

Research Article

A Study on Regional Financial Risks Based on CoCVaR Model

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For the purpose of accurate measurement of regional systemic financial risks and prevention of regional economic turmoil, this paper proposes a new measure called the CoCVaR model, based on the tail mean loss, which is applied to measure the impact of stock returns of each listed company on the overall stock returns in Guangdong Province, China, from January 2010 to December 2020. It is found that there are significant CoVaR and CoCVaR for real estate, finance, utilities, and energy companies, while the risk spillover to the real economy market in Guangdong Province is more significant when companies in these industries are in extreme situations. There are insignificant CoCVaR for daily consumption, information technology, and health care. The risk spillover to the real economy market in Guangdong Province is smaller when companies in these industries are in crisis.

1. Introduction

In the current economic downturn, the impact of new industries, led by the Internet industry, on traditional sectors as well as overcapacity and other reasons, make China's economic environment increasingly unstable. This has led to increased regional economic and financial risks, resulting in challenges of business operations and occasional defaults. It is noted that most of the loans led by emerging enterprises and private enterprises improve their credit ratings with mutual and joint guarantees. They gradually form industrial or regional guarantee chains and loops, featuring of large amount and extensive coverage. If their capital chains are broken, the risk of default will keep spreading through the guarantee loop [1].

If we want to prevent the outbreak of systemic financial risks, we should measure the systemic risks accurately and effectively. Prior to the U.S. subprime crisis, systemic risks were often evaluated with early warning indicators of risk from macroeconomic variables and balance sheet data, and single indicators were synthesized appropriately to reflect systemic risks as a whole (Calvo et al. [2], Frankel and Rose [3], Bordo et al. [4], Illing and Liu [5], and Vanaga and Sloka [6]). The financial crisis in the United States will lead to the

economic downturn. Due to economic globalization, many foreign trade enterprises in China will be greatly affected and even form regional systemic financial risks.

If real-time regulation of key companies in the regional economy is achieved, it is necessary to implement the policies to each organization. Especially after the subprime crisis, countries worldwide have recognized the importance of preventing regional financial risks. What are the key companies in the regional economy? How can we identify them? These questions reflect that it is complex and challenging to identify key companies in the regional economy, and a lot of research on regional risks and regional importance has been conducted at home and abroad with many key results achieved. However, the CoVaR approach is more sophisticated to measure systemic financial risks, but more efforts should be made to measure the regional importance of listed companies.

Against this background, this paper proposes CoCVaR, an improved measure of CoVaR financial risks for listed companies in Guangdong Province, China, to enhance the prevention system of the regional financial risks. For listed companies, the business is multiple, the relationship between enterprises is complex, and the tail risk is more prominent. Our model can accurately measure the average

tail loss of listed companies. By proposing an improved risk measurement theory, this paper explores the regional financial risks in Guangdong Province, justifying the importance of listed companies in the region, and ultimately makes good guidance for regulators, with the closing prices of listed companies in the province as an object of study. This study plays a positive role effectively in the regional financial stability in Guangdong, while its results also contribute to the financial stability in other provinces.

2. Literature Review

Scholars have explored financial risks. García-Herrero and Wooldridge focused on financial integration to explore the cross-border financial connections among different economic regions [7]. They argue that financial integration is related to the spreading of regional risks. It should be strengthened by monitoring the spreading channels associated with financial integration if the potential regional risks are to be reduced. Galesi and Sgherri characterized the financial spillover effects among 27 countries with a GVAR model [8]. They found that asset prices, stock prices, and credit growth can be important channels of risk spreading under certain circumstances. The study prudently showed the key elements and spreading methods that transform regional threats into systemic ones. Zhu et al. created a financial stress index for China with monetary and credit variables, asset price variables, macroeconomic variables, and other explanatory variables as fundamental and proposed an optimal forecasting equation to predict the systemic financial risks [9].

There have been increasing studies on regional financial risks in China in recent years. Wang et al. studied the potential regional financial risks arising from local government debts from an audit perspective and proposed methods to prevent and address regional financial risks arising from local government debts from an audit monitoring perspective [10]. Zhang and Yu argued that the prevention of regional financial risks focuses on local corporate financial institutions and nonbank financial institutions [11]. Gao and Zhang discussed the performance and the root causes of regional risks in China and proposed valuable conclusions for preventing regional risks in eight aspects, such as enhanced monitoring of the central bank and strengthened monitoring and alerting of regional financial risks [12].

In general, the theories related to regional risks have become increasingly sophisticated and perfect. However, the measurement of regional financial risks based on *CoVaR* and its extended models is still a cutting-edge research. For example, the *CoES* model proposed by Zhang et al. focused on the tail mean losses to calculate the systemic risks of financial institutions more accurately [13]. Roengpitya and Rungcharoenkitkul measured the systemic risks of Thai banks and the external spillover effect of individual banks on the industry as a whole with *CoVaR* [14]. They concluded that the contribution of the banking industry to systemic risks had grown significantly after the Asian financial crisis. It is valuable and important to improve the *CoVaR* model and measure the regional risks from theoretical and practical

perspectives. Due to multiple business operations, complex interenterprise relationships, and significant tail risks in listed companies, we have to look at their tail mean losses. Thus, this paper proposes *CoCVaR*, a new model for measuring regional risk based on the *CoVaR* model, to study the mean losses suffered by the regional economy when an extreme risk occurs for a listed company.

