefiting from the booming real estate market, Vanke Group experienced exponential growth from 2005 to 2008. Although it suffered a huge blow during the 2008 financial crisis and its stock price fell more seriously, it has grown exponentially since about 2009. Before 2020, it was basically an upward trend, and the market value has almost reached and surpassed the peak in 2008. However, people can see that with the change of the central government's housing policy and the concept of "housing to live without speculation", the stock price has suffered a big drop since 2020, showing investors' concerns about the real estate industry and Vanke. In this context, using a suitable model to fit the trend of Vanke's stock price and make predictions can provide good advice for our investment decisions, which is the original intention of this research.

2. RESEARCH BACKGROUND AND LITERATURE REVIEW

In the process of studying the returns of individual stocks, the volatility of assets is always an unavoidable problem. GARCH models are widely used because they include the interpretation of returns and volatility in the model, and the fitting effect is good. The first systematic framework model for volatility modeling is the ARCH (autoregressive conditional heteroskedasticity) model proposed by Engle [1]. The ARCH model has two assumptions. That is, the disturbance sequence of asset returns is not correlated before and after, but not independent; the independence of this perturbation sequence can be described by a simple quadratic function of its lag value. However, the ARCH model usually leads to too many explanatory variables, which does not meet the principle of model simplicity. In order to obtain a more concise model to explain asset volatility, Bollerslev [2] proposed the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, which added the lag term of the disturbance sequence itself when describing the independence of the disturbance sequence. The model has been widely used since it was proposed. Hui Xiaofeng et al. [3] used the GARCH model to fit the RMB exchange rate, and made predictions based on the obtained results, and found that the predicted exchange

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rate of the GARCH model was very close to the actual exchange rate. The fitted curve can almost completely keep up with the real exchange rate trend, which confirms the effectiveness of this model in dealing with practical problems. Since then, many people have extended the GARCH model. For example, in order to describe the persistent effect of the squared term of the lag term of the disturbance series on the disturbance series, the unit root GARCH model can be used; if people try to describe the impact of volatility on asset returns, the GARCH-M model can be used. In addition, in the research of individual stock returns, in order to reflect the impact of positive asset returns and negative asset returns on the asymmetric effect of volatility (i.e., leverage effect), Nelson [4] proposed the Exponential GARCH (i.e., EGARCH) model. Similarly, the threshold GARCH (TGARCH) model proposed by G losten et al. [5] and Zakoian [6], and the NGARCH proposed by Engle and Ng [7] are often used to deal with this problem. Although the GARCH model has been used by countless papers, after searching, it is found that there are few studies using the GARCH model to analyze the real estate industry in China. Wang Qing and Han Xintao [8] used the GARCH model to analyze the real estate prices., the fluctuation correlation between money supply and economic growth and the impact of their various fluctuations on economic growth rate, Tan Zhengxun and Wang Cong [9] used multivariate GARCH model to analyze the impact of credit expansion and house price fluctuations on financial stability in China. experience mechanism. Few scholars have used GARCH models to study issues related to the real estate industry. At the same time, the extended GARCH models, such as the EGARCH model, take into account the leverage effect, which is very helpful for studying the volatility of individual stocks. In addition, Harvey [10] and Jaequier [11] introduced an innovation into the conditional variance of a to obtain a Stochastic Volatility Model(SV Model), which also has a good effect on simulating the evolution of volatility in financial time series. Therefore, this study attempts to use a suitable GARCH model to simulate the return and volatility of Vanke Group's stock price.

3. DATA DESCRIPTIVE STATISTICS AND ANALYSIS

3.1. Data descriptive statistics

This paper uses the Vanke Group (000002) stock price and daily rate of return considering cash dividends as the research object. The data source is the CSMAR database, and the time span is from November 7, 2016 to November 5, 2021. There are a total of 1212 observations, and the data obtained by adding the daily rate of return considering cash dividends and taking the logarithm are used as the logarithmic rate of return data. The descriptive statistics of the daily closing price and logarithmic rate of return data are shown in Table 1:

