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A COMPARATIVE STUDY OF MARKET RISK MEASUREMENT MODELS FOR THE CHINESE STOCK MARKET

UM ESTUDO COMPARATIVO DOS MODELOS DE MEDIÇÃO DO RISCO DE MERCADO PARA O MERCADO DE AÇÕES CHINÊS

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Abstract
The purpose of this study is to compare two major risk measurement models in financial markets—the Value at Risk (VaR) model and the Conditional Value at Risk (CVaR) model—and to evaluate their effectiveness and limitations in stock market risk management. First, through an in-depth analysis of the theoretical foundations of stock market risk, the paper clarifies the importance of risk for investment decision-making, in particular its impact on asset allocation and risk management strategies. The findings show that VaR, as a traditional risk measurement tool, is simple and convenient and enables a rapid assessment of market risk; however, when confronted with extreme tail events it exhibits certain shortcomings and cannot fully capture the true risk of extreme losses. By contrast, CVaR, by focusing on tail risk, makes it possible to identify potential extreme losses more accurately; especially during periods of sharp market volatility, its early-warning function substantially outperforms VaR. In the empirical part of the article, historical data for the Shanghai A-share index are used. The GARCH-M model is applied to estimate VaR and CVaR, and their values are compared when measuring stock market risk. The results indicate that, at the same confidence level, CVaR is always greater than VaR, which further confirms the advantage of CVaR in reflecting risk losses more accurately, especially tail risk. Overall, this study not only provides a theoretical basis for risk management in financial markets, but also offers recommendations for improving risk measurement methods in the

Resumo
O objetivo deste estudo é comparar dois dos principais modelos de medição de risco nos mercados financeiros — o modelo Value at Risk (VaR) e o modelo Conditional Value at Risk (CVaR) — e avaliar sua eficácia e limitações na gestão de risco do mercado de ações. Primeiro, por meio de uma análise aprofundada dos fundamentos teóricos do risco do mercado de ações, o artigo esclarece a importância do risco para a tomada de decisões de investimento, em particular seu impacto na alocação de ativos e nas estratégias de gestão de risco. Os resultados mostram que o VaR, como ferramenta tradicional de medição de risco, é simples e conveniente e permite uma avaliação rápida do risco de mercado; no entanto, quando confrontado com eventos extremos de cauda, ele apresenta certas deficiências e não consegue capturar totalmente o risco real de perdas extremas. Em contrapartida, o CVaR, ao se concentrar no risco de cauda, torna possível identificar perdas extremas potenciais com mais precisão; especialmente durante períodos de forte volatilidade do mercado, sua função de alerta precoce supera substancialmente o VaR. Na parte empírica do artigo, são utilizados dados históricos do índice A-share de Xangai. O modelo GARCH-M é aplicado para estimar o VaR e o CVaR, e seus valores são comparados na medição do risco do mercado de ações. Os resultados indicam que, no mesmo nível de confiança, o CVaR é sempre maior que o VaR, o que confirma ainda mais a vantagem do CVaR em refletir as perdas de risco com mais precisão, especialmente o risco de cauda. No geral, este

stock market, emphasizing the need to account for tail risk when making investment decisions. The conclusions have important reference value for investors seeking to develop more scientifically grounded risk control strategies in a dynamic market environment.

Keywords: Stock Market Risk. Var Model. Cvar Model. Risk Measurement. Market Volatility. Liquidity Risk.

estudo não apenas fornece uma base teórica para a gestão de risco nos mercados financeiros, mas também oferece recomendações para melhorar os métodos de medição de risco no mercado de ações, enfatizando a necessidade de levar em conta o risco de cauda ao tomar decisões de investimento. As conclusões têm um importante valor de referência para investidores que buscam desenvolver estratégias de controle de risco mais cientificamente fundamentadas em um ambiente de mercado dinâmico.

Palavras-chave: *Risco do mercado de ações. Modelo Var. Modelo Cvar. Medição de risco. Volatilidade do mercado. Risco de liquidez.*

1 INTRODUCTION

In today's global economic environment, effective measurement of stock market risk is not only a prerequisite for investors to make scientifically grounded decisions, but also a fundamental guarantee of financial market stability [1]. Although stock markets can provide investors with substantial returns, their inherent volatility and uncertainty can also lead to significant losses. Therefore, an in-depth understanding of stock market risk has become one of the key topics in financial research; in particular, when constructing portfolios and developing risk management strategies, it is critical to apply appropriate risk measurement models [2]. In recent years, the academic community has widely discussed risk measurement models, and such modern indicators as Conditional Value at Risk (CVaR) and Value at Risk (VaR) have gradually attracted increasing attention [3].

The present study primarily relies on a literature review and case analysis and aims to compare these two approaches, identify their strengths and weaknesses, and thereby provide theoretical support for investment decisions.

Traditional risk measurement models, such as standard deviation or volatility, can effectively describe fluctuations in returns, but often ignore the tail risk of the return distribution [4]. Especially under extreme market conditions, such models experience difficulties in assessing the potential losses faced by investors. For example, during the 2008 global financial crisis, many portfolios suffered unprecedented losses under extreme market conditions, which demonstrated the tendency of traditional models to underestimate extreme risk [5]. Accordingly, innovative risk measurement tools emerged, and the introduction of VaR and CVaR was intended precisely to address this problem [6].

A comprehensive analysis of the construction of VaR and CVaR, their advantages and disadvantages, as well as their results in practical applications, not only provides investors with a more detailed risk assessment, but also deepens the understanding of risk measurement theory in the market [7]. This study seeks to identify the practical effectiveness of these two instruments under different market conditions, thereby providing a more scientific basis for investment decisions and ultimately promoting the healthy and sustainable development of financial markets.

