

Research on Investment Risks of Transportation REITs Based on the GARCH-VaR Model

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ABSTRACT

This study focuses on China's transportation Real Estate Investment Trusts (REITs). Addressing the issues of complex return volatility characteristics and the inability of traditional risk models to accurately depict extreme risks, a dynamic risk measurement framework based on the GARCH-VaR model is constructed. Daily return data of three transportation REITs—Ping An Guangzhou-Guangzhou-Hengyang Expressway REIT, China Universal Yuexiu Expressway REIT, and Zheshang Shanghai-Hangzhou-Ningbo Expressway REIT—are selected. Descriptive statistics, stationarity tests, and ARCH effect tests are conducted to verify their leptokurtic, fat-tailed, and volatility clustering characteristics. On this basis, the GARCH model is established to calculate VaR values at the 95% confidence level, and the Kupiec failure rate test is used to evaluate model effectiveness. The results show that the GARCH-VaR model provides accurate risk measurement for Ping An Guangzhou-Guangzhou-Hengyang Expressway REIT and Zheshang Shanghai-Hangzhou-Ningbo Expressway REIT, but underestimates the risks of China Universal Yuexiu Expressway REIT. This study offers a more scientific dynamic risk early warning tool for REITs investors and empirical evidence for regulatory authorities to improve risk management mechanisms.

KEYWORDS

Transportation REITs; GARCH; VaR; Investment risk; Volatility

1 Introduction

As an investment tool combining real estate attributes and financial liquidity, Real Estate Investment Trusts (REITs) have developed rapidly in China's capital market. Especially in the infrastructure sector, transportation REITs are highly associated with the macroeconomy and logistics prosperity, presenting complex and diverse risk structures. Traditional risk measurement methods such as historical simulation or VaR under the normal distribution assumption struggle to capture the "leptokurtic and fat-tailed" and volatility clustering characteristics of financial time series, leading to insufficient identification of extreme risks. Therefore, constructing a dynamic risk model suitable for REITs holds significant theoretical and practical significance.

Although existing domestic and foreign studies have made progress in REITs risk modeling, most focus on the overall market or specific asset types (e.g., logistics, industrial parks). Systematic risk modeling and model applicability testing specifically for transportation REITs remain insufficient. To address this gap, this study focuses on transportation REITs, employs the GARCH-VaR model for risk measurement, and evaluates the model's applicability across different REITs through the failure rate test. The innovations of this study lie in: stronger industry targeting of the research object, more systematic and in-depth model testing, and direct reference value of the conclusions for investors' risk decision-making and regulatory policy formulation.

2 Literature Review

2.1 Foreign Literature Review

The foreign REITs market is mature, and relevant research has formed a multi-dimensional system. In terms of risk research, Gyourko and Keim (1992) empirically revealed the strong correlation between REITs returns and macroeconomic indicators such as GDP growth rate and inflation rate, confirming the significant impact of economic cycles on their risk levels^[1]; Chen and Tzang (2008) focused on interest rate risk, pointing out that rising interest rates exacerbate REITs return volatility through the dual paths of increasing financing costs and reducing asset valuations^[2]. In the field of credit risk, Fabozzi et al. (2007) emphasized that credit ratings are the core basis for assessing REITs default risk, while asset quality and liability structure are key variables determining rating levels; in liquidity risk research^[3], Wang and Yue (2010) confirmed that market scale and diversified investor structure can effectively improve REITs liquidity and reduce liquidity risk^[4].

In terms of model application, foreign scholars have earlier verified the adaptability of the GARCH-VaR model. Zhou and Jian (2012) compared multiple models and found that GARCH-VaR models such as EGARCH-skewt and GARCH-t can accurately capture the leptokurtic, fat-tailed, and volatility clustering characteristics of REITs returns, achieving the optimal risk prediction effect^[5]; subsequent studies further expanded the model application scenarios, improving the calculation accuracy of VaR values under different market environments by adjusting lag orders and distribution

assumptions, making it a mainstream tool for REITs risk measurement.