Table 1. Descriptive Statistics for Closing Prices and Logarithmic Returns

	Clsprc	rtn
Nobs	1212.000000	1212.000000
Nas	0.000000	0.000000
Minimum	17.640000	-0.097164
Maximum	41.130000	0.095424
1. Quartile	23.850000	-0.011975
3. Quartile	28.860000	0.009530
Mean	26.550503	-0.000097
Median	26.910000	-0.001077
Sum	32179.210000	-0.117913
SE Mean	0.110180	0.000648
LCL Mean	26.334339	-0.001369
UCL Mean	26.766667	0.001175
Variance	14.713106	0.000510
Stdev	3.835767	0.022574
Skewness	0.215826	0.399460
Kurtosis	0.431335	2.769473

Clsprc in Table 1 is the daily closing price data of each trading day, and rtn is the logarithmic rate of return obtained by adding one to the daily rate of return after considering the cash dividend and then taking the logarithm. As can be seen from the table, there are 1 212 observations in both datasets; no null value; the stock price fluctuates from 17 to 42, and the logarithmic return fluctuates very small, ranging from -0.1 to 0. Fluctuates within the range of 1. The mean of the closing price is about 26.55, and the mean of the logarithmic return is very close to 0. In addition, it should be noted that the skewness of the two samples is not 0, which may imply that people may need to consider some problems in the later modeling process. A biased t-distribution model.

3.2. Analysis before modeling

First, the time series chart of the daily closing price is drawn as shown in Figure 1. It can be seen that the stock price of Vanke Group has fluctuated greatly in the past five years. It has experienced several ups and downs from the low point at the end of 2017. It is a historical low, so it can be observed that the volatility of this stock should be of high research value.

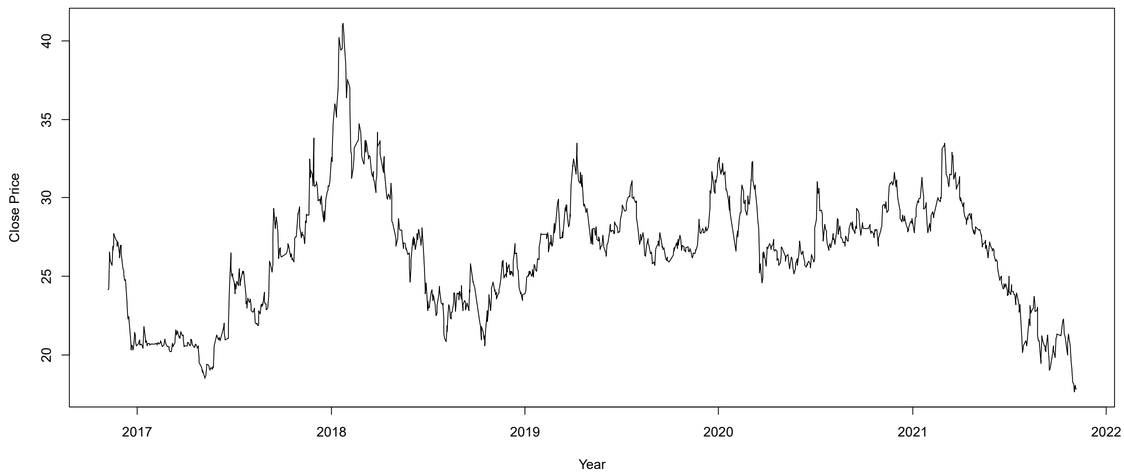

Figure 1. Vanke A closing price timing chart

Secondly, the time series diagram of the logarithmic rate of return is drawn. As can be seen from Figure 2, the volatility of the logarithmic rate of return is generally large, especially from 2017 to 2019, and the volatility of the logarithmic rate of return is extremely high. After 2019, the logarithmic volatility is relatively small, but there is still considerable volatility.

