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Abstract

Using principal components quantile regression (PCQR) method, we construct a systemic financial risk index that aggregate information from 16 popular measures of systemic risk. The empirical results indicate that our index is able to accurately predict the distribution of subsequent shocks to the real economy in China.

Key words: Systemic financial risk, Principal Components Quantile Regression, Real Economy

JEL Classificaion: G32, E44, E51

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1. Introduction

On May 24, 2017, the investor service of the rating agency, Moody, downgraded China's sovereign credit rating from Aa3 to A1.[2] In response, Chinese government charges Moody for exaggerating China's economic difficulty while downplaying its reform efforts.[3] Despite debates like this, waves of financial risk in China will nevertheless affect the international financial market because China has been so deeply integrated into the global economy and has become a driving force for global economic growth. Monitoring China's systemic risk therefore is vital not only for China but also for the global economy.

Since the outbreak of the global financial crisis in 2008, researchers have constructed various risk indexes vis-à-vis a wide range of systemic risk. However, most indexes only cover a certain aspect of systemic risk and hence lack the capacity of measuring the innately complex systemic risk in a comprehensive way. In addition, all existing indexes of systemic risk focus exclusively on the financial market and, consequently, overlook its connection with real economy (Brenda Gonzalez-Hermosill, 1996; Kaufman, 2000; Borio, 2003).

In this study, using the principal components quantile regression (PCQR), we synthesize a number of financial risk measures to construct a comprehensive index of the financial systemic risk of China. Our results show that this index is able to measure multi-dimension financial risk and more accurately predict its impact on the real economy of China than do most other existing risk indexes such as term spreads.

The rest of the paper proceeds as follows: Section 2 introduces the systemic risk index we construct. Section 3 shows the empirical results derived from this index. Section 4 concludes the paper.

[2] The report of Moody's agency can be accessed at https://www.moodys.com/research/Moodys-downgrades-Chinas-rating-to-A1-from-Aa3-and-changes--PR_366139

[3] The response of China's ministry of finance was reported by Shanghai Daily and can be accessed at http://www.shanghaidaily.com/business/China-dismisses-Moodys-downgrade-of-Chinas-rating/shdaily.shtml

2. Method

2.1. The Approach of Forecasting the Real Economy

A recursive out-of-sample quantile regression is employed as the main econometric methodology. We denote the shock to real economy as y_{t+1}, and the probability of y_{t+1} being smaller than a constant, y, is $P(y_{t+1} \leq y)$; and the cumulative distribution function of y_{t+1} is the following:

$$F(\mathrm{y}) = P(y_{t+1} \leq y) \tag{1}$$

Hence the τth quantile of y_{t+1} is its inverse probability distribution function, which is further discussed in the next subsection.

We define the quantile loss function of the τth quantile of y_{t+1} as follows

$$\rho_\tau(x) = x(\tau - I_{x<0}) \tag{2}$$

where $I_{x<0}$ is an indicator function

$$I_{x<0} = \begin{cases} 1, x < 0 \\ 0, x \geq 0 \end{cases} \tag{3}$$

The quantile function can be shown as the solution to an optimization problem as follows

$$Q_\tau(y_{t+1}) = arg\,\underset{q}{inf}\, E[\rho_\tau(y_{t+1} - q)] \tag{4}$$

or, the minimization as follows

$$min\,\{\textstyle\sum_{y_{t+1}\geq q} \tau|y_{t+1} - q| + \sum_{y_{t+1}<q}(1-\tau)|y_{t+1} - q|\} \tag{5}$$

As in the specification of Koenker and Bassett (1978), assuming that conditional quantiles of y_{t+1} are affine functions of observables x_t

$$Q_\tau(y_{t+1}|\mathcal{I}_t) = \beta_{\tau,0} + \beta_\tau{}' x_t \tag{6}$$

we have

$$\widehat{\beta_\tau} = argmin\{\textstyle\sum \rho_\tau(y_{t+1} - \beta_{\tau,0} - \beta_\tau{}' x_t)\} \tag{7}$$

Following Giglio et al. (2016), we set τ to be 0.2, 0.5 and 0.8 respectively in our regression to examine how systemic risk influences real economy at both end percentiles and the median of the sample.

