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Research on the Application of Computer Big Data Artificial Intelligence Technology in Financial Institutions' Digital Sensitivity Analysis Economic Risk Model

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ABSTRACT

This paper uses a risk factor model to construct a joint distribution of returns on major risk exposures of financial institutions. This paper also examines the sensitivity of the overall risk of the study to changes in the financial business portfolio and changes in risk correlations. The author mainly introduces VaR, ES and ARMA, the quantitative risk analysis methods widely recognized by the financial industry recently. A measure of the overall risk of a financial institution in terms of returns. At the same time, the sensitivity of different risk measurement tools to changes in financial business portfolio and changes in risk correlation.

KEYWORDS

VaR; ES; ARMA; Financial institutions; Sensitivity; Risk measurement

1. INTRODUCTION

Financial risk refers to the possibility of loss in capital raising and use due to uncertainties in business operations. Financial risks include: market risk, which refers to various risks caused by various financial assets or debts existing in the market; credit risk refers to a danger caused by the failure or failure of the other party to perform the contract; business Danger refers to the danger caused by the inability to carry out the scheduled business; liquidity risk refers to the risk caused by the lack of liquidity or lack of funds of financial institutions. In the whole financial system, the two categories of credit and market are the most important. In the past, in relatively stable financial markets, there has been little attention to credit risk and little impact on the market [1].

After the global financial turmoil in 2008, the global financial system issues have received great attention from governments and scholars [2]. Systemic risk is seen as "substantially impairing a large number of market participants at the same time and quickly spreading throughout the system." Currently, regulators such as the Basel Accord are focusing more on individual financial risk, but cannot effectively monitor the financial risk of the entire system, which makes the financial system easily affected. In VaR, "Value-at-Risk" refers to the maximum risk for a specified period and a certain degree of confidence. VaR is a conventional risk measurement method, which is simple in calculation, versatile and easy to evaluate. However, the existing empirical results show that VaR does not fully reflect the overall financial crisis of China, and it is likely to underestimate the impact of various industries (organizations) on it. Along with this development, a new generation of risk measurement methods such as "marginal expected loss method", "conditional risk-at-value method" and "etc" are used to measure the contribution of individuals to the overall economic risk in the financial crisis, and then describe the The overall level of risk across the system.

2. CONCEPTS OF VAR AND ES:

VaR is a generally recognized measurement method. In 2001, the Barr Council listed the VaR model as a risk indicator for measuring banks. It can be defined as the maximum loss of an asset or portfolio in a specific time in the future under a certain confidence level p, or the quantile point of the portfolio's return-loss distribution function. Assuming that X represents the return of a financial asset and its density function is $f(x)$, then VaR can be expressed as:

$$VaR_p = -\inf\{x \mid f(X \le x) > (1-p)\} \tag{1}$$

When the density function $f(x)$ is a continuous function, it can also be written as: $VaR_p = -F^{-1}(p)$, where F^{-1} is called the fractional function, which is defined as the inverse function of the loss distribution $F(x)$. The model is simple to calculate. When the portfolio loss A conforms to a normal distribution and the number of securities in the portfolio does not change, the risk of the portfolio can be effectively controlled. However, the VaR model only cares about the frequency exceeding the VaR value, and does not care about the loss distribution exceeding the VaR value, and it is unstable when dealing with the loss conforming to the non-normal distribution and the investment portfolio changes. Not Satisfied Artzner (1999) proposed the subadditivity of the consistent risk measurement model.

$$VaR_p(X+Y) \ge VaR_p(X) + VaR_p(Y) \tag{2}$$

$ES_{(p)}$ satisfies the subadditivity, homogeneity, monotonicity, and translation invariance conditions proposed by Artzner (1999), and is a consistent risk measurement model [3]. It is defined as follows: Under a given confidence level p, let X be a random variable describing the loss of a portfolio, $F(x) = P[X \le x]$ be its probability distribution function, and let $F^{-1}(\alpha) = \inf\{x \mid F(x) \ge \alpha\}$, then $ES_{(\alpha)}(X)$ can be expressed as:

$$ES_{(p)}(X) = -\frac{1}{p}\int_0^{1-p} F^{-1}(\alpha)d\alpha \tag{3}$$

When the density function of loss X is continuous, $ES_{(p)}$ can be simply expressed as: $ES_p = -E\{x \mid F(x) \le (1-p)\}$. This chapter will choose these two models to measure the risk of financial assets, and give the estimation method and confidence interval under the revised extreme value model.