3. Model and Methodology

3.1. *CoVaR* Model. *VaR*, known as “value at risk,” is a measure of the risk, which refers to the maximum possible loss of a financial asset (or portfolio) in a fixed time frame in the future at a certain confidence level [15].

With the practice of risk management, it is gradually found that *VaR* has specific limitations. Its biggest shortcoming is that it can only estimate the potential risk of a portfolio under “normal” market conditions but does not cover extreme market conditions [16]. To address the shortcomings of *VaR*, Adrian and Brunnermeier proposed Conditional Value at Risk or *CoVaR* based on the risk spillover perspective [17].

The mathematical expression of Conditional Value at Risk or *CoVaR* is as follows (note: in this paper, all calculations of the value at risk are performed at a confidence level of 95%):

$$P(X^j \leq \text{CoVaR}_q^{ji} | X^i = \text{VaR}_q^i) = 1 - q, \quad (1)$$

where CoVaR_q^{ji} denotes the maximum potential risk that financial market j faces when the risk of financial market i is at VaR_q^i . It includes both unconditional and spillover value at risk. We define the spillover value at risk of i to j as $\Delta \text{CoVaR}_q^{ji}$ and describe the expression of the risk spillover effect through the numerical relationship of the sum and as follows:

$$\Delta \text{CoVaR}_q^{ji} = \text{CoVaR}_q^{ji} - \text{VaR}_q^i, \quad (2)$$

Since the unconditional value-at-risk varies widely across financial markets, $\Delta \text{CoVaR}_q^{ji}$ does not fully capture the intensity of risk spillovers, for which we normalize it as follows:

$$\% \text{CoVaR}_q^{ji} = \left(\frac{\Delta \text{CoVaR}_q^{ji}}{\text{VaR}_q^i} \right) * 100\%, \quad (3)$$

where $\% \text{CoVaR}_q^{ji}$ removes the effect of magnitude and more accurately captures the intensity of risk spillover to j from the maximum possible loss of i .

The *CoVaR* model combines the risk spillover effect with the popular *VaR*, while $\Delta \text{CoVaR}_q^{ji}$ accurately and effectively reflects the influence and contribution of individual financial markets to systemic risks, with more accurate reflection of the true risk level. It is particularly significant for regulatory authorities concerned about the risk of the entire financial system to ensure a stable financial system by imposing severe regulation on financial markets with higher risk contribution.

3.2. *Measure CoVaR Values with Quantile Regression.* The quantile regression approach is an extension of the least squares method, which is based on the classical conditional mean model, and it estimates the overall model through multiple quantile functions [18]. Koenker and Basset first introduced the idea of quantile regression in 1978, regressing each independent variable according to the conditional quantile set by the dependent variable [19]. It results in a quantile regression model with full quantile premise, which more comprehensively reflects some dependent variables influenced by the independent variable.

For examining the risk spillover effect of the risk generated by financial market j on financial market i , the following q -quantile regression model is created:

$$R_q^i = \alpha + \beta X_i + \varepsilon, \quad (4)$$

where R^i and R^j represent the return series of i and j , respectively, and R_q^i reflects the estimated excess return i under the q quantile. According to the definition of value at risk, it can be defined as

$$VaR_q^i | R^j = \widehat{R}_q^i. \quad (5)$$

The above equation indicates that the value-at-risk estimate is obtained using quantile regression with series j as the predicted underlying return i with the existing condition R^j , which yields $\widehat{\alpha}$ and $\widehat{\beta}$ of parameter estimates corresponding to quantile q . The value-at-risk estimate is

$$\widehat{VaR}_q^i = \widehat{\alpha} + \widehat{\beta} R^j. \quad (6)$$

According to the definition of *CoVaR*, $CoVaR_q^{ij}$ is expressed as the value at risk of i when return j is at its VaR_q^j level, and with quantile regression, our measure for *CoVaR* can be simply defined as

$$CoVaR_q^{ij} = VaR_q^i | VaR^j = \widehat{\alpha} + \widehat{\beta} VaR_q^j. \quad (7)$$

In turn, we can get $\Delta CoVaR_q^{ji}$ and $\%CoVaR_q^{ji}$.

3.3. *CoCVaR and Its Measurements.* *CVaR* (conditional value at risk) is a measure of investment risk developed by Rockafeller and Uryasev in 1999 to overcome the shortcomings of *VaR*, which is the average of the portfolio's losses greater than a given *VaR* value, with its mathematical expression as follows [20]:

$$CVaR_\alpha = -E[Y|Y < -VaR_\alpha]. \quad (8)$$

Compared to *VaR*, *CVaR* satisfies positive homogeneity, subadditivity, transfer invariance, and monotonicity, and it is a consistent risk measure optimized by linear programming algorithms noted by more organizational investors.

