Advances in Management & Applied Economics, vol.9, no.1, 2019, 67-117
ISSN: 1792-7544 (print version), 1792-7552 (online)
Scienpress Ltd, 2019

Measuring Systemic Risk and Identifying SIFIs in China's Financial System

Chen Xiangpeng[1], **He Biqing**[2], **Xu Siyu**[3] **and Wang Yuan**[4]

Abstract

Chinese regulators pay very close attention to systemic risk after entering into the tough development phase of "the New Normal". To monitor the systemic risk in China, we construct several measures at the macro and micro levels. On the macro level, we find that, both $CATFIN$ and DCI have strong predictive power for future macroeconomic downside, the former one effectively forecasts the macroeconomic downside from 1 up to 12 months, and the latter one plays a complementary role in predicting MCI from 12 months to 20 months. On the micro level, we employ several widely used measures in a unified framework to measure the systemic contribution of individual firms and we show that it is reasonable for regulators to bring the top 20 firms which are ranked by systemic measures into the systemic risk regulatory system because there is a big gap between the top 20 firms and the rest.

JEL classification numbers: G21; G28; G12; G29
Keywords: systemic risk; tail risk; macroeconomic downside

[1] PBC School of Finance, Tsinghua University.
[2] PBC School of Finance, Tsinghua University.
[3] PBC School of Finance, Tsinghua University.
[4] China Construction Bank, Shenzhen Branch.

Article Info: *Received* : August 30, 2018. *Revised* : October 1, 2018
Published online : January 1, 2019

1 Introduction

1.1 Literature review

After more than two decades of double-digit growth rate, China has now entered into a new development phase of "balanced transition" (also known as the "new normal") — annual GDP growth rate has slowed down to a 25-year low of 6.9 percent in 2015 — an inevitable result of economic restructuring. During the transforming period, China has to deal with the following serious problems: chronic overcapacity in many manufacturing industries; rising local public debt; the aftermath of a real-estate bubble in some big and medium-sized cities; the rapid expansion of shadow banking sector; an increasing amount of bad loans for commercial banks; the notoriously volatile stock markets, so market participants in mounting numbers began to consider the worst-case scenarios. One of the greatest concerns was the systemic risk of Chinese financial system, which was an overarching problem for the central government during the period of stock market "abnormal fluctuation". If sustained high non-performing loans, especially property loans, were to threaten the sound operation of Chinese banking system, the resulting financial instability could be disastrous. This type of scenario highlights the need for linking macroeconomic activities with systemic risk [1], identifying and measuring the contribution of individual financial institutions to systemic risk in Chinese financial system.

In this paper, built on the existing research on macroprudential regulation (Huang et al., 2009, 2012; Adrian and Brunnermeier, 2014; Acharya et al., 2012; Banulescu et al.(2015); Allen, Bali and Tang (2012); Bisias et al.(2012); Giglio et al.(2016)), we construct quite a few systemic measures to monitor the systemic risk in Chinese market at the macro and micro levels. The measures employed here include CATFIN, DCI, Turbulence, Realized Volatility, Market Leverage, Amihud, MES, SES, CES, CoVaR and SRISK.

Our paper contributes to the academic literature on systemic risk of Chinese financial system. In the past decade, only a few studies investigate systemic risk in China. Chen et al.(2014) [2] employ an indicator-based approach proposed by Basel Committee to identify domestic systemically important banks (D-SIBs) in China and find that the systemic importance of major banks is decreasing, while some banks becoming more systemically important should require tight regulations. Wang et al.(2015) [3] apply a Merton model to estimate the default probability of banks to construct a systemic risk index of banks, and show that default correlations exist among asset price of inter banks and different types of banks have a crisis of infectious to the other banks but contagion degree is different. Huang et al. (2015) examine systemic risk in the Chinese banking system by estimating the conditional value at risk (CoVaR), the marginal expected shortfall (MES), the systemic impact index (SII) and the vulnerability index (VI) for 16 listed banks in China, suggest that systemic risk in the Chinese banking system decreased after the financial crisis, but started rising in 2014. As far as we know, this is the first study to construct quite a few measures at the macro and micro levels to monitor the systemic risk in Chinese financial sector and identify the SIFIs in China from both the “Too big to fail” and “Too interconnected to fail” logics.

Our results show that, on the macro level, both $CATFIN$ (tail risk measure) and DCI (comovement index) have strong predictive power for future economic downside in China, the former one effectively forecast the macroeconomic downside (indexed by Macro-economic Climate Index, MCI) from one month up to twelve months, the latter one plays a complementary role in predicting MCI from twelve months to twenty months, while those measures (Turbulence, Realized Volatility, Market Leverage) related to instability, volatility reveal none predictive ability for macroeconomic downturns. Moreover, the linear combination index, which aggregate the information reflected by DCI, Turbulence, Realized Volatility, Market Leverage and Amihud, has much lower predictive power for future macroeconomic downside than DCI. It declares the failure of aggregating the predictability through the simple linear combination, and we will try to use nonlinear methods to construct a systemic risk index combined the information of comovement, contagion, instability and illiquidity in future further research. On the micro level, we employ several widely used measures in a unified framework to measure the systemic contribution of individual firms and find that the systemic contributions of most financial firms reached their peaks in July 2015 during the period of stock market “abnormal fluctuation”. Moreover, in terms of SIFIs ranking, we show that, there is a big gap between the top 20 firms and the 21th one, and it is reasonable for Chinese regulators to bring the top 20 firms which are ranked by the relative systemic measures into the Systemic risk regulatory system.

1.2 Overview of Chinese Financial System

In the early years of reform and opening up [4], the "Big Four" banks[5] are almost equivalent to the entire financial system. On the basis of fully understanding of shortcomings of financial repression and the importance of developed financial markets, Deng and his successors[6] in the helm of CCP(Chinese Communist Party) pushed forward stages of financial reforms to develop a financial market "commensurate with its economic strength. As a result of the unfinished reforms, China"s current financial system is characterized by a number of key features, which are described and analyzed as follows[5].

1. **The banking sector dominates Chinese financial system.**

   After the reforms, the banking sector became more and more comprehensive, diversified and competitive, playing a dominant role in Chinese financial markets. By the end of 2015, it comprised of 3 development banks, 5 large-scale commercial banks, 12 nation-wide joint-stock commercial banks, more than 1000 municipal commercial banks, rural commercial banks and other financial institutions according to the statistical data from CBRC[7]. On one side, since 2008, the banking sector has accounted for over 70 percent of total asset of the financial system (including the central bank) and kept its ROE over 15%. On the other hand, compared to other emerging powers and advanced economies, the high bank credit-to-GDP ratio stands out even if the share of financing via stock market, bond market and the shadow banking system has grown over the past years. In the latter one, commercial banks play a crucial role as well.

   Besides, we should also notice the following negative data, (1) the overall asset quality of Chinese banks continues to slide, in the fourth quarter of 2015, non-performing loan ratio reached 1.67% which is the highest level since 2009; (2) the slowing profit growth rate prompts the banking industry to change its traditional profit mode; (3) Credit risks are getting higher for the sectors with excess capacity, such as concrete, steel and

[5] Industrial and Commercial Bank of China(ICBC), China Construction Bank(CCB), Bank of China(BOC), Agricultural Bank of China(ABC).

[6] The financial reforms in China were mainly marked by Dengxiaoping, Jiangzemin, Zhurongji, Hujingtao, Wenjiabao, Xijingping and Likeqiang

[7] CBRC: the China Banking Regulatory Commission.

aluminium, and with the accelerated elimination of backward production capacity, regulators expect the occurrence of the rising tide of mortgage defaults in those industries.

2. **The volatile and insulated stock market**

   By the end of Q1 2016, the combined market capitalisation of China's Shanghai and Shenzhen bourses surpassed 6.9 trillion USD, a significant rise compared to 400 billion USD in July 2005. Combined, these bourses have surpassed the Tokyo Stock Exchange, which stood at less than 5 trillion USD at the same quarter end. Over 2800 companies are now listed on the Shanghai or Shenzhen stock exchanges.But in comparison with banking sector, the equity industry is too much smaller both in asset size and financing scale.

   Moreover, different from other developed stock market, Chinese stock market is unique in that it is driven more by individual retail investors than institutional investors, which in turn makes it the worlds most volatile stock market outside Greece. In the meantime, unlike the U.S. stock market, which tends to respond to the economic state of the country, the Chinese stock market is only tenuously tied to the Chinese economy. A good example is the stock market "abnormal fluctuation" last year. Both the exuberance and its subsequent plunge seem all the more strange given that the real economy is not doing that well or badly any more.

3. **The uneven Bond Market**

   Triggered by the launch of short term bonds in the inter-bank market in 2005 and the introduction of corporate bonds by the CSRC[8], Chinese bond market scaled up fast in the past few years and has played an important role in the implementation of monetary policies, financial reforms, and economic stimulus packages. But like the equity market, the bond markets role in resource allocation remains limited and it has not been able to satisfy the demand created by China's dramatic economic growth. On the one hand, the composition of bond issuers is uneven. More than 80 percent of the outstanding bonds comprises government bonds, cen-

[8]CBRC: the China Securities Regulatory Commission.

tral bank notes and financial bonds but the share of credit bonds remains very low. On the other hand, the approval and regulatory organisations are still not unified and a market-oriented issuance system has yet to be realised. What is puzzling is that, three main regulators supervise China's interbank bond market: the PBoC, which overseas banks' participation; the National Development and Reform Commission(NDRC), which regulates state-owned enterprises; and the China Banking Industry Association, which is under supervision of the PBoC, which regulates the issuance of commercial paper and medium-term notes. In the meantime, the China Securities Regulatory Commission, which supervises the stock market, therefore overseas private corporate bond market. Therefore, we need to deepen financial reform unswervingly and further development of the municipal and corporate bond markets will help reduce the systematic risk of the economy, especially the banking sector.

Besides, from a trading perspective, the exchange, bank counter and inter-bank markets have become the three main bond markets. Structurally, The inter-bank bond market, which accounts for over 90% bonds in depository, continues to be the main platform for allocating capital and conveying monetary policies, the bank counter market is an extension of the inter-bank bond market and also supports the retail market, and the exchange bond market has grown slowly since the first corporate bonds were issued.

Finally, it needs to be emphasized is, what is still very worrying is the huge regional and local government debt, which equates one third of China's GDP, while the total debt-to-GDP ratio remains moderate.

4. **The shadow banking sector**

   The shadow banking sector, which includes micro loans, bank acceptance bills, entrusted loans, trust products, and leasing activities, has grown dramatically in the years since financial crisis as banks have been hit by tough new regulations that have squeezed some of their traditional activities. Undoubtedly, it is not a uniquely Chinese phenominon, in the past years, constitutes a dual-track pragmatic approach to gradually liberalize the country's repressed interest rate policy[6], and could hold the key to the country's continued growth in the future. However because of the lack of effective regulation, Shadow banking will likely pose risks for financial stability, such as credit and liquidity mismatch, intransparency, increases in off-balance sheet exposures and moral hazards.

The remainder of the paper is organized as follows. Section 2 outlines the methodology and analyzes the systemic risk sources. Section 3 presents empirical results from both the macro and micro levels. The last section concludes.

2 Data and Methodology

Chinese systemic risk measures are based on data for financial institutions from CSMAR and Wind. In details, all the individual stock data, include transaction data and financial information, are downloaded from CSMAR, the index data (i.e. CSI300 index and financial industry index, etc) are obtained from Wind, and those macroeconomic variables data are provided by Wind.

Before surveying and constructing systemic measures in Chinese financial system, it is necessary to briefly analyze sources of systemic risk and the corresponding economic mechanisms as a whole.

Consider N financial firms indexed by i, each with a risk exposure x_i. According to the standard CAPM model, we can simply divide x_i into two parts, the systematic part $y_i^S = \alpha_i x_i$ and the idiosyncratic part $y_i^I = (1-\alpha_i)x_i$, where α_i denotes the proportion of the exposure concerns the systematic risk. Suppose returns on the systematic and idiosyncratic exposures are $r^S + \epsilon^S$ and $r^I + \epsilon^I$ respectively, where both ϵ^S and ϵ^I are independently distributed with zero mean. Hence the return R_i could be simply illustrated as follows without consideration of the particularity of the financial industry,

$$\hat{R}_i = (r^S + \epsilon^S)y_i^S + (r^I + \epsilon^I)y_i^I \tag{1}$$

here, the idiosyncratic shock ϵ^I will not affect any other firms. But as firm i is featured with financial externality, its own negative shock ϵ^I may quickly spread through the financial sector, and the extent of the contagion depends on the size of ϵ^I and the links of i with other institutions, which denoted by the N × N dynamic correlation matrix B. Therefore the actual return of firm i should be written as $R_i = R_i(y_i^S + y_i^i + B + \epsilon^I + \epsilon^I)$, which is different from $\hat{R}_i$. Although *systemic risk* does not yet have an agreed upon formal definition in academia, in general, the occurrence of *systemic events*, which are triggered by either all the R_i below a certain threshold or the sum of R_i behaves terribly for a certain time, must be related to the joint distribution of R_i. So it is useful to categorize the economic mechanisms (sources) of systemic risk in our framework.

Risk-taking is related to the distribution of x_i and α_i in the system. Generally speaking, financial institutions have the ability to adjust its systematic component to remain below the benchmark level, but Central bankers and supervisors increasingly worry about the endogeneity of financial firms in choosing a high-level systematic exposure. *Contagion and Amplification* rationalize the reason why small shocks, especially the idiosyncratic one, can turn into large losses in some situations, i.e., the financial crisis which is triggered by Lehman's bankruptcy. On the one hand, a small negative systematic shock ϵ_S may hit a institution with a high-level systematic exposure to liquidate its assets and further worsen the situation of other market participants through the price mechanism. That is to say, the overall systematic exposure may be larger than the cumulative value. On the other hand, a large enough negative idiosyncratic shock ϵ_i on a financial institution i can heavily hurt firm j through the balance sheet channel and liquidity channel if $b_{i,j}$ is positively large enough.

Bisias et al.(2012)[7] and Giglio et al.(2016)[8] not only do a great job on categorizing and collecting those systemic risk measures which are widely used in recent years, but also remind us that there is not yet an agreed upon (universally acceptable) approach to systemic risk measurement. So we should construct Chinese systemic risk measures for strengthening regulations on SIFIs in China on the basis of China's realities and the effectiveness of the indicators. Below we provide a brief review and summary of both the macro-level and micro-level measures that we will adopt in this research.

2.1 Macromeasure of systemic risk and economic downturns

On the one hand, the financial crisis of 2007-2009, which triggered the global great recession, has demonstrated the significance of understanding and measuring systemic risks and predicting systemic events at the macro level, on the other hand, the risks of a shock to economic and financial stability in China have increased notably in the transition phase of "new normal", thus, a couple of macro-level systemic risk measures are applied to Chinese financial system in this paper.

