**Systematic Risk Measurement of China's Unlisted Insurance Companies Based on SVM-SRISK**

School Of Finance And Statistic, HNU

**Speaker :Lin Zhang**

1




2

## Abstract

- Object Of Study
- Method
- Conclusion

3

## 01 Abstract

With the development of the capital market and the increasingly close ties with the countries of the world, the insurance industry continues to grow and expand, but the possibility of cross-shareholding, payment system interaction, reinsurance, and derivative risk transfer also increasing. In terms of scale and extent, the possibility of systemic risks and the possible impact on the real economy are also expanding.

A suitable method to comprehensively measure the systematic risk of china's insurance companies in general.

1 **Object:** Top 18 insurance companies, which account for 70% of market share.

2 **Method:** We build the SVM-SRISK model, it makes full use of the financial information of unlisted company and improves the estimation accuracy of their LRMES.

3 **Main Conclusions:** The average annual growth rate of total SRISK in china's insurance industry is increased significantly. The average contribution of unlisted companies to systemic risk condition capital shortage is about 5.53% in 2014, which was lower than the 5.67% of listed companies, and it rose to 6.3% in 2015 but fell to 6.0% in 2016.

4

## Introduction and Review of the Literature

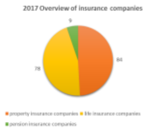
- background
- Literature review
- Main contribution

5

## 1 The Background

**Necessity**

**With** the development of the capital market and the increasingly close ties with the countries of the world, the insurance industry continues to grow and expand, but the possibility of cross-shareholding, payment system interaction, reinsurance, and derivative risk transfer also increasing. **In** terms of scale and extent, the possibility of systemic risks and the possible impact on the real economy are also expanding.





**Current Status in China**

6

## 2.1 Literature Review--Systemic Risk

Measuring Systemic Risks

1

**One** method focuses on the contagion effects between risks, for instance, the conditional risk value CoVaR measure of the intensity of a single financial institution's risk spillover to other financial institution (Adrian and Brunnermeier 2009), and it includes the estimate models such as quantile regression, GRACH, COPULA (Jiang et al., 2014) etc.

2

**The** other method assumes that under the condition of a systemic risk caused by external shocks, the institution that causes the risk to spread further by exiting from the capital market, so the institution is called the one that contributes to the systemic risk or called a systemically important financial institutions. For example, MES (Acharya et al., 2012) calculates the marginal contribution of individual financial institutions to the systemic loss of the financial system. Then there are some improvement models based on it, such as, LRMES (Long Run Marginal Expected Shortfall), the CES (Components Expected Shortfall) method which considers the scale, and the SRISK (Conditional Shortfall of Systemic Risk) which measures a financial institution's liabilities, size, relevance, leverage and other factors.

7

## 2.1 Literature Review--Systemic Risk

Measuring Systemic Risks

1

**Benoit et al., ( 2013)** found that SRISK has a broader use by comparing MES, ΔCoVaR and SRISK. He discovered that MES plays a very small role in the rankings of systemically important financial institutions, and there is a strong positive correlation between MES and company beta rankings; ΔCoVaR strongly correlates with its VaR in terms of predicting systemic risks, compared with VaR, the added value of ΔCoVaR in forecasting systematic risk is very limited. But the SRISK made a very good compromise between the "too big to fail" and "too interconnected to fail". What's more, the overall shortfall of capital emphasized by the SRISK model can be caused by poor management of financial institutions, external macroeconomic fluctuations or monetary policies.

- **Benoit, S, G Colletaz, C Hurlin, and Christophe Perignon. 2013. A Theoretical and Empirical Comparison of Systemic Risk Measures. *Social Science Electronic Publishing***

8

## 2.1 Literature Review--Systemic Risk

Measuring Systemic Risks

2

**Brownlees and Engle (2016)** considered that the stability and sensitivity of SRISK method are superior to those of SES measured in advance, and verified by Lehman Brothers Bank, AIG and other agencies that triggered the systemic crisis in 2008. The results shown that SRISK has a good risk warning signal, and reflects the ability of individual financial institutions to resist risks and facilitate macro-level prudential supervision.

- **Brownlees, C, and R F. Engle. 2016. SRISK: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies* 30 (1):48-79.**

9

## 2.1 Literature Review--Systemic Risk

3

Measuring Systemic Risks

**Wang and Yuan (2017)** found that MES and CES indicators are more effective and applicable, and that SRISK is slightly less effective, but it has a more comprehensive and leveraged approach, by comparing the effectiveness and applicability of MES, SRISK and CES evaluation methods in the Chinese market. The assessment results such as rates are more reliable. By comparing MES, SRISK and CES methods to evaluate the validity and applicability of systematic importance of listed financial institutions in China, Wang and Yuan (2017) found that the MES and CES indicators are more time-efficient, and SRISK is more reliable and less time-sensitive in evaluating the scale, leverage and other information.

