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A Financial Risk Meter for China

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Abstract

This paper develops a new risk meter specifically for China – FRM@China – to detect systemic financial risk as well as tail-event (TE) dependencies among major financial institutions (FIs). Compared with the CBOE FIX VIX, which is currently the most popular financial risk measure, FRM@China has less noise. It also emitted a risk signature much earlier than the CBOE FIX VIX index in the 2020 COVID pandemic. In addition, FRM@China uses a single quantile-lasso regression model to allow both the assessment of risk transfer between different sectors in which FIs operate and the prediction of systemic risk. Because the risk indicator in FRM@China is based on penalization terms, its relationship with macro variables are unknown and non-linear. This paper further expands the existing FRM approach by using Shapley values to identify the dynamic contribution of different macro features in this type of "black box" situation. The results show that short-term interest rates and forward guidance are significant risk drivers. This paper considers the interaction among FIs from mainland China, Hong Kong and Taiwan to provide an enhanced regional tool set for regulators to evaluate financial policy responses. All quantlets are available on quantlet.com.

JEL Classification: C30, C58, G11, G15, G21.

Keywords: FRM (Financial Risk Meter), Lasso Quantile Regression, Financial Network, China, Shapley value.

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1 Introduction

China is a key driver of economic growth in Asia, surpassing Japan to become the world's second-largest economy in 2010. Taking even more steps towards an open economy, Chinese financial markets are becoming more integrated with developed markets and are becoming increasingly influential globally. There is no doubt that financial market fluctuations in advanced economies create spillover effects, especially on emerging market economies. Bagliano and Morana (2012), Syriopoulos et al. (2015), and Georgiadis (2016) employed VAR models for their risk analysis and its transmission channels from the core country, especially from the US. However, there are two major limitations. Firstly, the VAR model can not reflect tail event (TE) transmissions. Secondly, it does not provide information on systemic risk. Some other risk measures also have shortages.

In this paper, we explore the TE dependencies in China by using FRM (Yu et al.; 2019), an established measure of systemic risk that reflects the full picture of TE dependencies in a network of financial risk factors. We find that the risk driver at the end of 2019 was the banking sector, but that this shifted to the security sector at the beginning of 2020. In addition, the systemic risk rose dramatically after the breakout of the pandemic. We also utilize Shapley values to detect the importance of four macro features on systemic risk in the context of unknown non-linear relationship. The two-year Chinese treasury yield rate and 10-2 year treasury yield spread contribute the most. However, the importance of equity market return and implied volatility increased dramatically after the pandemic and peaked in July of 2020.

Regarding financial market risk, there are three major trends in measurement. The first uses information from inter-bank markets and interconnected bank balance sheets to determine the risk transmission, see (Allen and Gale (2004), Freixas et al. (2000), Bluhm and Krahnen (2014)). The second strand monitors high frequency information in the stock price. Wang et al. (2018) investigated volatility connections among Chinese public-traded commercial banks. Fang et al. (2018) analyzed the Chinese stock market crash from 2015 to 2016 by constructing a tail risk network based on daily stock returns. The third focuses on contagion in the market. Systemic risk arises from the financial institutions (FIs)' inter-connectedness. High interconnection levels facilitate the spread of external shocks between FIs, financial markets, and the real economy (Battiston et al. (2012), Cai et al. (2018)). For example, FIs are often connected by holding each other's assets. The deep and broad connection of FIs brings development of financial industries as well as risk contagion. The risk of one FI could transmit to the entire industry. In fact, a Chinese stock market crash from 2015 to 2016 drew the attention of policy makers on how to control risk contagion to maintain the stable development of financial systems (Fang and Bessler; 2018). It is therefore of great importance to construct the associated financial network between FIs in China.

Existing literature has employed several methods to characterize risk contagion across financial markets. Concerning tail event risk, a popular concept is Value-at-Risk(VaR) proposed by J. P. Morgan and then offered to a wider client base under the Risk Metrics trademark (Morgan; 1997). To extend this unilateral approach and measure bilateral contagion, Adrian and Brunnermeier (2016) introduced the Conditional Value-at-Risk (CoVaR) to investigate the spillover between two financial institutions. Acharya et al. (2017) and Brownlees and Engle (2016) also used a quantile regression based model such as a linear bivariate model to analyze tail risk contagion. However, the CoVaR model only captures the extent of risk spillovers for a simple bivariate system and cannot simultaneously measure the risk spillover effects across a network of multiple financial markets and institutions. Härdle et al. (2016) developed the Tail Event NETwork (TENET) risk approach by generalizing the CoVaR to be able to accommodate all nodes in a financial system as risk factors. Financial Risk Meter (FRM) is a novel risk predictor based on TENET, which compresses the high-dimensional TE into a single indicator ((Yu et al.; 2019); (Mihoci et al.; 2020)). The FRM is based on Lasso quantile regression designed to examine TE co-movements of financial securities. It also provides a systemic risk measurement based on penalization terms. The FRM level contains fundamental information about the active set of influential neighboring nodes and about the contributors to systemic risk. This indicator has proven an efficient systemic risk measure in the US, Europe, and emerging markets. Ren et al. (2021) further expanded the FRM by incorporating the idea of expectiles to measure the actual tail loss in a stressful FI network. Another example from existing literature is Ben Amor et al. (2021). They applied FRM in emerging markets and propose a portfolio allocation mode based on TEs.

Even though the FRM has been proven to be a good TE risk indicator in the US, Europe, and BRIMST (Brazil, Russia, India, Mexico, South Africa, Turkey) emerging markets, it is still not evident that it performs well for the Chinese stock market. The Chinese financial market has unique features quite different from those in the US and other developed economies. For example, China has a price-limit rule and short-selling restrictions. Therefore, it is imperative to explore the performance of FRM in China. The existing scholars accept that the macro features are important. However, these variables' dynamic influence on and contribution to systemic risk have not been thoroughly studied. Which macro feature contributes the most during a certain period is a key information set for policymakers and market regulators, especially in the interest of financial market stability. It is more suitable to use regional macroeconomic risk factors to measure regional risk than to use macroeconomic risk factors in the US market. It therefore makes more sense to use Chinese macro features for an analysis on China. The international center-periphery hypothesis suggests that the Chinese mainland market should play a leading role in the transmission of information (Cheung and Mak (1992), Eun and Shim (1989)). Because Taiwan and Hong Kong are geographically near and culturally close to China, both are likely to be influenced by mainland China, and vice versa. In addition, after the announcement of the Shanghai-Hong Kong Stock Connect initiative, there is an increasing spillover effect between the mainland and Hong Kong (Huo and Ahmed; 2017). Therefore, it is crucial to include Taiwan and Hong Kong in analyzing the tail risk contagion of Chinese financial institutions. However, most studies do not consider the FIs' interactions between mainland China, Hong Kong, and Taiwan when analyzing systemic financial risk in China.

Our study aims to answer the above questions. We use the data of the largest 50 Chinese FIs with the greatest influence in financial system, which are traded on the Shanghai Shenzen, Hong Kong, and Taiwan stock exchanges. We utilize FRM to identify the TE transmission network dynamically and estimate the systemic risk over time. We find that the risk driver was the banking sector before 2020 Covid pandemic but it transformed to the security sector after the pandemic broke out. Another change in Chinese financial market after the pandemic was that its systemic risk increased significantly. Because the systemic risk measurement in FRM is based on the penalization terms in quantile-lasso regression, the relationship between systemic risk and risk factors is unknown and non-linear. In this context we also utilize Shapley values to calculate the contribution of different macro features over time. We find that the monetary policies, presented by the 2-year Chinese treasury yield and 10-2year treasury yield spread, make the greatest contribution to systemic risk.

The remainder of this paper is organized as follows. Section 2 presents a brief review of risk measurement and feature importance methods. The empirical results of tail events transmission and the importance of macro features are discussed in Section 3. Section 4 compares the systemic risk based on FRM with other risk measurements. Section 5 concludes our research findings.

2 Methodology and Data Description

The methodology part contains four subsections. In the first subsection, we construct an FRM model based on the macro features and the daily return of Chinese FIs. In the second subsection, we calculate the daily TE dependencies across Chinese FIs and construct an FRM index based on this model. In the third subsection, we further explore the relationship between different FIs based on hierarchical tree clustering approach. In the final subsection, we introduce Shapley value to calculate different macro features' contribution to systemic risk. In the part of data description, we show the statistical information of all the variables that are used in this study.

2.1 Financial Risk Meter

The basic element of the FRM is the CoVaR (Adrian and Brunnermeier; 2016). The FRM is also known for allowing all or a subset of nodes to be at risk, thereby measuring individual contribution to systemic risk in quantile regression. Systemic risk can be understood as a new class of risk requiring specific risk management (Mieg; 2020). The FRM like CoVaR is based on quantile lasso regression and TENET ideas, which creatively combines systemic risk measurements with TE transmission.

Linear quantile lasso regression for log return series $X_{j,t}$ in a window of k days is given by

$$X_{j,t} = \alpha_j + A_{j,t}\beta_j + \varepsilon_{j,t}, \quad j \in \{1, 2, ..., N\} \tag{1}$$

with N FIs and m macroeconomic variables. $A_{j,t} = [X_{-j,t}, M_{t-1}]$ represents a $p = N + m - 1$ dimensional vector of covariates. T denotes the total number of observations and $t \in \{1, ..., T\}$. $X_{-j,t}$ is the log return of all the FIs except the jth FI on day t. M contains the macroeconomic variables, for example, the daily market return of the ETF traded in the US that tracks the FTSE China 50 index, the equity implied volatility of the Chinese market, the short-term Chinese treasury yield rate, and the slope of the yield curve. The β_j collects $p \times 1$ vector.

The estimated coefficients are obtained by minimizing for each rolling window k

$$\min_{\alpha_j, \beta_j} \left\{ \frac{1}{k} \sum_{t=1}^{k} \rho_\tau \left(X_{j,t} - \alpha_j - A_{j,t}\beta_j \right) + \lambda_j \left\| \beta_j \right\|_1 \right\} \tag{2}$$

with L_1-norm penalization, lasso parameter λ_j, and loss function ρ_τ. The quantile loss function here is denoted as:

$$\rho_\tau(u) = |\tau - \mathbf{I}\{u \le 0\}||u| \tag{3}$$

given tail risk level τ. The quantile level τ represents the probability of tail events,

$$\tau = \mathrm{P}\left(X_{j,t} \le q_{\tau,j} \right)$$

with $q_{\tau,j}$ quantile for company j at tail risk level τ at rolling window k.

λ_j is selected by minimizing Generalized Approximate Cross-Validation (GACV) (Yuan; 2006).

$$\lambda_j = \arg\min GACV\left(\lambda_j\right) = \arg\min \frac{\sum_{t=1}^{k} \rho_\tau \left(X_{j,t} - \alpha_j - A_{j,t}\beta_j \right)}{s - df} \tag{4}$$

with df a measure of the effective dimensionality of the fitted model. Coefficients β_j depend on λ_j, so λ_j can be an indicator of tail risk. It also works for high dimensional cases when p is larger than k. FRM daily index is defined as:

$$\mathrm{FRM}_k = \frac{1}{N}\sum_{j=1}^{N} \lambda_j \tag{5}$$

The standard FRM index is the average of the penalty parameters of the quantile lasso regression. The evolution of averaged λ_j in a window of length k represents the variation of the systemic tail risks (Härdle et al. (2016), Mihoci et al. (2020), Ren et al. (2020)), thus the FRM index measures joint tail events. Various markets' FRM indices are reported on http://frm.wiwi.hu-berlin.de.

2.2 Tail-event driven network and centrality

The quantile lasso regression coefficients from equation (2) can be arranged into an adjacency matrix $A = \{\beta_{j,i}\}$ where $\beta_{j,j} = 0$ for every considered day. The adjacency matrix representation, in turn, allows us to identify the interaction between the selected FIs in the spirit of graph theory.

A $N \times N$ adjacency matrix for FIs A at the k th rolling window can be denoted as:

$$A = \begin{pmatrix} \beta_{1,1} & \beta_{1,2} & \cdots & \beta_{1,N} \\ \beta_{2,1} & \beta_{2,2} & \cdots & \beta_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{N,1} & \beta_{N,2} & \cdots & \beta_{N,N} \end{pmatrix} \tag{6}$$

which represents total interdependencies across FIs. Degree centrality is a natural measure of centrality, which is defined as:

$$D = \sum_{j=1}^{N}\sum_{i=1}^{N} \mathbf{1}(\beta_{j,i}) \tag{7}$$

$$\mathbf{1}(\beta_{j,i}) = \begin{cases} 1 & \text{if } \beta_{j,i} \neq 0 \\ 0 & \text{if } \beta_{j,i} = 0 \end{cases}$$

Degree centrality captures total connectedness in a graph. In-degree is the number of FIs influencing one node representing a specific FI. In-degree centrality of FIs j is:

$$Ind_j = \sum_{i=1}^{N} \mathbf{1}(\beta_{j,i}) \tag{8}$$

where FI j is now a risk receiver. Similarly, out-degree is the number of out-going links from one node representing one specific FI, influencing other FIs. Out-degree centrality of an FI i is:

$$Outd_i = \sum_{j=1}^{N} \mathbf{1}(\beta_{j,i}) \tag{9}$$

where FI i is a risk emitter. We take the case of a network with 20 FIs as an example. For CITIC on 2020-01-20, its in-degree is 10 (blue lines) and its out-degree is 5 (orange lines). In the graphs in section 3, we take as an example the case of total degree centrality in a network with 50 FIs.

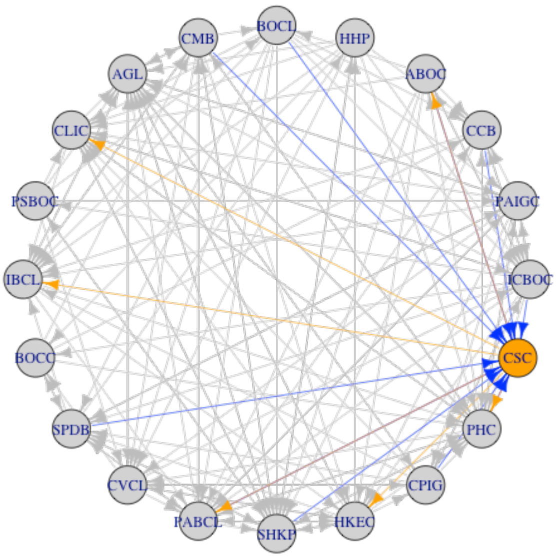


Figure 1: Network Example on 2020-01-20 with China FI CITIC Securities (600030 CH) as the central node, its in-degree and out-degree edges

2.3 Tree Clustering and Dendrogram

In line with the first step in Ben Amor et al. (2021) in applying Hierarchical Risk Parity (HRP) Asset Allocation, we generate a dendrogram based on a hierarchical tree clustering algorithm on adjacency matrix A. We briefly discuss the results in Section 3 and exemplify how to combine an analysis of the clusters with results obtained from direct analysis of the adjacency matrix A_k as outlined in Section 2.2.