1. **Tail Risk Measure: CATFIN**

   CATFIN, a measure of the collective catastrophic (tail) risk of the financial sector that forecasts future macroeconomic declines (GDP, industrial production, etc), has been proposed by Allen, Bali and Tang (2012)[9]. In addition to making predictions regarding economic downturns around six months into the future, CATFIN can accurately forecasts macroeconomic declines in Euro and Asia for 8 months and 6 months respectively. Moreover, the authors argue that, the predictability arises from the special role of financial institutions in economic activities, going forward, risk taking in the financial sector is linked to real economic performance, in contrast, the collective risk of non-financial firms have no predictive power. Furthermore, CATFIN is able to forecast economic and financial uncertainty by considering index options and credit default swap spreads.

   In essence, CATFIN is a cross-sectional tail risk measure based on equity returns for all financial firms from two perspectives: VaR(value at risk) and ES(Expected Shortfall). To be specific, Allen, Bali and Tang (2012) firstly take the excess returns on all financial firms (cross-sectional returns) at each period, then estimate the tail risk measures (VaR and ES) through a small group of parametric and non-parametric estimation approaches (i.e. Generalized Pareto distribution, Skewed generalized error distribution, etc), and after repeating the estimation process for each period we can get a group of time series of VaR and Expected shortfall measures[9], finally, the arithmetic averages of the different tail risk mea-

[9]ES_based CATFIN is not presented in this preliminary version, please ask the authors for that via email if you want.

sures are the VaR_based CATFIN and ES_based CATFIN respectively[10]. To a certain extent that the macro-level measure is broad-based and robust to methodological estimation approaches, CATFIN is resistant to possible manipulation concerns. Regulators in each country can estimate an early warning threshold level of CATFIN through historical data, especially in times of crisis. A larger value of CATFIN signals a high likelihood of macroeconomic downturns in the near future.

One might consider the use of Adrian and Brunnermeir (2011)[10] $\Delta CoVaR$ in replace of CATFIN because the two both evaluate systemic risk from the cross-sectional tail risk of financial institutions. However, $\Delta CoVaR$, which is constructed at the micro-level, measures the tail dependency and captures how much an institution adds to the overall risk of the financial system, and cannot appropriately aggregate the individual contributions due to lack of subadditivity, in contrast, CATFIN, which measures the likelihood that a financial collapse will occur in the short run, is defined as the 1% average of VaR (or ES) of the periodical cross-sectional returns of firms estimated using parametric and non-parametric approaches. Besides, it should be emphasized that the effectiveness of this macro-level index relies on the validity of these estimation methods to capture the cross-sectional tail risk. In this paper, we adopt the GPD (Generalized Pareto distribution) and non-parametric approaches only as those skewed fat-tailed distributions(i.e. skewed generalized error distribution (SGED), skewed generalized t (SGT), exponential generalized beta of the second kind (EGB2),etc) cannot fit cross-sectional returns of Chinese financial sector well.

2. **Dimension Reduction Estimators: comovement and instability**

   Giglio, Kelly and Pruitt (2016) points out that, these systemic risk measures summarized by Bisias et al.(2012) reveal low predictive power for future macroeconomic downturns, but an index that aggregates individual measures consistently performs well in forecasting downturns. At the same time, quite a few systemic risk measures related to comovement, contagion, illiquidity, instability and volatility are applicable in

[10]The original measures are always negative as they are estimated from the left tail of distribution, we routinely multiply the values by -1, such that the higher measures indicate larger catastrophic losses.

China. As a consequence, we propose to aggregate systemic risk information over a few macro-level individual indicators through principal components and try to detect a relation between the "synthetic" measure of systemic risk and the macroeconomy, besides the cross-sectional tail risk measure (the risk-taking channel) above. Specifically, we applies these individual indicators (with available data), summarized by Giglio, Kelly and Pruitt (2016) and Bisias et al.(2012), to China and select these applicable indicators below in Chinese financial market.

DCI is the abbreviation of *Dynamic Causality Index* from Billio et al.(2012)[11], which aims to capture the size and the degree of interconnectedness of the financial institutions. concretely speaking, it firstly measure the direction of the relationship between institutions using Granger causality as the following mathematical formulation:

$$\begin{aligned} X_t &= \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \epsilon_t \\ Y_t &= \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t \end{aligned} \tag{2}$$

The causality is based on tests of the null hypothesis that coefficients b_j or c_j are equal to zero. That is to say, in each window, we can obtain the number of causal relationships between the cross-sectional institutions, and then get the *Dynamic Causality Index* as follow:

$$DCI_t = \frac{number\ of\ causal\ relationships\ in\ each\ window}{total\ possible\ number\ of\ causal\ relationships} \tag{3}$$

Clearly, an increase in the DCI indicates a higher level of system interconnectedness.

Turbulence, which is proposed by Kritzman and Li (2010)[12], describes a condition in which asset prices, given their historical patterns of behavior, behave in an uncharacteristic fashion, including extreme price patterns, decoupling of correlated firms, and interdependency of uncorrelated firms. It is always quantified via Mahalanobis distance, which measures the statistical unusualness of the return series given the historical covariance matrix, as follows,

$$Turbulence_t = (y_t - m)^{'} \Sigma^{-1} (y_t - m) \tag{4}$$

where y_t is a $(n \times 1)$vector of asset returns at time t, m is the average vector of asset returns in the past period, and Σ is covariance matrix of asset returns in the past period.

By running this equation overtime, one can generate a time series of the $Turbulence$ index. Kritzman and Li (2010)[13] defines those days for which $Turbulence_t$ lies in the 75% percentile of the time series as the $Turbulence\ Days$ and the others as the $Quiet\ Days$.

RV measures the actual degree of the market's volatility and instability in the past. In this paper, we first construct individual volatility series (monthly frequency) of financial firms from the daily data, and then construct the aggregate series of RV by average the individual volatility in each month. Of course, it should be emphasize that a financial institution would be excluded from the cross section of firms in each month if the number of observations of the institution in that period is less than 10. *illiquidity.*AIM, which is short for Amihud , captures a weighted average of stock-level illiquidity $AIM_{i,t}$:

$$AIM_{i,t} = \frac{1}{K} \sum_{\tau=t-K}^{t} \frac{|r_{i,\tau}|}{turnover_{i,\tau}} * multiple \tag{5}$$

So we can construct the illiquidity index by averaging the Amihud across the financial institutions.

Market Leverage. In general, the higher the financial industry is levered, the contagion will spread faster and be more destructive if a big shock occurs, so we construct a aggregate leverage index of the financial sector by averaging the market leverage across the financial firms to capture the potential for instability and shock propagation.

Beyond doubt, the five indicators above are widely applied to measure overall systemic risk in United States, Euro Zone and other developed regions, so after obtaining time series of DCI, Turbulence, RV, illiquidty and Market Leverage, we should firstly examine whether each indicator of the five could used to monitor systemic risk and forecast future economic downside in China. If two or more are applicable in China, we can try to use principal component analysis, principal component quantile regression and other related methods to aggregate systemic risk information from these indicators and examine whether the integrated systemic risk index has stronger power to forecast economic downturns in China.

2.2 Microlevel systemic risk measures and SIFIs

Undoubtedly monitoring dynamic changes in the overall systemic risk is essential to central bankers and regulators, but the realization of the safety and stability of financial system depends on the measurement of each financial firm's contribution to the overall systemic risk, the identification of SIFIs and the corresponding institutional supervision. Contrary to measures based on periodical financial data and confidential information, public market-based systemic risk measures can be freely updated in real time and may be better able to detect sudden shifts in systemic risk regimes for both the regulators and the academia.

In addition, it needs to be emphasized that, the global financial crisis highlighted that a small turmoil incurred by an individual financial giant such as the Lehman Brothers can cause a big fallback in the financial system – mainly because it is a large-scale enterprise and financial institutions form a highly interconnected network. Thus an outstanding systemic risk measure should be a hybrid measure, which combines the *Too Interconnected To Fail* (TITF) and *Too Big To Fail* (TBTF) logics.

In this paper, we will construct a basic framework of "microlevel" systemic risk measures to identify "systemically Important" institutions in each subsector and determine the contribution of each institution to overall systemic risk in China. Considering the limitations of data in Chinese public market, this paper adopt prominent examples of market-data based measures as follows[11]: *Marginal Expected Shortfall* (MES) and *Systemic Expected Shortfall* of

[11] in this paper, we abandon *Distress Insurance Premium* (DIP) of Huang, Zhou and Zhu(2012)[14] for the inaccuracy of probability of Default (PD) which can only be derived from KMV model based on the volatile stock market data in China

Acharya et al.(2010)[15], *Systemic Risk Measure* (SRISK) of Brownlees and Engle (2012), $\Delta CoVaR$ of Adrian and Brunnermeier (2011), *Component Expected Shortfall* (CES) of Banulescu et al.(2015)[16].

MES, SES and CES. Firstly let's suppose a stock market comprised of N individual firms, denote $r_{i,t}$ the stock return of firm i at time t and $r_{m,t}$ the corresponding aggregate return of the whole market. The aggregate return is the value-weighted average of all individual returns, $r_{m,t} = \sum_{i=1}^{N} w_{i,t} r_{i,t}$, where $w_{i,t}$ is the weight of firm i in the aggregate return at time t.

Expected Shortfall (ES) has attracted the attention of numerous scholars in the systemic risk context, and is applied to measure the aggregate risk of the financial system by the conditional version:

$$ES_{mt}(C) = \mathbb{E}_{t-1}(r_{m,t}|r_{m,t} < C) = \sum_{i=1}^{N} w_{i,t}\mathbb{E}_{t-1}(r_{i,t}|r_{m,t} < C) \tag{6}$$

where C is a threshold, which is always defined as the worst 5% market outcomes or a constant -2%. Then Scaillet (2004) proposed the marginal version – MES, which is the partial derivative of the system conditional ES with respect to the weight of firm i in the market:

$$MES_{it}(C) = \frac{\partial ES_{mt}(C)}{\partial w_{i,t}} = \mathbb{E}_{t-1}(r_{i,t}|r_{m,t} < C) \tag{7}$$

not a few scholars believe that MES could measure the contribution in the aggregate risk of the system (ES) induced by a certain firm i, however, strictly speaking, the condition in ES and MES, which is defined by the threshold, is more a "normal" tail event but not the extreme tail event or the systemic event, furthermore, it is obvious that, MES is designed for the "TITF" logic but does not account for "TBTF". As a consequence, Achaya et al.(2010) made a massive breakthrough and proposed a new indicator "SES", which corresponds to an financial institution's equity drops below its supervision requirement in case of a systemic event defined as the aggregate capital is less than its target level.

$$SES^i = \mathbb{E}[za^i - w_1^i|W_1 < zA] \tag{8}$$

where A denotes the aggregate assets in the financial sector, a^i the total assets of firm i, z the relative target level and W_1, which equals to $\sum_{i=1}^{N} w_1^i$, is the aggregate capital of the financial system. That is, the systemic event is regarded as the "extreme" tail event $W_1 < zA$ in the context of SES. And then using extreme value theory (power law), Achaya et al.(2010) establishes a connection between the "normal" and "extreme" tail events:

$$SES^i = w_0^i[z\frac{a^i}{w_0^i} + kMES^i + \Delta^i] \tag{9}$$

where k and Δ^i are constant terms.

Besides, Banulescu et al.(2015) improves upon MES by multiplying it with the weight of the firm i in the market and proposed *Component Expected Shortfall* (CES):

$$CES_{it}(C) = w_{i,t}\frac{\partial ES_{mt}(C)}{\partial w_{i,t}} = w_{i,t}\mathbb{E}_{t-1}(r_{i,t}|r_{m,t} < C). \tag{10}$$

Obviously, CES combines the TBTF and TITF logics and quantifies the absolute contribution of firm i to the financial system's "normal" tail risk.

Δ **CoVaR**. Artzner et al. (1999)[17] put forward that, VaR, which is the traditional tail-risk measure, cannot pick up potential "tail" losses in the context of extreme events, but on the micro level, its conditional version, $CoVaR^{m|\mathbb{C}(r_{it})}$, is widely applied to estimate individual firm's systemic risk contribution:

$$Pr(r_{mt} < CoVaR_t^{m|\mathbb{C}(r_{it})}|\mathbb{C}(r_{it})) = \alpha. \tag{11}$$

it corresponds to the VaR of the market return when distress event $\mathbb{C}(r_{it})$ of firm i occurs, then $\Delta CoVaR$ is defined as the difference between the VaR of the system conditional on firm i being in distress and that conditional on firm i being in its normal state. specifically, Adrian et al.(2011)[10] defines the distress situation as α % VaR of firm i:

$$\Delta CoVaR_{it}(\alpha) = CoVaR_t^{m|r_{it}=VaR_{it}(\alpha)} - CoVaR_t^{m|r_{it}=Median(r_{it})}, \tag{12}$$

in essence, $\Delta CoVaR$ reverses the conditioning of MES, and measures the degree of impact on the entire market exerted by the institution i's tail event. To a certain extent, it could be considered as a way of improving the definition of tail events in MES as systemic events are always triggered by individual normal tail event, but still suffers the same shortcoming of neglecting TBTF as MES does.

SRISK. following Brownlees and Engle (2010)[18], we define SRISK as follows:

$$SRISK_{it} = max[0; \overbrace{k(D_{it} + (1 - LRMES_{it})W_{it})}^{required\ capital} - \overbrace{(1 - LRMES_{it})W_{it}}^{available\ capital}], \quad (13)$$

where k is the prudential capital ratio, D_{it} the book value of total liabilities of firm i at time t, W_{it} the corresponding market value of equity, and $LRMES_{it}$ denotes the long run marginal expected shortfall, which could be simply regarded as the long run version of daily frequency MES above: $LRMES_{i,t} = MES_{i,t+h}(C) = \mathbb{E}(R_{i,t:t+h}|R_{m,t:t+h} < C)$ in the context of SRISK, the extreme event of firm i is defined as the long-run capital shortfall, which is almost the same as that of SES in equation(4).

So it is indeed an improvement over MES because of the two advantages: (1) combine TITF and TBTF logics; (2) the long-run tail event measured by LRMES is a better indicator for the system's extreme event than the normal daily-frequency tail event. Of course, it still need to be emphasized that long run tail event is not equal to systemic event in China. For example, Chinese stock market abnormal fluctuation in 2015 did not incur subsequent financial crisis or other systemic events.

3 Empirical Findings

In this section, we apply the methodology described in section 3 and examine both the macro-level and micro-level systemic risk in Chinese financial system. We estimate the macromeasures and testify whether the aggregate systemic risk measures can predict future economic declines in the first subsection, then calculate the contribution of individual firms to the overall systemic risk and identify the *Systemically Important Financial Institutions* in each sub-industry of China using those micromeasures mentioned above.

