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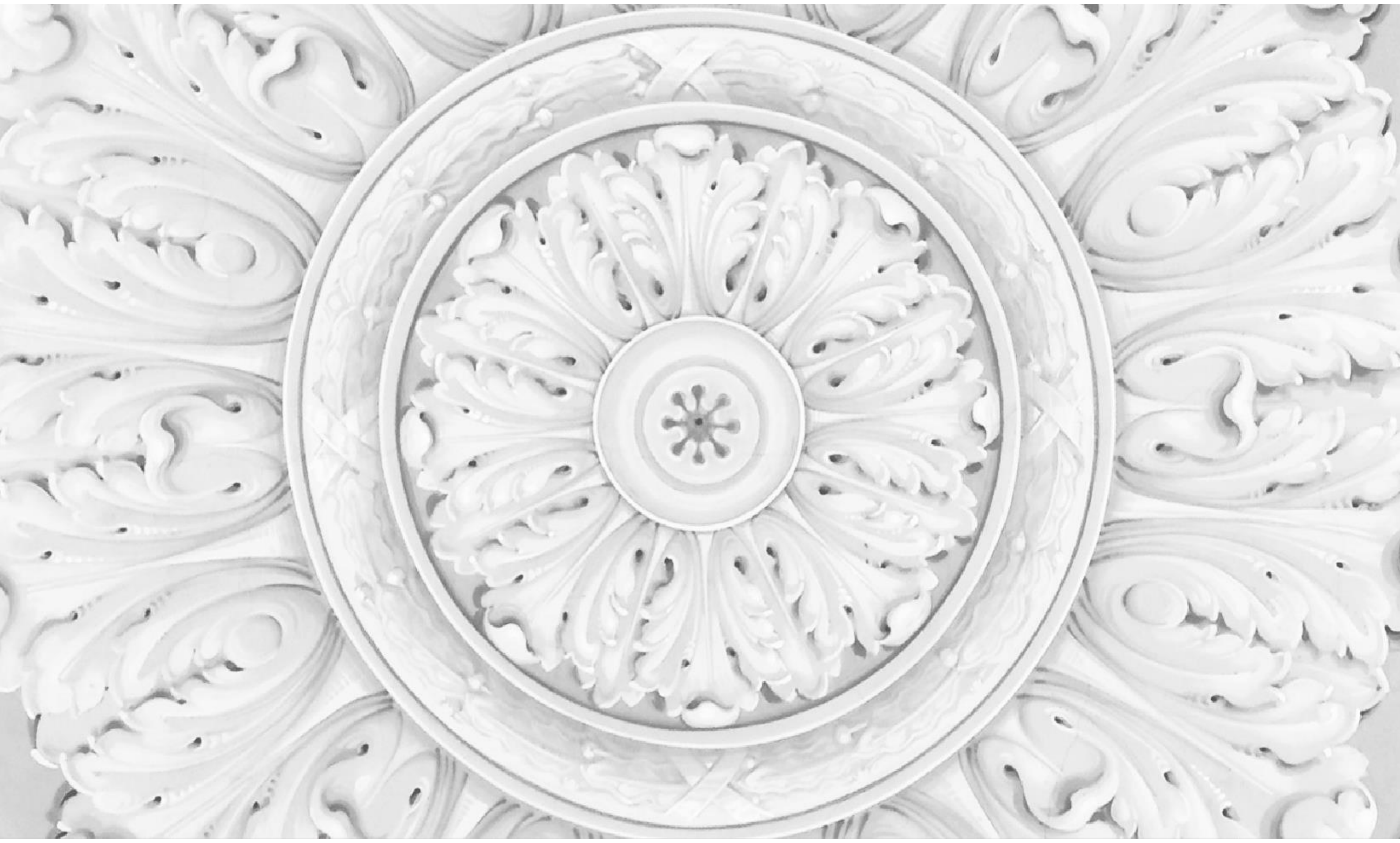

