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Systemic Risk Contributions of Financial Institutions during the Stock Market Crash in China

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Abstract: This paper investigates the systemic risk contributions of each financial institution during the stock market crash in China using systemic risk beta. Based on the FARM-Selection (Factor Adjusted Regularized Model Selection) approach, we calculate the systemic risk beta, implying the importance of each financial institution during the stock market crash. We find that security firms are the main contributors to systemic risk. In addition, some macro variables have a significant influence on systemic risk, including changes in March Treasury rates and the AAA-rated bond and 10-year Treasury credit spreads. This paper provides an important perspective to identify the SIFIs (Systemically Important Financial Institutions) during the stock market crash.

Keywords: systemic risk; the stock market crash; systemic risk beta

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1. Introduction

As evidenced by the varying degrees of financial crises experienced around the world over the past two decades, as more and more economic and trade activities continue to increase, financial institutions in a financial system become more and more interconnected. Thus, when one individual institution in the system suddenly crashes or goes bankrupt, risk transmits to other institutions through the interinstitutional linkages, which maybe lead to a financial crisis. Since 2016, the government of China has repeatedly pointed out at various conferences the need to strengthen the political approach to systemic risk regulation. Preventing systemic financial risks has become a central theme in the development and regulation of China's financial markets. The most important aspect of the study of systemic financial risk is to clarify the transmission paths and modes of financial risk in the system, based on whether it is more important for the government to provide timely and accurate relief in the event of a systemic crisis than to measure and prevent systemic risk. Almost all definitions of systemic financial risk have addressed the contagion mechanisms that affect the financial system as a whole. For example, in the 1993–1994 Annual Report, the Bank for International Settlements defines systemic risk: systemic risk is the risk that the failure of a market participant to meet its contractual obligations may lead to the default of other participants, leading to wider financial distress as the chain reacts (BIS, 1994). Therefore, the exploration of systemic financial risk based on the study of risk contagion is in line with the perception of systemic financial risk formation and can provide an important reference for the measurement and prevention of systemic financial risk. From 15 June to 9 July 2015, the Chinese capital market witnessed the bloodiest round of stock market crashes in its history. The Shanghai Stock Exchange Index fell from 5174 to 3373, or 34.8%; the Shenzhen Stock Exchange Index fell from 18,182 to 10,850, or 40.3%; the CSI 500, the core index representing growth stocks, fell from 11,589 to 6444, or 44.4%; by the close of business on 8 July, 2139 and 1390 companies had fallen by more than 30% and 50%, respectively, accounting for 77% and 50% of the total. The number of companies that had fallen by more than 30% and 50% as of the close of 8 July was 2139 and 1390, respectively, accounting for 77% and 50%, with another 1400 companies choosing to suspend trading to avoid. The stock market crash in 2015 triggered a violent turmoil in China's overall financial market, an event that caused deep concern from the government as well as worries about the arrival of systemic risk events, and even more so, fears of a domestic financial crisis. Although the stock market is a barometer of the real economy, it can, in turn, have an impact on the real economy, as proven by the century-long history of capital market development. A stock market that becomes out of control and wipes out investors' money will have a fatal dampening effect on consumption. At the same time, the stock market would lose its financing and other functions, triggering and exacerbating financial or economic crises. Therefore, this paper aims to estimate the contribution of each financial institution to systemic financial risk during the stock market crash, further identifying the importance of which financial institutions need to be closely monitored.

Existing research has studied systemic risk contagion using the network model. Allen and Gale (2000) firstly study the financial risk contagion using a sample network model including complete and periodic topologies, and find that complete structures are more resistant to liquidity shocks than periodic diagrams [1]. Eisenberg and Noe (2001) focus on the debt network model to study systemic risk [2]. Even when financial institutions are not transacting directly, commonality in their exposures leads to a correlation in their values. This can be tracked via a network in which a (weighted) link between two institutions captures the correlation between their portfolios (Acharya and Yorulmazer (2007), Allen et al. (2012), Diebold and Yılmaz (2014), Cabrales et al. (2017)) [3–6]. Betz et al. (2016) propose a framework for estimating time-varying systemic risk contagion that applies to high-dimensional and interconnected financial systems, which finds that network dependencies in extreme risks are more important than correlations to regulate the financial system [7]. The framework provides regulators with a tool that captures the impact of markets on tail dependence and the contribution of systemic risk. Countervailing forces in financial networks lead contagion to be nonmonotonic in network density. This is a point studied in detail by Elliott et al. (2014), and it applies to a variety of models, including those by Cifuentes et al. (2005), Gai and Kapadia (2010), Wagner (2010), Elliott et al. (2014), Gofman (2017), and Jackson and Pernoud (2019) [8–13].