3.1 Monitoring the overall systemic risk in China

The methodologies in subsection 3.1 yield three VaR indicators for each month over the sample period ranges from January 2006 to February 2016. The broad financial industry here, which in fact includes all the real estate and financial firms on the A share market, is quite similar to that of United States which is composed of all NYSE-,AMEX- and NASDAQ- traded financial common stocks(SIC code $\geq$ 6000 and SIC code $\leq$ 6999), and the corresponding return data are downloaded from CSMAR database. In each month over the sample period, the number of firms in the broad industry are far different from each other for the two reasons: (1) a large number of listed companies in Chinese A-share market were suspended from trading at different times for different reasons; (2) not a few firms in this sector went to public in Chinese stock market over the sample period. The average number of cross-sectional financial firms at each month is 162, and the maximum and minimum values are 180 and 135 respectively.

From the upper panel of Figure 1, it is easy to find that, the three 5% VaR indicators from the GPD, the GEV and the nonparametric methods are extremely close to each other, so like the treatment in Allen, Bali and Tang (2012), we define the $CATFIN$ in China as the arithmetic average of the above three VaR indicators, instead of other complicated methods (for example, the first principal component of the three measures). Figure 1 illustrates the monthly 5% VaR indicators in the upper panel and the $CATFIN$ indicator in the lower one over the sample period, and in a certain degree shows that, with the significant positive jump of CATFIN, PMI tends to decline and even drops below 50 around the periods of the financial crisis and the second half of 2015 (after the stock market abnormal fluctuation), but visibly turned up rapidly since CATFIN drops significantly at the start of 2009 and remains at the relatively high level ($\leq$ 50) from 2009 to 2014 in which CATFIN keeps stable at the low level.

[Place Figure 1 about here]

Generally speaking, the big picture which is depicted by CATFIN in Figure 1 accords well with our intuitive sense of the overall systemic risk in China, but it is obviously not enough since CATFIN can only describe systemic risk from the cross-sectional tail risk as what mentioned before, so we will oversight the market-wide systemic risk from the dimensions of interconnectedness, contagion, illiquidity, instability and volatility.

In accordance with the methodology in section 3.1, we calculate DCI, Turbulence, Realized Volatility, Market Leverage and Amihud of Chinese financial sector as what Figure 2 depicts below. Here, it should be note that, the Amihud index , which is applied to measure the liquidity of the financial industry, is directly estimated from the CSI Financial Index (000992.SH) but not average the individual Amihud indicator across all the financial firms in China, and the multiple here is 10^{12}.

A cursory glance at the results reflects that increases in DCI, Turbulence, Realized Volatility and Market Leverage are concentrated in the period from late 2014 to mid 2015, and the decrease in Amihud (illiquidity index) is also clustered in this stage. After careful comparison of the time series of the five indicators, it is easy to find that, Turbulence is much more volatile than others. For example, in the two periods of late 2013 and late 2014, Stock market and macroeconomy both behave well and stably in China, however, turbulence surged up abnormally during that time. We think it may be caused by individual abnormal fluctuations and probably does enormous damage to its performance in monitoring overall systemic risk.

[Place Figure 2 about here]

[Place Figure 3 about here]

As we know, DCI, Turbulence, Realized Volatility, Market Leverage and Amihud reflect different information of systemic risk in Chinese financial sector. To be specific, DCI corresponds to comovement of financial firms, Turbulence to excess volatility in financial markets, Realized Volatility to aggregate volatility, Market Leverage to instability and Amihud to illiquidity. So it may be useful to synthesize the information in the five dimensions to measure overall systemic risk in China more comprehensively. However, as what Figure 3 describes, consistent with the abnormal behaviour of Turbulence during late 2013 and late 2014, the synthesized (five indicators) “Macrolevel systemic risk index” (MacroSys) rises sharply in these periods. Added with the result that Turbulence reveals none predictive ability for macroeconomic downturns in China, we determine to exclude Turbulence from the MacroSys. MacroSys (without Turbulence) depicted by Figure 4 behaves much more stable than that in Figure 3. Consistent with Figure 2, the MacroSys (without Turbulence) remains stable at a relative low level before late 2014 and then tends to rise from the start of 2015 to the abnormal fluctuation period of Chinese stock market.

[Place Figure 4 about here]

3.2 Predictive Power of Systemic Risk for Economic Downturns

In this subsection, we have constructed two kinds of macro-level systemic risk indicators to monitor overall systemic risk in Chinese financial sector from both the tail-risk (risk taking) and "comovement&instability" dimensions above, but the primary condition to convince both the regulators and the academia of the validity of the indexes is to examine whether they can forecast future economic downturns in China.

In United States, the Chicago Fed National Activity Index(CFNAI), which is a weighted average of 85 monthly indicators of national economic activity, is the most widely used index to measure the U.S. aggregate economy, however there is not such a monthly macroeconomic index with high authority, so we select both "macro-economic climate index" and "PMI" to measure Chinese economic activity. It needs to be added that, the "macro-economic climate index" consists of three sub-indexes: pre-warning index, coincident index and leading index.

Firstly, we estimate the following n-month-ahead multivariate predictive regression of "macro-economic climate index(MCI)" and "PMI" on CATFIN and the "macrolevel systemic risk index" (MacroSys) respectively after controlling for one-month lag of the national economic activity indexes:

$$MCI_{t+n} = \alpha + \gamma CATFIN_t + \lambda MCI_{t-i+1} + \epsilon_{t+n} \tag{14}$$

$$MCI_{t+n} = \alpha + \gamma MacroSys_t + \lambda MCI_{t-i+1} + \epsilon_{t+n} \tag{15}$$

$$PMI_{t+n} = \alpha + \gamma CATFIN_t + \lambda PMI_{t-i+1} + \epsilon_{t+n} \tag{16}$$

$$PMI_{t+n} = \alpha + \gamma MacroSys_t + \lambda PMI_{t-i+1} + \epsilon_{t+n} \tag{17}$$

Figure 5 presents the slope coefficients of the four national economic activity indexes on CATFIN, obviously, all the coefficients of the four indexes remain at a large negative value until n approaches to 10, then rise slightly and exceed zero when n $\leq$ 15. The full set of estimates is reported in Table 1. The results indicate that after controlling for one-month MCI (or PMI), the coefficients of the entire three MCIs on CATFIN are all negative and highly significant up to 8 months in advance, and that of PMI on CATFIN remains negative and highly significant up to 4 months. From the two- to six-month-ahead prediction of CATFIN, the coefficients of all MCIs are found to be in high level and strongly significant with Newey-West t-stats ranging from -2.20 to -4.15. The adjusted R_2 values are economically significant in the range of 24% to 91% from two- to six-month-ahead predictability. In comparison with the early-warning and leading index, Coincident Index performs even much better in the regressions. The coefficient remains at the 1% significant level from the two- to fourteen-month-ahead prediction of CATFIN, and the adjusted R_2 values maintain above 20% from one- to nine-month-ahead predictability. In contrary, the prediction of CATFIN on PMI performs much worse. The coefficient becomes insignificant when n > 4 and the adjusted R_2 value is close to zero when n = 3. In a word, as a systemic risk measure, CATFIN has significantly predictive power for future economic downturns in China, and it is reasonable to apply CATFIN to monitor overall systemic risk of Chinese financial sector.

[Place Figure 5 about here]

Then we examine whether the four indictors (excludes Turbulence) reveal predictive ability for future macroeconomic downturns in China. Firstly after running the equations above, we find that, market leverage and realized volatility show none predictability for the four national economic activity indexes, but the performance of DCI is strongly significant for all the three macro-economic climate indexes as Table 2 represents. In details, from the seven- to twenty-month-ahead prediction of DCI, the coefficients of all MCIs are found to be in high level and strongly significant with Newey-West t-stats ranging from -1.94 to -4.84. The corresponding adjusted R_2 values are economically significant in the range of 20% to 70%. In the Contrary, although the coefficients of PMI are found to be in high level and strongly significant from the twelve- to twenty-month-ahead prediction, the negative corresponding adjusted R_2 value shows the unreliability of the regression result. Besides, it is interesting that, the forecast horizon of DCI is complementary with that of CATFIN, in other words, the complementary phenomenon may be caused by that cross-sectional tail-risk mainly reflect the short-run systemic risk while DCI predicts systemic risk in the much longer horizon. On the whole, DCI reveal strong predictive ability for future macroeconomic downturns in China.

[Place Figure 6 about here]

Then we do wonder that whether we can improve the predicative power by aggregating the predictability reflected via all the four indicators through the principal component analysis. But the result shown in Table 3 declares the failure of aggregating the predictability through the simple linear combination. And we will try to use nonlinear methods to construct a systemic risk index combined the information of comovement, contagion, instability and illiquidity in future further research.

[Place Table 2 about here]

[Place Table 3 about here]

3.3 The framework of "microlevel" systemic risk measures

In this section, we will estimate all the micromeasures mentioned above of all the public Chinese financial institutions in an common GARCH-DCC context, and present the results for the framework of "microlevel" systemic risk measures which includes MES, SES, Δ CoVaR, SRISK and CES. Then we estimate pairwise correlations and compare these indicators to get a better understanding of the degree of systemic risk in Chinese financial system. The sample period in this subsection is from Oct 2010 to Dec 2015.

1. **The common GARCH-DCC context**

   The five micromeasures analyzed in this paper have been developed with different frameworks. For instance, Adrian and Brunnermeier (2011) [10] estimates Δ CoVaR with both the quantile regression and the GARCH-DCC model.Differently, Brownlees and Engle(2012) and Banulescu et al.(2015) runs the MES, LRMES, SRISK and CES in a multivariate GARCH-DCC model. Hence, their direct comparison is not straightforward and unified since potential empirical differences exist due to the estimation methods. As a consequence, this paper estimate all the five micromeasures within a unified GARCH-DCC process to provide level-playing field by referring to Benoit et al.(2013). [27]

Following both Brownlees and Engle(2012) and Benoit et al.(2013), we can construct a bivariate GARCH-DCC model for Chinese financial firms:

$$r_t = H_t^{1/2} \upsilon_t \tag{18}$$

where $r_t^{'} = (r_{mt} r_{it})$ denotes the return vector of the stock market and the individual firm and υ_t is a random normally i.i.d vector with zero expected value and a 2×2 identity matrix. The H_t denotes the dynamic conditional variance-covariance matrix:

$$H_t^{1/2} = \begin{pmatrix} \sigma_{mt}^2 & \sigma_{it}\sigma_{mt}\rho_{it} \\ \sigma_{it}\sigma_{mt}\rho_{it} & \sigma_{it}^2 \end{pmatrix} \tag{19}$$

where σ_{mt} and σ_{it} denote the conditional standard deviation and ρ_{it} the conditional correlation between the market and individual firm returns. In the context of GARCH-DCC model, ρ_{it} is time-varying and can fully capture the interdependence.

After obtaining conditional correlation and the standardized residuals through the GARCH-DCC model, one can calculate MES and CoVaR referring to the technical details represented in Brownlees and Engle(2012) and Benoit et al.(2013).

2. **Results for TITF-related measures**

We have summarized that MES, Δ CoVaR and LRMES, which only account for the "TITF" logic, differ in the definitions of tail events and calculation methods in section 3. In this part, we will present results for these TITF-related measures (MES, Δ CoVaR and LRMES).

Figure 7 shows cross-sectional average values of TITF-related measures, where the distressed state of CoVaR is defined as the 5% quantile of each firm, the threshold of MES as the conditional VaR of the market return, and the market index as CSI 300 Index. After obtaining the times series of TITF-related measures of individual firms, we calculate the corresponding arithmetic average of these measures across all the financial firms.Besides, ΔCoVaR-DCC in Figure 7 denotes ΔCoVaR values estimated through the GARCH-DCC model and ΔCoVaR-quant ΔCoVaR values estimated through quantile regression.

[Place Figure 7 about here]

In general, the four indicators remains in the same pattern, and are highly correlated with each other during the sample period (see Table 5). That is to say, the comovement could help us the supervise the systemic risk of the entire industry. From late 2010 to the second half of 2014, the entire financial sector maintains in a steady state in terms of systemic risk, but things worsen dramatically in November 2014 which is reflected by the sharp surges of these indicators. The instability of the whole sector culminates around the period of abnormal fluctuation of Chinese stock market.

[Place Table 4 about here]

[Place Table 5 about here]

In terms of individual indicators, the average value of LRMES is much larger than that of others because it measures the long-run shortfall condition on the long run tail events, while the other three correspond to the short-run shortfall and short-run tail events. At the same time, the fact that the average value of MES is roughly two times larger than that of Δ CoVaR can be easily explained by their different constructive logics. The former one is the expected shortfall of an individual firm condition on the distress state of the market index, while the latter on the VaR of market index conditional on this particular firm being in financial distress if the distribution is symmetric. From Artzner et al. (1999)[17], we know that, VaR cannot pick up potential "tail" losses in the context of extreme events while expected shortfall is the expected return conditional on the tail events. Moreover, it is reasonable that a particular firm's sensitive degree towards the tail event of the market index is much larger than that in the opposite direction. In addition, Table 4 shows that (1) MES is much more volatile than others; (2) the four indicators have obvious attribute of leptokurtosis and fat-tail. Besides, we find that, ΔCoVaR-DCC remains remarkably consistent with ΔCoVaR-quant in the sample period except for a bit ahead of the latter one. It implies that, the different methods of ΔCoVaR have little influences on the estimation results of ΔCoVaR.

There is not enough room in this paper for represent all the TITF-related measures of the 48 public financial firms in Chinese financial system, so we select 19 most important institutions from the three subsectors (the banking industry, the security industry and the insurance industry) and illustrate their TITF-related measures in Figure 9. Overall, the TITF-related measures of the "big Four" are smaller than other banks, security and insurance companies, indicating a relatively negative correlation between Market Cap and the TITF-related measures. In other words, a bigger firms tends to have lower TITF-related measures, contributing less to the systemic risk of the financial system in terms of interdependence.

3. **Results for measures combined TITF and TBTF**

We have mentioned above that, an outstanding micro-level systemic risk measure should be a hybrid measure, which combines the *Too Interconnected To Fail* (TITF) and *Too Big To Fail* (TBTF) logics. In this part, we will represent results for these hybrid measures, which consist of SES, Scaled-ΔCoVaR, SRISK and CES.