3. PROPERTIES OF THE ARMA MODEL

Model:

$$y_t = \mu + \sum_{i=1}^{p}\phi_i y_{t-i} + \sum_{j=1}^{q}\xi_j \varepsilon_{t-j} + \varepsilon_t \tag{4}$$

Among them, ε_t is an independent and identically distributed random variable whose expectation is 0 and the variance is constant σ^2, and the model can be expressed as $AR(\infty)$ when it is reversible. The model assumes that the conditional expectation of y_t is available and the conditional variance is constant, which can usually be used to explain the correlation of time series, and can make short-term prediction of time series [4]. However, the assumption that the conditional variance of the model is constant makes it unable to effectively explain the volatility clustering phenomenon that is often observed in financial time series. For this reason, we need to further introduce the $GARCH$ model into the model.

We let $\varepsilon_t = z_t h_t$, where z_t is an independent and identically distributed random variable with expectation 0 and variance constant 1, and h_t^2 be the conditional variance of ε_t at time t. Here we use the simplest $GARCH(1,1)$ model commonly used, the conditional variance can be expressed as: $h_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + bh_{t-1}^2$ and $GARCH(1,1)$ the model can also be expressed in the form of square error ε_t^2:

$$\varepsilon_t^2 = a_0 + (a_1 + b)\varepsilon_{t-1}^2 - b(\varepsilon_{t-1}^2 - h_{t-1}^2) + (\varepsilon_t^2 - h_t^2) \tag{5}$$

Where $E((\varepsilon_t^2 - h_t^2) \mid F_{t-1}) = 0$, so $GARCH(1,1)$ model is essentially ARMA(1,1) of square error ε_t^2. The introduction of the $GARCH(1,1)$ model can not only capture the volatility clustering phenomenon of financial time series, but also improve the z_t tail phenomenon to a certain extent, because

$$k_{h4} = \frac{E\varepsilon_t^4}{(E\varepsilon_t^2)^2} = \frac{Ez_t^4}{(Ez_t^2)^2}\frac{Eh_t^4}{(Eh_t^2)^2} \geq \frac{Ez_t^4}{(Ez_t^2)^2} = k_{z4} \tag{6}$$

Among them, k_{h4} and k_{z4} represent the kurtosis of h_t and z_t, respectively, and the kurtosis of h_t is obviously greater than or equal to the kurtosis of z_t.

4. ESTIMATION METHOD OF VaR AND ES CONFIDENCE INTERVALS FOR SERIES z_t

Usually, for the estimation method of parameter confidence interval, in the case of large samples, we can get it from the idea of Likelihood Ratio Test. The likelihood ratio test is used to test how well two models of the same type fit well [5]. The likelihood ratio of two models of the same type follows an χ^2 distribution with degrees of freedom equal to the number of newly added parameters in the complex model. Taking the POT model as an example, to estimate the confidence interval of parameters ξ and σ at a given confidence level α can be obtained by the following formula:

$$L(\xi,\sigma) > L(\hat{\xi},\hat{\sigma}) - \frac{1}{2}\chi_{\alpha,2}^2 \tag{7}$$

Among them, $\hat{\xi}$ and $\hat{\sigma}$ are the estimated optimal values, and $L(x,y)$ represents the likelihood function. In this way, we have obtained the joint confidence interval of ξ and σ. If we want to obtain the estimated value of VaR_p, we can inversely solve σ according to formula (17) and bring it into formula (13) to obtain $L(\xi, VaR_p)$, so that the confidence interval of $\bar{L}(VaR_p) = \max_{\xi} L(\xi, VaR_p)$, VaR_p can be obtained by The following formula is obtained:

$$\bar{L}(VaR_p) > L(\hat{\xi}, \hat{\sigma}) - \frac{1}{2}\chi^2_{\alpha,1} \tag{8}$$

However, since the amount of extreme data exceeding the threshold is not large, the asymptotic effect of this estimation may not be good. To this end, we introduce the Bootstrap method to obtain estimates of confidence intervals. Since the obtained sequence $\{z_t\}$ is independent and identically distributed, we can independently extract N points from it each time to form a new sequence, use this sequence to estimate VaR_p and ES_p, and repeat this operation to obtain a series of VaR_p and ES_p estimated values, find the empirical distribution of VaR_p and ES_p, and finally get the confidence interval of VaR_p and ES_p according to the empirical distribution, and take the expected value of VaR_p and ES_p as the estimated value of VaR_p and ES_p. Here we only give the method for calculating the VaR_p confidence interval in the POT model, and the confidence intervals for other parameters can be obtained similarly. This method not only determines the confidence interval, but also a method to test the stability of the model.