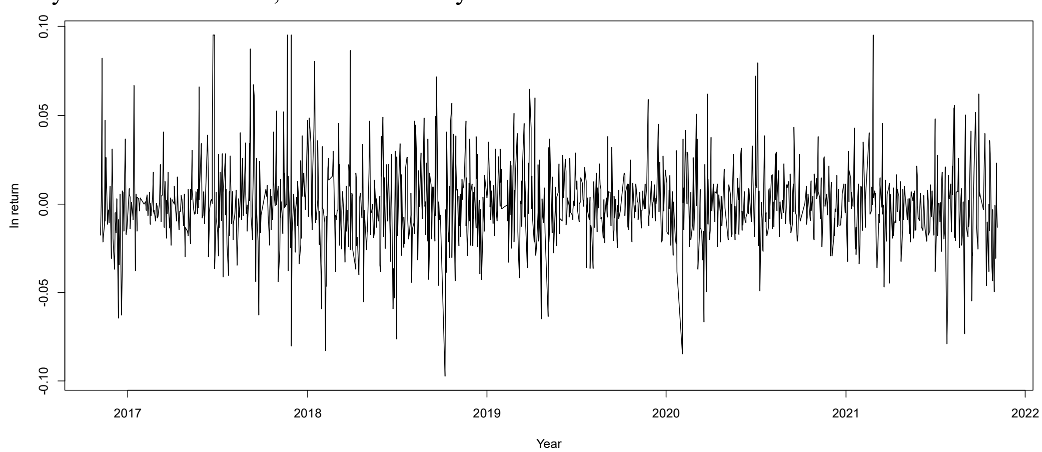

Figure 2. Vanke logarithmic rate of return time series chart

Finally, people can observe the histogram of the logarithmic rate of return. As can be seen from Figure 3, the logarithmic rate of return has the characteristics of a right-side fat tail and belongs to a biased normal distribution, which further verifies the previous observations in descriptive statistics. The logarithmic rate of return has a certain skewness, which means that in the subsequent modeling process, it is necessary to consider the establishment of a GARCH model with a biased Student's distribution, so that the model can achieve a better interpretation effect.

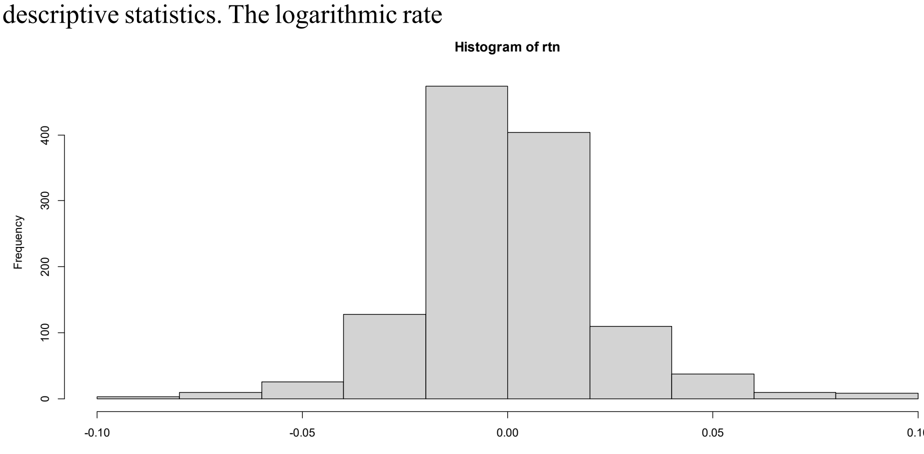

Figure 3. Logarithmic Return Histogram

4. MODEL BUILDING AND GOODNESS-OF-FIT ANALYSIS

4.1. Model correlation analysis

Ljung-Box test is performed on the logarithmic rate of return. Because the logarithmic rate of return uses daily data, the Ljung-Box test of orders 10 and 20 is performed respectively. The obtained p-value is shown in Table 2. From the table, it can be seen that the p-values of the two tests are greater than 0.05. That is, the null hypothesis that the logarithmic rate of return has no before and after autocorrelation should be accepted, and it is believed that the logarithmic rate of return series does not exist before and after the autocorrelation. In order to ensure the accuracy of the results, the autocorrelation function graph and the partial autocorrelation function graph of the logarithmic rate of return series are drawn at the same time. As can be seen from Figure 4, only the partial autocorrelation function graph is truncated after the third order, and it can be considered that the logarithmic return series does not have a front-to-back autocorrelation.