Here it is necessary to note, (1)ΔCoVaR only accounts for the TITF logic, but Scaled-ΔCoVaR, which is calculated by Scaled-$\Delta CoVaR_{i,t} = \Delta CoVaR_{i,t} \times book\_equity_{it}$, contains the size information of firm and to some extent can be regarded as a hybrid measure; (2)Acharya et al.(2010) proposes that SES is a linear combination of MES and leverage, and one can use the information contained in the moderately bad days (MES) and firm's leverage to estimate what would happen during a real crisis (SES), so after obtaining MES and leverage indicators of a particular firm at each period, we can calculate the corresponding SES through the linear coefficients. But the real financial crisis, like the 2009-2008 global financial crisis, never appears in China, and we can not select a real crisis period to estimate the coefficients as what Acharya et al.(2010) does, for robustness, we adopt two groups of coefficients in this paper: the stock market slump period 2008.1 to 2008.12 is assumed to be Chinese financial crisis, and the group of coefficients estimated from this period is denoted as Coefficient_China; the group of coefficients in Acharya et al.(2010) is adopted too, and is denoted as Coefficient_US.

[**Place Figure 10 to reffig:11 about here**]

Figure reffig:8 to reffig:11 represent time series of the four hybrid measures of all the 48 public firms in Chinese financial system[12]. For ease of comparison between the four hybrid measures (SES takes two forms), each risk measure (SES, ΔCoVaR, SRISK and CES) is represented by the form of relative systemic risk measure. In details, the relative systemic risk measure of a particular firm is calculated by dividing its real value at each point in time by the average value for the public financial institutions over the sample period. After carefully examining the performance of these relative systemic risk measures across all the financial firms, it is easy to summarize that, (1) the "big five banks" (ICBC,CCB,ABC,BOC,BANKCOMM) unsurprisingly are ranked in the first group and China Life could also be groupped in this category; (2) the two insurance giants (PING AN of China and CPIC) and those Nationwide Joint-stock Commercial Banks (such as PAB, CMB, SPD,etc) rank in the second group, and the low rankings of most security companies may be accounted for their small size relative to those large-scale banks and insurance companies; (3) CITIC, HAITONG and HTSC rank in the top of the security companies.

[**Place Table 6 about here**]

In addition, Table 6 represents the 20 most important public financial firms in China ranked by time series average of the hybrid measures

[12]Refer to table "Abbreviation for public financial institutions in China" in the appendix if you are not familiar with Chinese financial market

across these financial institutions, and Table 6 lists the corresponding average values of hybrid measures corresponding to the top 25 firms. Combined with the information shown in both Table 6 and Table 6, it is not difficult to draw the following conclusions: (1) the "big five banks" (ICBC,CCB,ABC,BOC,BANKCOMM) rank in the top 6 of all the relative hybrid measures; (2) The three insurance giants(China Life, PING AN of China and CPIC)are among in the top firms according SES_CHN, Scaled Δ CoVaR and CES, but are ranked much lower in the context of other two measures, especially SRISK. In the rankings of SRISK, the four insurance giants(China Life, PING AN of China, CPIC and NCI) are in the bottom 4. The main reason is that, in the old insurance solvency supervision system, all the insurance companies are adequately capitalized and it is somewhat impossible to approach the capital threshold; (3) CITIC, HAITONG, HTSC, ORIENT SEC and GUOSEN SEC rank in the top of the security companies; (4) There is a large gap between top 20 firms and the 21th firm according to all the relative hybrid measures. We think it is very valuable for Chinese regulators, because it is unreasonable to strictly supervise the systemic risk of all the financial firms or group all the public financial firms as the SIFIs (Systemically Important Financial Institutions), so it is the realistic action to classify the top 20 public financial firms as the SIFIs, and strictly supervise in real time on account of low regulatory cost and great real-time performance.

4 Conclusion

As the ratio of bad loans has moved up sharply after China entered into a tough development phase of "balanced transition", concerns have mounted about the possibility of a financial crisis due to distress in Chinese real enterprise. Although the banking industry has enough capability to make up for losses caused by the surging bad loan in this stage, it is necessary for the regulators and financial institutions in China to monitor the system risk both in the macro and micro levels. If a systemically important Chinese financial firms were to fail, it would cause serious problems in China and around the world.

In this paper, built on the existing research on macroprudential regulation (Huang et al., 2009, 2012; Adrian and Brunnermeier, 2014; Acharya et al., 2012; Banulescu et al.(2015); Allen, Bali and Tang (2012); Bisias et al.(2012); Giglio et al.(2016)), we construct quite a few systemic measures to monitor the systemic risk in Chinese market at the macro and micro levels. The measures employed here include CATFIN, DCI, Turbulence, Realized Volatility, Market Leverage, Amihud, MES, SES, CES, CoVaR and SRISK.

Our results show that, on the macro level, both $CATFIN$ (tail risk measure) and DCI (comovement index) have strong predictive power for future economic downside in China, the former one effectively forecast the macroeconomic downside (indexed by Macro-economic Climate Index, MCI) from one month up to twelve months, the latter one plays a complementary role in predicting MCI from twelve months to twenty months, while those measures (Turbulence, Realized Volatility, Market Leverage) related to instability, volatility reveal none predictive ability for macroeconomic downturns. Moreover, the linear combination index, which aggregate the information reflected by DCI, Turbulence, Realized Volatility, Market Leverage and Amihud, has much lower predictive power for future macroeconomic downside than DCI. It declares the failure of aggregating the predictability through the simple linear combination, and we will try to use nonlinear methods to construct a systemic risk index combined the information of comovement, contagion, instability and illiquidity in future further research. On the micro level, we employ several widely used measures in a unified framework to measure the systemic contribution of individual firms and find that the systemic contributions of most financial firms reached their peaks in July 2015 during the period of stock market “abnormal fluctuation”. Moreover, in terms of SIFIs ranking, we show that, there is a big gap between the top 20 firms and the 21th one, and it is reasonable for Chinese regulators to bring the top 20 firms which are ranked by the relative systemic measures into the Systemic risk regulatory system.

Besides, it needs to be stressed that this paper is the first preliminary version of our research on systemic risk of Chinese financial sector, and we should do more robustness tests and other related improvements to make it more convincing.

References

[1] Viral V Acharya. A theory of systemic risk and design of prudential bank regulation. *Journal of financial stability*, 5(3):224–255, 2009.

[2] Yibing Chen, Yong Shi, Xianhua Wei, and Lingling Zhang. Domestic systemically important banks: A quantitative analysis for the chinese banking system. *Mathematical Problems in Engineering*, 2014, 2014.

[3] Yajie Wang, Xiaoliang Shan, and Junqiong Geng. Estimating the systemic risk of chinas banking industries based on merton model. *Applied Mathematics & Information Sciences*, 9(2):957–964, 2015.

[4] Franklin Allen, Jun Qian, and Meijun Qian. China's financial system: past, present, and future. *Present, and Future (March 28, 2007)*, 2007.

[5] Franklin Allen, Jun Qian, Chenying Zhang, Mengxin Zhao, et al. China's financial system: opportunities and challenges. Technical report, National Bureau of Economic Research, 2012.

[6] Hao Wang, Honglin Wang, Lisheng Wang, and Hao Zhou. Shadow banking: China's dual-track interest rate liberalization. *Available at SSRN 2606081*, 2015.

[7] Dimitrios Bisias, Mark D Flood, Andrew W Lo, and Stavros Valavanis. A survey of systemic risk analytics. *US Department of Treasury, Office of Financial Research*, (0001), 2012.

[8] Stefano Giglio, Bryan Kelly, and Seth Pruitt. Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics*, 2016.

[9] Linda Allen, Turan G Bali, and Yi Tang. Does systemic risk in the financial sector predict future economic downturns? *Review of Financial Studies*, 25(10):3000–3036, 2012.

[10] Tobias Adrian and Markus K Brunnermeier. Covar. Technical report, National Bureau of Economic Research, 2011.

[11] Monica Billio, Mila Getmansky, Andrew W Lo, and Loriana Pelizzon. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559, 2012.

[12] Mark Kritzman, Yuanzhen Li, Sebastien Page, and Roberto Rigobon. Principal components as a measure of systemic risk. 2010.

[13] Mark Kritzman and Yuanzhen Li. Skulls, financial turbulence, and risk management. *Financial Analysts Journal*, 66(5):30–41, 2010.

[14] Xin Huang, Hao Zhou, and Haibin Zhu. Assessing the systemic risk of a heterogeneous portfolio of banks during the recent financial crisis. *Journal of Financial Stability*, 8(3):193–205, 2012.

[15] Viral V Acharya, Lasse Heje Pedersen, Thomas Philippon, and Matthew P Richardson. Measuring systemic risk. 2010.

[16] Georgiana-Denisa Banulescu and Elena-Ivona Dumitrescu. Which are the sifis? a component expected shortfall approach to systemic risk. *Journal of Banking & Finance*, 50:575–588, 2015.

[17] Philippe Artzner, Freddy Delbaen, Jean-Marc Eber, and David Heath. Coherent measures of risk. *Mathematical finance*, 9(3):203–228, 1999.

[18] Christian T Brownlees and Robert Engle. Volatility, correlation and tails for systemic risk measurement. *WP NYU-Stern*, 2010.

[19] Zhiguo He and Wei Xiong. Rollover risk and credit risk. *The Journal of Finance*, 67(2):391–430, 2012.

[20] Xin Huang, Hao Zhou, and Haibin Zhu. A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, 33(11):2036–2049, 2009.

[21] Larry Eisenberg and Thomas H Noe. Systemic risk in financial systems. *Management Science*, 47(2):236–249, 2001.

[22] Xin Huang, Hao Zhou, and Haibin Zhu. Systemic risk contributions. *Journal of financial services research*, 42(1-2):55–83, 2012.

[23] Andrew G Haldane and Robert M May. Systemic risk in banking ecosystems. *Nature*, 469(7330):351–355, 2011.

[24] Giulio Girardi and A Tolga Ergün. Systemic risk measurement: Multivariate garch estimation of covar. *Journal of Banking & Finance*, 37(8):3169–3180, 2013.

[25] María Rodríguez-Moreno and Juan Ignacio Peña. Systemic risk measures: The simpler the better? *Journal of Banking & Finance*, 37(6):1817–1831, 2013.

[26] Monica Billio, Mila Getmansky, Andrew W Lo, and Loriana Pelizzon. Econometric measures of systemic risk in the finance and insurance sectors. Technical report, National Bureau of Economic Research, 2010.

[27] Sylvain Benoit, Gilbert Colletaz, Christophe Hurlin, and Christophe Pérignon. A theoretical and empirical comparison of systemic risk measures. *HEC Paris Research Paper No. FIN-2014-1030*, 2013.

[28] Sylvain Benoit, Jean-Edouard Colliard, Christophe Hurlin, and Christophe Pérignon. Where the risks lie: a survey on systemic risk. *HEC Paris Research Paper*, 2015.

[29] Yakov Amihud and Haim Mendelson. Asset pricing and the bid-ask spread. *Journal of financial Economics*, 17(2):223–249, 1986.

[30] Yakov Amihud. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, 5(1):31–56, 2002.

[31] Nicholas Chan, Mila Getmansky, Shane M Haas, and Andrew W Lo. Systemic risk and hedge funds. Technical report, National Bureau of Economic Research, 2005.

[32] Andrew W Lo and Jiang Wang. Trading volume: definitions, data analysis, and implications of portfolio theory. *Review of Financial Studies*, 13(2):257–300, 2000.

[33] Monica Billio and Loriana Pelizzon. Value-at-risk: a multivariate switching regime approach. *Journal of Empirical Finance*, 7(5):531–554, 2000.

[34] Carlo Acerbi and Dirk Tasche. On the coherence of expected shortfall. *Journal of Banking & Finance*, 26(7):1487–1503, 2002.

[35] Carlo Acerbi and Dirk Tasche. Expected shortfall: a natural coherent alternative to value at risk. *Economic notes*, 31(2):379–388, 2002.

[36] Olivier Scaillet. Nonparametric estimation and sensitivity analysis of expected shortfall. *Mathematical Finance*, 14(1):115–129, 2004.

[37] Olivier Scaillet. Nonparametric estimation of conditional expected shortfall. *Insurance and Risk Management Journal*, 74(1):639–660, 2005.

[38] Turan G Bali. An extreme value approach to estimating volatility and value at risk*. *The Journal of Business*, 76(1):83–108, 2003.

[39] Turan G Bali and Panayiotis Theodossiou. A conditional-sgt-var approach with alternative garch models. *Annals of Operations Research*, 151(1):241–267, 2007.

[40] Xin Huang, Hao Zhou, and Haibin Zhu. Systemic risk contributions. *Journal of Financial Services Research*, pages 1–29, 2010.

[41] Lamont Black, Ricardo Correa, Xin Huang, and Hao Zhou. The systemic risk of european banks during the financial and sovereign debt crises. *Journal of Banking & Finance*, 63:107–125, 2016.

[42] Daron Acemoglu, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608, 2015.

[43] Oliver De Bandt and Philipp Hartmann. What is systemic risk today? *Risk Measurement and Systemic Risk*, pages 37–84, 1998.

[44] Olivier De Bandt and Philipp Hartmann. Systemic risk: a survey. 2000.

[45] Qiubin Huang, Jakob de Haan, and Bert Scholtens. Analyzing systemic risk in the chinese banking system. 2015.

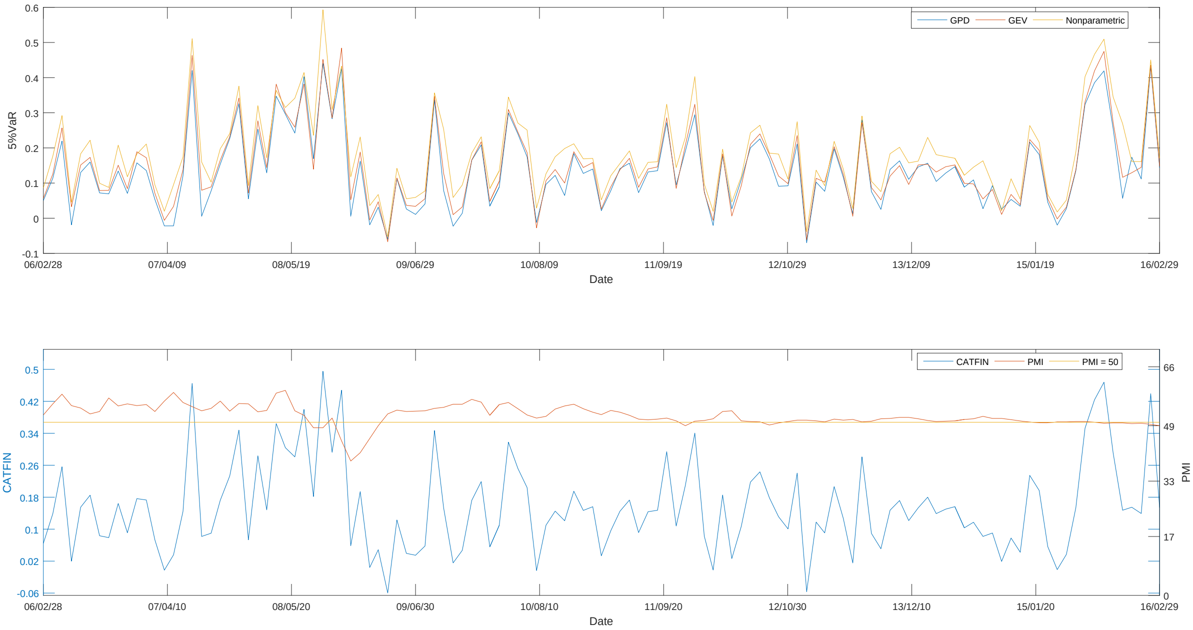


Figure 1:

Five percent VaR and the CATFIN of Chinese financial system. The upper panel depicts the monthly 5% VaR of Chinese financial sector.estimated from the GPD, the GEV and the nonparametric methods, while the lower one presents the monthly CATFIN, measured as the arithmetic mean of the above three 5% VaR indicators, and the PMI index of China.