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Systemic Risk and Financial Fragility in the Chinese Economy: A Dynamic Factor Model Approach

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Abstract

This paper studies systemic risk and financial fragility in the Chinese economy, applying the dynamic factor model approach. First, we estimate a dynamic factor model to forecast systemic risk that exhibits significant out-of-sample forecasting power, taking into account the effect of several macroeconomic factors on systemic risk, such as economic growth slowdown, large corporate debt, rise of shadow banking, and real estate market slowdown. Second, we analyse the historical dynamics of financial fragility in the Chinese economy over the last ten years using factor-augmented quantile regressions. The results of the analysis demonstrate that the level of fragility in the Chinese financial system decreased after the Global Financial Crisis of 2007-2009, but has been gradually rising since 2015.

Key words: *systemic risk, financial fragility, factor model, quantile regressions, China*
JEL classification: C58, E44, G2.

1. INTRODUCTION

The slowdown of economic growth, together with high financial leverage of the Chinese economy, are topics of much debate among macroeconomists in business and academia. In combination, these developments point to the presence of financial risks in China. Given the significant role of China in the world economy, the materialization of financial risks in this country may spread to the world economy and hit hard global financial markets.

The economic growth in China reached its lowest rate of 6.7% in 2016, and it is likely that it will not return to two digit rates in the foreseeable future. Lower economic growth rates will not necessarily lead to a financial crisis, but can aggravate existing financial risks. For example, a decrease in economic growth can negatively affect the financial stability of individual companies and financial institutions. Low growth rates can also affect asset prices, for instance, in the real estate market, causing defaults on mortgages.

Several risks have been identified in the literature as possible threats for financial stability in China. The first threat is a high leverage and the large amount of non-performing loans in the corporate sector (e.g. Lipton (2016), Zhang et al. (2015), and Roberts and Zurawski (2016)), especially in heavy industries and state-owned companies that were one of the key sources of economic growth in China over the last three decades. Chinese authorities distributed vast resources to such industries in the form of credits and investments. However, because of a decrease in the marginal return on capital, the growth of real wages, and the export growth slowdown, these industries currently face problems with debt repayment. Credit financing of these industries was mainly provided through the financial repression policy, under which the Chinese government regulates the spread between credit and deposit interest rates. This allowed Chinese companies to take credits at a low interest rate. Moreover, the main banks in the Chinese banking system are state-owned, so they can potentially provide credits to companies according to the government’s instructions.

The second threat to financial stability in China is the extensive growth of shadow banking (e.g. Liang (2016), Liu et al. (2016), Jie and Yang (2015)). The development of shadow banking in China was also caused mainly by financial repression policy. The limitations on credit interest rates stimulated banks in China to create alternative methods of funding borrowers, such as trusts, funds, and wealth management products. These instruments allow banks to provide funds to clients at high interest rates. According to data from the Global Shadow Banking Monitoring Report 2015, China made the largest contribution in the world to the growth of the global shadow banking sector in 2015.

The third threat originates from the real estate market risks (e.g. Zhang et al. (2016), Hsu and Yu (2014), and Xie (2016)). Banks have provided not only large amounts of funding for mortgages to householders, but also have lent to real estate companies. So, the fall in real estate prices in China may have a double-negative effect on the stability of the financial system.

The macroeconomic literature on quantifying systemic risk and financial stability has greatly expanded after the Global Financial Crisis of 2007–2008.[1] Several frameworks from this branch of the literature have been applied to the analysis of systemic risk in China. Chen et al. (2014) use the methodology of the Basel Committee for identifying systemically important banks In China. Wang et al. (2015) construct a systemic risk index using a Merton model. Huang et al. (2017) estimate the Conditional Value at Risk (CoVaR), the Marginal Expected Shortfall (MES), the Systemic Impact Index (SII), and the Vulnerability Index (VI) for Chinese banks. Xie and Zhao (2016) also compute the MES. Yao et al. (2017) use an Expected Default Based Score (EDBS) for Chinese banks. Derbali (2017) employs the SRISK measure.

