Prediction of stock prices of Yuexiu REITs based on GARCH models

Jia Jin*

Department of Finance, Nanjing University of Science and Technology, Nanjing, China

* Corresponding Author Email: jss337@163.com

Abstract. As a new type of financial instrument, on the one hand, REITs can play the role of resource allocation in the securities market, enabling better coordination between project parties and funding parties, accelerating investment speed, and improving investment efficiency. On the other hand, they can also leverage high-quality infrastructure assets that were previously only available to some large infrastructure units. The income from some real estate projects allows ordinary institutions and investors to share this long-term stable cash flow return. Due to the initial exploration stage of REITs in mainland China and the relatively mature development of the Hong Kong REITs market, this article selects Yuexiu REITs, the first REITs fund in China with mainland property assets as the underlying asset, listed in Hong Kong, for specific empirical research. This article selects the closing prices of Yuexiu REITs from November 1, 2018 to November 1, 2022 as research data, and based on the GARCH model theory, establishes GARCH (1,1) model, EGARCH (1,1) model, IGARCH (1,1) model, and GARCH-M (1,1) model based on normal distribution, t-distribution, and GED distribution. According to the AIC criterion, the GARCH (1,1) model based on t-distribution and the IGARCH (1,1) model were selected to predict the future closing prices of Yuexiu REITs. The results showed that the GARCH (1,1) models under t-distribution had a narrower confidence interval range and higher accuracy.

Keywords: REITs, GARCH models.

1. Introduction

Since the birth of Real Estate Investment Trusts (REITs) in the United States in the 1960s, more and more countries and regions have begun to explore and issue REITs. Currently, about 42 countries and regions have formed the REITs market. On April 30, 2020, the China Securities Regulatory Commission and the National Development and Reform Commission jointly issued the "Promotion of Real Estate Investment Trusts (REITs) in the Infrastructure Sector" The Notice on Pilot Work and the Guidelines for Public Offering of Infrastructure Securities Investment Funds (Trial) (Draft for Soliciting Opinions) signify that China's REITs market has entered a new stage of development

As an innovative real estate financing tool, on the one hand, REITs can effectively connect the real estate market and land capital market, providing real estate enterprises with financing channels to improve fund utilization efficiency and land use efficiency. On the other hand, REITs can provide a new investment path choice for many investors, helping them to allocate assets more effectively. However, REITs are still in its early stages in China, The relevant laws and regulations, market access conditions, supervision and management systems, and tax preferential policies are not yet perfect and mature. Compared with some developed countries, China started exploring REITs relatively late, and research on REITs is relatively scarce. It is worth conducting in-depth research and analysis. With the increasingly flexible and diversified financing methods in the real estate industry, the proportion of high-quality property asset securitization in China is increasing, REITs will have broad development space in China.

This article first outlines the basic concepts and development history of REITs to facilitate understanding of this emerging financial product. Secondly, it introduces the relevant theories of the GARCH model. In terms of empirical analysis, this article selects Yuexiu REITs, the first listed company in Hong Kong with mainland assets as the target, as the research object, and conducts data analysis, processing, modeling, and prediction on them, I hope it can provide reference and supplement for the future development and research of REITs in China.

2. Theoretical Basis

2.1. Overview of REITs Theory

2.1.1. The Concept of REITs

Real estate investment trust funds, abbreviated as REITs, are a type of trust fund that raises funds from a specific majority of investors through the issuance of beneficiary certificates, and is managed by specialized investment management institutions for real estate investment operations. The comprehensive investment income is distributed proportionally to investors. Real estate trust investment funds concentrate on investing in real estate projects that can generate income, such as shopping centers, office buildings, etc Hotels and serviced residences provide regular income for investors through rental income and real estate appreciation. REITs were born in the United States in 1960 and have rapidly developed globally. Currently, more than 40 countries and regions, including Australia, Singapore, and Hong Kong, China, have actively explored and developed REITs.

2.1.2. Classification of REITs

According to the issuance method, it can be divided into public REITs and private REITs. Public REITs raise funds from the public with a relatively low investment threshold; Private REITs raise funds through non-public means from specific investors, who are mostly investment institutions such as insurance companies and pension funds participating in investment transactions

According to the direction of capital investment, there are three types of REITs: equity REITs, mortgage REITs, and mixed REITs. Equity REITs own and operate real estate, while providing property management services. Investors receive income from rent and appreciation of real estate; Mortgage based REITs provide mortgage credit directly to real estate owners or developers, or indirectly provide financing through the purchase of mortgage backed securities, with their main source of income being loan interest; Hybrid REITs are a combination of equity REITs and mortgage REITs

According to organizational form, it can be divided into corporate REITs and contractual REITs. Corporate REITs are essentially investment companies, where investors become shareholders by purchasing the company's stocks, and the company uses the raised funds for real estate investment and operation; Contractual REITs are established in accordance with the Trust Law, and REITs trust institutions raise funds to purchase real estate. The ownership of the real estate is transferred to the custodian, who then transfers the property management rights to professional managers for investment operations.

