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1. Introduction

In recent years, China's policy reactions to the global financial crisis significantly increased the leverage. According to IMF (2013), the stock of total social financing has increased by 60 percent of GDP in four years since 2009. Much of the increased liquidity went to the housing sector, leading to a potential bubble (Wang and Sun, 2013). Moreover, economic growth slows down. China's real GDP growth rate was 10.4 percent in 2010. It declined to 9.3 percent in 2011, and then declined to 7.8 percent in 2012. As a result, concern about the systemic risk in China's financial sector increases.

In this paper, we construct an indicator of China's systemic risk, using the marginal expected shortfall (Acharya et al., 2012) of China's public listed financial institutions. Then, we use the time-varying structural vector auto-regression (TVP-SVAR) model of Primiceri (2005) to study the impact of an unexpected expansionary monetary policy on this indicator. We find strong evidence that expansionary monetary policy increased the systemic risk during the period after the onset of the global financial crisis. Moreover, the expansionary monetary policy did not successfully raise output. This result addresses the importance of a more prudential monetary policy by the People's Bank of China (PBOC).

We proceed as follows. Section 2 introduces our systemic risk indicator. Section 3 builds a model of systemic risk, inflation, output gap, and monetary policy and fits it to monthly data. Section 4 concludes.

2. Measuring the Systemic Risk in China's Financial Sector

Acharya et al. (2012) suggest that the marginal expected shortfall (MES) of a financial institution reflects the marginal contribution of a financial institution to the systemic risk of the financial sector. More specifically, the expected loss of the entire financial sector during a financial crisis is

$$ES \equiv -E(R|the\ financial\ sector\ is\ in\ crisis) \tag{1}$$

$$= -\sum_i E[y_i E(r_i|the\ financial\ sector\ is\ in\ crisis)], \tag{2}$$

where R is the return of the financial sector, y_i and r_i are respectively the market share and return of financial institution i, E is the expectation operator. It is easy to see that, $E(r_i|\textit{the financial sector is in crisis}) = \frac{\partial \mathrm{ES}}{\partial \mathrm{y_i}}$, the marginal contribution of institution i to the total loss of the financial sector in the crisis.[1]

The problem is that financial crisis is an extreme event which we do not often observe. Using the extreme value theory, Acharya et al. (2012) show that the average equity return of financial institution i during the bad days of a normal period can be a

[1] We follow Acharya et al. (2012) to assume that the share of institution i in the crisis is unaffected by changes in the returns during the crisis.

good predictor for $E(r_i|\textit{the financial sector is in crisis})$. Such an average equity return is termed "MES" by Acharya et al. (2012). More specifically, the MES of financial institution i is its average equity return when the entire stock market has its worst 5% outcomes. That is,

$$MES^i_{5\%} \equiv \frac{1}{N} \sum_{t:\ market\ is\ in\ its\ 5\%\ tail} R_t(i), \tag{3}$$

where $MES_{5\%}^{i}$ is the MES of institution i, N is the number of days that the market is in its 5% tail, $R_t(i)$ is the stock market return of institution i.

We estimate the monthly MES*s* of China's publicly listed financial institutions with a fixed one-year window. We start the sample from October, 2008 because one of the big three banks, the China Construction Bank, is listed since September, 2007. Institutions which have missing data from October, 2008 to November 2013 are dropped from the sample.

Generally speaking, just knowing the marginal systemic risk contributions of the individual institutions is not enough for us to estimate the systemic risk because y_i, the share of each institution *during the crisis period*, is unknown. However, the systemic risk increases if the marginal systemic risk contribution of all individual institutions increase, given the distribution of y_i. This means that we can use the common trend in MES*s* of individual institutions to measure the systemic risk if the MES*s* follow similar time series trends. Table 1 suggests that this is actually the case for China in the years after the onset of the global financial crisis. The total variances of the MES*s* are decomposed into a "Commonality" component explained by a common factor and an idiosyncratic component called "Uniqueness". The common factor can explain more than 50 percent of the total variances in the MES*s* of most financial institutions in our sample.