2.2 Domestic Literature Review

Domestic research aligns with the development practice of public REITs, focusing on risk characteristics and model applications in the local context. In terms of risk identification, Chen Canbin (2019) pointed out that China's REITs combine both real estate and securities attributes, facing overlapping risks from policy changes, market fluctuations, and product-specific operational issues^[6]; Gao Siyu (2020) empirically showed that low interest rates have a positive effect on REITs returns, while strong exchange rate volatility has an inhibitory effect. In specialized asset research^[7], Du Yanhui et al. (2022) sorted out the core risk factors of industrial park REITs^[8], while Liu Qian and Wang Heidi (2022) focused on the market risk transmission mechanism of commercial real estate REITs^[9].

In terms of model application, domestic scholars have conducted extensive empirical studies based on local data. Zhang Hong et al. (2016) took Hong Kong REITs as samples and confirmed the effectiveness of the GARCH-VaR model in risk measurement^[10]; Wang Guihan et al. (2023) studied the first batch of public infrastructure REITs and found that the GARCH-VaR model under the t-distribution has the best estimation effect, with toll road REITs having the highest risk and industrial park REITs the lowest. In addition^[11], Jin Lin and Song Xin (2021) extended the model to logistics real estate REITs^[12]; Xue Ying (2022) took mainland Chinese real estate REITs listed in Hong Kong as the research object, combining the GARCH-VaR and VEC models to analyze the impact of macroeconomic factors on risks^[13]. Recent studies have measured the risk spillover effect of the REITs market through the DCC-GARCH- Δ CoVaR model, finding a strong correlation with the mainland stock market.

3 Research Methods

This study adopts an empirical research approach, conducting time series modeling and testing based on EViews software. The specific steps are as follows:

3.1 Return Calculation

The logarithmic return formula is used to calculate the daily returns of the three REITs, where r_{it} denotes the logarithmic return and p_{it} denotes the closing price.

$$r_{it} = \ln(p_{it}) - \ln(p_{it-1})$$

3.2 Data Preprocessing and Testing

Including descriptive statistics, Jarque-Bera (JB) normality test, ADF unit root test, autocorrelation test, and ARCH-LM effect test to confirm whether the series meets the conditions for establishing the GARCH model.

3.3 GARCH Model Construction

A GARCH(1, 1) model is established, including a mean equation and a variance equation. Parameter estimation and stability testing are conducted to verify whether the model can effectively capture volatility clustering characteristics, where ε_{it} denotes the residual of the mean equation and σ_{it}^2 denotes the conditional variance.

Mean equation: $r_{it} = \mu_i + \varepsilon_{it}$

Variance equation: $\sigma_{it}^2 = c_i + a\varepsilon_{it-1}^2 + b\sigma_{it-1}^2$

3.4 VaR Calculation

Based on the conditional variance estimated by the GARCH model, the dynamic VaR value at the 95% confidence level is calculated, where $\phi(95\%)$ denotes the critical value of the 95% quantile of the normal distribution.

$$VaR_{it} = \phi(95\%) \sigma_{it}$$

3.5 Model Effectiveness Testing

The Kupiec failure rate test is adopted to evaluate the accuracy of the GARCH-VaR model's risk prediction by comparing the number of days when actual losses exceed VaR with the theoretical expected value.

Data are sourced from the Wind database, with the sample period ranging from January 2022 to December 2024, covering complete daily trading data of three REITs: Ping An Guangzhou-Guangzhou-Hengyang Expressway REIT, China Universal Yuexiu Expressway REIT, and Zheshang Shanghai-Hangzhou-Ningbo Expressway REIT. These three transportation REITs are selected mainly because they were listed earlier, have sufficient data volume, and strong representativeness.