Table 2. Logarithmic rate of return Ljung-Box test value

Order	1 0	2 0
P value	0.1936 _	0.5301 _

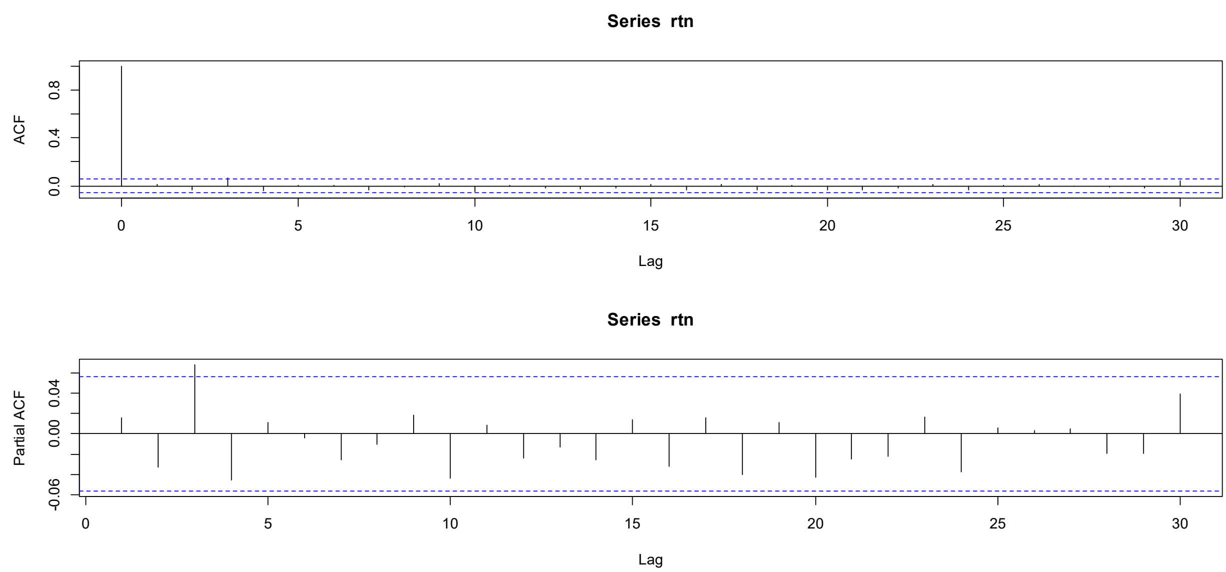

Figure 4. Logarithmic Return Autocorrelation Function and Partial Autocorrelation Function Plot

Next, the logarithmic rate of return series is tested for the ARCH effect to determine whether it is suitable for building a GARCH-like model. Let the difference between the logarithmic rate of return and the mean of the logarithmic rate of return sequence be the sequence a, and perform the Ljung-Box test and the archTest test on the square term of a. The results are shown in Table 3.

Table 3. ARCH effect test

Test name	Ljung -Box test	ArchTest test
P value	1.139e-8 _	1.559e-7 _

From the results in Table 3, it can be seen that the p-values of the two tests are extremely small, so the assumption that the squared residuals have no autocorrelation before and after is rejected, and the logarithmic return series has a strong ARCH effect.

4.2. Model establishment

In order to confirm whether the mean equation contains a constant term, a t-test is performed on the logarithmic return series. The p-value obtained by the test is 0.8808, which is greater than 0.05. Therefore, the null hypothesis of $\mu=0$ in the mean equation should be accepted. This implies that the mean equation does not contain a constant term, but it will inevitably carry a constant term in the subsequent in-software modeling process, so it can boldly speculate that no matter what kind of GARCH model is built in the future, the constant term in the obtained results will be all the same.

The obtained data follows the GARCH (1,1) model, whose innovation follows a Gaussian distribution. Considering that there is a certain skewness in the data distribution, a GARCH (1,1) model whose innovation obeys Student's t distribution and skewed Student's t distribution is established.