- **Wang, Peihui, and Wei Yuan. 2017. Financial Institutions System Importance Evaluation Methods Comparison and Application. *Wuhan Finance* (8):40-45.**

10

## 2.2 Literature Review--Credit Risk

1

Measuring The Credit Risk Of Unlisted Companies

**The** domestic and foreign methods for measuring the credit risk of unlisted companies include the option pricing PFM model proposed by Moody's KMV, but the accuracy of the PFM model for the measurement of nonlinear sample data is poor.

**Xie et al., (2016)** used the propensity score matching (PSM) to improve the PFM. By matching the market value of assets and volatility of listed company and unlisted company, they calculated the default distance as a measure of credit risk.

- **Xie, Yuantao, xiaoke Sun, and Hang Sun. 2016. Unlisted insurance company credit risk dynamic measurement *Insurance Research*, (7):35-43.**

11

## 2.2 Literature Review--Credit Risk

2

Measuring The Credit Risk Of Unlisted Companies

**Liu and Cui (2016)** adopted the SVM (support vector machine) regression in data mining to measure the credit risk of four unlisted companies in China's four different industries. Compared with the traditional quantitative regression model, SVM regression has higher accuracy and more robustness. Considering the fact that there are few data samples of listed companies in China's insurance industry, while the application of PSM (propensity score method) is based on large samples.

- **Liu, YanChun, and Yongsheng Cui. 2016. Research on Credit Risk Measurement of Unlisted Corporations in China --Analysis of PFM Model Based on Option Pricing and SVM Regression Analysis of Support Vector Machine *Journal of Liaoning University (Philosophy and Social Sciences Edition) 2016-02* 44 (6):88-97.**

12

## 2.2 Literature Review--Credit Risk

3

Measuring The Credit Risk Of Unlisted Companies

**In** the case of small samples, when the propensity scores of the treatment group and the control group do not overlap, the comparability between the groups is poor, and the appropriate stratification or matching cannot be performed (**Chiba and VanderWeele 2011**); the construction of BP neural network requires training data set, assessment data set and test data set, and the requirements for data are also higher. Compared with the method of PSM and BP, SVM is more effective and superior in the case of small samples, and is widely used in credit risk assessment (**Hu et al., 2012**) and motor vehicle insurance fraud recognition (**Zhao et al., 2015**).


- **Chiba, Yasutaka, and Tyler J. VanderWeele. 2011. A Simple Method for Principal Strata Effects When the Outcome Has Been Truncated Due to Death. *American Journal of Epidemiology* 173 (7):745-751.**
- **Hu, Haiqing, Wei Zhang, and Daohong Zhang. 2012. Research on Credit Risk Assessment of SMEs from the Perspective of Supply Chain Finance---Comparative Study Based on SVM and BP Neural Network. *Management Review* 24 (11):70- 80.**
- **Zhao, Shangmei, Ting Zhao, and Jianlei Hou. 2015. Introducing Support Vector Machine SVM into Motor Vehicle Insurance Fraud Identification. *China Insurance* (8):15-19.**


13

## 2.3 Paper' s structure

Paper's structure

**The** remainder of this paper is organized as follows. The "Basic Principles of Model" section introduces the SRISK theoretical basis and the Support Vector Machine principle. The "SRISK-SVM model framework" section explains the conditional capital shortfall of systemic risk model used. In the "Data Analysis and Variable Selection" section, the stock price data set is described and the financial data variable is selected by co-linearity test. The SRISK and SRISK% of the 18 insurance companied results and stability test are discussed in the "SVM-SRISK empirical analysis" section. The "Supervision of systemically important insurance institutions" section provides an assessment of the leverage ratio supervision. Finally, the "Concluding Remarks" section concludes.

14

## 3 Main Contribution

**A Innovation Point**

**The** SRISK method proposed by Brownless and engel(2012) was used to measure the capital shortage of listed companies. SVM was applicable to the characteristics of small sample, non-linear and high-dimensional data, and the correlation model between financial data and systemic risk was established by SVM regression.

**B Contribution 1**

**The** size of systemic risk of the top 18 insurance companies in china is able to work out, which premium income accounted for 70% of the market share.

**C Contribution 2**

**By** calculating the prudent leverage ratio applicable to each company, it provides a certain complement to current solvency regulation. This can not only measure the capital shortage of the whole insurance industry comprehensively, but also provide reference for macro-prudential regulation.

15

## Basic Principles of Model

03

SRISK

SVM

SVM-SRISK

16

### 1.1 SRISK--Theory

Theory

1

**Brownlees et al., (2012)** pointed out that the objective of the SRISK model is to measure the capital shortfall that a financial firm is expected to experience conditional on a systemic event. The SRISK calculation is analogous to the stress tests that are regularly applied to financial firms, and it is done with publicly available information only. The capital shortfall can be thought as the negative impact of the company's working capital. When the capital shortfall is negative, the company has the capital surplus, and the company can operate properly. But when the capital shortfall is positive, the enterprise will encounter financial difficulties.