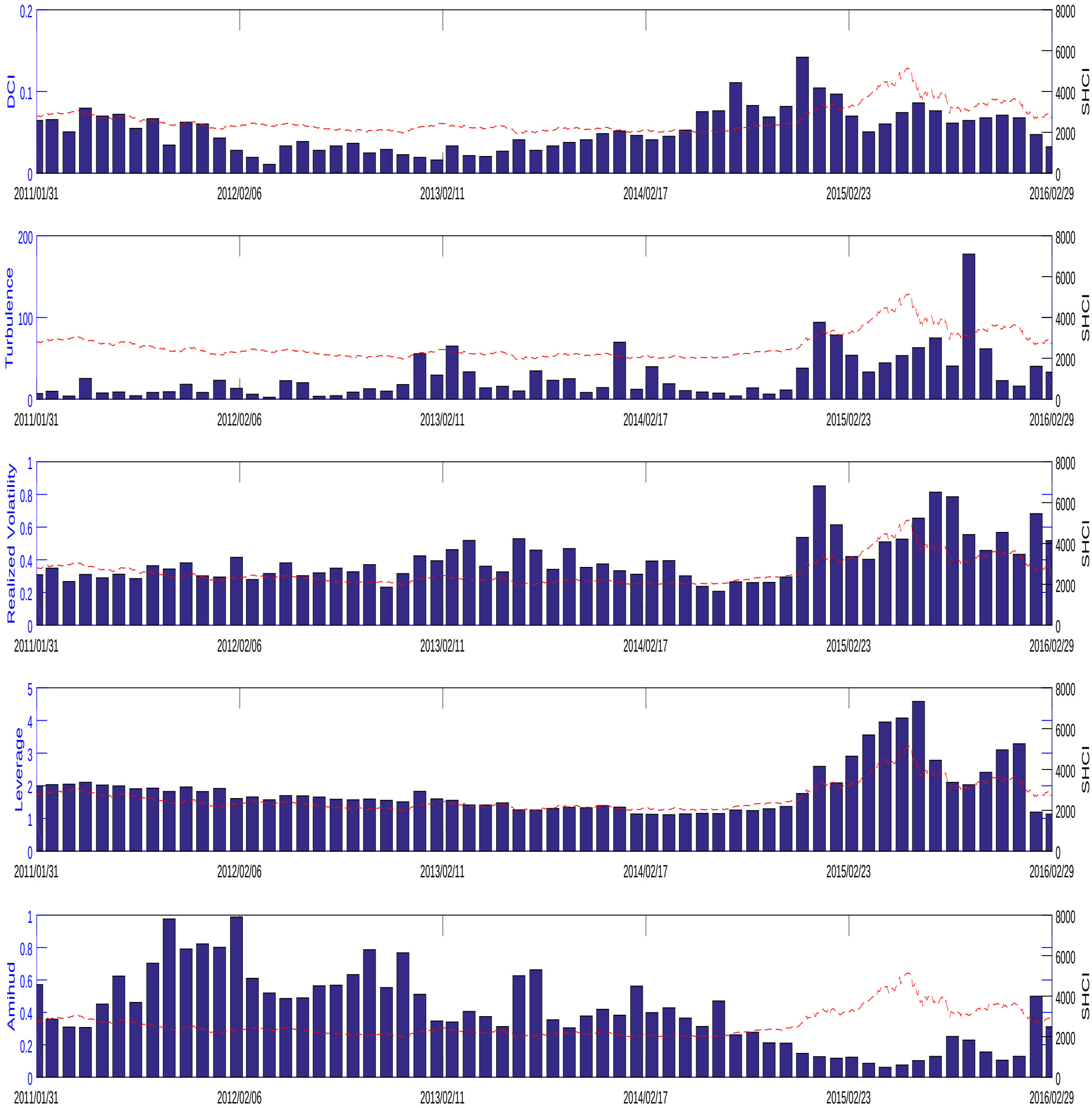


Figure 2:

Measures related to comovement and illiquidity

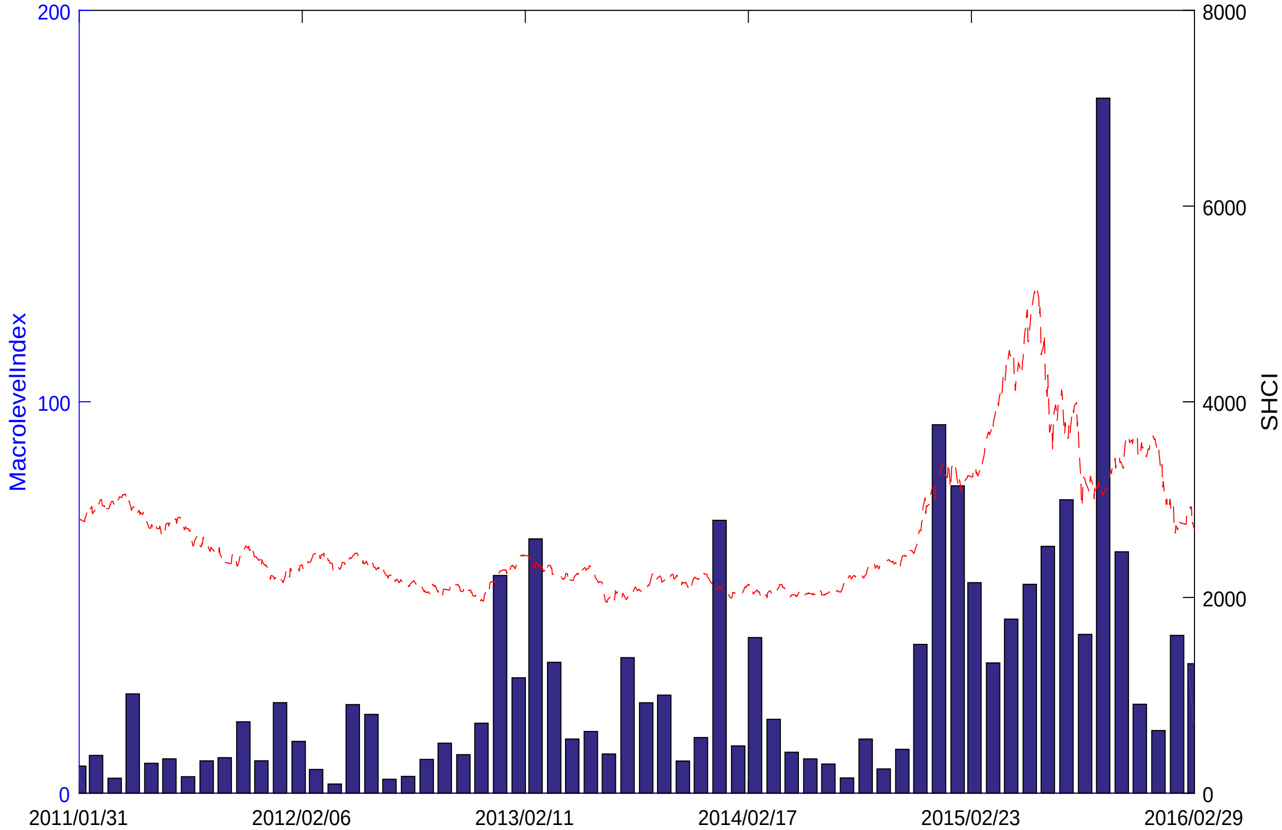


Figure 3:

Macrolevel systemic risk

The macrolevel systemic risk index in Figure 3 aggregate the information reflected by DCI, Turbulence, Realized Volatility, Market Leverage and Amihud measures in China.

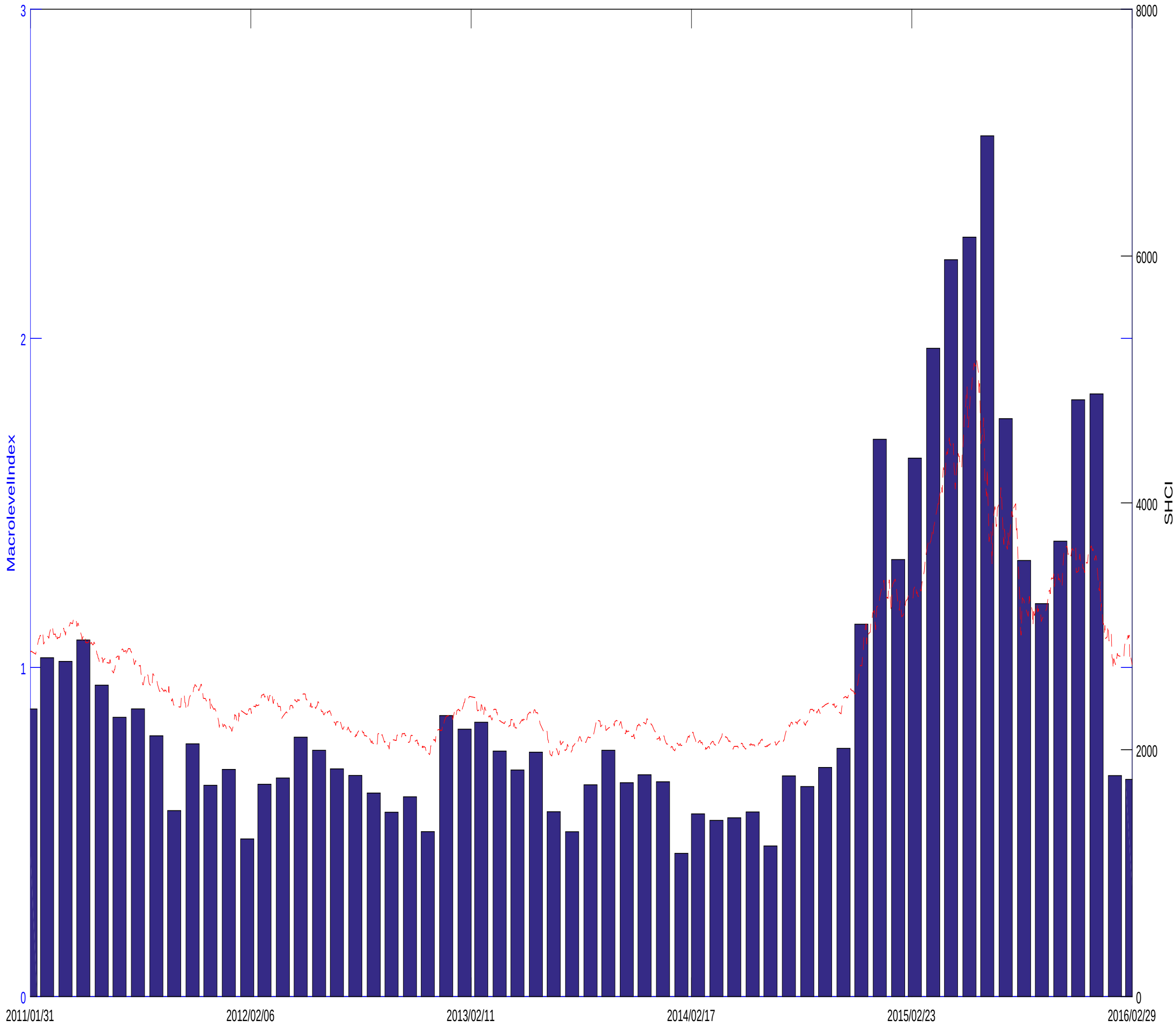


Figure 4:

MacroSys (without Turbulence)
The macrolevel systemic risk index (without Turbulence) in Figure 4 aggregate the information reflected by DCI, Realized Volatility, Market Leverage and Amihud measures in China.

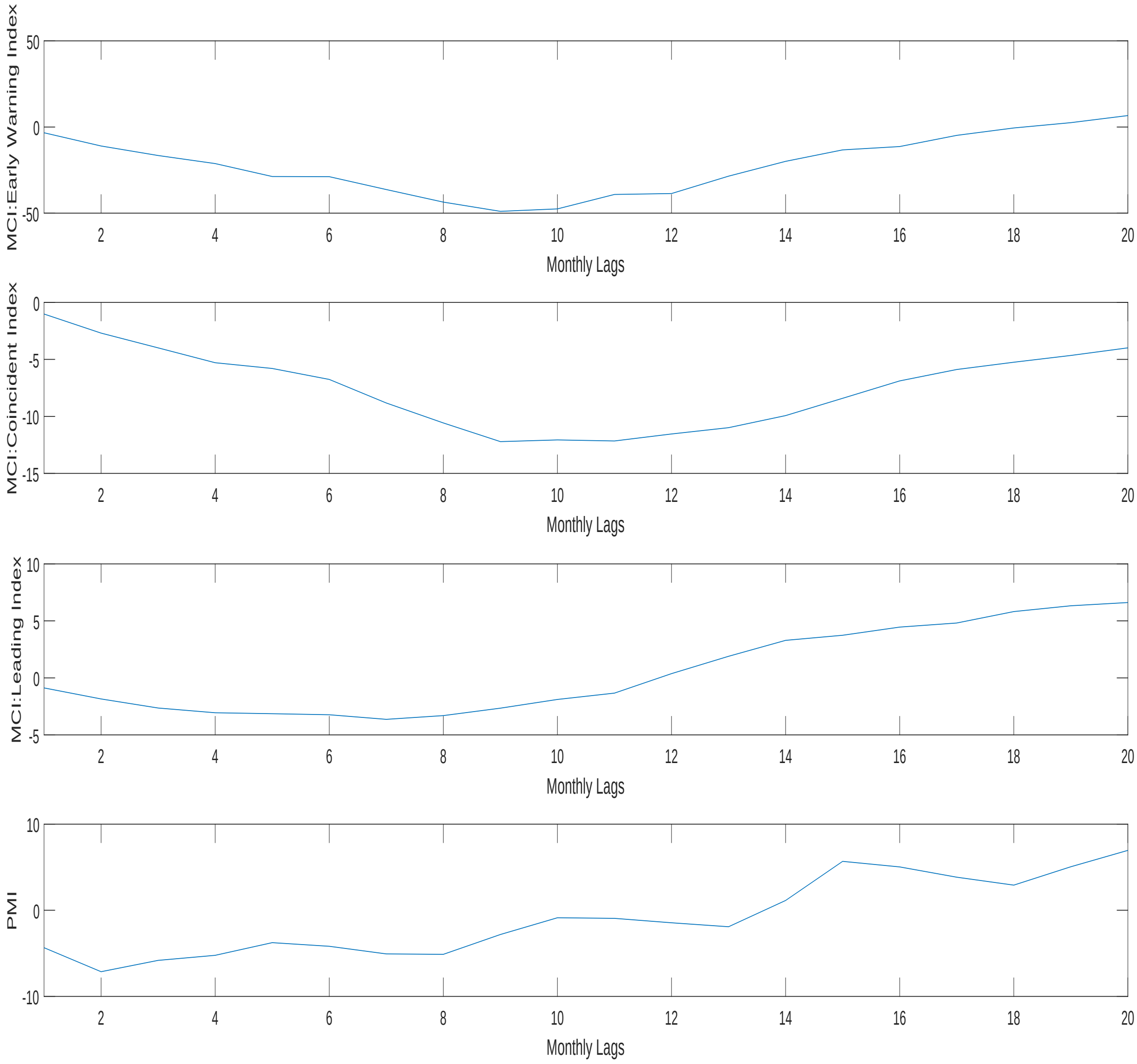


Figure 5:

Predictive ability of CATFIN for future economic downside
The four panels from top to bottom in Figure 5 depict the coefficients of MCI: pre-warning index, MCI:coincident index, MCI:leading index and PMI index on CATFIN respectively. The sample period is from Feb 2006 to Feb 2016.

