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Measurement and Management of Interest Rate Risk of Commercial Banks: Based on VaR-GARCH Model of a Case Study of SHIBOR

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Abstract: With the acceleration of financial liberalization in China and the tremendous changes in the international financial situation, China's commercial banks face considerable interest rate risks. The profitability and solvency of commercial banks have been impacted, leading to increased operational uncertainty and even systemic risks. The Shanghai Interbank Offered Rate, launched in 2007, tends to approach the benchmark interest rate in the financial market. Therefore, this paper selects The Shanghai Interbank Offered Rate (SHIBOR) overnight lending rate from January 2017 to July 2021 as a sample and adopts a method combining the VaR and GARCH models. Through empirical analysis, this paper establishes a GARCH model to eliminate the heteroscedasticity phenomenon in the data. The results show that the SHIBOR series has the characteristics of stationary, non-normal distribution, serial autocorrelation, and heteroscedasticity. The GARCH (2,2) model under the generalized error distribution (GED) is the most effective for measuring interest rate risk. Based on this, this article puts forward suggestions that commercial banks should enhance their awareness of interest rate risk management and should actively use financial derivatives to hedge interest rate risks.

Keywords: SHIBOR; VaR model; GARCH model; Interest rate risk; Interest rate liberalization

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1. Introduction

At present, China is accelerating financial liberalization and the reform of interest rate marketization is deepening. Commercial banks that use traditional deposit-loan spreads as their primary source of income are facing huge interest rate risks. The relaxation of the ceiling on deposit interest rates has increased the pressure on the banking industry, forcing the banking industry to rely more on interbank funds. At the same time, to maintain good market competitiveness and the ability to survive and develop, commercial banks have to reduce loan interest rates while increasing deposit interest rates, thereby significantly reducing the deposit-loan spreads and thus reducing their profitability. In addition, the probability of commercial banks encountering a financial crisis is closely related to interest rate marketization [1]. Commercial banks use hedging tools to prevent and control the risk positions of off-balance-sheet businesses by increasing capital adequacy ratio management and reserve requirements to reduce the probability of financial crises [2]. Commercial banks should attach importance to risk management and accurately measure risks after identifying them in the face of interest rate risks and unavoidable operating pressures brought about by interest rate fluctuations.

With the intensification of financial risks, banks are constantly researching and adjusting the risk measurement methods of interbank lending rates. The shortcomings of traditional interest rate risk measurement have gradually emerged, such as the interest rate sensitive gap model and duration gap model. In contrast, the VaR model is time-sensitive, intuitive and comprehensive, and is more suitable for analyzing the risk of interbank lending rates. Therefore, this paper adopts the VaR model to measure commercial banks' interbank lending interest rate risk.

Many studies have focused on the application of the VaR model to interest rate risk measurement. Wu et al. consider the persistence characteristics of interest rate futures in the financial market and construct a VaR algorithm based on the GARCH model and the FIGARCH model to measure the value at risk. Results show that, compared with the traditional model, the compound model can perform a more accurate dynamic calculation of the risk level of interest rate futures [3]. Slim et al. study the performance of 21 VaR models based on GARCH, GJR, and FIGARCH under seven distributions [4]. Peng et al. find through empirical research that the t-distribution is not suitable for describing the distribution of China's interbank lending rate returns, while the Generalized Error Distribution (GED) can better describe the distribution of China's interbank lending rate [5]. In general, previous studies first fit conditional heteroscedasticity models under different distributions, then obtain VaR values under different models, and finally obtain the optimal model by comparing the failure rate and likelihood ratios (LR) value.

Based on the analysis of relevant research results, this paper studies standard interest rate risk measurement, including interest rate sensitive gap model, duration method, and VaR method, and analyzes the applicability of different risk measurement models. This paper uses the GARCH-VaR model for empirical testing and selects the Shanghai Interbank Offered Rate (SHIBOR) from January 2017 to July 2021 as the sample data. The author first processed the data of SHIBOR, then analyze its statistical characteristics and select a suitable conditional heteroscedasticity model to fit the mean equation and variance equation of the sample sequence. Next, the author calculated the VaR value and compare it with the actual profit and loss value to analyze the validity of the model and its applicability in China. Finally, the author put forward a proposal to improve the risk management level of Chinese commercial banks.

