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Master in Economic Development and Growth

Systemic Risk of China's Financial Sector: Evidence from the Stock Market

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Abstract: China, with the fast developing financial market, experienced two dramatic stock market crisis in recent ten years under government constrains. Thus, monitoring the systemic risk in China is crucial and meaningful. This paper applies *CoVaR* methodology to measure the dynamic systemic risk of China's financial market from 1996 to 2016. The financial market is divided into bank and non-bank sectors. Security, insurance and diversified financial institutions are included in the non-bank sector. Market capitalization of each sector is conducted to calculate the *Value at Risk* combing with state variables of US treasury return and domestic real estate return loss. Δ*CoVaR* and *Exposure*-Δ*CoVaR* are the indicators of the systemic risk. The estimation results reveal bank sector contributes the most to the total risk and it is also the most at risk sector facing the crisis. The risk contribution of diversified financial institutions increase during the crisis infers the rapid development of this sector in the market. *Exposure*-Δ*CoVaR* of all the sectors share the same law. The risk exposure to the whole financial market increases before the crisis and then sharply decreases during the distress. The strong positive correlation between *VaR* and Δ*CoVaR* in China allows the market regulations to be sufficient based on sector level. This paper provides general suggestions for the market regulations and plots the dynamic systemic risk comovements with the sectors.

Key words: Systemic Risk, CoVaR, China

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1 Introduction

The systemic risk is the uncontrollable aggregate risk outside of the financial entity. It is affected by externalities, such as macro government policies, international financial environment, herd behavior, the linkages within institutions, and market structure failure. The risk can drive the market price away from its actual value and can't be reduced by diversification of the portfolios (Hansen 2012, Adrian and Brunnermeier 2014). It can be materialized when financial crisis come through the price change.

In China, the aggregate risk of the financial industry is contributed by government through separate institutions, real estate bubbles and the international financial environment. Financial institutions can be roughly divided into banks and non-bank financial institutions. The financial market of China began to recover since 1978. Meanwhile, since China's economic globalization, it has experienced over 30 years' fast economic growth, especially during the period from year 2000 to year 2008[1]. It took around 10 years to rebuild the financial market after the Cultural Revolution. In 1990, the stock market in Shanghai and Shenzhen established. Because of the typical political issues in China, state-owned banks were the largest entities in the society. Later around the end of 1990s, in the process of globalization, the diversification of financial institutions emerged in the historical arena.

While in recent years, due to both national and international factors, the economic growth in China seems to be slowing down. Catastrophic financial turbulences occurred from the end of year 2007 to the end of 2008[2], and from July 2015 to February 2016. During the first depression, the stock market index dropped from 5824.12 in October,

[1] According to the data from National Bureau of Statistics of China, although affecting by the crisis in year 2008 China's economic growth (roughly calculated by real GDP increase) decreased from 24.85% to 11.26% in 2009, it kept increasing in the following two years, while the growth rate decreased in recent years.

[2] Set the stock market depression from year 2007 to 2008 to the first turbulence. Similarly, from 2015 to 2016 is treated as the second depression of China's financial market in this paper.

2007 to 1876.02 in November, 2008 within one year. Correspondingly, Shanghai Stock Exchange Composite Stock Price Index dropped from 5178.19 to 2997.84 within one month and jumped to the lowest 2655.66 in January 28th, 2016. The index stands at around 3000 points till now.

It is well known that regions will possibly suffer from the crisis during the integration of the world trade affecting by certain external factors, such as, sudden stop of foreign capital or world demand and the bubble of the whole economy. China is the second largest economy nowadays with a typical political system. Government plays a crucial role in the market, and thus, the efficiency of the stock market is controversial. In addition to the data validity and availability, the measure of the systemic risk is challenging but important. To better understand the build-up of the systemic risk in China can shed light on the risk construction of financial sectors.

More in detail for nowadays China, state-owned banks, commercial banks, securities and insurance companies, and diversified financial are the crucial financial institution categories. Different financial institutions in the market contribute contrastive spillovers when they take the existing price directly, as the price is determined by the whole economy. So, the spillovers change from time to time based on the individual behaviors affected by the government, and the systemic risk along the timeline is thus dynamic. The risk path can leave clues to financial or even the whole economic stability.

When facing a booming credit economic, for instance at the beginning of the globalization from 1990 to 2007, spillovers were also accumulating, from one institution to another. They tended to invest in the portfolios which have the highest premium during the good state, and then, when the stock market crisis came, because of the same assets that institutions would hold, the impacts of bad events will immediately spread within the market[3]. The volatile systemic risk series were used to track and explain its

[3] This is the basic concept of the tail dependency

pattern or turning point during the crisis. The measures of systemic risk came to the stage especially after the worldwide financial system impaired in 2009 and large amounts of analysis have been conducted from the perspectives of methodologies, estimations and predictions of the systemic risk.

Various approaches have been proposed to compose a better indicator for the market stability. Based on the statements we proposed, the contemporaneous systemic level is somewhat misleading, and therefore we need time series to catch the risk build-up process. This paper will adopt the conditional value at risk (*CoVaR*) to analyze the construction of the systemic risk series in China's financial market.

$CoVaR_q^{j|C(market\ \ capitalization^i)}$ is the conditional probability distribution of the maximum loss at q% quantile level for *j* institution when institution *i* is under different market states (Adrian, Brunnermeier 2014). Instead of evaluating isolating individual institution, *CoVaR* can reflect the exposure of institution *i* to the systemic risk and the contribution of a certain institution to the overall systemic risk without distributional assumptions, thus adequately taking into consideration the tail dependency between institutions.

This paper aims to empirically evaluate the systemic risk build-up of China's financial market with Δ*CoVaR*. We will depict the composition of the systemic risk of China's financial market based on the conditions of international financial environment and national real estate sector using quantile regression and the concept of *CoVaR*. The risk contribution and exposure of each sector of financial institutions during the great turbulence can be measured, and the results will infer the tail dependency of different types of institutions. Our results can also give suggestions to the financial market regulations.

In this paper, Section 2 presents related literature review including the concept of systemic risk and the different measures of it. The model and the methodology will be

introduced in Section 3. Data, assumptions and indicators will be stated in Section 4. The estimation of the risk via regressions and the comparison with the developed countries will be conducted in Section 5. The comparison includes both before crisis and during crisis. After the comparison study, in Section 6, with the systemic risk estimations, we then propose conclusions and regulation suggestions of China's financial market. Further study will be discussed after the conclusions. In what follows, we start with the literature review about relevant concepts and models.

2 Literature Review

Systemic risk varies from different institutions, sectors, and changes along the time line. Different ways are proposed to make systemic risk a better indicator of the individuals or financial sector. In this part, the concept and the theoretical motivation of systemic risk will demonstrate in the first place. Then, the measures of the risk will be concluded in the second part. After the general explanation of concepts and measures, the status and the estimation for systemic risk of China will be discussed in the third part.

2.1 The Basic Concept and Theoretical Background of Systemic Risk

Unlike the stable price level in the general theory, the real value of the item is fluctuating according to the market status in reality. So when institutions pick the general market price as given in the changing market, spillovers will form (Bhattacharya 1982). The externality across individuals spreads the risk to the whole sector or even to the whole world. When the gap between the nominal and real value exceeds certain degree, the belief will be crushed and then crisis will come (Li 2009).

When the financial economic system is put as a whole, multi-agent counterpart of a systemic risk-shifting action occurs (Jesen and Meckling 1976). Banks and institutions can win a positive externality by investing in the assets that have greater correlation with others (Acharya 2009). The connections credit when the economy blooming. On the contrary, this limited liability of the agents can also lead to contagion when crisis comes

(Claessens and Forbes 2001). This is the tail dependency that exists in the financial market. However, it is known that the normal distribution does not suffice to capture the tail dependency. Therefore, we resort to quantile regression which does not rely on the assumption of normality.

2.2 Quantile Regression

Before reviewing the literature of quantile regression, we first briefly review the OLS estimation, in order to compare the pros and cons of the two regression methodologies. For OLS regression, set the sample mean of the dependent variable $\mu = X\beta$. The estimation of the coefficient β shows below:

$$\min_{\beta \in R^k} \sum_{i=1}^{n} (y_i - x_i^T \beta)^2$$

On the other hand, quantile regression generalizes a new statistics aiming to capture different influences of different quantile of the observations instead of only focusing on the means.

$$\min_{\beta \in R^k} \sum_{i=1}^{n} \rho_\theta (y_i - x_i^T \beta)$$

θ is the chosen quantile percentage of the series, and $0 < \theta < 1$; ρ_θ is the linear loss function which equals to $(\theta - 1)$ when $\hat{y}_i - \hat{x}_i^T \hat{\beta} < 0$, and equals θ when $\hat{y}_i - \hat{x}_i^T \hat{\beta} > 0$. Thus, when $\theta = 50\%$, the coefficient infers the impacts of independent variables x on the median of the dependent variable y.