The tree clustering in the HRP algorithm groups similar FIs into clusters based on the distance metric. The calculating steps are as follows.

1. An $N \times N$ adjacency matrix A_k represents inter-dependencies of FIs , $\beta = \{\beta_{i,j}\}_{i,j=1,\dots,N}$ where $\beta_{i,j}$ is the coefficient between a pair of FIs $\{i, j\}$ in quantile-lasso regression (see Equation (1) and Equation (6)).

2. Define a distance measure d between different FI pairs according to the adjacency matrix A_k

$$d : (i, j) \subset B \rightarrow R \in [0, 1]$$
$$d_{i,j} = \sqrt{\frac{1}{2}(1 - \beta_{i,j})} \tag{10}$$

where B is the Cartesian product of items in $\{1, ..., i, ...N\}$. This forms a metric space D.

3. Transform d into a new distance matrix $\tilde{d}$ which is the Euclidean distance on D:

$$\tilde{d}_{i,j} = \tilde{d}[d_i, d_j] = \sqrt{\sum_{n=1}^{N}(d_{n,i} - d_{n,j})^2} \tag{11}$$

where $\tilde{d}_{i,j} : (d_i, d_j) \subset B \rightarrow R \in [0, \sqrt{N}]$.
Note that for two FIs i and j, $d_{i,j}$ represents the distance between column vectors of FIs, however, $\tilde{d}_{i,j}$ is defined as the column vectors of D, a distance of distances.
4.Cluster together the pair of columns (i^*, j^*) based in Equation(11), the cluster set is defined as $C[1]$:

$$C[1] = (i^*, j^*) = \underset{i \neq j}{\operatorname{argmin}} \{\tilde{d}_{i,j}\} \tag{12}$$

5. Calculate the updated $\tilde{d}$.
6. Apply steps 4-5 recursively until all $N-1$ clusters are formed.

Finally, we get the visualised clusters in a dendrogram. See (Härdle and Simar; 2019) (p. 363-393) for more details.

2.4 Importance of Macro Features

Existing FRM studies (Yu et al. (2019), Ben Amor et al. (2021), Ren et al. (2021)) just use macro features in the algorithm and treat the mean value of their coefficients β in the adjacency matrix as their contribution to the FRM index. However, the FRM index is the mean value of penalization terms in quantile lasso regressions, thus its relationship with macro features is unknown and non-linear. Since the mean value of β is unable to reflect the macro features' contribution to the FRM index precisely, we need to find a way to interpret the features' contributions to the final regression results in this type of "black box" situation. A Shapley value is ideal for explaining the marginal feature effects in a machine learning context (Lundberg and Lee (2017), Aas et al. (2019)). The Shapley value (Shapley; 1997) determines the contribution of different actors in a coalition or a cooperative game. The basic idea is that a feature's importance is its marginal contribution to the payoff of all possible feature combinations. By combining it in the FRM framework, we evaluate the accurate contribution of different macro features and fundamentally answer the question "what is the most important risk driver in systemic risk".

In formal terms, the feature j's Shapley value is a weighted sum over all possible feature value combinations:

$$\phi_j = \sum_{S \subseteq \{x_1,\ldots,x_p\} \setminus \{x_j\}} \frac{|S|!(p-|S|-1)!}{p!} \left\{ \hat{f}(S \cup x_j) - \hat{f}(S) \right\} \tag{13}$$

where S is a subset of the features in the model excluding x_j and x is the vector of macro variables and p the number of variables. $\hat{f}$ is the FRM. $\hat{f}(S)$ calculates feature values in set S. $\hat{f}(S \cup x_j)$ is the FRM index calculated with feature values in set $S \cup x_j$.

The contributions of two macro variable feature values j and k should be the same if they contribute equally to all possible coalitions. If:

$$\hat{f}[S \cup \{x_j\}] = \hat{f}[S \cup \{x_k\}] \tag{14}$$

for all

$$S \subseteq \{x_1, ..., x_p\} \tag{15}$$

then

$$\phi_j = \phi_k \tag{16}$$

if the macro variable does not change the prediction value, its Shapley value should be 0. if

$$\hat{f}(S \cup \{x_j\}) = \hat{f}(S) \tag{17}$$

for all

$$S \subseteq \{x_1, ..., x_p\} \tag{18}$$

then

$$\phi_j = 0 \tag{19}$$

All possible coalitions (sets) of feature values have to be evaluated with and without the j-th macro variable to calculate the exact Shapley value. In our case, we focus on four macro features x_a, x_b, x_c, x_d, where x_a is FIX US Equity, x_b is VXFIX, x_c is CY2YR, and x_d is CN210SLOPE. The steps to calculate x_a are as follows:

If there is no macro feature in S, the contribution of x_a is

$$\phi_a^1 = \frac{0!(4 - 0t - 1)!}{4!} \left\{ \hat{f}(S^{'} \cup x_a) - \hat{f}(S^{'}) \right\} \tag{20}$$

where $S^{'} = \{50FIs'stockreturn\}$

If there is one macro feature in S, the contribution of x_a is

$$\begin{aligned} \phi_a^2 = \frac{1!(4 - 1 - 1)!}{4!} & \left\{ \hat{f}(S^{'} \cup x_a \cup x_b) - \hat{f}(S^{'} \cup x_b) \right. \\ & + \hat{f}(S^{'} \cup x_a \cup x_c) - \hat{f}(S^{'} \cup x_c) \\ & + \hat{f}(S^{'} \cup x_a \cup x_d) - \hat{f}(S^{'} \cup x_d)\} \end{aligned} \tag{21}$$

If there are two macro features in S, the contribution of x_a is:

$$\begin{aligned} \phi_a^3 = \frac{2!(4 - 2 - 1)!}{4!} & \left\{ \hat{f}(S^{'} \cup x_a \cup x_b \cup x_c) - \hat{f}(S^{'} \cup x_b \cup x_c) \right. \\ & + \hat{f}(S^{'} \cup x_a \cup x_b \cup x_d) - \hat{f}(S^{'} \cup x_b \cup x_d) \\ & + \hat{f}(S^{'} \cup x_a \cup x_c \cup x_d) - \hat{f}(S^{'} \cup x_c \cup x_d)\} \end{aligned} \tag{22}$$

If there are three macro features in S, the contribution of x_a is

$$\phi_a^4 = \frac{3!(4 - 3 - 1)!}{4!} \left\{ \hat{f}(S^{'} \cup x_a \cup x_b \cup x_c \cup x_d) - \hat{f}(S^{'} \cup x_b \cup x_c \cup x_d) \right\} \tag{23}$$

ϕ_a, The Shapley value of x_a, is

$$\phi_a = \phi_a^1 + \phi_a^2 + \phi_a^3 + \phi_a^4 \tag{24}$$

Using the same ideas, we calculate the Shapley value of the other three macro features(ϕ_b, ϕ_c, ϕ_d).

2.5 Data Description

Since the performance of FIs is influenced by the macroeconomic environment, we aim to study the impacts of specific macroeconomic risk variables on the inter-connectedness of FIs. As for the macroeconomic data, we select indices which reflect option market implied volatility, short-term risk-free level, yield curve spreads. Our macro features are:

(i) The daily market return based on the ISHARES TRUST CHINA LARGE-CAP ETF, an exchange-traded fund incorporated in the USA. The ETF tracks the FTSE China 50 Index, investing in large cap stocks (Bloomberg ticker: FIX US Equity) and is associated with great comovement of asset price. We select the log difference of this equity index.

(ii) For the equity implied volatility, we select the log difference of CBOE CHINA ETF VOLATILITY INDEX (Bloomberg ticker: VXFIX Index). This volatility index is based on the price of FIX US Equity. The construction method is the same as for the VIX index which is based on SP500 options.

(iii) For the short term yield we select the daily change of the 2-year Chinese treasury yield rate(CN2YR).

(iv) the slope of the yield curve (CN210SLOPE), measured by the daily change of spread between the 10-year and the 3-month treasury rate are obtained from WIND database.

In this paper we study the 50 largest regional Chinese FIs. Their stocks are traded on the Shanghai, Shenzhen, Hong Kong, and Taiwan stock exchanges. The size criterion is market capitalisation on the last trading day. We take the log difference of the close price as the daily return. The data are from the Bloomberg database. Both the market capitalisation and price are in US dollars. The data also span 2019-01-02 to 2021-02-10 as macro features. A longer time series for FRM China is available on http://frm.wiwi.hu-berlin.de

We report the variables' statistical description in Table 1.

Table 1: Statistical Description

	n	mean	sd	median	min	max
FIX US Equity	497	0.00062	0.028	0.00088	-0.19	0.18
VXFIX Index	497	-0.000230	0.120	-0.0058	-0.63	0.71
CN2YR	497	9.26e-05	0.028	0	-0.27	0.12
CN210SLOPE	497	-3.22e-05	0.022	0	-0.10	0.22
Stock Returns	93436	0.00032	0.021	0	-0.45	1.40
Market Cap (USD bn)	92530	17528	37777	5166	21	309324

3 Empirical Results

3.1 Network Analysis

When the FI i comes under high pressure, its risk will spillover towards an entire financial system and this phenomenon is called "CoStress". To capture the dynamic changes of "CoStress", we also calculate the network in the sample of the largest 50 FIs based on the market capitalisation of 2019-12-10. The sample's sectors contain banks, diversified financials which are mainly securities trading companies, real estate, insurance companies, capital goods, and consumer services based on the Bloomberg industry classification system. To explore the changes in risk receivers, we select the largest risky FI based on its λ from 2019-12-10 to 2020-2-10 each day. The result is shown in Table 2. In late 2019, the banking sector suffered the most. However, it spilled over to the security sector in early 2020. It is also interesting that the mean value of λ jumps from around 3 to over 5 after the breakout of pandemic.

The banking system plays a crucial role in any economy because there is a strong degree of interconnection among banks and the companies they finance. In China, 80% of corporations' credit is from bank loans. At the end of 2019, HUAXIA BANK CO LTD-A, POSTAL SAVINGS

BANK, CHINA MINSHENG BANKING, GUOTAI JUNAN SECURITIES, INDUSTRIAL BANK CO LTD -A, and CITIC SECURITIES (CITIC) were the riskiest banks. Except for POSTAL SAVINGS BANK, these FIs are not state-owned. Compared to the biggest five banks by market capitalisation, joint-stock commercial banks are more remote from any government guarantee and the debtors are mainly SMEs with higher default risk. POSTAL SAVINGS BANK is a commercial retail bank with approximately 40,000 outlets, covering over 600 million private customers. The bank focuses on providing financial services to Sannong customers, urban and rural residents, and SMEs. The lack of large and long-term enterprise debtors potentially introduces risks to its profit outlook.

The pandemic caused great panic around the real world as well as on the stock market. The security trading sector's special characteristics make it vulnerable to systemic shocks. In addition, close business connections among different security companies lead to a "robust-yet-fragile" setup. We then analyze the spillover effects of CITIC, the largest risk receiver after the pandemic, to see whether there is any transforming pattern. The network figures of 2020-01-20 and of 2020-02-03 are shown in Figure 2 and Figure 3.

CITIC is the largest security trading company in China. Its business encompasses funds, capital management, and futures trading. According to financial reports from 2017 to 2019, the revenue, net profit, and total assets rank first in the security trading sector. We utilize the absolute value of β of the other 49 FIs in the regression of CITIC to measure the risk input and the sum of the absolute value of β of CITIC in the regressions of other 49 FIs to identify CITIC's risk output. Its spillover effect to other FIs is shown in Table 3 and Table 4 . CITIC's risk transferred from other FIs is shown in Table 5 and Table 6. We find that the effect of CITIC tail risk towards other FIs (β) diminish and the number of FIs that CITIC affects are decreases. However, the number of FIs that has spillover effects on CITIC is increasing.

To explore the risk of FIs listed on the Taiwan and Hong Kong stock exchanges, Figures 4 to 7 depict the network of FUBON FINANCIAL HOLDING CO (FUBON) and HSBC HOLDINGS PLC (HSBC). Even though they play a less important role in overall systemic risk, as the graphs show, they interact in tail-event scenarios with the FIs listed on the mainland stock exchange.

Table 2: Highest Co-stress Financial Institutions

date	Top1_Name	Top1_Sector	Top1_λ
20191210	HUAXIA BANK CO LTD-A	Banks	2.29
20191211	POSTAL SAVINGS BANK OF CHI-A	Banks	4.19
20191212	POSTAL SAVINGS BANK OF CHI-A	Banks	2.70
20191213	HUAXIA BANK CO LTD-A	Banks	2.48
20191216	HUAXIA BANK CO LTD-A	Banks	2.42
20191217	POSTAL SAVINGS BANK OF CHI-A	Banks	3.35
20191218	CHINA MINSHENG BANKING-A	Banks	2.29
20191219	CHINA MINSHENG BANKING-A	Banks	2.57
20191220	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	2.36
20191223	CITIC SECURITIES CO-A	Diversified Financials	2.66
20191224	INDUSTRIAL BANK CO LTD -A	Banks	2.35
20191225	CHINA MINSHENG BANKING-A	Banks	2.86
20191226	CHINA MINSHENG BANKING-A	Banks	2.68
20191227	EAST MONEY INFORMATION CO-A	Diversified Financials	2.10
20191230	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	2.50
20191231	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	2.60
20200102	CHINA MINSHENG BANKING-A	Banks	2.81
20200103	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	2.53
20200106	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	2.43
20200107	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	2.31
20200108	CITIC SECURITIES CO-A	Diversified Financials	2.24
20200109	BOC HONG KONG HOLDINGS LTD	Banks	2.39
20200110	HENDERSON LAND DEVELOPMENT	Real Estate	2.23
20200113	CITIC SECURITIES CO-A	Diversified Financials	2.29
20200114	HENDERSON LAND DEVELOPMENT	Real Estate	2.56
20200115	HENDERSON LAND DEVELOPMENT	Real Estate	2.74
20200116	BANK OF COMMUNICATIONS CO-A	Banks	3.27
20200117	CITIC SECURITIES CO-A	Diversified Financials	2.62
20200120	BOC HONG KONG HOLDINGS LTD	Banks	2.66
20200203	CITIC SECURITIES CO-A	Diversified Financials	5.74
20200204	CITIC SECURITIES CO-A	Diversified Financials	5.49
20200205	CITIC SECURITIES CO-A	Diversified Financials	5.48
20200206	CITIC SECURITIES CO-A	Diversified Financials	5.90
20200207	CITIC SECURITIES CO-A	Diversified Financials	6.01
20200210	CITIC SECURITIES CO-A	Diversified Financials	5.96