Table 4. Fitting results of GARCH (1,1) model with Gaussian distribution of innovation

	Estimate	Std.Error	T value	Pr (>|t|)	
mu	1.707e-04	5.977e-04	0.286	0.7752	
omega	1.561e-05	5.183e-06	3.012	0.0026	**
alpha1	5.911e-02	1.274e-02	4.640	3.48e-06	***
beta1	9.115e-01	1.879e-02	48.512	<2e-16	***

Table 5. Standardized residuals test table of GARCH (1,1) model with Gaussian distribution

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	502.942	0
Shapiro-Wilk Test	R	W	0.9547164	0
Ljung-Box Test	R	Q(10)	12.50934	0.2524125
Ljung-Box Test	R	Q(15)	14.52004	0.486509
Ljung-Box Test	R	Q(20)	15.83341	0.7269041
Ljung-Box Test	R^2	Q10)	7.444912	0.68288
Ljung-Box Test	R^2	Q(15)	12.42081	0.6469383
Ljung-Box Test	R^2	Q(20)	23.80026	0.251226
LM Arch Test	R	TR^2	10.63752	0.5602121

Table 6. Fitting results of GARCH (1,1) model with student's t distribution

	Estimate	Std.Error	T value	Pr (>|t|)	
Mu	-9.276e-04	4.896e-04	-1.895	0.058125	.
Omega	1.115e-05	5.761e-06	1.935	0.052946	.
alpha1	7.177e-02	2.014e-02	3.564	0.000365	***
beta1	9.203e-01	2.080e-02	44.239	<2e-16	***
shape	3.478e+00	3.902e-01	8.913	<2e-16	***

Table 7. Standardized residual test table of GARCH (1,1) model with student t distribution

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	559.9198	0
Shapiro-Wilk Test	R	W	0.9527112	0
Ljung-Box Test	R	Q(10)	12.47931	0.2542574
Ljung-Box Test	R	Q(15)	14.79089	0.4665819
Ljung-Box Test	R	Q(20)	15.92579	0.7212173
Ljung-Box Test	R^2	Q(10)	5.560176	0.8507638
Ljung-Box Test	R^2	Q(15)	11.85666	0.6898449
Ljung-Box Test	R^2	Q(20)	23.71586	0.2550242
LM Arch Test	R	TR^2	9.509287	0.6589243

Table 8. Fitting results of GARCH (1,1) model with biased Student's t distribution

	Estimate	Std.Error	T value	Pr (>|t|)	
mu	1.983e-04	5.804e-04	0.342	0.732649	
omega	1.198e-05	5.848e-06	2.049	0.040448	*
alpha1	7.941e-02	2.147e-02	3.699	0.000217	***
beta1	9.123e-01	2.147e-02	42.486	<2e-16	***
skew	1.146e+00	4.316e-02	26.547	<2e-16	***
shape	3.586e+00	4.138e-01	8.666	<2e-16	***

Table 9. Standardized residuals test table of GARCH (1,1) model with biased Student's t distribution

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	573.2138	0
Shapiro-Wilk Test	R	W	0.9520818	0
Ljung-Box Test	R	Q(10)	12.40539	0.2588407
Ljung-Box Test	R	Q(15)	14.71865	0.4718669
Ljung-Box Test	R	Q(20)	15.78639	0.7297849
Ljung-Box Test	R^2	Q(10)	5.675604	0.8417416
Ljung-Box Test	R^2	Q(15)	12.04779	0.6754082
Ljung-Box Test	R^2	Q(20)	23.21601	0.2783129
LM Arch Test	R	TR^2	9.559899	0.6545087

As can be seen from the table, as shown by the results of the t-test, the constant term mu in the three models is not significant. That is, the mean equation should not contain a constant term, but other coefficient terms have different degrees of significance. The standardized residual test table of the three models shows that whether it is the standardized residual or the square of the standardized residual, the p-value of the Ljung-Box test is much greater than 0.05. That is, the standardized residuals of the three models are considered to be different. There is an autocorrelation before and after, which is close to the white noise sequence, that is, the three models are well fitted.

But this is not the final model. Considering that the research object is the return of individual stocks, it must be considered whether the leverage effect should be considered in the model. Therefore, the EGARCH model is simulated for it. The ARMA explanatory variables can make the model fit better, so consider establishing the ARMA-EGARCH model for comparison. The simulation results are shown in the table below.