One concern is that the fourth largest bank, the Agricultural Bank of China (ABC), is only listed since October 2010. Therefore, its MES is available only since October 2011. However, as can be seen from Figure 1, the MES of the ABC follows a very similar trend as the common factor we extracted, using the sample without the data of the ABC. Therefore, the common factor (henceforth denoted F_t) is a good indicator of the systemic risk. Since the MES*s* are constructed as indicators of average equity returns during the financial crisis. A lower F_t suggests a worse outcome in the crisis. From Figure 1, we see that China's systemic risk was highest during in 2009 when the government kept the fiscal and monetary policy expansionary as a reaction to the global financial crisis. The situation becomes better in early 2010 as the monetary expansion becomes less aggressive (PBOC, 2010). End of 2011 was also a period with high systemic risk. As we shall show, it is partly due to a surge in the global financial risk.

Figure 1: The MES of the ABC and the common factor of the MESs

The solid line is the MES of the ABC and dashed line is the common factor of the MESs.

Table 1: Variance decomposition of the MESs

Institution	Commonality	Uniqueness
Pingan Bank	0.76	0.24
Hong Yuan Securities	0.34	0.66
Shaanxi International Trust and Investment	0.62	0.38
Northeast Securities	0.57	0.43
Guoyuan Securities	0.55	0.45
Bank of Ningbo	0.80	0.20
Shanghai Pudong Development Bank	0.95	0.05
Huaxia Bank	0.76	0.24
Minsheng Bank	0.94	0.06
CITIC Securities	0.78	0.22
China Merchants Bank	0.96	0.04
Sinolink Securities	0.40	0.60
Haitong Securities	0.69	0.31
Bank of Nanjing	0.82	0.18
Industrial Bank	0.98	0.02
Bank of Beijing	0.84	0.16
Pingan	0.66	0.34
Bank of Communications	0.95	0.05
Industrial and Commercial Bank of China	0.53	0.47
China Life	0.36	0.64
China Construction Bank	0.86	0.14
Bank of China	0.86	0.14
CITIC Bank	0.88	0.12

Sample period: 2008M10-2013M11.

Source: The Wind database.

3. Monetary Policy and the Systemic Risk

In this section, we investigate the impact of monetary policy on the systemic risk in China. For this purpose, we construct a structural vector auto-regression (SVAR) model of the systemic risk, inflation, output and a monetary policy variable. The first variable is our variable of interest while the last three variables are conventional in a parsimonious SVAR model for monetary policy analysis. More specifically, the systemic risk indicator in the VAR model is the change rate of F_t. We use the change rate rather than the level of F_t in the model because unit root test suggests that F_t is not stationary in our sample period (see Table 2). We denote the change rate of F_t by S_t. Inflation is measured by the monthly CPI inflation rate and we denote it by π_t. Because real GDP data is not available at the monthly frequency, we use constant-price industrial value added as a proxy for the aggregate output level. Using monthly growth rate and year-on-year growth rate of the industrial value added, we can obtain a constant-price index of the industrial value added. Then, the output gap is obtained using the HP filter. We denote the output gap by $\tilde{y}_t$. As for the monetary policy variable, we use monthly M2 growth rate rather than the policy interest rate widely used in monetary analysis of advanced economies. The reason is that interest rates were regulated in the sample period and quantitative measures, such as the monetary aggregates, were more important in China's monetary policy practice.

We denote the M2 growth rate by M_t. Except our systemic risk measure, all data are retrieved from the CEIC database. All data are seasonally adjusted by the Census X12 method. Unit root test results suggest that S_t, π_t, $\tilde{y}_t$ and M_t are all stationary variables.[2]

Table 2: Unit root test results

	F_t	S_t	π_t	$\tilde{y}_t$	M_t
ADF test statistic	-1.31	-6.52	-4.07	-2.31	-6.71
1% critical value	-3.54	-3.54	-3.54	-3.54	-3.54
5% critical value	-2.91	-2.91	-2.91	-2.91	-2.91
10% critical value	-2.59	-2.59	-2.59	-2.59	-2.59
Philips-Perron test statistic	-1.66	-8.17	-4.07	-3.35	-6.82
1% critical value	-3.54	-3.54	-3.54	-3.54	-3.54
5% critical value	-2.91	-2.91	-2.91	-2.91	-2.91
10% critical value	-2.59	-2.59	-2.59	-2.59	-2.59

Lags in the ADF test selected by the Schwarz information criterion. All tests include a constant but no deterministic trend.