2.1.3. The Development History of REITs in China

Exploration and research stage (2005-2014). In 2005, the Ministry of Commerce began exploring financing channels for domestic REITs. In 2009, Beijing, Shanghai, and Tianjin also gradually launched mortgage based REITs pilot projects. However, due to the impact of the financial crisis and the tightening of policies in the real estate industry at that time, China's REITs did not make substantial progress in the early exploration stage.

Class REITs Stage (2014-2019). In 2014, the People's Bank of China and the China Banking Regulatory Commission jointly issued the "Notice on Further Improving Housing Financial Services", which sent a positive signal that the country should focus on developing REITs. During this stage, China's REITs market achieved rapid development. In 2014, the first equity REIT product in China, "CITIC Sailing," was officially listed on the Shenzhen Stock Exchange, and the first public REIT in China, "Penghua Qianhai Surgical REITs," was officially launched It was officially launched in 2015, and from 2014 to 2019, China issued a total of 64 REIT products. These explorations have provided rich experience and reference significance for China to launch truly meaningful REIT products in the future.

The stage of public REITs (2020 present). In 2020, the National Development and Reform Commission and China Securities Regulatory Commission jointly issued a notice on promoting the pilot work of Real Estate Investment Trusts (REITs) in the infrastructure sector, indicating that China will shift its development focus to the field of public REITs. In 2021, the first nine REITs in China were officially listed and traded on the Shanghai and Shenzhen Stock Exchanges, This is another important milestone in the development process of REITs in China. Only 9 REITs products cover four major fields: industrial parks, warehousing and logistics, toll roads, and ecological protection. The overall quality is high-quality, and it is currently showing good overall performance in the market.

2.2. Overview of GARCH Theory

2.2.1. ARMA Model

The ARIMA model, also known as the Autoregressive Integrated Moving Average Model, is a famous time series prediction method proposed by Box and Jenkins in the 1970s. The ARIMA model essentially simulates the random changes of data through autocorrelation and partial autocorrelation functions, in order to achieve the goal of predicting the future trend of data changes. The ARIMA (p, q) model can be expressed as:

$$\mathrm{d}X_t = c + \sum_{i=1}^{p} \phi_i dX_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{1}$$

Among them, p, d, and q are the autoregressive order, difference order, and moving average order, respectively. X_t is the time series of time t, ϕ_i and θ_j are stationary polynomial operators of order p and q, respectively, and ε_t is a random error term.

2.2.2. ARCH Model

The ARCH model, also known as the Autoregressive Conditional Heteroscedasticity Model [13], is composed of a mean equation and a conditional heteroscedasticity equation. The structure of the ARCH (p) model is represented as:

$$y_t = x_t \phi + u_t, u_t \sim N(0, \sigma_t^2) \tag{2}$$

$$\sigma_t^2 = Var(y_t \mid I_{t-1}) = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots + \alpha_p u_{t-p}^2 \tag{3}$$

Equation (2) is the mean equation, equation (3) is the conditional heteroscedasticity equation, is the order of the ARCH model, and are the dependent variable and explanatory variable, respectively, are the disturbance terms without sequence correlation, and are the variance of the disturbance term at time t under the known information set conditions at time t-1.

2.2.3. GARCH Model

The basic idea of the GARCH model is that, based on the ARCH model, in order to avoid excessive lag terms, the method of adding a lag term of σ_t^2 can be used to reduce the number of parameters . The standard GARCH (p, q) model structure is as follows:

$$y_t = x_t \phi + u_t, u_t \sim N(0, \sigma_t^2) \tag{4}$$

$$\sigma_t^2 = Var(y_t \mid I_{t-1}) = \alpha_0 + \sum_{t=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{5}$$

2.2.4. GARCH Family Models

Nelson proposed the EGARCH model in 1991, which describes the different impacts of positive and negative messages. The structure of the model is as follows:

$$x_t = f(t, x_{t-1}, x_{t-2}, ...) + \varepsilon_t \tag{6}$$

$$\ln h_t = \omega + \sum_{i=1}^{p} \eta_i \ln h_{t-i} + \sum_{j=1}^{q} \lambda_j g(e_{t-j}) \tag{7}$$

Among them, the deterministic information fitting model for{ x_t }is the logarithm of the conditional variance, which can be positive or negative.