- **Brownlees, C T, R Engle, and G Aielli. 2012. Volatility, correlation and tails for systemic risk measurement. *Social Science Electronic Publishing*:16-18.**

2

**We** define the capital shortfall of firm i at time t as $CS_{it} = kA_{it} - W_{it} = k(D_{it} + W_{it}) - W_{it}$, where $W_{it}$ is the book value of equity, $D_{it}$ is the book value of debt, $A_{it}$ is the value of quasi-assets and k is the prudential capital fraction[1]. We are concerned about predicting the capital shortfall that financial institutions may face under the conditions of a systemic crisis. As for different definitions of systemic crises, we choose the definition that the rate of decline of the market falls below a threshold C for a period of time h proposed by **Acharya et al., (2010).**

- **1:Under the minimum capital adequacy requirement of Basel III, we fixed the prudential capital fraction at 8%.**
- **Acharya, V., L. Pedersen, T. Philippon, and M. Richardson. 2010. Measuring Systemic Risk: Department of Finance ,NYU.**

17

### 1.1 SRISK--Theory

Assumption & Formula

1

**In** order to generate a meaningful measure of the pressure capital shortfall, we assume that the system event corresponds to a sufficiently extreme scenario. We define the market return between period t + 1 and t + h as $R_{mt+1:t+h}$ and systemic event as$\{R_{mt+1:t+h} < C\}$. In this paper we set the horizon h to one season (that is 57 periods) and the threshold C to −20%. We denote SRISK as the expected capital shortfall conditional on a systemic risk event

$$
\begin{aligned}
SRISK_{it} &= E_t\left(CS_{it+h} \mid R_{mt+1:t+h} < C\right) \\
&= kE_t\left(D_{it+h} \mid R_{mt+1:t+h} < C\right) - (1-k)E_t\left(W_{it+h} \mid R_{mt+1:t+h} < C\right) \\
&= kD_{it} - (1-k)W_{it}\left(1 - LRMES_{it}\right)
\end{aligned}
$$

18

## 1.1 SRISK--Theory

Assumption & Formula

2

**where** $LRMES_{it}$ is the long run marginal expected shortfall, the expectation of the firm equity multi–period arithmetic return conditional on the systemic risk event, that is $LRMES_{it} = -E_t(R_{it+1:t+h} | R_{mt+1:t+h} < C)$, where $R_{mt+1:t+h}$ is the multi–period arithmetic firm equity return between period t + 1 and t + h. Then, the capital shortfall of the single financial institution i relative to the financial system can be represented as:

$$SRISK\%_{it} = \frac{SRISK_{it}}{\sum SRISK_{i,t}}$$

The greater the value of SRISK% is, the more significant the importance of financial institution i in the financial system is.

19

## 1.2 SRISK-Calculation Step

**In** order to calculate the value of SRISK, the estimation of LRMES should be obtained firstly. At present there are many ways to estimate the LRMES and the GARCH-DCC (**Engle 2002**) model is selected in this paper.

1 **Returns Of The Firm And The Market**

**We** denote the logarithmic returns of the firm and the market as $r_{it} = \ln(1 + R_{it})$ and $r_{mt} = \ln(1 + R_{mt})$, respectively. Suppose that conditional on the information set $F_{t-1}$ is available at time t – 1, the return pair has an (unspecified) distribution D with zero mean and time varying covariance,

$$\begin{bmatrix} r_{it} \\ r_{mt} \end{bmatrix} | F_{t-1} \sim D\left(0, \begin{bmatrix} \sigma_{it}^2 & \rho_{it}\sigma_{it}\sigma_{mt} \\ \rho_{it}\sigma_{it}\sigma_{mt} & \sigma_{mt}^2 \end{bmatrix}\right)$$

**This** approach requires specifying formula for the evolution of the dynamics volatilities $\sigma_{it}^2$ and $\sigma_{mt}^2$, and correlation $\rho_{it}$.

- **Engle, R. . 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics* 20 (3):339-350.**

20

## 1.2 SRISK-Calculation Step

2 **GJR-GARCH**

**Considering** the asymmetry of the financial market and the unique, peak and heavy tail of the stock return data, we select the GJR-GARCH model to describe the volatility and the DCC model to describe the correlation coefficient of stock prices. The GJR–GARCH model formulas for the volatility dynamics are

$$\sigma_{it}^2 = \omega_{Vi} + \alpha_{Vi} r_{i\ t-1}^2 + \gamma_{Vi} r_{i\ t-1}^2 I_{i\ t-1}^- + \beta_{Vi} \sigma_{i\ t-1}^2$$
$$\sigma_{mt}^2 = \omega_{Vm} + \alpha_{Vm} r_{mt-1}^2 + \gamma_{Vm} r_{mt-1}^2 I_{mt-1}^- + \beta_{Vm} \sigma_{mt-1}^2$$

**where** $I_{it}^- = 1$ if $r_{it} < 0$ and $I_{mt}^- = 1$ if $r_{mt} < 0$. Compared with positive signals, negative signals of stock market can lead to a great increasing of volatility, so we use the GJR-GARCH model to examine the extent of leverage effect in stock market.