To test the effectiveness of the systemic risk index on its forecasting capacity of macroeconomic shocks, we construct an accuracy index, R^2:

$$R^2 = 1 - \frac{\sum_t[\rho_\tau(y_{t+1} - \hat{\alpha} - \hat{\beta}X_t)]}{\sum_t[\rho_\tau(y_{t+1} - \hat{q}_\tau)]} \tag{8}$$

where $\hat{q}_\tau$ is τth quantile of the dependent variable, y_{t+1}.

Equation (8) captures the typical loss using conditional information relative to the loss derived from the unconditional forecast. The out-of-sample R^2 is positive if conditional quantile regression offers a more accurate forecast than does the unconditional forecast; and negative otherwise.

We adopt the adjusted mean squared prediction error (MSPE) statistic in Clark and West (2007) to test the significance of the quantile regression:

$$f_{t+1} = (y_{t+1} - \hat{q}_\tau)^2 - [(y_{t+1} - \hat{\alpha} - \hat{\beta}X_t)^2 - (\hat{q}_\tau - \hat{\alpha} - \hat{\beta}X_t)^2] \tag{9}$$

In order to gauge the relative accuracy and effectiveness of our PCQR index, we cons truct the root mean squared error (RMSE) in the following way:

$$RMSE = \sqrt{\sum(y_{t+1} - \hat{\alpha} - \hat{\beta}X_t)^2 / n} \tag{10}$$

We choose a random walk model without any systemic risk index as the benchmark, b ased on which the ratio between two RMSEs can be calculated:

$$Ratio = \frac{RMSE_{with\ risk\ index\ i}}{RMSE_{benchmark}} \tag{11}$$

Accordingly, any *Ratio* defined above that is smaller than one indicates efficient forecasti ng performance of risk index *i*. In section 3.4, we show the empirical results of the RMSE as well as the *Ratio* in Table 3 and 4 followed by the discussion of the effectiveness of a variety of risk indexes.

2.2 The Construction of Systemic Risk Index

We assume that the τth quantile of y_{t+1} conditional on information set $\mathcal{I}_t$ is a linear function of the unobservable univariate factor f_t:

$$Q_\tau(y_{t+1}|\mathcal{I}_t) = \alpha f_t \tag{12}$$

$$y_{t+1} = \alpha f_t + \eta_{t+1} \tag{13}$$

where f_t is a latent variable, hence unobservable; η_{t+1} is the error term of quantile regression.

We then define individual measures of systemic risk as vector variable x_t,

$$x_t = \Lambda F_t + \varepsilon_t \equiv \phi f_t + \psi g_t + \varepsilon_t \qquad (14)^4$$

where ε_t is the heterogeneous error term. Equation (14) shows that x_t is driven by two factors: a latent variable f_t which contains the information that helps forecast macroeconomic shocks; and an extra information variable g_t which is irrelevant for the forecasting of y_{t+1}.

Then we estimate $\hat{F}_t$ as the common factor:

$$\hat{F}_t = (\Lambda'\Lambda)^{-1}\Lambda' x_t \qquad (15)$$

where Λ is the eigenvector (a matrix in this case) of the first K eigenvalues of $\sum_{t=1}^{T} x_t\, x_t{}'$.

In forecasting, we use out-of-sample quantile regression of y_{t+1} on $\hat{F}_t$ as follows

$$Q_\tau(y_{t+1}|\mathcal{I}_t) = \hat{\alpha}'\hat{F}_t \qquad (16)^5.$$

The common factor estimated above is a comprehensive systemic risk index that can reflect on a wide range of market information.

