Chapter 24
Measuring Systemic Risk in the Chinese Financial System Based on Asymmetric Exponential Power Distribution

Helong Li, Tianqi Luo, Liuling Li, and Tiancheng Liu

Abstract We propose an extension of CoVaR approach by employing the Asymmetric Exponential Power Distribution (AEPD) to capture the properties of financial data series such as fat-tailedness and skewness. We prove the new model with AEPD has better goodness-of-fit than traditional model with Gaussian distribution, which means a higher precision. Basing on the Chinese stock market data and the new model, we measure the contribution of 29 financial institutions in bank, security, insurance and other industries.

Keywords Asymmetric Exponential Power Distribution (AEPD) · Systemic Risk · Conditional Value-at-Risk (CoVaR)

24.1 Introduction

The global financial crisis of 2008 has alerted the public to the importance of systemic risk. In this context, Adrian and Brunnermeier [11] proposed Conditional Value-at-Risk (CoVaR) to measure systemic risk contributions from individual institutions to the financial system. Then CoVaR method is improved from different perspectives e.g. [1, 2] and practiced in many countries e.g. [3–6]. AR-GARCH was applied to the CoVaR estimation by Gao and Pan [7] to capture the time-varying systemic risk exposure of an individual institution, based on the Student-t

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distribution. Liu and Gu [8] and Lin et al. [9] estimated the CoVaR of the real estate industry and the insurance institutions by AR-GARCH model, assuming the innovation follows the Gaussian and the Student-t distribution respectively.

However, the Gaussian and the Student-t distribution cannot accommodate properties such as asymmetric fat-tailedness and skewness of financial series. Zhu and Zinde-Walsh [10] proposed AEPD which contained the skewness parameter and the decay rates of left and right tails. They proved that AEPD had good performance in error fitting and VaR forecasting.

Hence, AEPD is used as the innovations of the AR-GARCH and CoVaR model. The result of goodness-of-fit confirms that our approach is an adequate method in improving systemic risk measurement. By the new method, we estimate Chinese financial systemic risk from 2008 to 2016.

24.2 Model and Methodology

24.2.1 VaR

Given the daily returns of a particular institution i (R_t^i) and the confidence level q, VaR is defined as the q-quantile of the return distribution of institution i.

$$\mathrm{Prob}\left(R_t^i \le VaR_{q,t}^i\right) = q \tag{24.1}$$

VaR of each institution i is computed by estimating the following model

$$R_t^i = \beta_1^i + \beta_2^i R_{t-1}^i + \beta_3^i R_t^m + u_t^i \tag{24.2}$$

$$\sigma_t^i 2 = \theta_1^i + \theta_2^i {u_{t-1}^i}^2 + \theta_3^i {\sigma_{t-1}^i}^2 \tag{24.3}$$

$$u_t^i = \sigma_t^i \varepsilon_t^i \tag{24.4}$$

$$\varepsilon_t^i \sim \mathrm{AEPD}\left(\alpha^i, p_1^i, p_2^i\right) \tag{24.5}$$

where $\xi^i = \left(\alpha^i, p_1^i, p_2^i, \beta_1^i, \beta_2^i, \beta_3^i, \theta_1^i, \theta_2^i, \theta_3^i\right)$ is parameter vector to be estimated by Maximum Likelihood Estimation method. R_t^m is the return of stock market. ε_t^i is the innovation with zero mean and unit variance. σ_t^i is the conditional standard deviation, i.e., volatility. With the innovation series ε_t^i sorted, the q-quantile value z_q^i is obtained. The VaR of institution i can be estimated as follow

$$VaR_{q,t}^i = \widehat{R_t^i} + z_q^i \sigma_t^i \tag{24.6}$$

The same process is repeated for financial system by substituting R_t^{sys} with R_t^i to obtain the parameter vector $\xi^{sys} = \left(\alpha^{sys}, p_1^{sys}, p_2^{sys}, \beta_1^{sys}, \beta_2^{sys}, \beta_3^{sys}, \theta_1^{sys}, \theta_2^{sys}, \theta_3^{sys}\right)$ and the unconditional $VaR_{q,t}^{sys}$.