Finance is the core of the modern economy. Financial markets occupy a critically important position within the market economy system, and the “domino effect” of financial crises, combined with the high risk inherent in finance, means that the safe, efficient, and sustainable functioning of the financial system plays a key role in overall economic stability and development. The stock market is an important component of financial investment, and fluctuations in stock market risk directly affect the stability and development of the financial system [8–11].

In the article “Portfolio Selection—Efficient Diversification of Investments,” published by Markowitz (1952) [12], portfolio theory was proposed. For the first time, the “mean–variance” model was introduced as a mathematical basis for measuring portfolio returns and risk, and the optimal allocation of portfolios under uncertainty was examined, marking the transition of financial investment research into the era of quantitative analysis. Portfolio theory is the foundation of modern investment theory.

The VaR model is an important tool for assessing financial risk [13] and has become a standard method used by many financial institutions and banks to measure market risk. The VaR risk measurement method was originally proposed by risk management specialists at J.P. Morgan to calculate a firm’s potential losses over the next 24 hours, which led to the development of an information system for computing VaR. The concept of VaR is easy to understand, but its computation is more complex. In general, parametric methods and historical simulation are used to calculate this measure. Allen (1994) [14] conducted a comparative study of these two calculation methods. Subsequently, Philippe Jorion (1996) [15], in his book Value at Risk: VaR, provided a detailed discussion of the concept, properties, and various methods for estimating VaR. Based on differences in VaR estimation under the normal distribution and the Student’s t-distribution, he emphasized the characteristics and applicability of different methods. As academic research deepened, the shortcomings of the VaR approach gradually became apparent.

Beder (1995) [16] empirically identified two notable weaknesses of the VaR method: first, VaR is unreliable in forecasting the approach of major adverse events; second, VaR estimates are subject to statistical measurement error and cannot guarantee accuracy.

Dowd (1998) [17] argued that VaR derived from the overall return distribution cannot adequately reflect extreme losses and proposed using a tail distribution model beyond a certain return threshold to calculate extreme VaR. Accordingly, an extreme value model was proposed. He also pointed out that when measuring stock market volatility, VaR often overestimates risk in "bear" markets and underestimates risk in "bull" markets.

Favre and Galeano (2002) [18] noted that values computed under the assumption of normality and by ignoring skewness and kurtosis do not conform to the patterns of financial market fluctuations. Therefore, they proposed a mean-modified VaR model and applied it to the construction of hedge fund portfolios.

Although the VaR model reflects market risk to some extent, its calculation methods still have limitations; for example, it cannot effectively measure the average magnitude of losses that may arise when tail events occur.

In modern financial risk management, CVaR, as an important risk measurement tool, has gradually attracted wide attention and has found application among both researchers and practitioners [19]. The key idea of CVaR is to estimate the expected value of potential losses that exceed a pre-specified VaR threshold. The introduction of CVaR serves as a supplement and extension to the traditional VaR model and is intended to provide a more comprehensive understanding and measurement of risk levels under extreme market conditions [20].

The origins of the CVaR model trace back to the 1990s. Initially, VaR served as the primary tool of risk management; however, as uncertainty and volatility in financial markets increased, VaR alone proved insufficient to account for risks with extreme characteristics [21]. As a result, CVaR emerged, combining intuitiveness with higher accuracy and enabling investors to obtain more reliable support for decision-making under tail risk. CVaR is formed on the basis of the tail part of the loss distribution beyond a specified confidence level; by computing expected losses in this tail region, it provides a statistic of a portfolio's potential losses under extreme conditions.

For further analysis of the theoretical foundation of the CVaR model, it is first necessary to consider the probability theory on which it is based, in particular the "distribution assumption" [22]. CVaR estimation typically assumes that market returns follow a certain statistical distribution, such as the normal distribution or the Student's t-distribution. The validity of this assumption directly affects the accuracy of CVaR; therefore, selecting an appropriate distributional model is crucial in practical applications. One advantage of CVaR is that it can reflect dynamic changes in market conditions and adapt to different financial environments. Compared with VaR, it better identifies potential extreme risks and provides risk managers with more complete information for decision-making.

Nevertheless, the CVaR model also has certain limitations in application. Its estimation depends on a large volume of historical data, and a lack or insufficiency of market data may reduce the model's predictive capability [23]. Because CVaR is sensitive to the shape of the data distribution, its effectiveness under non-normal distributions is often questioned, which is particularly evident when accounting for heteroskedasticity in financial markets [24]. Therefore, although CVaR offers a deeper perspective for risk assessment, its practical application requires comprehensive consideration of data characteristics and the market environment.

2 COMPARATIVE ANALYSIS OF VAR AND CVAR

When conducting a comparative analysis of VaR (Value at Risk) and CVaR (Conditional Value at Risk), it is first necessary to clarify the fundamental differences between these two risk measurement models and their interrelationship [25]. As a widely used tool for quantitative risk assessment, VaR mainly reflects the maximum expected loss that may occur in the future at a given confidence level. However, although VaR is intuitive for explaining market risk, its limitations cannot be ignored—especially under extreme market conditions, where VaR often fails to adequately capture potential tail risk.

By contrast, CVaR's sensitivity to tail risk makes it an important instrument for measuring extreme market volatility. CVaR accounts not only for losses up to the level defined by VaR, but also explicitly takes into account additional losses beyond this level;

therefore, it is a more comprehensive indicator when assessing severe portfolio risks. For example, during the 2008 global financial crisis, many financial institutions relied on VaR in risk management but ultimately incurred substantial losses, which demonstrated the shortcomings of the model under extreme conditions [26]. This example underscores the significance of CVaR in risk assessment, since it provides a more detailed perspective for evaluating systemic risk.