The innovation of this paper is to combine the VaR model with the GARCH model for empirical analysis and explore the applicability of the VaR model in China's interbank lending market to give insights for commercial banks to better manage and respond to interest rate risks. There are still deficiencies in the research process of the article. The selection of sample data is only for SHIBOR overnight data and does not involve data on other interest rate-related products in the market. Therefore, the effectiveness of the results on the overall market still needs to be improved.

2. Methodology

2.1. Interest rate sensitive gap model

J.P Morgan first proposed the interest rate sensitive gap (ISG) in 1983. This method divides assets and liabilities according to their sensitivity to interest rates. Financial assets whose income generated by assets and liabilities are easily affected by market interest rates are interest rate sensitive assets (IRSA), and vice versa are interest rate sensitive liabilities (IRSL). The calculation formula is:

$$\mathrm{ISG} = \mathrm{IRSA} - \mathrm{IRSL} \tag{1}$$

In addition, the interest rate sensitivity coefficient (λ) can be used to measure the bank's interest rate risk. The calculation formula is:

$$\lambda = \frac{\mathrm{IRSA}}{\mathrm{IRSL}} \tag{2}$$

As an absolute indicator, ISG is the absolute difference between IRSA and IRSL, a numerical value. Correspondingly, the coefficient λ, as a relative indicator, is the ratio of IRSA to IRSL, which is a proportional relationship. Suppose there is a consistent change in the interest rate of deposits and loans. In that case, the sensitivity of commercial banks' interest rate differential income to changes in interest rates can be measured by the ISG indicator. When ISG is positive, λ is greater than 1, an asset sensitivity gap forms, and the bank interest rate is positively related to net interest income. When ISG is negative, λ is less than 1, a liability sensitivity gap forms, and the bank interest rate is negatively related to the net interest income. When ISG is zero, λ equals 1, the sensitivity gap of this state is zero, and the bank interest rate is irrelevant to the net interest income. **Table 1** shows the impact of ISG and λ on interest income.

Table 1. The impact of interest rate sensitive gap and coefficient on interest income

λ	ISG	Interest rate rise			Interest rate fall		
		Interest income	**Interest expense**	**Net interest margin**	**Interest income**	**Interest expense**	**Net interest margin**
>1	positive	increase	increase	increase	decrease	decrease	decrease
<1	negative	increase	increase	decrease	decrease	decrease	increase
=1	zero	increase	increase	decrease	decrease	decrease	unchanged

Conservative banks can adjust the size of interest rate sensitive assets and liabilities to make ISG equal to 0 so that net income is not affected by changes in interest rates. On the contrary, there is no need for radical banks to set ISG to 0. In this way, banks can predict the trend of interest rate changes while controlling the gap to increase the profits of commercial banks.

2.2. Duration gap model

F.R. Macaulay first proposed the concept of duration in 1938 [6], mainly used to calculate the average time required to recover the investment, representing the length of time for the bond or investment portfolio exposed to interest rate risk. Under normal circumstances, the longer the duration, the longer the risk exposure, and the greater the interest rate risk. To get the duration, first, convert the cash flow generated in the future into the present value, then multiply the present value by the bond's maturity date, sum up, and finally divide by the bond's current price. The calculation formula is:

$$D = \frac{\sum_{t=1}^{T} C_t \times \frac{t}{(1+r)^t}}{\sum_{t=1}^{T} \frac{C_t}{(1+r)^t}} \tag{3}$$

D represents the Macaulay duration, t represents the period of cash flow generation, r represents the yield to maturity, C represents the cash flow generated in period t, and T represents the remaining maturity of the bond.

When the duration gap is positive, the net capital value of commercial banks is inversely proportional to the interest rate, and the net capital value of commercial banks decreases when the interest rate rises. Conversely, when interest rates fall, the net capital of commercial banks increases. Correspondingly, when the duration gap is negative, the net capital value of commercial banks is directly proportional to the interest rate. When the interest rate rises, the net capital value of commercial banks increases. Conversely, when the interest rate falls, the net capital value of commercial banks decreases. In other words, as long as the absolute value of the commercial bank's duration gap is not zero, changes in interest rates will affect its net capital, and interest rate risks will exist. Furthermore, the absolute value of the duration gap is directly proportional to the interest rate risk of commercial banks.