4 Empirical Results

The logarithmic returns of Ping An Guangzhou-Guangzhou-Hengyang Expressway REIT, China Universal Yuexiu Expressway REIT, and Zheshang Shanghai-Hangzhou-Ningbo Expressway REIT are denoted as R_GZGH , R_YXGS , and R_HHY , respectively.

4.1 Trend Charts

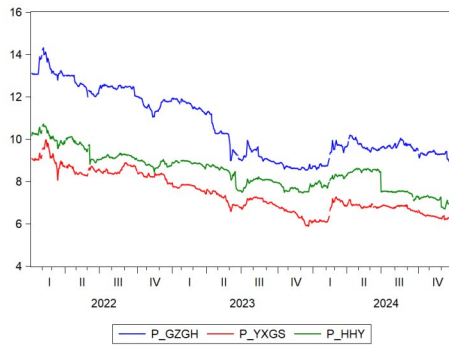


Figure 1 Closing Prices of Three Transportation REITs

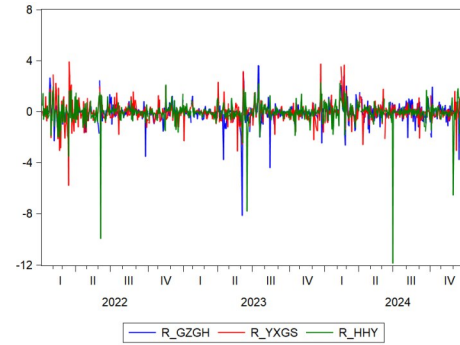


Figure 2 Logarithmic Returns of Three Transportation REITs

As shown in the figures, from 2022 to 2024, the closing prices of the three transportation REITs generally showed a volatile downward trend. Their logarithmic returns fluctuated around zero, with large fluctuations followed by large fluctuations and small fluctuations followed by small fluctuations, indicating strong volatility clustering.

4.2 Descriptive Statistics

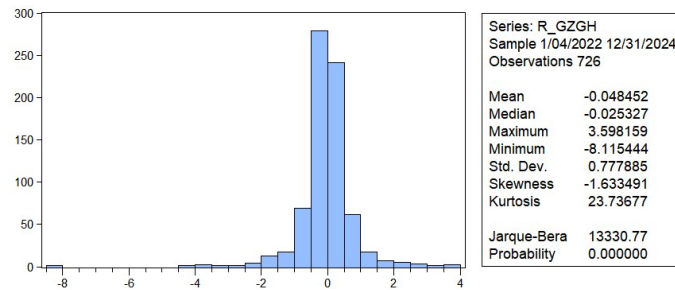


Figure 3 Descriptive Statistics of R_GZGH

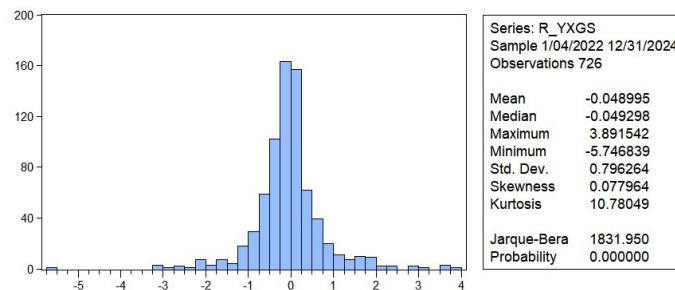


Figure 4 Descriptive Statistics of R_YXGS

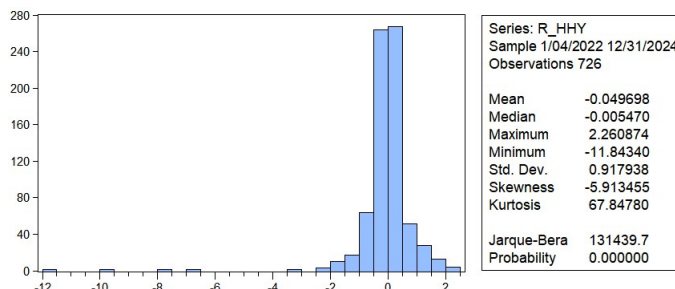


Figure 5 Descriptive Statistics of R_HHY

As shown in the figures, the logarithmic returns of the three transportation REITs have negative means and kurtosis greater than 3. The JB statistic shows a P-value of 0, indicating rejection of the null hypothesis that the returns follow a normal distribution. This reflects the leptokurtic and fat-tailed distribution characteristics of financial time series.