21

## 1.2 SRISK-Calculation Step

3 **DCC**

**The** correlation coefficient of the DCC model through volatility adjusted returns $\epsilon_{it} = r_{it}/\sigma_{it}$ and $\epsilon_{mt} = r_{mt}/\sigma_{mt}$

$$Cor\begin{pmatrix} \varepsilon_{it} \\ \varepsilon_{mt} \end{pmatrix} = R_t = \begin{bmatrix} 1 & \rho_{it} \\ \rho_{it} & 1 \end{bmatrix} = diag(Q_{it})^{-1/2} Q_{it} diag(Q_{it})^{-1/2}$$

**where** $Q_{it}$ is the so-called pseudo-correlation matrix. The DCC model establishes a regression model by the pseudo-correlation matrix $Q_{it}$ as

$$Q_{it} = (1-\alpha_{ci}-\beta_{ci})S_i + \alpha_{ci}\begin{bmatrix} \varepsilon_{it-1} \\ \varepsilon_{mt-1} \end{bmatrix}\begin{bmatrix} \varepsilon_{it-1} \\ \varepsilon_{mt-1} \end{bmatrix}' + \beta_{ci} Q_{it-1}$$

**where** $S_i$ is the unconditional correlation matrix of the firm and market adjusted returns, and $S_i = E(\varepsilon_{it}\varepsilon_{it}')$. In the high DCC model, you can estimate $S_i$ directly with the following simple average formula,$S_i = \frac{1}{n}\sum \varepsilon_{it}\varepsilon_{it}'$, which greatly reduces the complexity of the calculation. At the same time, the parameters estimated should satisfy the conditions of $\alpha_{ci} > 0, \beta_{ci} > 0, \alpha_{ci} + \beta_{ci} < 1$ to ensure that the matrix $Q_{it}$ is positive.

22

## 1.2 SRISK-Calculation Step

4 **LRMES**

**For** such dynamic models, LRMES are usually not available in a closed form. However, accurate LRMES prediction can be obtained based on simulation. The procedure consists of simulating a random sample of size *S* of *h-period* firm i and market m arithmetic returns conditional on the information set available on day t.

$$\begin{bmatrix} r^s_{it+1:t+h} \\ r^s_{mt+1:t+h} \end{bmatrix} F_t \quad s = 1,2,\ldots,S(One\ season\ contents\ h-period)$$

**In** order to obtain the returns, firstly, we need to simulate the time series of random variables （$\varepsilon_{mt}, \varepsilon_{it}$）, and substitute the DCC-GARCH model which have calculated the parameters according to the historical data, then we can obtain the simulation sequence of the returns. Then, calculating the quarter returns $R^s_{iT+1:T+h}$ of the firm and market, the LRMES for day t is then calculated using the Montel Carlo average of the simulated arithmetic h-period returns.

$$LRMES^s_{iT} = -\frac{\sum_{s=1}^{S} R^s_{i\,T+1:T+h} I\{R^s_{m\,T+1:T+h} < C\}}{\sum_{s=1}^{S} I\{R^s_{m\,T+1:T+h} < C\}}$$

**where**$I\{\ \}$ is an indicative function, and when the expression inside the bracket is true, its value is 1, otherwise it is 0. Then substituting the LRMES value into the formula at the begining, we can obtain the value of SRISK.

23

## 2.1 SVM

1

**Theory**

**Support** Vector Machine was firstly proposed by Cortes and Vapnik (1995). The core idea is to find the optimal classification super in the sample space, maximizing the interval between different types of training samples to achieve the optimal classification effect. The SVM is mainly used to slove small sample statistical problems. It not only considers the requirements for progressive performance, but also seeks to seek optimal results with limited information. It is also exhibits many unique advantages in solving nonlinear and high-dimensional pattern recognition problems. Compared with neural networks, the SVM solves the problem of over-adaptation and has a global optimal solution. In addition, by introducing a kernel function to map data to a high-dimensional space, the problem of dimensionality disaster can be solved.

24

## 2.1 SVM

2

Theory

The SVM regression is based on a given sample data set$\{(x_i, y_i)|\mathrm{i} = 1, \dots, \mathrm{k}\}$, where $x_i$ is the predict influence factor value and$y_i$ is the predict target value. SVM is seeking an optimal functional connection reflecting the sample data. The SVM function have the following form:

$$f(x) = w * \phi(x) + b$$

where $w$ and $b$ are the weights and offsets of the SVM regression function, respectively, and f is a regression function for any corresponding x and y. Optimal is means that the error function reaches the minimum value. The $\epsilon$-insensitive error function ($\epsilon \geq 0$) is commonly used in SVM regression, which is simply referred to as $\epsilon$-SVR algorithm. In order to minimize the "total deviation" of all sample points from the optimal hyper-plane, the concept of similar spacing is used to define the $\epsilon$ -insensitive loss function $|y - f(x)|_\epsilon = max\{0, |y - f(x)| - \epsilon\}$, by introducing two slack variables $\zeta_i$and $\zeta_i^*$, the objective function and constraints become:

$$\min \frac{1}{2}||w||^2 + c\sum_{i=1}^{l}(\zeta_i + \zeta_i^*)$$

$$\text{s.t} \begin{cases} (w * \phi(\mathrm{x})) + b - y_i \leq \zeta_i^* + \epsilon, i = 1,2, \dots, l \\ y_i - (w * \phi(\mathrm{x})) - b \leq \zeta_i + \epsilon, i = 1,2, \dots, l \\ \zeta_i, \zeta_i^* \geq 0 \end{cases}$$