A stock market collapse is defined as a drop of at least 20% in the main index (Mishkin and White, 2002) [14]. On 28–29 October 1929, the DJIA fell by 24.5 percent, while on 19 October 1987, it fell by 22.6 percent. For instance, the sequence of panic selling on 9, 12, 16, and 23 March of 2020 resulted in a cumulative 26 percent decrease in the DJIA. Surprisingly, the financial crisis of 2007–2009 did not result in a comparable magnitude drop, and the stock market loss was instead prolonged in time (Anand, Puckett, Irvine, and Venkataraman, 2013) [15]. Furthermore, the Sep. 2015 stock market fall in China does not correspond to the deflation of an asset price bubble. On the contrary, for the first time in economic history, a collapse occurs when fundamentals are strong, and the drop in market capitalizations is due to a population lockdown and the shutdown of most manufacturing and service businesses, for example the bankruptcy of Zhuangji Group in Wenzhou. Han et al. (2019) used efficiency and multifractality analysis to study the Chinese stock market before and after the 2015 stock market crash [16]. Zhu et al. (2018) applied MF-DFA (Multifractal detrended fluctuation analysis) to analyze the multifractal structure of the Chinese stock market in the CSI 800 index, which consists of the CSI 500 index and CSI 300 index, finding that the fluctuation of the closing logarithmic returns has multifractal properties and that the shape and width of multifractal spectrum are dependent on the weighing order [17]. Feng et al. (2021) investigated the relationships between environmental, social, and corporate governance (ESG) ratings and stock price crash risk, finding a statistically and economically significant negative relationship for Chinese firms [18]. Pan et al. (2021) adopting the perspective of institutional investors, explored the reasons for the difference in crash sensitivity in China's stock market [19].

This paper provides a framework to investigate the Chinese stock market crash in 2014–2015, especially for the contribution of each institution to systemic risk. Previous studies on stock market crashes mainly focus on the stock return volatility, financial markets, and risk spillover. From previous studies of systemic risk, studies of systemic risk based on dynamic network models are relatively few. Therefore, we focus on the framework of dynamic systemic risk contagion proposed by Betz et al. (2016), where we find that the estimation of high-dimensional regression models is carried out simply by using the LASSO (Least absolute shrinkage and selection operator) model, which does not provide a good analytical study of our financial data [7]. Therefore, our model adds the FARM-Selection (Factor-Adjusted Regularized Model Selection) model proposed by Fan et al. (2020) to the network model proposed by Betz et al. (2016) to better address the problem when the data show both cross-sectional and serial-correlation-model selection consistency for high-dimensional sparse regression problems when the data show both cross-sectional and serial correlations [7,20]. This model can reduce the presence of covariate dependence through factor models and compensate for the shortcomings of the previous model that uses LASSO models to estimate parameters one-sidedly. In addition, the dynamic network model takes into account not only changes in relevant domestic macro indicators when considering macro factors, but also some internationally relevant variables, including the RMB/USD exchange rate, the fluctuation of WTI crude oil price, etc. The inclusion of these variables takes into account more of the connectivity between domestic financial markets and the international arena, making the model more effective.

The novelty of this paper is summarized as follows. First, although many researchers pay attention to the influences of the stock crash, there are few studies to calculate systemic risk during the stock crash and contributions of financial institutions to systemic risk. Thus, we focus on the contribution of each financial institution to systemic risk during the stock crash, which is critical to prevent financial crises for regulators. Moreover, for the first time, we use the FARM-Selection model in constructing a dynamic time-varying financial tail risk contagion network, which has much greater variable-selection power than the LASSO model and a more convincing selection of variables. In addition, we considered not only macro variables but also the impact of the financial institutions' operating conditions to maximize the integration of currently available information to obtain more accurate results.

The main findings of this paper are as follows. Firstly, it appears that securities-type firms tend to make a higher contribution to overall systemic risk. Then, we analyzed two important time points in the stock market crash period and found that macro variables had a more uniform impact on the overall systemic network formation in September 2015. In terms of overall systemic risk, the macro variables of the change in March Treasury rates and the credit spread between AAA-rated bonds and 10-year Treasuries had a greater impact on overall financial systemic risk.

The remainder of this paper is organized as follows. Section 2 describes the network model, variables, and FARM-Selection approach. The empirical analysis is mentioned in Section 3. Section 4 concludes the paper.

2. Model Description

2.1. Systemic Risk Beta

Given a set of financial-institution-specific tail-risk driving factor W_t^i, this paper uses the conditional value at risk to measure the tail risk. We denote X_t^i as the stock return of each financial institution at time t, specifically

$$\Pr\left(-X_t^i \geq VaR_{q,t}^i \middle| W_t^i\right) = \Pr\left(X_t^i \leq Q_{q,t}^i \middle| W_t^i\right) = q \tag{1}$$

where $VaR_{q,t}^i = VaR_{q,t}^i(W_t^i) = -Q_{q,t}^i$, representing the conditional q-quantile of return X_t^i. The corresponding tail-risk driving factor W_t^i of the i-th financial institution includes the lagged macroeconomic variables M_{t-1}, the lagged financial institution's i-specific balance sheet characteristics C_{t-1}^i, and loss exceedances by $\boldsymbol{E}_t^{-i} = \left(E_t^j\right)_{j \neq i}$, which is mainly applied to capture the interaction between financial institutions in the system through the simultaneous occurrence of excess losses. Specifically, the excess loss of financial institution j can be defined as $E_t^j = X_t^j 1\left(X_t^j \leq \hat{Q_{0.1}^j}\right)$, where $\hat{Q_{0.1}}$ is the unconditional 10% sample quantile of X^j. Based on the above assumptions, we regard VaR_t^i of financial institution i as a linear function at time point $t = 1, \ldots, T$ as follows:

$$VaR_t^i = W^{i'}{}_t \xi^i{}_t. \tag{2}$$

Then, we estimate the above linear high-dimensional regression model for time variation by rolling windows.