4.3 Q-Q Plots

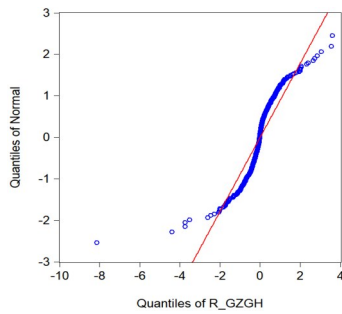


Figure 6 Q-Q Plot of R_GZGH

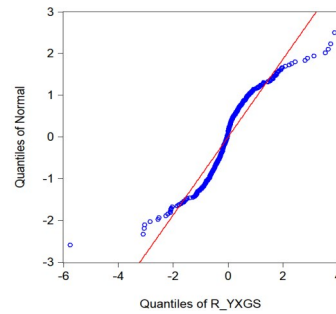


Figure 7 Q-Q Plot of R_YXGSTransportationREITs

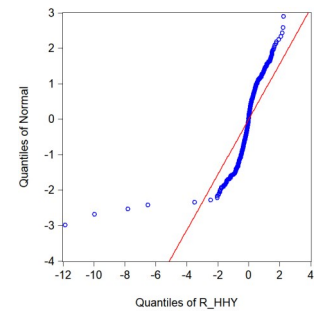


Figure 8 Q-Q Plot of R_HHY

As shown in the figures, the vertical axis represents the quantiles of the normal distribution, and the horizontal axis represents the quantiles of the logarithmic return distributions of the three transportation REITs. The red line denotes the normal distribution line, and the blue scatter points correspond to the quantiles of each logarithmic return distribution. The closer the blue scatter points are to the line, the closer the actual distribution is to the normal distribution; otherwise, it is less consistent. It can be clearly seen that the logarithmic return distributions of the three transportation REITs deviate from the red reference line, thus confirming that they do not follow a normal distribution, which is consistent with the conclusion of the JB statistic.

4.4 ADF Unit Root Test

Table 1 ADF Unit Root Test Results

	ADF-Statistic	Prob.
R_GZGH	-18.4599	0.0000
R_YXGS	-22.2839	0.0000
R_HHY	-25.2024	0.0000

As shown in the table, the ADF unit root test's null hypothesis is the existence of a unit root (non-stationary series). It is found that the P-values of the logarithmic returns of the three transportation REITs are all 0.0000, rejecting the null hypothesis at the 1% significance level. This indicates that the logarithmic returns of the three REITs are stationary series with good statistical properties.

4.5 Autocorrelation Test

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.270	0.270	52.953	0.000
		2 -0.050	-0.133	54.806	0.000
		3 -0.111	-0.066	63.829	0.000
		4 -0.013	0.036	63.945	0.000
		5 0.056	0.037	66.204	0.000
		6 0.073	0.042	70.062	0.000
		7 -0.022	-0.051	70.433	0.000
		8 -0.043	-0.007	71.794	0.000
		9 -0.028	-0.009	72.357	0.000
		10 0.023	0.021	72.736	0.000

Figure 9 Autocorrelation Test of R_GZGH

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.183	0.183	24.475	0.000
		2 -0.048	-0.085	26.178	0.000
		3 0.018	0.045	26.422	0.000
		4 0.050	0.035	28.275	0.000
		5 0.103	0.094	36.058	0.000
		6 0.038	0.005	37.102	0.000
		7 -0.149	-0.154	53.477	0.000
		8 -0.048	0.007	55.189	0.000
		9 0.013	-0.008	55.308	0.000
		10 0.027	0.024	55.858	0.000