Koenker and Bassett (1978) and Koenker (2005) systemically discussed the efficiency of quantile regression estimation and the superior performance over the non-Gaussian error distributions. Nowadays, quantile regression is widely used in varies fields. In this paper, the assumption of multivariate normal distributions does not hold for financial

institutions' return loss because of the contagion between institutions. Thus, quantile regression is applied in the *CoVaR* estimation.

2.3 The Measures of Systemic Risk

Systemic risk can be treated as a portfolio when financial institutions are treated as individual assets. Some researchers focus on separate micro institutions, while some others try to analyze the macro systemic risk as a whole. It applies to accounting, finance and economics fields.

2.3.1 Different Measures of Aggregate Risk

Acharya et al. (2010) divided methodologies into structural and the reduced form approach. What's more, Biasias et al. (2012) classified the methodologies into 6 categories and totally 31 different ways. According to the data requirements, we have macroeconomic measures, granular foundations and network measures, forward-looking risk measures, stress-test measures, cross-sectional measures and measures of illiquidity and insolvency. Whichever measure is focus on a better parameter in certain society or institution. In the following literature review, we divided the related literature into mainly three aspects, accounting, microeconomics and macroeconomics.

In accounting points of view, accounting measures of β correlated with the expected security, risk-free and market rate of return is the most general one. Hamada-Rubinstein formulas involved the financial structure into the analysis (Hamada 1972, Rubinstein 1973). Based on the decomposition of the systemic risk, we can decompose Betas into operating risk and financial risk. Hill and Stone (1980) emphasized the importance of financial structure on systemic analysis and prediction.

In microeconomics field, systemic risk is discussed widely in isolated company or bank context. Value at Risk (*VaR*) is the most common measure for separate agents. The method is used for evaluating the systemic risk of portfolios, and it applied to quantify

the risk of certain entity exposed to the market. By using statistics, *VaR* can prudentially reflect the possible loss in certain confidence intervals (Linsmeier and Pearson 2000). While *VaR* can't well evaluate the correlation inter-banks and decompose the contribution of different types of institutions to the systemic risk. In the capital asset pricing model, correlation between the rates of market portfolio's return and asset's return measures the systemic risk (Sharpe 1964).

In macroeconomics field, conventional literatures have different ways to estimate the systemic risk. Huang etc (2009) and Giesecke and Kim (2011) applied similar methodology to capture the dynamic systemic risk. They applied maximum likelihood regression and used the failure probability of the institutions in the financial market instead of the loss return change as the observations. The model does not require the distribution assumptions and default rate is a good indicator to observe, but this indicator is not suitable for China's case. Due to the fact that Chinese government can leave some impacts on the financial market, the default rate of the institutions can be underestimate. Other indicators, for example, the price of the insurance estimated by Zhang etc. (2009) used the credit default swap (CDS) as a control variable also has the same problem for China's case. Chen etc. (2012) also applied CDS to measure the systemic risk of the insurance sector using both linear and non-linear Granger causality tests. While, CDS is not an appropriate indicator for China's financial market.

Estrada (2002) applied D-CAPM model to estimate the aggregate risk of emerging markets. He argued that the estimated semivariance of return performance could reflect the systemic risk with OLS regression. Semivariance and downside-β can leave hint for investors about the requiring return of the assets, while for OLS regression, the multivariate normal distribution is tail-independent (Schmidt and Stadtmuller 2003) which inferred that it can't capture tail dependency when the crisis come. Nandha and Hammoudeh (2007) used international factor model to estimate the systemic beta signs of the stock markets of the Asia-Pacific regions towards oil price and exchange rate

sensitivities. The sign can provide evidence of the direction of the impacts, but it is hard to depict the systemic trend during the crisis.

2.3.2 *CoVa*R and Δ*CoVa*R

Based on the contagion between the institutions in the market and the financial environment of China, this paper will conduct reduced-form Conditional *VaR (CoVaR)* to measure China's systemic risk of financial market.

The concept of *CoVa*R and Δ*CoVa*R is first proposed by Adrian and Brunnermeier in year 2008 and published in American Economic Review in July, 2016. They used this method to capture the systemic risk change of United States during the crisis. *CoVa*R is the the Value at Risk of institution *j* conditioning on the Value at Risk of institution *i*. Thus, when VaR^j is the dependent variable on behalf of the entire financial market and VaR^i is one of the independent variable standing for separate institutions, the estimated dependent value, $CoVaR^{j|VaR^i}$ reflects the *Va*R of the system conditioning on the *Va*R of institution *i*. And then, Δ*CoVa*R of institution *i* can be obtained to reflect the *CoVa*R change when institution *i* is under distress.

They provided both reduced-Δ*CoVa*R and forward-Δ*CoVa*R. The reduced form can capture the systemic risk build-up with state variables of the financial market. In the paper, they used state variables which could affect the conditional return loss of the market. Market leverage, maturity mismatch and asset price booms are the main characteristics involved in the model. State variables are not necessarily to catch all the externalities considering the problem of overfitting. With the outcomes of the estimated Δ*CoVa*R, forward-Δ*CoVa*R can be predicted based on the characteristics of the market. Adrian and Brunnermeier (2016) estimated the efficiency of the *CoVa*R estimation for US financial market with the prediction.

Wong and Fong (2010) used the CDS spread of Asia-Pacific as the indicator with the methodology of $\Delta CoVaR$ to estimate the systemic risk of banks. While in our case, only reduced-$\Delta CoVaR$ will be applied due to state variables of China's financial market focus on the international impact and the influence of the national real estate instead of the structure of the financial market. Next, the related literature focusing on the financial market systemic risk of China is provided in the next section.

2.4 Systemic Risk of China's Financial Market

According to the fact that the participation of the government in the economy, relevant researches also aim to give suggestions for the regulation of the market with qualitative analysis. As we stated in the Introduction Section, banks dominate China's financial market since 1990s, the analysis of the systemic risk of China also focus on banks or isolated institution. Bao (2005) proved the existence of contagion effects within bank sector using the structure of the bank assets. He emphasized that the correlations between banks could cause the systemic distress which inferred normal distribution assumption should not hold. To capture the risk trend along the timeline, $CoVaR$ estimation is the best choice.

The researches of the systemic risk of the stock market focus on the required return of the portfolios or the stock market efficiency. Market economy in China is still at issue in the whole world market nowadays, so the efficiency of Chinese stock market data is ambiguous in some case. Firth, Lin and Wong (2008) emphasized that the stock returns in China can't truly inform the market-level information. The authors picked the sales growth of each bank to replace of the returns of the stock market to estimate the relations between leverage and investment of the state-owned banks.

While in our case, the market capitalization loss is chosen as a reasonable indicator to detect the systemic risk contribution and exposure of bank, securities, insurance, and diversified financial during the stock market crisis. With the globalization, the stock price

in China will surely be affected by the externalities of international financial environment. What's more, as the pillar industry of the economic growth, real estate is an important state variable which can impact the conditional Value at Risk of the financial market. The price, regulations of the real estate can build-up the spillovers of the financial market (Zhang 2006).

In this paper, we will choose the market value loss of different sectors to evaluate their contribution and exposure to the market systemic risk with the indicator $\Delta CoVaR$ under the global market effects and the development of the real estate industry. In Section 3, definition of the estimation and the process of our analysis will be explained.

3 Methodology

As we elaborate in Section 2, $\Delta CoVaR$ is the main indicator applied in this paper. To detail the methodology, the review of the definition of VaR is shown in Section 3.1.

3.1 VaR and State Variables

As one of the most common measure of systemic risk for isolate institutions, VaR is the estimated return loss of the financial market or market sector given q%. When q = 50, the Value at Risk of institution *i* in the median state can be estimated.

$$\Pr\left(X^i \leq VaR_q^i\right) = \text{q\%}$$

X^i is defined as the returns of total market capitalization (*MC*) of institution *i*, which stands for the loss of the financial system or different financial sectors in our case with typical state variables. As the definition of VaR illustrate the loss at q% of the institution (0< q <100), $X_t^i = -\Delta MC_t^i / MC_{t-1}^i$. Thus, larger VaR is, more *MC* loss is expected at quantile level q%. Given different q, the institution gets different $VaR_{t,q}^i$. To capture the tail dependency of the spillovers, q equals to 99, 95, and 90. With q = 99, we can calculate VaR_{99}^i conditioning on state variables at the worst 1% impaired level.

Considering the characteristics of China's financial market, we divided the financial market into roughly two types in this paper, bank and non-bank sectors. Securities, insurance and diversified financial institutions are included in the non-bank sector. International financial conditions and national real estate returns are the state variables in this paper which affect conditional return loss of the financial market.