For the tail risk of financial institution in Equation (1), the systemic tail risk VaR_{pt}^s is determined by the systemic rate of return X_t^s and the value at risk VaR_{qt}^i of each financial institution, as well as other factors. We quantify the contribution of each financial institution to systemic risk as the effect of marginal changes in the tail risk of financial institution i on the tail risk of the system. Thus, we define systemic risk beta as the marginal effect of financial institution i on systemic tail risk, as

$$\frac{\partial VaR_{pt}^s\left(V_t^i, VaR_{qt}^i\right)}{\partial VaR_{qt}^i} = \beta_{pq}^{s|i} \tag{3}$$

where V_t^i presents the control variables, meaning the character of each financial institution, also regarded as inverse asset-pricing relationship in the quantile. In this case, the q-th quantile of return for institution i drives the p-th quantile of the system, taking into account network-specific effects, the financial institution's own characteristic variables, and macroeconomic-condition variables. Based on the statistical significance of the upper $\beta_{pq}^{s|i}$ at a given level and the magnitude of the overall effect, we classify the systemic correlation of financial institutions as follows:

$$\overline{\beta}_{pq}^{s|i} \beta_{pq}^{s|i} VaR_t^i \tag{4}$$

which is for realized systemic risk contributions. The realized systemic risk contribution measure captures the impact of increased tail risk of financial institution i on $\beta_{pq}^{s|i}$ compared to the marginal systemic risk beta, and compares the impact across financial institutions.

Based on unbiased estimates of the marginal effects of tail risk for financial institutions, we apply a model VaR^s specific to each financial institution in Equation (3) that correctly assesses the desired marginal effect $\beta_{pq}^{s|i}$. In particular, in each local VaR model, it is necessary to control for VaR^s in the network for each institution with i-specific risk drivers that are relevant in the network. Conversely, variables that are not relevant for VaR^i do not affect the systemic risk contribution of financial institution i and can therefore be omitted in the corresponding simplified model. In this way, we circumvent the theoretical problems of alternative integrated structural general equilibrium models as well as econometric feasibility and precision issues. Even if correctly assumed, such a full model suffers from the high dimensionality and relevance of financial data in the presence of limited data availability.

Similarly, based on a linear model of the systemic VaR, the estimated institution i-specific systematic risk $\beta_{pq}^{s|i}$ index can be represented by the following model:

$$VaR_{pt}^s = V_t^{i'} \gamma_p^s + \beta_{pq}^{s|i} VaR_{qt}^i \tag{5}$$

where the vector $V_t^i = \left(1, M_{t-1}, VaR_{qt}^{-i}\right)$ includes a constant effect, a lagged macroeconomic state variable and the tail risk of all financial institutions in the risk driver determined for financial institution i as calculated by model (2).

The systemic risk $\beta_{pq}^{s|i}$ in Equation (5) is a time-varying index that accounts for the fact that not only do the exposures of individual financial institutions change during market turbulence, but also the marginal effects as well as the importance of each institution in the system may change. In particular, we can estimate the time-varying $\beta^{s|i}$ by means of a linear model, where the observation Z^i represents the prosperity or distress of a financial institution i. As a lagged feature of the model, the conditional systemic risk β and the corresponding systemic risk rating are predictable, which has important implications for the forward-looking regulation of the financial system. Furthermore, given that these data are quarterly, the linearity of $\beta^{s|i}_{pqt}$ in the distress factor Z^i_{t-1} specific to each financial institution i yields stable main effects. In general, the characteristics of the available data themselves limit improvements from other models or parameter estimation methods, which in any case would significantly increase the statistical complexity and computational burden in a two-step model. Therefore, we can assume that

$$\beta^{s|i}_{pqt} = \beta^{s|i}_{0pq} + Z^i_{t-1}{}' \eta^{s|i}_{pq} \tag{6}$$

where $\eta^{s|i}_{pq}$ is the parameter driving the time-varying tail risk.

The financial-institution-specific time-varying systematic risk β index $\beta^{s|i}_{pqt}$ can be estimated from the time-varying nature of VaR^s_p according to the second step of the quantile regression model in Equation (5), i.e., Equation (5). Specifically, the model can be expressed as

$$X^s_t = -\beta^{s|i}_{0pq} V\hat{a}R^i_{qt} - \left(V\hat{a}R^i_{qt} \cdot Z^i_{t-1} \right)' \eta^{s|i}_{pq} - \hat{V}^{i\prime}{}_t \gamma^s_p + \varepsilon^s_t, \tag{7}$$

where $Q_p \left(\varepsilon^s_t \middle| V\hat{a}R^i_{qt}, \hat{V}^i{}_t, Z^i_{t-1} \right) = 0$. Thus, in the first step of the regression in the previous section, all components of the systematic risk index $\beta^{s|i}_{pqt}$ for each financial institution can be obtained from the following minimization quantile regression:

$$\frac{1}{T} \sum_{t=1}^{T} \rho_p \left(X^s_t + V^i_t \xi^s \right) \tag{8}$$

where the parameter ξ^s is unknown and $\boldsymbol{B_t} \equiv \left(VaR^i_t, VaR^i_t \cdot Z^i_{t-1}, V^i_t \right)$ is a vector synthesized from all regressors of VaR^i_p. For a given Z^i_{t-1}, the final estimate of the full time-varying marginal effect $\hat{\beta}^{s|i}_{pq}$ can be derived as

$$\hat{\beta}^{s|i}_{pqt} = \hat{\beta}^{s|i}_{0pq} + Z^i_{t-1}{}' \hat{\eta_{pq}}^{s|i} \tag{9}$$

