

Research on Risk Measurement in Chinese Stock Market - Based on GARCH-VaR Modeling

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Abstract. Chinese stock investors, whether he is an individual investor or working for a investment company, are always worried about the risk of their asset, it is difficult to measure the risk without a functional model, thus, using a model to solve it is of the pivot. The initial aim of this paper is to measure and predict the risk of Chinese stock market using GARCH-VAR model. By analyzing historical stock index return data, this paper develops a dynamic model to capture the volatility and risk correlation of the stock market. The comprehensiveness and accuracy of the results are ensured by using recent data, including stock indices that broadly cover different industries and market capitalization. The findings suggest that significant volatility and risk correlations exist in the Chinese stock market. This paper provides an effective methodology to measure and predict the level of risk in the stock market, which provides investors and risk management organizations with valuable references and decision-making bases and is important for understanding and managing the risk in the Chinese stock market, which helps stock investors to make informed optimal decisions on risk management and asset allocation.

Keywords: Chinese stock market, GARCH-VaR model, Risk management.

1. Introduction

With the fast growth of the Chinese stock market, risk measurement has become an important issue of concern to investors and market regulators.

China's stock market started late, it was in 1990 and 1991 that the Shanghai Stock Exchange and Shenzhen Stock Exchange are set up respectively, since that Chinese people began trading in stock market. China's stock market has the feature of rapid growth, in only three decades, China formed a large and massive stock market. According to World Federation of Stock Exchanges (WFE) 2016 annual report, Shanghai Stock Exchange and Shenzhen Stock Exchange is in the rank of fourth and sixth place in the regard of the total market capitalization of listed companies. However, China's Stock market has some drawbacks in various ways it is still a very naive one. China market is deprived in the degree of liberalization, of the 21 largest stock exchange centers, China's Shanghai and Shenzhen stock exchange are the only two which have no international plate, whereas the stock exchange in Singapore, Hongkong, even developing country India have a over 40 percent of international companies in their total companies [1]. China stock market also has some anomalies due to a lack of regulations and supervisions. According to Chinese observers, from 1996 to 2016, there is an increased tendency of cases of manipulation of inside information. After the year of 2006, this tendency soared up [2]. Another observer points out that China's stock market has a super short cycle period. In only 30 years, China's stock market experienced 11 times of up and down cycles [3].

Chinese stock investors have a preference on short term investments, from the perspective of individual investors in China, they are more likely to buy more short-term stocks, and the institutional investors are inclined to take advantage of their own information and capital strength to make hotspot and manipulate in the stock market [4]. Chinese individual investors have a feature of over-confidence, this is manifested in the regard that individuals are prone to attribute their success to their abilities and knowledge and their information, on the contrary they are likely to take their failure as a result of the objectivity [5]. Chinese stock investors are more likely to follow what other investors do, which is called herd effect, once they see what others are buying, they quickly follow to buy that, vice versa, this lead a result that Chinese stock market is unstable and full of noise and irrational cases [6].

From the basic situation of Chinese stock market people can see that it is important to investigate on the risk of the asset, since too much unstable factors are affecting the stock prices. Previous studies have already done some experiment in the realm of the risk measurement. This paper implements the GARCH-VAR model.

This thesis aims to measure and analyze the risk of Chinese stock market by applying GARCH-VAR model. Firstly, this paper selects three stock indices covering different industries and market capitalization, namely, SSE index, GEM index and SZSE index, and by analyzing the historical stock price data, this paper will study the volatility and other features of the Chinese stock market. This will help us understand the risk profile of the Chinese stock market and the challenges faced by investors. Second, the GARCH-VAR model is introduced and measures the risk of the Chinese stock market. The GARCH-VAR model combines the generalized autoregressive conditional heteroskedasticity (GARCH) model and the VAR model to capture the volatility and correlation of the stock market more accurately. This research will estimate the parameters of the model and conditional heteroskedasticity to measure and predict the risk of the Chinese stock market.