The common disadvantage of the mentioned frameworks is that they do not simultaneously consider main macroeconomic factors that can become causes of a financial crisis in the Chinese economy. In contrast to the previous literature on quantifying systemic risk in China, the present paper investigates systemic risk and financial stability in the Chinese economy, paying particular attention to the effect of macroeconomic factors on systemic risk. For this purpose, we apply a dynamic factor model (DF model) estimated using a large number of time series in the 2007:Q1-2017:Q4 period. Approximately one half of all time series display specific risks for the Chinese economy, such as large corporate debt, the development of shadow banking, and the real estate market slowdown. The remainder are the key macroeconomic variables, for example, Consumer Price Index, money supply, and exchange rates. According to this model, the value of the systemic risk measure in the next quarter depends on the estimated dynamic factor in the current quarter. The model exhibits significant out-of-

[1] A review of the current state of the literature on systemic risk and financial stability can be found in Gabriele and Moessner (2013) and Benoit et al. (2017).

sample forecasting power and can be used for predicting future changes in systemic risk caused by changes in macroeconomic factors.

Using the considered DF model, we also measure historical levels of financial fragility in the Chinese economy, applying factor-augmented quintile regressions. This approach was first proposed for the analysis of systemic risk by De Nicolo and Lucchetta (2012, 2013, 2017), who show that the Value-at-Risk (VaR) of systemic risk measure estimated by factor-augmented quintile autoregressions can be a good proxy for the fat tails of systemic risk in the economy. The results of our analysis demonstrate that the level of the Chinese financial system fragility decreased after the Global Financial Crisis of 2007-2009, but has been rising since 2015. Moreover, the joint analysis of the systemic risk forecast and the current value of the VaR of the systemic risk measure can be used as an early warning indicator for financial crisis prediction.

The paper is organized as follows. The econometric framework is presented in Section 2. Section 3 details the data used for estimation. Section 4.1 describes the evaluation of the dynamic factors model's forecasting power, while Section 4.2 reports the analysis of the financial fragility and the setup of the early warning indicator for financial crisis prediction. Finally, Section 5 concludes.

2. ECONOMETRIC FRAMEWORK

2.1. Systemic risk measure

The preliminary stage in our econometric framework is the construction of a systemic risk measure based on CDS and interbank market data. This systemic risk measure is used in further analysis as a proxy variable for the level of systemic risk in the Chinese economy. CDS and interbank market data for computation were selected for two reasons. First, market-based systemic risk measures can be calculated in real time without an accounting lag, therefore they respond faster to unexpected events than systemic risk measures that are based on non-market data.[2] Second, systemic risk measures based on CDS and interbank market data perform better than those based on other sources of market data (for example, stock market, bond market, etc.) according to causality tests as it was shown in Rodríguez-Moreno and Peña (2010, 2013).[3]

[2] A survey of existing systemic risk measures can be found in Bisias et al. (2012) or in Benoit et al. (2017).
[3] Rodríguez-Moreno and Peña (2013) is a significantly changed version of Rodríguez-Moreno and Peña (2010).

Due to the lack of data on individual CDS spreads for the main Chinese banks, we mainly base the systemic risk measure on the spread between interbank and government bond interest rates in the Chinese financial system denoted as the '*Financial system risk premium*':

Financial system risk premium = 1-year interbank interest rate – 1-year government bond interest rate (1)