25

## 2 SVM

3

Theory

**Now**, it has converted into a problem of solving a quadratic convex programming. The first constraint makes the function flatter, thus improving the generalization ability. The second constraint is to reduce the error, the constant c is the penalty coefficient, and ε controls the regression precision. Finally, introducing the Lagrange multiplier make the original problem transform into its dual optimization problem, and the final regression formula f(x) expression is eventually solved as follows,

$$f(x) = \sum_{i=1}^{l}(a_i - a_i^*)K(x_i, x_j) + b$$

**The** basic thought of SVM is to find a feature mapping function $\phi(.): R^N \to \mathrm{H}$ from the input space to the output space, map the input data x into the high-dimensional feature space H, and the appropriate kernel function $K(x_i, x_j)$ can replace the vector inner product in the high-dimensional feature space, so the type and complexity of the SVM is determined by the form and parameters of the kernel function. The common kernel functions include linear, polynomial, and radial basis (RBF). RBF kernel functions is suitable to the low-dimensional, high-dimensional and small sample. The function has the characteristics of rotational symmetry and separability, and it has a wide convergence domain, so it is the most widely used kernel function.

26

## 3 SVM-SRISK

**The** SRISK model is based on the decline in the stock price of the listed company conditional on the systemic crisis event, and combine the company's equity-liability data into to get the company's conditional capital shortfall. The traditional method, such as MES, ΔCoVaR, CES and SRISK, both have a shortcoming, which is the unlisted company cannot provide stock market price information.

**In** order to overcoming this shortcoming, firstly, we use the random simulation to obtain the LRMES values of all listed insurance groups, the SVM model is used to establish the connection between the LRMES of the listed groups and its corresponding annual financial data. Then, sought the optimal parameters through cross-checking, the well-trained SVM regression model was finally obtained. Finally, through substituting the financial data of the unlisted company into the well-trained model, we can calculate the LRMES value of the unlisted company and then the SRISK, which considered the scale, assets and leverage effect, is obtained by using formula.

1 Collect The Listed Companies' Data

Calculate The LRMES Of Listed Insurance Groups

2 Build Index System

Build SVM Model

3 Calculate The LRMES Of Unlisted Companies

Calculate SRISK And SRISK%

27

# Empirical Analysis

Data Analysis & Variable Selection

SVM-SRISK Empirical Analysis

Stability Test

28

## 1.1 Data Analysis

Data

**The** first category: listed insurance group market data.

1) Due to the large differences in trading rules, market practices and investor expectations between the China's Mainland Stock Exchange and the Hong Kong Stock Exchange, in this paper, we does not consider the PICC Group and Taiping Insurance Group which are listed in Hong Kong Stock Exchange.
2) In terms of time dimension, due to the existence of accounting rules of fair value measurement and the pro-cyclical financial supervision system, the economic cycle has upward and downward periods, that is, systematic risks have certain periodicity (**Jiang et al., 2014; Xu et al., 2016**). We treat each year's data of each listed group as an independent samples, and set them as a training samples. There are totally 34 independent samples: China Ping An (2007~2016), China Life Insurance (2007~2016), Pacific Insurance (2008~2016), Xinhua Insurance (2012~2016). The closing stock price data of the industry is obtained through weighted average of the total capital stock calculated by Wind Database.


- **Jiang, Tao, Weixing Wu, and Tianyi Wang. 2014. Systematic Risk Measurement in Financial Industry Based on Tail Dependence Perspective** ***Systems Engineering Theory and Practice*** **34 (s1):40-47.**
- **Xu, Hua, Mengxin Wei, and Xi Chen. 2016. Systematic Risk Assessment and Influencing Factors in China's Insurance Industry.** ***Insurance***


29

## 1.1 Data Analysis

Data

**The** second category: each insurance company financial data.

1) On the one hand, china's insurance market has a high degree of concentration, and the number of unlisted insurance companies is large, the scale is different, the mechanism is not perfect. China's regulators do not require complete disclosure of financial information, so the data acquisition is difficult.
2) On the other hand, systemic risks are mostly caused by companies with large marker sizes. So we select 18 insurance companies accounted for 70% of the market share in 2016 to calculate the size of the SRISK and SRISK% in 2014-2016. The financial data is obtained from its annual financial statement data and solvency reports disclosed on the official website.

30

## 1.2 Variable Selection

Variables

**Xie et al., (2016)** combined with the characteristics of the insurance industry, selected insurance company-specific business indicators such as underwriting potential, comprehensive loss ratio, and retention ratio as factors affecting the relative asset value and volatility of the company, thereby measuring the credit risk of unlisted insurance companies. **Zeng et al., (2017)** selected indicators such as total return on assets, operating profit margin, quick ratio, and asset-liability ratio.

Due to lack of domestic research on the systemic risks of unlisted insurance companies, and according to the characteristics of the insurance industry and availability of data, we select 12 business indicators that may affect the LRMES of insurance institutions. However, based on the co-linearity and correlation between input variables, making data processing and screening, we finally get the six indicators as shown in Table 1, which is the predictive influence factor input variables of the SVM.