Finally, this article will conduct an empirical study of the GARCH-VAR model using historical data to assess the performance of different indices in market risk measurement by comparing and analyzing the results of different stock indices and present the corresponding conclusions and recommendations.

2. Brief Description of Methodology

2.1. Data Collection and Processing

In this study, in order to make sure the comprehensiveness and accuracy rate of the results, the SSE index, GEM index, and CSI 300 index are selected for the study, and the historical data of Chinese stock indices covering different industries and market capitalizations are used to conduct in-depth research on the risk of the Chinese stock market. The daily opening and closing price data of the SSE, GEM, and CSI indices from 2020.07 to the present are collected through the Tom Tom software, and the daily returns of the stock indices are calculated from these data, which are used to reflect the volatility of the market. After collecting the data, the data were pre-processed accordingly, including the removal of missing values and outliers, to ensure the reliability and accuracy of the data.

2.2. Principle of the GARCH-VaR model

2.2.1. Principle of GARCH Model

The GARCH model is also known as the generalized autoregressive conditional heteroskedasticity model, which was proposed and developed by Engle [7] & Bollerslev [8], which is mainly applicable to the quantitative forecasting problem of batch data in the field of financial research and is especially suitable for the volatility analysis of a large amount of financial time series data. Equations (1) and (2) show the basic equation form of the model, where is the series to be analyzed (e.g., the closing price of each stock index in the paper), μ is the expected mean of the series R, ε is the residual, and σ is the volatility variance of the series.

$$R_t = \mu_t + \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \alpha + \sum_{i=1}^q \beta \varepsilon_{t-i}^2 + \sum_{j=1}^p \gamma \sigma_{t-j}^2 \quad (2)$$

$$\sigma_t^2 = \alpha + \beta \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 \quad (3)$$

α , for β the coefficients γ to be estimated, p and q represents the maximum lag order of the prior variance and prior residuals, at this point called equation (2) for the GARCH (p, q) model, that is, containing p GARCH terms and q ARCH terms, respectively. The implication of Eq. (2) is that the

variance of the sequence R in period t is affected by the combined effect of the invariant variance, the prior variance estimates and the prior new information residuals. This suggests that if the variance in period ($t1$) of the series R is large, traders will estimate the next period's variance even larger, i.e., financial time series data tend to exhibit volatility clustering characteristics. If p and q in equation (2) are both equal to 1, equation (2) becomes equation (3), and equation (3) is said to be a GARCH (1,1) model, i.e., the model contains an ARCH term and a GARCH term.

The most used model in financial time series analysis is the GARCH (1,1) model, which is sufficiently necessary ($\beta + \gamma < 1$) for the model to be smooth in equation (3).

2.2.2. Principle of VaR Modeling

The Value at Risk (VaR) model [9] originated from the discussions of the G30 Group in the 1990s during the financial risk assessment process. The model is shown in equation (2.4), where c is the confidence level, and VaR the maximum loss that may be incurred by a certain financial product in a certain period of time and at a certain confidence level, $\Delta Loss$ represents the true level of loss in the next period of the financial product. For formula (4), if this paper takes the table confidence level c is 99%, the meaning is that the stock next period loss is greater than the VaR value of the probability of 1%, that is, the next period of the loss of the financial product over the VaR value of the probability of only 1%.