When the international financial system is impaired, for instance during the global financial crisis, the confidence of the investors towards China's financial market will therefore change. Value at Risk of the market will be affected, and the volatility increase can threat the investors or Chinese government to delever further. Crowded trades will make the situation worse. The returns of US treasury, U_t, and national returns of the real estate sector, RE_t are the indicators of the state variables. We need to note that the state variables are conditioning variables only reflects the contagion between the sectors instead of causal sense.

What's more, we can learn from the reality that investors will change their expectations of period t+1 according to the state of period t. So, U_{t-1} and RE_{t-1} will applied to $VaR_{t,q}^i$ calculation of period t using quantile regression.

$$X_t^i = \alpha_q^i + \beta_{1q}^i U_{t-1} + \beta_{2q}^i RE_{t-1} + \varepsilon_{q,t}^i$$

$$VaR_{t,q}^i = \hat{\alpha}_q^i + \hat{\beta}_{1q}^i U_{t-1} + \hat{\beta}_{2q}^i RE_{t-1} \quad (3\text{-}1)$$

$\hat{\alpha}_q^i$, $\hat{\beta}_{1q}^i$ and $\hat{\beta}_{2q}^i$ are the estimated coefficients of the quantile regression. After deriving $VaR_{t,q}^i$ for each sector, we come to the *CoVa*R estimation.

3.2 $\Delta CoVaR$ estimation

According to the definition by Adrian and Brunnermeier, 2016, *CoVa*R can be written as below,

$$\Pr\left(X^j|\mathrm{C}(X^i) \leq CoVaR_q^{j|C(X^i)}\right) = \mathrm{q}\%$$

$\mathrm{C}(X^i)$ is a random event happened to *i* which can make the entity in an extremely impaired situation. Thus, for instance, when q = 99, $CoVaR_{99}^{j|X^i=VaR_{99}^i}$ reflects the Value at Risk of *j*[4] when *i* is in distress.

We conducted two ways to measure *CoVa*R, $CoVaR_q^{system|X^i=VaR_q^i}$ and $CoVaR_q^{i|X^{system}=VaR_q^{system}}$. The difference between these two measures is the direction of the *CoVa*R estimation is reversed. According to the definition of Conditional Value at Risk, $CoVaR_q^{system|X^i=VaR_q^i}$ reflects the system Value at Risk conditioning on sector *Va*R and $CoVaR_q^{i|X^{system}=VaR_q^{system}}$ infers the Value at Risk of sector *i* when the entire market return loss equals to VaR_q^{system}.

Define $CoVaR_{q,t}^i$ as the $VaR_{q,t}^{system}$ conditioning on the $VaR_{q,t}^i$ to abbreviate $CoVaR_{q,t}^{system|X^i=VaR_q^i}$. *Exposure*-$CoVaR_{q,t}^i$ is defined as the exposure risk of sector *i* conditioning on the estimated $VaR_{q,t}^{system}$.

3.2.1 Estimation of $Network - \Delta CoVaR_{q,t}^i$

With the estimated $VaR_{q,t}^i$, $Network - CoVaR_{q,t}^i$ is estimated below using quantile regression,

$$X_{q,t}^{system} = \alpha_q^{system|i} + \beta_{1q}^{system|i} U_{t-1} + \beta_{2q}^{system|i} RE_{t-1} + \gamma_q^{system|i} X_t^i + \varepsilon_{q,t}^{system|i}$$

[4] *j* also represents the entire financial market or market sectors.

$$Network - CoVaR_{q,t}^{i} = \hat{\alpha}_{q}^{system|i} + \hat{\beta}_{1q}^{system|i} U_{t-1} + \hat{\beta}_{2q}^{system|i} RE_{t-1} + \hat{\gamma}_{q}^{system|i} VaR_{t}^{i} \quad (3\text{-}2)$$

Define $Network - \Delta CoVaR_{q,t}^{i}$ as the market systemic risk change when institution is in distress. It reflects the systemic risk contribution of sector *i*.

$$Network - \Delta CoVaR_{q,t}^{i} = CoVaR_{q,t}^{i} - CoVaR_{q,t}^{system|X^{i}=VaR_{50}^{i}}$$

(3-3)

$$= \hat{\gamma}_{q}^{system|i}(VaR_{q,t}^{i} - VaR_{50,t}^{i})$$

q equals to 99, 95, 90 is applied in the regression to capture the tail dependency in the market. $Network - \Delta CoVaR_{q,t}^{i}$ is the indicator to reflect the contribution of each financial sector to the total systemic risk of the market.

3.2.2 Estimation of *Exposure*-$\Delta CoVaR_{q,t}^{i}$

In China, the institutions will not only generalize systemic risk, but also be affected by both international and domestic financial markets. So, to estimate the Value at Risk of the sectors when the entire market is in a crisis is also necessary. Shifting the direction of the conditioning reversely to $CoVaR_{q}^{i|X^{system}=VaR_{q}^{system}}$, we can focus on the risk increases of sector *i* when the whole financial market is suffering.

$$X_{q,t}^{i} = \alpha_{q}^{i|system} + \beta_{1q}^{i|system} U_{t-1} + \beta_{2q}^{i|system} RE_{t-1} + \gamma_{q}^{i|system} X_{t}^{system} + \varepsilon_{q,t}^{i|system}$$

$$Exposure - CoVaR_{q,t}^{i} = \hat{\alpha}_{q}^{i|system} + \hat{\beta}_{1q}^{i|system} U_{t-1} + \hat{\beta}_{2q}^{si|system} RE_{t-1} + \hat{\gamma}_{q}^{i|system} VaR_{q,t}^{system} \quad (3\text{-}4)$$

$$Exposure - \Delta CoVaR_{q,t}^{i} = Expososure - CoVaR_{q,t}^{i} - CoVaR_{q,t}^{i|X^{system}=VaR_{50}^{system}} \quad (3\text{-}5)$$
$$= \hat{\gamma}_{q}^{i|system}(VaR_{q,t}^{system} - VaR_{50,t}^{system})$$

Applying q equals to 99, 95, 90 in the estimation to capture the contagions in the financial market. $\text{Exposure} - \Delta CoVaR_{q,t}^{i}$ is the indicator to measure the risk increases of financial sector *i* under the exposure of the financial system.

$\Delta CoVaR_{q,t}^{i}$ and *Exposure*-$\Delta CoVaR_{q,t}^{i}$ are the main indicators to measure the financial market's systemic risk. In Section 4, we come to the collection and the calculation of the data.

4 Data

In this paper, data include mainly two parts, the return loss for different sectors and state variables.

First, we come to the calculation of the return loss X_t^i. Based on the definition of *CoVaR*, we applied weekly market capitalization of the financial market and the separate sectors to compute the return loss $X_t^i = -{(MC_t^i - MC_{t-1}^i)}/{MC_{t-1}^i}$. The change of the market value can reflect the aggregate credit spread in the entire economy. All the weekly data from November 15th, 1996 to August 5th, 2016 can be obtained in iFind financial database[5]. The calibration of the return loss removed the impacts of the sector size.

And then, we use daily US three-month Treasury bill rate as the state variable U_t and the weekly return of the market value of national real estate industry is applied to capture

[5] iFind is one of the largest financial database in China which developed by Zhejiang RoyalFlush network. It contains large amount of data of both listed and non-listed companies. Both balance sheet and off-balance-sheet are included in the database.

the externalities from the price of real estate sector. The statistics of state variables are provided in Appendix I. Other state variables (national bond yields, gdp growth rate, stock market index, risk-free return and Shibor) we finally excluded from the model are obtained from iFind and World Bank. The quantile regression results when using these state variables at 10% quantile are explained in Appendix II.

The longest stock market time spread of China's financial market starts from year 1990. The financial market value involved only few Banks in. Insurance market value is available from November, 1996, and thus we pick our starting point from November 15th, 1996 for every sector. To conclude, for each sector, 993 observations is obtained to compute the systemic index. We divided the financial market into 5 different aspects.

We also consider to analyze the contribution of the huge financial institutions, such as Bank of China, China Construction Bank and Industrial and Commercial Bank of China etc., to total systemic risk of China separately. Nevertheless, Due to the consideration of the protection of the state-owned assets, the state-owned banks are permitted to be on the market since the late 2000s and only quarterly market value are available. Thus, the evaluation of the parameter will be possibly biased. This fact also infers the advantages of the classification applying in this paper. The return loss change during this period is a good reference to credit build-up. With the total market value of the sector, we can capture the long-term financial credit build-up in China excluding the effects of the government regulations.

After the modeling and the data collection, Section 5 will provide the estimation results of the systemic risk and comparisons with the credit build-up in United States during financial crisis.

5 Estimations and Comparisons

The program of the estimations of the model using Eviews are shown in Appendix III. Based on the methodology stated in Section 3, we can compute the indicators VaR_q^i, $Network - \Delta CoVaR_{q,t}^i$, $Exposure - \Delta CoVaR_{q,t}^i$ during recent 20 years. The basic statistics of the estimated systemic risk is provided in Table 5-1. The differences between q = 50 and q = 99 of both *VaR* and *CoVaR* are obvious. In the following analysis, we focus on the estimation when q equals to 99. The results of $\Delta CoVaR_{95,t}^i$ and $\Delta CoVaR_{90,t}^i$ will also be provided as control groups.