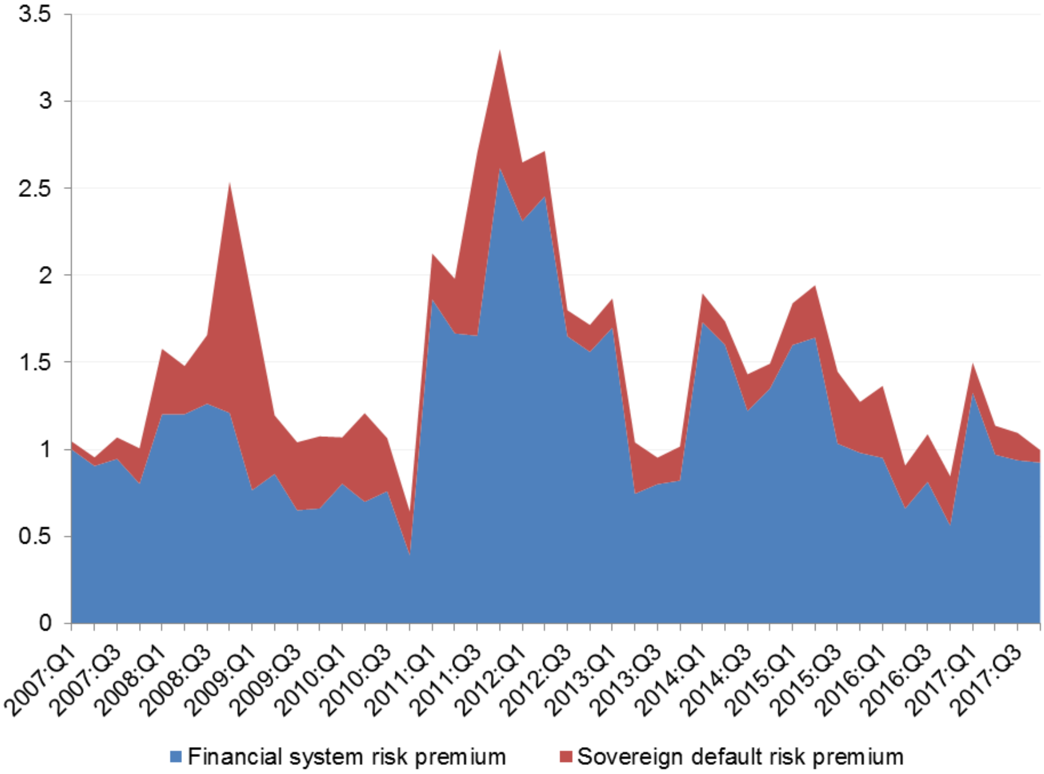
A feature of the Chinese financial system is the state ownership of the main financial institutions. Because of implicit government guarantees to the main financial institutions, the probability of their default will highly depend on the probability of the government default. So the financial system risk premium in equation (1) will not fully take into account such a risk. Moreover, for emerging markets, the country-specific risk can be an important source of systemic risk. Taking into consideration mentioned reasons, the systemic risk measure for the Chinese economy is calculated as follows:

Systemic risk measure (SRM) = financial system risk premium + sovereign default risk premium, (2)

Where '*sovereign default risk premium'* is 1-year sovereign CDS spread. For reasonable interpretations to be made, accurate calculation is necessary based on all components of approximately the same maturity. 1-year maturity allows the construction of the longest time-series for the chosen specification of the systemic risk measure from the first quarter of 2007. The dynamics of the constructed systemic risk measure, the financial systemic risk premium, and the sovereign default risk premium are demonstrated in Figure 1 for the 2007:Q1-2017:Q4 period.

Figure 1 shows why it is important to add the sovereign default risk premium in the calculation of the systemic risk measure. During the Global Financial Crisis of 2007-2008, the financial system risk premium did not change significantly in comparison with volatile dynamics of the government bond interest rate and the interbank interest rate, because they changed synchronously.