5. CASE STUDY

First of all, this paper uses "value at risk" (VaR), "marginal loss expectation method" (ES), "ARMA model to measure the systemic financial risk of each sector, and thus the systemic financial risk of each financial sector in China. For further analysis, we calculated the VaR, ES and ARMA risk metrics of each department based on the principle of arithmetic average, and displayed the results in Figure 1. At the same time, for the convenience of identification, we use the gray shaded area to mark the obvious fluctuations of each metric. As shown in Figure 1, VaR and ES indicators are generally more sensitive to systemic risk, and their volatility is more obvious than ARMA. At the same time, we have reached consistent conclusions based on these three different measurement methods [6]. Among them, the banking sector’s The four risk measurement indicators all showed a significant increase at the end of 2015, and reached a periodical high in 2016. At the same time, we also found that the risk measurement indicators of the banking sector have gradually declined since 2020, indicating that the overall risk of Chinese banking sector is relatively stable in the emerging stage. level of control.

For the securities sector, the systemic risk index showed a phased rise at the end of 2017, which means that the financial risk of the securities industry has also increased. We can also find that the ES index and VaR index of the real estate sector, respectively, in March 2016, the State Council issued the "Notice on Continuing to Do a Good Job in the Regulation of the Real Estate Market", and the regulation policy continued to increase. After a certain negative impact, it reached two stage peaks. At the same time, the ES index and VaR index of other financial industries also reached periodic highs in June 2016. This is due to the tightness of funds between banks and the rising interest rates of funds, and financial institutions such as trusts, asset management, and private equity have been impacted by the risk of money shortages. All four risk metrics rose to historic peaks.

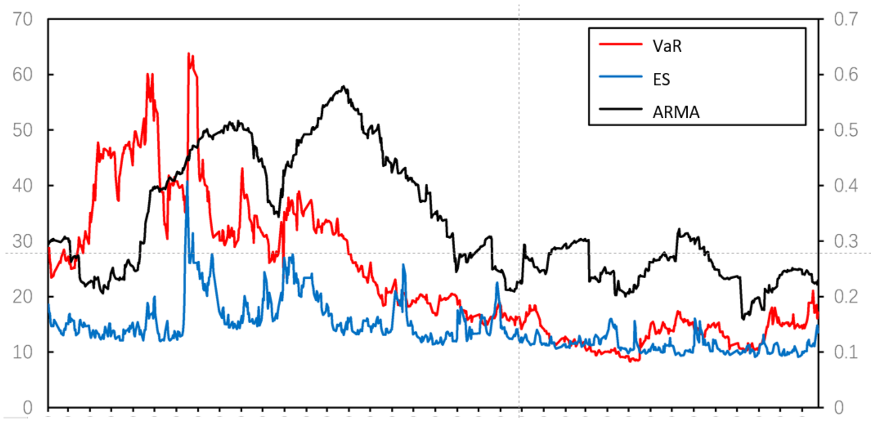

Figure 1. Systematic risk trend of various sectors of the stock market

Based on the average value of the risk metrics of all sample companies, we construct a measure of the overall systemic risk of Chinese financial institutions and draw it in Figure 2. Figure 2 shows that the overall risk to the financial system showed two small peaks in 2016. The first peak occurred in early March, when risks in the banking and real estate sectors rose sharply; the second peak occurred in 6 In June, the money shortage incident led to the rise of the overall risk of financial institutions [7]. At the same time, during the stock market turmoil in mid-to-late 2018 and the 1,000-share limit-down caused by the circuit breaker mechanism in early 2019, financial risks measured based on ES, VaR and ARMA indicators rose significantly. After entering 2020, the four indexes gradually declined, and in the second half of the year, they gradually fell to historical lows in the past seven years.