3. Empirical Results

3.1 Measures of Systemic Risk

Following Giglio et al. (2016), we choose 16 measures of systemic risk covering the four main aspects of systemic risk. Table 1 summarizes the definitions and quantifying methods of the measures.[6]

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[4] We follow Giglio et al. (2016) by making the same assumption about g_t that "[t]he vector g_t is also a latent factor that drives the risk measures but does not drive the conditional quantile of y_{t+h}." And without loss of generality, we also assume that f_t is orthogonal to g_t. Thus, the common variation among predictors has two distinct parts, one that is forecast-relevant for y_{t+1}, and the other that is irrelevant to y_{t+1}. Since the focus of this paper is to analyze the foresting power of the systemic index, g_t is pretty much ignored and accordingly so is the partial quantile regression method that is employed in Giglio et al. (2016).

[5] As Theorem 1 in Giglio et al. (2016), it can be proved that: $\forall t$, as N, $T \to \infty$, $\hat{\alpha}'\hat{F}_t - \alpha' f_t \xrightarrow{p} 0$, namely, conditional quantile regression of y_{t+1} with PCQR is able to provide consistent forecasts.

[6] Giglio et al. (2016) also consider default spreads based on corporate debts data but due to the lack of their counterparts in China, we do not include it in this study.

Table 1 Summary of the Measures of Systemic Risks

Measures	Notation	Definition	Source
Institution-specific Risk	*CoVaR*	*Conditional VaR (CoVaR)*	*Adrian and Brunnermeier(2011)*
	$\Delta CoVaR$	*Difference in CoVaR*	*Adrian and Brunnermeier(2011)*
	MES	*Marginal Expected Shortfalls*	*Acharya et al.(2010)*
Comovement and Contagion	*Absorption*	*Absorption Ratio (AR)*	*Kritzman et al. (2011)*
	ΔAbs	*Difference in AR*	*Kritzman et al. (2011)*
	DCI	*Dynamic Causality Index*	*Billio et al.(2012)*
Volatility and Instability	*Volatility*	*Average Equity Volatility*	*Giglio et al. (2016)*
	Turbulence	*Covariance*	*Kritzman and Li (2010)*
	Catfin	*Financial Sector Volatility*	*Allen et al. (2012)*
	Book leverage	*Individual Loan Ratio*	*Total Debts/Total Assets*
	Market leverage	*Market Loan Ratio*	*Total Debts/Total Market Cap.*
	Size con	*Size Concentration*	*Herfindahl-Hirschman Index*
Liquidity and Credit	*AIM*	*Illiquidity Measure*	*Amihud (2002)*
	TED	*Difference in LIBOR and T-bill*	*Difference between 3-month SHIBOR* [7] *and 3-month Government Bond Yield*
	Term spread	*Difference in Rate by maturity*	*Difference between 3-month and 10-year Government Bond Yield*

The time span of our sample is from 2005 to 2016 as most variables are available since 2005. We use daily closing price of public financial corporations to calculate individual stock yield, adopt the yield of *China Securities Index* (CSI) 300[8] as market yield, and access quarterly reports of public corporations to get the leverage. The rest of data is drawn

[7] Shanghai Interbank Offered Rate.

[8] According to the *CSI300 index methodology*, "CSI300 consists of 300 stocks with the largest market capitalization and liquidity from the entire universe of listed *A* share companies in China. Launched on April 8, 2005, the index aims to measure the performance of all the *A* shares traded on the Shanghai and Shenzhen stock exchanges." *A* share in China refers to the stock shares that are denominated in Chinese currency, RMB, and listed in Shanghai and Shenzhen stock exchanges. Here is the link of *the CSI300 index methodology*:
http://www.csindex.com.cn/uploads/indices/detail/files/en/145_000300_Index_Methodology_en.pdf

from the *China Stock Market & Accounting Research* (CSMAR)[9] and Wind database[10]. We follow Giglio et al. (2016) by averaging main indexes of all public financial corporations to quantify the measures of systemic risk except for CoVaR and MES that are specifically targeted at individual institution. All data are monthly[11].