It is often assumed that the log returns of a portfolio will follow a normal distribution. However, scholars such as Rachev and Mittnik have shown that the log returns of financial assets do not obey a normal distribution in many cases with spikes and thick tails [21]. The Laplace distribution was fitted to the financial data to depict anomalous spikes in the vicinity of the mean. It is found that the

individual order moments are finite and more relevant to the general financial theory. If the distribution density of the random variable X is

$$LA(x, \mu, \sigma) = \frac{1}{2} \exp\left(-\frac{|x - \mu|}{\sigma}\right), \quad (-\infty < \mu < \infty), (-\infty < x < \infty). \quad (9)$$

If x follows a Laplace distribution with parameters μ (location parameter) and σ (scale parameter), it is denoted as

$$x \sim LA(\mu, \sigma). \quad (10)$$

The distribution function is as follows:

$$LA(x) = \begin{cases} \frac{1}{2} \exp\left(\frac{x - \mu}{\sigma}\right), & x \leq \mu, \\ 1 - \frac{1}{2} \exp\left(\frac{\mu - x}{\sigma}\right), & x \geq \mu. \end{cases} \quad (11)$$

Let x be a random variable of a financial asset gain or loss; following the distribution $LA(\mu, \sigma)$, for a given confidence level, α can be obtained as

$$\begin{cases} VaR_\alpha = F^{-1}(1 - \alpha), \\ VaR_\alpha = \sigma \ln(2 - 2\alpha) + \mu, \\ CVaR_\alpha = \mu - \sigma(1 - \ln(2 - 2\alpha)). \end{cases} \quad (12)$$

Substitute VaR_α and $CVaR_\alpha$ (both less than μ) into the distribution function of the gain or loss on financial assets x , respectively, to obtain

$$\begin{cases} LA(VaR_\alpha) = 1 - \alpha, \\ LA(CVaR_\alpha) = \frac{1 - \alpha}{e}. \end{cases} \quad (13)$$

This yields that VaR_α corresponds to the $1 - \alpha$ quantile of the distribution and $CVaR_\alpha$ corresponds to the quantile of the distribution $1 - \alpha/e$. The conclusions obtained in the *VaR* and *CVaR* measures with the Laplace distribution show that *CVaR* can be converted to a quantile of the return distribution concerning an ex-ante set confidence level, while *CoCVaR* is essentially a conditional *CVaR*. As a result, $CoCVaR_\alpha^{ji}$ can be measured with quantile regression.

$CoCVaR_\alpha^{ji}$ represents the extreme risk faced by financial market j at confidence level q , with the risk level of financial market i under the *CVaR* condition. It is defined as

$$CoCVaR_\alpha^{ji} = CVaR_\alpha^j | CVaR_\alpha^i = E[X^j | (X^j < VaR_\alpha^j \cap X^i = VaR_\alpha^i)]. \quad (14)$$

In summary, under the condition that the risk level is at *CVaR* and the confidence level is α ($0 < \alpha < 1$), $CoCVaR_\alpha^{ji}$ is calculated as

$$CoCVaR_\alpha^{ji} = \widehat{\alpha} + \widehat{\beta}(X I_i = CVaR_\alpha^i), \quad (15)$$

where the estimated $\widehat{\alpha}$ and $\widehat{\beta}$ of the regression coefficients can be obtained by quantile regression.

4. Empirical Analysis

4.1. Data and Processing. In this paper, the daily closing prices of stocks of 500 listed companies in Guangdong Province are selected as the research object, and the data of 358 stocks are sampled from January 4, 2010, to December 31, 2020. The data include two recessions (September 2011 and December 2014) and one financial crisis (European Debt Crisis in 2011). Extreme risks exist in the region during this timeline, and the observation sample is very representative and valuable for research. Adopt the arithmetic average of the closing price of each stock as the overall closing price of Guangdong. There are 1,702 observations of trading days in the sample with all data from the Wind database, which covers stocks, funds, bonds, foreign exchange, insurance, futures, financial derivatives, spot trading, macroeconomic, financial news, and other fields.

To make the data representative, delete the data of listed stocks with less than 200 observations, and normalize the closing price data of the remaining 329 stocks with log returns $R_t = 100 * (\ln P_t - \ln P_{t-1})$.

From the above, the logarithmic return of financial assets is distributed by Laplace and has the characteristics of peak and tail. So it includes basic descriptive statistics, smoothness test, spike test, and thick-tail test.

4.1.1. Basic Descriptive Statistics. The histograms of the minimum, maximum, and mean log returns for each listed company are shown in Figure 1.

The histogram made by the average log return of each listed company tends to be the standard normal distribution, with more values greater than 0, indicating that the province is generally in stable profitable development.

4.1.2. Data Smoothing Test. The data smoothness is the basis and prerequisite for time series analysis. The most popular method for the smoothing test of the series is the graphical method, the unit root test, and the autocorrelation coefficient test. The above two methods are preliminary and intuitive judgments on the smoothness of the time series, which are highly subjective and generally used as auxiliary methods. The most popular test today is the unit root test. At a significance level of 0.05, the series can be considered as smooth as long as the p value is less than 0.05, and the results show that all log-return series are smooth.