Table 10. The fitting results of the EGARCH (1,1) model with normal distribution

	Estimate	Std.Error	T value	Pr (>|t|)
Mu	0.000377	0.000641	0.58851	0.556188
Omega	-0.229410	0.042730	-5.36879	0.000000
alpha1	0.040089	0.009178	4.36800	0.000013
beta1	0.968754	0.005522	175.44353	0.000000
gamma1	0.118867	0.018438	6.44704	0.000000

Table 11. Fitting results of the EGARCH (1,1) model whose innovation obeys Student's t distribution

	Estimate	Std.Error	T value	Pr (>|t|)
Mu	-0.000914	0.000543	-1.68281	0.092412
Omega	-0.139933	0.016101	-8.69117	0.000000
alpha1	0.018608	0.021276	0.87463	0.381776
beta1	0.981426	0.002097	468.00849	0.000000
gamma1	0.147339	0.033209	4.43677	0.000009
Shape	3.469533	0.386906	8.96737	0.000000

Table 12. Fitting results of EGARCH (1,1) model with biased Student's t distribution

	Estimate	Std.Error	T value	Pr (>|t|)
Mu	0.000241	0.000579	0.41614	0.677308
Omega	-0.152446	0.017653	-8.63562	0.000000
alpha1	0.025372	0.021368	1.18741	0.235066
beta1	0.979606	0.002278	429.94958	0.000000
gamma1	0.157562	0.034205	4.60634	0.000004
Skew	1.147828	0.043375	26.46298	0.000000
Shape	3.584837	0.411889	8.70341	0.000000

Table 13. Fitting results of ARMA-EGARCH (1,1) model with normal distribution

	Estimate	Std.Error	T value	Pr (>|t|)
Mu	0.000400	0.000610	0.65594	0.511864
ar1	-0.847398	0.046175	-18.35172	0.000000
ma1	0.904725	0.036067	25.08476	0.000000
Omega	-0.234659	0.026859	-8.73680	0.000000
alpha1	0.041692	0.014809	2.81539	0.004872
beta1	0.968129	0.003285	294.74227	0.000000
gamma1	0.121614	0.007382	16.47483	0.000000

Table 14. The fitting results of the ARMA-EGARCH (1,1) model with Student's t distribution

	Estimate	Std.Error	T value	Pr (>|t|)
Mu	-0.000916	0.000602	-1.52324	0.127698
ar1	-0.857702	0.031218	-27.47453	0.000000
ma1	0.900110	0.026209	34.34312	0.000000
Omega	-0.138806	0.020406	-6.80215	0.000000
alpha1	0.020543	0.021317	0.96369	0.335200
beta1	0.981657	0.002772	354.17284	0.000000
gamma1	0.150176	0.035100	4.27854	0.000019
Shape	3.537993	0.399312	8.86023	0.000000

Table 15. The fitting results of the ARMA-EGARCH (1,1) model with a biased Student's t distribution

	Estimate	Std.Error	T value	Pr (>|t|)
Mu	0.000272	0.000479	0.56734	0.570482
ar1	-0.852104	0.063797	-13.35647	0.000000
ma1	0.897878	0.053211	16.87406	0.000000
Omega	-0.151432	0.018258	-8.29406	0.000000
alpha1	0.027561	0.021436	1.28573	0.198538
beta1	0.979805	0.002363	414.72175	0.000000
gamma1	0.160691	0.034315	4.68278	0.000003
Skew	1.155634	0.042587	27.13605	0.000000
Shape	3.662725	0.426464	8.58859	0.000000

It can be seen from the above fitting results that, except for the initial EGARCH (1,1) model, other models have the problem that the alpha term is not significant, and besides these two terms, other coefficient terms are very significant, and each coefficient item has no minimum value, indicating that each coefficient has a certain influence. The selection and description of the specific model will be expanded in the next section.

4.3. Model comparison and selection

In order to compare the goodness of fit of the models, the AIC values of each model are now compared, and the AIC values of each model are shown in Table 16.