$$Pr o b(\Delta Loss > VaR) = 1 - c \tag{4}$$

Assume that the initial investment amount of this financial product is W_0 and the sequence R is its yield sequence. Then the expected asset value in the next holding period is $W = W_0(1 + R)$, assuming that the expectation and standard deviation of the sequence of rates of return at this time are μ and σ respectively, when the confidence level c of this investment is determined, the minimum value of this financial investment is W^* , and the corresponding minimum rate of return at this time is R^* . At this time relative to the expected value of the at-risk value VaR is calculated as equation (6), that is, the at-risk value VaR is the difference between the expected value and the minimum value at a certain confidence level. The meaning of the confidence level c is given as equation (7), i.e., the probability that the expected value of the financial investment is bigger than the minimum value W^* is the confidence level c , where $f(W)$ is the probability distribution of the level of return of the financial investment. Assuming that the distribution of the return R of the financial investment to meet the normal distribution, that is $R \sim N(\mu, \sigma^2)$, it is necessary to convert it to the standard normal distribution probability density function $\Phi(x) \sim N(0,1)$, the conversion formula is equation (8). After completing the standard normal conversion of the return series R of $f(W)$, the confidence level c can be changed to formula (9), which Z_c is the deviation value of the standard normal distribution probability density function $\Phi(x)$ when the confidence level is c . On this basis formula (2.10) can be obtained, and then put the formula (10) into the formula (6). This part obtains the at-risk level VaR calculation equation: (11). It is worth noting that the holding period t in equation (11) is 1. If t is not 1, then equation (11) needs to be transformed into equation (5)

$$VaR = W_0 Z_c \sigma \sqrt{t} \tag{5}$$

$$VaR = E(W) - W^* = E[W_0(1 + R)] - W_0(1 + R^*) \tag{6}$$

$$= W_0(1 + \mu) - W_0(1 + R^*) = -W_0(R^* - \mu) \tag{7}$$

$$c = \int_{-\infty}^{W^*} f(W) dW = Pr o b(W \leq W^*) = F(W^*) \tag{8}$$

$$x = \frac{R - \mu}{\sigma} \sim N(0,1) \tag{9}$$

$$c = \int_{-\infty}^{W^*} f(W) dW = \int_{-\infty}^{-Z_c} \Phi(x) dx \tag{10}$$

$$-Z_c = \frac{R - \mu^*}{\sigma} \Rightarrow R^* = \mu - Z_c \sigma \tag{11}$$

$$VaR = W_0 Z_c \sigma \tag{12}$$

The object of the full paper is the problem of measuring the risk of indexes in the Chinese stock market, whose trading prices have typical financial time series characteristics, and the data characteristics are very suitable for empirical modeling with the GARCH model. Therefore, the GARCH model is initially used to model the return series of each index in the Chinese stock market to identify its volatility and find the standard deviation σ of its return series is found by estimating the model, and then its online value at different confidence levels is calculated according to the VaR model, and the risk comparison of the at-risk value is made in different market contexts.

3. Results and Analysis

As the research methodology of this paper is consistent for the three different indices, considering the space issue, only the modeling process of the risk of the SSE index is shown in the main text.

3.1. Descriptive statistics of the return data for each trading day of the three indices

The daily return of the index on the current trading day is calculated through the opening and closing prices of the index on that trading day by the following formula, where P_{end} is the closing price of the day and P_{begin} is the opening price of the day. After obtaining the yield data of each trading day of the three indices, descriptive statistics are carried out, and the specific descriptive statistics results are illustrated in Table 1 below.

Table 1. Descriptive statistics of the returns of the three indices

Variable Name	Sample Size	Maximum value	Minimum Value	Mean Value	Standard Deviation	Kurtosis	Skewness	Coefficient of Variation (CV)
SSE	700	3.2%	-4.4%	0.048%	0.009	1.772	-0.373	19.0959
GEM Index	700	6.9%	-6.0%	-0.007%	0.016	0.791	-0.025	-225.6440
CSI	700	5.6%	-5.4%	0.0015%	0.012	1.404	-0.228	81.4542

By comparing the three indices can be analyzed that the average return and median of the three indices are close to 0, but their standard deviations and coefficients of variation have more obvious differences, indicating that the degree of volatility of the three different indices is not the same, i.e., there is a difference in the size of the risk faced by investing in the three indices of the stock.