[2] Although the ADF test cannot reject the unit root hypothesis of $\tilde{y}_t$, the Phillips-Perron test reject the unit root hypothesis at the 5% level. Given the relatively limited power of unit root tests in small samples, we choose to model the output gap as a stationary variable. This is also a common practice in the literature.

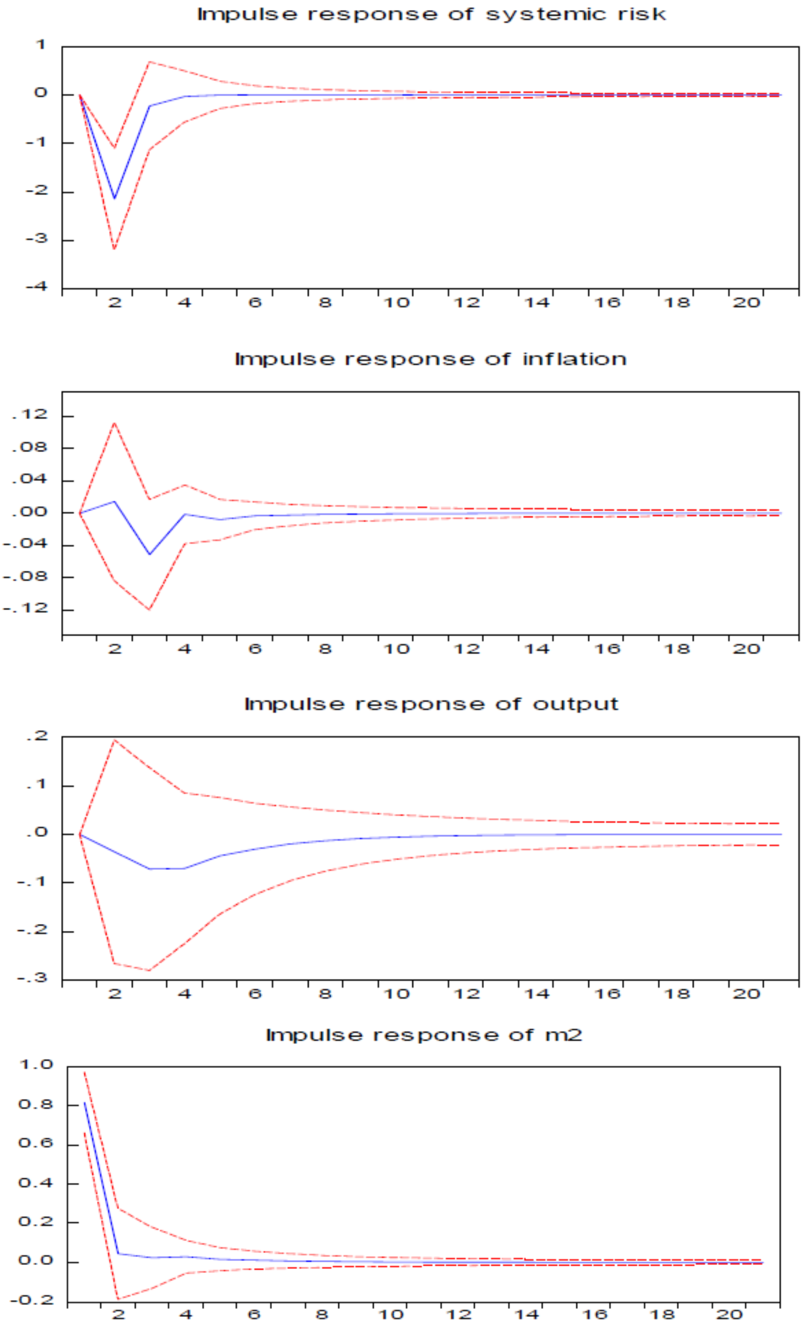
For structural analysis, the identification of economic shocks are important. We use the popular recursive identification scheme in this paper. For recursive identification, the ordering of variables is the key. We follow Primiceri (2005) to order π_t before $\widetilde{y}_t$ and $\widetilde{y}_t$ before M_t. Therefore, the monetary policy affects output and inflation with lags. We order our systemic risk measure S_t first. As observed by Reinhart and Rogoff (2009), accumulation of the risk which eventually leads to a financial crisis takes a long time. Particularly, financial crises usually happen after a long period of fundamental changes in real activities. Taylor (2009) also suggests that one source of the US subprime crisis was a *prolonged period* of over-expansionary monetary policy.