Table 3: CITIC's Risk Spilling to Others

Date	Top1 Name	Top1 Sector	Top1 Beta	Num of FIs
20191210	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.59	9
20191211	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.68	7
20191212	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.59	6
20191213	EAST MONEY INFORMATION CO-A	Diversified Financials	0.49	7
20191216	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.64	6
20191217	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.68	5
20191218	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.70	6
20191219	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.68	7
20191220	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.60	7
20191223	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.56	7
20191224	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.60	6
20191225	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.45	8
20191226	EAST MONEY INFORMATION CO-A	Diversified Financials	0.41	4
20191227	EAST MONEY INFORMATION CO-A	Diversified Financials	0.44	5
20191230	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.43	6
20191231	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.40	4
20200102	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.37	7
20200103	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.61	5
20200106	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.61	6
20200107	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.50	5
20200108	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.49	5
20200109	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.50	7
20200110	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.48	6
20200113	CSC FINANCIAL CO LTD-A	Diversified Financials	0.49	5
20200114	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.29	3
20200115	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.24	3
20200116	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.21	1
20200117	AGRICULTURAL BANK OF CHINA-A	Banks	0.01	3
20200120	HUATAI SECURITIES CO LTD-A	Diversified Financials	0.15	3
20200203	SHENWAN HONGYUAN GROUP CO-A	Diversified Financials	0.15	3
20200204	SHENWAN HONGYUAN GROUP CO-A	Diversified Financials	0.17	3
20200205	SHENWAN HONGYUAN GROUP CO-A	Diversified Financials	0.17	1
20200206	SHENWAN HONGYUAN GROUP CO-A	Diversified Financials	0.12	2
20200207	CTBC FINANCIAL HOLDING CO LT	Banks	0.11	3
20200210	CTBC FINANCIAL HOLDING CO LT	Banks	0.07	2

Table 4: Information on FIs that Receive CITIC's Risk

Date	Top_1	Top_2	Top_3	Top_4	Top_5	Top_6	Top_7	Top_8	Top_9
20191210	HSCL (DF)	EMIC (DF)	GJSC (DF)	SHGC (DF)	HSCL (DF)	PHC (I)	CVCL (RE)	NCLIC (I)	CMB (B)
20191211	HSCL (DF)	EMIC (DF)	GJSC (DF)	SHGC (DF)	HSCL (DF)	PHC (I)	CVCL (RE)		
20191212	HSCL (DF)	EMIC (DF)	GJSC (DF)	HSCL (DF)	PHC (I)	CVCL (RE)			
20191213	EMIC (DF)	HSCL (DF)	GJSC (DF)	HSCL (DF)	PHC (I)	CVCL (RE)	CMB (B)		
20191216	HSCL (DF)	EMIC (DF)	GJSC (DF)	HSCL (DF)	PHC (I)	CVCL (RE)			
20191217	HSCL (DF)	EMIC (DF)	GJSC (DF)	PHC (I)	HSCL (DF)				
20191218	HSCL (DF)	EMIC (DF)	GJSC (DF)	HSCL (DF)	PHC (I)	CVCL (RE)			
20191219	HSCL (DF)	EMIC (DF)	GJSC (DF)	HSCL (DF)	PHC (I)	CVCL (RE)	HBCL (B)		
20191220	HSCL (DF)	EMIC (DF)	GJSC (DF)	PHC (I)	HSCL (DF)	CVCL (RE)	CFHC (I)		
20191223	HSCL (DF)	GJSC (DF)	EMIC (DF)	HSCL (DF)	SHGC (DF)	CVCL (RE)	HBCL (B)		
20191224	HSCL (DF)	EMIC (DF)	GJSC (DF)	SHGC (DF)	HBCL (B)	CVCL (RE)			
20191225	HSCL (DF)	EMIC (DF)	GJSC (DF)	HBCL (B)	CVCL (RE)	PHC (I)	SHGC (DF)	HSCL (DF)	
20191226	EMIC (DF)	HSCL (DF)	GJSC (DF)	CVCL (RE)					
20191227	EMIC (DF)	GJSC (DF)	HSCL (DF)	CFCL (DF)	CMB (B)				
20191230	HSCL (DF)	PHC (I)	SHGC (DF)	BHKHL (B)	EMIC (DF)	IBCL (B)			
20191231	HSCL (DF)	BHKHL (B)	CVCL (RE)	IBCL (B)					
20200102	HSCL (DF)	PHC (I)	ABOC (B)	IBCL (B)	BHKHL (B)	EMIC (DF)	CVCL (RE)		
20200103	HSCL (DF)	CFCL (DF)	BHKHL (B)	ABOC (B)	IBCL (B)				
20200106	HSCL (DF)	CFCL (DF)	ABOC (B)	IBCL (B)	BHKHL (B)	EMIC (DF)			
20200107	HSCL (DF)	CFCL (DF)	CVCL (RE)	ABOC (B)	IBCL (B)				
20200108	HSCL (DF)	CFCL (DF)	SHGC (DF)	HSBL (B)	IBCL (B)				
20200109	HSCL (DF)	CFCL (DF)	SHGC (DF)	ABOC (B)	EMIC (DF)	IBCL (B)	CL (CG)		
20200110	HSCL (DF)	CFCL (DF)	ABOC (B)	SHGC (DF)	HSBL (B)	IBCL (B)			
20200113	CFCL (DF)	HSCL (DF)	ABOC (B)	NCLIC (I)	HBCL (B)				
20200114	HSCL (DF)	ABOC (B)	IBCL (B)						
20200115	HSCL (DF)	ABOC (B)	IBCL (B)						
20200116	HSCL (DF)								
20200117	ABOC (B)	IBCL (B)	HSCL (DF)						
20200120	HSCL (DF)	PHC (I)	IBCL (B)						
20200203	SHGC (DF)	HSCL (DF)	PABCL (B)						
20200204	SHGC (DF)	CFHC (I)	HSCL (DF)						
20200205	SHGC (DF)								
20200206	SHGC (DF)	ABOC (B)							
20200207	CFHCL (B)	HKEC (DF)	ABOC (B)						
20200210	CFHCL (B)	ABOC (B)							

Table 5: CITIC's Risk Spilling from Others

Date	Top1 Name	Top1 Sector	Top1 Beta	Num of FIs
20191210	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.54	8
20191211	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.55	9
20191212	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.53	8
20191213	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.5	8
20191216	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.48	9
20191217	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.48	9
20191218	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.4	8
20191219	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.41	8
20191220	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.46	9
20191223	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.48	4
20191224	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.4	6
20191225	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.43	9
20191226	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.49	8
20191227	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.27	6
20191230	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.26	6
20191231	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.4	5
20200102	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.37	5
20200103	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.38	4
20200106	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.28	4
20200107	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.34	4
20200108	SHENWAN HONGYUAN GROUP CO-A	Diversified Financials	0.25	7
20200109	SHENWAN HONGYUAN GROUP CO-A	Diversified Financials	0.25	7
20200110	SHENWAN HONGYUAN GROUP CO-A	Diversified Financials	0.24	9
20200113	HAITONG SECURITIES CO LTD-A	Diversified Financials	0.26	5
20200114	CHINA MERCHANTS SECURITIES-A	Diversified Financials	0.18	7
20200115	EAST MONEY INFORMATION CO-A	Diversified Financials	0.2	8
20200116	HAITONG SECURITIES CO LTD-A	Diversified Financials	0.21	6
20200117	HAITONG SECURITIES CO LTD-A	Diversified Financials	0.21	5
20200120	HAITONG SECURITIES CO LTD-A	Diversified Financials	0.21	5
20200203	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.4	8
20200204	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.4	8
20200205	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.4	8
20200206	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.44	7
20200207	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.46	7
20200210	GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	0.52	7

Table 6: Information on FIs that transmit Risk to CITIC

Date	Top_1	Top_2	Top_3	Top_4	Top_5	Top_6	Top_7	Top_8	Top_9
20191210	GJSC (DF)	HSCL (DF)	PAIGC (I)	CMS (DF)	CCBCL (B)	CVCL (RE)	CFHC (I)	SHGC (DF)	
20191211	GJSC (DF)	HSCL (DF)	PAIGC (I)	CCBCL (B)	CMB (B)	CVCL (RE)	CFHC (I)	CMS (DF)	HSBL (B)
20191212	GJSC (DF)	HSCL (DF)	PAIGC (I)	CCBCL (B)	CMB (B)	CMS (DF)	CFHC (I)	CVCL (RE)	
20191213	GJSC (DF)	HSCL (DF)	PAIGC (I)	CMS (DF)	CCBCL (B)	CVCL (RE)	CFHC (I)	SHGC (DF)	
20191216	GJSC (DF)	HSCL (DF)	CMS (DF)	PAIGC (I)	CCBCL (B)	CVCL (RE)	CMB (B)	CFHC (I)	SHGC (DF)
20191217	GJSC (DF)	HSCL (DF)	CMS (DF)	PAIGC (I)	CCBCL (B)	CVCL (RE)	CMB (B)	CFHC (I)	SHGC (DF)
20191218	GJSC (DF)	CMS (DF)	HSCL (DF)	PAIGC (I)	CCBCL (B)	CVCL (RE)	CFHC (I)	SHGC (DF)	
20191219	GJSC (DF)	CMS (DF)	HSCL (DF)	PAIGC (I)	CCBCL (B)	CVCL (RE)	CFHC (I)	CMB (B)	
20191220	GJSC (DF)	HSCL (DF)	CCBCL (B)	CMS (DF)	PAIGC (I)	CPIG (I)	CMB (B)	CFHC (I)	SHGC (DF)
20191223	GJSC (DF)	HSCL (DF)	SHGC (DF)	CVCL (RE)					
20191224	GJSC (DF)	CMS (DF)	HSCL (DF)	SHGC (DF)	CPIG (I)	CMB (B)			
20191225	GJSC (DF)	CMS (DF)	CMB (B)	HSCL (DF)	CCBCL (B)	CFHC (I)	ABOC (B)	CVCL (RE)	SHKP (RE)
20191226	GJSC (DF)	CMB (B)	CMS (DF)	HSCL (DF)	CFHC (I)	CPIG (I)	HSCL (DF)	CVCL (RE)	
20191227	GJSC (DF)	CMS (DF)	HSCL (DF)	CFHC (I)	SHGC (DF)	HSCL (DF)			
20191230	GJSC (DF)	HSCL (DF)	CMS (DF)	CFHC (I)	SHGC (DF)	CAHL (RE)			
20191231	GJSC (DF)	HSCL (DF)	SHGC (DF)	CFHC (I)	CMB (B)				
20200102	GJSC (DF)	HSCL (DF)	SHGC (DF)	CFHC (I)	CMB (B)				
20200103	GJSC (DF)	SHGC (DF)	HSCL (DF)	CFHC (I)					
20200106	GJSC (DF)	HSCL (DF)	SHGC (DF)	CVCL (RE)					
20200107	GJSC (DF)	SHGC (DF)	HSCL (DF)	HSCL (DF)					
20200108	SHGC (DF)	HSCL (DF)	HSCL (DF)	EMIC (DF)	CPIG (I)	CFHC (I)	CMSI (RE)		
20200109	SHGC (DF)	HSCL (DF)	HSCL (DF)	EMIC (DF)	CFHC (I)	CPIG (I)	CFCL (DF)		
20200110	SHGC (DF)	HSCL (DF)	HSCL (DF)	EMIC (DF)	CCBCL (B)	CFHC (I)	CFCL (DF)	CPIG (I)	GJSC (DF)
20200113	HSCL (DF)	EMIC (DF)	CMS (DF)	PDAH (RE)	CFHC (I)				
20200114	CMS (DF)	EMIC (DF)	HSCL (DF)	CFCL (DF)	CMSI (RE)	CFHC (I)	BOBCL (B)		
20200115	EMIC (DF)	HSCL (DF)	CFCL (DF)	CMS (DF)	GJSC (DF)	CFHC (I)	CMSI (RE)	PDAH (RE)	
20200116	HSCL (DF)	EMIC (DF)	CFCL (DF)	CMS (DF)	CFHC (I)	GJSC (DF)			
20200117	HSCL (DF)	EMIC (DF)	CFCL (DF)	CMS (DF)	CFHC (I)				
20200120	HSCL (DF)	EMIC (DF)	CFCL (DF)	CMS (DF)	CFHC (I)				
20200203	GJSC (DF)	SHGC (DF)	HSCL (DF)	HSCL (DF)	NCLIC (I)	EMIC (DF)	CAHL (RE)	WREI (RE)	
20200204	GJSC (DF)	SHGC (DF)	HSCL (DF)	HSCL (DF)	NCLIC (I)	EMIC (DF)	CAHL (RE)	WREI (RE)	
20200205	GJSC (DF)	SHGC (DF)	HSCL (DF)	HSCL (DF)	NCLIC (I)	EMIC (DF)	CAHL (RE)	WREI (RE)	
20200206	GJSC (DF)	SHGC (DF)	HSCL (DF)	HSCL (DF)	NCLIC (I)	CAHL (RE)	WREI (RE)		
20200207	GJSC (DF)	SHGC (DF)	HSCL (DF)	HSCL (DF)	NCLIC (I)	CMB (B)	WREI (RE)		
20200210	GJSC (DF)	SHGC (DF)	HSCL (DF)	HSCL (DF)	NCLIC (I)	CMB (B)	CMS (DF)		

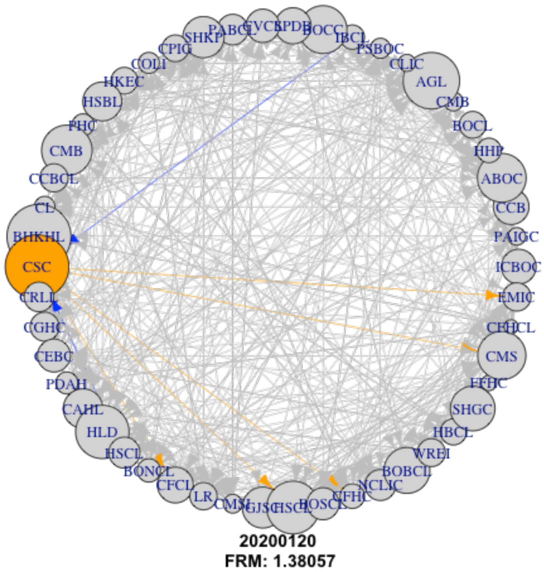


Figure 2: Network of FIs on 2020-01-20 with China FI CITIC Securities (600030 CH) as the central node, its in-degree and out-degree edges

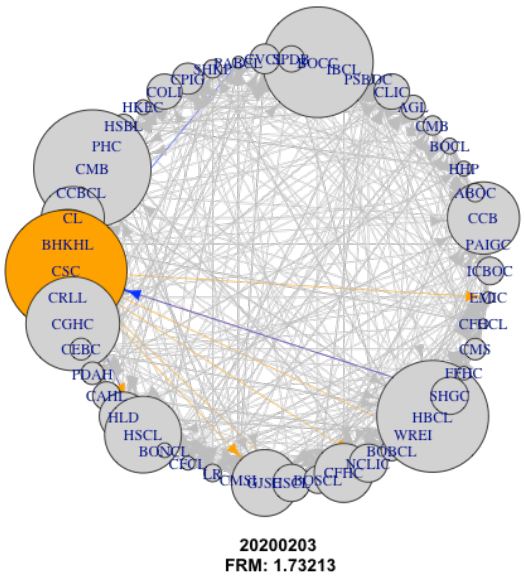


Figure 3: Network of FIs on 2020-02-03 with China FI CITIC Securities (600030 CH) as the central node, its in-degree and out-degree edges