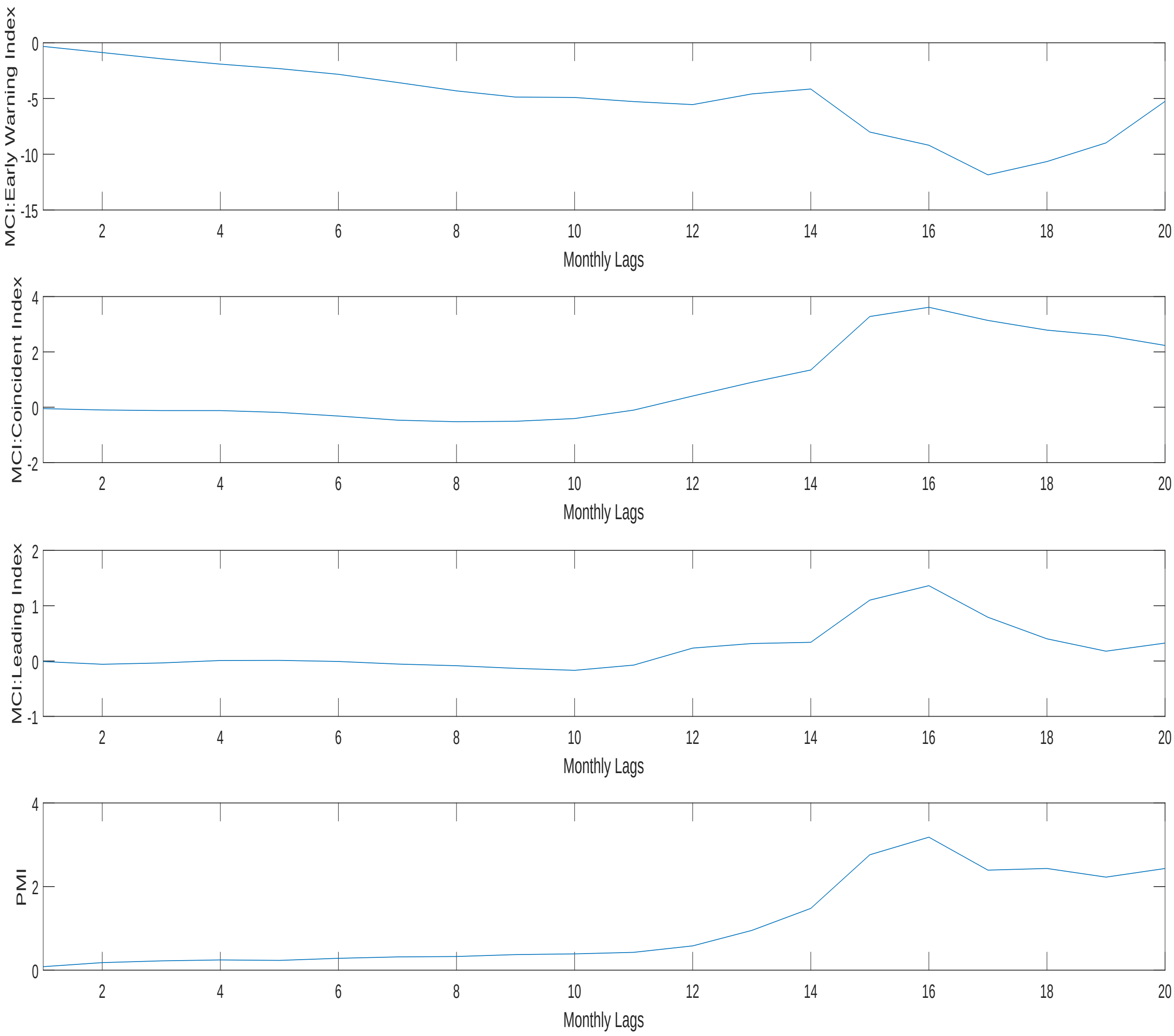


Figure 6:

Predictive ability of MacroSys (without Turbulence) for future economic downside

The four panels from top to bottom in Figure 6 depict the coefficients of MCI: pre-warning index, MCI:coincident index, MCI:leading index and PMI index on CATFIN respectively. The sample period is from Feb 2006 to Feb 2016.

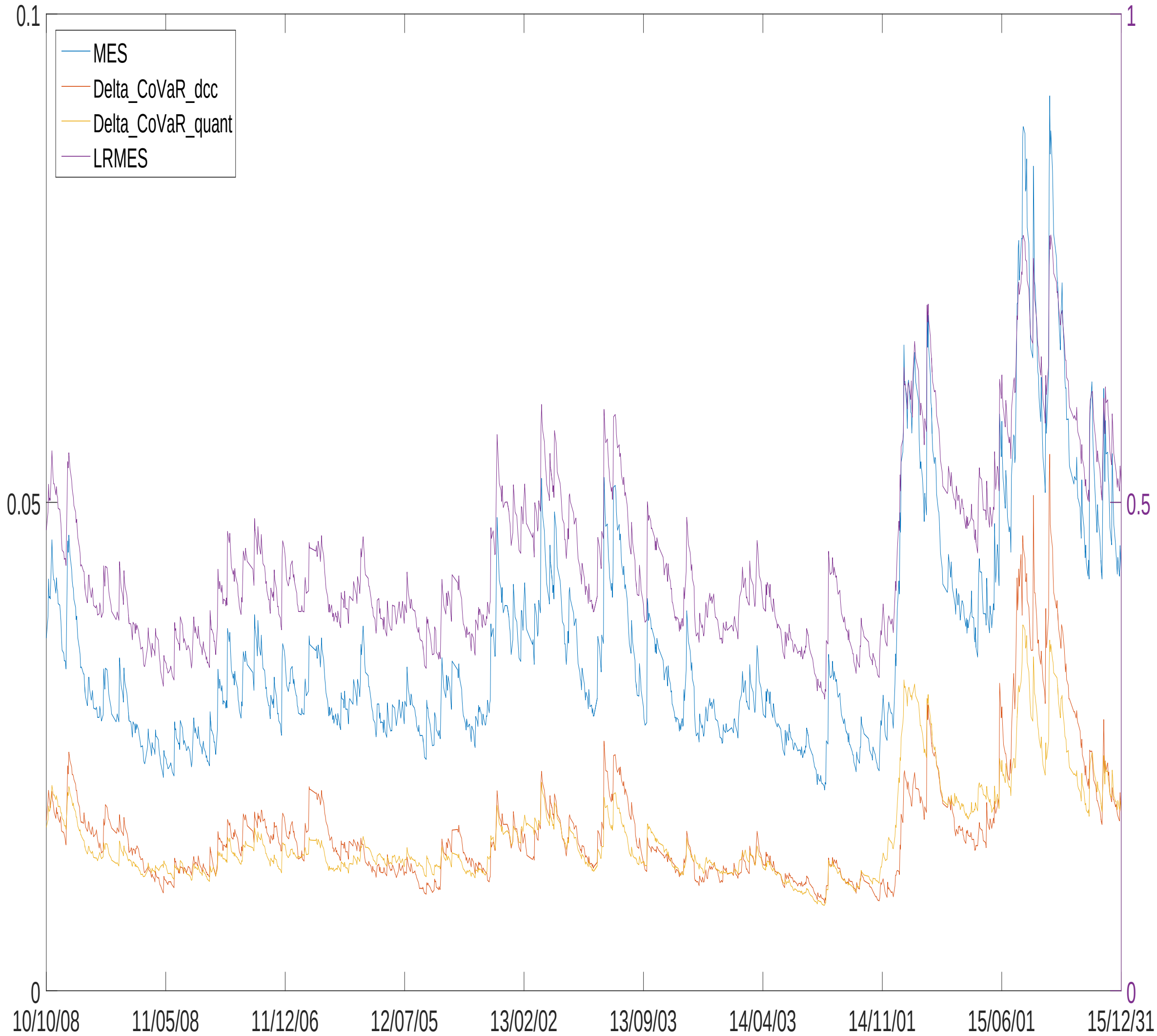
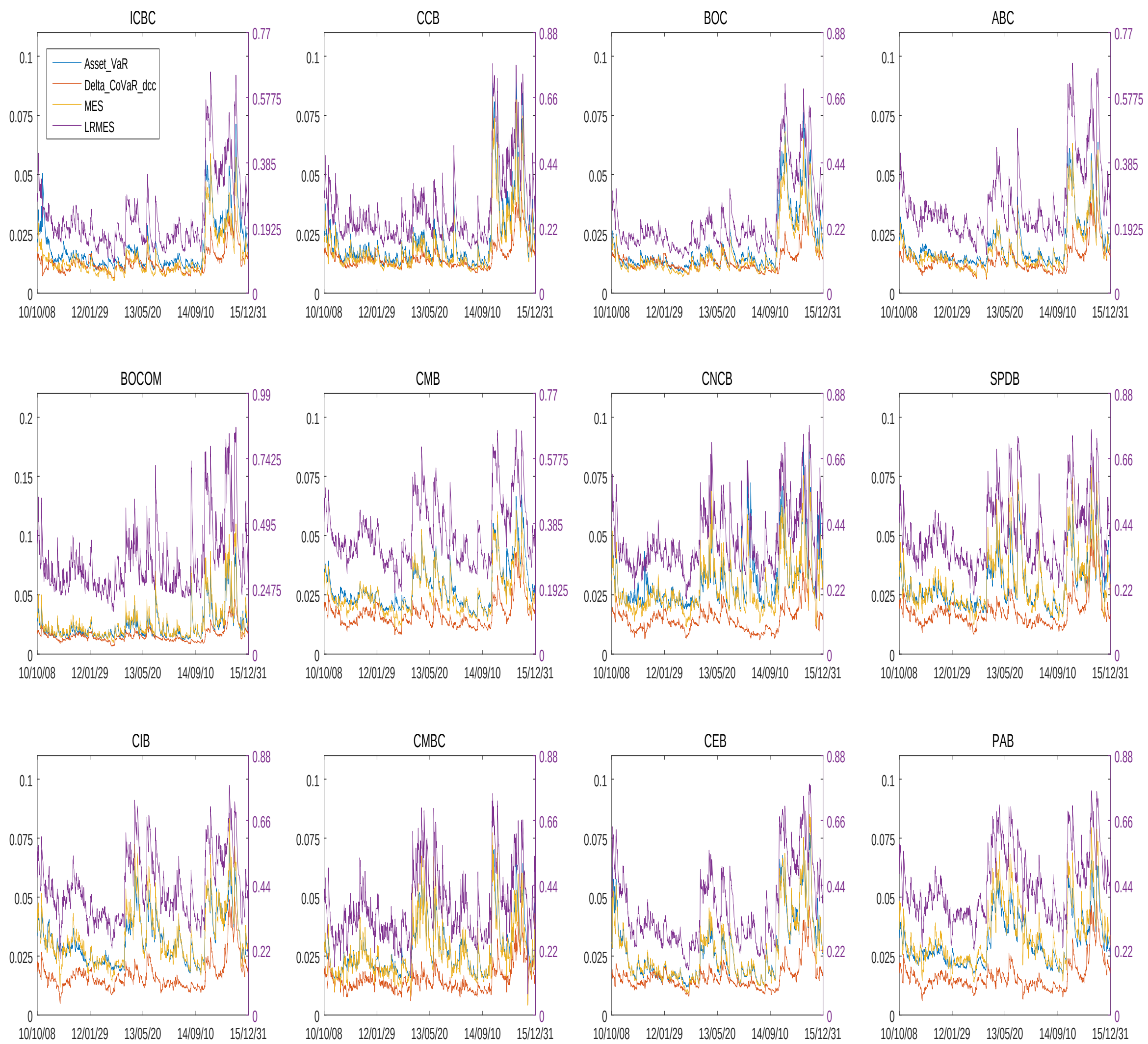


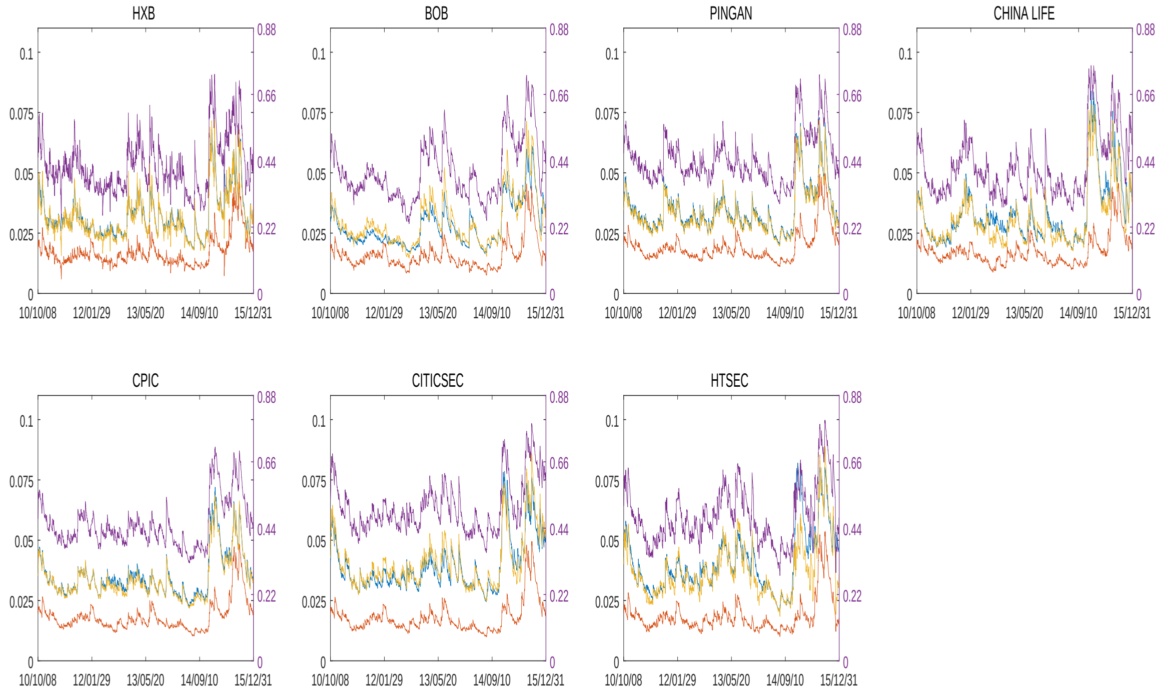
Figure 7:

Time series of TITF-related measures across all the financial firms After obtaining the times series of TITF-related measures of individual firms, we calculate the corresponding arithmetic average of these measures across all the financial firms. Here, it should be noted that the distressed state of CoVaR is defined as the 5% quantile of each firm, the threshold of MES as the conditional VaR of the market return, and the market index as CSI 300 Index. Besides, ΔCoVaR-DCC in Figure 7 denotes ΔCoVaR values estimated through the GARCH-DCC model and ΔCoVaR-quant ΔCoVaR values estimated through quantile regression.