If the constraints of the GARCH model are rewritten as:

$$\sum_{i=1}^{p} \eta_i + \sum_{j=1}^{q} \lambda_j = 1 \tag{8}$$

It constitutes the IGARCH model. For the IGARCH model, the unconditional variance of the disturbance term is unbounded, so its unconditional variance is meaningless. The GARCH model is suitable for describing conditional heteroscedasticity with unit root characteristics (random walks). From a theoretical perspective, the IGARCH phenomenon may be caused by volatility with a constant drift term.

The construction idea of the GARCH-M model is that there is a certain correlation between the sequence mean and the conditional variance. In this case, the conditional standard deviation can be used as an additional regression factor for modeling. The model structure is as follows:

$$x_t = f(t, x_{t-1}, x_{t-2}, ...) + \delta\sqrt{h_t} + \varepsilon_t \tag{9}$$

$$h_t = \omega + \sum_{i=1}^{p} \eta_i \ln h_{t-i} + \sum_{j=1}^{q} \lambda_j \varepsilon_{t-j}^2 \tag{10}$$

Among them, $f(t, x_{t-1}, x_{t-2}, ...)$ is the deterministic information fitting model for { x_t }.

3. Empirical Analysis

3.1. Data Selection

This article selects Yuexiu REITs as the research object. Yuexiu REITs was officially listed on the Hong Kong Stock Exchange on December 21, 2015. It is the first offshore REITs with domestic property assets as the subject. This article uses a total of 987 closing prices from November 1, 2018 to November 1, 2022 as sample data, all of which are from Yingwei Financial Information.

3.2. Data Analysis

3.2.1. Draw a Timing Chart

Draw a time series chart of the daily closing prices of Yuexiu REITs:

```
library(tseries)
p<-ts(yx$p)
plot(p)
```

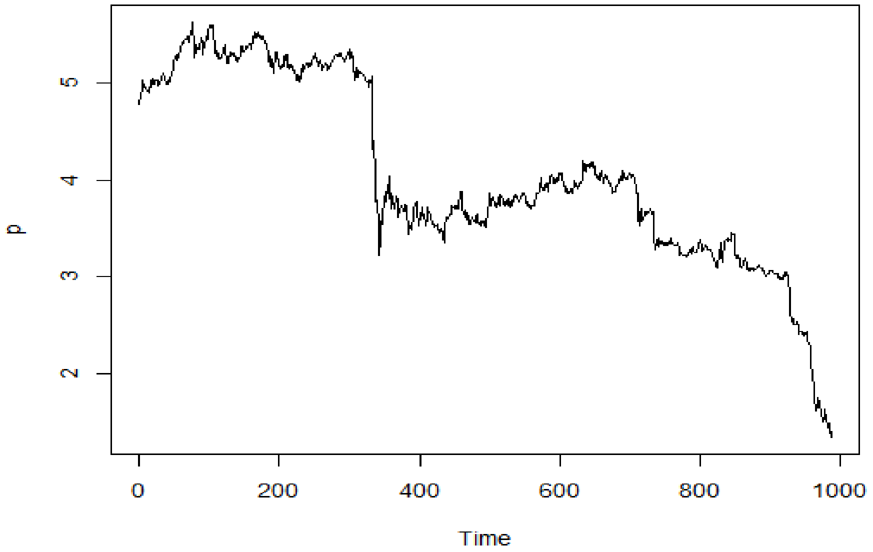

Fig. 1 Time series diagram of Yuexiu REITs

As shown in Figure 1, the time series chart shows a continuous decreasing trend in the closing price of Yuexiu REIT, showing significant non-stationary characteristics.