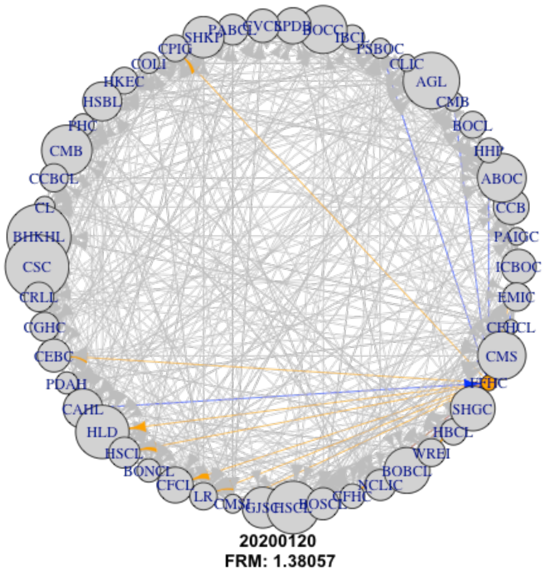


Figure 4: Network of FIs on 2020-01-20 with China FI FUBON FINANCIAL HOLDING CO (2881 TT CH) as the central node, its in-degree and out-degree edges

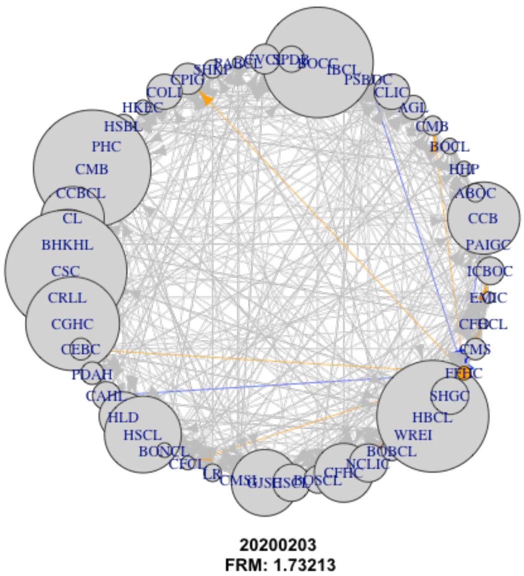


Figure 5: Network of FIs on 2020-02-03 with China FI FUBON FINANCIAL HOLDING CO (2881 TT CH) as the central node, its in-degree and out-degree edges

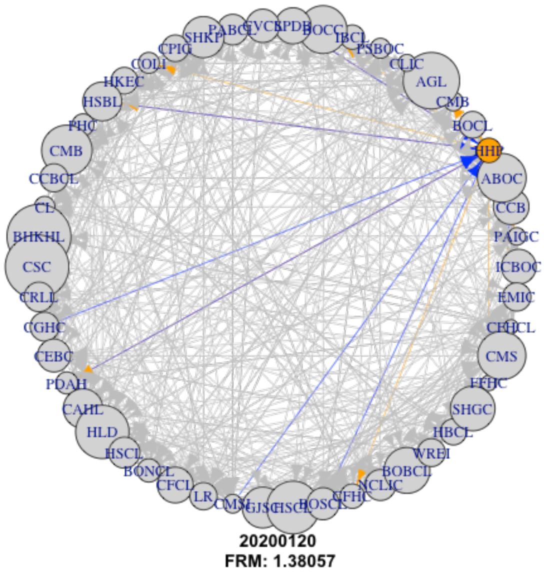


Figure 6: Network of FIs on 2020-01-20 with China FI HSBC HOLDINGS PLC(5 HK CH) as the central node, its in-degree and out-degree edges

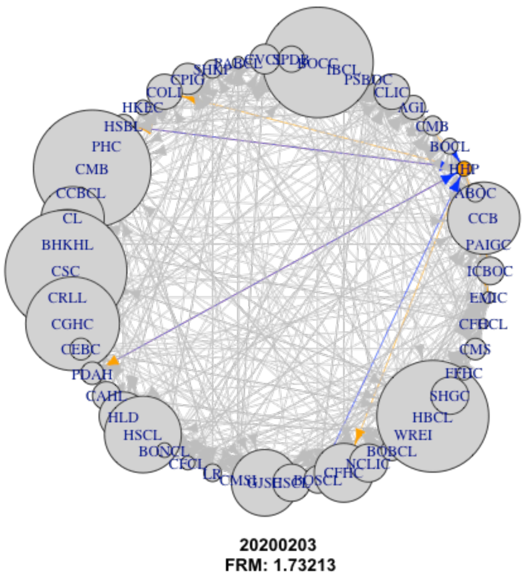


Figure 7: Network of FIs on 2020-01-20 with China FI HSBC HOLDINGS PLC(5 HK CH) as the central node, its in-degree and out-degree edges

As outlined in Section 2.2, the adjacency matrix $A = \{\beta^k_{j,i}\}$ where $\beta^k_{j,j} = 0$ can be analysed for more details in addition to the above depictions of the network of Chinese FIs. In Figures 8 to 10 we depict the respective daily adjacency matrix, where Figure 8 is an example of the full network, and the other two are reduced set examples that we want to examine in more detail. Focusing again on CITIC on 2020-02-03, we emphasize the situation of CITIC listed on the Shanghai stock exchange and CITIC LTD listed on the Hong Kong stock exchange which is also owned by CITIC Group. We discover that CITIC's TE is explained by a cluster of FIs from the same capital markets and security trading sector. On the other hand, CITIC LTD's TE is better explained by the TE of FIs in the real estate sector. Some weeks into the crisis, on 2020-04-29, the intra-sector linkages remain and CITIC LTD has become more sensitive to the TE of FIs in the banking sector.

Similarly, when looking at the Taiwanese insurance company FUBON, we discover that this FI's TE is largely explained by insurance companies in Taiwan on 2020-02-03. However, it is influenced by a wider range of regional FIs on 2020-04-29. Its TE risk driver clusters are mainly composed of Taiwanese companies, such as CATHAY REAL ESTATE DEVELOPMENT (CATHAY) and MEGA FINANCIAL HOLDING CO LT (MEGA). FUBON also has intra-sector links to the Hong Kong based insurance Company AIA GROUP LTD.

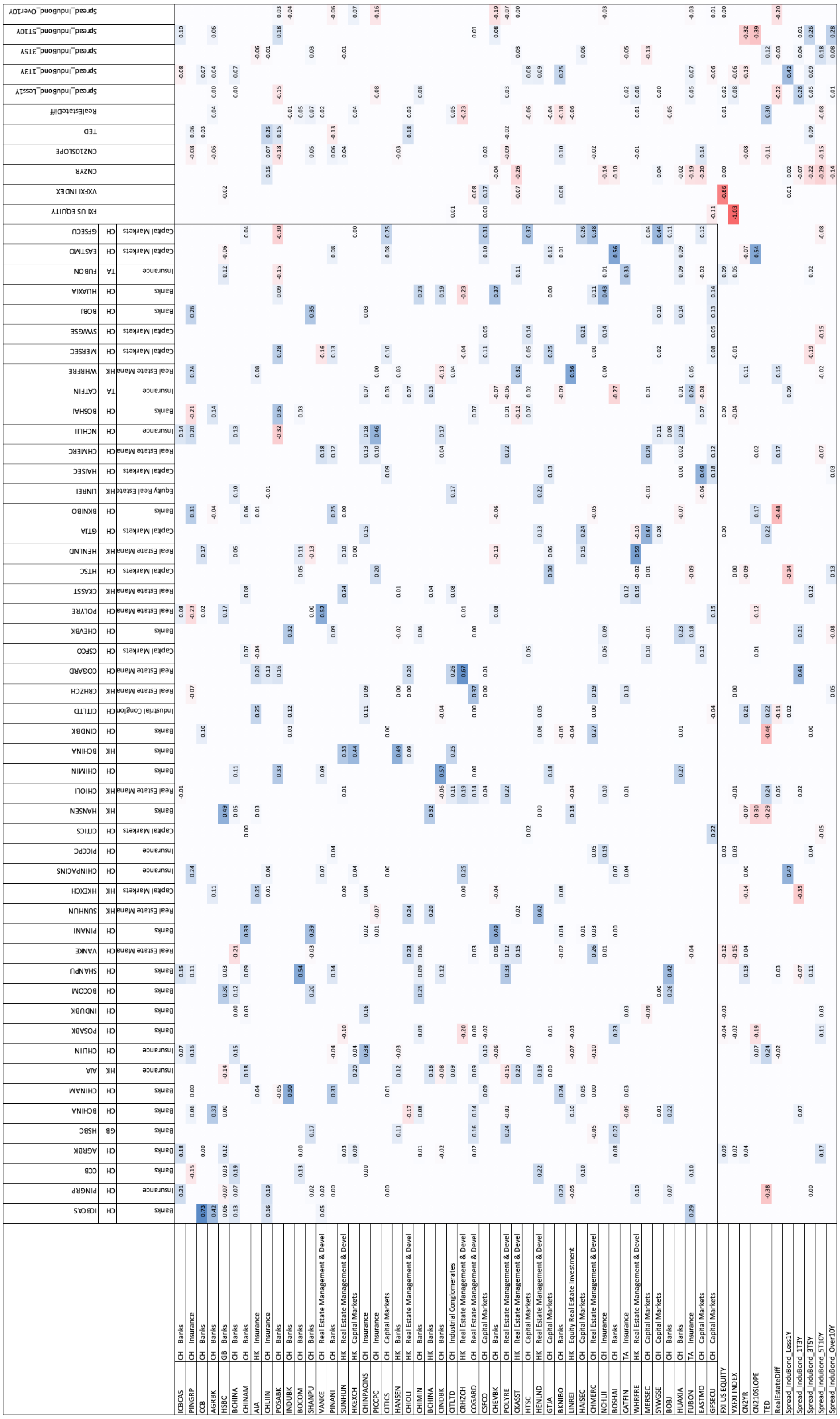


Figure 8: Adjacency Matrix of FIs on 2020-01-20

20200203, tau=0.05			ICBCAS	CHINAM	BOCOM	SHANPU	CHIOLI	BCHINA	CHIMIN	CSFCO	COGARD	CHEVBK	CKASST	LINREI	HTSC	BKNIBO	GTJA	HAISEC	CATFIN	NCHLII	SYWGSE	GFSECU	FXI US EQUITY	VXFXI INDEX	CN2YR	CN210SLOPE	TED	RealEstateDiff	Spread_InduBond_Less1Y	Spread_InduBond_1T3Y	Spread_InduBond_3T5Y	Spread_InduBond_5T10Y	Spread_InduBond_Over10Y
			CH	CH	CH	CH	HK	HK	CH	CH	CH	CH	HK	HK	CH	CH	CH	CH	TA	CH	CH	CH											
			Banks	Banks	Banks	Banks	Real Estate Ma	Banks	Banks	Capital Market	Real Estate Ma	Banks	Real Estate Ma	Equity Real Esta	Capital Market	Banks	Capital Market	Capital Market	Insurance	Insurance	Capital Market	Capital Market											
CITICS	CH	Capital Markets											0.01		0.13	0.03	0.34	0.10		0.05	0.24												
CITLTD	HK	Industrial Conglomerates		0.03		0.06	0.11	0.16	0.02		0.28		0.11	0.22																			
FUBON	TA	Insurance	0.06		0.00					-0.08		0.22		0.10					0.38	0.04		0.16			-0.11			0.05		0.05			

Figure 9: Adjacency Matrix of FIs on 2020-02-03 (τ = 0.05)

20200429, tau=0.05			CHINAM	AIA	HSBC	CHINPACINS	CHIMIN	HANSEN	CSFCO	CRHZCH	CHEVBK	HTSC	HENLND	GTJA	CHMERC	LINREI	HAISEC	CATFIN	SYWGSE	FUBON	MEGA	GFSECU	FXI US EQUITY	VXFXI INDEX	CN2YR	CN210SLOPE	TED	RealEstateDiff	Spread_InduBond_Less1Y	Spread_InduBond_1T3Y	Spread_InduBond_3T5Y	Spread_InduBond_5T10Y	Spread_InduBond_Over10Y
			CH	HK	GB	CH	CH	HK	CH	HK	CH	CH	HK	CH	CH	HK	CH	TA	CH	TA	TA	CH											
			Banks	Insurance	Banks	Insurance	Banks	Banks	Capital Market	Real Estate Ma	Banks	Capital Market	Real Estate Ma	Capital Market	Real Estate Ma	Equity Real Esta	Capital Market	Insurance	Capital Market	Insurance	Banks	Capital Market											
CITICS	CH	Capital Markets		0.00					0.08		0.02	0.16		0.37					0.27			0.11								0.03			
CITLTD	HK	Industrial Conglomerates			0.17		0.03	0.22		0.33			0.05	0.00	0.05	0.05	0.00		0.19	-0.11								-0.16					
FUBON	TA	Insurance	0.05	0.16		0.01			-0.05									0.34			0.29		0.10				-0.11	0.06					

Figure 10: Adjacency Matrix of FIs on 2020-04-29 ($\tau = 0.05$)

As outlined in Section 2.3, we further analyze the formation of clusters using the examples of dendrograms for 2020-02-03 (Figure 11) and 2020-04-29 (Figure 12), which present the cases at the beginning and after the crisis respectively. The x-axis shows FI names and the y-axis indicates the distance between two merging FIs. The dendrogram for 2020-02-03 shows that three clusters appeared at the beginning of pandemic where the green cluster encompasses 43 FIs, and five FIs are in a blue cluster whose sub-cluster contains two FIs (orange). The blue cluster contains FIs from all three regions, namely from the mainland (POSTAL SAVINGS BANK, BANK of COMMUNICATIONS, PEOPLE's INSURANCE COMPANY), from Hong Kong (CHINA RESOURCES LAND), and from CTBC FINANCIAL HOLDING CO LT in Taiwan. The orange sub-cluster contains FIs which can be characterised as non-state-owned commercial banks (CHINA MERCHANT SHEKOU IND-A, EVERBRIGHT SECURITIE CO -A), which offer similar services with a similar structure. Among the FIs, the height of the link between HONG KONG EXCHANGES CLEARING LTD and HANG SENG BANK LTD is the lowest, which means they are expected to be most similar. Note that the first one is the stock exchange in Hong Kong and the latter is one of the largest banks in Hong Kong. The height of the link that joins POSTAL SAVINGS BANK OF CHINA and other FIs is the highest, which can be interpreted by their different operation models: other FIs are profit-oriented but POSTAL SAVING BANK focuses on public service.