- **Xie, Yuantao, xiaoke Sun, and Hang Sun. 2016. Unlisted insurance company credit risk dynamic measurement Insurance Research, (7):35-43.**
- **Zeng, Lingling, Xiao Pan, and Man Ye. 2017. Measurement of credit risk of unlisted companies based on BP-KMV model. *Economic Accounting Monthly* (18):47-55.**


31

## 1.2 Variable Selection

**Table 1**

| Variable | Definition | Calculation formula |
|---|---|---|
| $X_1$ | Underwriting potential | (insurance business income - the ceded-out premium) / (share capital or paid-in capital + surplus reserve + capital reserve) |
| $X_2$ | Surrender rate | surrender value / insurance business income |
| $X_3$ | Asset-liability ratio | Liabilities / Assets |
| $X_4$ | Total Assets Profit Margin | Net Profit / Total Assets (Return on Investment) |
| $X_5$ | Market share | the company's original premium income / total industry premium income |
| $X_6$ | Combined ratio | (claims paid - Reimbursement expenditure +Extraction of outstanding compensation reserves - Repay the outstanding claims reserves) / Earned Premium |

32

## 2.1 Solving The LRMES For The Listed Groups

1 CARCH-DCC parameter estimates

**Table 2**

| Variable Statistic | GJR-GARCH | | | | DCC | |
|---|---|---|---|---|---|---|
| | $w_{v_i}$ | $\alpha_{v_i}$ | $\gamma_{v_i}$ | $\beta_{v_i}$ | $\alpha_{c_i}$ | $\beta_{c_i}$ |
| **Xinhua** | 0.0000178 | 0.083963 | 0.051306 | 0.874084 | 0.067434 | 0.845015 |
| **z-Statistic** | 2.132053 | 3.566923 | 1.428442 | 33.66375 | 5.576657 | 30.96201 |
| **Ping An** | 0.00000215 | 0.108616 | -0.04689 | 0.929695 | 0.074605 | 0.809632 |
| **z-Statistic** | -0.53924 | 3.124021 | -1.67438 | 122.9485 | 8.595556 | 44.7053 |
| **China Life** | 0.00000537 | 0.054334 | 0.004166 | 0.935572 | 0.032892 | 0.894681 |
| **z-Statistic** | 1.95527 | 3.918968 | 0.232192 | 69.87027 | 5.810482 | 57.54937 |
| **Pacific** | 0.00000297 | 0.043081 | 0.005634 | 0.949816 | 0.008211 | 0.983456 |
| **z-Statistic** | 1.576624 | 3.14928 | 0.342602 | 83.4379 | 3.081625 | 143.4733 |

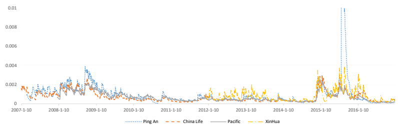
**The** computation of LRMES requires estimation of the GARCH-DCC model parameters for each company in the panel. Using the company's stock closing price data from the date of listing to December 31, 2016, we estimate the parameters by quasi-maximum likelihood. We show the parameter estimates of the GJR-GARCH and DCC models for the four insurance groups in table 2. The dynamics of the groups in the panel do not have a strong degree of heterogeneity. The GJR-GARCH parameters do not fluctuate much, and γ_(v_i )show that except Ping An, the other three groups are not sensitive to the shocks of stock market whether it increasing or decreasing, while Ping An signaling higher sensitivity to large volatility increase in case of a drop of the stock.

33

## 2.1 Solving The LRMES For The Listed Groups

2
The resulting dynamic volatility

Fig. 1 Dynamic volatility



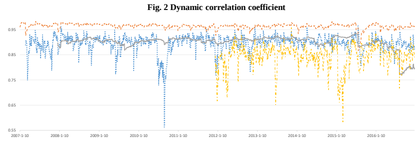

**Except** Ping An Group, the fluctuations of other three groups are relatively stable, ranging from 0 to 0.004. In July 24, 2015, the volatility of Ping An have shown an abnormal point, while in other time periods it was relatively stable. Due to share price dividends, the total assets of Ping An remained unchanged, but the shareholding increased doubled, causing the stock closing price from 80 decrease to around 30 and an abnormal point in volatility.