24.2.2 CoVaR and ΔCoVaR

Adrian and Brunnermeier [11] defined $CoVaR_{q,t}^{sys|i}$ as financial system's VaR conditional on institution i being in financial distress in time t, i.e., its return being at its VaR.

$$Prob\left(R_t^{sys} \leq CoVaR_{q,t}^{sys|i} | R_t^i = VaR_{q,t}^i\right) = q \tag{24.7}$$

For each i, we estimate the following model

$$R_t^{sys} = \beta_1^{sys|i} + \beta_2^{sys|i} R_{t-1}^{sys} + \beta_3^{sys|i} R_t^i + u_t^{sys|i} \tag{24.8}$$

$$\sigma_t^{sys|i2} = \theta_1^{sys|i} + \theta_2^{sys|i} u_{t-1}^{sys|i2} + \theta_3^{sys|i} \sigma_{t-1}^{sys|i2} \tag{24.9}$$

$$u_t^{sys|i} = \sigma_t^{sys|i} \times \varepsilon_t^{sys|i} \tag{24.10}$$

$$\varepsilon_t^{sys|i} \sim AEPD\left(\alpha^{sys|i}, p_1^{sys|i}, p_2^{sys|i}\right) \tag{24.11}$$

where $\xi^{sys|i} = \left(\alpha^{sys|i}, p_1^{sys|i}, p_2^{sys|i}, \beta_1^{sys|i}, \beta_2^{sys|i}, \beta_3^{sys|i}, \theta_1^{sys|i}, \theta_2^{sys|i}, \theta_3^{sys|i}\right)$ is parameter vector to be estimated for each institution. Then we generate the predicted values from these regressions to obtain $CoVaR_{q,t}^{sys|i}$

$$CoVaR_{q,t}^{sys|i} = \widehat{\beta_1^{sys|i}} + \widehat{\beta_2^{sys|i}} R_{t-1}^{sys} + \widehat{\beta_3^{sys|i}} VaR_{q,t}^i + z_q^i \times \sigma_t^{sys|i} \tag{24.12}$$

We define the systemic risk contribution of a particular financial institution i by $\Delta CoVaR_{q,t}^{sys|i}$, which means the change degree on financial system's VaR conditional on the financial distress of institution i for unit change on institution i's VaR.

$$\Delta CoVaR_{q,t}^{sys|i} = \frac{CoVaR_{q,t}^{sys|i} - VaR_{q,t}^{sys}}{VaR_{q,t}^i} \tag{24.13}$$

24.2.3 AEPD

The recent distribution class, Asymmetric Exponential Power Distribution, is introduced to fit all the innovations above ($\varepsilon_t^i, \varepsilon_t^{sys}$ and $\varepsilon_t^{sys|i}$). To embed this distribution in the ARX-GARCH model, AEPD is standardized by the same way of Zhu and Galbraith [12] and Li et al. [13]. The probability density function is given by

$$f(z)=\begin{cases}\delta\left(\frac{\alpha}{\alpha*}\right)K(p_1)\exp\left(-\frac{1}{p_1}\left|\frac{\omega+z\delta}{2\alpha*}\right|^{p_1}\right), z\le-\frac{\omega}{\delta}\\ \delta\left(\frac{1-\alpha}{1-\alpha*}\right)K(p_2)\exp\left(-\frac{1}{p_2}\left|\frac{\omega+z\delta}{2(1-\alpha*)}\right|^{p_2}\right), z>-\frac{\omega}{\delta}\end{cases} \tag{24.14}$$

$$\alpha^*=\frac{\alpha K(p_1)}{\alpha K(p_1)+(1-\alpha)K(p_2)} \tag{24.15}$$

$$K(p)=\frac{1}{2p^{1/p}\Gamma(1+1/p)} \tag{24.16}$$

The $\alpha \in (0, 1)$ is the skewness parameter. $p_1 > 0$ and $p_2 > 0$ are the left and right tail parameters. When $\alpha = 0.5$, $p_1 = p_2 = 2$, AEPD will be reduced to Normal(0,1). The mean and variance of the Standard AEPD are given as follows

$$\omega=\frac{1}{B}\left[(1-\alpha)^2\frac{p_2\times\Gamma(2/p_2)}{\Gamma^2(1/p_2)}-\alpha^2\frac{p_1\times\Gamma(2/p_1)}{\Gamma^2(1/p_1)}\right] \tag{24.17}$$