Table 5-1 Statistics of the systemic risk indicators

	Mean	Standard Deviation	Observations
X_t^i	-0.0496	3.2061	5958
VaR_{99}^i	0.1251	0.0256	4965
VaR_{50}^i	-0.0013	0.0055	4965
VaR_{99}^{system}	0.0792	0.0409	4965
VaR_{50}^{system}	-0.0033	0.0806	4965
$CoVaR_{99,t}^i$	0.1046	0.0173	4965
$CoVaR_{50,t}^i$	0.0008	0.0021	4965
$Network - \Delta CoVaR_{99,t}^i$	0.0238	0.0212	4965
Exposure-$\Delta CoVaR_{99,t}^i$	0.0194	0.0232	4965

In this section, the analysis based on *CoVaR* methodology will be conducted in Section 5.1. And then, combining the relevant literature of United States, comparisons between the systemic risk of United States and China will be explained in Section 5.2. First, we come to the Δ*CoVaR* analysis of each sector.

5.1 *Network - ΔCoVaR* Analysis

As we explained in Section 3, two different directions of the conditioning will be applied in our paper. We will first focus on $Network - \Delta CoVaR_{q,t}^i$ and then, $Exposure -$

$\Delta CoVaR_{q,t}^{i}$. This paper is focus on $\Delta CoVaR$ indicator, so the plot of VaR_{q}^{i} will provided in Appendix IV.

5.1.1 Network $-\ \Delta CoVaR_{q,t}^{i}$ Analysis

Recall that $Network - \Delta CoVaR_{q,t}^{i}$ is the contribution of the sectors to the total systemic risk of the financial market. Figure 5-1 reflects *Network*-$\Delta CoVaR$ estimator for bank, nonbank, institutions from 22nd November, 1996 to 5th August, 2016. Securities, insurance and diversified financial sectors risk trends will be depicted in Figure 5-2.

When comparing the credit build-up trend between bank and nonbank sectors, it's obvious that their contributions to the market systemic risk are quite different at 1% and 5% worst quantile[6]. According to the graph, banks contribute more to the market systemic risk since the end of 1996 and the systemic risk contribution of the bank sector has a much higher volatility. The estimated systemic risk in recent years does not apparently increase. The financial market is stable recently based on our model.

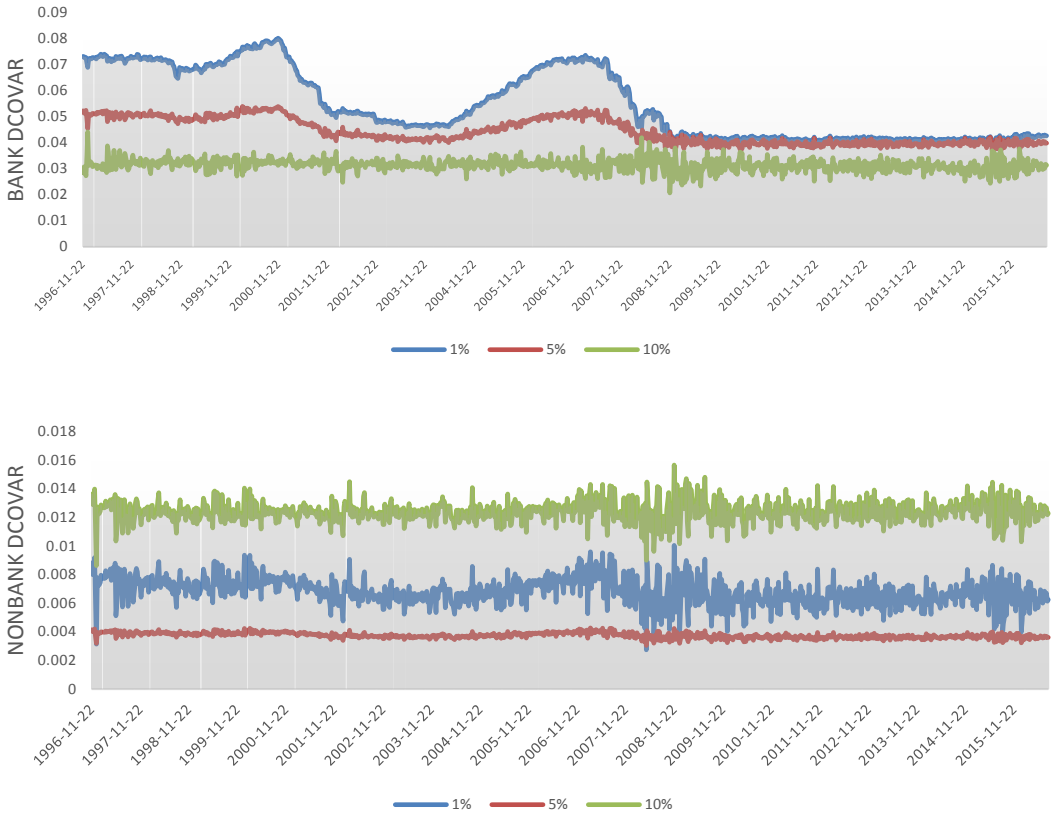
The credit build-up of bank sector starts from the end of 2003 and climbs to the peak in 2007. Bank sector begins to delever from the end of 2007 to the end of 2008 and the premium of the bank sector stays around 0.04 $\Delta CoVaR$ level from 2009 to 2016. What's more, in the beginning of 2001, the systemic risk contribution of banks also experiences a sharp decrease. The reason for the downside trend is because of the divestment of the government.

While, the contribution of the non-bank sector is stable even during the crisis which infers the systemic risk of the non-bank sector was not materialized through this $\Delta CoVaR$ direction. China's non-bank sector started to fast develop in 1996. The

[6] 1% is represented the $\Delta CoVaR$ of institution i at the worst 1% quantile (q = 99); 5% reflects the worst 5% quantile when q = 95; 10% infers the quantile when q = 90.

comparatively small institutions acted as a herd according to the market regulations, so the level of the overall contribution change to the total systemic risk is much lower. Although $\Delta CoVaR$ of non-bank sector is more stable, the slightly decrease between 2007 and 2008, 2015 to 2016 is detected. The decease explained the impacts of the stock market crisis.

Figure 5-1 Sector's contribution of the systemic risk



Securities, insurance and diversified financial are the main classification of the non-bank financial institutions in China. Figure 5-2 describes the credit build-up of the three sectors. According to the results, the risk contribution change of the non-bank financial institutions shows significant differences.

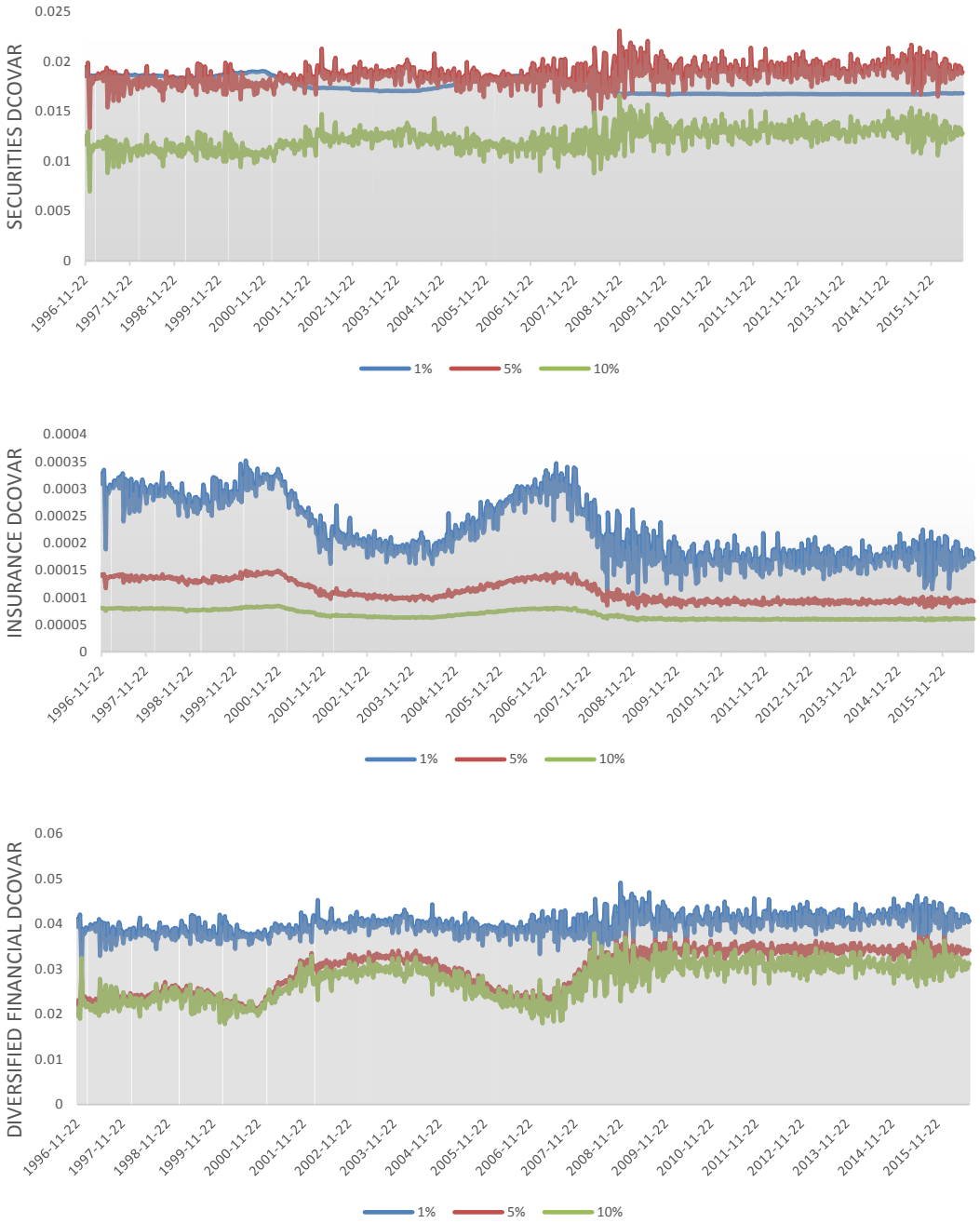
For securities, the risk contribution is not sensitive to the stock market crisis. During the first crisis, the contribution stays around 0.013. After the first crisis, security institutions increase their contribution to the market risk to 0.015 and maintain the level until 2016.