Similar to ISG, conservative banks will adjust the duration gap to 0 to avoid the impact of interest rate fluctuations on income. Aggressive banks use active gap management strategies to obtain higher returns when interest rate fluctuations are consistent with expectations.

2.3. VaR model

VaR (Value at Risk) was first proposed by the G30 Group based on derivatives research. Later, the VaR model launched by J.P Morgan was widely used to calculate value at risk. It represents the maximum loss that a financial asset or a combination of financial assets may face under a certain confidence level. Its mathematical expression is:

$$P(\Delta > \text{VaR}) = 1 - \alpha \tag{4}$$

Among them, α is the confidence level and the commonly used confidence level is 90%-99%. ΔP is the possible profit and loss of the asset portfolio during a specific holding period. VaR represents the maximum value of ΔP within the confidence level α. Assuming that the probability distribution of the portfolio's return is known, the VaR value of the portfolio can be expressed as follows:

$$VaR_t = -V_0 \times Z_\alpha \times \sigma \times \sqrt{\Delta t} \tag{5}$$

Among them, α is the confidence level, and the commonly used confidence level is 90%-99%. V_0 represents the initial value of a financial asset or investment portfolio, and Z_α is the quantile corresponding to the corresponding confidence level. Δt is the holding period. σ represents the volatility of the investment portfolio.

2.4. Applicability of different risk measurement models

With the continuous advancement and reform of interest rate liberalization in China, the shortcomings of the traditional gap models have gradually been exposed in recent years. First of all, when calculating ISG, the criteria for dividing IRSA and IRSL are highly subjective, and these assets and liabilities are the main targets of commercial banks' regulation. Therefore, it is difficult for banks to maintain the accuracy of the gap. Secondly, the measurement of the duration gap is based on the assumption that the commercial bank's asset and liability interest rate levels and interest rate fluctuations are the same. This is inconsistent with reality, thus limiting the practicability and accuracy of the duration gap model. Finally, the gap model is a static measurement method based on the judgment of the macroeconomy, so it is impossible to measure the size of the risk.

Compared with traditional interest rate risk measurement methods, the VaR model can more accurately measure the bank's maximum loss in a given period, that is, the amount of interest rate risk it faces. According to the principles and characteristics of the VaR model, four main advantages can be summarized. First, the VaR model is a comprehensive measurement method. Under the framework of the comprehensive application of the VaR model, all possible market risk factors are considered, and the future market value of the investment portfolio is simulated by determining market factors and mapping the head of the investment portfolio. Second, the VaR model calculates the probability of occurrence of each predictable situation encountered in the future and the benefit of loss at the same time. Third, the VaR value is more dependent on the time range of the selection interval, and the selected probability level is the crucial factor. The former is positively related to it, and the latter is negatively related. Fourth, the VaR method also fully considers the correlation of different asset prices in changes, thereby reflecting the diversification of the investment portfolio and its contribution to risk reduction. In summary, the VaR model has universal applicability to the current risk management of various financial markets. At the same time and quality, the VaR model describes the loss more efficiently.

The primary interest rate used in the Chinese interbank lending market is SHIBOR. As a short-term fund borrowing market, overnight borrowing rates are frequently used. For financial institutions, interest rate risk management is dynamic, and financial institutions need to accurately measure the risk of the interbank lending positions held on the next trading day. Therefore, this paper uses the VaR model to measure it.

3. Data

3.1. Data and sample

This paper selects the overnight (O/N) data of Shanghai Interbank Offered Rate (SHIBOR) from January 2017 to July 2021, a total of 1142 samples. The determination of SHIBOR is based on the arithmetic average interest rate calculated regarding the quotations of 18 commercial banks approved by the People's Bank of China with higher credit ratings and larger transaction scales. Therefore, it is objective and accurate, and the information disclosed is sufficient. At the same time, as China's benchmark interest rate, slight changes in SHIBOR can drive changes in other market interest rates, so it can sensitively reflect the supply and demand relationship of currencies in the market. Therefore, SHIBOR is chosen as the sample for empirical analysis. SHIBOR data comes from the Shanghai Interbank Offered Rate website (http://www.shibor.org), and the time-frequency is daily data, using Eviews12 and Excel for empirical analysis.

3.2. Stationarity test

The stationarity test is to test whether there is a trend effect in the data. Only when the data satisfies the stability, the corresponding model can be established. Before using the GARCH model to fit the SHIBOR from January 2017 to July 2021, the stability of the financial time series must be ensured.