$$\begin{aligned}\delta^2=\frac{1}{B^2}\Bigg\{&(1-\alpha)^3\times\frac{{p_2}^2\times\Gamma(3/p_2)}{\Gamma^3(1/p_2)}+\alpha^3\times\frac{{p_1}^2\times\Gamma(3/p_1)}{\Gamma^3(1/p_1)}\\ &-\left[(1-\alpha)^2\times\frac{p_2\times\Gamma(2/p_2)}{\Gamma^2(1/p_2)}+\alpha^2\times\frac{p_1\times\Gamma(2/p_1)}{\Gamma^2(1/p_1)}\right]^2\Bigg\}\end{aligned} \tag{24.18}$$

$$B=\alpha K(p_1)+(1-\alpha)K(p_2) \tag{24.19}$$

24.3 Data and Results

24.3.1 Data

We consider 29 Chinese financial institutions listed before 2008. The codes and names are presented by industry group in Appendix Table. 24.1. The CSI 300 Financials Index and Shanghai Composite Index are used as proxies for the financial system and market respectively. Sample period is from 1/2/2008 to 30/12/2016. The VaR and CoVaR are computed at $q = 5\%$ confidence level. The data is obtained from Wind database. Summary statistics for daily returns are presented in Appendix Table. 24.2.

24.3.2 Goodness-of-Fit

Assuming the innovation follows the AEPD distribution and the Gaussian distribution respectively, we obtain the estimated parameters and innovation series. Then, the kernel density estimation curves of innovation series and the distributional

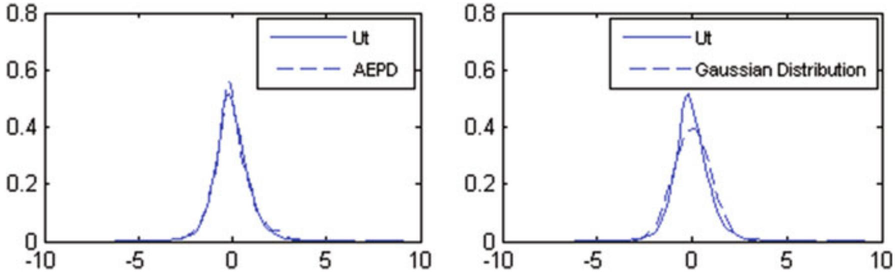

Fig. 24.1 Simulated density and distributional fit of innovation (Bank of China)

simulated curves are compared. We take innovation in Eq. (24.10) of the Bank of China as an example. Figure 24.1 compares the difference between innovation (expressed as Ut) and the AEPD, as well as the difference between innovation and the Gaussian distribution. The simulated curve of AEPD is closer to the innovation than the Gaussian distribution, which shows better goodness-of-fit. The results of goodness-of-fit for other equations and institutions are almost similar.

24.3.3 Chinese Systemic Risk

We obtain ΔCoVaR for each institution i and time period t, through the empirical calculation. The result shows that the state-owned banks (Bank of China, Industrial and Commercial Bank, Construction Bank and Bank of Communications) are the systemically important financial institutions. It is in line with the system-critical banks issued by the Financial Stability Board.

Average ΔCoVaR is computed for each group. The Monetary and Financial Services Group has the greatest contribution to systemic risk (0.68). The second systemically important financial industry is Others (0.64), the third is the Insurance (0.56), and the last is the Capital Market Services (0.51).

According to the time trend of ΔCoVaR presented in Appendix Fig. 24.2, Chinese systemic risk can be divided into three periods: (1) Between 2008 and 2009, the systemic risks of China were considerably high, which may be related to the remaining influence of international financial crisis. (2) From 2009 to 2013, the systemic risk showed a downward trend and the overall ΔCoVaR reduced by about 0.15. (3) Since 2014, the systemic risk witnessed a dramatical increase. Chinese systemic risk in 2015 was even higher than the level of financial crisis in 2008.