Figure 12 is significantly different from 11. Forty-nine out of 50 FIs form one cluster, and the one outstanding FI is HSBC HOLDINGS PLC (HSBC) which operates globally and is more risk diversified. On the one hand, this can mean that HSBC Holdings' business connections with outside China protect it from the depression in China at that period. On the other hand, the FIs operating in the Chinese regions shift to behave mainly as one cluster, which shows that regional coordination of financial institution oversight is of great importance during tail event scenarios so as to swiftly calm market turmoil.

Then, we look at adjacency matrix A_k on 2020-04-29 to see who contributes the most to HSBC's TE risk. We find that HSBC's TE is mostly driven by that of CITIC of China, CATHAY of Taiwan, and the Chinese corporate spread to government bonds in the 5-10yr maturity range. HSBC also influences HANG SENG BANK LTD, CITIC, and EAST MONEY INFORMATION CO-A. Therefore, the HSBC - CITIC linkage requires closer understanding for a financial market regulator, especially with regard to worldwide financial market intervention since risk could be transferred from HSBC to CITIC, and then to the whole Chinese regional FIs.

For a regulatory authority in the region, the result of risk clustering provides a valuable insightful suggestion for targeted policy. Regional coordinated financial market intervention should be done to reduce spillover effects in risk transmission. The policy response would be more effective after considering the importance of macro features, which will be outlined in the next section.

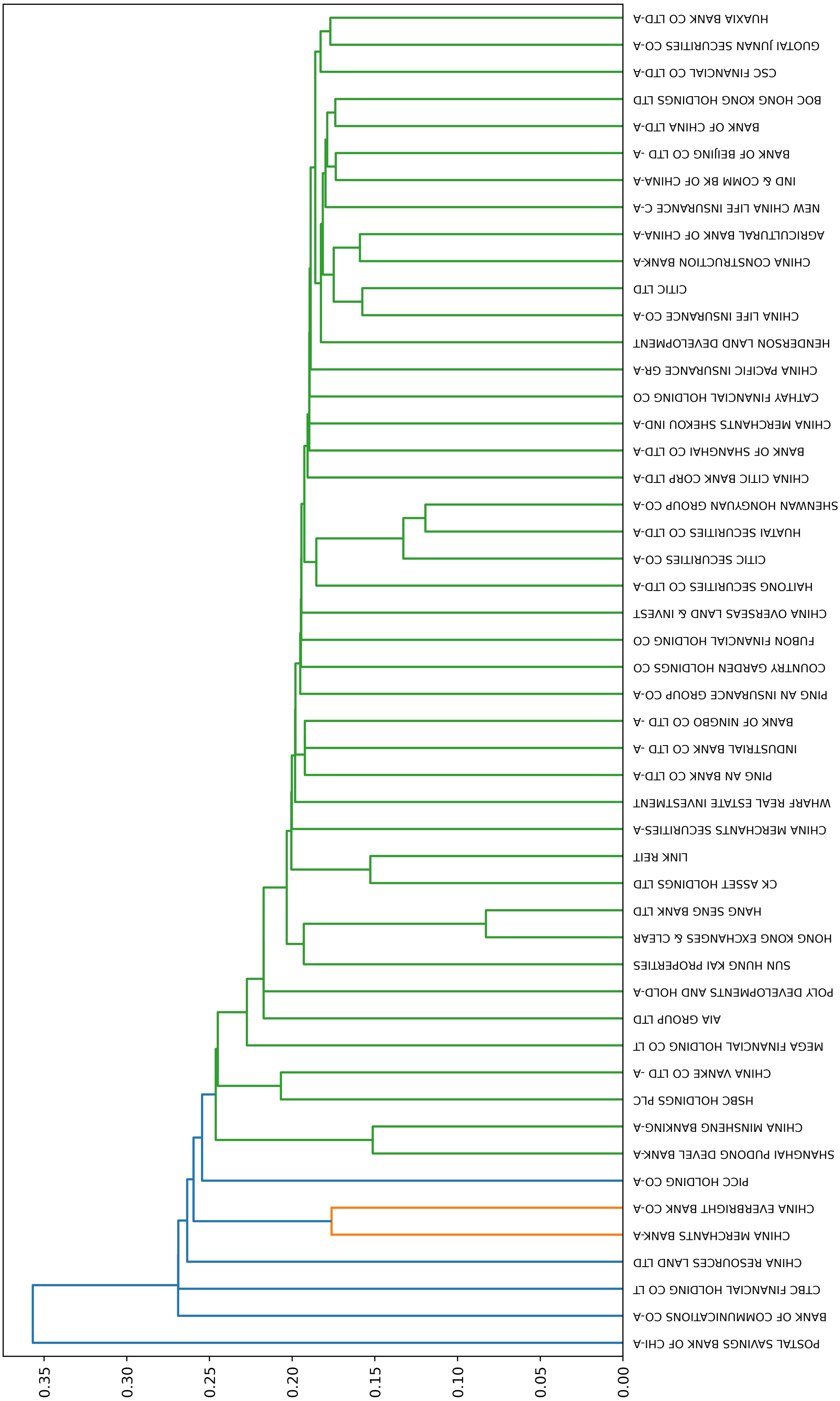


Figure 11: HRP Clusters of FIs on 2020-02-03

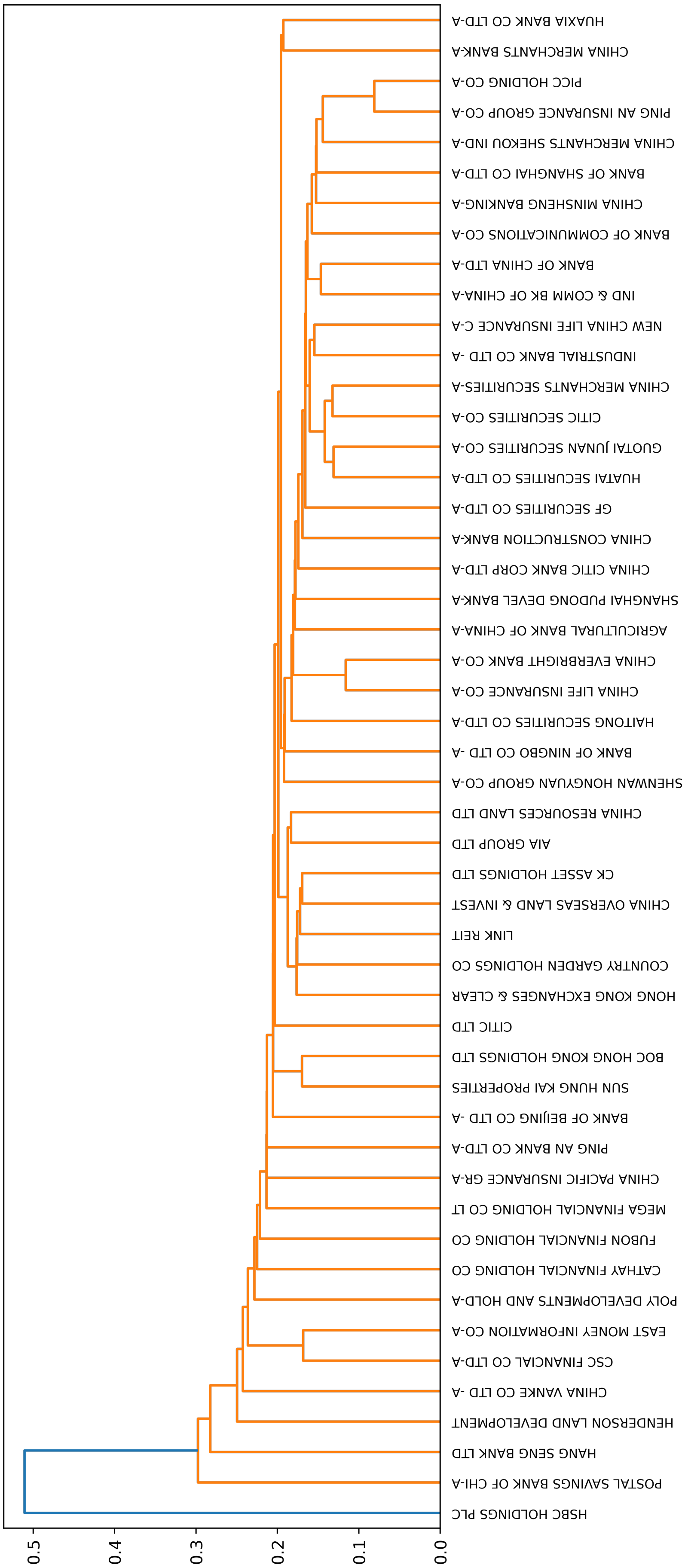


Figure 12: HRP Clusters of FIs on 2020-04-29

3.2 Feature Importance of Macro Variables

The FRM index is the mean value of penalization terms in quantile-lasso regressions, thus its relationship with macro features is unknown and non-linear. The existing FRM papers use the mean value of β to reflect features' contribution; however, its accuracy is questionable. To solve this problem, we use Shapley values to interpret the features' contributions to the final regression results. The result of the most important macro features based on a permutation method is shown in Figures 13, 14, 15, 16, and Table 7. Figure 13 shows that the mean value of these four macro features is around 0.02. Figure 14 shows that the importance of the Chinese 2-year treasury yield rate and 10-2year spread are relatively higher than the FXI US EQUITY and VXFXI index. It implies that the Chinese systemic financial risk is sensitive to short-term monetary policy and forward guidance. But around crises, both equity market returns and implied volatility embedded in options markets are key drivers of financial risk in China.

Figure 15 compares the situation before and after Covid-19. We use the results before 2020-01-23 as "before Covid-19" because the central government of China imposed a lockdown in Wuhan on 23 January 2020. We take the results after 2020-02-03 as "after Covid-19" because Wuhan lifted its lockdown on 8 April, 2020. In 2019, there were several events that accelerated the capital market's opening process in China: the elimination of investment restrictions for Qualified Foreign Institutional Investor(QFII) and RMB Qualified Foreign Institutional Investor(RQFII), Chinese A share's increasing influence in MSCI index, and SP Emerging BMI's including Chinese listed companies. These events induced foreign capital to flow into the Chinese stock market, which promoted investors' confidence and a high return on the stock market, with a 22% increase on the Shanghai index (`https://www.financialnews.com.cn/zq/stock/202001/t20200103_174649.html`). Therefore, the FXI US EQUITY and VXFXI Index, which are based on stock market performances, played a less important role in financial risk than liquidity measurements (Chinese 2-year treasury yield rate and 10-2year spread). These results also support the view of existing studies that monetary policy impacts financial risk (Thorbecke (1997), Rigobon and Sack (2004),Bernanke and Kuttner (2005)). One of the transmitting channels by which monetary policies influence financial systemic risk is through the default rate. Monetary policies influence default rates and non-performing loans which are related to how bank systems operate. In the context of a bank-based economy, this will ultimately impact the systemic risk.

However, the situation changed when the pandemic broke out. To encourage economic recovery, China promptly responded to Covid-19 by injecting RMB 3.33 trillion into the banking sector via open market operations and RMB 1.8 trillion as an expansion to re-lending and re-discounting facilities. In addition, the Chinese central bank reduced the 7-day, and 14-day reverse repo rates by 30and 10 bps, respectively. The 1-year medium-term lending facility (MLF) rate and the targeted MLF rate were also reduced by 30 and 20 bps, respectively (Rizwan et al.; 2020). These expansionary monetary policies reduced the public's concern towards the liquidity shortage. On the other hand, the VXFXI index increased sharply and the return in FXI US EQUITY become volatile. The first indicator reflects the public's uncertainty towards stock markets and the latter is based on the ETF's performance which is associated with co-movement of asset prices and investors' behaviour. Therefore, the importance of the two liquidity measurements diminished. However, the contributions of the indicators reflecting public investors' uncertainty and ETF performance to Shapley values increased after Covid-19.

We also took the mean value of four macro features' Shapley values in rolling windows (63 days). The result is displayed in Figure 16, which shows the importance of FXI.US.EQUITY and VXFXI.INDEX in the beginning of 2020. With the rapid spread of Covid-19 in early 2020, the impact of this pandemic led to spillover effects of financial risks among various sectors in China as well as in global stock markets. This event generated uncertainty in the economic outlook and raised public fear which was reflected in the dramatic increase of stock prices and option implied volatility, as well as in negative stock market returns. The FIX US Equity and VXFIX index represent the Chinese large-cap stock market performance. It has been shown that the 2020 pandemic would induce uncertainty around stock market valuation and investors' preference for cash holdings (Ramelli and Wagner; 2020), resulting in higher stock market volatility. The severe market stress caused by the crisis would also undermine the financial institutions' business through credit channels (Zhang et al.; 2020). Therefore, after the breakout of Covid-19, from the end of 2019 to March 2020, the tail risk of financial institutions was sensitive to the market performance and this is very well captured in the selected macro-economic risk variables' importance.

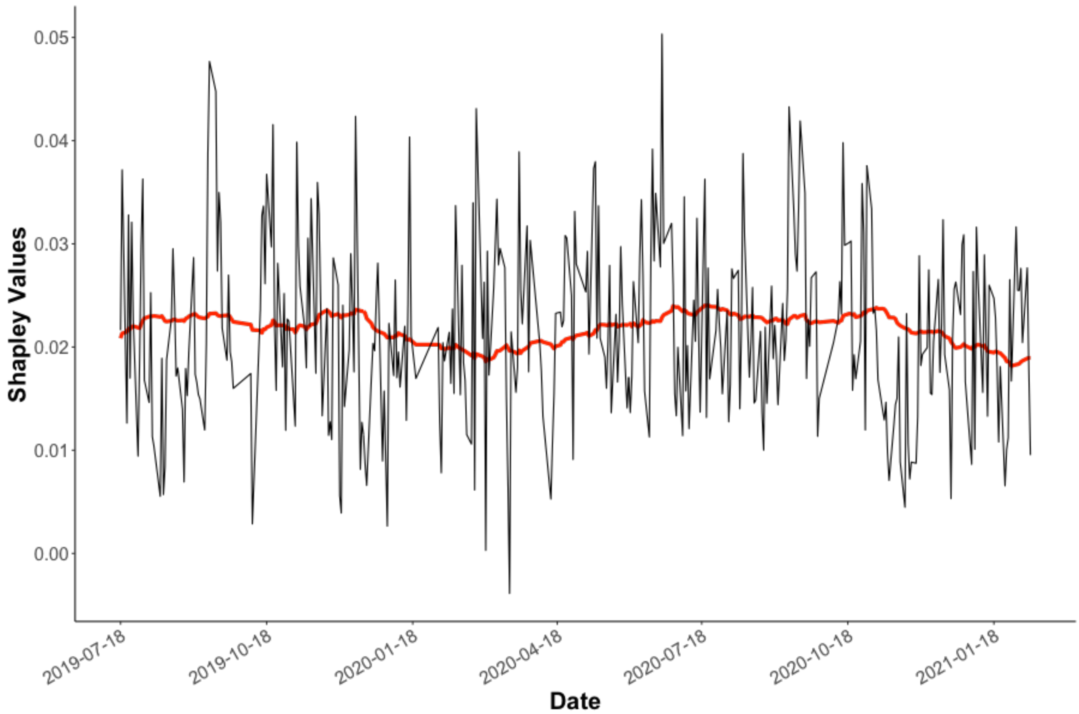


Figure 13: The Mean Shapley Value of 4 macro features ($\tau = 0.05$,The Mean Shapley Value, The Mean Shapley Value with Rolling Windows = 63 days)