The intuitive way to test the stationarity of the SHIBOR time series is to draw its time series diagram. **Figure 1** shows the time series of SHIBOR from January 2017 to July 2021. It can be seen that SHIBOR has significant instability. If it is directly used for modeling and analysis, serious autocorrelation and volatility problems will occur. Therefore, to obtain relatively stable overnight SHIBOR time series data, the author took the logarithm of the interbank offered rate and then differentiate to obtain the rate of return on the interbank offered rate, which is calculated as:

$$R_t = lnShibor_t - lnShibor_{t-1} \tag{6}$$

Among them, $lnShibor_t$ and $lnShibor_{t-1}$ are the SHIBOR overnight rate of return on day t and t-1, respectively, and R_t is the logarithmic differential rate of return of the overnight SHIBOR rate on day t. Hereafter, the time series is called the return rate series. The Time Series Diagram of R_t is shown in **Figure 2**. According to **Figure 2**, the apparent trend has been eliminated, showing that the logarithmic rate of return has volatility clustering.

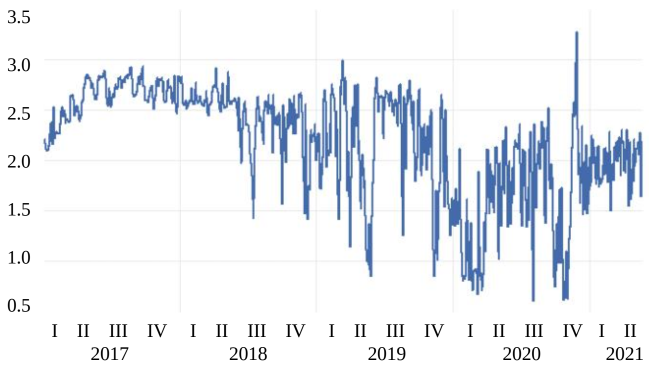

Figure 1. Time series diagram of SHIBOR (Source: Eviews12)

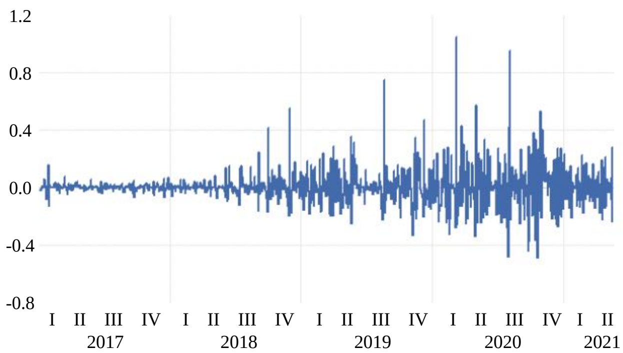

Figure 2. Time series diagram of R_t (Source: Eviews12)

To further verify the stationarity of the return rate series, the Augmented Dickey-Fuller (ADF) test is performed below. The ADF test refers to the process of testing whether there is a unit root in the series. It can be proved that if there is a unit root process in the series, it must be unstable, which will lead to spurious regression in the regression analysis.

Table 2 shows the ADF value of the sequence R_t under the three test forms. In the first test form, which includes the constant, the ADF statistic of R_t is -25.48344, which is significantly smaller than the corresponding t statistic at 1%, 5%, and 10% confidence levels: -3.435881, -2.863870, -2.568061. The probability corresponding to the ADF statistical value is 0.0000, so the null hypothesis that there is a unit root is rejected, and the R_t series is considered stationary. In the same way, under the other two test forms, the R_t series is also stationary. Therefore, it can be concluded that there is no unit root process in the return rate series, and it has good stability.

Table 2. Stationarity test results of return rate series

Null Hypothesis: R_t has a unit root				
		Constant	**Constant, Linear Trend**	**None**
t-Statistic		-25.48344	-25.47219	-25.49470
Prob.*		0.0000	0.0000	0.0000
	1% level	-3.435881	-3.966131	-2.566996
Test critical values	5% level	-2.863870	-3.413766	-1.941102
	10% level	-2.568061	-3.128953	-1.616512

*MacKinnon (1996) one-sided p-values. Source: Eviews12

3.3. Normality test

The VaR model's measurement of asset risk is based on the assumption of normal distribution. However, the normal distribution is rare in reality, and most financial time series do not meet this assumption. Therefore, a normality test is performed on the rate of return data. The normality of the R_t series can be judged by the Quantile-Quantile(Q-Q) graph, and it can also be analyzed according to the descriptive statistics of the sequence.