$$r = \frac{P_{end}}{P_{begin}} - 1 \tag{13}$$

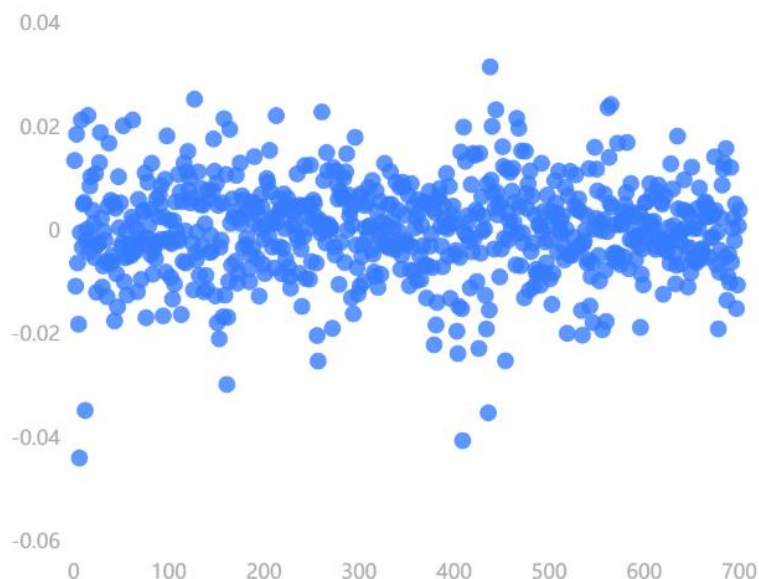


Figure 1. Scatterplot of the returns of the SSE index for each trading day

Photo credit: Original

3.2. Construction of GARCH Model

3.2.1. Smoothness Test

By analyzing the results of the ADF test, it is found that the significance level based on the variable of return P-value is 0.000, which is significant at the level, so the original hypothesis is rejected and the series is considered as a smooth time series (see Table 2).

Table 2. Smoothness test of SSE index return series

Variable	t	P	Critical value		
			1%	5% of the total value	10% of the total
Yield	27.037	0.000***	3.44	2.866	2.569

Note: ***, **, * represent 1%, 5% and 10% significance levels respectively

3.2.2. ARCH Effect Test

The following Table 3 shows the results of the ARCHLM Lagrange multiplier test [10], showing the 112th order ARCH test, it can be found that the P-value of the LM test is smaller than the significance level of 0.05, so it can be deduced that the variance of the series is non-uniform, there is an ARCH effect, and the ARCH model can be established:

Table 3. ARCH LM Lagrange multiplier test results

Lag order (1-12)	X ²	P
1	4.476	0.034**
2	17.353	0.000***
3	20.621	0.000***
4	22.518	0.000***
5	22.131	0.000***
6	40.457	0.000***
7	42.482	0.000***
8	38.531	0.000***
9	41.999	0.000***
10	43.857	0.000***
11	44.108	0.000***
12	28.814	0.004***

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively

3.2.3. GARCH model parameter estimation

Due to the existence of ARCH effect in the return series, the GARCH (p, q) model is chosen for empirical modeling. According to the AIC and SIC information criterion, by constantly changing the size of the values of p and q, it is found that the GARCH model fits best when the lag order of both p and q in the GARCH model is 1. Therefore, the GARCH (1, 1) model is selected in this paper (see Table 4 & Figure 2).