4.1.3. Spike Test. Let the mathematical expectation of the function $(X - E(X))^k$, $k = 1, 2, \dots$, of the random variable X exist, and it is called $E(X - E(X))^k$ as the k th-order central distance of X , noted as $\mu_k(X) = E(X - E(X))^k$, $k = 1, 2, \dots$. The ratio of the fourth-order central distance of the random variable X to the squared second-order central distance is defined as the kurtosis coefficient, denoted as K , and its expression is

$$K = \frac{\mu_4}{\mu_2^2} = \frac{E(X - E(X))^4}{D(X)^2}. \quad (16)$$

If $X \sim N(\mu, \sigma^2)$, its kurtosis coefficient is given by

$$K = \frac{\mu_4}{\mu_2^2} = \frac{3\sigma^4}{(\sigma^2)^2} = 3. \quad (17)$$

In general, the kurtosis coefficient of a normal distribution is subtracted by 3 for the convenience of comparing its spike. $K = 0$ signifies that the kurtosis of the distribution is the same as that of the normal distribution with no spiking issue; $K > 0$ suggests that the distribution has a higher kurtosis than the normal distribution. Then, the kurtosis coefficient of the financial asset return series is

$$K = \frac{n \sum_{t=1}^n (x_t - \bar{x})^4}{\left(\sum_{t=1}^n (x_t - \bar{x})^2\right)^2} - 3. \quad (18)$$

At the 0.05 significance level, the results show that the kurtosis coefficients of all stock log return series are greater than zero, indicating that the log return data are spiky distributed.

4.1.4. Thick-Tailed Test. If the distribution function $F(x)$ of the random variable X satisfies $\lim_{t \rightarrow \infty} 1 - F(tx) / 1 - F(t) = x^{-1/r}$, ($r > 0, x > 1$), then X is an upper "thick-tailed" distribution and r is the upper-tailed extreme index. When $r = 0$ given $x > 1$, the distribution follows the normal distribution (also known as the thin-tailed distribution) and vice versa $r > 0$ for the thick-tailed distribution.

Let the sequence X_1, X_2, \dots, X_n of financial asset returns be independently distributed $X_{1,n} \leq X_{2,n} \leq \dots \leq X_{n,n}$ as its sequence statistic; then, the moment-type estimate formula is

$$\hat{r} = M_n^1 + 1 - \frac{1}{2} \left(1 - \frac{M_n^2}{M_n^1} \right)^{-1}. \quad (19)$$

Considering the tail exponent only, when $\sqrt{m}\hat{r}_n > \mu_\alpha$, the random variable is in a thick-tailed distribution; conversely, it is a thin-tailed distribution, where μ_α is the one-sided critical value of the standard normal distribution, i.e., $P(X > \mu_\alpha) = \alpha$, $X \sim N(0, 1)$. $m = [n/m]$ is always thought to be the best choice.

At a significance level of 0.05, the results show that the tail extreme values of the log-return series for all stocks $\sqrt{m}\hat{r}_n > \mu_{0.05} = 1.64$. Therefore, log-return sequences are in thick-tailed distribution.

4.2. Specific Measurement of Regional Risks

4.2.1. Regional Risk Measurement Based on CoVaR. At a significance level of 5%, solving the original data with Laplace hypothetical distribution yields

$$VaR_\alpha = \hat{\sigma} \ln(2 - 2\alpha) + \hat{\mu}. \quad (20)$$

Calculate the VaR of log returns of all stocks, and the smallest 10 stock names and their corresponding VaR are given in Table 1.

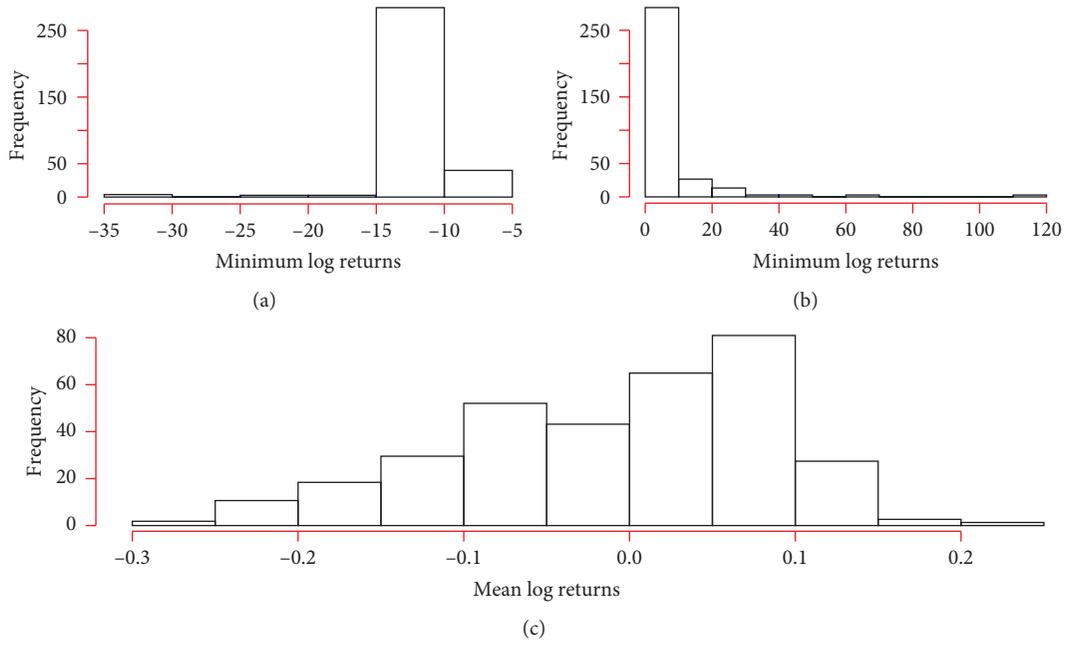


FIGURE 1: Descriptive statistics of return.