We proceed in two steps in this section. First, we show some preliminary results from the conventional SVAR model with constant coefficients and volatility. One limitation of the conventional SVAR is that the coefficient constancy assumption may not be valid due to the on-going economic reforms in China. Another limitation is that the constant volatility assumption may fail to capture changes in the shock sizes during our sample period. We use the TVP-SVAR with stochastic volatility of Primiceri (2005) to overcome those limitations.

3.1 Impulse responses of the conventional SVAR model

Figure 2 presents the impulse responses of the variables in the conventional SVAR model, in the sample period 2008M10-2013M11, to an expansionary monetary policy shock. Notably, zero lies in the 95% confidence bands of the impulse response of inflation and output gap, so unexpected monetary policy actions did not significantly affect inflation and output. By contrast, the impulse responses of the systemic risk indicator are significantly lower than zero for almost one quarter. This result suggests that an unexpected monetary expansion increases the systemic risk in China.

Figure 2: Impulse responses to an expansionary monetary policy shock



The solid line presents the mean responses and the dashed lines are the 95% confidence bands (based on 10000 Monte Carlo simulations). Numbers on the horizontal axis are months.

3.2 Impulse responses of the TVP-SVAR model

3.2.1 The TVP-SVAR model

The TVP-SVAR model can be written in a compact way as follows

$$y_t = X_t' B_t + A_t^{-1} \Sigma_t e_t, \tag{4}$$

$$X_t' = I_4 \otimes [1, y_{t-1}', ..., y_{t-k}'], \tag{5}$$

where $y_t = [S_t, \pi_t, \tilde{y}_t, M_t]$, I_4 is an identity matrix with dimension four, $\otimes$ denotes the Kronecker product, e_t is the vector of structural shocks which have zero means and unit variances.

Denote the vector of non-zero and non-one elements of A_t by a_t. Denote the diagonal elements of Σ_t by σ_t. Time variations of a_t reflect changing effects of the ith economic shock on the jth variable. Time variations of σ_t reflect the changing shock sizes or stochastic volatility. Following Primiceri (2005), dynamics of the parameters are modeled as follows:

$$B_t = B_{t-1} + u_t, \tag{6}$$

$$a_t = a_{t-1} + v_t, \tag{7}$$

$$log\sigma_t = log\sigma_{t-1} + w_t, \tag{8}$$

Where u_t, v_t and w_t are error terms.

The covariance matrix of the error terms is

$$V = Var([e_t\ u_t\ v_t\ w_t]') = \begin{pmatrix} I_4 & 0 & 0 & 0 \\ 0 & P & 0 & 0 \\ 0 & 0 & Q & 0 \\ 0 & 0 & 0 & T \end{pmatrix}, \tag{9}$$

where P, Q, T are positive definite matrices.

As the TVP-SVAR has a larger number of parameters than the conventional SVAR and our sample size is small, we estimate the model using Bayesian methods. We follow Primiceri (2005) to use uninformative priors for estimation. Details on the priors are available in Primiceri (2005). The posterior distribution is simulated using Gibbs sampling.