Figure 1. Systemic risk measure over the period 2007:Q1-2017:Q4



2.2. Dynamic Factor Model and Factor-Augmented Quantile Regressions

In our analysis, we assume that the dynamics of the systemic risk measure is explained by the following dynamic factor model (DF model):[4]

$$X_t = \Lambda F_t + \nu_t \quad (3)$$
$$F_t = \Omega F_{t-1} + \zeta_t \quad (4)$$
$$SRM_{t+1} = \gamma F_t + e_t \quad (5)$$

Where X_t is the matrix of observed time series at quarter t, F_t is the matrix of several identified latent factors (we use two factors), SRM_{t+1} is the value of the systemic risk measure at quarter $t+1$, Λ, Ω, γ are matrices of estimated unknown parameters, and ν_t, ζ_t, e_t are idiosyncratic error terms.

The DF model has two important advantages in comparison with other types of systemic risk models. First, it can simultaneously take into account the effect of many important macroeconomic factors on systemic risk in China, such as the growth slowdown, large corporate debt, the rise of shadow banking, and the real estate market

[4] In comparison to De Nicolo and Lucchetta (2012, 2013, 2017) an autoregressive term in the equation (3) is not used, because in the preliminary analysis the model without the autoregressive term had more reasonable dynamics, as well as better forecasting power. This result is in line with the Schwaab et al. (2011) model.

slowdown. Second, as several authors mention (e.g., Holz (2003, 2008), Nakamura et al. (2014)), the Chinese authorities could misrepresent some official data. However, for the estimation of the DF model a large number of time series are used, and any misrepresented data do not significantly distort estimation.

For the analysis of historical levels of financial fragility in the Chinese economy we follow De Nicolo and Lucchetta (2012, 2013, 2017) and estimate the Value-at-Risk of the systemic risk measure using fitted values of quantile regressions based on the DF model (3)-(5) as follows:

$$SRM_{t+1} = \alpha^q + \mathrm{Z}^q F_t + e_t^q \tag{6}$$
$$VaR_q(SRM_{t+1}) = \hat{\alpha}^q + \hat{\gamma}^q F_t, \quad q = 1{,}5{,}10\%, \tag{7}$$

where $VaR_q(SRM_{t+1})$ is the VaR of the systemic risk measure at the $q\%$ probability level. De Nicolo and Lucchetta (2017) show that quantile regressions estimate systemic tail risks better than an ordinary regression or a GARCH model.

3. DATA AND ESTIMATION

The distinctive feature of our analysis is the choice of data for the estimation of factors, according to the principal components method. We choose 30 time series, which cover almost all sectors in the Chinese economy, from the CEIC China Premium database. However, the majority of them represent macroeconomic factors that could trigger a financial crisis in the Chinese economy, such as non-performing loans, the real estate market, shadow banking, the economic activity of heavy industries. The data range for the systemic rick measure constructed in Section 2.1 is 2007:Q1-2017:Q4, while the data range for time series used for dynamic factors estimation is 2006:Q4-2017:Q3. A detailed description of data can be found in Appendix 1.

One problem that arises in the choice of time-series data is that the set of time-series needs to be balanced. For example, it is difficult to find more than four time series that represent shadow banking risks. This reason limits the number of time series used for the estimation of factors. For the choice of the number of factors, we use the criteria of Bai and Ng (2002) and Hallin and Liska (2007) and finally choose the DF model with two static and two dynamic factors.

4. FORECASTING AND FINANCIAL FRAGILITY ANALYSIS

4.1. Forecasting power

To compare the forecast performance of the model (3)-(5) with a naïve forecast in pseudo real-time we compute the Mean Absolute Error (MAE), Mean Squared Error (MSE) and the share of periods, in which the DF model correctly predicts the sign of a change in the systemic risk measure (SRM), for one-, two-, three-, and four-quarters-ahead forecast in the period 2011:Q1-2017:Q4. All time series, including the systemic risk measure, are transformed to stationary time series. In the case of the systemic risk measure, the first difference transformation is used, and zero is the best naïve forecast (it has minimum MAE and MSE) among all possible naïve forecasts, such as random walk, the value of the last observation, and the AR(1) model. Following De Nicolo and Lucchetta (2017), we calculate a multi-period forecast as the cumulative change in the systemic risk measure, because of the first difference transformation.