34

## 2.1 Solving The LRMES For The Listed Groups

3
The Dynamic Correlation Coefficient

Fig. 2 Dynamic correlation coefficient




35

## 2.1 Solving The LRMES For The Listed Groups

**Table 3 The LRMES Results Of Listed Insurance Groups**

| Listed insurance groups | LRMES | Listed insurance groups | LRMES |
|---|---|---|---|
| China Life 2007 | 0.25734 | Ping An2007 | 0.28108 |
| China Life 2008 | 0.29222 | Ping An 2008 | 0.33311 |
| China Life 2009 | 0.24262 | Ping An 2009 | 0.30265 |
| China Life 2010 | 0.25072 | Ping An 2010 | 0.24109 |
| China Life 2011 | 0.24376 | Ping An 2011 | 0.27532 |
| China Life 2012 | 0.26081 | Ping An 2012 | 0.25428 |
| China Life 2013 | 0.24414 | Ping An 2013 | 0.26612 |
| China Life 2014 | 0.2614 | Ping An 2014 | 0.26638 |
| China Life 2015 | 0.26931 | Ping An 2015 | 0.39307 |
| China Life 2016 | 0.28708 | Ping An 2016 | 0.20717 |
| Pacific 2007 | 0.25743 | Xin Hua 2011 | 0.26478 |
| Pacific 2008 | 0.28193 | Xin Hua 2012 | 0.26145 |
| Pacific 2009 | 0.28818 | Xin Hua 2013 | 0.27113 |
| Pacific 2010 | 0.27851 | Xin Hua 2014 | 0.27115 |
| Pacific 2011 | 0.25169 | Xin Hua 2015 | 0.22685 |
| Pacific 2012 | 0.2331 | Xin Hua 2016 | 0.33922 |
| Pacific 2013 | 0.24123 | Pacific 2015 | 0.25763 |
| Pacific 2014 | 0.22231 | Pacific 2016 | 0.22507 |

36

## 2.2 Solving LRMES For The Unlisted Companies

Steps

**The** process of SVM regression model estimation: select the variables associated with the predictor variables —→ data pre-processing—→ use cross-validation to select the optimal parameters —→ select samples to training and get well-training model—→substitute test samples set for prediction.

**Firstly,** we pre-processed the data to avoid excessive differences caused by the difference in the dimensions of input indicators. If we directly use the original data, it may cause SVM regression model estimation a large range of deviations and affect it accuracy. Therefore, input data of training samples set and test samples set need to be preprocessed. So, we choose the normalization method to scale the data make it between [0,1]. Next, the optimal hyper-plane of the SVM regression is sought to make the "total deviation" of all sample points from it is minimized. The SVM regression model parameters c and g are roughly selected, and then use cross-validation method, that is, divided the sample, one part is used as training samples set, and the other part is used as test samples set, then according to the model training output and error to adjustment the parameter, making the error smallest and the precision highest. At this time, c and g are represent the optimal penalty parameters and optimal kernel function width parameters, respectively. After the parameter optimization process, the SVM regression model has a better estimation effect. We use the finally well-trained SVM model to predict the test samples set.

37

## 2.2 Solving LRMES For The Unlisted Companies

**Substituting** the data of the listed insurance groups to train the SVM regression model, and obtain the regression relationship between the LRMES of the listed groups and it's corresponding annual financial data. Using the RBF kernel function and according to the difference between the well-trained model output samples and the actual samples, we can obtain the accuracy and error of the SVM regression model.

Parameter Estimation

| MATLAB output information | output value |
|---|---|
| Number of iterations | 86 |
| Minimum value obtained by quadratic programming | -0.26934 |
| Constant term b of the decision function | -0.28728 |
| Number of Support vectors | 29 |
| Number of support vectors on the boundary | 0 |
| Mean square error of regression | 9.14E-05 |
| Regressive coefficient | 0.935616 |

38

## 2.2 Solving LRMES For The Unlisted Companies

**Substituting** the data of the listed insurance groups to train the SVM regression model, and obtain the regression relationship between the LRMES of the listed groups and it's corresponding annual financial data. Using the RBF kernel function and according to the difference between the well-trained model output samples and the actual samples, we can obtain the accuracy and error of the SVM regression model. The output information of MATLAB and the SVM regression performance are shown in Table 4 and Fig 3.

**Table 4**

| MATLAB output information | output value |
|---|---|
| Number of iterations | 86 |
| Minimum value obtained by quadratic programming | -0.26934 |
| Constant term b of the decision function | -0.28728 |
| Number of Support vectors | 29 |
| Number of support vectors on the boundary | 0 |
| Mean square error of regression | 9.14E-05 |
| Regressive coefficient | 0.935616 |

39

## 2.2 Solving LRMES For The Unlisted Companies

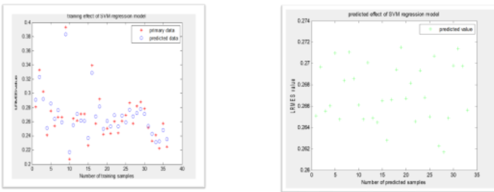
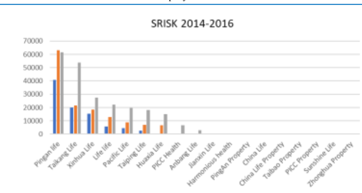



Fig. 3 Fitting effect diagram and prediction effect diagram of SVM regression model

40

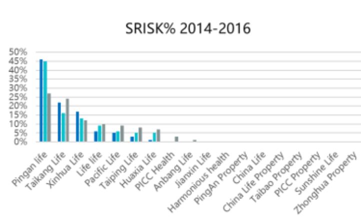
## 2.3 The SRISK And SRISK% Value Of 18 Insurance Companies In 2014-2016

**Based** on the SVM optimal regression model from the above step, we substitute the financial data of the top 18 insurance companies with 70% market share and can obtain the corresponding LRMES value. Then we substitute the corresponding debt and equity data to compute the SRISK and SRISK% for each insurance company




41

## 2.3 The SRISK And SRISK% Value Of 18 Insurance Companies In 2014-2016




42

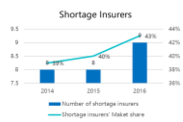
## 2.4 Analysis The SRISK And SRISK% Value

1

Analysis
And
Conclusions

**SRISK increased significantly**

**The** large increase in SRISK means that the insurance industry's conditional capital shortfall is widening, and the possibility of systemic risks in the insurance industry increases in the face of external risk shocks.