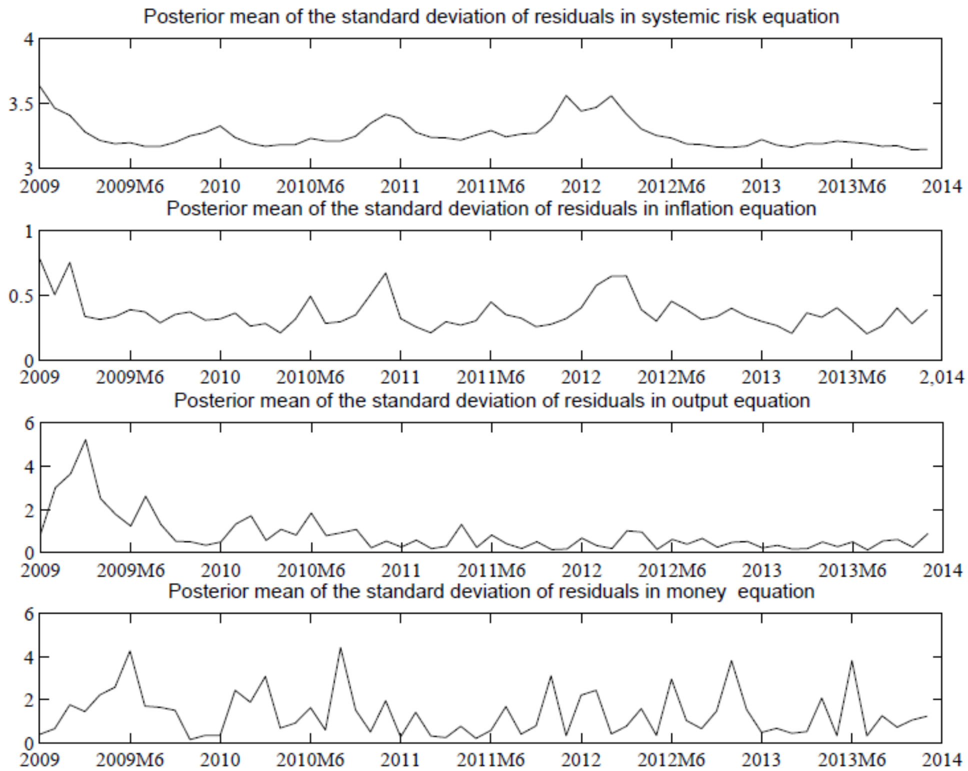
The main results are summarized in the next two subsections.

3.2.2 Stochastic Volatility

Figure 3 presents the estimated posterior means of the stochastic volatility of the model variables. As can be seen, the size of the shock to China's systemic risk jumped upward at the beginning of 2009. This reflects the impact of the global financial crisis on China's financial system. Around that period, several Chinese banks reported losses from investments in the United States.[3] The global financial crisis also affected the size of the shock to China's inflation and output. This can be seen from the jump in the stochastic volatility of those two variables in 2009.

[3] http://en.wikipedia.org/wiki/List of write downs due to subprime crisis

Figure 3: Stochastic volatility



Another period of high systemic risk volatility starts from the end of 2011 and ends in early 2012. This again reflects the impact of a surge in global financial risk. To see this, we plot a measure of jump risk in the US financial market in Figure 4. The jump risk measure is constructed following Alexander and Kaeck (2008). More specifically, the jump risk is measured by the difference between 30-day VIX[4] and 3-month VIX. This is motivated by the fact that a decrease in short-term volatility compared with long-term volatility indicates a lower likelihood of downward jumps in equity prices over the shortterm than over the longer term. From Figure 4, we see that the global financial risk significantly increased in the end of 2011, after a relatively tranquil period. Analysts believed that this surge in the global financial risk raised sovereign credit risk in the emerging market countries including China.[5] Figure 4 shows that the credit default swap (CDS) spread of China's sovereign bond, usually taken as the insurance premium on China's sovereign bond, indeed increased in the end of 2011.[6] However, the surge in the global financial risk is not the only reason why China's sovereign credit risk increases. Growth slowdown concerns and the worry about the burst of a housing bubble also added to the sovereign risk at the time. No matter what are the reasons for the change in China's sovereign credit risk, the increase in the sovereign credit risk may have increased the uncertainty in the financial sector.