TABLE 1: The 10 stocks with the smallest VaR values.

Stock name	VaR
Guanhao Bio	6.870
Youngy Co., Ltd.	6.197
NASDA	6.163
Macsun Solar Energy Technology	5.941
Biolight	5.913
Shenzhen Hifuture Information Technology	5.900
Guangdong Shirong Zhaoye	5.740
Sunway Communication	5.734
AVIT	5.732
Guangzhou Yuetai Group	6.124

The financial crisis in 2011 had a significant impact on our economy. The VaR value of each stock dropped significantly, and the VaR risk increased rapidly. Since 2012, the government increased its focus on risk, and the risk gradually decreased.

The CoVaR measures the risk spillover to be exposed as a whole in the event of a maximum possible risk loss for a listed company. $CoVaR^{j|i}$ denotes the maximum possible risk of institution j under the maximum possible risk for institution i . $\Delta CoVaR_q^{sys|i}$ quantifies the difference between the systematic risks when institution i is in crisis and stable, which act as the risk premium of each listed company. The histogram of $\Delta CoVaR$ for log returns of the sampled stock is given in Figure 2.

As shown in the histogram, the $\Delta CoVaR$ of the log returns of each stock tends to be [2.0, 2.5] in distribution which are all less than zero, i.e., all listed companies increase the overall systematic risk of the province when they are in crisis.

The 10 listed companies with the smallest $\Delta CoVaR$ and their corresponding $\Delta CoVaR$ are shown in Table 2.

The financial crisis caused serious damage to the stable Guangdong economy and significantly expanded the overall systemic risk in the province, with a large trough in 2010-2011. After the financial crisis, the government focused on risk regulation and improved the relevant system, and the $\Delta CoVaR$ gradually increased in 2013-2015, and the impact of systemic risk decreased step by step. With speedup of the interest rate and exchange rate market reform, the state guides private capital to enter the financial industry. Due to awash interbank tractions, liquidity tension, and explosive growth of shadow banking, a small trough occurred in 2011-2013, when a crisis in listed companies expanded the overall systemic risks in the province to some extent.

Box-and-line diagrams of $\Delta CoVaR$ and its industry categories are made for $\Delta CoVaR$ measurement in Figure 3.

From the box-and-line diagram by industries, it can be seen that real estate, finance, and utilities have small $\Delta CoVaR$, which will greatly expand the overall systemic risk in the province during a crisis. Daily consumption, information technology, and health care have significant $\Delta CoVaR$, and the impact of a crisis on systemic risks is relatively small.

The scatter plot of $\Delta CoVaR$ and time to market of companies is made for the measurement of $\Delta CoVaR$ in Figure 4.

From the scatter plot of listing time, it can be seen that, for listed companies before 2011, $\Delta CoVaR$ is discrete with a small value, and the impact caused by a crisis is significant; for companies listed around 2014, $\Delta CoVaR$ is more concentrated with a large value, and the impact caused by a crisis

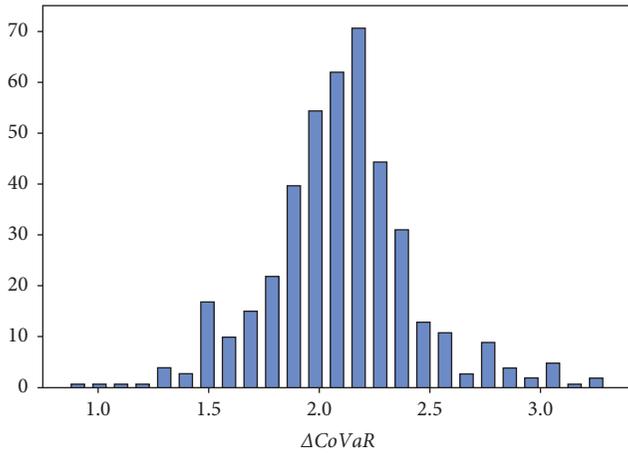


FIGURE 2: Histogram of $\Delta CoVaR$.

TABLE 2: 10 stocks with the smallest $\Delta CoVaR$.