Table 16. Comparison of AIC values of each model

Model	AIC	Model	AIC
GARCH(1,1)-norm	-4.801479	EGARCH(1,1)-skew t	-4.9385
GARCH(1,1)-t	-4.931039	ARMA- EGARCH(1,1)-norm	-4.8086
GARCH(1,1)-skew t	-4.940007	ARMA- EGARCH(1,1)-t	-4.9341
EGARCH(1,1)-norm	-4.8004	ARMA- EGARCH(1,1)-skew t	-4.9442
EGARCH(1,1)-t	-4.9294		

ARMA-EGARCH (1,1) model whose innovation obeys the biased Student's t distribution is the smallest. At the same time, the QQ plot of the standardized residuals was drawn, and the results obtained are shown in Table 17 and Figure 5.

Table 17. Ljung -Box test of standardized residuals and standardized residual squares of ARMA-EGARCH (1,1) model with biased Student's t distribution

	Standardized Residuals Test		Standardized residual squared test	
	statistic	p-value	statistic	p-value
Lag[1]	0.03259	0.8567	0.5398	0.4625
Lag[2*(p+ q)+(p+q)-1][5]	1.38141	0.9993	1.8921	0.6441
Lag[4*(p+ q)+(p+q)-1][9]	2.87080	0.9092	3.0647	0.7482
d. of =2				

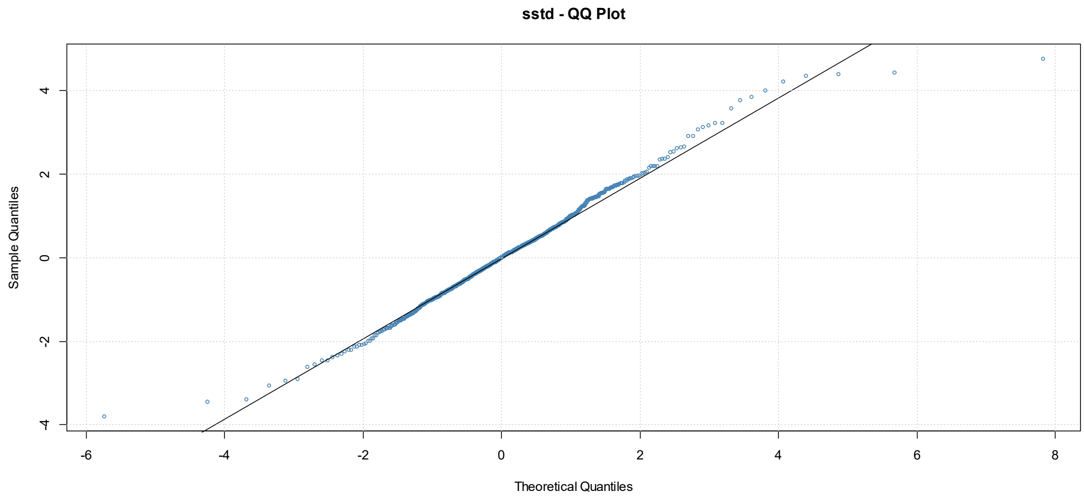

Figure 5. The model standardized residual QQ plot

From Table 17. it can be seen that the p-values of the Ljung -Box test of different orders of the standardized residuals and the squared terms of the standardized residuals are all greater than 0.05, that is to say, the null hypothesis should be accepted, and it is considered that the standardized residuals of the model and the standardized residuals The residual squared term has poor autocorrelation before and after, which is close to a white noise sequence, and the model fits well. At the same time, it can be observed from the QQ plot of the standardized residuals of the model that the standardized residuals are basically distributed around the diagonal line, which also implies that the model fitting is adequate. But it can be observed from the QQ plot that the distribution of this standardized residual is slightly asymmetric, i.e. it deviates less from the diagonal on the left, but it deviates more from the diagonal on the right. It can be concluded that, even if the data is fitted with a model whose innovation obeys a biased Student's t distribution, there is still a certain degree of skewness in the residual term that has not been fitted, so the model is still not perfect.

ARMA-EGARCH (1,1) model whose innovation obeys the biased Student's t distribution as the explanatory model for this data. The model is in the form of:

$$r_t = 0.000272 - 0.852104 r_{t-1} + a_t - 0.897878 a_{t-1} \qquad a_t = \sigma_t \varepsilon_t \quad \varepsilon_t \sim t^*_{1.16,3.66} \tag{1}$$

$$\ln(\sigma_t^2) = -0.151432 + 0.028(|\varepsilon_{t-1}| - 0.9798\varepsilon_{t-1}) + 0.9196 \ln(\sigma_{t-1}^2) \tag{2}$$

4.4. Model prediction

The above model is adopted, and the ugarchforecast function in the rugarch package is used to predict the model with a rolling forward of 15 steps. The prediction results are shown in Table 18.