The Q-Q graph depicts the actual quantile of the sequence on the graph. If the logarithmic return data obey a normal distribution, the data are displayed on a straight line; otherwise, there will be a bending phenomenon. The Q-Q graph of the R_t logarithmic return series is shown in **Figure 3**. The arrangement of the data presents an S-curved state, indicating that the sequence does not obey the normal distribution, and there is a fat-tailed phenomenon.

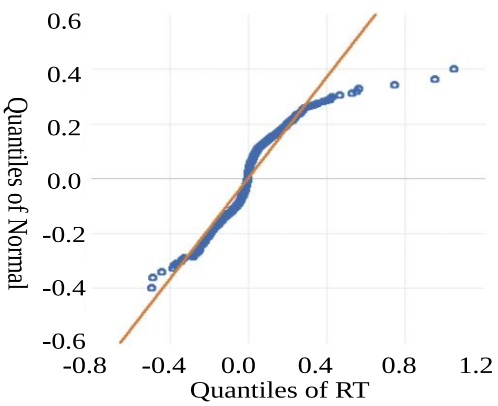

Figure 3. Q-Q graph of return rate series

Source: Eviews12

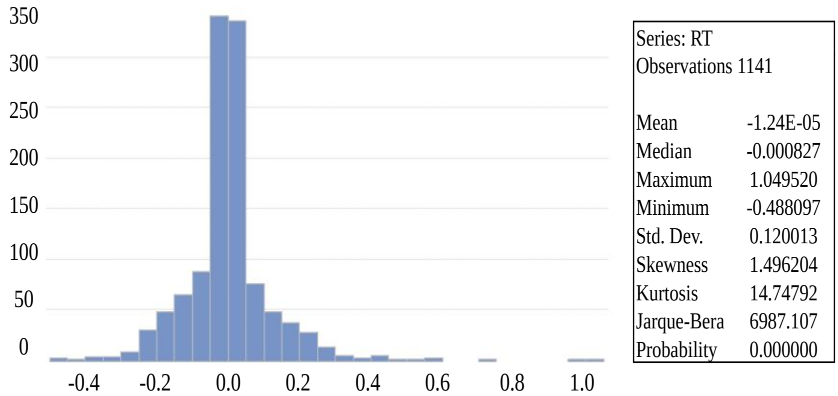

Figure 4. Normality test results of return rate series

Source: Eviews12

As shown in **Figure 4**, the skewness value of the R_t series is greater than 0, so it is a right-skewed distribution with right-tailing while the kurtosis value is 14.74792, which is much larger than the kurtosis value of 3 of the normal distribution. Thus, there is a leptokurtosis feature. The J-B statistic is 6987.107, and its corresponding P-value is significantly less than 0.05, rejecting the null hypothesis of normal distribution. Therefore, it can be concluded that the R_t series does not obey the normal distribution, and its distribution has apparent characteristics of leptokurtosis and fat-tailed

3.4. Correlation test

Empirical research shows that financial time series data often exhibit significant time inertia due to the lag of economic behavior, the inertia of economic variables, the influence of other random accidental factors, and the processing of observational data. That is, the data at different points in the time series have a certain degree of interrelationship. If the autocorrelation of the data is not considered, it will lead to the failure of the model prediction and the significance test and the invalid parameter estimation. Therefore, it is necessary to conduct autocorrelation analysis on the R_t series.

The autocorrelation coefficient (AC) and partial correlation coefficient (PAC) of each lag period are shown in **Table 3**. It can be seen that the AC and PAC of the R_t series are not all zero. The AC and PAC lagging one order are both 0.112, the AC and PAC lagging eighth order are both -0.028, and the AC and PAC lagging eleventh order are both -0.038. Moreover, Q-Statistics increases with the increase of the lag order, which is greater than the critical value of a certain confidence level (95%), and the P-value of the test result is far less than 0.05. Therefore, it can be concluded that there is serial autocorrelation in the sequence of the R_t series.