Figure 10 Autocorrelation Test of R_YXGS

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.063	0.063	2.8723	0.090
		2 -0.062	-0.066	5.6893	0.058
		3 -0.038	-0.030	6.7714	0.080
		4 -0.029	-0.029	7.3832	0.117
		5 0.015	0.014	7.5448	0.183
		6 -0.007	-0.014	7.5844	0.270
		7 -0.047	-0.046	9.1960	0.239
		8 0.024	0.030	9.6369	0.291
		9 0.056	0.047	11.920	0.218
		10 0.035	0.029	12.841	0.233

Figure 11 Autocorrelation Test of R_HHY

As shown in the figures, the autocorrelation test's null hypothesis is no autocorrelation in the series. It is found that the P-values of the first 10 lags of autocorrelation tests for R_GZGH and R_YXGS are all 0, indicating obvious autocorrelation. Therefore, the mean equation of the subsequent GARCH model needs to adopt an AR model to improve autocorrelation; the P-values of the first 10 lags of the autocorrelation test for R_HHY are all greater than 0.05, indicating no autocorrelation (a white noise process). Thus, the mean equation of the subsequent GARCH model only needs to include a constant term.

4.6 ARCH-LM Effect Test

Table 2 ARCH-LM Effect Test Results

R_GZGH	F-statistic	14.7770	Prob. F(1,723)	0.0001
	Obs*R-squared	14.5211	Prob. Chi-Square(1)	0.0001
R_YXGS	F-statistic	135.3780	Prob. F(1,723)	0.0000
	Obs*R-squared	114.3424	Prob. Chi-Square(1)	0.0000
R_HHY	F-statistic	0.0136	Prob. F(1,723)	0.9072
	Obs*R-squared	0.0136	Prob. Chi-Square(1)	0.9071

As shown in the table, the ARCH-LM effect test's null hypothesis is no ARCH-LM effect in the residual series. It is found that the P-values of the residual tests for R_GZGH and R_YXGS are less than 0.01, rejecting the null hypothesis at the 1% significance level. This indicates that the residuals of R_GZGH and R_YXGS have obvious ARCH-LM effects, making them more suitable for establishing the GARCH model; the P-value of the residual test for R_HHY is 0.9072, indicating no ARCH-LM effect in its residuals, and the fitting effect of the GARCH model needs further observation.

4.7 GARCH Model Parameter Estimation

Table 3 GARCH Model Parameter Estimation of R_GZGH

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.1118	0.0217	-5.1607	0.0000
AR(1)	0.1661	0.0410	4.0546	0.0001
Variance Equation				
C	0.0906	0.0102	8.8770	0.0000
RESID(-1)^2	0.4939	0.0385	12.8261	0.0000
GARCH(-1)	0.4858	0.0327	14.8459	0.0000

For the GARCH modeling of R_GZGH, the parameter estimation results show that the P-values of all parameters are less than 0.01, indicating statistical significance at the 1% level. In addition, the ARCH term parameter is 0.4939, and the GARCH term parameter is 0.4858. Both are greater than 0, and their sum is less than 1, satisfying the stability condition of the GARCH model, indicating that the GARCH model is stable and effective. The specific equations are as follows:

Mean equation: $r_t = -0.1118 + 0.1661r_{t-1} + \mu_t$

Variance equation: $\sigma_t^2 = 0.0906 + 0.4939\mu_{t-1}^2 + 0.4858\sigma_{t-1}^2$

For the GARCH modeling of R_YXGS, the parameter estimation results show that except for the constant term of the mean equation, the P-values of other parameters are less than 0.01, indicating statistical significance at the 1% level. In