The contribution change of insurance sector is similar to the situation of bank sector. The contribution of bank sector increases since the end of 2003 and climbs up until the end of 2006. And then insurance institutions begin to delever from 2007 to the end of 2009. *Network*-Δ*CoVa*R level holds at around 0.00015 from 2009 to 2016.

Diversified financial institutions give us a reverse trend of the contribution change. When we focus on the worst 1% quantile, it is similar to security institutions and non-bank sector, but it contributes more to the market risk. Taking 5% and 10% quantile into consideration, diversified financial institutions provide an increase proportion towards the total systemic risk. The definition of diversified financial sector is entities that mainly engaged in financial products and derivatives transactions. This sector is fast developing in recent years. I suspect the comparatively lower contribution of the system is due to the early regulations. Considering the high level contribution to the system, the regulations and the monitoring indicators can give more attention to this sector.

The systemic risk contribution of different sectors can capture the risk that is generalized by the institutions. In other direction, when the financial system is impaired conditioning on the international financial system or other sectors, the change of Value at Risk can represent the exposure of the sector to a financial crisis. Then, *Exposure*-Δ*CoVa*R is used as the indicator to measure which sector is the most exposed to the systemic impacts.

Figure 5-2 *Network* - Δ*CoVaR* of non-bank sectors



5.1.2 *Exposure*-Δ*CoVaR* Analysis

The *Exposure*-Δ*CoVaR* of each sector is provided in Figure 5-3. Compared to the results of $\Delta CoVaR_{q,t}^{i}$ estimations, trends of *Exposure*-Δ*CoVaR* show same characteristics towards all sectors. Bank sector is also the most exposed sector to the financial market crisis. All the sectors experience an obvious decrease of the *Exposure*-Δ*CoVaR* during the

first crisis. To the second crisis, only volatility increase can be observed according to the obtained information. More evidence is needed for the second crisis in China's stock market.

We can conclude that when the whole financial system of China is in a crisis, all the sectors will tend to delever during the crisis. Banks will be the institutions which will be affected most in the distress. What's more, the premiums of sectors increase before the market crisis, and then keep steady.

Figure 5-3(1) *Exposure-ΔCoVaR* of different sectors

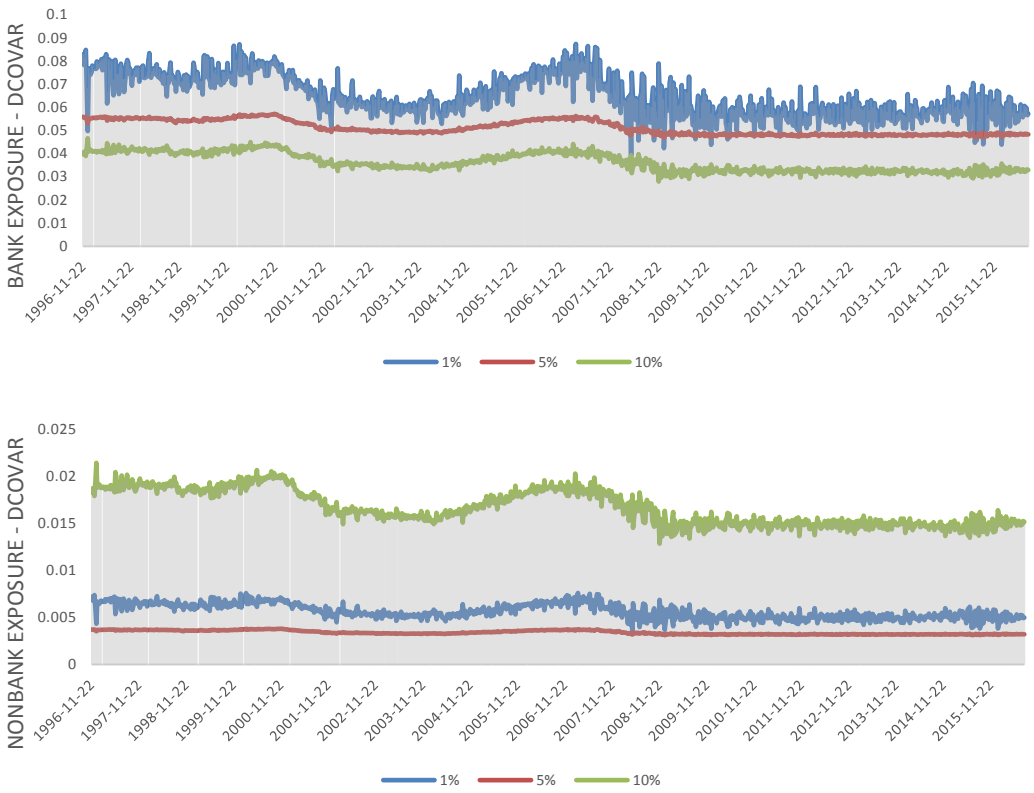
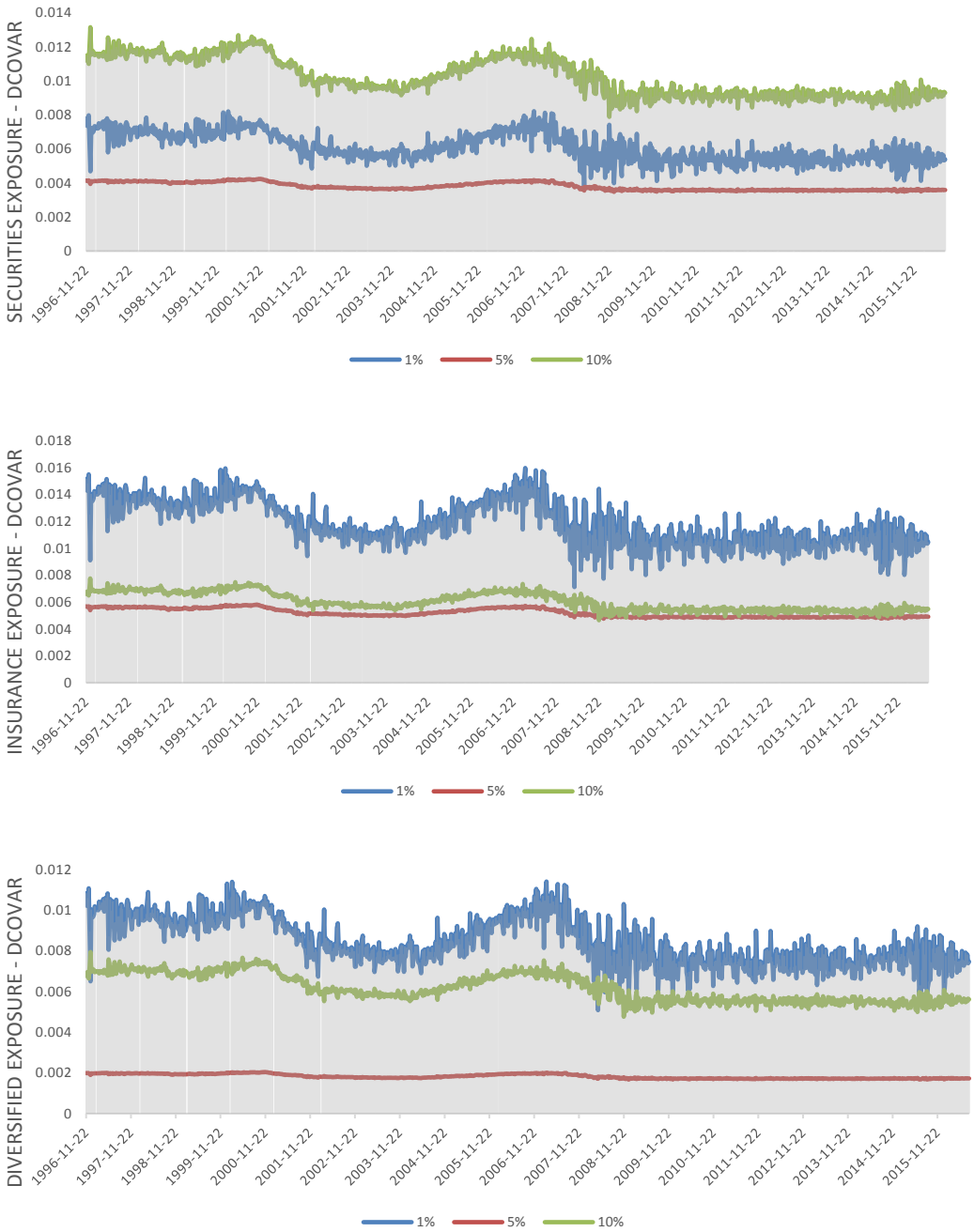