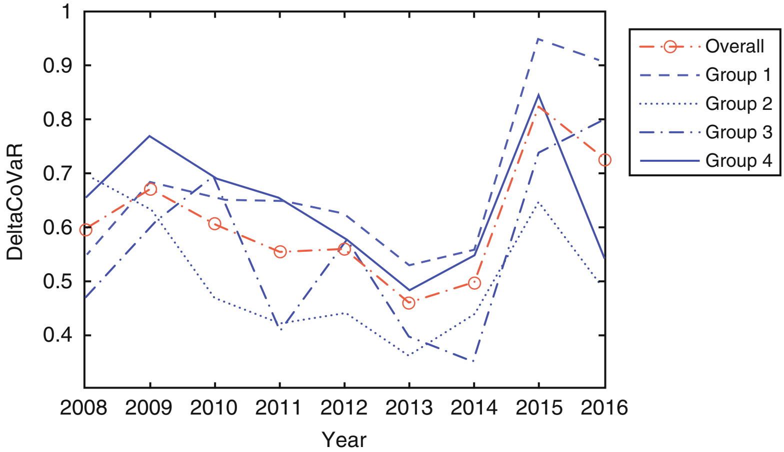

Fig. 24.2 The time trend of ΔCoVaR

24.4 Conclusion

To capture the skewed and fat-tailed property of financial data series, this paper generalizes the CoVaR model of Adrian and Brunnermeier [11] by introducing AEPD of Zhu and Zinde-Walsh [10]. By comparing the kernel density estimation curve of innovation series and the distributional simulated curve, we prove that the goodness-of-fit of AEPD is better than the Gaussian distribution.

Using the AEPD and the CoVaR model, we calculate the systemic risk contribution by four industry groups. The result shows that Monetary and Financial Services Group was the largest contributors to systemic risk, especially the four state-owned banks. Since 2014, Chinese systemic risk becomes considerable, thus the regulators should increase efforts to control the risk of infection.

Appendix

Table. 24.1 Stock codes, names and classifications of Chinese financial institutions

Group1: Monetary and financial services	Group2: Capital market services
000001 Ping An Bank 002142 Bank of Ningbo 600000 Shanghai Pudong Development Bank 600015 Hua Xia Bank 600016 China Minsheng Banking 600036 China Merchants Bank 601009 Bank of Nanjing 601166 Industrial Bank 601169 Bank of Beijing 601328 Bank of Communications 601398 Industrial & Commercial Bank of China 601939 China Construction Bank 601988 Bank of China 601998 China CITIC Bank	000686 Northeast Securities 000712 Guangdong Golden Dragon 000728 Guoyuan Securities 000783 Changjiang Securities 600030 CITIC Securities 600109 Sinolink Securities 600369 Southwest Securities Investment 600837 HAITONG Securities 601099 The Pacific Securities
Group3: Insurance	**Group4: Others**
601318 Ping An Insurance 601601 China Pacific Insurance 601628 China Life Insurance	000563 Shaanxi International Trust 600643 Shanghai AJ 600816 Anxin Trust

Table. 24.2 Summary statistics for the daily returns

	Mean	Std	Skewness	Kurtosis	JB-stat	P-value
CSI 300 Financials Index	−0.0002	0.0209	−0.19	6.29	999.90	0.00
Shanghai Composite Index	−0.0002	0.0175	−0.53	7.09	1636.70	0.00
Ping An Bank	0.0000	0.0255	0.06	6.46	1098.04	0.00
China Minsheng Banking	0.0002	0.0225	0.09	6.92	1407.51	0.00
Bank of China	−0.0001	0.0173	0.32	10.83	5643.22	0.00
Northeast Securities	−0.0002	0.0343	−0.16	4.60	242.92	0.00
Changjiang Securities	−0.0001	0.0331	−0.15	4.93	349.67	0.00
HAITONG Securities	−0.0002	0.0320	−0.10	5.32	496.13	0.00
Ping An Insurance	−0.0001	0.0250	−0.14	6.07	870.66	0.00
China Pacific Insurance	−0.0002	0.0258	−0.01	5.21	446.45	0.00
SH China Life Insurance	−0.0003	0.0254	0.20	5.92	792.08	0.00
Shaanxi International Trust	0.0002	0.0338	−0.24	4.76	302.32	0.00
Shanghai AJ	0.0001	0.0318	−0.09	5.23	456.25	0.00
Anxin Trust	0.0003	0.0321	−0.11	5.31	492.33	0.00

Notes: The daily returns are calculated as $R_t = 100\,\% \times [\ln(P_t) - \ln(P_{t-1})]$, where P_t is the market price of a stock on the closing of day t. Given space limitations, the table shows the summary statistics for 12 institutions (3 for each groups).

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