Table 4. Estimation results of model parameters of SSE index

	Estimated value	Standard Error	Statistic	P	Maximum Likelihood	AIC
Constant term	0.035	0.016	2.229	0.026**	909.695	2.608
RESID(1)^2	0.058	0.021	2.716	0.007***		
GARCH(1)^2	0.897	0.03	29.988	0.000***		

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively

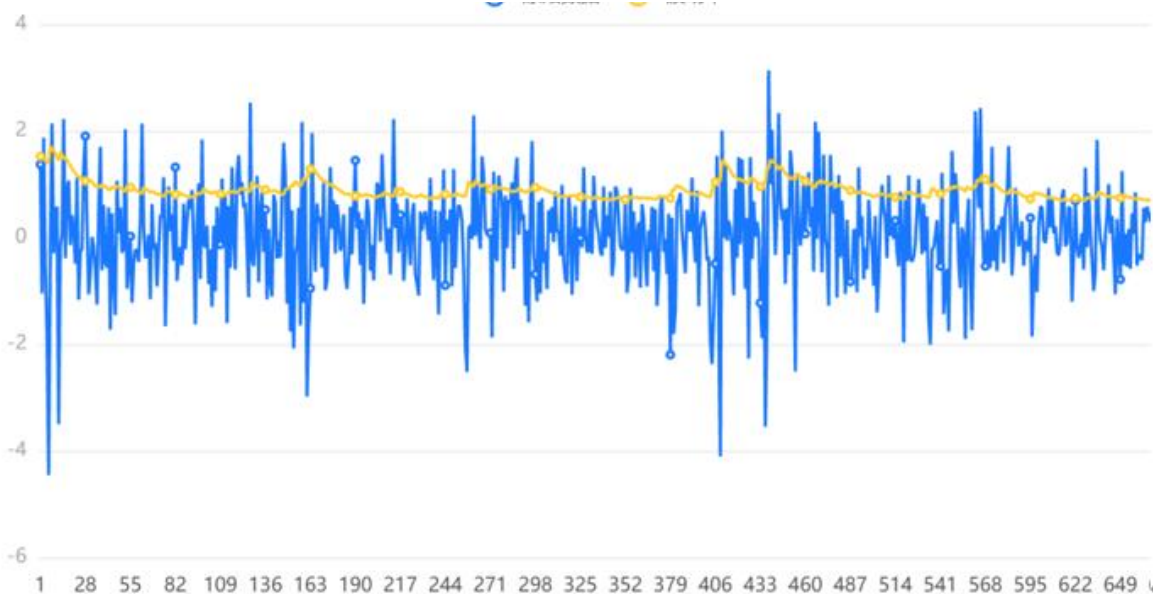


Figure 2. Effectiveness of GARCH model in fitting the volatility characteristics of the original series

Photo credit: Original

Table 5. Model estimation results for the three indices

Correlation Index	α	β	γ
SSE Index	0.035	0.058	0.897
Venture Index	0.025	0.051	0.937
CSI Index	0.034	0.061	0.913

According to the estimation results of GARCH model of different indexes (see Table 5), the variance relationship equation of three indexes can be obtained as follows (where σ_{t1}^2 is the variance of SSE index in the next period, σ_{t2}^2 is the variance of GEM index in the next period, σ_{t3}^2 is the variance of SZSE index in the next period):

$$\begin{cases} \sigma_{t1}^2 = 0.035 + 0.058\varepsilon_{t-1}^2 + 0.897\sigma_{t-1}^2 \\ \sigma_{t2}^2 = 0.025 + 0.051\varepsilon_{t-1}^2 + 0.937\sigma_{t-1}^2 \\ \sigma_{t3}^2 = 0.034 + 0.061\varepsilon_{t-1}^2 + 0.913\sigma_{t-1}^2 \end{cases} \quad (14)$$

Based on the variance relationship equation of the three indices, it is possible to predict the variance and standard deviation of the index trading price fluctuation for the next period. $\sigma^2\sigma$ Select the current trading date one year before the data, after getting the standard deviation of the next period of fluctuations of each index trading return series, assuming that the initial value of the investment amount of 1000 yuan. Under the confidence level of 95% and 99%, the VaR values of different indices at different confidence levels are obtained for the holding period of one year from the current trading date (see Table 6).