Table 4 GARCH Model Parameter Estimation of R_YXGS

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.2650	36.6457	0.1710	0.8643
AR(1)	1.0000	2.60E-06	385037.0000	0.0000
Variance Equation				
C	0.0005	6.39E-05	7.9799	0.0000
RESID(-1)^2	0.3551	0.0430	8.2606	0.0000
GARCH(-1)	0.5150	0.0432	11.9204	0.0000

addition, the ARCH term parameter is 0.3551, and the GARCH term parameter is 0.5150. Both are greater than 0, and their sum is less than 1, satisfying the stability condition of the GARCH model, indicating that the GARCH model is stable and effective. The specific equations are as follows:

$$\text{Mean equation: } r_t = 6.2650 + r_{t-1} + \mu_t$$

$$\text{Variance equation: } \sigma_t^2 = 0.0005 + 0.3551\mu_{t-1}^2 + 0.5150\sigma_{t-1}^2$$

Table 5 GARCH Model Parameter Estimation of R_HHY

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.0024	0.0069	-0.3414	0.7328
Variance Equation				
C	0.0466	0.0035	13.2258	0.0000
RESID(-1)^2	1.5945	0.0978	16.3093	0.0000
GARCH(-1)	0.4673	0.0194	24.0999	0.0000

For the GARCH modeling of R_HHY, the parameter estimation results show that except for the constant term of the mean equation, the P-values of other parameters are less than 0.01, indicating statistical significance at the 1% level. In addition, the ARCH term parameter is 1.5945, and the GARCH term parameter is 0.4673. Both are greater than 0, but their sum is greater than 1, indicating strong volatility. Combined with the previous trend chart of R_HHY's logarithmic returns, there are many extreme values, with the minimum value close to -12%. The specific equations are as follows:

$$\text{Mean equation: } r_t = -0.0024 + \mu_t$$

$$\text{Variance equation: } \sigma_t^2 = 0.0466 + 1.5945\mu_{t-1}^2 + 0.4673\sigma_{t-1}^2$$

4.8 GARCH-VaR Calculation

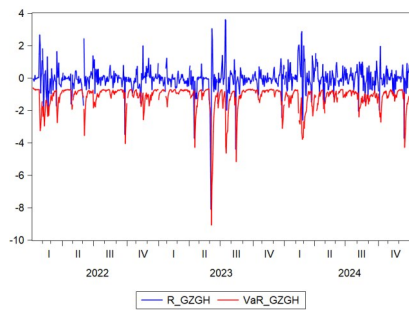


Figure 12 95% VaR vs. Return Comparison Chart of R_GZGH

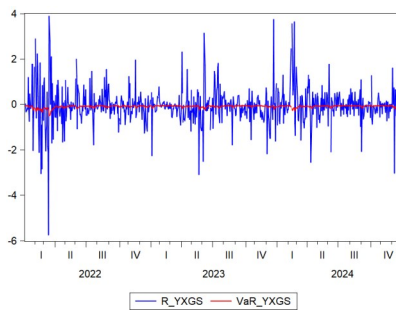


Figure 13 95% VaR vs. Return Comparison Chart of R_YXGS

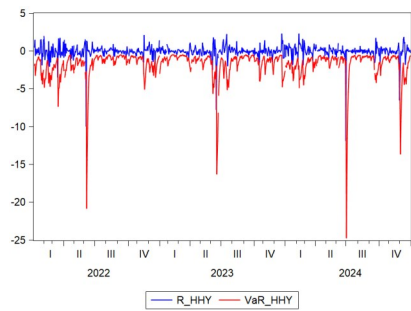


Figure 14 95% VaR vs. Return Comparison Chart of R_HHY

As shown in the figures, the comparison charts of 95% VaR (calculated by the GARCH model) and returns of the three transportation REITs. It can be intuitively seen that for R_GZGH and R_HHY, most returns are above the 95% VaR, and only a small proportion break through the VaR downward, indicating that the VaR for extreme risks measured by the GARCH model is relatively accurate; for R_YXGS, there are many trading days when returns break through the VaR downward, indicating the possibility of risk underestimation.