To demonstrate more concretely the risk-control capabilities of the two models, we conducted an empirical study in which we measured the risk of a given portfolio during periods of market turbulence. Using historical simulation, VaR and CVaR were computed. Compared with VaR at a 95% confidence level, CVaR analyzes potential losses in the situation where losses exceed the VaR threshold, thereby reflecting the possibility of severe capital deterioration. For example, based on a set of historical return data, we found that for a monthly horizon VaR equals 100,000 yuan, while CVaR reaches 150,000 yuan [27]. This empirical result not only confirms the advantage of CVaR in identifying tail risk, but also reflects its practical significance for investment decision-making.

In different market conditions, the applicability of VaR and CVaR also differs substantially. VaR is more suitable for stable market conditions, enabling a rapid assessment of ordinary risk. Under high volatility, by contrast, CVaR shows higher measurement value; in particular, for risk-averse investors, choosing CVaR as a risk assessment tool better reflects their risk tolerance.

The comparative analysis of VaR and CVaR indicates that selecting an appropriate risk measurement model is crucial for an accurate understanding of investment risk and for developing scientifically grounded risk management strategies [28]. Combining theory and empirical results helps deepen the understanding of the application areas and suitability conditions of these two measures and thus contributes to the improvement of risk management practice.

A review of the literature shows that in recent years research has focused on how to apply different risk measurement models to stock market risk management [29]. Comparing the strengths and weaknesses of VaR and CVaR leads to the conclusion that VaR is relatively simple and intuitive when stating possible losses; however, its inherent limitation lies in ignoring tail risk. By contrast, CVaR emphasizes the magnitude of losses under extreme conditions and is therefore better suited for risk assessment in an extreme market environment. For example, under high-frequency trading (HFT), the CVaR model can effectively capture potential extreme losses caused by liquidity risk [30].

3 THEORETICAL MODELS OF VAR AND CVAR

Empirical Comparative Risk Analysis of the Shanghai A-share Index Based on VaR and CVaR Methods

Analysis of Volatility Characteristics of Returns of the Shanghai A-share Index

3.1 Data collection

The raw data used in this study were mainly obtained from the Yahoo Finance database. The sample includes daily closing prices of the Shanghai A-share index for the period from January 2, 2019 to December 29, 2023, covering a total of 1,215 trading days. The sample period includes the COVID-19 pandemic in 2020–2022, and the data cover a full market cycle, which ensures high research value.

Based on the closing price data, a series of logarithmic returns is computed to characterize volatility in the price series. The logarithmic return is calculated by the following formula:

$$x_t = \ln p_t - \ln p_{t-1} \quad (1)$$

here:

x_t denotes the return at time t,

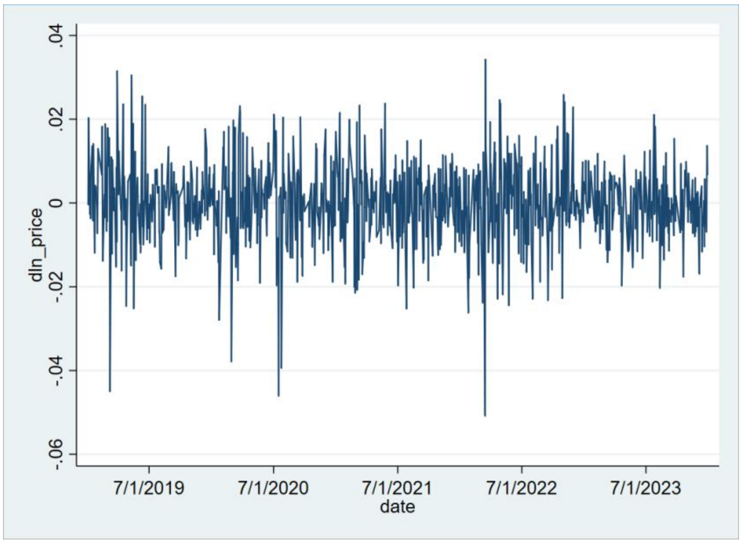
and p_t denotes the closing price at time t.

The empirical analysis was performed using Stata.

Figure 1 presents the time plot of the return series. The volatility of daily returns is a stochastic process, and the fluctuations display a pronounced clustering effect. During 2020–2021, stock market volatility was relatively moderate, as daily returns generally fluctuated within the range from −0.025 to 0.025, characterized by comparatively small positive and negative values. However, around January 2020 and toward the end of 2021, market volatility was substantial, as daily returns were mainly within the range from −0.055 to 0.035, with noticeably larger positive and negative values.

Figure 1

Time plot of the return series



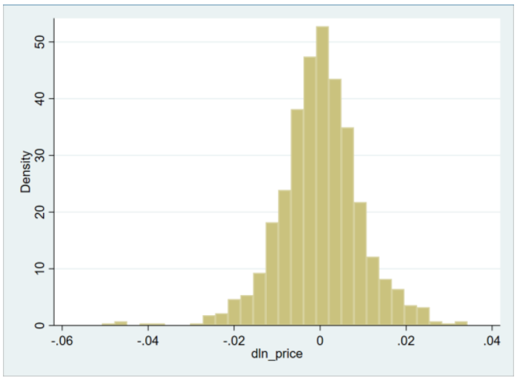
3.2 Descriptive statistical analysis

It is commonly assumed that for a normal distribution the kurtosis equals 3 and the skewness equals 0. Kurtosis reflects the features of changes in the distribution's shape, while skewness characterizes its asymmetry. Skewness indicates the degree to which a distribution deviates from symmetry. When skewness equals 0, the distribution is symmetric around the center; when it is greater than 0, i.e., the right tail is heavier, the distribution is right-skewed; when it is less than 0, i.e., the left tail is heavier, the distribution is left-skewed. If kurtosis exceeds 3, the distribution exhibits "peakedness" and "fat tails"; when kurtosis equals 3, the distribution is close to normal.