Table 6. VaR value of each index at 95% confidence level

Related Indexes	σ Estimated Value	Confidence level	Z	VaR
SSE	0.1873	95% of the total value of the index	1.65	309.0
GEM Index	0.1589	95% of the total number of shares in the market	1.65	262.1
SZSE Composite Index	0.1847	95% (%)	1.65	304.83
SSE Index	0.1873	99% 0.1873	2.33	436.4
GEM Index	0.1589	99% 0.1589	2.33	370.2
SZSE Composite Index	0.1847	0.1847	2.33	430.5

3.3. Economic analysis of the results of the model run

Due to the existence of up and down stop system in the stock market, and this paper does not set the maximum value of the day's up and down, so the results of the model calculations for the assumption that there is no limit of up and down VaR value, the specific results of the calculations may be part of the difference.

The meaning of VAR is: Assuming normal market fluctuations, an investment may incur the maximum loss in the future trading process under a certain confidence level. In the above table, for example, the 95% confidence level of the SSE index return series, as this paper gives the initial investment of \$1,000, the investment in the SSE index under the at-risk value of VaR is 309.0, which can be interpreted as two meanings ① from the current trading day from the one-year period, the purchase of 1,000 yuan of the SSE index of the probability of loss of more than 309 yuan of shares is not more than 5%. ② When the confidence level of 95% is determined, the maximum possible loss of the stock of the SSE index in the next one year is \$309.

4. Conclusion

By comparing the VaR values of three different indices at confidence levels of 95% and 99%, the following conclusions can be achieved:

The VaR values of SSE and SZSE are very close to each other regardless of the 95% and 99% confidence levels, which indicates that there is not much difference in the risk of purchasing the stocks of SSE and SZSE.

Whether at 95% confidence level or 99% confidence level, the VaR value of GEM index is larger than that of SSE index and SZSE index, indicating that the risk of investing in GEM stocks is larger than that of SSE index and SZSE index; the results of the model run are also in line with the restriction that the upward and downward range of GEM stocks should be 20% larger than that of SSE index and SZSE index stocks by 10%.

The findings manifest that significant volatility and risk correlations happen in the Chinese stock market. This paper gives an effective methodology to measure and predict the level of risk in the stock market, which provides investors and risk management organizations with valuable references and decision-making bases and is important for understanding and managing the risk in the Chinese stock market, which helps investors to make informed decisions on risk management and asset allocation.

References

- [1] Shao Jiehao. China's securities market competitiveness and the IPO pricing research [D]. China university of measurement, 2019.
- [2] Li Le. China's securities market insider trading behavior identify research [D]. Shandong university of finance and economics, 2021.
- [3] Wang Meiyang. Research on China's securities market cycle based on Institutional economics [D]. Shanghai University of Finance and Economics, 2021.
- [4] Deng Zenghong. Research on Behavioral Characteristics of Major Participants in Chinese Stock Market [D]. Wuhan University, 2013.
- [5] Li Xue. Empirical Analysis of Chinese residents' Stock Investment Behavior [D]. Jinan University, 2012.
- [6] Li Ming. Study on the influence of investor Sentiment on the herd effect of Chinese Stock Market [D]. Nanjing University of Information Science and Technology, 2023.
- [7] Engle R. F. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U. K. Inflation [J]. *Econometrica*, 1982 (50): 987 - 1008.
- [8] Bollerslev T. Generalized Autoregressive Conditional Heteroskedasticity [J]. *Journal of Econometrics*, 1986 (31): 307 - 327.
- [9] Yanlai S, Stanford S, Jianying H, et al. Interactions of Logistic Distribution to Credit Valuation Adjustment: A Study on the Associated Expected Exposure and the Conditional Value at Risk [J]. *Mathematics*, 2022, 10 (20).
- [10] Lucia G, Silvia C, Irini M, et al. Use of the Lagrange Multiplier Test for Assessing Measurement Invariance Under Model Misspecification [J]. *Educational and Psychological Measurement*, 2022, 82 (2).