43

## 2.4 Analysis The SRISK And SRISK% Value

2

Analysis
And
Conclusions

**A significant contribution differences of systemic risks in Property insurers and Life insurers**

**Among** the 18 insurance companies that accounted for 70% of the market share in 2014~2016, we can see that there were 5 property insurers, accounting for 27.8%, but their total shortfall contribution to systemic risk was zero for three years.


44

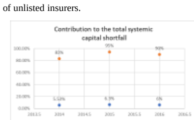
## 2.4 Analysis The SRISK And SRISK% Value

3

Analysis
And
Conclusions

**Unlisted insurers outstanding performance**

**Although** unlisted companies have less financing channels than listed companies, their disclosure requirements are not as strict as listed ones and their decision power of the management are relatively more centralized. Therefore, it is very important to measure comprehensively and systematically the systemic risk in China's insurance industry and strengthen the supervision of unlisted insurers.




45

## 2.4 Analysis The SRISK And SRISK% Value

Analysis
And
Conclusions

4

### Systematic risk factors analysis

**(1)The** factor of scale is not the only factor that determines whether the insurance institution has a systemic capital shortage. With the feature of high and stable state-owned equity ratio, relatively single business and high fixed-income investment ratio, the conditional capital shortfall in china life is zero, though it ranked first in market share. Maybe the above features have certain resistance to systemic risk.

(2) **PingAn**: Mixed business pattern and activity scope, and active presence in the global market make it face greater risk exposure and more susceptible to fluctuations in international markets.

(3) **Ambang:** Regulators should strengthen the regulation of spiral leverage and asset bubbles caused by non-core businesses.

46

## 3.1 Stability Test

**In** this section, we assess the sensitivity of the SRISK rankings to the choice of the SRISK parameters. On each of the ranking dates of table 5, we compute Spearman's correlation between the SRISK rankings obtained from a number of modifications of the default settings. We consider increasing the prudential capital ratio $k$ to 10% or decreasing the system event threshold $C$ to -30%. Overall, in most cases, the results show the rankings are highly correlated, both above 0.84. As we can see from formula (1), as $k$ increases or $C$ decreases the SRISK is increased. But in our dataset, the annual SRISK rankings are not influenced excessively by the change of parameter.

**We** also compare the SRISK rankings with the ones obtained from a set of firm characteristic and alternative risk measures. The firm characteristic are the book value of debt and the owner's equity. The risk measurement method includes the absolute value of LRMES calculated according to the GARCH-DCC model. Table 6 reports the results of the comparison, we can see that the highest correlation indicator is debt, which all exceed 0.61. That indices the size of debt has a significant impact on insurer's SRISK rankings in our dataset.

| | SRISK Parameters | | Risk Measures | Firm Characteristics | |
|---|---|---|---|---|---|
| **Year** | K=10% | C=30% | Lrmes | Debt | Equity |
| **2014** | 0.957*** | 0.992*** | 0.357** | 0.621*** | 0.332** |
| **2015** | 0.907*** | 0.962*** | 0.084 | 0.611*** | 0.245* |
| **2016** | 0.841*** | 0.965*** | -0.172 | 0.692*** | 0.247* |

47

05

## Concluding Remarks

48

## 01 Conclutions

- The SVM-SRISK model not only contains static financial information that reflects the market fluctuation, but also makes full use of the financial information of unlisted company and improves the estimation accuracy of their LRMES, thus expanding the scope of application in the current situation of China's insurance market, whose development is unbalanced and have fewer listed companies.
- The result shows, firstly, an average annual growth rate of total SRISK over 50%, which surpasses the growth rate of premium income, which means that the growth rate of systemic risk is much higher than the business scale one.
- Secondly, the average contribution to SRISK% of unlisted insurance company is about 5.53% in 2014, which was slightly lower than the 5.67% of listed companies one, and it increased to about 6.3% in 2015 but slightly decreased to 6.0% in 2016. The results mean that it is urgent to strengthen the supervision of systematic risk in unlisted companies.

49

## 01 Conclutions

- Thirdly, the market share of non-life insurance companies is about 27.8%, while the total SRISK% was 0. We can know from that different business lines lead to great difference of SRISK. On the other hand, the supervision of non-core business should be strengthen.
- In addition, when the minimum capital adequacy ratio is 8%, we find that the actual financial leverage of most life insurance companies is significantly greater than the applicable leverage. Therefore, in order to ensure the safe and stable operation of the insurance system, while implementing the solvency adequacy ratio regulation for systemically important insurance institutions, the insurers should appropriately reduce it leverage ratio.

50

# Thank You

School Of Finance And Statistic, HNU

Speaker :Lin Zhang

51