Figure 5-3(2) *Exposure*-Δ*CoVaR* of different sectors



Two different Δ*CoVaR* measures depict the dynamic systemic risk change from 1996 to 2016. According to $Network - \Delta CoVaR_{q,t}^{i}$ analysis, banks contribute more risk to the system. Banks and insurance companies experience credit boom before 2007 and cool down during the crisis. While, the systemic risk contribution of securities and diversified financial institutions are not sensitive to the financial crisis. The systemic risk of

diversified financial institutions even increased during the crisis. The reason for the increase is securities and diversified financial sectors are fast develop recently. Based on the estimations of *Exposure*-Δ*CoVaR* indicators, all sectors have an increase exposure to the financial market before the crisis. Banks are estimated as the most exposed to the crisis, which infers banks are most at risk when a financial market crisis occurred.

As a developing country, China's financial market is still experiencing trial and error. The comparisons with the developed countries can provide useful principals for the market development. In Section 5.2, we will compare the results of China's systemic risk with US based on the research conducted by Adrian and Brunnermeier (2016).

5.2 Comparisons with United States

According to Adrian and Brunnermeier (2016), in the 2008 financial crisis, *Network*-Δ*CoVaR* level of Lehman Brothers increased sharply before going bankrupt. Δ*CoVaR* is an efficient financial market monitor in US. However, Δ*CoVaR* estimation in China can only reflect the composition of the systemic risk instead of predicting the crisis. Securities and diversified financial institutions still under credit boom period during the stock market crisis in 2007. *Exposure*-Δ*CoVaR* is more reasonable in China's case.

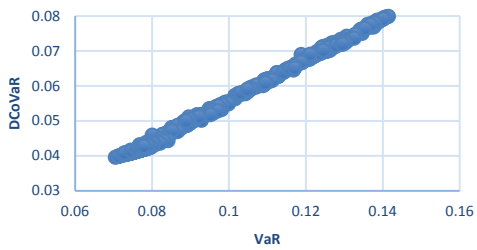
What's more, Adrian and Brunnermeier (2016) discussed the correlation between Δ*CoVaR* and *VaR*. They used scatter-plot to show that there is only weak cross-sectional links between the two measures. The correlations between Δ*CoVaR* and *VaR* of China is provided in Figure 5-4 and 5-5. X-axis is the estimated value of *VaR,* y-axis stands for the Δ*CoVaR* level.

Both *Network*-Δ*CoVaR* and *Exposure*-Δ*CoVaR* display a strong positive correlation with *VaR* in China's case. For *Network*-Δ*CoVaR,* the correlation is even stronger compared to *Exposure*-Δ*CoVaR*. This fact infers that, to against systemic risk, applying financial regulation based on sector level is sufficient enough for nowadays China. I suspect the

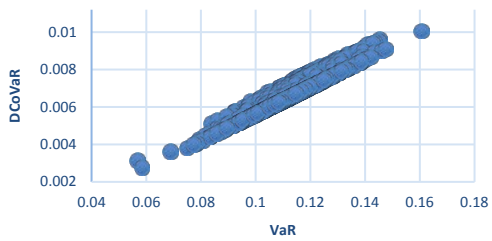
correlation explains that most of financial institutions in China act as a herd and they are shaped by the marker regulations. It' better for the stability, but the financial innovation can be improved in the future.

Figure 5-4 The correlation between *VaR* and *Network*-Δ*CoVaR*

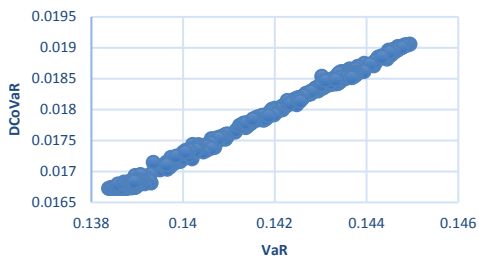
Bank



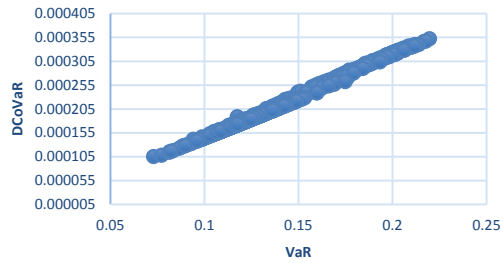
Non-Bank



Securities



Insurance



Diversified Financial

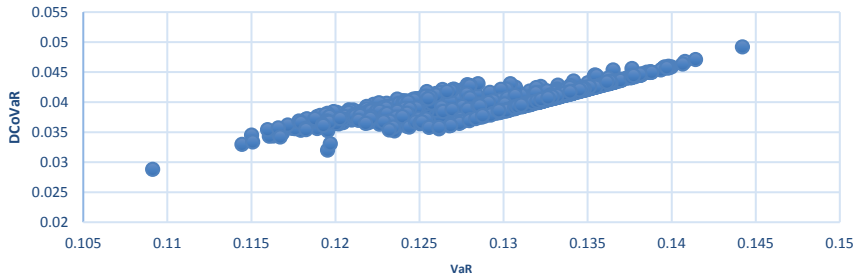
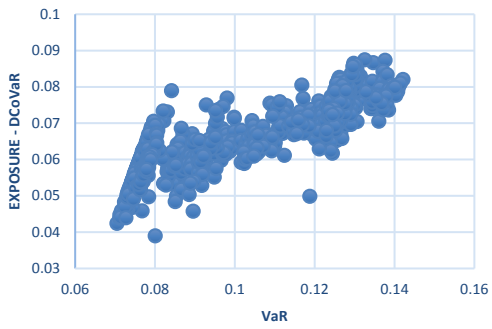
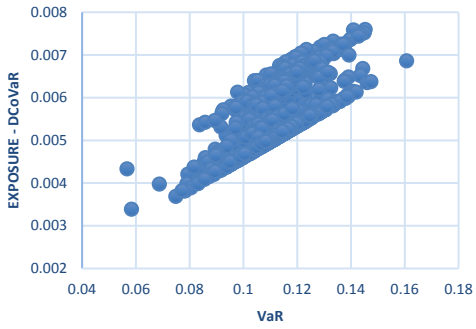