Figure 1 Main Systemic Risk Measures

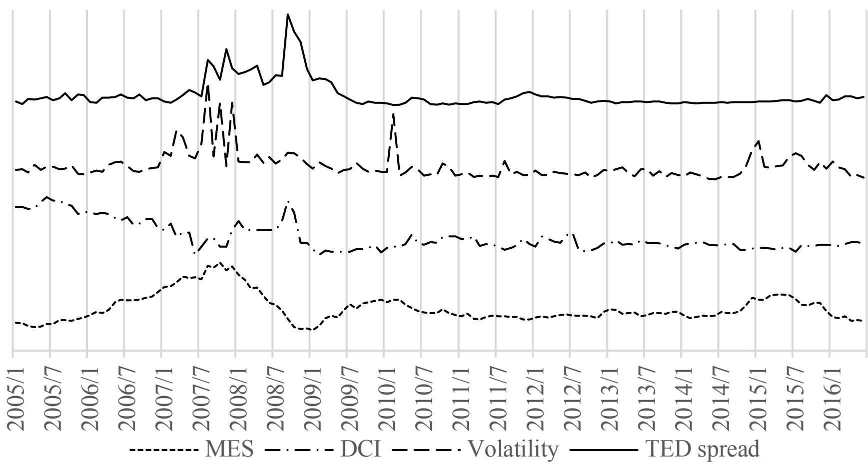


Figure 1 demonstrates the time trend of the four typical standardized measures of systemic risk in our sample.[12] From figure 1, on the one hand, we can see some similarities of the four measures in both general trend and fluctuations. For example, all measures fluctuated significantly during 2008 financial crisis and to a lesser extent around 2015 when Chinese stock market plunged alarmingly. On the other hand, there are also evident distinctions among the measures: in the early episode of the sample, DCI went down while

[9] The CSMAR (China Stock Market & Accounting Research) research database system was jointly established by GTA Information Technology Co. Ltd, the University of Hong Kong and the China Accounting and Finance Research Center of the Hong Kong Polytechnic University. It integrates the 50 GTA major databases and consists of several parts, including Macroeconomics, China's Listed Companies, Stock Market, Bond Market and Banking. Here is the link of the user's guide: https://www.library.hbs.edu/docs/csmarcorporategovernanceuserguide.pdf

[10] Wind is a financial information services company that provides real-time information. The Wind Economic Database pairs over 1.3 million macroeconomic and industry time series of China's economy. Here is the link of the company's website: http://www.wind.com.cn/en/default.html

[11] Similar results are obtained when we use quarterly data, which is available upon request.

[12] To simplify figure 1, we pick one each out of four categories in Table 1 to show their time-varying patterns. The remaining measures basically demonstrate similar pattern and available upon request.

all the others are rising; right after that, MES plummeted abruptly while the rest are relatively stabilized. Varying performances of those indexes justify our choice of PCQR model that can extract the common information from different measures of systemic risk and improve forecasting accuracy by reducing noise of any individual measure.

3.2 Measurement of Macroeconomic shocks

We use the growth rate of real industrial value-added to measure monthly change of real economy. The data source is CEIC[13]. Following Giglio et al. (2016), we run auto-regression on the growth rate of real industrial value-added, Y_t, to get the error term as the macroeconomic shock.

3.3 Out of Sample Forecast

We then run conditional quantile regression of the systemic risk measures on real economic variable to test the effectiveness of their forecasting capacity. The results are listed in Table 2.

Table 2 Systemic Risk and Real Economy[14]

	20 percentile	Median	80 percentile
Panel 1:Single Measures of Systemic Risk			
AIM	0.1007**	0.0254***	0.0167***
CoVaR	0.1952***	0.0479***	0.0145
ΔCoVar	0.1809***	0.0874***	0.0288***
MES	0.1319**	0.1819***	0.0592***
DCI	0.2388**	0.2234***	0.0480***
Size Con	0.2474***	0.0458***	0.0092
Volatility	0.0865*	0.0908***	0.0738***
Turbulence	0.1948***	0.0741***	0.0626***

[13] CEIC data can be accessed at https://www.ceicdata.com/en.

[14] The package of quantile regressions provided two methods to compute the standard errors. One is assuming the residuals are independent identically distributed (i.i.d.), and the other is using nonparametric density estimation technique. In our paper the standard errors, t statistics, and significance levels are computed by assuming the residuals are i.i.d. We also calculated the standard errors using nonparametric density estimation, and found a robust result.