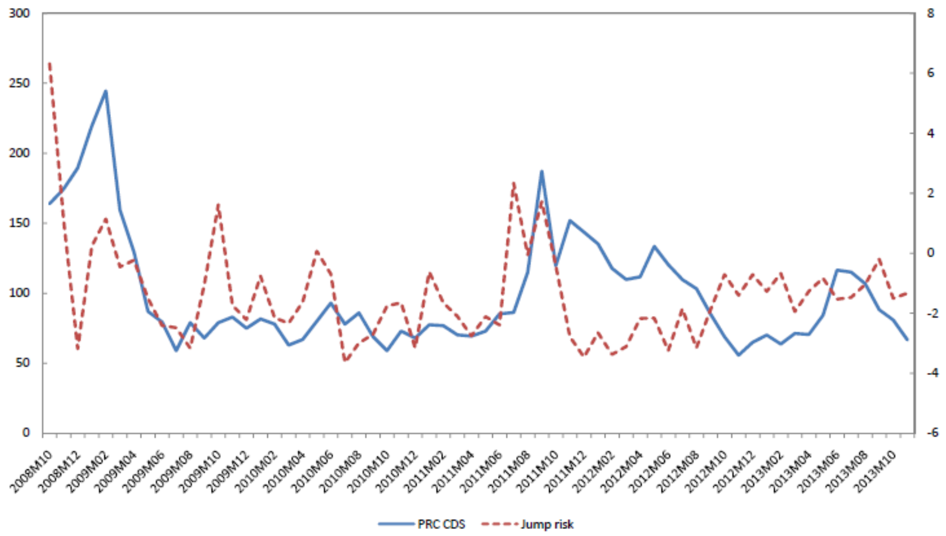
[4] VIX is the symbol for the Chicago Board Options Exchange Market Volatility Index, a measure of market expectations of near-term stock market volatility conveyed by the stock index option prices.

[5] See, for example, http://www.piie.com/blogs/china/?p=480

[6] We report the 5-year CDS spread because it is the most liquid market segment of sovereign CDS.

Particularly, it has been documented by Demirg-Kunt and Huizinga (2013) that an increase in the credit risk of the public sector could increase the risk in the financial sector.

Figure 4: Jump Risk in the global financial market and China's 5-year sovereign CDS spread

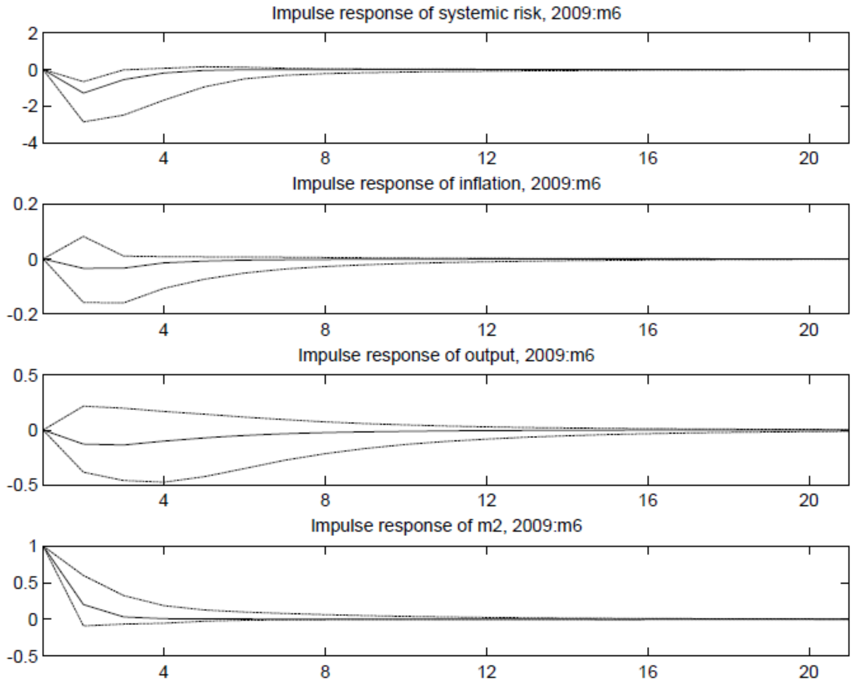


The solid line is the CDS spread, the dashed line is the jump risk. The left axis is the CDS spread (in basis points), the right axis is the jump risk.