Figure 5-5 The correlation between *VaR* and *Exposure-ΔCoVaR*

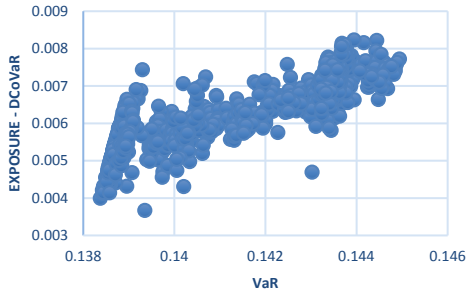
Bank



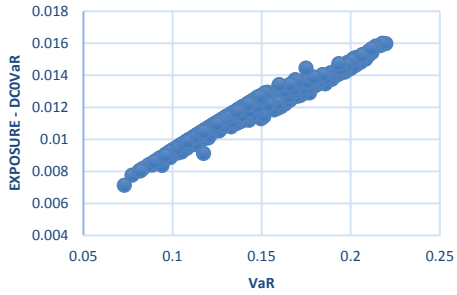
Non-Bank



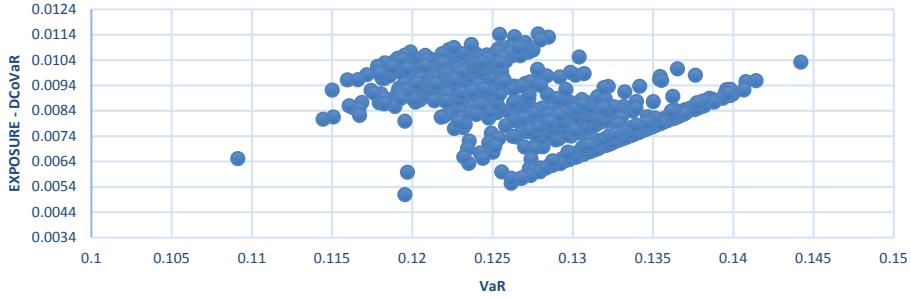
Securities



Insurance



Diversified Financial



6 Conclusions

Using *Network-ΔCoVaR* and *Exposure-ΔCoVaR* as the systemic risk indicator, this paper measures the dynamic systemic risk change of China's financial market. The financial market is divided into bank and non-bank sectors based on the importance of commercial and state-owned banks. In non-bank sector, securities, insurance and diversified financial sectors are included. Market capitalization of sectors are applied to

calculate the return loss. US treasury and national returns of the real estate sector are the state variables that can change the conditioning Value at Risk.

Estimated *Network*-Δ*CoVaR* shows different dynamic systemic risk change of the sectors. Banks are the biggest risk contribution sector. Bank and insurance sector have the same law of systemic risk change. They experience credit boom before the crisis and cool down afterwards which share the same trend with the financial institutions of United States. However, security and diversified financial sectors in China are crediting from 2007 to 2016. The risk contribution of these two sectors keep steady during the crisis at worst 1% quantile. Diversified financial institutions became riskier after 2007 at both worst 5% and 10% quantile. The dynamic change of *Exposure*-Δ*CoVaR* of all the sectors share the same law. The risk exposure of the sectors increases before the crisis and decrease during the crisis. The results also reveal bank sector is most at risk.

Different market characteristics and development stage bring different correlations between *VaR* and Δ*CoVaR* of China and United States. The linkage between the two indicators of US is loose, whereas it shows a strong positive correlation between *VaR* and Δ*CoVaR* in China. The positive correlations reflect that higher the *VaR* of the isolate sector is, higher the Δ*CoVaR* it will have, so financial regulation towards one sector is sufficient in China to control the overall systemic risk.

The results of Δ*CoVaR* estimation explain the composition of China's systemic results and emphasize the importance of bank sector. With the fast development of diversified financial institutions, the regulation and the stability monitor of this sector also need to be stressed.

For further studies, we should obtain sufficient data of the structure of the financial sectors, such as leverage, loans etc. to efficiently predict the future systemic risk of China's financial market and thus, it will be possible to see the stability of the investment

environment in the future to give further regulation suggestions. What's more, with the fast development of the internet finance in China, the classification of the financial market can be more accurately.

Appendix

I. The Statistics of State Variables

	Mean	Standard Deviation	Skewness	Min	Max	Coefficient (1%)
Real Estate Return Loss	-0.004	0.046	0.125	-0.210	0.232	0.0291
United States Three-month Yield	2.191	2.170	0.444	0.004	6.404	0.0007

II. Regression Results for Excluded State Variables

	Mean	Standard Deviation	Skewness	Min	Max	Coefficient (10%)
GDP Growth Rate	9.600	2.112	0.556	6.400	14.400	0.002
National Bond Yields	2.353	0.729	0.078	0.862	4.149	-0.00014
Stock Market Index	2412.790	1101.223	0.459	888.80	5219.500	0.00012
Shibor	3.708	1.249	-0.214	1.204	6.461	-
Risk-free Return	3.627	9.864	4.922	0.350	60.000	-0.007

III. Eviews Program to Compute *VaR*, *CoVaR* and *ΔCoVaR*

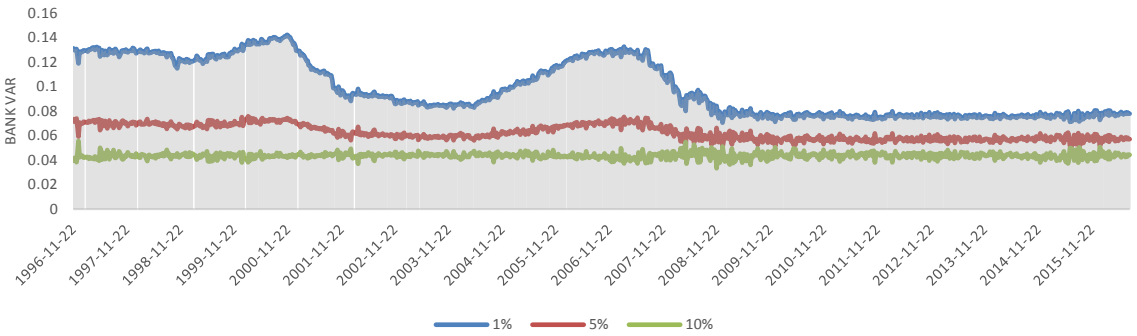
```
wfselect MYWORKFILE

'matrix(1,5) testM
'for !i=1 to 5
'  testM(1, !i) = !i *2
'next

'matrix(4,3) results_bank
'matrix(4,3) results_nonbank
'matrix(4,3) results_secu
'matrix(4,3) results_ins
'matrix(4,3) results_mult

vector(4) qset
qset(1) = 0.99
qset(2) = 0.95
qset(3) = 0.9
qset(4) = 0.5

group xs
for %i BANK NONBANK SECURITIES INSURANCE MULTIF
```

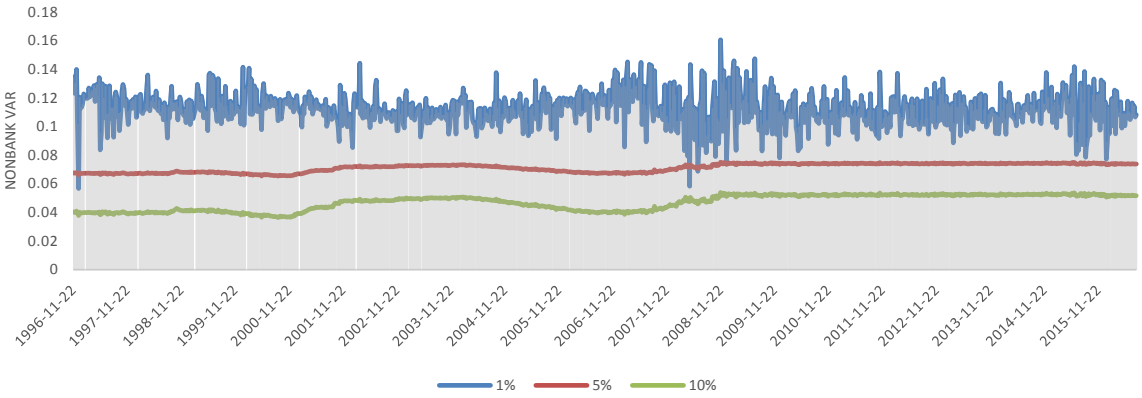
```
  xs.add {%i}
next

equation eq

group cs

'VaR X
for !i = 1 to 5
  %iname = xs.@seriesname(!i)
  matrix(4,3) results_{%iname}
  for !q = 1 to 4
    eq.qreg(quant = qset(!q)) {%iname} c ust_1 ret_1
    for !j = 1 to 3
      results_{%iname}(!q, !j) = eq.@coefs(!j)
    next
  next
next
'VaR Y
equation eqY
for !i = 1 to 5
  %iname = xs.@seriesname(!i)
  matrix(4,4) Y_{%iname}

  for !q = 1 to 4
    eqY.qreg(quant = qset(!q)) yt c ust_1 ret_1 {%iname}
    for !j = 1 to 4
      Y_{%iname}(!q, !j) = eqY.@coefs(!j)
    next
  next
next


for %iname BANK NONBANK SECURITIES INSURANCE MULTIF
  matrix(4,993) covar_{%iname}
  matrix(4, 993) var_{%iname}
  matrix(4, 993) vary_{%iname}
  for !t = 1 to 993
    for !q = 1 to 4
    '%iname = covs.@seriesname(!i)
    covar_{%iname}(!q, !t) = Y_{%iname}(!q, 1)+ Y_{%iname}(!q, 2)*ust_1(!t) + Y_{%iname}(!q, 3)*ret_1(!t) +
Y_{%iname}(!q, 4)*(results_{%iname}(!q, 1) + results_{%iname}(!q, 2)*ust_1(!t)    + results_{%iname}(!q,
3)*ret_1(!t) )
var_{%iname}(!q, !t) = results_{%iname}(!q, 1) + results_{%iname}(!q, 2)*ust_1(!t)    + results_{%iname}(!q,
```