(a)

Figure 8: **Time series of TITF-related measures across all the financial firms**



(a)

Figure 9: **Time series of TITF-related measures across all the financial firms**

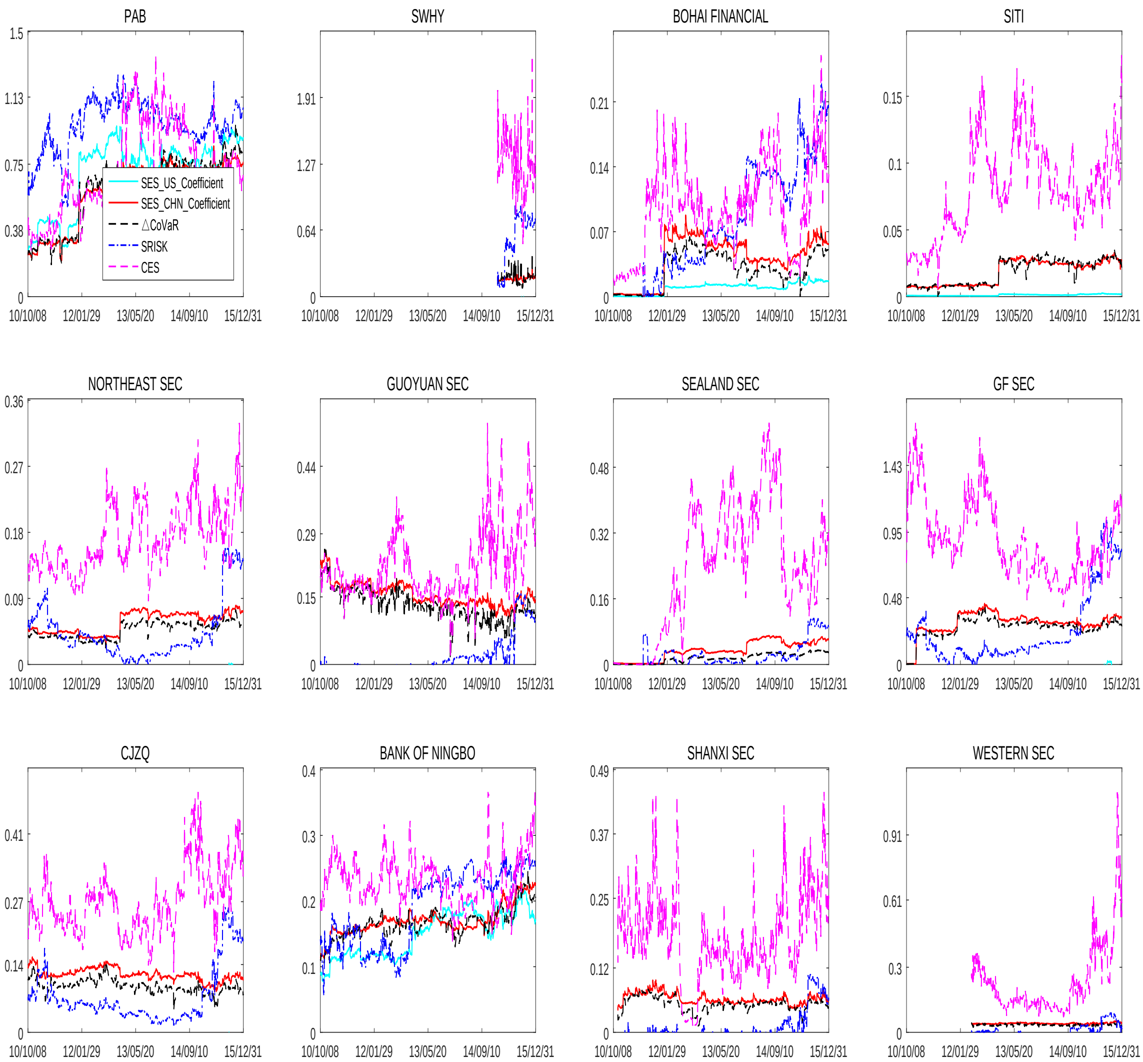


Figure 10:

Relative Systemic Risk Measures Over SES, ΔCoVaR, SRISK and CES (a)

(1) The relative systemic risk measure (SES, ΔCoVaR, SRISK and CES) is calculated by dividing a firms systemic measure at each time point by the average SES value for all the public financial institutions over the sample period;(2)SES-US and SES-CHN are calculated from US-coefficients and CHN-coefficients respectively.

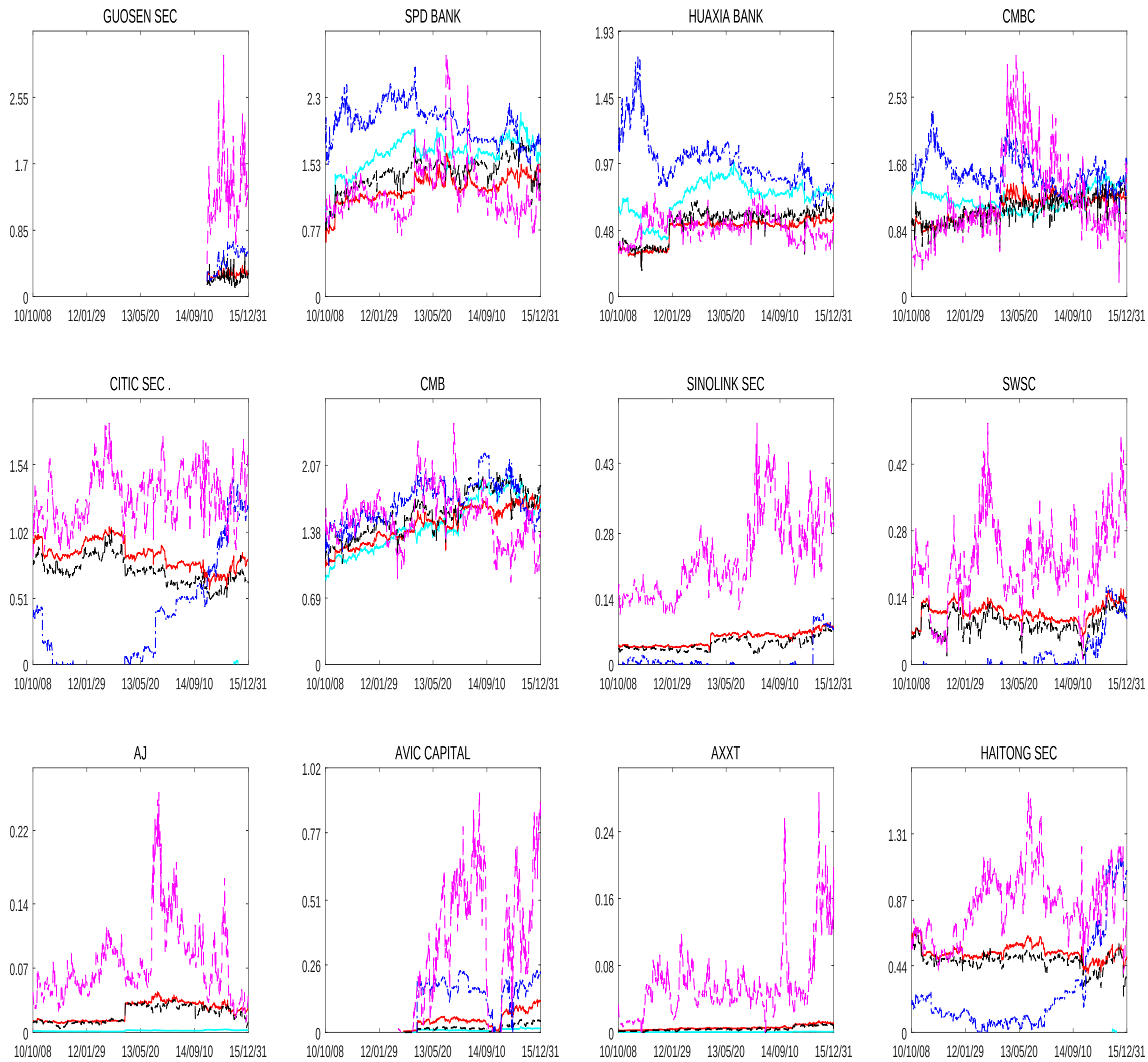


Figure 11:

Relative Systemic Risk Measures Over SES, ΔCoVaR, SRISK and CES (b)

(1) The relative systemic risk measure (SES, ΔCoVaR, SRISK and CES) is calculated by dividing a firms systemic measure at each time point by the average SES value for all the public financial institutions over the sample period;(2)SES-US and SES-CHN are calculated from US-coefficients and CHN-coefficients respectively.

Figure 12:

Relative Systemic Risk Measures Over SES, ΔCoVaR, SRISK and CES (c)

(1) The relative systemic risk measure (SES, ΔCoVaR, SRISK and CES) is calculated by dividing a firms systemic measure at each time point by the average SES value for all the public financial institutions over the sample period;(2)SES-US and SES-CHN are calculated from US-coefficients and CHN-coefficients respectively.

Figure 13:

Relative Systemic Risk Measures Over SES, ΔCoVaR, SRISK and CES (d)

(1) The relative systemic risk measure (SES, ΔCoVaR, SRISK and CES) is calculated by dividing a firms systemic measure at each time point by the average SES value for all the public financial institutions over the sample period;(2)SES-US and SES-CHN are calculated from US-coefficients and CHN-coefficients respectively.

Table 1: **Predictive ability of CATFIN for MCI and PMI.**

	Pre-warning Index		Coincident Index		Leading Index		PMI	
Lead	CATFIN	Adj.R2	CATFIN	Adj.R2	CATFIN	Adj.R2	CATFIN	Adj.R2
n = 1	-3.33	0.95	-1.02**	0.97	-0.88**	0.95	-4.35***	0.66
	(-1.2)		(-2.24)		(-2.5)		(-3.16)	
n = 2	-11.01**	0.88	-2.69***	0.91	-1.85***	0.85	-7.13***	0.27
	(-2.43)		(-3.21)		(-2.89)		(-3.43)	
n = 3	-16.54***	0.79	-3.99***	0.81	-2.64***	0.71	-5.82**	0.01
	(-2.74)		(-3.35)		(-2.98)		(-2.44)	
n = 4	-21.22***	0.69	-5.29***	0.71	-3.06***	0.56	-5.23**	-0.17
	(-2.84)		(-3.56)		(-2.79)		(-2.01)	
n = 5	-28.73***	0.59	-5.8***	0.59	-3.14**	0.4	-3.76	-0.28
	(-3.34)		(-3.26)		(-2.43)		(-1.38)	
n = 6	-28.82***	0.47	-6.76***	0.47	-3.23**	0.24	-4.18	-0.44
	(-2.91)		(-3.33)		(-2.2)		(-1.43)	
n = 7	-36.3***	0.36	-8.82***	0.37	-3.64**	0.09	-5.07	-0.7
	(-3.19)		(-3.84)		(-2.19)		(-1.54)	
n = 8	-43.58***	0.26	-10.57***	0.28	-3.31*	-0.06	-5.12	-0.94
	(-3.41)		(-4.15)		(-1.79)		(-1.42)	
n = 9	-48.95***	0.18	-12.21***	0.2	-2.66	-0.2	-2.82	-1
	(-3.51)		(-4.45)		(-1.32)		(-0.76)	
n = 10	-47.52***	0.09	-12.06***	0.09	-1.89	-0.34	-0.87	-0.99
	(-3.22)		(-4.11)		(-0.89)		(-0.24)	
n = 11	-39.14**	-0.01	-12.15***	-0.01	-1.33	-0.47	-0.94	-0.93
	(-2.5)		(-3.91)		(-0.59)		(-0.26)	
n = 12	-38.61**	-0.06	-11.54***	-0.11	0.37	-0.58	-1.45	-0.87
	(-2.39)		(-3.51)		(0.16)		(-0.4)	
n = 13	-28.52*	-0.11	-10.99***	-0.18	1.89	-0.63	-1.91	-1.04
	(-1.73)		(-3.22)		(0.79)		(-0.5)	
n = 14	-19.92	-0.13	-9.93***	-0.25	3.29	-0.64	1.14	-1.17
	(-1.19)		(-2.82)		(1.37)		(0.29)	
n = 15	-13.27	-0.13	-8.41**	-0.31	3.74	-0.63	5.68	-1.14
	(-0.79)		(-2.33)		(1.55)		(1.49)	
n = 16	-11.33	-0.13	-6.89*	-0.35	4.46*	-0.6	5.03	-1.16
	(-0.67)		(-1.87)		(1.86)		(1.32)	
n = 17	-4.84	-0.12	-5.89	-0.37	4.81**	-0.56	3.84	-1.13
	(-0.29)		(-1.58)		(2.04)		(1.01)	
n = 18	-0.55	-0.09	-5.25	-0.39	5.82**	-0.49	2.92	-1.09
	(-0.03)		(-1.39)		(2.52)		(0.77)	
n = 19	2.54	-0.07	-4.65	-0.42	6.33***	-0.44	5.05	-1.12
	(0.15)		(-1.23)		(2.81)		(1.32)	
n = 20	6.65	-0.05	-3.99	-0.45	6.61***	-0.4	6.95	-1.19
	(0.41)		(-1.04)		(2.99)		(1.8)	