Perform first-order differencing on the sequence, extract deterministic trend information, and draw a time series diagram after differencing:

plot(diff(p))

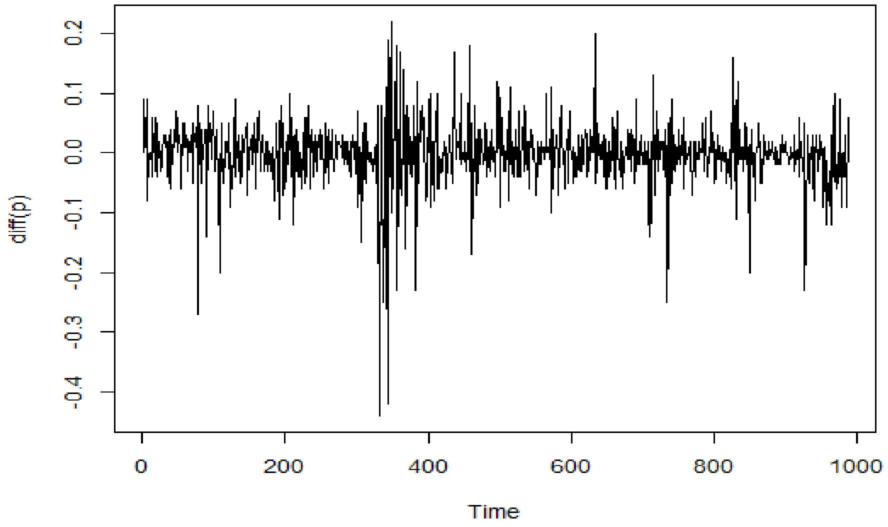

Fig. 2 Sequence time diagram of Yuexiu REITs after first-order differential analysis

As shown in Figure 2, the sequence of Yuexiu REITs after differencing fluctuates around 0, with absolute values mostly within twice the standard deviation. It is relatively stable for most of the time and only fluctuates violently in a few time periods, indicating that there is a phenomenon of wave aggregation in the sequence of Yuexiu REITs after first-order differencing.

3.2.2. Stationarity Test

Perform PP test on the differential sequence of Yuexiu REITs:

```
> PP.test(diff(p))

        Phillips-Perron Unit Root Test

data:  diff(p)
Dickey-Fuller = -31.922, Truncation lag parameter = 7, p-value = 0.01
```

Fig. 3 Stability test result

The PP test shows that the value of the delayed 7th order statistic is -31.922, and the value of the test statistic is 0.01. The null hypothesis is rejected, indicating that the differenced sequence is stationary.

3.2.3. Pure Randomness Test

Perform a pure randomness test on the differential sequence:

```
> for(k in 1:4) print(Box.test(diff(p),lag=6*k,type="Ljung-Box"))

        Box-Ljung test

data:  diff(p)
X-squared = 20.779, df = 6, p-value = 0.00201


        Box-Ljung test

data:  diff(p)
X-squared = 28.212, df = 12, p-value = 0.00515


        Box-Ljung test

data:  diff(p)
X-squared = 42.47, df = 18, p-value = 0.0009503


        Box-Ljung test

data:  diff(p)
X-squared = 47.338, df = 24, p-value = 0.003045
```

Fig. 4 Pure randomness test result

Examine specific autocorrelation coefficients:

```
> print(acf(diff(p),lag=24))

Autocorrelations of series 'diff(p)', by lag

     0      1      2      3      4      5      6      7      8      9     10 
 1.000 -0.014  0.023 -0.017  0.012  0.140 -0.017  0.051 -0.024 -0.023 -0.003 
    11     12     13     14     15     16     17     18     19     20     21 
 0.057 -0.022 -0.067 -0.005  0.003  0.025 -0.089  0.034  0.047 -0.013 -0.009 
    22     23     24 
-0.019 -0.043  0.013 
```

Fig. 5 Autocorrelation coefficient

The tested values are all less than 0.05, rejecting the null hypothesis, so the white noise test result is that the sequence is a non white noise sequence. However, the delayed values of each order show that the correlation between the sequences is very small, with the maximum ρ_{17} =-0.089. After comprehensive consideration, it can be considered that the Yuexiu REITs differenced sequence is approximately a pure random sequence.

Based on the above analysis, establish the mean model of the closing price sequence of Yuexiu REITs as the model:

$$\mathrm{x}_t = x_{t+1} + \varepsilon_t$$

3.2.4. ARCH Effect Test

Perform a pure randomness test on the differential sequence:

```
> p.fit<-arima(p,order=c(0,1,0))
> arch.test(p.fit)
ARCH heteroscedasticity test for residuals
alternative: heteroscedastic

Portmanteau-Q test:
     order  PQ p.value
[1,]     4 142       0
[2,]     8 232       0
[3,]    12 401       0
[4,]    16 436       0
[5,]    20 450       0
[6,]    24 465       0
Lagrange-Multiplier test:
     order   LM  p.value
[1,]     4 1238 0.00e+00
[2,]     8  482 0.00e+00
[3,]    12  215 0.00e+00
[4,]    16  152 0.00e+00
[5,]    20  119 2.22e-16
[6,]    24   92 3.25e-10
```