The results of comparison are demonstrated in Table 1. Although, the DF model for systemic risk have lower MAE and MSE for all forecast periods, it does not significantly surpass the naïve forecast in the case of the one-quarter-ahead forecast. However, the differences between the forecasting power of the DF model and the naïve forecast for the cases of two, three, and four quarter forecasts differ from 0 at 10% level (and at 5% level for MAE in the case of three-quarter-ahead forecast).

As can be seen in Table 1, the DF model can predict well the signs of the systemic risk measure changes, but does not capture variation. Moreover, this model exhibits superior forecasting power for longer periods than for a one quarter period. Such performance may be caused by the efficiency of financial markets that stipulates the impossibility of forecasting exact changes in market-based systemic risk measures, especially in the short run.

Table 1. Forecasting power

	DFM	Naive forecast	The share of periods, in which the DF model correctly predicts the sign of a change in SRM.
One quarter			
MAE	0.328	0.353	65%
MSE	0.183	0.206	
Two quarters			
MAE*	0.465	0.494	80%
MSE*	0.323	0.358	
Three quarters			
MAE**	0.521	0.58	80%
MSE*	0.382	0.466	
Four quarters			
MAE*	0.476	0.531	85%
MSE*	0.36	0.48	

*Notes: ** and * indicate the significance of the difference in forecasting errors between DFM and naïve forecast at the 5% and 10% levels, respectively; the standard deviation of the first differences of the systemic risk measure is 0.478.*

4.2. Financial fragility and an early warning indicator

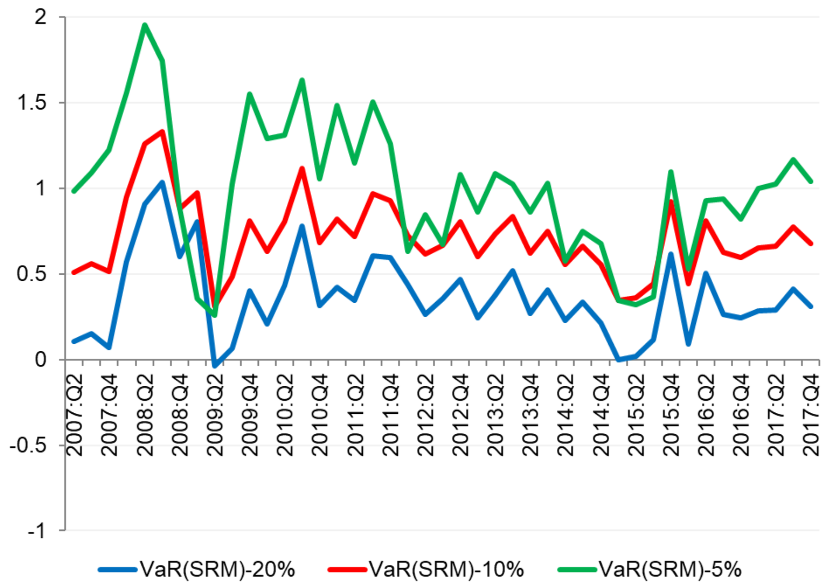
In this section, we analyze the financial fragility in the Chinese economy, measuring the VaR of the systemic risk measure – $\mathrm{VaR(SRM)}$. We also discuss how the forecast of the DF model and $\mathrm{VaR(SRM)}$ can be used together as an early-warning indicator for financial crisis in China.

By construction, $\mathrm{VaR(SRM)}$ shows possible values for the systemic risk measure in the case of rare and unexpected negative shocks to financial stability, when several financial institutions can default. Thus, $\mathrm{VaR(SRM)}$ significantly correlates with the probability of financial institutions' default in a crisis time. In other words, it can be a good proxy for the level of fragility of the Chinese financial system. If $\mathrm{VaR(SRM)}$ grows, the financial system will be more fragile in the case of negative shocks and vice versa.