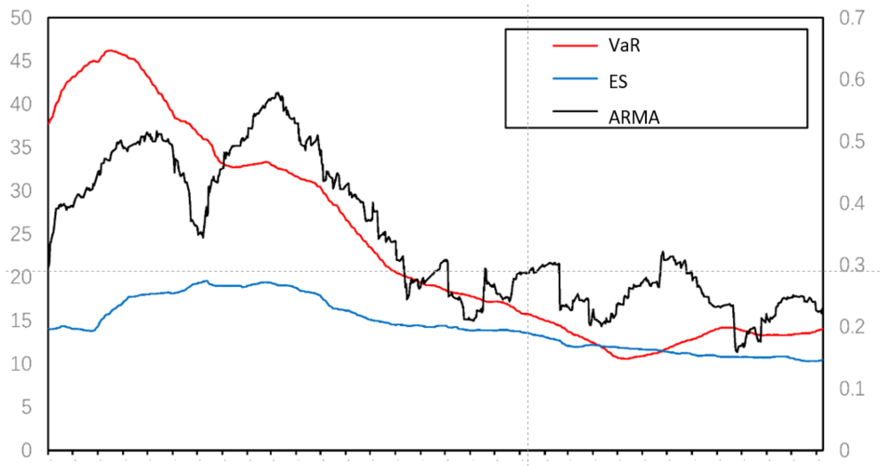

Figure 2. Trends in the measurement of systemic risk in the financial system

On the basis of the previous analysis, we rank the risks of the financial sector according to the size of ES, VaR, and ARMA measures, and the results are listed in Table 1. It can be found that for ES, VaR and ARMA, the real estate industry has basically been the sector with the highest systemic risk since 2011 due to its large number of listed companies, high leverage ratio and high probability of capital loss. Risk is next. This means that in Chinese financial system, there are obvious financial risks in the real estate, securities and banking industries. At the same time, we also found that the ranking results of ES and VaR are basically the same, and the measurement results of the ARMA indicator are only different in the risk size of banks and securities. The reason is that ES emphasizes the risk impact of changes in the financial system on individual institutions during times of crisis, while ARMA focuses more on the marginal changes in systemic risk contributed by individual institutions, which means that Chinese banking sector is in crisis. The marginal change in risk over time was higher, while the financial crisis had a bigger shock to the securities sector [8]. At the same time, in the measurement analysis based on the ARMA method, the banking sector has become the sector with the highest systemic risk in the financial system, followed by the securities industry, and other financial industries have the lowest risk. Relevant studies have shown that different measurement indicators place different emphasis on information in time series, so the systematic risk ranking based on different indicators will be different, but the overall measurement results are roughly the same. In addition, the measurement results will be different during different crises, and the risk ranking will change accordingly. We further examine the net effect of risk contagion in the overall sample and the stock market turbulence of the five sectors, and list the ranking analysis results based on the VaR and ARMA measurement methods in Table 1. From the analysis results of the NET indicators in Table 1, we can see that during the overall sample period, the securities and insurance industries are both net risk exporters, while banks are the most affected by the net risk spillover. Beginning in the turbulent period of China's stock market in June 2018, in addition to the insurance sector, real estate has become the main sector with net external risk spillovers, while the securities sector has become a net recipient of risks from a net exporter of risks. The clear impact of the net spillover of risk contagion.

Table 1. Ranking analysis of net exporters and receivers of risk contagion

VaR					
Sort	Industry	NET	TO	FROM	GROSS
1	Insurance	7.7	64.3	55.5	229.7
2	Securities	5.5	69.3	63.7	233.2
3	Real estate	–0.9	57.2	59.0	227.2
4	Other	–3.4	47.3	50.7	97.0
5	Bank	–9.9	46.4	56.4	202.7
ES					
Sort	Industry	NET	TO	FROM	GROSS
1	Real estate	24.3	72.3	67.0	250.4
2	Insurance	22.9	72.0	69.0	252.0
3	Bank	–4.2	60.4	64.4	224.7
4	Securities	–7.5	67.2	74.7	242.0
5	Other	–25.7	56.5	72.2	227.7
ARMA					
Sort	Industry	NET	TO	FROM	GROSS
1	Securities	7.2	72.0	63.7	234.7
2	Insurance	5.5	64.6	59.2	223.7
3	Real estate	–2.9	56.9	57.9	225.7
4	Other	–5.0	46.4	52.3	97.7
5	Bank	–5.7	52.9	57.7	222.6

6. CONCLUSION

Since the risks of financial institutions do not have complete covariance and normality, the linear addition VaR overestimates the overall risk, while ES underestimates the overall risk. Therefore, the value estimated by ARMA can better measure the overall risk of financial institutions in China. In Chinese financial institutions, the increase in the proportion of financial business portfolios related to market risk will increase the overall risk. Therefore, in practice, financial regulators need to pay attention to the risks brought about by the increase in the proportion of financial institutions' trading assets. With the increase of operational risk, the peak and thick tail characteristics of operational risk have a greater impact on the overall risk of financial institutions.

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