Figure 2 reports the corresponding descriptive statistics for the return series. As shown in Figure 2, the normality test results indicate that the distribution deviates significantly from normality. The p-value of the skewness test equals 0.0000, which indicates pronounced asymmetry (i.e., a non-symmetric distribution); the p-value of the kurtosis test equals 0.0000, which suggests that tail thickness differs significantly from the normal distribution.

Figure 2

Descriptive statistics for the return series



In addition, Table 1 shows that the p-value of the joint test equals 0.0000, which further confirms that the variable deviates statistically significantly from the normal distribution in terms of skewness and kurtosis. Therefore, the return series does not follow a normal distribution, and at the 5% significance level the null hypothesis of normality of the return series is rejected.

Table 1

Normality Test Results for the Return Series (Skewness–Kurtosis Test)

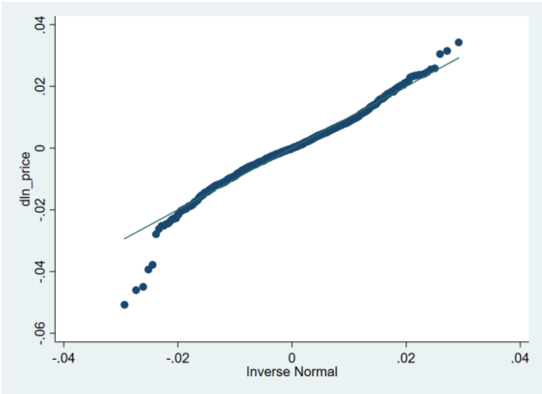
Variable	***Obs***	***Pr(Skewness)***	***Pr(Kurtosis)***	***adj chi2(2)***	***Prob>chi2***
dln_price	957	0.0000	0.0000	64.07	0.0000

According to the basic theory of a Q–Q plot, if the Q–Q plot is close to a straight line, the data are considered to follow a normal distribution; if the lower part of the Q–Q plot deviates to the left of the line or the upper part deviates to the right of the line, the data distribution is characterized by “fat tails.” Figure 3 shows the Q–Q plot of the return series.

As shown in Figure 3, the straight line reflects the distribution of the return series under the normality assumption, while the curve shows the actual distribution of returns. The deviations of the curve from normality in the upper and lower parts become increasingly pronounced, indicating clear “fat-tail” features in the return series.

Figure 3

The straight line reflects the distribution of the return series under the normality assumption



3.3 Stationarity test

Testing the stationarity of time series is a necessary condition for constructing GARCH models. In this study, the Augmented Dickey–Fuller (ADF) test is used to test for unit roots in the model variables, with the null hypothesis being that the series contains at least one unit root. If the test confirms that the series is stationary, the null hypothesis is rejected; otherwise, the null hypothesis is accepted, meaning that the series is non-stationary. The ADF test was applied to the return series, and the results are reported in Table 2.

Table 2

Stationarity Test of the Return Series (ADF Test)

Statistic	Value
Number of obs	703
ADF test statistic Z(t)	-26.313
Critical value (1%)	-3.960
Critical value (5%)	-3.410
Critical value (10%)	-3.120
MacKinnon approximate p-value	0.0000

The ADF test results show that the test statistic Z(t) for this variable equals −26.313, which is substantially smaller than the critical values at the 1%, 5%, and 10% significance levels (−3.960, −3.410, and −3.120, respectively); the corresponding p-value equals 0.0000. Therefore, we reject the null hypothesis, meaning that the series contains no unit root, which indicates stationarity.

3.4 ARCH effect test

When performing autocorrelation and partial autocorrelation tests for stock market returns, as shown in Table 3, some autocorrelation is observed at lags 1–6; the optimal lag order is 4.

Table 3

Correlation Test Statistics for the Series

LAG	AC	PAC	Q	Prob>Q
1	-0.0617	-0.0617	3.649	0.0561
2	0.0096	0.0058	3.7382	0.1543
3	-0.0019	-0.0009	3.7415	0.2908
4	-0.0903	-0.0912	11.601	0.0206
5	0.0009	-0.0104	11.602	0.0407
6	-0.0447	-0.0448	13.533	0.0353
7	-0.0038	-0.0103	13.547	0.0599
8	-0.0003	-0.0094	13.547	0.0944
9	0.015	0.013	13.763	0.131
10	-0.0465	-0.0543	15.861	0.1037
11	-0.0161	-0.0247	16.111	0.137
12	-0.0039	-0.0093	16.126	0.1855
13	-0.0155	-0.0151	16.358	0.2303
14	-0.0027	-0.0153	16.365	0.2916
15	0.0033	-0.0011	16.376	0.3575
16	0.0363	0.0309	17.664	0.3439
17	-0.014	-0.0161	17.855	0.3981
18	0.0054	-0.0002	17.884	0.4634
19	-0.0029	-0.0022	17.892	0.5297
20	0.0185	0.0213	18.227	0.5724
21	-0.0629	-0.067	22.106	0.3934
22	0.0505	0.0462	24.614	0.3159
23	-0.0092	-0.0059	24.697	0.3661
24	0.0427	0.0447	26.49	0.3288
25	-0.0445	-0.0542	28.443	0.2879
26	-0.017	-0.0096	28.728	0.3236
27	-0.03	-0.0402	29.615	0.3317
28	-0.034	-0.0281	30.755	0.3281
29	0.0526	0.0413	33.486	0.2586
30	-0.0324	-0.0236	34.524	0.2604
31	0.0319	0.0096	35.53	0.2633
32	-0.0233	-0.0304	36.068	0.284
33	-0.0113	-0.0105	36.194	0.3218
34	0.0176	0.012	36.502	0.3532
35	-0.0232	-0.017	37.036	0.3752
36	0.0161	0.0058	37.294	0.4094
37	-0.0702	-0.0716	42.212	0.2558
38	0.0323	0.0125	43.253	0.257