Figure 3 presents $\mathrm{VaR(SRM)}$ at 5%, 10%, and 20% levels for the Chinese economy over the 2007:Q2-2017:Q4 period. We can see that the level of financial fragility had its maximum values in the time of Global Financial Crisis of 2007-2008. It fell significantly after the government launched the stimulation program, including the restructuring of non-performing loans in Q4 of 2008, as a reaction on the Global Financial

Crisis. Despite this, the level of financial fragility in the Chinese financial system still had a high value at the end of 2009. After that, it consistently decreased before the end of 2015, but then started growing again.

Figure 3. Financial system fragility

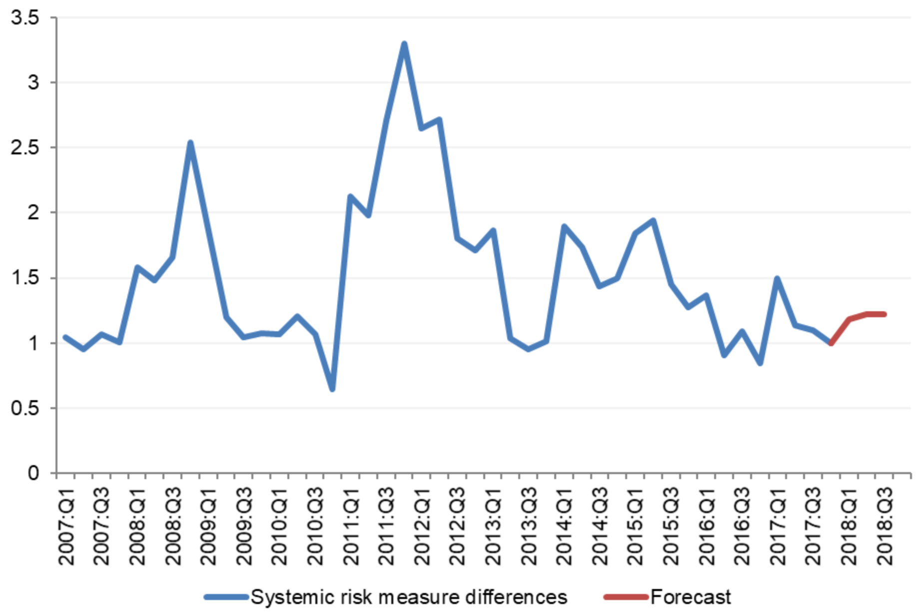


The joint dynamics of VaRs and the estimated forecast of the DF model can be used as an early-warning indicator of a financial crisis. The clear signal of the financial crisis will be the combination of two factors:

1. The levels of VaRs should exceed observed historical levels of financial fragility.
2. The DF model should predict growth in the systemic risk measure.

Figure 4 shows the forecast of the changes in the systemic risk measure made at the Q3 of 2017 year for the period 2018:Q1-2018:Q3. We can see that the DF model predicts the growth of systemic risk in China. As we discuss earlier, the DF primarily allows to predict the sign of changes in the systemic risk measure, but not the variation of this measure. Despite the predicted growth of systemic risk, the VaRs in Figure 3 do not indicate abnormal levels of financial fragility in the Chinese economy. Moreover, after 2009 there have not been periods with a higher level of financial fragility than the period of the Global Financial Crisis. So, we can conclude that there is currently no signal for the onset of a financial crisis in China.

Figure 4. Forecast of the DF model.



5. CONCLUSION

In this paper, we apply the dynamic factor model approach to forecast changes in the level of systemic risk and analyze the fragility of the Chinese financial system. The dynamic factors model for systemic risk can simultaneously take into account the effect of many important macroeconomic factors on systemic risk in China, such as economic growth slowdown, large corporate debt, rise of shadow banking, and real estate market slowdown. Furthermore, this model demonstrates significant out-of-sample forecasting power in the 2007:Q1-2017:Q4 period.