Catfin	0.1295***	0.0490*	0.0359***
Absorption	0.2835	0.1936***	0.0621***
ΔAbs	0.0925***	0.0502***	0.0274***
TED	0.1248***	0.0293**	0.0220***
Term spread	0.2013**	0.1908***	0.2033***
Panel 2:Systemic Risk Index			
PCQR	0.4152***	0.3974***	0.3077***

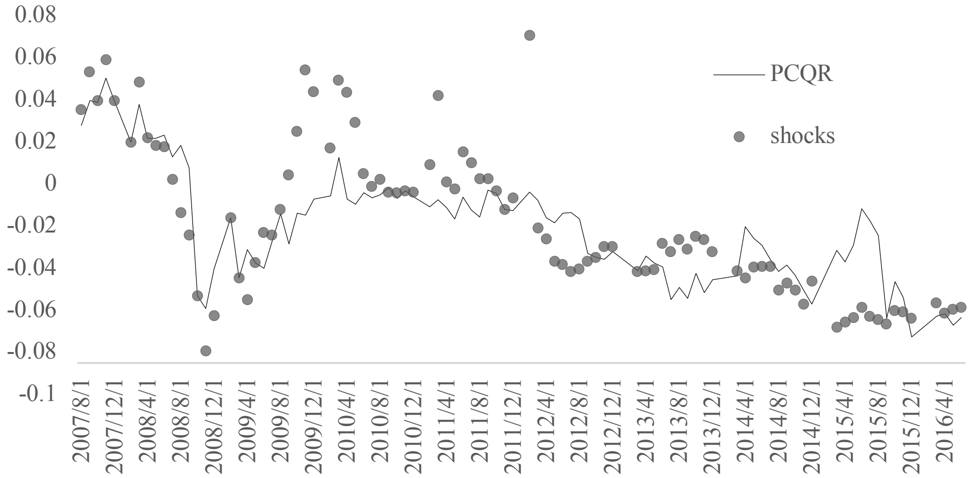
Note: ***, **, * denotes significant at 1, 5, 10 percent respectively.

Panel 1 of Table 2 shows that the out-of-sample statistic of every systemic risk measure is positive suggesting that those measures can provide useful information on macroeconomic shocks. 10 out of 13 singular measures in all 20, 50 and 80 percentiles demonstrate significant forecasting capacity showing that systemic risk of Chinese financial market can be captured by the majority of individual measures despite of their different focuses in measuring financial risk. It also shows systemic financial risk can virtually be multi-channeled into real economy and generate macroeconomic shocks. We also find that 11 of 13 measures present larger R-square in the 20th percentile than in the median; and 12 of 13 measures present greater R-squares in the median than in the 80th percentile. This finding suggests that there is asymmetric connection between systemic financial risk and the real economy. More specifically, systemic risk indexes tend to perform much better in forecasting the lower tail distribution of macroeconomic shocks.

Panel 2 of Table 2 shows that our PCQR index is indeed able to provide strong out-of-sample forecasting power of macroeconomic shocks. The R-squares of 20th, 50th, 80th percentiles estimated by PCQR are 41.52%, 39.74%, 30.77%, respectively, which are much higher than their counterparts of individual measures showing greater forecasting power of the PCQR index. Consistent with the pattern of individual measures, our index also has better forecasting power at the lower tail.

Figure 2 depicts the time series of the 20th percentile forecasts by the PCQR index (solid line) and the growth rate of real industrial value-added (dots). The forecasts match the actual shocks quite well. Particularly, it captures the negative spillover effect from the U.S. subprime crisis in 2008 and the subsequent slowdown of China's economy since 2012. In particular, during our sample period after March 2012 China's producer price had been in deflation, which might result from insufficient effective demand.