39	0.0176	0.0201	43.562	0.2835
40	-0.0267	-0.0316	44.276	0.296

To test the autocorrelation of squared residuals, an ordinary least squares (OLS) regression was performed: an ARCH–LM test was carried out on the residuals of the model for the variable r_t in order to further examine the presence of an ARCH effect in the residual series of the regression model. The test results are reported in Table 4. The ARCH–LM test in Table 4 shows that the p-values for lags 1–4 are all below 0.05, indicating a statistically significant ARCH effect in the data.

Table 4

ARCH–LM Test for Residuals

Lag (p)	chi2	df	Prob > chi2
1	6.941	1	0.0084
2	12.028	2	0.0024
3	13.583	3	0.0035
4	15.520	4	0.0037

3.5 Comparative Analysis of the GARCH Family of Models Based on the Shanghai A-share Index

Financial time series typically exhibit pronounced volatility clustering, i.e., a tendency for volatility to concentrate over time, as well as “peakedness” and “fat tails.” In addition, the leverage effect in the stock market indicates that the impact of good and bad news on stock volatility is asymmetric. Models of the GARCH family can effectively account for these features and provide more accurate volatility modeling [7–9].

In this study, based on the preliminary analysis of return volatility of the Shanghai A-share index, several GARCH-family models are constructed to describe the volatility characteristics of the index return series. Then, by comparing the goodness of fit of different GARCH models, the optimal model is determined. Finally, based on the selected best model, the conditional variance is computed and VaR and CVaR are further estimated for assessing and quantifying the level of stock market risk.

3.5.1 GARCH model

An overly complex model may lead to overfitting; as a rule, a GARCH model is sufficient to describe the volatility characteristics of the series. In this study, a GARCH model is used to analyze return volatility; the mean equation and the variance equation are specified as follows:

$$syl_t = \alpha_0 + \mu_t \qquad (2)$$

$$\delta_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 + \beta_2 \delta_{t-1}^2 \qquad (3)$$

Comparing the estimation results for the three GARCH models—GARCH(1,1), GARCH(1,1)-GED, and GARCH(1,1)-t—shows first that in all models both the ARCH and GARCH effects are statistically significant. This indicates pronounced volatility clustering and high volatility persistence in the return series of the Shanghai A-share index. In particular, the ARCH effect is significant in all three models, implying that past volatility has a substantial impact on current return fluctuations. As shown in Table 5, the GARCH effect reflects strong autocorrelation in volatility: the GARCH coefficient equals 0.893 for GARCH(1,1), 0.898 for GARCH(1,1)-GED, and 0.905 for GARCH(1,1)-t; all values indicate a relatively long-lasting impact of past volatility on future volatility.

Table 5

Estimation Results for GARCH Models

Variable	GARCH(1,1)	GARCH(1,1)-GED	GARCH(1,1)-t
Mean equation			
_cons	-0.000218	-0.000132	-0.0000418
	(-0.76)	(-0.50)	(-0.15)
Variance equation			
L.arch	0.0685***	0.0604**	0.0553**
	(4.69)	(2.82)	(2.82)
L.garch	0.893***	0.898***	0.905***
	(33.44)	(22.69)	(24.92)
_cons	0.00000357*	0.00000366	0.00000358
	(2.50)	(1.72)	(1.79)

The mean equation takes the following form:

$$syl_t = -0.000218 + \mu_t \qquad (4)$$

The conditional variance equation:

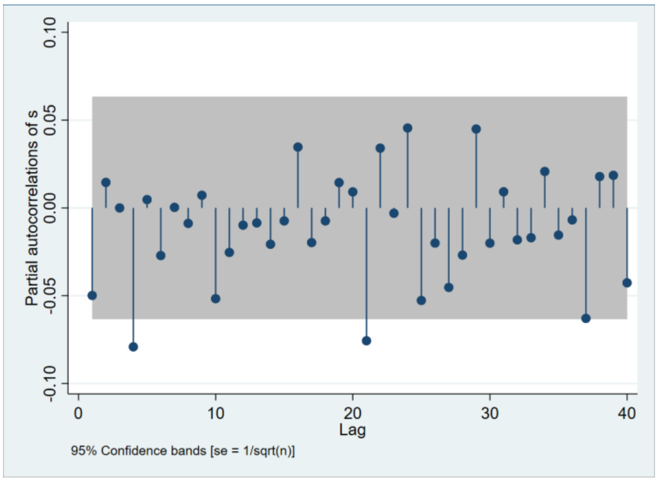
$$\delta_t^2 = 0.00000357 + 0.0685 \cdot \mu_{t-1}^2 + 0.893 \cdot \delta_{t-1}^2 \qquad (5)$$

According to the GARCH estimation results, the conditional mean of the Shanghai A-share index equals 0.0000357, i.e., the average value of the return series is essentially zero. This indicates the absence of a pronounced long-run return bias for the index and an overall stable state. The value β1+β2=0.961 is very close to 1, which indicates persistence in the impact of conditional variance shocks on the return series. The GARCH process is stationary; therefore, scientifically grounded forecasting of the return series is possible under the condition that future volatility gradually decays.