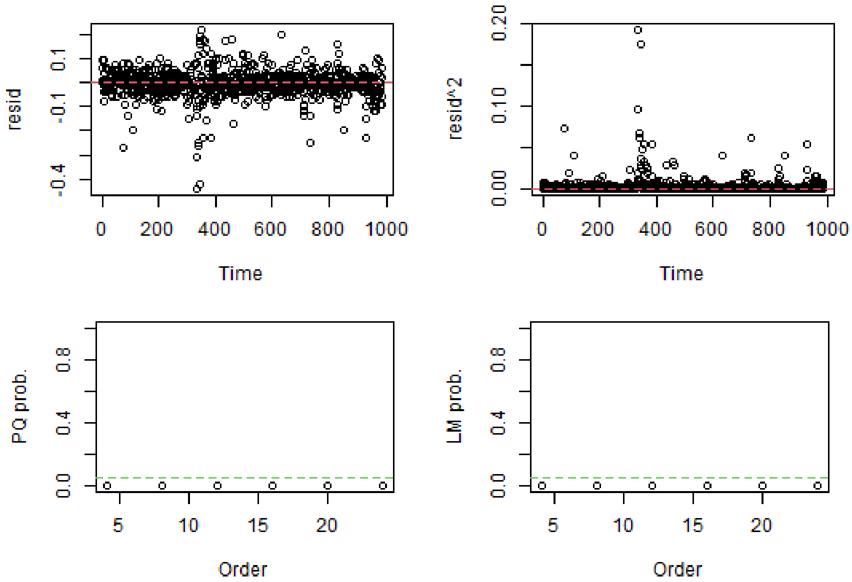

Fig. 6 ARCH effect test

As shown in Figures 6, both the test and the 24th order delay indicate significant non-homogeneity in the sequence, indicating the existence of long-term correlation in the residual sequence. Therefore, the correlation contained in the residual squared sequence can be extracted using a low order model. Next, this article will establish GARCG (1,1) models based on normal distribution, distribution, and three different distributions, and compare GARCH family models based on the three distributions to determine the optimal model and make predictions.

3.3. Establish GARCH (1,1) Model

3.3.1. GARCH (1,1) Model Under Normal Distribution

```
library(rugarch)
spec11<-ugarchspec(
  mean.model=list(armaOrder=c(0,0),include.mean=F),
  variance.model=list(garchOrder=c(1,1),model="sGARCH"),
  distribution.model="norm")
fit11<-ugarchfit(spec11,data=diff(p),method="CLS")
fit11

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
omega    0.00057    0.000093   6.1325        0
alpha1   0.33967    0.061111   5.5582        0
beta1    0.50731    0.059196   8.5699        0
```

Fig. 7 GARCH (1,1) model under normal distribution

3.3.2. GARCH (1,1) Model Under t-Distribution

```
spec12<-ugarchspec(
  mean.model = list(armaOrder=c(0,0),include.mean=F),
  variance.model = list(garchOrder=c(1,1),model="sGARCH"),
  distribution.model="std")
fit12<-ugarchfit(spec12,data=diff(p))
fit12

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
omega   0.000282    0.000109   2.5967 0.009413
alpha1  0.269120    0.081556   3.2998 0.000967
beta1   0.682979    0.078189   8.7350 0.000000
shape   3.340091    0.369241   9.0458 0.000000
```

Fig. 8 GARCH (1,1) model under t-distribution

3.3.3. GARCH (1,1) Model Under GED Distribution

```
spec13<-ugarchspec(
  mean.model=list(armaOrder=c(0,0),include.mean=F),
  variance.model=list(garchOrder=c(1,1),model="sGARCH"),
  distribution.model="ged")
fit13<-ugarchfit(spec13,data=diff(p),method="CLS")
fit13

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
omega   0.000337    0.000120   2.8167 0.004852
alpha1  0.297738    0.089717   3.3186 0.000905
beta1   0.637566    0.088803   7.1795 0.000000
shape   0.833937    0.064291  12.9713 0.000000
```

Fig. 9 GARCH (1,1) model under GED distribution

As shown in the figure, the sum of parameters of the GARCG (1,1) model based on normal distribution, distribution, and three different distributions is less than 1, indicating effective modeling.