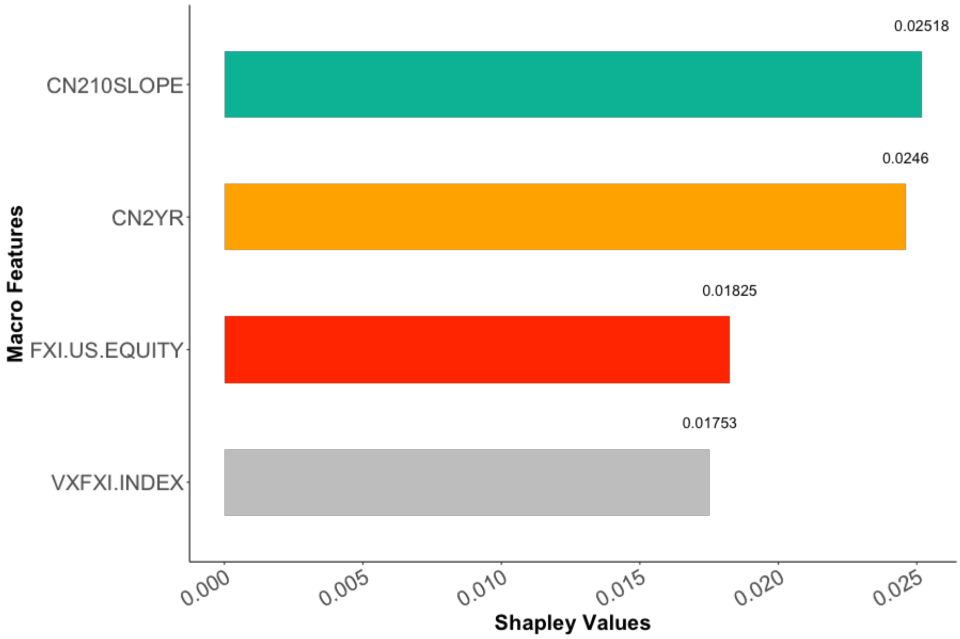


Figure 14: The Mean Shapley Value Grouped by 4 macro features ($\tau = 0.05$), FXI.US.EQUITY, VXFXI.INDEX, CN2YR, CN210SLOPE

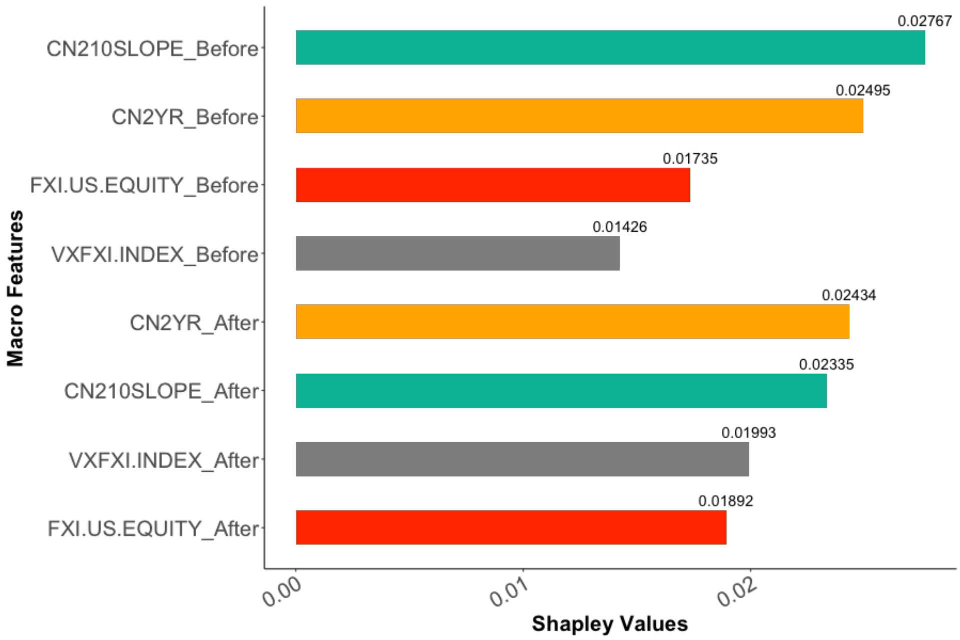


Figure 15: The Shapley value of Macro Features before and after Covid ($\tau = 0.05$), FXI.US.EQUITY, VXFXI.INDEX, CN2YR, CN210SLOPE

Table 7: Mean Shapley Value Grouped by 4 macro features ($\tau = 0.05$)

Macro	Mean	Max	Min	Std
FXI.US.EQUITY	0.018	0.079	-0.030	0.017
VXFIX Index	0.018	0.092	-0.040	0.016
CN2YR	0.025	0.113	-0.028	0.020
CN210SLOPE	0.025	0.087	-0.037	0.019
FRM	1.400	2.560	1.060	0.272

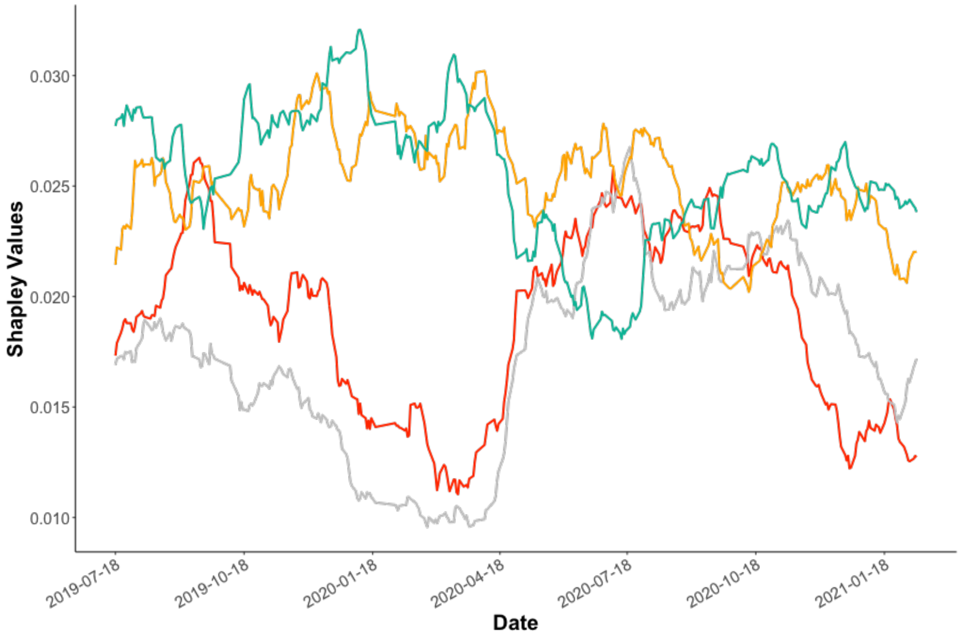
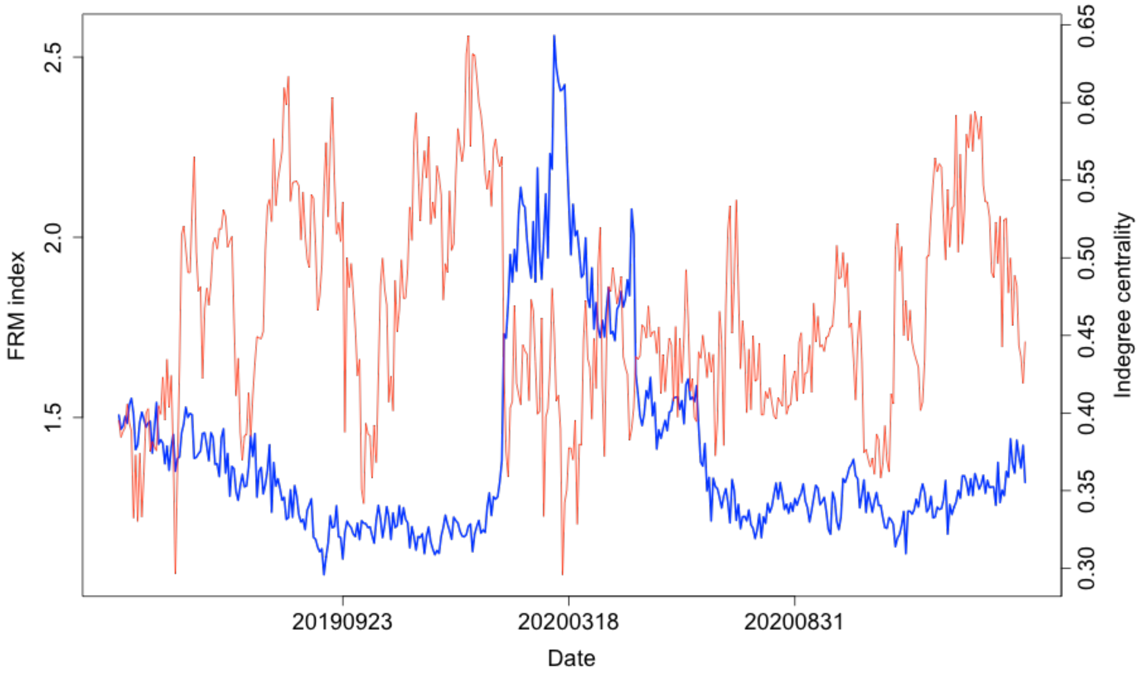


Figure 16: Feature importance based on Shapley Value ($\tau = 0.05$, rolling window = 63 days), FXI.US.EQUITY, VXFXI.INDEX, CN2YR, CN210SLOPE

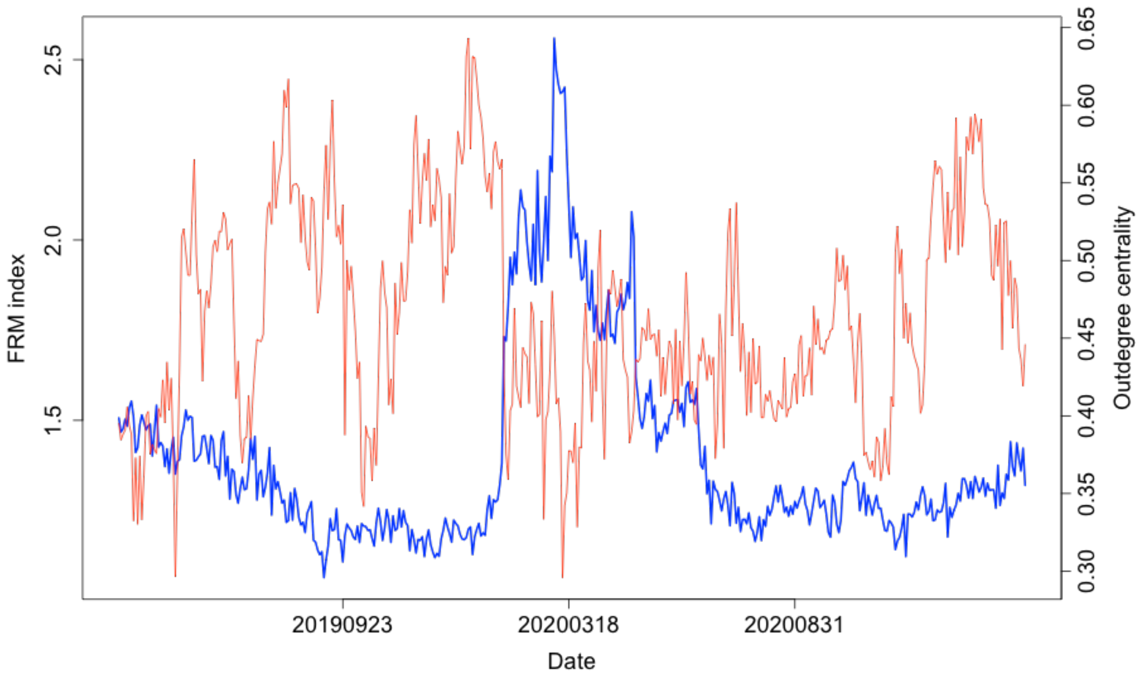
4 Comparison with Other Risk Measures

4.1 Comparison with Existing China Region based Risk Measures

In Figure 17, we show the time series of the FRM against various centrality measures. We observe that when the FRM rises, the number of β_{ij} equal to zero increases. We observe that in- and out-degree centrality drop when the FRM rises because the edges or connections between FIs have reduced sharply. Thus the transfer or spill-over channels of risk have concentrated on fewer nodes. With the FRM technology the increased risk environment is alerted when the FRM rises, and a detailed look at matrix A then yields conclusions on the most targeted policy responses.



(a) FRM and In-degree



(b) FRM and Out-degree

Figure 17: FRM at $\tau = 0.05$ and Centrality measures

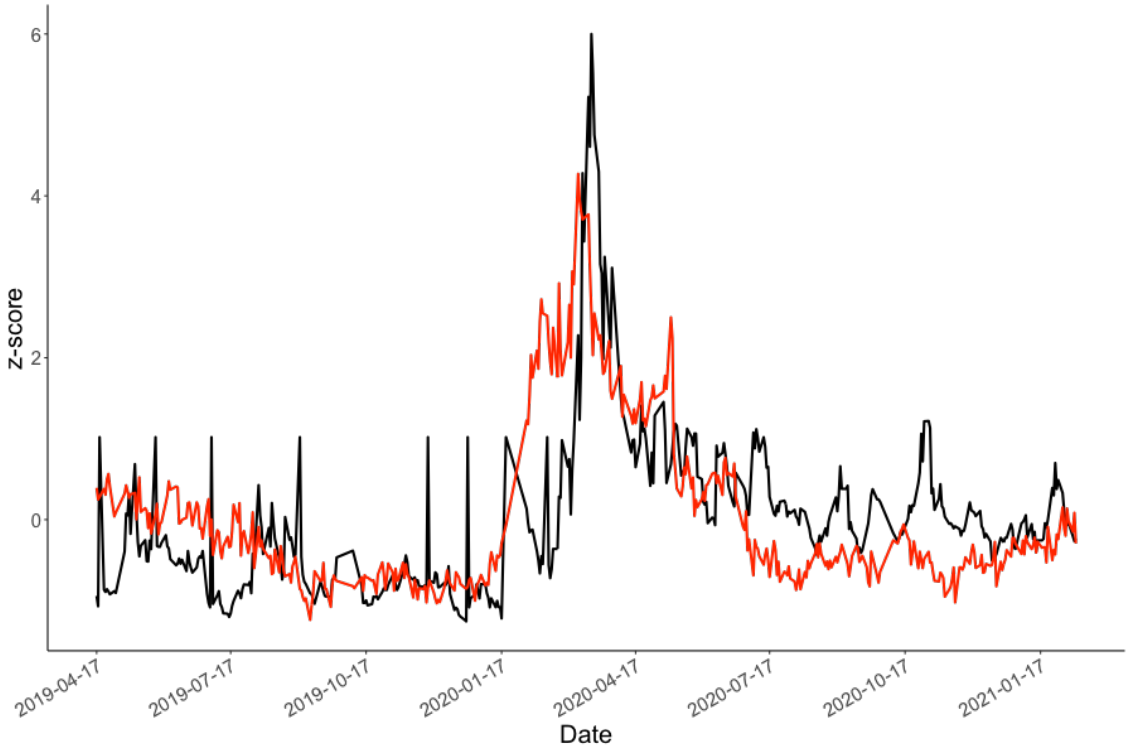
To illustrate whether FRM@China has a better risk predictive ability, we compare it with CBOE FIX VIX Index, the most popular financial risk measures. Table 8 shows that the volatility of the FRM is much less than that of the CBOE FIX VIX Index. Figure 18a shows the Z-score of the two indexes. The Z-score formula is $score = (Index - \mu)/\sigma$, where μ is the mean value of the index and σ is the standard deviation. FRM@China has less noise and more predictive power than the CBOE FIX VIX Index.