Table 3. Correlation test results of return rate series

Lag Order	AC	PAC	Q-Statistics	Prob	Lag Order	AC	PAC	Q-Statistics	Prob
1	0.112	0.112	14.368	0.000	19	0.024	-0.013	137.77	0.000
2	-0.172	-0.187	48.370	0.000	20	-0.036	-0.056	139.24	0.000
3	-0.221	-0.186	104.23	0.000	21	0.005	0.000	139.27	0.000
4	-0.049	-0.037	106.99	0.000	22	0.048	0.021	141.90	0.000
5	0.054	-0.006	110.34	0.000	23	0.060	0.026	146.11	0.000
6	-0.008	-0.074	110.42	0.000	24	0.025	0.022	146.82	0.000
7	-0.047	-0.053	112.91	0.000	25	0.019	0.042	147.24	0.000
8	-0.028	-0.028	113.81	0.000	26	-0.012	-0.003	147.41	0.000
9	0.059	0.035	117.81	0.000	27	-0.027	-0.021	148.25	0.000
10	0.011	-0.034	117.95	0.000	28	-0.074	-0.082	154.67	0.000
11	-0.038	-0.038	119.64	0.000	29	-0.042	-0.039	156.76	0.000
12	-0.085	-0.071	127.93	0.000	30	0.001	-0.038	156.76	0.000
13	-0.052	-0.059	131.05	0.000	31	0.019	-0.037	157.19	0.000
14	-0.000	-0.044	131.05	0.000	32	-0.031	-0.073	158.29	0.000
15	-0.057	-0.117	134.81	0.000	33	-0.034	-0.050	159.68	0.000
16	-0.025	-0.055	135.55	0.000	34	0.063	0.053	164.34	0.000
17	0.031	-0.011	136.55	0.000	35	0.020	-0.026	164.80	0.000
18	0.020	-0.053	137.10	0.000	36	-0.024	-0.027	165.49	0.000

Source: Eviews12

3.5. Heteroskedasticity test

It can be seen intuitively from **Figure 2** that the volatility of the R_t series has a certain degree of continuity, and there is a phenomenon of volatility clustering. Moreover, the R_t series fluctuates to a different extent in different periods: the volatility in the first half is relatively flat while the volatility in the second half increase. This means that the return rate series may have heteroscedasticity. Therefore, it is necessary to perform a heteroscedasticity test.

The test method is to first use the least-squares method to construct a first-order autoregressive on 1142 SHIBOR data series and then use Eviews12 to perform a lagging one-order ARCH-LM test on the return rate to quantitatively judge whether the return rate sequence has an ARCH effect. **Table 4** shows the test results. From the results of the ARCH-LM test, the P-value is less than 0.05. That is, within a specific confidence interval, the null hypothesis should be rejected, and the alternative hypothesis should be accepted. The residual error of the return rate series has a significant ARCH effect under the above conditions, proving the feasibility of applying the GARCH model to fit the heteroscedasticity of the return rate series. Therefore, it can be concluded that the R_t series has heteroscedasticity. In summary, the R_t series is a series of stationary, non-normal distribution, serial autocorrelation, and heteroscedasticity.

Table 4. Heteroskedasticity test results of return rate series

Heteroskedasticity Test: ARCH			
F-statistic	11.69079	Prob.F(1.877)	0.0007
Obs*R-squared	11.56330	Prob.Chi-Square(1)	0.0007

Source: Eviews12

4. Results

4.1. GARCH model

The above analysis shows that the GARCH model can describe the volatility of the rate of return. The GARCH (p, q) model equation is as follows:

Conditional mean equation: $r_t = \gamma r_{t-1} + \mu_t$ (7)

Conditional variance equation: $r_t {\sigma_t}^2 = \alpha_0 + \alpha_1 {\mu^2}_{t-1} + \beta_1 {\sigma^2}_{t-1}$ (8)

According to the experience of existing empirical research, p=1 or 2, q=1 or 2 can better characterize the financial time series. Therefore, the author use Eviews12 to test and analyze GARCH-N, GARCH-GED and GARCH-t model, and the results are shown in **Table 5, Table 6** and **Table 7**, respectively.