Clearly, the constant systematic risk β can be obtained in the special case where $\eta^{s|i}_{pq} = 0$ and the estimated Equation (8) $\hat{\beta}^{s|i}_{pqt} = \hat{\beta}^{s|i}_{0pq} = \hat{\beta}^{s|i}_{pq}$. The realised systematic risk β can be estimated from $\hat{\hat{\beta}}^{s|i}_{pqt} \hat{\beta}^{s|i}_{pqt} V\hat{a}R^i_t$.

2.2. FARM-Selection Approach

FARM-Selection is applicable to a wide range of high-dimensional sparse regression issues, including but not limited to linear models, extended linear models, Gaussian graphical models, robust linear models, and group LASSO. The suggested method for sparse linear regression is analogous to projecting response variables and covariance onto a linear space orthogonal to the linear space spanned by the estimate factor. Even if the covariance is strongly correlated, existing approaches such as LASSO, SCAD, and elastic nets can estimate the findings, but we do not know what the correct model for the problem is. The correct model can still be selected using FARM-Selection.

To solve the above high-dimensional regression, we apply the FARM-Selection method to obtain the true model and give consistent estimators. The detailed method is as follows:

$$\widetilde{\xi}_t^i = argmin_{\xi^i} \frac{1}{T} \sum_{t=1}^{T} \rho_q \left(X_t^i + W_t^{i'} \xi^i \right) + \lambda R_n \left(\xi^i \right), \tag{10}$$

where $R_n : R^p \to R_+$ is a norm used to penalize the nonsparse vector ξ^i and $\lambda > 0$. The key idea is to choose the optimal norm to select the relevant variables in the regression.

Next, we introduce the detailed implementation steps.

Step 1. Initial estimation. Given a design matrix $X \in R^{n\times p}$, we apply Principal Component Analysis (PCA) to estimate the approximate factor model.

Step 2. Augmented M-estimation. Defining $\hat{W} = \left(1_n, \hat{U}, \hat{F}\right) \in R^{n\times(p+K)}$ and $\theta = \left(\xi^T, \gamma^T\right)^T \in R^{p+K}$, ξ^T can be estimated by the augmented problem

$$\hat{\theta} \in argmin_{\theta \in R^{p+K}} \left\{ L_n\left(\mathrm{y}, \hat{W}\theta\right) + \lambda R_n\left(\theta_{|p|}\right) \right\} \tag{11}$$

After raising the dimensionality of the space to a higher level, the model-selection problem with highly correlated covariates X in problem (10) is successfully converted to a model-selection problem with weakly correlated or uncorrelated parameters. The augmentation problem (11) is a convex optimization problem that can be minimized by many existing convex optimization algorithms, such as coordinate descent and ADMM (Alternating Direction Method of Multipliers). The model mentioned by this paper is implemented by R Studio.

3. Results

In this section, a brief description and statistical analysis of this paper's sample data are provided, as well as the characteristics of the contribution of each financial institution to the overall financial system tail risk. Finally, we analyze the impact of macro variables on the systemic risk contagion.

3.1. Data Description

Based on the duration of the stock market crash, the sample for the empirical study includes 42 financial institutions in the Chinese financial sector. Specifically, the criteria for sample selection were as follows: firstly, we screened out all financial institutions that were listed before 2013; secondly, those financial institutions that could not give quarterly reports on time were removed; finally, as the empirical study required daily price data of stocks, it continued to remove those that failed, or delisted financial institutions. After the screening process, the empirical sample size was 42 financial institutions. It is noteworthy that the entire financial system temporarily consisted of these 42 financial institutions during the stock market crash. The stock return of samples is summarized in Table 1.

Samples contain 42 financial institutions, including 16 commercial banks, 18 securities companies, 4 insurance companies, and several investment companies and trusts, among others. The overall financial system calculated in the second stage is represented by the CSI 300 index so that daily observations can be obtained. For each financial institution, daily stock-price returns and balance-sheet data from 4 January 2013 to 22 October 2019 are considered. The total of observations in the sample is 1702. As a control variable Z_t^i for the i-th financial institution, a series of variables was chosen that can represent the characteristics of the financial institution in dilemma, including the leverage ratio (to capture the vulnerability of the financial institution); loan loss provisions and return on assets (to present the asset quality); cost-to-income ratio and market capitalization to book-price ratio (to determine the quality of the financial institution's management); stock-price return (to represent the firm's ability to generate income); total short-term borrowing to total liabilities and deposit-to-loan ratio (to capture liquidity risk). The macro variables are all available as daily data, and the balance-sheet data of financial institutions is quarterly, which is processed as daily data using Newton interpolation. As suggested by Adrain and Brunnermeier (2011), there should have been an iVIX, also known as the panic index, to measure market sentiment in China [21]. However, after 14 February 2018, the index was discontinued. Therefore, we removed this variable. In addition, we added the rate of change in the RMB/USD exchange rate to measure the international trade balance. As a large industrialized country, the impact of changes in the price of WTI crude oil on important domestic industries, such as the transport sector, the new energy sector and the petrochemical industry, cannot be underestimated. The macro variables mentioned of the model introduction also apply to the control variables Z_t^s in the regressions. In addition, $\boldsymbol{B}_t^i$ includes variables reflecting balance-sheet characteristics and macroprudential explanatory variables, where leverage and size are shown above. All data are sourced from the Wind database.