The stock market crash of 2020 began on Monday, March 9, with the largest point plunge for the Dow Jones Industrial Average (DJIA) up to that date. It was followed by two more record-setting point drops on March 12 and March 16. The Dow Jones's fall of nearly 3,000 points on March 16, 2020, was the largest single-day drop in U.S. stock market history to date. The Chinese stock market also suffered a negative shock; for example, the CSI 300 daily lost 4.3% and the Hang Seng index sank 4.03% on March 16, 2020. Towards such a global market shock, FRM@China released a risk signal in early February; by contrast, the CBOE FIX VIX index released a similar signal after March.

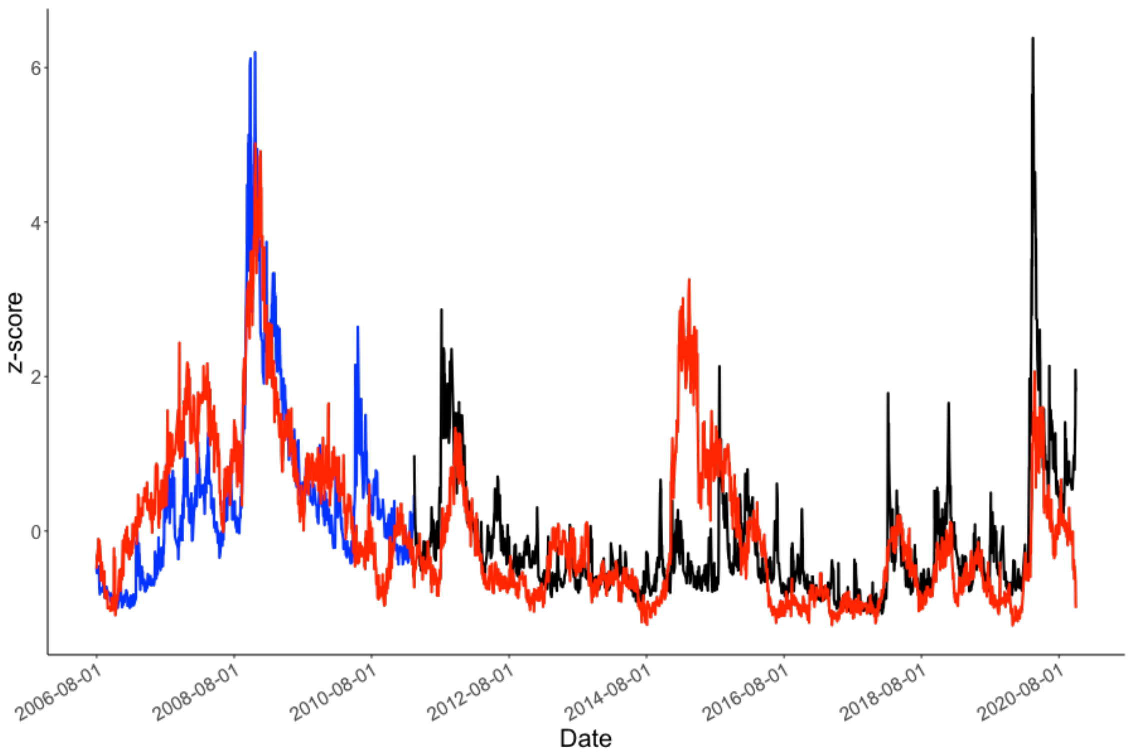
Performance of the CBOE FIX VIX index and FRM@China from August 1, 2006 to February 10, 2021 is shown in Figure 18b. In the period before March 16, 2011, we use the VIX index to replace the CBOE FIX VIX index because the latter did not have data during that time. For the Chinese stock market turbulence in 2015, FRM@China is much more sensitive than the CBOE FIX VIX index. The crisis prediction ability of the two indexes is similar in the 2008 global financial crisis and 2012 European debt crisis.

Table 8: Comparison of FRM and CBOE FIX VIX Index

Indicator	mean	sd	median	min	max
FRM	1.49	0.27	1.30	1.06	2.56
CBOE FIX VIX Index	25.40	7.31	24.27	16.20	69.28



(a) CBOE FIX VIX Index, FRM@China



(b) CBOE FIX VIX Index, FRM@China,VIX Index

Figure 18: Risk Measure Comparison

5 Conclusion

We propose a new financial market risk meter for China, FRM@China, which not only indicates the level of systemic risk, but also details potential spillover paths derived from co-movements of FIs in tail-event scenarios. We show that FRM@China is more sensitive to crises and has less noise than the CBOE FIX VIX index, the most popular risk measurement. Compared with commonly used risk measurements, FRM@China is able to detect the spillover channels among FIs and systemic risk in a single quantile-lasso regression model. The decreasing number of HRP clusters indicates that contamination in TE among FIs was more serious during the crisis period. The existing FRM studies have never looked at the contribution of different macro features to systemic risk. This paper therefore utilizes Shapley values to explore this question in "black box" situations where the relationship among FRM index features is unknown and non-linear. We also indicate how their contribution changes over time, which equips policymakers with timely policy responses impacting macro-economic variables. For example, during the March 2020 crisis, short-term interest rate policy(CN2YR) and forward guidance (CN210SLOPE) would be the more important risk drivers compared to market volatility and equity market returns. We are thereby able to select macro features for the Chinese region, in line with what Adrian and Brunnermeier (2016) have proposed for the U.S. stock market. FRM@China also equips regulators in China with a regional tool set for financial market policy responses by considering the interaction of FIs from mainland China, Hong Kong, and Taiwan.

References

Aas, K., Jullum, M. and Løland, A. (2019). Explaining individual predictions when features are dependent: More accurate approximations to shapley values, *arXiv preprint arXiv:1903.10464* .

Acharya, V. V., Pedersen, L. H., Philippon, T. and Richardson, M. (2017). Measuring systemic risk, *The Review of Financial Studies* **30**(1): 2–47.

Adrian, T. and Brunnermeier, M. K. (2016). CoVaR, *The American Economic Review* **106**(7): 1705.
URL: *https://doi.org/10.1257/aer.20120555P*

Allen, F. and Gale, D. (2004). Financial intermediaries and markets, *Econometrica* **72**(4): 1023–1061.
URL: *https://doi.org/10.1111/j.1468-0262.2004.00525.x*

Bagliano, F. C. and Morana, C. (2012). The great recession: US dynamics and spillovers to the world economy, *Journal of Banking Finance* **36**(1): 1–13.
URL: *https://doi.org/10.1016/j.jbankfin.2011.06.002*

Battiston, S., Gatti, D. D., Gallegati, M., Greenwald, B. and Stiglitz, J. E. (2012). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk, *Journal of Economic Dynamics and Control* **36**(8): 1121–1141.
URL: *https://doi.org/10.1016/j.jedc.2012.04.001*

Ben Amor, S., Althof, M. and Härdle, W. K. (2021). FRM Financial Risk Meter for Emerging Markets, *Research in International Business and Finance, Accepted* .
URL: *http://dx.doi.org/10.2139/ssrn.3785488*

Bernanke, B. S. and Kuttner, K. N. (2005). What explains the stock market's reaction to federal reserve policy?, *The Journal of Finance* **60**(3): 1221–1257.
URL: *https://doi.org/10.1111/j.1540-6261.2005.00760.x*

Bluhm, M. and Krahnen, J. (2014). Systemic risk in an interconnected banking system with endogenous asset markets, *Journal of Financial Stability* **13**(C): 75–94.
URL: *https://doi.org/10.1016/j.jfs.2014.04.002*

Brownlees, C. and Engle, R. F. (2016). SRISK: A Conditional Capital Shortfall Measure of Systemic Risk, *The Review of Financial Studies* **30**(1): 48–79.
URL: *https://doi.org/10.1093/rfs/hhw060*

Cai, J., Eidam, F., Saunders, A. and Steffen, S. (2018). Syndication, interconnectedness, and systemic risk, *Journal of Financial Stability* **34**: 105–120.
URL: *https://doi.org/10.1016/j.jfs.2017.12.005*

Cheung, Y. L. and Mak, S. C. (1992). The international transmission of stock market fluctuation between the developed markets and the Asian-Pacific markets, *Applied Financial Economics* (1): 43–47.
URL: *https://doi.org/10.1080/758527545*

Eun, C. S. and Shim, S. (1989). International transmission of stock market movements, *Journal of Financial and Quantitative Analysis* pp. 241–256.
URL: *https://doi.org/10.2307/2330774*

Fang, L. and Bessler, D. A. (2018). Is it China that leads the asian stock market contagion in 2015?, *Applied Economics Letters* **25**(11): 752–757.
URL: *https://doi.org/10.1080/13504851.2017.1363854*

Fang, L., Chen, B., Yu, H. and Xiong, C. (2018). The effect of economic policy uncertainty on the long-run correlation between crude oil and the us stock markets, *Finance Research Letters* **24**: 56–63.
URL: *https://doi.org/10.1016/j.frl.2017.07.007*

Freixas, X., Parigi, B. M. and Rochet, J. C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank, *Journal of Money, Credit and Banking* **32**(3): 611–638.
URL: *https://doi.org/10.2307/2601198*

Georgiadis, G. (2016). Determinants of global spillovers from us monetary policy, *Journal of International Money and Finance* **67**: 41–61.
URL: *https://doi.org/10.1016/j.jimonfin.2015.06.010*

Härdle, W. K. and Simar, L. (2019). Applied Multivariate Statistical Analysis, 5 edn, Springer, pp. 363–393 & 431–442.
URL: *https://doi.org/10.1007/978-3-030-26006-4*

Härdle, W. K., Wang, W. and Yu, L. (2016). TENET: Tail-Event Driven NETwork Risk, *Journal of Econometrics* **192**(2): 499–513.
URL: *https://doi.org/10.1016/j.jeconom.2016.02.013*

Huo, R. and Ahmed, A. D. (2017). Return and volatility spillovers effects: Evaluating the impact of shanghai-hong kong stock connect, *Economic Modelling* **61**: 260–272.
URL: *https://doi.org/10.1016/j.econmod.2016.09.021*

Lundberg, S. M. and Lee, S. I. (2017). A unified approach to interpreting model predictions, *Proceedings of the 31st international conference on neural information processing systems*, pp. 4768–4777.

Mieg, H. A. (2020). Volatility as a transmitter of systemic risk: Is there a structural risk in finance?, *Risk Analysis* .
URL: *https://doi.org/10.1111/risa.13564*

Mihoci, A., Althof, M., Chen, C. Y. H. and Härdle, W. K. (2020). FRM Financial Risk Meter, *The Econometrics of Networks (Advances in Econometrics)*, Vol. 42, Emerald Publishing Limited.
URL: *https://doi.org/10.1108/S0731-905320200000042016*

Morgan, J. P. (1997). Introduction to creditmetrics, *Technical document* .

Ramelli, S. and Wagner, A. F. (2020). Feverish stock price reactions to covid-19, *The Review of Corporate Finance Studies* **9**(3): 622–655.
URL: *https://doi.org/10.1093/rcfs/cfaa012*

Ren, R., Althof, M. and Härdle, W. K. (2020). Tail risk network effects in the cryptocurrency market during the COVID-19 crisis, *The Singapore Economic Review, submitted* .
URL: *http://dx.doi.org/10.2139/ssrn.3753421*

Ren, R., Lu, M., Li, Y. and Härdle, W. K. (2021). Financial Risk Meter based on expectiles, *accepted by Journal of Multivariate Analysis* .
URL: *http://dx.doi.org/10.2139/ssrn.3809329*

Rigobon, R. and Sack, B. (2004). The impact of monetary policy on asset prices, *Journal of Monetary Economics* **51**(8): 1553–1575.
URL: *https://doi.org/10.1016/j.jmoneco.2004.02.004*

Rizwan, M. S., Ahmad, G. and Ashraf, D. (2020). Systemic risk: The impact of covid-19, *Finance Research Letters* **36**: 101682.
URL: *https://doi.org/10.1016/j.frl.2020.101682*

Shapley, L. S. (1997). A value for n-person games, *Classics in game theory* **69**.
URL: *https://doi.org/10.1515/9781400881970-018*

Syriopoulos, T., Makram, B. and Boubaker, A. (2015). Stock market volatility spillovers and portfolio hedging: Brics and the financial crisis, *International Review of Financial Analysis* **39**: 7–18.
URL: *https://doi.org/10.1016/j.irfa.2015.01.015*

Thorbecke, W. (1997). On stock market returns and monetary policy, *The Journal of Finance* **52**(2): 635–654.
URL: *https://doi.org/10.1111/j.1540-6261.1997.tb04816.x*

Wang, G. J., Xie, C., Zhao, L. F. and Jiang, Z. Q. (2018). Volatility connectedness in the chinese banking system: Do state-owned commercial banks contribute more?, *Journal of International Financial Markets, Institutions and Money* **57**: 205–230.
URL: *https://doi.org/10.1016/j.intfin.2018.07.008*

Yu, L., Härdle, W. K., Borke, L. and Benschop, T. (2019). An AI approach to measuring financial risk, *The Singapore Economic Review* pp. 1–21.
URL: *https://doi.org/10.1142/S0217590819500668*

Yuan, M. (2006). GACV for quantile smoothing splines, *Computational Statistics & Data Analysis* **50**(3): 813–829.
URL: *https://doi.org/10.1016/j.csda.2004.10.008*

Zhang, D., Hu, M. and Ji, Q. (2020). Financial markets under the global pandemic of covid-19, *Finance Research Letters* **36**: 101528.
URL: *https://doi.org/10.1016/j.frl.2020.101528*