3.4. Establish GARCH Family Model

3.4.1. EGARCH (1,1) Model

EGARCH (1,1) model under normal distribution:

```
spec21<-ugarchspec(
  mean.model = list(armaOrder=c(0,0),include.mean=F),
  variance.model = list(garchOrder=c(1,1),model="eGARCH"),
  distribution.model="norm")
fit21<-ugarchfit(spec21,data=diff(p),solver = "gosolnp")
fit21

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
omega  -1.082896    0.216968  -4.9910 0.000001
alpha1  0.082105    0.033587   2.4445 0.014504
beta1   0.812013    0.036128  22.4759 0.000000
gamma1  0.455124    0.052991   8.5887 0.000000
```

Fig. 10 EGARCH (1,1) model under normal distribution

EGARCH (1,1) model under t-distribution:

```
spec22<-ugarchspec(
  mean.model = list(armaOrder=c(0,0),include.mean=F),
  variance.model = list(garchOrder=c(1,1),model="eGARCH"),
  distribution.model="std")
fit22<-ugarchfit(spec22,data=diff(p),solver = "gosolnp")
fit22

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
omega  -0.550764    0.191857 -2.87069 0.004096
alpha1 -0.027951    0.035750 -0.78185 0.434306
beta1   0.909013    0.031586 28.77861 0.000000
gamma1  0.381831    0.071178  5.36446 0.000000
shape   3.293094    0.359283  9.16574 0.000000
```

Fig. 11 EGARCH (1,1) model under t-distribution

EGARCH (1,1) model under GED distribution:

```
spec23<-ugarchspec(
  mean.model = list(armaOrder=c(0,0),include.mean=F),
  variance.model = list(garchOrder=c(1,1),model="eGARCH"),
  distribution.model="ged")
fit23<-ugarchfit(spec23,data=diff(p),solver = "gosolnp")
fit23

 Optimal Parameters
 ------------------------------------
         Estimate  Std. Error  t value Pr(>|t|)
 omega    2.05773    0.607683  3.38619 0.000709
 alpha1  -9.99975   18.186978 -0.54983 0.582436
 beta1   -0.03925    0.194852 -0.20144 0.840358
 gamma1  -9.95772   11.714380 -0.85004 0.395301
 shape    0.10000    0.001885 53.05781 0.000000
```

Fig. 12 EGARCH (1,1) model under GED distribution

3.4.2. IGARCH (1,1) Model

IGARCH (1,1) model under normal distribution:

```
spec31<-ugarchspec(
  mean.model = list(armaOrder=c(0,0),include.mean=F),
  variance.model = list(garchOrder=c(1,1),model="iGARCH"),
  distribution.model="norm")
fit31<-ugarchfit(spec31,data=diff(p))
fit31

 Optimal Parameters
 ------------------------------------
         Estimate  Std. Error  t value Pr(>|t|)
 omega   0.000499    0.000083   6.0475        0
 alpha1  0.514215    0.057319   8.9710        0
 beta1   0.485785          NA       NA       NA
```

Fig. 13 IGARCH (1,1) model under normal distribution

IGARCH (1,1) model under t-distribution:

```
spec32<-ugarchspec(
  mean.model = list(armaOrder=c(0,0),include.mean=F),
  variance.model = list(garchOrder=c(1,1),model="iGARCH"),
  distribution.model="std")
fit32<-ugarchfit(spec32,data=diff(p))
fit32

spec32<-ugarchspec(
  mean.model = list(armaOrder=c(0,0),include.mean=F),
  variance.model = list(garchOrder=c(1,1),model="iGARCH"),
  distribution.model="std")
fit32<-ugarchfit(spec32,data=diff(p))
fit32
```

Fig. 14 IGARCH (1,1) model under t-distribution

IGARCH (1,1) model under GED distribution:

```
spec33<-ugarchspec(
  mean.model = list(armaOrder=c(0,0),include.mean=F),
  variance.model = list(garchOrder=c(1,1),model="iGARCH"),
  distribution.model="ged")
fit33<-ugarchfit(spec33,data=diff(p))
fit33

 Optimal Parameters
 ------------------------------------
         Estimate  Std. Error  t value Pr(>|t|)
 omega   0.000303    0.000115   2.6305 0.008526
 alpha1  0.358528    0.091145   3.9336 0.000084
 beta1   0.641472          NA       NA       NA
 shape   0.799580    0.057559  13.8915 0.000000
```