Stock name	$\Delta CoVaR$
Sunlord Electronics	2.565
Shenzhen Laibao Hi-Tech Co., Ltd.	2.538
Shenzhen Topband Co., Ltd.	2.484
SG Holding A	2.473
Shenzhen Jinjia Group Co., Ltd.	2.465
Shenzhen Zhongjin Lingnan Nonfemet Co., Ltd.	2.445
Shenzhen Batian Ecotypic Engineering Co., Ltd.	2.419
Shenzhen Hifuture Information Technology	2.436
YGSOFT Inc.	2.495
Gree Electric Appliances Inc.	2.427

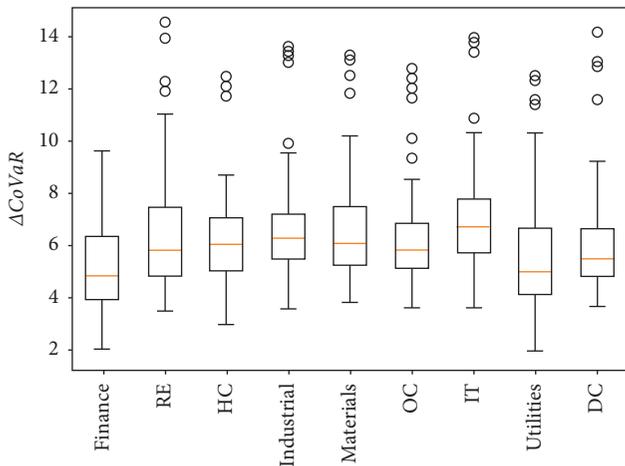


FIGURE 3: Box-and-line diagram of $\Delta CoVaR$ after industry classification.

is small. With unsound national policies in the early days, listed companies may act as leaders in the industry, resulting in more discrete $\Delta CoVaR$ values. Later, with sound policies and the state stresses controlling risks, the $\Delta CoVaR$ values are more concentrated, with less impact on systemic risks.

4.2.2. *Regional Risk Measurement Based on CoCVaR.* Calculate the *CVaR* of log returns of the stocks. And, the stock names and their corresponding *CVaR* are given as follows. The names of the 10 stocks with the smallest *CVaR* values and the corresponding *CVaR* are shown in Table 3.

The *CoCVaR* is able to measure the extreme risk loss that could occur as a whole in the event of an extreme risk loss for a listed company. The $\Delta CoCVaR$ for the log returns of each stock tend to be [1.8, 2.7] in distribution, i.e., all listed companies in an extreme crisis will increase the systemic extreme risks in aggregate in the province. Thirty listed companies with the smallest $\Delta CoCVaR$ and the corresponding $\Delta CoCVaR$ are shown in Table 4, and the histograms are given in Figure 5.

Figures 6–8 show that there are large *CoVaR* and *CoCVaR* for real estate, finance, utilities, and energy companies, and the risk spillover to the entire real economy market in Guangdong Province is significant when companies in these sectors are under extreme conditions; there are smaller *CoCVaR* for daily consumption, information technology, and healthcare, and the risk spillover to the entire real economy market in Guangdong Province is insignificant when companies in these sectors are in crisis.

4.3. *Analysis of CoVaR vs. CoCVaR.* The *CoVaR* and *CoCVaR* methods both measure the risk of one institution when another institution is at risk.

The scatter plots of *VaR* and *CVaR* are made through the closing price data of listed companies in Guangdong Province in Figure 9. They have a strong positive correlation, and the correlation coefficient is close to 1. Figure 10 shows a strong positive correlation between $\Delta CoVaR$ and $\Delta CoCVaR$, and the listed companies above the fitted line are those with significant $\Delta CoVaR$ at the same $\Delta CoCVaR$ level, which have less impact on the overall systemic extreme risk in the province when an extreme risk occurs in this category.

5. Summary

This paper verifies the feasible *CoCVaR* through empirical analysis, and the model can measure the extreme risks of the whole financial conditions under the premise of extreme risks generated by financial institutions (or financial markets) and propose a new measurement model for preventing financial risks. Comparison with the traditional *CoVaR* model reveals that the model can better measure the comprehensive risks. Although the chances of extreme risk generation are low, it may bring enormous damages in an unignorable way for regulators. It possible to measure financial risks more comprehensively by combining the model with other risk measurement models (e.g., *CoVaR* model) and provide a strong guarantee against the financial risks.

Different industries have various impacts on the collective systemic risk of the state’s stock market under risks,

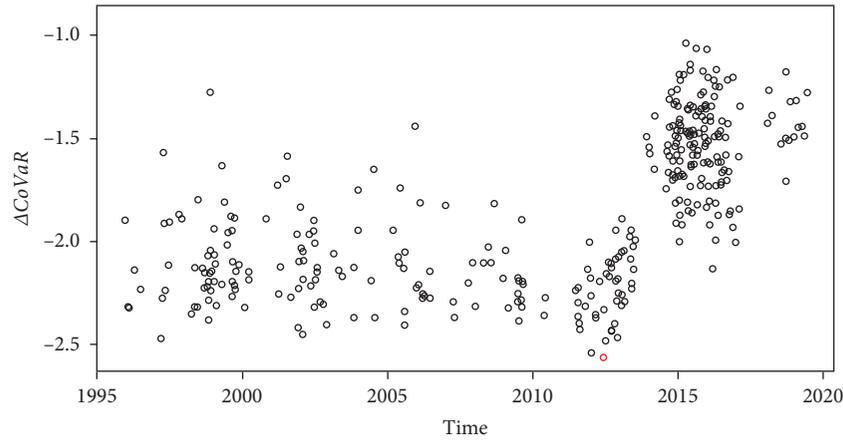


FIGURE 4: Scatter plot of $\Delta CoVaR$ and time to market.