3.2.3 Impulse responses

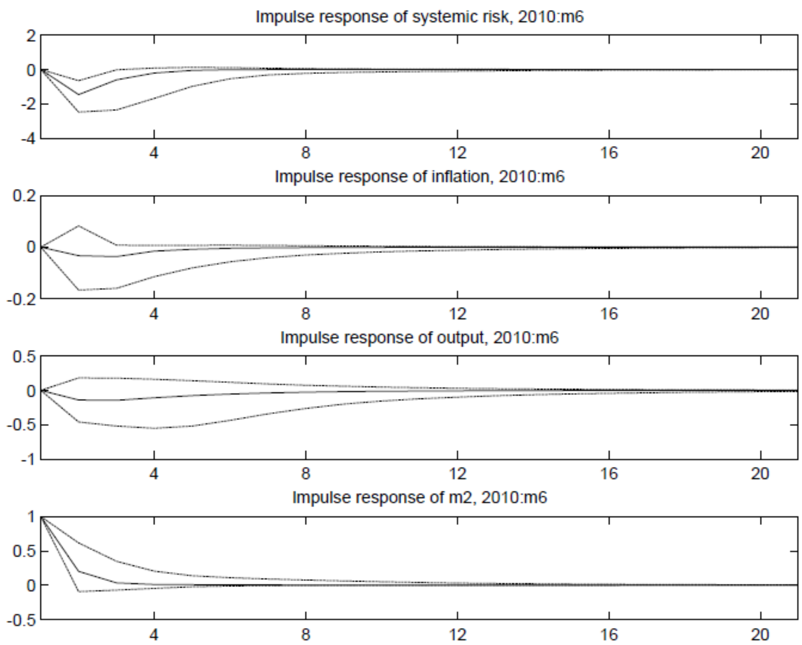
As we have discussed, one advantage of the TVP-SVAR model over the conventional SVAR model is that it allows the coefficients to vary over time, and therefore, takes into consideration the impact of economic reforms and other structural changes in the Chinese economy. As a result, we can investigate the impact of monetary policy on the systemic risk in different time periods. We consider four different periods. Two periods (2009M6, 2011M10) features high volatility of systemic risk, and therefore, are relatively turbulent periods in terms of financial stability. Another three (2010M6, 2012M6) features relatively low volatility of systemic risk, and therefore, are relatively tranquil periods in terms of financial stability. The impulse responses of the variables to an unexpected expansionary monetary policy are summarized in Figure 5 to 8. Although the impulse responses differ quantitatively, the qualitative results are very similar. An expansionary monetary policy shock significantly raises the systemic risk in all periods which we considered. The impact is largest in the second month after the shock and gradually fades away after about one quarter. There is no significant impact of an expansionary monetary policy on inflation and output. This suggests that China may have already been in a liquidity trap. In this case, there is not enough effective demand in the real sector, and it is not attractive for entrepreneurs to invest in new projects. More liquidity supply stimulated by a monetary policy does not necessarily encourage investment in new projects in the production economy. Instead, it can be used for speculative purpose. Speculation then increases the risk of lenders and raises the systemic risk in the financial sector.

Figure 5: Impulse responses to an expansionary monetary policy shock, 2009M6



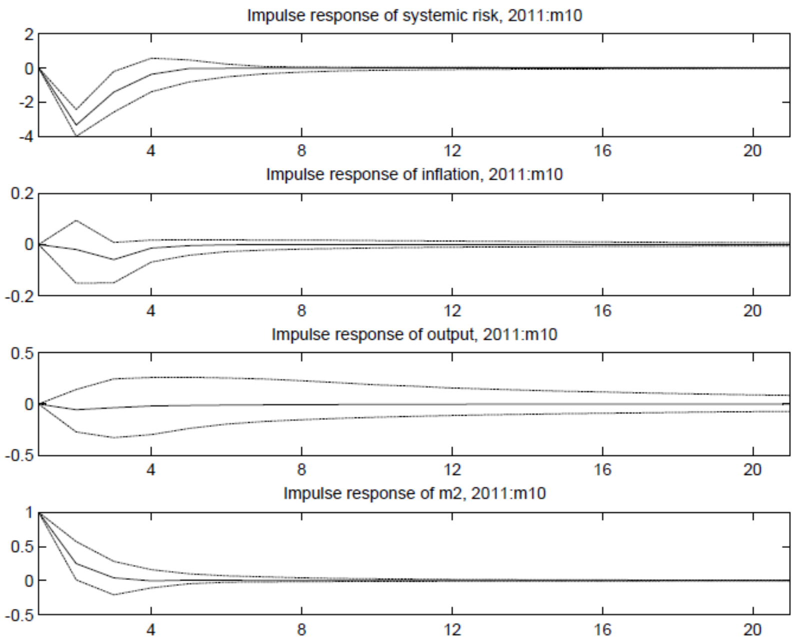
The solid line presents the posterior median responses and the dashed lines are the 0.025 and 0.975 quantiles (based on 10000 simulations, burn in 2000 draws). Numbers on the horizontal axis are months.

