Monetary Policy Uncertainty, Credit Risk and China’s Macroeconomic Fluctuations

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Abstract

China’s economy faces a dramatic increase of economic uncertainty in the recent years, and credit risk has become one of the main challenges faced by China’s financial system. By constructing a DSGE model with credit risk and uncertainty shock, this paper puts forward a new source of China’s credit risk which might be neglected before, that is the uncertainty in China’s monetary policy. Then we provide a specific measure for China’s monetary uncertainty through Bayesian MCMC method, while identifying the credit risk adopting the time-varying dynamic factor model. By constructing the Bayesian VAR model, we provide further empirical evidence for the model. The main findings are as follows: firstly, the increase of China’s monetary policy uncertainty could bring about negative effects on economic activity and exacerbate the credit risk. Secondly, credit risk could amplify the negative impact of the monetary policy uncertainty and further depress the real economy. Additionally, credit risk currently makes the greatest contribution to China’s overall financial risks. The most important policy implication of this paper is that: China’s government should reduce its policy uncertainty along with preventing the financial risks.

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1 Introduction

In the last five years, the average global uncertainty index has been about 60 percent higher than in previous years, surpassing even the period around the 2008 financial crisis and recession. Concerns arouse particularly to China, whose decelerating growth has unnerved the markets. According to the Economic Policy Uncertainty (EPU) index measured by Baker et al. (2016), China’s economic uncertainty rise dramatically since 2012 and records a new high recent year. In 2018, the United States started to hike tariffs on Chinese imports, and the trade war erupting between the U.S. and China might further depress the global economy and raise the economic uncertainty significantly. In the meanwhile, after years of hyper rapid credit-fueled growth, China’s central bank now has put forward reducing its credit risk as the priority work. The booming shadow banking system and the massive local government debt caused wide public concern of China’s financial security. The International Monetary Fund has repeatedly warned of risks stemming from China’s high debt-to-GDP ratio and called for speedy deleveraging. In October 2017, the former Governor of China’s central bank, Zhou Xiaochuan pointed out that we shall focus on preventing “Minsky Moment” and holding the bottom line of “no outbreak of systemic financial risk”. After the 19th CPC National Congress, Chinese Prime Minister Li Keqiang also pointed out preventing financial risks was one of the country’s “three fundamental battles” along with fighting poverty and pollution.

Motivated by growing concerns about the credit risk of financial system and increasing economic uncertainty faced by China, this paper aims to provides some new insight to better understand China’s financial risks and its policy uncertainty. China offers an excellent place to study monetary policy uncertainty for the following rationales. First of all, China is a transition economy from the central-planed system to a market-based economy, a dual-track or gradualist approach has been adopted to handle the fundamental issues, during which China’s officials might face some economic condition or policy environment that they had never experienced before.”Crossing the river by feeling the stone” has been the hallmark feature of China’s market liberalization reform, which also implied the underlying uncertainty associated with China’s economic policy to some degree. Secondly, China’s monetary policy also exist potential uncertainties. According to Sun (2017), the People’s Bank of China (PBC), does not follow the standard one-instrument operating procedure that most developed economies adopt Instead, they use multiple tools to deal with various tasks, including both the conventional tool, such as M2 and interest rate, and some emerging tools, like Short-term Liquidity Operations (SLO), Standing Lending Facility (SLF) and Pledged Supplemental Lending (PSL) et al. However, the public might have no idea about when and how those policy tools should be carried out, thus giving rise to potential uncertainties in China’s monetary policy. Song and Xiong (2018) also pointed out the PBC has frequently used its policy tools to regulate the funding cost and liquidity of the whole economy, while those active government interventions can be entirely counterproductive and deliver unintended consequences. All of these extensive policy interventions by the government might lead to the increase of monetary policy uncertainty in China. In addition, the monetary policy uncertainty in US has also increase substantially recent years, especially when President Trump takes office in the White House, which might spillover to other country and pose certain impacts on China’s monetary policy-making and
implementation.

Thus, when studying China's credit risk, we choose to focus on the role of China's policy uncertainty. This consideration differs significantly from generally accepted views on China's credit risk. It is commonly believed that China's credit risk lies in high leverage, massive shadow banking, or booming housing sector and so on. Instead of delving more into those generally believed sources of credit risk, this paper points out that there exists another important source of China's credit risk—the uncertainty of China's monetary policy, which might be neglected by our government before. The main idea keeps in line with Song and Xiong (2018) which emphasized the effect of policy risk on the efficiency of the financial system and the systemic risk in China. Chinese officials seldom link their policy behaviors to the buildup of financial risks since they are reluctant to admit their wrongdoings in some cases, while in reality, the Chinese government has played a highly dominant role in managing the whole financial system. The policy uncertainty could have important implications for the credit risk of the financial system. Therefore, investigating the patterns of China's credit risk and macroeconomic fluctuations from the perspective of monetary policy uncertainty is of great significance for Chinese government to prevent credit risk and maintain financial stability.

The remaining part of this paper is arranged as follows: the second part review some related literature, the third part constructs the DSGE model with credit risk and monetary policy uncertainty shock, where the impact of monetary policy uncertainty on China's credit risk and real economy is investigated, and then constructs a specific measure for China's monetary policy uncertainty through the MCMC method; the fourth part identifies China's credit risk from the whole financial risks by using a large time-varying dynamic factor model. And in the fifth part, we analyze the relationship among China's monetary policy uncertainty, credit risk and China's real economy activities by using the Bayesian VAR model; the last part is the conclusion and policy implications of this paper.