Fig. 15 IGARCH (1,1) model under GED distribution

3.4.3. GARCH-M (1,1) Model

GARCH-M (1,1) model under normal distribution:

```
spec41<-ugarchspec(
  mean.model = list(armaOrder=c(0,1),include.mean=F, archm =T),
  variance.model = list(garchOrder=c(1,1),model="sGARCH"),
  distribution.model="norm")
fit41<-ugarchfit(spec41,data=diff(p))
fit41

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.039970    0.045441  0.87959  0.37908
archm  -0.050071    0.031057 -1.61225  0.10691
omega   0.000552    0.000091  6.04054  0.00000
alpha1  0.338996    0.061155  5.54318  0.00000
beta1   0.514054    0.058704  8.75676  0.00000
```

Fig. 16 GARCH-M (1,1) model under normal distribution

GARCH-M (1,1) model under t-distribution:

```
spec42<-ugarchspec(
  mean.model = list(armaOrder=c(0,1),include.mean=F, archm =T),
  variance.model = list(garchOrder=c(1,1),model="sGARCH"),
  distribution.model="std")
fit42<-ugarchfit(spec42,data=diff(p))
fit42

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ma1    -0.003737    0.035192 -0.10619 0.915431
archm  -0.021644    0.023896 -0.90575 0.365071
omega   0.000280    0.000108  2.59875 0.009356
alpha1  0.268071    0.080865  3.31503 0.000916
beta1   0.684921    0.077112  8.88213 0.000000
shape   3.335242    0.369118  9.03571 0.000000
```

Fig. 17 GARCH-M (1,1) model under t-distribution

GARCH-M (1,1) model under GED distribution:

```
spec43<-ugarchspec(
  mean.model = list(armaOrder=c(0,1),include.mean=F, archm =T),
  variance.model = list(garchOrder=c(1,1),model="sGARCH"),
  distribution.model="ged")
fit43<-ugarchfit(spec43,data=diff(p))
fit43

Optimal Parameters
------------------------------------
        Estimate  Std. Error   t value Pr(>|t|)
ma1     0.000000    0.000085 -0.000024 0.999981
archm   0.000000    0.000062 -0.000014 0.999989
omega   0.000337    0.000119  2.826642 0.004704
alpha1  0.298712    0.089771  3.327510 0.000876
beta1   0.636872    0.088684  7.181344 0.000000
shape   0.833929    0.064213 12.986944 0.000000
```

Fig. 18 GARCH-M (1,1) model under GED distribution

3.5. Model Fitting

3.5.1. Model Optimization Selection

Table 1. Parameter test results

Numble	GARCH(1,1)	EGARCH(1,1)	IGARCH(1,1)	GARCH-M(1,1)
N	-3.2339	-3.2297	-3.2252	-3.2335
t	-3.4902	-3.4859	-3.4905	-3.4870
GED	-3.4837	-4.3678	-3.4845	-3.4796

According to the AIC criterion, the IGARCH (1,1) model under the t-distribution has the smallest AIC value of -3.4905, followed by the GARCH (1,1) model under the t-distribution with an AIC value of -3.4902. Next, model validation and prediction will be conducted based on these two models.

3.5.2. Parameter Significance Test

Perform significance tests on each parameter of GARCG (1,1) model and IGARCH (1,1) model based on t-distribution:

```
> fit12@fit$matcoef
         Estimate   Std. Error  t value     Pr(>|t|)
omega  0.0002823128 0.0001087211 2.596669 0.0094132501
alpha1 0.2691196027 0.0815555272 3.299833 0.0009674245
beta1  0.6829788594 0.0781885859 8.735020 0.0000000000
shape  3.3400910534 0.3692413867 9.045820 0.0000000000

> fit32@fit$matcoef
         Estimate  Std. Error   t value     Pr(>|t|)
omega  0.0002803467 0.000116242  2.411750 1.587615e-02
alpha1 0.3142460075 0.078306301  4.013036 5.994276e-05
beta1  0.6857539925          NA        NA           NA
shape  3.1263428703 0.238289127 13.119956 0.000000e+00
```

Fig. 19 Result of parameter significance test

The output results show that when the significance level is set to 0.5, the P-values of the parameter tests for the GARCH (1,1) model under the t-distribution are all less than 0.05. Through the significance test, it indicates that the parameters are significantly non-zero, and the GARCH (1,1) model based on the t-distribution is effective; Similarly, the IARCH (1,1) model under the t-distribution also passed the parameter significance test.