Figure 6: Impulse responses to an expansionary monetary policy shock, 2010M6



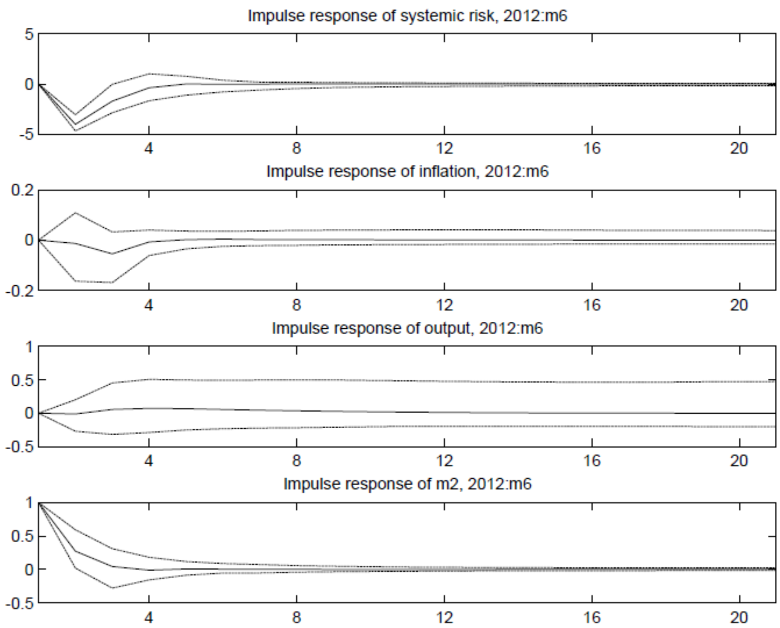
The solid line presents the posterior median responses and the dashed lines are the 0.025 and 0.975 quantiles (based on 10000 simulations, burn in 2000 draws). Numbers on the horizontal axis are months.

Figure 7: Impulse responses to an expansionary monetary policy shock, 2011M10



The solid line presents the posterior median responses and the dashed lines are the 0.025 and 0.975 quantiles (based on 10000 simulations, burn in 2000 draws). Numbers on the horizontal axis are months.

Figure 8: Impulse responses to an expansionary monetary policy shock, 2012M6



The solid line presents the posterior median responses and the dashed lines are the 0.025 and 0.975 quantiles (based on 10000 simulations, burn in 2000 draws). Numbers on the horizontal axis are months.

4. Conclusion

We construct an indicator of the systemic risk in China's financial sector. According to this indicator, China's systemic risk was very high in 2009. One reason of this surge in the systemic risk was an increase in the size of the shock to China's financial stability.

Particularly, the collapse of the Lehman Brothers triggered an increase in the jump risk of the global financial market. Another important reason, according to our analysis, is the excessively expansionary monetary policy since the end of 2008, as a response to the global financial crisis. The target of the monetary expansion was to reduce the impact of the global financial crisis on China's real economy, and to prevent a deflation and recession. However, we find that the monetary expansion did not raise inflation or output. Rather, it significantly raised the systemic risk in the financial sector. Our results call for a more prudent monetary policy to prevent the accumulation of financial risk which could ultimately lead to a financial crisis and disturb China's economic development.

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