Table 6 Descriptive Statistics of VaR

	VaR_GZGH	VaR_YXGS	VaR_HHY
Mean	-1.1894	-0.0896	-1.7728
Median	-0.9438	-0.0707	-1.2104
Maximum	-0.6135	-0.0540	-0.4973
Minimum	-9.0802	-0.4976	-24.6906

As shown in the table, the descriptive statistics of 95% VaR calculated by the GARCH model for the three transportation REITs. It can be seen that R_HHY has the largest absolute value of 95% VaR, followed by R_GZGH, and R_YXGS has the smallest.

4.9 Kupiec Failure Rate Test

The Kupiec failure rate test results in the following table show that the total number of days is 726. R_GZGH has 29 failure days, R_HHY has 26 failure days, and R_YXGS has 349 failure days. The failure rate of R_GZGH is 4.00%, which is closest to the 5% significance level, followed by R_HHY with a failure rate of 3.58%, while R_YXGS has a failure rate of 48.07%, which is far from the 5% benchmark failure rate.

Table 7 Kupiec Failure Rate Test Results

REITs	Total Days	Failure Days	Failure Rate	LR	Prob.
R_GZGH	726	29	4.00%	1.6547	0.1983
R_YXGS		349	48.07%	198.3726	0.0000
R_HHY		26	3.58%	3.3996	0.0652

As shown in the table, the Kupiec failure rate test results indicate that the total number of days is 726. R_GZGH has 29 failure days, R_HHY has 26 failure days, and R_YXGS has 349 failure days. The failure rate of R_GZGH is 4.00%, closest to the 5% significance level, followed by R_HHY at 3.58%, while R_YXGS's failure rate of 48.07% is significantly deviated from the 5% benchmark.

From the P-values of the Kupiec failure rate test, R_GZGH and R_HHY pass the likelihood ratio test, while R_YXGS does not. This indicates that the GARCH model accurately measures the extreme risk VaR of R_GZGH and R_HHY, but is inaccurate in measuring the extreme risk of R_YXGS, leading to an excessively high failure rate and underestimating R_YXGS's extreme risks. Further comparing the extreme risk measurement effects of R_GZGH and R_HHY, R_GZGH has the highest P-value (0.1983) among transportation REITs, indicating that the GARCH model most accurately depicts the extreme risks of R_GZGH, corresponding to the failure rate of 4.00%, which is very close to 5%, neither overestimating nor underestimating risks. For R_HHY, the test P-value is 0.0652, and the accuracy of depicting extreme risks is lower than that of R_GZGH.

In summary, the GARCH model most accurately depicts the extreme risk VaR of R_GZGH, relatively accurately depicts that of R_HHY, and inaccurately depicts that of R_YXGS (underestimating risks).

5 Conclusions

This study constructs the GARCH-VaR model to measure the risks of three transportation REITs, with the following main findings: First, transportation REITs returns exhibit significant leptokurtic, fat-tailed, and volatility clustering characteristics, making them suitable for modeling with GARCH-type models; second, the GARCH-VaR model provides accurate risk measurement for Ping An Guangzhou-Guangzhou-Hengyang Expressway REIT and Zheshang Shanghai-Hangzhou-Ningbo Expressway REIT, with failure rates close to the theoretical level, while systematically underestimating the risks of China Universal Yuexiu Expressway REIT; third, there are obvious differences in risk characteristics and model applicability among different REITs, which may be related to underlying asset structures, operational environments, and other factors.

This study has certain theoretical and practical significance: at the theoretical level, it verifies the applicability and limitations of the GARCH-VaR model in transportation REITs risk measurement; at the practical level, it provides a dynamic risk monitoring tool for investors and references for regulatory authorities to identify systemic risks and improve the REITs market risk management mechanism. However, this study still has limitations, such as a sample covering only three REITs and not including macroeconomic variables. Future research can expand the sample scope, introduce multi-factor models, or combine methods such as Copula and CoVaR to further analyze the risk spillover effects of the REITs market.

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