Table 18. The model rolls forward 15 steps to predict the results

0-roll	forecast	[T0=2021-10-22]:
	Series	Sigma
T+1	-3.370e-03	0.03088
T+2	3.546e-03	0.03070
T+3	-2.323e-03	0.03053
T+4	2.658e-03	0.03036
T+5	-1.569e-03	0.03020
T+6	2.018e-03	0.03004
T+7	-1.026e-03	0.02988
T+8	1.557e-03	0.02973
T+9	-6.347e-04	0.02958
T+10	1.225e-03	0.02944
T+11	-3.531e-04	0.02930

T+12	9.865e-04	0.02917
T+13	-1.503e-04	0.02903
T+14	8.144e-04	0.02890
T+15	-4.252e-06	0.02878

At the same time, a prediction map is drawn according to the prediction result, and the prediction map is shown in Figure 6.

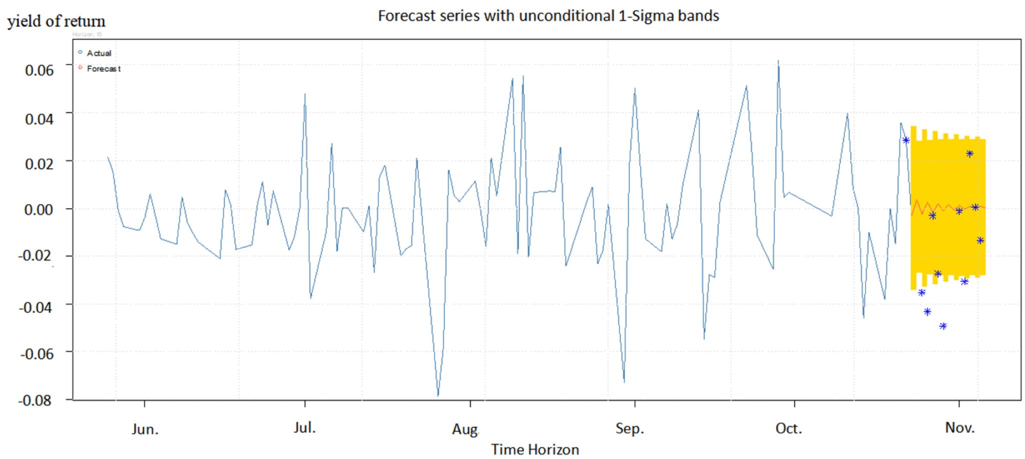

Figure 6. The model is 15 steps ahead of the prediction result

The red line part in the figure is the prediction result, the yellow part is the prediction confidence interval, and the blue asterisk represents the part of the data reserved before. It can be seen that a considerable part of the previously reserved data is within the prediction confidence interval, but the stock price of Vanke Group is indeed volatile. Besides, there are still three actual observations outside the confidence interval. In general, the predicted results are reasonable. It can be considered that the model is adequately fitted and reasonably predicts the fluctuation range of the stock price ahead of 15 days, i.e., the model is ideal.

5. CONCLUSION

After the selection of data in this paper, the fitting of the model and the selection by the AIC criterion, the ARMA-EGARCH (1,1) model whose innovations obey the biased Student's t distribution is finally selected as the explanation for the stock price and volatility of Vanke Group. After the model is selected, the model is tested for adequacy of fitting. Through the Ljung-Box test of the standardized residual of the model and the square term of the standardized residual, it is proved that these two items are close to the white noise sequence, and the original ARMA-EGARCH model has a good fit, and the results of the QQ plot of model-standardized residuals also support this view. Finally, this model is used to make a simple prediction of the logarithmic rate of return of the stock price. Seven of the ten reserved data falls within the confidence interval of the prediction, which proves that the prediction effect of the model is good, so this model can better explain and predict the logarithmic rate of return on the Vanke Group's share price.

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