We study the historical levels of financial fragility in the Chinese economy by estimating the Value-at-Risk of the systemic risk measure based on factor-augmented quantile regressions. The results of the analysis show that the fragility of the Chinese financial system decreased after the Global Financial Crisis of 2007-2009 but has been rising since 2015. We also propose an early-warning indicator of a financial crisis in China based on the joint dynamics of the Value-at-Risk of the systemic risk measure and the estimated forecast of future changes in the level of systemic risk from the considered dynamic factor model. Currently, this early-warning indicator does not predict the onset of a financial crisis in China in the period 2018:Q1-2018:Q3.

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Appendix A.

For the factor estimation we use data downloaded from the CEIC China Premium Database and listed below in Table A1. The sample period for all time series is 2006:Q4-2017:Q1. Column “Data series” includes time series description. Column “Categories” shows which sectors of the Chinese economy time series represent. Some time series are linked to the potential causes of a future financial crisis in China, such as the growth of non-performing loans, shadow banking, imbalances in the real estate sector, or the financial problems of companies from heavy industries. Others relate to the main parts of financial and real sectors. We seasonally adjust all time series using the X-13 procedure, and then transform them into stationary time series. Column “T” shows the number of a transformation procedure, where (1) means first difference and (2) means the first difference of logarithms.

Table A1. Data summary.

	Data series	Categories	T
1	NPL: Commercial Bank: Substandard Loan	Corporate debt	2
2	NPL: Commercial Bank: Doubtful Loan	Corporate debt	2
3	NPL: Commercial Bank: Loss Loan	Corporate debt	2
4	Housing Mortgage Loan	Corporate debt / Real estate sector	2
5	Real Estate Inv: New Increased	Real estate sector	2
6	Market Cap: Shanghai SE: Real Estate	Real estate sector	2
7	PE Ratio: Shanghai SE: Real Estate	Real estate sector risks	2
8	Aggregate Financing: New Increased: Entrusted Loan	Shadow banking	1
9	Aggregate Financing: New Increased: Trust Loan	Shadow banking	1
10	Banking: Total Asset: Other Financial Institution	Shadow banking	2
11	Banking Survey: Claims on Nonbank Financial Institutions	Shadow banking	2
12	Market Cap: Shanghai SE: Financial	Financial sector	2
13	PE Ratio: Shanghai SE: Financial	Financial sector	2
14	Index: Shanghai Stock Exchange: Industrial	Real sector	2
15	PE Ratio: Shanghai SE: Industrial	Real sector	2
16	Production of Primary Energy: Electricity	Real sector	2

17	Industrial Production: Cement	Real sector	2
18	Industrial Production: Computer: Micro Computer	Real sector	2
19	Consumer Confidence Index	Real sector	1
20	Government Expenditure	Real sector	2
21	Consumer Price Index	Real sector	1
22	Money Supply M2	Money	2
23	Exports: MTE: Electrical Machinery, Apparatus & Appliances	Real sector \ External sector	2
24	Real Effective Exchange Rate Index: BIS: 2010=100: Broad	Real sector\ External sector	2
25	Exchange Rate against US$: Monthly Average	External sector	2
26	Foreign Reserves	External sector	2
27	Shanghai Interbank Offered Rate (SHIBOR): Overnight	Interest rates	1
28	Bond Yield: Treasury Bond: 5 Year	Interest rates	1
29	Enterprise Bond (AAA) Yield: Yield to Maturity: 5 year - Bond Yield: Medium & Short Term Note (AAA): 3 Month	Interest rates	1
30	Enterprise Bond (AAA) Yield: Yield to Maturity: 5 year - Bond Yield: Treasury Bond: 5 Year Term Note (AAA): 3 Month	Interest rates	1