Table 1. Samples.

Financial Institutions	Mean	Std. Dev
Ping An Bank	0.0016	2.723
Shenwan Hongyuan Group	−0.069	3.9212
Shanxi International Trust	−0.0684	3.9223
Northeast Securities	−0.0157	3.1465
Guoyuan Securities	−0.0569	3.0041
Sealand Securities	−0.0063	2.5192
Gf Securities	−0.0182	3.2833
Changjiang Securities	0.0563	2.3737
Bank Of Ningbo	0.0052	2.9039
SHANXI SECURITIES	−0.0287	3.5717
Western Securities	0.0154	1.9005
Shanghai Pudong Development Bank	−0.0181	2.1661
Hua Xia Bank	−0.0157	1.944
China Minsheng Banking	0.0309	2.5579
Citic Securities	0.0595	1.9028
China Merchants Bank	−0.0433	3.3588
Sinolink Securities	−0.0406	3.1708
Southwest Securities	0.0089	2.7884
Shanghai AJ Group	−0.0631	3.6801
Avic Capital	−0.0667	4.344
Anxin Trust	0.0199	2.5522
Haitong Securities	0.0288	2.6321
CHINA MERCHANTS SECURITIES	−0.0011	2.6981
Bank Of Nanjing	−0.0283	3.0926
THE PACIFIC SECURITIES	0.0073	2.2318
Industrial Bank	−0.0312	2.0349
Bank Of Beijing	0.0135	1.5213
Agricultural Bank Of China	0.0394	2.8086
Ping An Insurance (Group) Company of China	0.007	1.7741
Bank Of Communications	0.0342	2.6105
New China Life Insurance Company	−0.0411	3.1497
CHINA INDUSTRIAL SECURITIES	0.0194	1.4991
Industrial And Commercial Bank Of China Limited	0.0084	2.8905
Soochow Securities	0.0269	2.2301
China Pacific Insurance (group)	0.0213	2.264
China Life Insurance Company Limited	0.0362	2.7713
Everbright Securities Company Limited	−0.0127	2.7783
China Everbright Bank Company Limited	0.0226	1.8712
FOUNDER SECURITIES	0.0271	2.7427
China Construction Bank	0.0272	1.7677
Bank of China	0.0134	1.6167
CHINA CITIC BANK	0.0227	2.1724

3.2. Systematic Risk Beta Estimation

We calculated the systemic risk beta and captured the systemically important institutions in the financial system. We found that the assessment of overall systemic risk should take into account combined effects. Therefore, the financial indices from the Wind database are used as the basis for measuring systemic risk and calculating *VaR*, by considering all financial institutions. In order to obtain a general impression of the financial institutions as a whole, the systemic risk beta was calculated for each financial institution at different times and summarized in Table 2. The systemic risk beta of financial institution *i* measures the marginal effect in the tail risk on the tail risk of the financial system given the underlying network structure. The average realized systemic risk beta referred to in Table 2 is the product of the entire systemic risk beta and the value at risk, which reflects the total realized effect of an increase in a financial institution *i* risk level on the risk of the entire system.

Table 2. The average systemic risk beta of each financial institution.

Financial Institutions	The Average Systemic Risk Beta	*VaR*	Systemic Risk Beta	Rank
Ping An Bank	−0.013	−3.208	0.041	9
Shenwan Hongyuan Group	−0.007	−5.126	0.038	12
Shanxi International Trust	0	−5.126	0	16
Northeast Securities	0.047	−4.826	−0.227	35
Guoyuan Securities	0.007	−4.716	−0.033	21
Sealand Securities	0.039	−3.954	−0.156	31
Gf Securities	0.001	−4.358	−0.002	17
Changjiang Securities	0.138	−3.405	−0.47	40
Bank of Ningbo	−0.013	−4.705	0.062	8
SHANXI SECURITIES	−0.01	−5.001	0.049	10
Western Securities	−0.006	−2.648	0.016	13
Shanghai Pudong Development Bank	0.037	−2.745	−0.1	29
Hua Xia Bank	0.043	−2.535	−0.109	33
China Minsheng Banking	0.011	−3.794	−0.04	23
Citic Securities	0.096	−2.827	−0.271	38
China Merchants Bank	−0.005	−5.032	0.027	14
Sinolink Securities	0.040	−4.332	−0.173	32
Southwest Securities	−0.008	−4.525	0.034	11
Shanghai AJ Group	0.012	−4.419	−0.055	24
Avic Capital	−0.018	−5.095	0.091	7
Anxin Trust	0.044	−3.874	−0.171	34
Haitong Securities	0.171	−4.03	−0.69	41
CHINA MERCHANTS SECURITIES	−0.038	−3.353	0.126	4
Bank of Nanjing	0.013	−4.361	−0.059	25
THE PACIFIC SECURITIES	0.028	−2.645	−0.073	28
Industrial Bank	0.207	−2.582	−0.536	42
Bank of Beijing	−0.08	−2.172	0.174	2
Agricultural Bank of China	−0.101	−2.981	0.302	1
Ping An Insurance (Group) Company of China	0.049	−2.669	−0.131	36
Bank of Communications	0.12	−3.963	−0.476	39
New China Life Insurance Company	0.016	−4.201	−0.066	26
CHINA INDUSTRIAL SECURITIES	0.001	−2.14	−0.002	18
Industrial and Commercial Bank of China Limited	−0.041	−4.674	0.192	3
Soochow Securities	0.022	−3.427	−0.074	27
China Pacific Insurance (group)	−0.022	−3.413	0.077	6