3.5.3. Model Significance Test

Perform white noise testing on standardized residual sequences and residual squares:

```
Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                    0.01172  0.9138
Lag[2*(p+q)+(p+q)-1][2]   0.28850  0.8021
Lag[4*(p+q)+(p+q)-1][5]   1.00139  0.8594
d.o.f=0
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                  0.0001191  0.9913
Lag[2*(p+q)+(p+q)-1][5] 0.9929867  0.8613
Lag[4*(p+q)+(p+q)-1][9] 1.7243484  0.9352
d.o.f=2

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.008345  0.9272
Lag[2*(p+q)+(p+q)-1][2]  0.296314  0.7978
Lag[4*(p+q)+(p+q)-1][5]  0.966230  0.8673
d.o.f=0
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                   0.007633  0.9304
Lag[2*(p+q)+(p+q)-1][5]  1.072113  0.8431
Lag[4*(p+q)+(p+q)-1][9]  1.864965  0.9205
d.o.f=2
```

Fig. 20 Result of model significance test

As shown in the figure, the standardized residual sequence test results of the GARCH (1,1) model under t-distribution show that the P-values of the delayed LB test statistic are all greater than 0.05, indicating that the selected mean model has sufficient information extraction; The test results of the standardized residual square sequence show that the P-values of the LB test statistic are also greater than 0.05, indicating that the GARCH (1,1) model is very sufficient for extracting volatility information. Therefore, it can be considered that the GARCH (1,1) fitting model based on the t-distribution is significantly valid; Similarly, the IARCH (1,1) model under the t-distribution also passed the model significance test.

3.5.4. Residual ARCH Effect Test

```
Weighted ARCH LM Tests
------------------------------------
             Statistic Shape Scale P-Value
ARCH Lag[3]   0.002308 0.500 2.000  0.9617
ARCH Lag[5]   0.361166 1.440 1.667  0.9236
ARCH Lag[7]   0.903110 2.315 1.543  0.9288

Weighted ARCH LM Tests
------------------------------------
             Statistic Shape Scale P-Value
ARCH Lag[3] 1.358e-06 0.500 2.000  0.9991
ARCH Lag[5] 3.812e-01 1.440 1.667  0.9180
ARCH Lag[7] 9.732e-01 2.315 1.543  0.9179
```

Fig. 21 Result of residual ARCH effect test

From Figure 21, it can be seen that at a 95% confidence level, the P-values of Yuexiu REITs are significantly greater than 0.05, indicating that there is no ARCH effect in the residual sequence of Yuexiu REITs. Similarly, the IARCH (1,1) model under t-distribution also eliminates heteroscedasticity effects.

3.6. Model Prediction

Table 2. GARCH (1,1) model prediction results

k	predictive value	standard deviation	95% confidence lower limit	95% confidence upper limit
1	1.41	0.066	1.2813	1.5387
2	1.41	0.093	1.2272	1.5928
3	1.41	0.115	1.1852	1.6348
4	1.41	0.133	1.1494	1.6706
5	1.41	0.150	1.1175	1.7025

Table 3. GARCH (1,1) model prediction results

k	predictive value	standard deviation	95% confidence lower limit	95% confidence upper limit
1	1.41	0.0713	1.270166	1.5498
2	1.41	0.1023	1.209541	1.6105
3	1.41	0.1269	1.161220	1.6588
4	1.41	0.1485	1.119009	1.7010
5	1.41	0.1681	1.080550	1.7395

Finally, the closing price sequences of Yuexiu REITs based on the GARCH (1,1) model and the IGARCH (1,1) model under t-distribution are predicted for the next 5 periods. It can be found that the true closing prices of Yuexiu REITs for the next 5 working days (November 2, 2022 to July 7, 2022) are:

1.41, 1.48, 1.40, 1.48, 1.58

Comparing Tables 3-2 and 3-3, it can be seen that the confidence intervals obtained from the GARCH (1,1) model and the IGARCH (1,1) model under the t-distribution both contain the true values of the sequence, but the GARCH (1,1) model under the t-distribution has a narrower range of confidence intervals and higher accuracy.

4. Summary

This article selects the closing prices of Yuexiu REITs from November 1, 2018 to November 1, 2022 as research data, and based on the GARCH model theory, establishes GARCH (1,1) model, EGARCH (1,1) model, IGARCH (1,1) model, and GARCH-M (1,1) model based on normal distribution, t-distribution, and GED distribution. According to the AIC criterion, the GARCH (1,1) model based on t-distribution and the IGARCH (1,1) model were selected to predict the future closing prices of Yuexiu REITs. The results showed that the GARCH (1,1) models under t-distribution had a narrower confidence interval range and higher accuracy.

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