TABLE 3: 10 stocks with the smallest $CVaR$ values.

Stock name	$CVaR$
Guanhao Bio	9.822
Youngy Co., Ltd.	8.900
NASDA	8.825
China East Sunshine Technology	8.819
Guangzhou Yuetai Group	8.812
Green View	8.76
Shenzhen Wongtee International Enterprise Co., Ltd.	8.691
Zhuhai Huajin Capital Co., Ltd.	8.691
Shenzhen Tellus Holding A	8.582
Ledman Optoelectronic Co., Ltd.	8.539

TABLE 4: 10 stocks with the smallest $\Delta CoCVaR$.

Stock name	$\Delta CoCVaR$
Gree Electric Appliances Inc.	2.655
Poly Developments And Holdings Group Co., Ltd.	2.554
Han's Laser	2.509
Shenzhen Deren Electronic Co., Ltd.	2.499
Sunlord Electronics	2.496
Shenzhen Laibao Hi-Tech Co., Ltd.	2.494
Dymatic Chemicals Inc.	2.480
Guangdong Goworld Co., Ltd.	2.456
Kingfa Sci. & Tech. Co., Ltd.	2.444
COSCO SHIPPING Specialized Carriers Co., Ltd.	2.429

which means that different sectors differ in importance to the stock market of the province [22]. When monitoring the systemic risk of the stock market in the province, we should focus on industries that have a high impact on the systemic risk, such as information technology and industrial and real estate.

There are significant $CoVaR$ and $CoCVaR$ for real estate, finance, and energy and utility companies, and the risk spillover to the real economy market in Guangdong Province is more significant when companies in these industries are in extreme situations. There are insignificant $CoCVaR$ for daily consumption, information technology, and health care. The risk spillover to the real economy market in Guangdong Province is smaller when companies in these industries are in crisis.

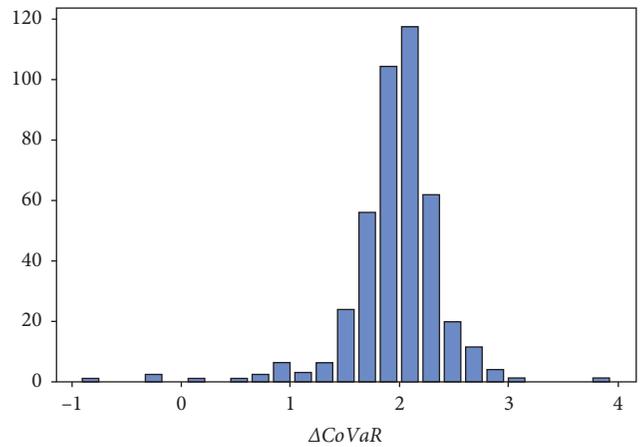


FIGURE 5: Histogram of $\Delta CoCVaR$.

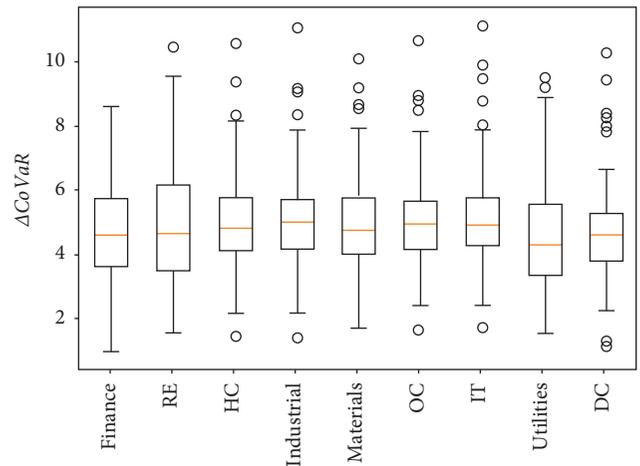


FIGURE 6: Box-and-line plot of $\Delta CoCVaR$ after industry classification.

The analysis of VaR , $CVaR$, $CoVaR$, and $CoCVaR$ indicators of individual enterprises shows that large enterprises (e.g., Ping An China Merchants Bank, Poly, ZTE, Gree, and Shenzhou) have significant $CoCVaR$ with low $CVaR$ values. For example, they are more resilient to risks

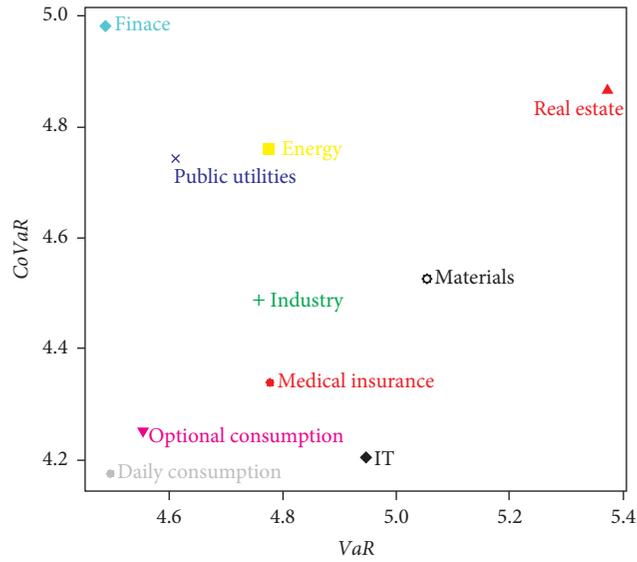


FIGURE 7: VaR vs. CoVaR by industry.