An autocorrelation test was performed for the model residuals; the results are shown in Figure 4. The figure indicates that residual autocorrelation is not statistically significant.

Figure 4

Autocorrelation test



Next, we examine whether the GARCH model eliminated the ARCH effect in the residuals. An ARCH–LM test was carried out on the model residuals; the results are reported in Table 6. Table 6 shows that all p-values exceed 0.05, indicating that the residual series of the GARCH model no longer contains an ARCH effect. Therefore, the model is correctly specified and can adequately describe the volatility of the return series.

Table 6

Residual Diagnostics Results

Lag (p)	**chi2**	**df**	**Prob > chi2**
1	0.067	1	0.7953
2	0.058	2	0.9716
3	0.184	3	0.9801
4	0.423	4	0.9806
5	3.283	5	0.6565
6	3.401	6	0.7571

3.5.2 GARCH–M model

The GARCH–M model is also known as the GARCH-in-Mean model. Because high returns are usually accompanied by high risk, financial modeling typically assumes a relationship between return and risk. Based on this idea, the conditional variance of returns is included in the mean equation. The specification of the GARCH–M model is as follows:

$$syl_t = \alpha_0 + \alpha_1 \mu_t + \mu_t \qquad (6)$$

$$\delta_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 + \beta_2 \delta_{t-1}^2 \qquad (7)$$

If X is greater than 0 and statistically significant, this means that higher risk caused by an increase in conditional variance leads to a higher mean return; therefore, α_1 is usually interpreted as a risk premium and is used to measure risk-induced returns. The model fitting results are reported in Table 7.

Table 7

Fitting Results for the GARCH–M Model

Variable	GARCH-M	GARCH-M-GED	GARCH-M-t
Mean equation			
_cons	-0.00149	-0.00142	-0.00151
	(-1.73)	(-1.67)	(-1.62)
Sigma2	16.21	16.39	18.34
	(1.62)	(1.61)	(1.67)
Variance equation			
L.arch	0.0693***	0.0626**	0.0586**
	(4.63)	(2.90)	(2.90)
L.garch	0.889***	0.891***	0.895***
	(32.50)	(22.29)	(23.89)
_cons	0.00000376*	0.00000411	0.00000415
	(2.56)	(1.85)	(1.95)

The estimation results in Table 7 indicate that all models show a pronounced volatility clustering effect in the return series, as well as a persistent volatility response to past shocks, reflecting the persistence of fluctuations in the stock market.

The GARCH_M model is suitable for describing conditional volatility of returns and shows good goodness-of-fit indicators; the GARCH_M_GED and GARCH_M_t models adjust the assumptions about the distributional form of volatility and allow the tail-risk characteristics of stock market returns to be captured more effectively.

The GARCH_M_GED and GARCH_M_t models provide more accurate volatility estimates, in particular by using the GED distribution and the t-distribution to adjust for the influence of extreme events; they are suitable for more complex market conditions.

The mean equation of the GARCH_M model takes the following form:

Mean equation:

$$syl_t = -0.00149 + \alpha_1 \delta_{t-1} + \mu_t \qquad (8)$$

Conditional variance equation:

$$\delta_t^2 = 0.00000376 + 0.0626 \cdot \mu_{t-1}^2 + 0.891 \cdot \delta_{t-1}^2 \qquad (9)$$

Table 8

Residual Diagnostics for the GARCH_M Model

Lag (p)	chi2	df	Prob > chi2
1	0.129	1	0.7191
2	0.106	2	0.9482
3	0.252	3	0.9687
4	0.481	4	0.9753
5	3.025	5	0.6962
6	3.181	6	0.7858

Next, we examine whether the GARCH_M model eliminated the ARCH effect in the residuals. An ARCH–LM test was carried out on the model residuals; the results are reported in Table 8. Table 8 shows that all p-values exceed 0.05, indicating that the residual series of the GARCH_M model no longer contains an ARCH effect. Therefore, the model is correctly specified and can adequately describe the volatility of the return series.

3.5.3 EGARCH model

The classical GARCH model has certain limitations. One of its assumptions is that positive and negative shocks have the same impact on the volatility of the series. In practice, however, the impact of negative shocks on the return series is often stronger than that of positive shocks; that is, a leverage effect (asymmetric behavior) is frequently observed in the stock market. One of the common models used to describe the leverage effect is the EGARCH model. It measures the asymmetric effect of positive and negative shocks on the stock market by including in the equation a term representing the ratio of the residual of the mean equation to the conditional standard deviation. The specification of the conditional variance in the EGARCH model is as follows:

$$\log\delta_t^2 = \beta_0 + \beta_1 \log\delta_{t-1}^2 + \beta_2\left|\frac{\mu_{t-1}}{\delta_{t-1}}\right| + \beta_3\frac{\mu_{t-1}}{\delta_{t-1}} \quad (10)$$

The model fitting results are reported in Table 9.