Table 2: **Predictive ability of DCI for MCI and PMI.**

	Pre-warning Index		Coincident Index		Leading Index		PMI	
Lead	MacroSys	Adj.R2	MacroSys	Adj.R2	MacroSys	Adj.R2	MacroSys	Adj.R2
n = 1	-3.91	0.96	-3.34	0.98	-0.88	0.9	-3.09	0.49
	(-0.34)		(-1.58)		(-0.55)		(-0.91)	
n = 2	-13.2	0.92	-6.55*	0.94	-0.73	0.75	-2.74	-0.11
	(-0.79)		(-1.89)		(-0.29)		(-0.56)	
n = 3	-22.37	0.87	-10.02**	0.89	-1.67	0.56	-3.44	-0.68
	(-1.07)		(-2.2)		(-0.51)		(-0.61)	
n = 4	-29.63	0.82	-12.98**	0.84	-3.59	0.42	-2.52	-1.37
	(-1.22)		(-2.41)		(-1)		(-0.4)	
n = 5	-40.84	0.79	-16.87***	0.79	-5.08	0.3	-2.83	-1.64
	(-1.56)		(-2.78)		(-1.33)		(-0.43)	
n = 6	-52.03*	0.76	-20.28***	0.73	-6.81*	0.25	-5.98	-1.27
	(-1.92)		(-3.05)		(-1.83)		(-0.98)	
n = 7	-56.41**	0.71	-24.9***	0.66	-7.43**	0.24	-7.69	-1.12
	(-1.96)		(-3.52)		(-2.12)		(-1.29)	
n = 8	-60.49*	0.65	-30.33***	0.59	-9.03***	0.28	-6.92	-1.12
	(-1.94)		(-4.05)		(-2.71)		(-1.15)	
n = 9	-73.34**	0.59	-37.11***	0.53	-9.16***	0.25	-8.8	-0.98
	(-2.16)		(-4.8)		(-2.68)		(-1.48)	
n = 10	-88.6**	0.56	-39.72***	0.42	-10.61***	0.2	-7.73	-0.93
	(-2.51)		(-4.85)		(-2.98)		(-1.29)	
n = 11	-90.5**	0.5	-39.56***	0.3	-10.92***	0.08	-7.05	-0.55
	(-2.45)		(-4.54)		(-2.84)		(-1.35)	
n = 12	-84.33**	0.44	-37.9***	0.2	-10.82***	-0.04	-10.37**	-0.38
	(-2.21)		(-4.13)		(-2.65)		(-2.08)	
n = 13	-80.42**	0.42	-38.41***	0.18	-9.54**	-0.17	-12.79**	-0.55
	(-2.07)		(-4.12)		(-2.25)		(-2.38)	
n = 14	-86.64**	0.41	-40.64***	0.14	-9.84**	-0.18	-14.96**	-0.86
	(-2.14)		(-4.13)		(-2.3)		(-2.44)	
n = 15	-82.39*	0.4	-45.59***	0.13	-10.97***	-0.05	-17.86***	-1.57
	(-1.89)		(-4.41)		(-2.62)		(-2.66)	
n = 16	-137.29***	0.43	-62.42***	0.24	-17.76***	0.32	-25.05***	-2.91
	(-2.63)		(-5.38)		(-4.39)		(-3.11)	
n = 17	-146.69***	0.44	-61.37***	0.23	-16.77***	0.53	-23.89***	-2.77
	(-2.68)		(-5.04)		(-4.8)		(-2.9)	
n = 18	-133.4**	0.45	-58.51***	0.23	-13.7***	0.68	-26.62***	-2.05
	(-2.37)		(-4.68)		(-4.63)		(-3.51)	
n = 19	-119.86**	0.45	-57.77***	0.26	-9.47***	0.65	-27.17***	-1.71
	(-2)		(-4.48)		(-2.92)		(-3.62)	
n = 20	-153.89**	0.48	-68.87***	0.35	-7.9*	0.55	-26.81***	-1.85
	(-2.17)		(-4.86)		(-1.84)		(-3.12)	

Table 3: **Predictive ability of MacroSys (without Turbulence) for MCI and PMI.**

	Pre-warning Index		Coincident Index		Leading Index		PMI	
Lead	MacroSys	Adj.R2	MacroSys	Adj.R2	MacroSys	Adj.R2	MacroSys	Adj.R2
n = 1	-0.33	0.96	-0.05	0.98	-0.01	0.9	0.08	0.48
	(-0.57)		(-0.46)		(-0.11)		(0.48)	
n = 2	-0.88	0.92	-0.1	0.94	-0.06	0.75	0.18	-0.11
	(-1.07)		(-0.55)		(-0.45)		(0.72)	
n = 3	-1.43	0.87	-0.12	0.88	-0.03	0.56	0.22	-0.67
	(-1.36)		(-0.49)		(-0.2)		(0.76)	
n = 4	-1.92	0.83	-0.12	0.83	0.01	0.41	0.25	-1.36
	(-1.53)		(-0.4)		(0.05)		(0.73)	
n = 5	-2.32*	0.79	-0.19	0.76	0.01	0.28	0.23	-1.63
	(-1.7)		(-0.54)		(0.06)		(0.66)	
n = 6	-2.83***	0.76	-0.32	0.68	-0.01	0.2	0.28	-1.28
	(-2)		(-0.83)		(-0.04)		(0.86)	
n = 7	-3.56**	0.72	-0.47	0.59	-0.05	0.18	0.32	-1.15
	(-2.38)		(-1.11)		(-0.27)		(0.97)	
n = 8	-4.32***	0.67	-0.52	0.47	-0.08	0.18	0.33	-1.13
	(-2.63)		(-1.12)		(-0.43)		(0.97)	
n = 9	-4.87**	0.6	-0.51	0.33	-0.13	0.15	0.37	-1.03
	(-2.36)		(-0.87)		(-0.57)		(0.97)	
n = 10	-4.91*	0.54	-0.41	0.15	-0.17	0.07	0.39	-0.96
	(-1.95)		(-0.57)		(-0.6)		(0.89)	
n = 11	-5.28*	0.47	-0.1	0	-0.07	-0.08	0.43	-0.58
	(-1.67)		(-0.12)		(-0.2)		(0.92)	
n = 12	-5.55	0.41	0.41	-0.08	0.23	-0.19	0.58	-0.47
	(-1.4)		(0.36)		(0.51)		(1.07)	
n = 13	-4.59	0.38	0.9	-0.1	0.32	-0.29	0.95	-0.66
	(-0.97)		(0.69)		(0.59)		(1.42)	
n = 14	-4.15	0.36	1.35	-0.16	0.34	-0.3	1.48*	-0.96
	(-0.78)		(0.93)		(0.6)		(1.86)	
n = 15	-8.01	0.36	3.28	-0.17	1.1	-0.15	2.76**	-1.61
	(-1.02)		(1.64)		(1.55)		(2.48)	
n = 16	-9.19	0.35	3.61	-0.18	1.36**	0.1	3.18**	-3.16
	(-0.96)		(1.62)		(1.97)		(2.54)	
n = 17	-11.85	0.37	3.14	-0.17	0.79	0.31	2.39*	-3.17
	(-1.21)		(1.4)		(1.29)		(1.88)	
n = 18	-10.66	0.39	2.79	-0.13	0.4	0.52	2.43**	-2.58
	(-1.08)		(1.26)		(0.78)		(2.04)	
n = 19	-8.98	0.41	2.59	-0.07	0.18	0.58	2.23*	-2.28
	(-0.92)		(1.19)		(0.37)		(1.93)	
n = 20	-5.25	0.42	2.23	0	0.32	0.51	2.43**	-2.16
	(-0.54)		(1.05)		(0.61)		(2.22)	

Table 4: **Descriptive statistics of MES, ΔCoVaR-DCC, ΔCoVaR-quant and LRMES**

	MES	ΔCoVaR-DCC	ΔCoVaR-quant	LRMES
Mean	0.0357	0.0166	0.0159	0.4474
std.dev	0.0122	0.0066	0.0051	0.0953
Max -Min	0.0711	0.0459	0.0287	0.4752
skewness	1.7554	2.3636	1.7086	1.1347
kurtosis	6.2513	9.7296	5.8428	3.8502

Table 5: **Correlation matrix of MES, ΔCoVaR-DCC, ΔCoVaR-quant and LRMES**

	MES	ΔCoVaR-DCC	ΔCoVaR-quant	LRMES
MES	1	0.93	0.97	0.99
ΔCoVaR-DCC	0.93	1	0.88	0.91
ΔCoVaR-quant	0.97	0.88	1	0.96
LRMES	0.99	0.91	0.96	1

Table 6: **The 20 most important financial firms ranked by the four hybrid measures**

	SES_US	**SES_CHN**	**Scaled Δ CoVaR**	**SRISK**	**CES**
1	ICBC	ICBC	ICBC	ABC	CCB
2	BANK OF CHINA	CCB	CCB	BANK OF CHINA	ICBC
3	ABC	BANK OF CHINA	BANK OF CHINA	ICBC	CHINA LIFE
4	CCB	ABC	ABC	CCB	ABC
5	BANKCOMM	BANKCOMM	BANKCOMM	BANKCOMM	BANK OF CHINA
6	SPD BANK	CHINA LIFE	CHINA LIFE	SPD BANK	PING AN OF CHINA
7	CNCB	CMB	CMB	INDUSTRIAL BANK	BANKCOMM
8	CMB	CNCB	PING AN OF CHINA	CMB	CMB
9	INDUSTRIAL BANK	SPD BANK	SPD BANK	CNCB	GUOSEN SEC
10	CMBC	PING AN OF CHINA	CNCB	CMBC	CPIC
11	CEB BANK	INDUSTRIAL BANK	INDUSTRIAL BANK	CEB BANK	INDUSTRIAL BANK
12	PING AN OF CHINA	CMBC	CMBC	HUAXIA BANK	GTJA
13	HUAXIA BANK	CITIC SEC	CEB BANK	GTJA	CITIC SEC .
14	PAB	CEB BANK	CPIC	PAB	CNCB
15	BOB	CPIC	CITIC SEC	BOB	SWHY
16	CHINA LIFE	PAB	PAB	SWHY	CMBC
17	CPIC	HAITONG SEC	HUAXIA BANK	GUOSEN SEC	SPD BANK
18	NJCB	HUAXIA BANK	HAITONG SEC	CITIC SEC	ORIENT SEC
19	BANK OF NINGBO	BOB	BOB	ORIENT SEC	GF SEC
20	NCI	HTSC	GTJA	HTSC	HAITONG SEC

Table 7: **The average values of hybrid measures corresponding to the top 25 firms**

	SES_US	SES_CHN	Scaled Δ CoVaR	SRISK	CES
1	7.8317	7.1677	6.5313	7.3028	4.4583
2	7.1444	6.27	6.4894	6.8228	4.136
3	6.4487	5.3417	5.3082	6.7683	3.5303
4	6.3966	4.7612	4.7135	5.8219	3.1449
5	2.9946	2.3475	2.4381	3.1176	2.8247
6	1.6346	1.6751	1.84	2.0051	2.6555
7	1.4967	1.4499	1.5739	1.9338	1.7392
8	1.4535	1.3565	1.4928	1.6944	1.519
9	1.4187	1.2449	1.4215	1.6588	1.3738
10	1.2337	1.1959	1.2855	1.5722	1.3637
11	1.0597	1.1464	1.2155	1.2787	1.3228
12	0.7399	1.1368	1.1083	0.9874	1.3204
13	0.7246	0.8413	0.8739	0.9806	1.3068
14	0.7033	0.8245	0.798	0.9717	1.2871
15	0.5384	0.7044	0.7207	0.6499	1.277
16	0.5228	0.5961	0.6043	0.5644	1.228
17	0.2182	0.5286	0.5381	0.4772	1.2084
18	0.1768	0.4851	0.4733	0.329	1.132
19	0.1498	0.4712	0.4681	0.301	0.9046
20	0.1214	0.3426	0.3815	0.3003	0.8427
21	0.0685	0.3068	0.2977	0.271	0.7377
22	0.0095	0.2976	0.2744	0.2362	0.7336
23	0.0089	0.2863	0.2637	0.1951	0.7173
24	0.0017	0.2738	0.2416	0.189	0.6116
25	0.0012	0.2716	0.2378	0.1858	0.5661

Table 8: **Abbr for China's public financial institutions**

Short Name	**English Name of the Company**
WESTERN SECURITIES	Western Securities
SWSC	Southwest Securities
SWHY	Shenwan Hongyuan Group
SPD BANK	Shanghai Pudong Development Bank
SITI	Shaanxi International Trust
SINOLINK SECURITIES	Sinolink Securities
SHANXI SECURITIES	Shanxi Securities
SEALAND SECURITIES	Sealand Securities .
SCS	Soochow Securities
PING AN OF CHINA	Ping An Insurance (Group) Company of China
PACIFIC SECURITIES	The Pacific Securities
PAB	Ping An Bank
NJCB	Bank of Nanjing
NCI	New China Life Insurance Company
IS	Industrial Securities
INDUSTRIAL BANK	Industrial Bank
ICBC	Industrial and Commercial Bank of China Limited
HUAXIA BANK	Hua Xia Bank
HTSC	Huatai Securities
HAITONG SECURITIES	HAITONG Securities Company Limited
GUOYUAN SECURITIES	Guoyuan Securities Company Limited
GUOSEN SECURITIES	Guosen Securities
GTJA	Guotai Junan Securities
GF SECURITIES	GF Securities
FOUNDER SECURITIES	Founder Securities
EBSCN	Everbright Securities Company Limited
DONGXING SECURITIES	Dongxing Securities Company Limited
CPIC	China Pacific Insurance (Group)
CNCB	China CITIC Bank Corporation
CMS	China Merchants Securities
CMBC	China Minsheng Banking
CMB	China Merchants Bank
CJZQ	Changjiang Securities Company
CITIC SECURITIES	CITIC Securities Company
CHINA LIFE	China Life Insurance Company
CEB BANK	China Everbright Bank
CCB	China Construction Bank Corporation
BOHAI FINANCIAL	Bohai Financial Investment Holding
BOB	Bank of Beijing
BANKCOMM	Bank of Communications
BANK OF NINGBO	Bank of Ningbo
BANK OF CHINA	Bank of China
AXXT	Anxin Trust
AVIC CAPITAL	AVIC Capital
AJ	Shanghai AJ
ABC	Agricultural Bank of China