6 Appendix

Table 9: Corporate Name Description

Stock Name	Sector Name	Short Name	Short Sector Name
PING AN BANK CO LTD-A	Banks	PABCL	B
CHINA VANKE CO LTD -A	Real Estate	CVCL	RE
SHENZHEN OVERSEAS CHINESE-A	Consumer Services	SOC	CS
SHENWAN HONGYUAN GROUP CO-A	Diversified Financials	SHGC	DF
FINANCIAL STREET HOLDINGS-A	Real Estate	FSH	RE
BOHAI LEASING CO LTD-A	Capital Goods	BLCL	CG
HUBEI BIOCAUSE PHARMACEUTI-A	Insurance	HBP	I
JINKE PROPERTIES GROUP CO -A	Real Estate	JPGC	RE
YANGO GROUP CO LTD-A	Real Estate	YGCL	RE
GUOYUAN SECURITIES CO LTD-A	Diversified Financials	GSCL	DF
GF SECURITIES CO LTD-A	Diversified Financials	GSCL	DF
CHANGJIANG SECURITIES CO L-A	Diversified Financials	CSCL	DF
JIANGSU ZHONGNAN CONSTRUCT-A	Real Estate	JZC	RE
CHINA MERCHANTS SHEKOU IND-A	Real Estate	CMSI	RE
BANK OF NINGBO CO LTD -A	Banks	BONCL	B
RISESUN REAL ESTATE DEVEL-A	Real Estate	RRED	RE
WESTERN SECURITIES CO LTD-A	Diversified Financials	WSCL	DF
GUOSEN SECURITIES CO LTD-A	Diversified Financials	GSCL	DF
CHINA GREAT WALL SECURITIE-A	Diversified Financials	CGWS	DF
CHINALIN SECURITIES CO LTD-A	Diversified Financials	CSCL	DF
QINGDAO RURAL COMMERCIAL B-A	Banks	QRCB	B
HANG LUNG PROPERTIES LTD	Real Estate	HLPL	RE
HANG SENG BANK LTD	Banks	HSBL	B
CHINA RESOURCES LAND LTD	Real Estate	CRLL	RE
CK ASSET HOLDINGS LTD	Real Estate	CAHL	RE
HENDERSON LAND DEVELOPMENT	Real Estate	HLD	RE
AIA GROUP LTD	Insurance	AGL	I
TRK CORP	Real Estate	TC	RE
HUA YU LIEN DEVELOPMENT CO	Real Estate	HYLDC	RE
GTM HOLDINGS CORP	Real Estate	GHC	RE
ADVANCETEK ENTERPRISE CO LTD	Real Estate	AECL	RE
CHYANG SHENG DYEING & FINISH	Consumer Durables & Apparel	CSDF	CDA
SUN HUNG KAI PROPERTIES	Real Estate	SHKP	RE
NEW WORLD DEVELOPMENT	Real Estate	NWD	RE
BETTER LIFE GROUP CO LTD	Real Estate	BLGCL	RE
RUN LONG CONSTRUCTION CO LTD	Capital Goods	RLCCL	CG
SHIHLIN PAPER	Materials	SP	M
WHARF REAL ESTATE INVESTMENT	Real Estate	WREI	RE
COUNTRY GARDEN HOLDINGS CO	Real Estate	CGHC	RE
BOC HONG KONG HOLDINGS LTD	Banks	BHKHL	B
CATHAY REAL ESTATE DEVELOPME	Real Estate	CRED	RE
KUOYANG CONSTRUCTION	Real Estate	KC	RE
PACIFIC CONSTRUCTION	Real Estate	PC	RE
CHAINQUI CONSTRUCTION DEVELO	Capital Goods	CCD	CG
PRINCE HOUSING & DEVELOPMENT	Real Estate	PHD	RE

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Stock Name	Sector Name	Short Name	Short Sector Name
LONG BON INTERNATIONAL CO LT	Real Estate	LBICL	RE
KINDOM DEVELOPMENT CO LTD	Real Estate	KDCL	RE
KING'S TOWN CONSTRUCTION CO	Real Estate	KTCC	RE
HUNG CHING DEVELOPMENT & CON	Real Estate	HCDC	RE
CROWELL DEVELOPMENT CORP	Real Estate	CDC	RE
DELPHA CONSTRUCTION CO LTD	Real Estate	DCCL	RE
HUNG SHENG CONSTRUCTION LTD	Real Estate	HSCL	RE
HONG PU REAL ESTATE DEVELOP	Real Estate	HPRED	RE
WE & WIN DEVELOPMENT CO LTD	Real Estate	WWDCL	RE
KEE TAI PROPERTIES CO LTD	Real Estate	KTPCL	RE
SAKURA DEVELOPMENT CO LTD	Real Estate	SDCL	RE
I-SUNNY CONSTRUCTION & DEVEL	Real Estate	ICD	RE
HIGHWEALTH CONSTRUCTION CORP	Real Estate	HCC	RE
HUANG HSIANG CONSTRUCTION CO	Real Estate	HHCC	RE
HUAKU DEVELOPMENT CO LTD	Real Estate	HDCL	RE
RUENTEX ENGINEERING & CONSTR	Capital Goods	REC	CG
CITIC LTD	Capital Goods	CL	CG
WAN HWA ENTERPRISE	Real Estate	WHE	RE
CHANG HWA COMMERCIAL BANK	Banks	CHCB	B
KING'S TOWN BANK	Banks	KTB	B
TAICHUNG COMMERCIAL BANK	Banks	TCB	B
UNION INSURANCE CO LTD	Insurance	UICL	I
CHINA BILLS FINANCE CORP	Diversified Financials	CBFC	DF
CHINA LIFE INSURANCE CO LTD	Insurance	CLICL	I
TAIWAN FIRE & MARINE INSURAN	Insurance	TFMI	I
TAIWAN BUSINESS BANK	Banks	TBB	B
BANK OF KAOHSIUNG	Banks	BOK	B
UNION BANK OF TAIWAN	Banks	UBOT	B
TAIWAN LAND DEVELOPMENT CORP	Real Estate	TLDC	RE
FAR EASTERN INTL BANK	Banks	FEIB	B
ENTIE COMMERCIAL BANK	Banks	ECB	B
SHINKONG INSURANCE CO LTD	Insurance	SICL	I
CENTRAL REINSURANCE CO LTD	Insurance	CRCL	I
FIRST INSURANCE CO LTD	Insurance	FICL	I
PRESIDENT SECURITIES CORP	Diversified Financials	PSC	DF
MERCURIES LIFE INSURANCE CO	Insurance	MLIC	I
HUA NAN FINANCIAL HOLDINGS C	Banks	HNFHC	B
FUBON FINANCIAL HOLDING CO	Insurance	FFHC	I
CATHAY FINANCIAL HOLDING CO	Insurance	CFHC	I
CHINA DEVELOPMENT FINANCIAL	Insurance	CDF	I
E.SUN FINANCIAL HOLDING CO	Banks	EFHC	B
YUANTA FINANCIAL HOLDING CO	Diversified Financials	YFHC	DF
MEGA FINANCIAL HOLDING CO LT	Banks	MFHCL	B
TAISHIN FINANCIAL HOLDING	Banks	TFH	B
SHIN KONG FINANCIAL HOLDING	Insurance	SKFH	I
IBF FINANCIAL HOLDINGS CO LT	Diversified Financials	IFHCL	DF
SINOPAC FINANCIAL HOLDINGS	Banks	SFH	B
CTBC FINANCIAL HOLDING CO LT	Banks	CFHCL	B

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Table 9 – continued from previous page

Stock Name	Sector Name	Short Name	Short Sector Name
FIRST FINANCIAL HOLDING CO	Banks	FFHC	B
O-BANK CO LTD	Banks	OCL	B
MERCURIES & ASSOCIATES HOLDI	Insurance	MAH	I
SINO HORIZON HOLDINGS LTD	Real Estate	SHHL	RE
EAST MONEY INFORMATION CO-A	Diversified Financials	EMIC	DF
GLOBAL VIEW CO LTD	Consumer Durables & Apparel	GVCL	CDA
ZONGTAI REAL ESTATE DEVELOPM	Real Estate	ZRED	RE
SUNTY DEVELOPMENT CO LTD	Real Estate	SDCL	RE
HONG KONG EXCHANGES & CLEAR	Diversified Financials	HKEC	DF
HSBC HOLDINGS PLC	Banks	HHP	B
LONGDA CONSTRUCTION & DEVELO	Capital Goods	LCD	CG
FARGLORY LAND DEVELOPMENT CO	Real Estate	FLDC	RE
SWEETEN REAL ESTATE DEVELOPM	Real Estate	SRED	RE
SHINING BUILDING BUSINESS CO	Real Estate	SBBC	RE
FOUNDING CONSTRUCTION & DEV	Real Estate	FCD	RE
CHONG HONG CONSTRUCTION CO	Real Estate	CHCC	RE
CHAILEASE HOLDING CO LTD	Diversified Financials	CHCL	DF
THE SHANGHAI COMMERCIAL & SA	Banks	TSCS	B
TAIWAN COOPERATIVE FINANCIAL	Banks	TCF	B
SHANGHAI PUDONG DEVEL BANK-A	Banks	SPDB	B
HUAXIA BANK CO LTD-A	Banks	HBCL	B
CHINA MINSHENG BANKING-A	Banks	CMB	B
CITIC SECURITIES CO-A	Diversified Financials	CSC	DF
CHINA MERCHANTS BANK-A	Banks	CMB	B
POLY DEVELOPMENTS AND HOLD-A	Real Estate	PDAH	RE
SDIC CAPITAL CO LTD-A	Diversified Financials	SCCL	DF
SINOLINK SECURITIES CO LTD-A	Diversified Financials	SSCL	DF
XINHU ZHONGBAO CO LTD-A	Real Estate	XZCL	RE
CHINA FORTUNE LAND DEVELOP-A	Real Estate	CFLD	RE
SOUTHWEST SECURITIES CO LT-A	Diversified Financials	SSCL	DF
GEMDALE CORP-A	Real Estate	GC	RE
MINMETALS CAPITAL CO LTD-A	Diversified Financials	MCCL	DF
CAPITAL SECURITIES CORP	Diversified Financials	CSC	DF
GREENLAND HOLDINGS CORP LT-A	Real Estate	GHCL	RE
SHANGHAI LUJIAZUI FIN&TRAD-A	Real Estate	SLF	RE
ANXIN TRUST CO LTD-A	Diversified Financials	ATCL	DF
HAITONG SECURITIES CO LTD-A	Diversified Financials	HSCL	DF
SHANGHAI LINGANG HOLDINGS-A	Real Estate	SLH	RE
BANK OF JIANGSU CO LTD-A	Banks	BOJCL	B
BANK OF HANGZHOU CO LTD-A	Banks	BOHCL	B
BANK OF XI'AN CO LTD-A	Banks	BOXCL	B
ORIENT SECURITIES CO LTD-A	Diversified Financials	OSCL	DF
CHINA MERCHANTS SECURITIES-A	Diversified Financials	CMS	DF
BANK OF NANJING CO LTD -A	Banks	BONCL	B
CSC FINANCIAL CO LTD-A	Diversified Financials	CFCL	DF
CAITONG SECURITIES CO LTD-A	Diversified Financials	CSCL	DF
SEAZEN HOLDINGS CO LTD-A	Real Estate	SHCL	RE
TIANFENG SECURITIES CO LTD-A	Diversified Financials	TSCL	DF

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Table 9 – continued from previous page

Stock Name	Sector Name	Short Name	Short Sector Name
INDUSTRIAL BANK CO LTD -A	Banks	IBCL	B
BANK OF BEIJING CO LTD -A	Banks	BOBCL	B
DONGXING SECURITIES CO LT-A	Diversified Financials	DSCL	DF
GUOTAI JUNAN SECURITIES CO-A	Diversified Financials	GJSC	DF
BANK OF SHANGHAI CO LTD-A	Banks	BOSCL	B
HONGTA SECURITIES CO LTD-A	Diversified Financials	HSCL	DF
AGRICULTURAL BANK OF CHINA-A	Banks	ABOC	B
PING AN INSURANCE GROUP CO-A	Insurance	PAIGC	I
PICC HOLDING CO-A	Insurance	PHC	I
BANK OF COMMUNICATIONS CO-A	Banks	BOCC	B
NEW CHINA LIFE INSURANCE C-A	Insurance	NCLIC	I
INDUSTRIAL SECURITIES CO-A	Diversified Financials	ISC	DF
IND & COMM BK OF CHINA-A	Banks	ICBOC	B
SOOCHOW SECURITIES CO LTD-A	Diversified Financials	SSCL	DF
BANK OF CHANGSHA CO LTD-A	Banks	BOCCL	B
CHINA PACIFIC INSURANCE GR-A	Insurance	CPIG	I
CHINA LIFE INSURANCE CO-A	Insurance	CLIC	I
HUATAI SECURITIES CO LTD-A	Diversified Financials	HSCL	DF
EVERBRIGHT SECURITIE CO -A	Diversified Financials	ESC	DF
CHINA EVERBRIGHT BANK CO-A	Banks	CEBC	B
RED STAR MACALLINE GROUP C-A	Real Estate	RSMGC	RE
BANK OF CHENGDU CO LTD-A	Banks	BOCCL	B
ZHESHANG SECURITIES CO LTD-A	Diversified Financials	ZSCL	DF
CHINA GALAXY SECURITIES CO-A	Diversified Financials	CGSC	DF
FOUNDER SECURITIES CO LTD-A	Diversified Financials	FSCL	DF
CHINA CONSTRUCTION BANK-A	Banks	CCB	B
BANK OF CHINA LTD-A	Banks	BOCL	B
BANK OF GUIYANG CO LTD-A	Banks	BOGCL	B
CHINA CITIC BANK CORP LTD-A	Banks	CCBCL	B
CAPITAL FUTURES CORP	Diversified Financials	CFC	DF
DA-LI DEVELOPMENT CO LTD	Real Estate	DDCL	RE
HOTAI FINANCE CO LTD	Diversified Financials	HFCL	DF
CHINA OVERSEAS LAND & INVEST	Real Estate	COLI	RE
LINK REIT	Real Estate	LR	RE
SINO LAND CO	Real Estate	SLC	RE
SINYI REALTY INC	Real Estate	SRI	RE
YULON FINANCE CORP	Diversified Financials	YFC	DF
RUENTEX DEVELOPMENT CO LTD	Real Estate	RDCL	RE
SAN FAR PROPERTY LTD	Real Estate	SFPL	RE
FIRST CAPITAL SECURITIES C-A	Diversified Financials	FCSC	DF
HUAAN SECURITIES CO LTD-A	Diversified Financials	HSCL	DF
POSTAL SAVINGS BANK OF CHI-A	Banks	PSBOC	B
CHINA ZHESHANG BANK CO LTD-A	Banks	CZBCL	B
CHONGQING RURAL COMMERCIAL-A	Banks	CRC	B
ZHONGTAI SECURITIES CO LTD-A	Diversified Financials	ZSCL	DF
BOC INTERNATIONAL CHINA CO-A	Diversified Financials	BICC	DF
NANJING SECURITIES CO LTD-A	Diversified Financials	NSCL	DF

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