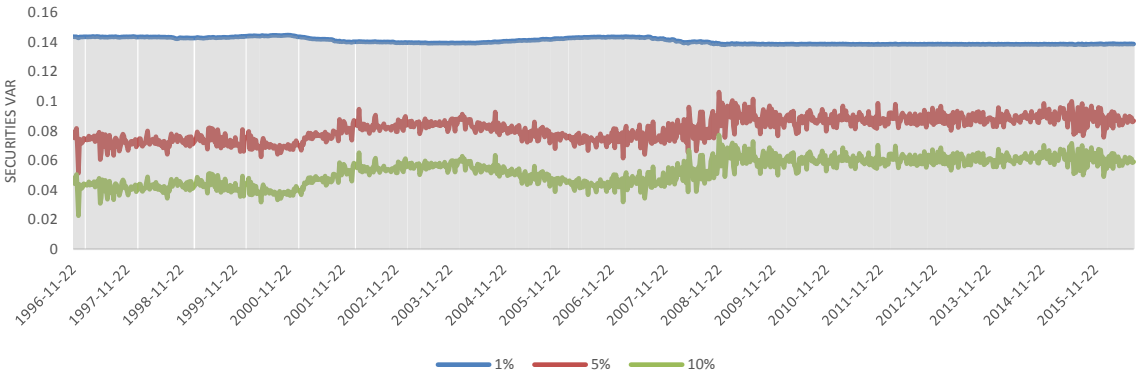
```
3)*ret_1(!t)
    'Compute VAR_Y given observations of Xt
    vary_{%iname}(!q, !t) = Y_{%iname}(!q, 1)+ Y_{%iname}(!q, 2)*ust_1(!t) + Y_{%iname}(!q, 3)*ret_1(!t) +
Y_{%iname}(!q, 4)*{%iname}(!t)

    next
  next
next

for %iname BANK NONBANK SECURITIES INSURANCE MULTIF
  matrix(4,993) DeltaCovar_{%iname}
  for !t = 1 to 993
    for !q = 1 to 4
    'Dcovar_{%iname}(!q, !t) = covar_{%iname}(!q, !t) - covar_{%iname}(4, !t)
    DeltaCovar_{%iname}(!q, !t)    = Y_{%iname}(!q, 4) *(var_{%iname}(!q, !t) - var_{%iname}(4, !t))
    next
  next
next


'exposureVAR x_i =    c    + Mt    + yt

'Yuncond
equation eqY_unCond

matrix(4,3) YunCond

for !q = 1 to 4
  eqY_unCond.qreg(quant = qset(!q)) yt c ust_1 ret_1
  for !j = 1 to 3
    YunCond(!q, !j) = eqY_unCond.@coefs(!j)
  next
next

equation ExpX

for %iname BANK NONBANK SECURITIES INSURANCE MULTIF
  matrix(4,4) ExpVar_{%iname} 'coefficients of xi = c + M + y
  for !q = 1 to 4
    ExpX.qreg(quant = qset(!q)) {%iname} c ust_1 ret_1 yt
    for !j = 1 to 4
      ExpVar_{%iname}(!q, !j) = ExpX.@coefs(!j)
    next
  next
```

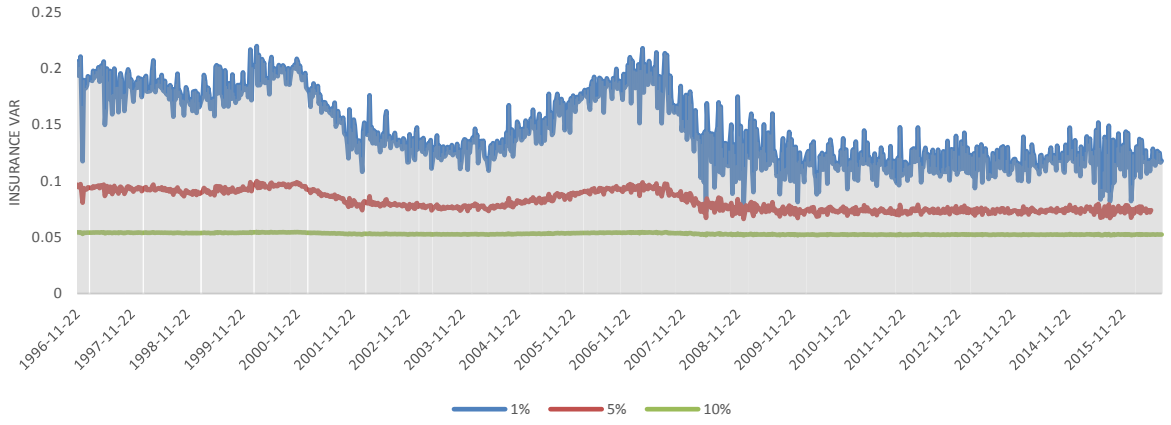
```
next

for %iname BANK NONBANK SECURITIES INSURANCE MULTIF
  matrix(4,993) ExpCoVar_{%iname} 'values of exposure covar_q
  matrix(4,993) ExpCoVarYmed_{%iname} 'values of exposure covar|Y=medium
  matrix(4,993) ExpDeltaCoVar_{%iname} 'values of exposure covar|Y=medium
  for !q = 1 to 4
    for !t = 1 to 993
    ExpCoVar_{%iname}(!q, !t) = ExpVar_{%iname}(!q, 1) + ExpVar_{%iname}(!q, 2)* ust_1(!t) +
ExpVar_{%iname}(!q, 3)*ret_1(!t) + ExpVar_{%iname}(!q, 4)*( YunCond(!q, 1) + YunCond(!q, 2)*ust_1(!t) +
YunCond(!q, 3)*ret_1(!t)     )
    ExpCoVarYmed_{%iname}(!q, !t) =     ExpVar_{%iname}(!q, 1) + ExpVar_{%iname}(!q, 2)* ust_1(!t) +
ExpVar_{%iname}(!q, 3)*ret_1(!t) + ExpVar_{%iname}(!q, 4)*( YunCond(4, 1) + YunCond(4, 2)*ust_1(!t) +
YunCond(4, 3)*ret_1(!t)     )
    ExpDeltaCoVar_{%iname}(!q, !t) = ExpCoVar_{%iname}(!q, !t) - ExpCoVarYmed_{%iname}(!q, !t)
    next
  next
next
```

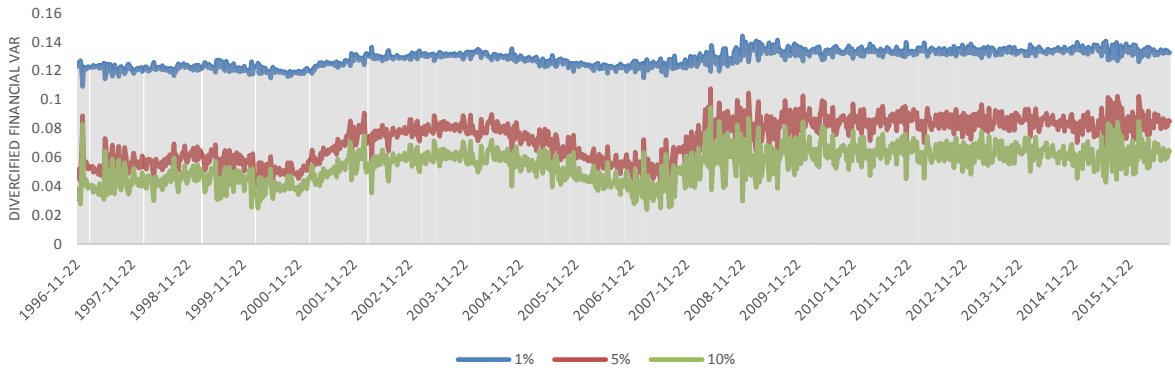
IV. The Plots of VaR_q^i








INSURANCE VAR
0.25
0.2
0.15
0.1
0.05
0
1996-11-22
1997-11-22
1998-11-22
1999-11-22
2000-11-22
2001-11-22
2002-11-22
2003-11-22
2004-11-22
2005-11-22
2006-11-22
2007-11-22
2008-11-22
2009-11-22
2010-11-22
2011-11-22
2012-11-22
2013-11-22
2014-11-22
2015-11-22
1%
5%
10%


DIVERCIFIED FINANCIAL VAR
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1996-11-22
1997-11-22
1998-11-22
1999-11-22
2000-11-22
2001-11-22
2002-11-22
2003-11-22
2004-11-22
2005-11-22
2006-11-22
2007-11-22
2008-11-22
2009-11-22
2010-11-22
2011-11-22
2012-11-22
2013-11-22
2014-11-22
2015-11-22
1%
5%
10%

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