Figure 2 PCQR Forecasts and Actual Macroeconomic Shocks (20th percentile)



To further test our index, we run a quantile regression at the 20th percentile of credit growth on our PCQR index. We obtain a coefficient of -0.0086, which is significant at 1 percent level. This suggests that a rise in systemic risk leads to a contraction in credit supply, which helps explain the strong correlation between the PCQR index and real economy in China: less credit supply resulting from systemic financial risk leads to economic slowdown. Comparing our results to that of Giglio et al. (2016), the PCQR index has a better performance in the case of China than of the U.S., the UK and the EU. Specifically, Giglio et al. (2016) find that the PCQR index improves forecasting power of economic downturn in those countries by up to 15 percent relative to that by a historical quantile regression. In the case of China, the improvement is 42 percent. Also, they find that the forecasting power of many individual measures is actually weak. While our Table 2 shows that almost all systemic risk measures are strong in forecasting China's economic fluctuations. The stark contrast may suggest that the correlation between financial market and real economy is stronger in China during 2005-2016 than in those advanced economies. And it might be attributed to the investment-led growth pattern of China, which relied heavily on high leverage of the corporate sector.

3.4 Forecast Comparison

Table 3 shows the root mean squared error (RMSE) of 13 measures of systemic risk and the PCQR index, Table 4 shows the *Ratio* defined in equation (11) between the RMSEs of the model with risk index and the benchmark model. It is shown clearly in both Table 3 and 4 that the PCQR index is able to provide strong out-of-sample forecasting power of macroeconomic shocks. In the short term (1 month), 12 of 13 popular systemic risk indexes can improve the forecast accuracy. And the PCQR index presents the strongest forecasting power, with the RMSE of 1.9891, which is significantly lower than that of the benchmark model (60% improvement) and other measures of systemic risk. In the comparison of the forecasting power of macroeconomic shocks in the medium (long) term, a quarter (two years) ahead, we also find that the PCQR index outperforms other indexes by improving the forecasting accuracy significantly by 70% when t=4 months (30% when t=24 months).

Table 3 Systemic Risk Index Forecast RMSE

	Forecast Horizon		
	t=1 month	*t=4 months*	*t=24 months*
Panel 1:Single Measures of Systemic Risk			
AIM	6.6845	7.8196	7.5056
CoVaR	6.5625	7.0876	7.827
ΔCoVar	6.2030	6.7854	7.5674
MES	6.5304	6.7858	7.3661
DCI	5.4686	5.9886	6.8649
Size Con	6.7913	7.0662	7.6339
Volatility	6.6256	6.8960	7.4500
Turbulence	6.6825	6.9496	7.5153
Catfin	6.5644	6.7882	7.1623
Absorption	5.9187	6.2425	7.0875
ΔAbs	5.4814	5.7450	6.4306
TED	6.7338	7.1057	7.5234
Term spread	5.4848	5.7794	6.1549
Panel 2:Systemic Risk Index			
PCQR	1.9891	2.0342	4.5402
Panel 3:Benckmark model			
Random walk	6.7366	6.9736	7.5392

Table 4 Relative Forecast Accuracy of Systemic Risk Index, the *Ratio*

	Forecast Horizon		
	t=1 month	*t=4 months*	*t=24 months*
Panel 1:Single Measures of Systemic Risk			
AIM	0.9923	1.1213	0.9955
CoVaR	0.9742	1.0163	1.0382

ΔCoVar	0.9208	0.9730	1.0037
MES	0.9694	0.9731	0.9770
DCI	0.8118	0.8588	0.9106
Size Con	1.0081	1.0133	1.0126
Volatility	0.9835	0.9889	0.9882
Turbulence	0.9920	0.9966	0.9968
Catfin	0.9744	0.9734	0.9500
Absorption	0.8786	0.8952	0.9401
ΔAbs	0.8137	0.8238	0.8530
TED	0.9996	1.0189	0.9979
Term spread	0.8142	0.8288	0.8164
Panel 2:Systemic Risk Index			
PCQR	0.2953	0.2917	0.6022

4. Conclusion

In this paper, we use the Principal Component Quantile Regression (PCQR) to construct a comprehensive systemic risk for China. Our PCQR index is able to provide an accurate forecast of macroeconomic shocks in China supported by the empirical results. A possible extension of this paper would be to collect the data, provided the accessibility, that the central bank of China uses for the construction of its own risk index and employ RMSE test to check if governmental indexes perform any better than our PCQR index does.

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