Table 5. AIC and SC values of GARCH-N model

(p,q)	**Significance test**	**AIC**	**SC**
(1,1)	Pass	-2.387245	-2.369578
(1,2)	Pass	-2.395957	-2.373873
(2,1)	Pass	-2.408018	-2.385934
(2,2)	Pass	-2.434746	-2.408245

Source: Eviews12

Table 6. AIC and SC values of GARCH-GED model

(p,q)	Significance test	AIC	SC
(1,1)	Pass	-2.568514	-2.546430
(1,2)	Pass	-2.571203	-2.544701
(2,1)	Pass	-2.585061	-2.558560
(2,2)	Pass	-2.605598	-2.574680

Source: Eviews12

Table 7. AIC and SC values of GARCH-t model

(p,q)	Significance test	AIC	SC
(1,1)	Pass	-2.551668	-2.529584
(1,2)	Pass	-2.554279	-2.527796
(2,1)	Pass	-2.566036	-2.539535
(2,2)	Fail	-2.560994	-2.530076

Source: Eviews12

According to the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), the author compared the goodness of fit of different distribution lag terms to determine the appropriate lag period length. In the target model, the author kept increasing the lag variable until the AIC value and SC value no longer decrease. In other words, the smaller the AC and SC values, the better model's fit. Therefore, this paper chooses the GARCH(2,2)-GED model to fit the return sequence, and two ARCH terms and two GARCH terms are included in the variance. The model regression results are shown in **Table 8**.

Table 8. Modeling results of GARCH(2,2)-GED

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2 + C(5)*GARCH(-1) + C(6)*GARCH(-2)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000475	0.000628	0.757466	0.4488
		Variance Equation		
C	7.48E-07	6.67E-07	1.122107	0.2618
RESID(-1)^2	0.559226	0.059515	9.396381	0.0000
RESID(-2)^2	-0.542053	0.055814	-9.711749	0.0000
GARCH(-1)	1.350904	0.050187	26.91729	0.0000
GARCH(-2)	-0.364684	0.046491	-7.844247	0.0000
GED PARAMETER	0.982084	0.048805	20.12260	0.0000
R-squared	-0.000017	Mean dependent var		-1.24E-05
Adjusted R-squared	-0.000017	S.D. dependent var		0.120013
S.E. of regression	0.120014	Akaike info criterion		-2.605598
Sum squared resid	16.41974	Schwarz criterion		-2.57468
Log likelihood	1493.494	Hannan-Quinn criter.		-2.593922
Durbin-Watson stat	1.771000			

Source: Eviews12

The equation for constructing the GARCH(2,2)-GED model is as follows.

Conditional mean equation:

$$r_t = -0.000017r_{t-1} + \mu_t \tag{9}$$

Conditional variance equation:

$$\sigma_t{}^2 = 7.48E - 07 + 0.559226\mu_{t-1}{}^2 - 0.542053\mu_{t-2}{}^2 + 1.350904\sigma_{t-1}{}^2 - 0.364684\sigma_{t-2}{}^2 \tag{10}$$

4.2. VaR

First of all, this paper fits the GARCH(2,2)-GED equation according to the return rate series and uses the VaR model to quantify commercial banks' maximum possible risk loss. The calculation formula is as follows:

$$VaR_t = Shibor_{t-1} \times \sigma_t \times \alpha \times \sqrt{\Delta t} \tag{11}$$

$Shibor_{t-1}$is the value of the day before the original series. σ is the conditional standard deviation, which can be obtained by extracting the conditional variance $\sigma_t{}^2$ of the best fit model GARCH(2,2)-GED and rooting the square. α is the critical value under a certain confidence level. This paper chooses the 95% confidence level, so σ is 1.96. Δt represents the holding period. Since the overnight borrowing rate of SHIBOR is used in the sample, the holding period Δt is 1. Therefore, VaR_t can be abbreviated as:

$$VaR_t = -1.65 \times Shibor_{t-1} \times \sigma_t \tag{12}$$

The negative value represents the most considerable possible loss value within a specific confidence interval.