Table 2. *Cont.*

Financial Institutions	The Average Systemic Risk Beta	*VaR*	Systemic Risk Beta	Rank
China Life Insurance Company Limited	−0.037	−4.477	0.166	5
Everbright Securities Company Limited	0.007	−4.355	−0.032	22
China Everbright Bank Company Limited	0.063	−2.723	−0.17	37
FOUNDER SECURITIES	0.007	−4.353	−0.029	19
China Construction Bank	−0.001	−2.605	0.001	15
Bank of China	0.007	−2.27	−0.016	20
CHINA CITIC BANK	0.039	−3.138	−0.121	30

Based on the results in Table 2, we ranked the systemic risk beta from smallest to largest, with the top five being Agricultural Bank of China, Bank of Beijing, Industrial and Commercial Bank of China, China Merchants Securities, and China Life Insurance Company Limited, while the bottom five, i.e., those with a high-risk contribution, are CITIC Securities, Bank of Communications, Changjiang Securities, Haitong Securities, and Industrial Bank. Regulators should focus on these lower-ranked financial institutions, as defaults by these financial institutions could bring about a financial crisis in the financial system as a whole, which is consistent with existing perceptions of these institutions, although some differ from our intuitive perceptions. For example, China Merchants Securities, an actively traded broker, has a low average systemic risk contribution, which may be due to its wide range of activities to diversify its risk or having China Merchants Bank as its backing. Furthermore, this is an average value, and the systemic risk contribution varies from one financial institution to another at each different moment in time. In the following, we will analyze the data specifically for Sep. 2015 as well as Oct. 2015 and identify the drivers of systemic risk. The specific data results are shown in Tables 3 and 4.

Table 3. The systemic risk beta of each financial institution in September 2015.

Financial Institution	Systemic Risk Beta	*VaR*	Realized Systemic Risk Beta	Rank
Ping An Bank	0	−5.402	0	7
Shenwan Hongyuan Group	0	−5.279	0	8
Shanxi International Trust	0	−5.279	0	9
Northeast Securities	0	−5.293	0	10
Guoyuan Securities	0	−5.914	0	11
Sealand Securities	0	−5.056	0	12
Gf Securities	−0.002	−5.16	0.01	6
Changjiang Securities	0	−4.485	0	13
Bank of Ningbo	−0.129	−5.762	0.743	1
SHANXI SECURITIES	0	−4.578	0	14
Western Securities	0	−5.456	0	15
Shanghai Pudong Development Bank	0	−4.416	0	16
Hua Xia Bank	0.083	−5.755	−0.475	36
China Minsheng Banking	0	−4.986	0	17
Citic Securities	0.281	−4.098	−1.15	41
China Merchants Bank	−0.017	−5.671	0.097	5
Sinolink Securities	0.298	−5.502	−1.642	42
Southwest Securities	0	−3.593	0	18
Shanghai AJ Group	0.052	−6.577	−0.339	34
Avic Capital	−0.083	−5.251	0.438	4
Anxin Trust	0.04	−5.783	−0.23	33
Haitong Securities	0	−5.738	0	19
CHINA MERCHANTS SECURITIES	0	−3.905	0	20
Bank of Nanjing	0	−3.948	0	21
THE PACIFIC SECURITIES	0.067	−4.484	−0.299	35
Industrial Bank	0.084	−3.678	−0.31	38
Bank of Beijing	−0.121	−2.907	0.353	3

Table 3. *Cont.*

Financial Institution	Systemic Risk Beta	*VaR*	Realized Systemic Risk Beta	Rank
Agricultural Bank of China	−0.125	−4.061	0.507	2
Hua Xia Bank	0.083	−5.755	−0.475	36
China Minsheng Banking	0	−4.986	0	17
Citic Securities	0.281	−4.098	−1.15	41
China Merchants Bank	−0.017	−5.671	0.097	5
Sinolink Securities	0.298	−5.502	−1.642	42
Southwest Securities	0	−3.593	0	18
Shanghai AJ Group	0.052	−6.577	−0.339	34
Avic Capital	−0.083	−5.251	0.438	4
Anxin Trust	0.04	−5.783	−0.23	33
Haitong Securities	0	−5.738	0	19
CHINA MERCHANTS SECURITIES	0	−3.905	0	20
Bank of Nanjing	0	−3.948	0	21
THE PACIFIC SECURITIES	0.067	−4.484	−0.299	35
Industrial Bank	0.084	−3.678	−0.31	38
Bank of Beijing	−0.121	−2.907	0.353	3
Agricultural Bank of China	−0.125	−4.061	0.507	2
Ping An Insurance (Group) Company of China	0	−2.961	0	22
Bank of Communications	0	−4.558	0	23
New China Life Insurance Company	0.083	−5.865	−0.485	37
CHINA INDUSTRIAL SECURITIES	0	−2.121	0	24
Industrial and Commercial Bank of China Limited	0	−4.776	0	25
Soochow Securities	0.167	−4.362	−0.727	39
China Pacific Insurance (group)	0.219	−3.223	−0.707	40
China Life Insurance Company Limited	0	−4.981	0	26
Everbright Securities Company Limited	0	−5.63	0	27
China Everbright Bank Company Limited	0	−3.508	0	28
FOUNDER SECURITIES	0	−5.512	0	29
China Construction Bank	0	−2.745	0	30
Bank of China	0	−2.281	0	31
CHINA CITIC BANK	0	−4.049	0	32