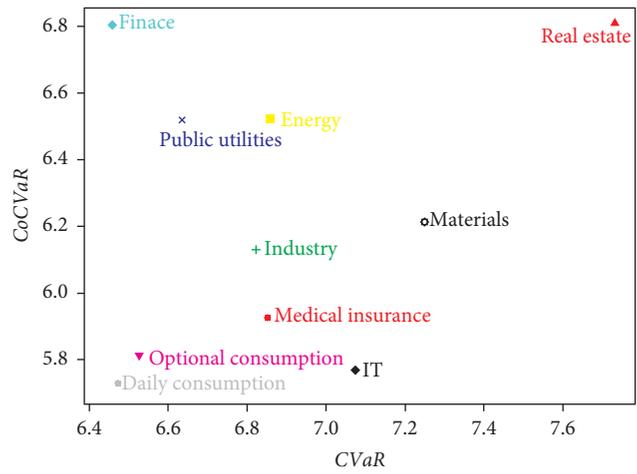


FIGURE 8: CVaR vs. CoCVaR by industry.

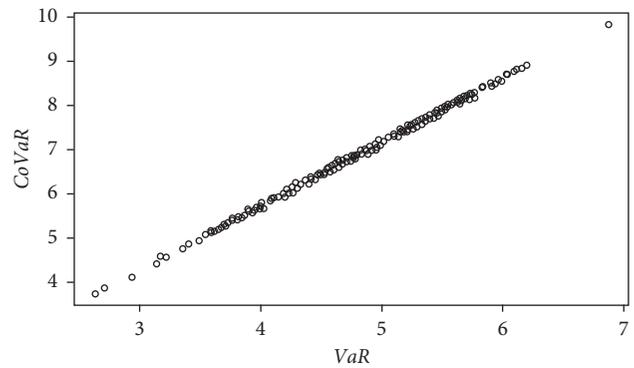
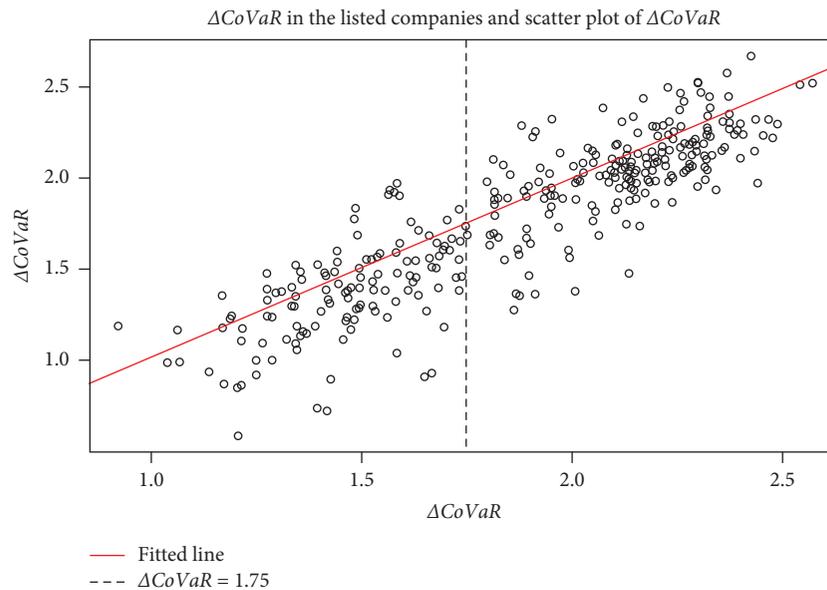


FIGURE 9: Scatter plot of VaR and CVaR.

but with a more significant regional systemic risk spillover for Guangdong Province. Some small manufacturing (materials) and information technology companies, which have

lower CoCVaR and significant CVaR values, are less resilient to risks but have less impact on the regional or systemic economy.

FIGURE 10: Scatter plot of $\Delta CoVaR$ and $\Delta CoCVaR$.

It is necessary to focus on the impact of China's real economic operation on the systemic risk in the securities market and real-time monitoring of the trading process, with a sound early warning system established. The state should fully consider the possible impact of its issuance and application on the securities market when formulating macroeconomic policies. Analysis is given to the systemic risks of the securities market and the systemic risk that existed in practice, and a pool of systemic risk scenarios is created via imitating various possible scenarios in the virtual market with the state-of-the-art computer technology.

Data Availability

The WIND database used to support the findings of this study is included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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