Table 9

Fitting Results for the EGARCH Model

Variable	EGARCH	EGARCH-GED	EGARCH-t
Mean equation			
_cons	-0.000241	-0.000151	0.00000587
	(-0.85)	(-0.57)	(0.02)
Variance equation			
L.egarch	1.066***	1.080***	-7.658
	(19.28)	(11.36)	(-0.95)
L.arch	744.9***	711.1**	-29.49
	(5.17)	(3.27)	(-0.37)
L.garch	-1780.9**	-1961.3	74550.1
	(-2.84)	(-1.77)	(0.82)
_cons	0.718	0.860	-87.49
	(1.25)	(0.87)	(-1.05)

The EGARCH estimation results in Table 9 show that all regression coefficients in the conditional variance equation are statistically significant; moreover, one is significantly greater than 0 and another is significantly less than 0, which indicates the presence of a leverage effect in the volatility of returns of the Shanghai A-share index. Consider, as an example, the results under the assumption of normally distributed residuals. The coefficient capturing the impact of a negative shock on conditional variance equals:

$$-711.1 - 1961.3 = -2672.4,$$

whereas the coefficient capturing the impact of a positive shock on conditional variance equals:

$$711.1 - 1961.3 = -1250.2.$$

This means that market volatility is more sensitive to negative news: bad news substantially amplifies market fluctuations, reflecting pronounced asymmetry. This result is consistent with the leverage effect in financial markets: when asset prices decline, market volatility tends to increase. This feature is important for risk management and investment decision-making and indicates the need to pay special attention, when constructing risk models, to the amplifying impact of negative information on market volatility.

3.4 TGARCH model

The specification of the conditional variance in the TGARCH model is as follows:

$$\delta_t^2 = \beta_0 + \beta_1\mu_{t-1}^2 + \beta_2\mu_{t-1}^2 d_{t-1} + \beta_3\delta_{t-1}^2 \quad (11)$$

Here:

d_{t-1} is a dummy variable: when $\mu_t < 0$, this variable takes the value 1; otherwise, it takes the value 0. Therefore, the effects of negative news $\mu_t < 0$ and positive news $\mu_t > 0$ on the conditional variance differ. The TGARCH model fitting results are reported in Table 10.

Table 10

Fitting Results for the TGARCH Model

Variable	TGARCH	TGARCH-GED	TGARCH-t
Mean equation			
_cons	-0.000244	-0.000172	-0.0000857
	(-0.83)	(-0.65)	(-0.31)
Variance equation			
L.arch	0.0752***	0.0746**	0.0703**
	(4.28)	(2.65)	(2.65)
L.tarch	-0.0126	-0.0277	-0.0314
	(-0.72)	(-0.97)	(-1.08)
L.garch	0.891***	0.895***	0.903***
	(33.20)	(22.32)	(24.42)
_cons	0.00000368*	0.00000389	0.00000378
	(2.55)	(1.78)	(1.85)

The TGARCH estimation results in Table 10 indicate the following. Using the TGARCH_GED results as an example, the coefficient capturing the impact of negative news on conditional variance equals −0.0277 + 0.895 = 0.8673, whereas the coefficient capturing the impact of positive news on conditional variance equals 0.895. This indicates the presence of a positive leverage effect in the return series: compared with negative news, shocks associated with positive news have a stronger impact on the return series.

3.5.5 Comparison of the GARCH Family of Models

The Akaike information criterion (AIC) is one of the widely used indicators for evaluating the goodness of fit of statistical models [17][18]. The AIC balances model complexity against goodness of fit; it is based on the concept of entropy. Preference is given to the model with the smallest AIC value, which helps effectively reduce the risk of overfitting. The AIC, which aims to select a model with the minimum number of free parameters while explaining the data as much as possible, is an effective tool. In this paper, the optimal model is selected based on the AIC statistic: the smaller the AIC, the better the model. Table 11 reports AIC values for the GARCH family of models.

Table 11

AIC Values for the GARCH Family of Models

Model	Z	t	GED
GARCH	-6247.8	-6287.6	-6286.2
GARCH_M	-6248.7	-6288.9	-6287.4
EGARCH	-6248.3	-6287.2	-6260.2
TGARCH	-6246.1	-6286.4	-6285.3

Table 11 shows that the AIC statistic of the GARCH_M model is the smallest under all considered distributions compared with other models, indicating that the GARCH_M model provides the best fit. However, differences between AIC values across models under different distributions are extremely small. Considering computational efficiency and the complexity of risk-measure calculations within GARCH models, the EGARCH_M model under the t-distribution is selected for further, more detailed measurement of VaR and CVaR.

Comparative Analysis of VaR and CVaR Based on the GARCH_M Model

Based on the estimated conditional variance values obtained from the GARCH_M model under the t-distribution, VaR and CVaR can be computed. The calculation formulas are given below:

$$VAR = -\mu - t_{\alpha} \cdot \delta_{t} \qquad (12)$$

here:

μ denotes the mean return,

t_{α} denotes the quantile of the t-distribution,

and δ_{t} denotes the conditional variance at each time t.

CVaR represents the expected losses conditional on exceeding the VaR level; the formula is as follows:

$$CVAR = -\mu - \tfrac{t_\alpha}{1-\alpha} \cdot \delta_t \quad (13)$$

here:

μ denotes the mean return, t_α

denotes the quantile of the t-distribution,

and δ_t denotes the conditional variance at each time t. α denotes the VaR confidence level (95% and 99%).