The author, first use Excel to substitute $Shibor_{t-1}$ and σ_t into the above formula to get a series of VaR_t, and then calculate the actual profit and loss value of SHIBOR, which is recorded as D_t:

$$D_t = Shibor_t - Shibor_{t-1} \tag{13}$$

Table 9. Descriptive statistical results of VaR

	Mean	Maximum	Minimum	Standard deviation
VaR	-0.31733926	-0.01979174	-2.91950317	0.24827393

Source: Eviews12

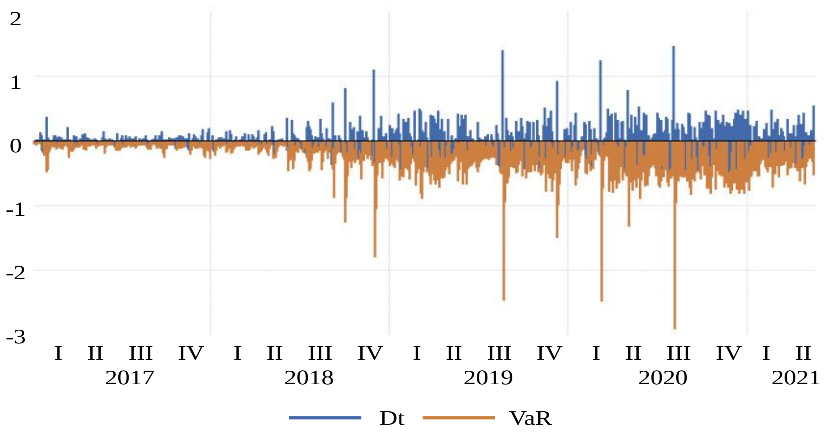

Figure 5. Volatility Comparison Chart of VaR_t and D_t **(**Source: Eviews12)

Finally, the author compared the calculated VaR_t with the actual profit and loss value D_t (VaR_t is a negative value), and the result is shown in **Figure 5**. It can be seen that the calculated value of VaR_t is consistent with D_t, which is the actual profit and loss, indicating that the calculated value of VaR_t can completely cover the actual loss and can reflect the actual changes of SHIBOR on each trading day. In addition, we can also see that the risk volatility of SHIBOR is closely related to its actual volatility. That is, when the SHIBOR volatility is large, the corresponding VaR volatility is also significant. Therefore, it can be proved that the VaR-GARCH model can effectively predict the risk of SHIBOR volatility.

5. Conclusion

With the advancement of China's interest rate liberation process, the interest rate risks faced by commercial banks have also increased. However, Chinese commercial banks have weak awareness of interest rate risk management and lack corresponding risk measurement compared with foreign banks. This paper selects the overnight SHIBOR from January 2017 to July 2021 as a sample and establishes a VaR-GARCH model to capture the volatility characteristics of the series. Through the study of its logarithmic rate of return, it concludes that: First, the return rate of SHIBOR has autocorrelation, that is, the return rate at the next moment is affected by the previous moment. It can be concluded that the level of liberalization of China's interbank lending rate is not significant. Second, there is substantial volatility in the interbank lending market, which has a specific cluster effect. It can be seen that the interest rate risks facing China cannot be ignored and also warns that interest rate fluctuations are sudden and will bring huge, unpredictable risks. Third, in the case of a low level of interbank lending liberalization, the rate of return of SHIBOR presents a non-normal distribution, which puts forward higher requirements for the application of the model. In future studies, non-parametric methods can be used to estimate the VAR model to avoid the influence of leptokurtosis and fat tail and fluctuations on the data.

Based on the above analysis, this paper gives the following suggestions: First, commercial banks should optimize the interest rate risk management system. They need to build an interest rate risk monitoring and evaluation system based on multiple measurement methods such as the interest rate sensitivity gap model, VaR model, and stress testing, to realize automatic identification and calculation. Second, commercial banks should actively use financial derivatives to hedge interest rate risks, including forward interest rate agreements, interest rate swaps, interest rate futures, and interest rate options. In this way, they can effectively avoid the risk of interest rate fluctuations and realize the optimization of the portfolio of asset and liability businesses and the reasonable control of interest rate risks. Third, the financial market must establish a sound regulatory system. At the macro level, the People's Bank of China must strengthen the macro monitoring of interest rate risks of commercial banks and bring the on-balance-sheet and off-balance-sheet businesses into a unified monitoring perspective. At the micro-level, the China Banking and Insurance Regulatory Commission follows the principle of differentiated supervision. In terms of risk measurement, system and model management, and application of measurement results, commercial banks must adapt to their systemic importance, risk status, and business complexity when applying relevant regulatory requirements and gradually improve the risk management capabilities of small and medium-sized banks.

Disclosure statement

The author declares no conflict of interest.

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