Table 4. The systemic risk beta of each financial institution in October 2015.

Financial Institution	Systemic Risk Beta	*VaR*	Realized Systemic Risk Beta	Rank
Ping An Bank	0	−5.421	0	12
Shenwan Hongyuan Group	0	−10.51	0	13
Shanxi International Trust	0	−10.51	0	14
Northeast Securities	0.099	−4.785	−0.475	33
Guoyuan Securities	0.032	−6.145	−0.196	29
Sealand Securities	−0.118	−5.162	0.607	2
Gf Securities	−0.054	−5.044	0.274	7
Changjiang Securities	−0.034	−4.594	0.158	8
Bank of Ningbo	−0.1	−5.679	0.565	4
SHANXI SECURITIES	0	−5.539	0	15
Western Securities	−0.082	−5.213	0.428	5
Shanghai Pudong Development Bank	0	−4.484	0	16
Hua Xia Bank	0.123	−5.015	−0.618	39
China Minsheng Banking	0	−4.802	0	17
Citic Securities	0.242	−4.427	−1.072	41
China Merchants Bank	0.018	−5.586	−0.1	26
Sinolink Securities	0.317	−5.365	−1.698	42
Southwest Securities	0.027	−3.736	−0.1	27
Shanghai AJ Group	0.047	−6.184	−0.29	30
Avic Capital	−0.062	−5.194	0.324	6
Anxin Trust	0.101	−5.527	−0.556	34
Haitong Securities	0.078	−5.525	−0.432	31
CHINA MERCHANTS SECURITIES	0	−3.969	0	18
Bank of Nanjing	−0.03	−4.047	0.122	9

Table 4. *Cont.*

Financial Institution	Systemic Risk Beta	*VaR*	Realized Systemic Risk Beta	Rank
THE PACIFIC SECURITIES	0.105	−4.757	−0.499	35
Industrial Bank	0.094	−4.142	−0.388	32
Bank of Beijing	−0.114	−2.881	0.329	3
Agricultural Bank of China	−0.189	−3.709	0.701	1
Ping An Insurance (Group) Company of China	0	−2.9	0	19
Bank Of Communications	0.165	−4.695	−0.774	40
New China Life Insurance Company	0.113	−5.232	−0.592	36
CHINA INDUSTRIAL SECURITIES	0	−2.193	0	20
Industrial and Commercial Bank of China Limited	−0.02	−4.78	0.094	11
Soochow Securities	0.118	−3.939	−0.466	38
China Pacific Insurance (group)	0.117	−3.363	−0.395	37
China Life Insurance Company Limited	0	−4.712	0	21
Everbright Securities Company Limited	0.029	−5.708	−0.163	28
China Everbright Bank Company Limited	0	−3.391	0	22
FOUNDER SECURITIES	−0.029	−5.536	0.161	10
China Construction Bank	0	−2.612	0	23
Bank of China	0	−2.143	0	24
CHINA CITIC BANK	0	−4.102	0	25

Based on the results shown in Table 3, Anxin Trust, Shanghai AJ Group, THE PACIFIC SECURITIES, Hua Xia Bank, New China Life Insurance Company, Industrial Bank, Soochow Securities, China Pacific Insurance (group), CITIC Securities, and Sinolink Securities all contribute significantly to the systemic risk of the financial system. These were mainly dominated by securities firms, with CITIC Securities and Sinolink Securities in particular having a systemic risk beta of 0.28 and 0.29, respectively. China Pacific Insurance (group) is one of the risk drivers in the system, and its systemic risk contribution under the system is high. Therefore, it is necessary to monitor it. CITIC Securities and Shanghai AJ Group, on the other hand, are risk takers in the system and their systemic risk contribution is also more pronounced. Some remaining institutions act as risk transmitters in the financial system and may turn out to be significant contributors to systemic risk when they do not control their operational balance at a certain time, such as Huaxia Bank and CITIC Securities. In addition, in the table there exists some systemic risk beta of financial institutions with zero, because we use high-dimensional linear regression to estimate the problem, which results in some financial institutions not being selected.