Table 12

VaR and CVaR Values for the Shanghai A-share Index

date	settlement	yield	VaR 95%	VaR 99%	CVaR 95%	CVaR 99%
1/3/2019	2,464.36	-0.0003	0.0184	0.0294	-0.0188	-0.0297
1/4/2019	2,514.87	0.0202	0.017	0.0285	-	-0.0082
1/8/2019	2,526.46	-0.0026	0.0198	0.0315	-0.0224	-0.0342
1/9/2019	2,544.34	0.0070	0.0192	0.0306	-0.0121	-0.0235
1/10/2019	2,535.10	-0.0036	0.0188	0.0301	-0.0225	-0.0337
...	...	...	...	...	...	...
12/22/2023	2,914.78	-0.0013	0.0154	0.0245	-0.0167	-0.0258
12/26/2023	2,898.88	-0.0068	0.0151	0.0240	-0.0219	-0.0309
12/27/2023	2,914.61	0.0054	0.0151	0.0241	-0.0097	-0.0187
12/28/2023	2,954.70	0.0136	0.0151	0.0240	-0.0014	-0.0104
12/29/2023	2,974.93	0.0068	0.0162	0.0258	-0.0094	-0.0190

Based on the VaR and CVaR values reported in Table 12, the following conclusions can be drawn: at a 99% confidence level, CVaR is always greater than VaR at the same confidence level, and at a 95% confidence level CVaR is also greater than VaR.

This result indicates that, at the same confidence level, CVaR is always greater than VaR. More specifically, CVaR takes into account average losses in the event of extreme occurrences, which allows it to reflect potential losses under extreme risk more accurately. VaR, by contrast, focuses only on the maximum loss at a given confidence level.

Therefore, at the same confidence level, CVaR measurements are generally higher and provide a more complete risk assessment. This indicates that when evaluating risks at higher confidence levels, CVaR may reveal a higher level of risk.

Table 13

Descriptive Statistics for VaR and CVaR Values

Statistic	VaR 95%	VaR 99%	CVaR 95%	CVaR 99%
Mean	0.0182	0.02897	-0.01893	-0.02905
Std. Dev.	0.00312	0.0049952	0.0091796	0.0104373
Min	0.01394	0.02218	-0.07054	-0.08228
Max	0.03151	0.05213	-0.00086	-0.00325
Median (50%)	0.01734	0.02762	-0.01818	-0.02846
Skewness	1.4243	1.4243	-1.0284	-0.7668
Kurtosis	5.2227	5.2227	6.0322	5.2138
Variance	9.73E-06	2.50E-05	8.43E-05	1.09E-04
Shapiro–Wilk test (p-value)	0	0	0	0

Table 13 shows that CVaR values fluctuate more strongly than VaR values, and at each point in time CVaR values generally exceed VaR values. This further confirms the descriptive statistical results, namely:

CVaR(99%) > VaR(99%) > CVaR(95%) > VaR(95%). When VaR cannot effectively measure extreme losses, CVaR provides a more accurate risk measure and thus compensates for VaR's shortcomings. Regardless of whether CVaR or VaR is considered, their dynamics are consistent with the dynamics of actual losses and show noticeable risk fluctuations in certain periods.

According to the data, periods of elevated risk are mainly concentrated in early 2020 and from late 2022 to early 2023. During these intervals, substantial risk fluctuations are observed; in particular, at the beginning of 2020 the COVID-19 outbreak triggered sharp turbulence in global markets, increasing uncertainty and sharply raising the level of risk in financial markets. As the pandemic gradually came under control, risk indicators stabilized in 2021 and in early 2022. However, from late 2022 to early 2023, under the impact of the aftereffects of the COVID-19 pandemic, market risk increased again, leading to a sharp rise in VaR and CVaR estimates and reflecting heightened market concern about future uncertainty. Therefore, CVaR, as a more forward-looking risk measure, provides a more sensitive response during peak-risk periods.

4 CONCLUSION

Based on the processing and analysis of closing prices of the Shanghai A-share index for the period from January 1, 2019 to December 31, 2023, this article reports descriptive statistics and distributional characteristics of the logarithmic return series. The results show that the return series does not follow a normal distribution and is characterized by pronounced “peakedness” and “fat tails,” which corresponds to typical properties of return distributions of financial assets. In addition, the ARCH effect test reveals a statistically significant ARCH effect, indicating the presence of volatility clustering: in some periods fluctuations are large, whereas in others they are relatively small.

When modeling the return series using GARCH-family models, the paper applies the GARCH, GARCH_M, EGARCH, and TGARCH models under different distributional assumptions (normal distribution, t-distribution, generalized error distribution (GED)).

It is found that in the GARCH_M model the risk premium coefficient is statistically significantly greater than zero, which means that higher systemic risk is accompanied by higher returns, and investors require greater compensation for taking on increased risk. At the same time, the leverage-effect coefficients in the EGARCH and TGARCH models confirm the presence of a leverage effect in the stock market, i.e., shocks driven by negative news have a more pronounced impact than shocks driven by positive news.

A comparison of the goodness of fit of different models under different distributions based on the AIC indicates that the best fit is achieved by the model with residuals following the GED distribution, and the GARCH_M model also shows relatively good fit compared with other models.

Based on the conditional variance estimated by the GARCH_M model, the article further computes VaR and CVaR values at different confidence levels. The comparison of VaR and CVaR shows that, at the same confidence level, CVaR values always exceed VaR values, which indicates that CVaR is better able to measure the risk of extreme losses and to compensate for the shortcomings of VaR. In addition, as the confidence level increases, the corresponding risk-measure values rise, reflecting a more cautious assessment of potential losses at higher confidence levels.

Overall, both VaR and CVaR exhibit dynamics that are highly consistent with the dynamics of actual losses and can effectively reflect market risk. Period-by-period analysis of risk estimates shows that periods of elevated risk are mainly concentrated in early 2020 (a period of market turbulence) and in certain volatile periods in 2022; the risk levels in these periods correspond to actual market conditions, further confirming the effectiveness and reliability of the VaR and CVaR models in risk assessment.

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Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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