Table 4 shows a summary of the systemic risk beta in October 2015. We used a cut-off of systemic risk beta greater than 0.1 to determine the financial institutions that contribute to overall systemic risk, specifically Anxin Trust, China Pacific Insurance (group), New China Life Insurance Company, THE PACIFIC SECURITIES, Soochow Securities, Hua Xia Bank, Bank of Communications, CITIC Securities, and Sinolink Securities. We found that securities and trust companies continue to be the main contributors to systemic risk. As a risk driver in the system, Anxin Trust is a high contributor to systemic risk across the financial system, meaning that if the financial institution is to default on a large scale or be on the verge of insolvency, the entire financial system would be shocked. THE PACIFIC SECURITIES, New China Life Insurance Company, Bank of Communications, and Sinolink Securities, as risk takers in the system at the time, are not good contributors to systemic risk and therefore need to be reasonably supervised. The rest of the financial institutions are risk transmitters in the system and should operate reasonably well to spread the risk, which is of course the normal outcome.

Based on the above analysis of the systemic risk beta, we find that the paths of contagion of the financial tail-risk contagion network change dynamically at different moments, and that different financial institutions assume different roles in these different paths, and that the contribution of these financial institutions to systemic risk varies. In the following, we analyze the impact of macro variables on overall financial systemic risk, as shown in the data structure in Table 5.

Table 5. The coefficients of macro variables.

Macro Variables	September 2015	October 2015	Mean
Short-term liquidity spreads	−0.0221	0	−0.00495
Change in yield on March maturity government bonds	0	0	0.026119
Change in the slope of the March Treasury yield	0	−0.12679	−0.04326
10-year and March Treasury rate spreads	0	−0.05627	−0.07003
Credit spreads on AAA-rated bonds and 10-year Treasuries	0	−0.07766	0.031857
CSI 300	0	0	−0.00273
Real Estate Index	−0.0174	−0.01297	−0.01495
WTI	0.003054	0.003618	0.000764
RMB/USD Exchange Rate	0	0	0.01018

Based on Table 5, we find that changes in March Treasury rates and credit spreads between AAA-rated bonds and 10-year Treasuries have a greater impact on overall financial systemic risk. This is because higher short-term Treasury yields signal a short-term depression in financial markets, so such an impact is normal. An increase in the credit spread between AAA-rated bonds and 10-year Treasuries, on the other hand, would indicate an increase in the probability of corporate defaults across the market, creating greater risk for investors and also providing a boost to systemic risk. In comparison, changes in the price of WTI crude oil have less impact on systemic risk. In contrast, changes in the exchange rate of the RMB against the US dollar, which is an international currency, has an impact on systemic risk, which is related to the fact that China is a large exporting country and the increase in the RMB against the US dollar has an important impact on our trade, which in turn has a positive impact on the overall systemic risk. Furthermore, based on the empirical results for September and October 2015, it is evident that the government regulates the overall financial system by adjusting some macro indicators at different times.

Both short-term liquidity spreads and real-estate index changes in September 2015 had a mitigating effect on the overall systemic risk. Changes in WTI crude oil in our country as an industrial country will inevitably have an impact on systemic risk in our financial markets. In October 2015, changes in the March maturity Treasury yield curve, the 10-year and March maturity Treasury rate spreads, the AAA-rated bond and 10-year Treasury credit spreads, and changes in the real-estate index all have a dampening effect on overall systemic tail risk. Of these, the growth in AAA-rated bonds and 10-year Treasury credit spreads, however, acted to mitigate tail risk, caused by the 10-year Treasury rate falling below 3% for the first time in 2015, and such an outcome stimulated financial activity to some extent in China, whose economic performance was under pressure at the time.

4. Conclusions

We used the FARM-Selection model for the first time to calculate the contribution of each financial institution to the overall systemic risk, as well as the impact of macro variables on the overall systemic risk at different times. In addition, the financial institutions with a high contribution to systemic risk were analyzed by focusing on their operating conditions and the impact of macro conditions, and ultimately finding the reasons for the high contribution to systemic risk. Finally, we proposed concrete and effective policy recommendations and regulatory measures in response to these results, which can also give institutions some advice on risk reduction.

Through our empirical research, we found that, in general, securities firms among financial institutions seem to have a higher risk profile and tend to act as risk drivers, while insurance companies tend to be risk takers in the system. In addition, securities firms are also represented in terms of their contribution to systemic risk. In terms of overall systemic risk, the macro variables of the change in March Treasury rates and the AAA-rated bond and 10-year Treasury credit spreads had a greater impact on overall financial systemic risk. These are only some of the conclusions from our results; more conclusions are available from our model results at different moments, but due to space constraints, only these are highlighted. The recent epidemic situation and the unusual fluctuations in the price of WTI crude oil must have also had a dramatic impact on the overall network, and such results are available from our model.

Based on the results, it is logical for financial-system regulators to pay higher attention to the tail risks of the risk drivers in the system in each period, and for these drivers to be ranked higher in the systemic risk contribution. In addition, the impact of macro variables on systemic risk is mitigated through the development of certain policies. In addition, our model has a predictive role, and if possible, we can also forecast future systemic risk beta, so that early attention can be paid to some financial institutions to prevent a larger crisis from breaking out. For financial institutions to managers, they can choose to work with moderate-risk institutions, and when their own risk is high, they can also simply analyze their indicators to see if there is a problem in their way of doing business, firstly to check themselves, and secondly to adjust their strategies, which reduces the systemic financial risk and maintains the long-term operational development of the whole financial system. For policy makers, this study provides some suggestions on controlling the tail risk of financial institutions, especially for recognizing the source of tail-risk contagion. Since the limitation of model and data, this paper only considers listed financial institutions to construct a financial system. In the future study, we will promote the framework to add unlisted financial institutions.

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