2 Literature review

A large and growing body of literature focuses on the uncertainty shocks in business cycles in recent years. Since the pioneering contribution by Bloom (2009), massive literature documented the effects of uncertainty shocks on macroeconomic dynamics in general equilibrium models. For instance, Fernández-Villaverde et al. (2011) found strong evidence of time-varying volatility in the real interest rates of emerging market economies, and showed that real interest rate volatility triggers a decline in output. Bloom et al. (2012) proposed uncertainty shocks as a new shock that drives business cycles, and found uncertainty shocks can explain the fluctuations in GDP of around 3%. Meanwhile, Baker et al. (2016) and Ng et al. (2015) also gave some empirical support to treat uncertainty as potential driving force of business fluctuations.

As Born and Pfeifer (2014) pointed out, there are several potential transmission channels through which aggregate uncertainty may affect economic activity. The first one is real option channel developed by Bloom (2009) in partial equilibrium models. This channel is further examined in general equilibrium models by Bloom et al. (2012) and Bachmann and Baye (2013). They introduced the irreversible investment cost and showed that the 'wait-and-see' attitude causes the delay of investment
when the economy suffered from uncertainty shock. The second channel is the precautional saving motive illustrated by Gourio(2012) and Basu and Bundick(2012). When faced with uncertainty shock, risk-averse households may choose to consume less and work more to self-insure against future shocks. This precautionary saving incentive occurs in response to the uncertainty regarding future income. On the other hand, Gilchrist(2012) maintained that financial distortions are the main propagation mechanism behind uncertainty shock, and the impact of uncertainty on investment occurs primarily through changes in credit spreads; Alfaro et al.(2016) also showed how financial frictions amplify the impact of uncertainty shocks on firm’s investment both theoretically and empirically. In addition, the existence of nominal rigidities, such as price stickiness and labor market friction, can also amplify the impact of uncertainty shocks on economic activities (Born and Pfeifer, 2014; Leduc and Liu, 2016). Wang et al.(2018) shows imperfect information can produce the self-fulfilling surge in financial uncertainty and real uncertainty.

Another branch of literature concentrates on the policy uncertainty, i.e., uncertainty about fiscal and monetary policy, and its impact on the macroeconomic fluctuations. For example, Fernández-Villaverde et al.(2015) find that unexpected changes in fiscal volatility shocks can have a sizable adverse effect on economic activity through the endogenous increase in markups. Handley and Limao(2015) discuss about the relation between policy uncertainty and export trade of the country; they discover that the trade policy uncertainties have lowered the investment and industrial entry of the export enterprises. Bianchi and Melosi(2017) show that policy uncertainty about the way debt will be stabilized excludes deflation at the zero lower bound because it induces inflationary pressure. However, Born and Pfeifer(2014) find that policy risk shocks are too small and not sufficiently amplified. There are also some literature focusing on China’s policy uncertainty and their effects on its financial systems. Hachem and Song(2017) show that stricter liquidity standards in China in the late 2000s generate unintended credit booms. Cai et al.(2017) point out that the tripling of stamp tax for stock trading in China on May 30, 2007, shifts the trading frenzy from the stock market to the put warrant market and lead to a speculative price bubble in China’s put warrant market. Xiong and Song(2017) point out that some of China’s policies and regulations might yield to unintended outcomes and thus lead to resource misallocation.

Due to its special institutional background, China provides an ideal place to investigate its policy uncertainty. While several literatures have examined the impacts of China’s policy uncertainties on its financial system, fewer scholars concentrated on China’s monetary policy uncertainty and its effects on credit risk. Song and Xiong(2018) point out that China’s policy risks can exacerbate the systemic risk, and Xiong et al.(2017) provide a simple model to illustrate a tension between government’s gradualist approach and the incentive of market participants to front-run gradual policy changes, showing that China’s active government intervention in financial markets reduce the informativeness of stock price. Nevertheless, those inspiring works do not give a specific measure of China’s monetary policy uncertainty and credit risk, their analysis also does not offer a direct evidence of the impact of China’s policy uncertainty on its credit risk and macroeconomics fluctuations.

To fill this gap, we investigate the impact of monetary policy uncertainty on China’s credit risk and real economy both theoretically and empirically. As a first step, we construct a DSGE model with credit risk following Bernanke et al.(1999)
and Christiano et al. (2014), and introduce monetary policy uncertainty shock by augmenting the Taylor rule with stochastic volatilities. Then we estimate the uncertainty of monetary policy in China by using the Bayesian MCMC method, and apply the time-varying dynamic factor model to measure China’s credit risk based on 29 macro and financial variables of China from 2006Q1 to 2017Q3. Furthermore, we provide some empirical evidences of the impact of China’s monetary policy uncertainty documented in the theoretical model by using Bayesian VAR model. The main findings can be summarized as follows: (1) The increase of the China’s monetary policy uncertainty can directly lead to the rise of credit risk and the decline of output. (2) The rise of credit risk will have a significant and sustained contractionary effect on real economic activities and will further aggravate the negative impact of the monetary uncertainty shocks. (3) China’s financial risks currently are most concentrated in its credit market.

This paper is linked with different streams of literature in macroeconomics concerning policy uncertainty shocks and the interaction between financial sector and macroeconomics. Firstly, this model can well replicate the traditional channels documented in the literature through which the uncertainty shock can tighten the economic activities and depress the output. For example, Precautionary saving channel (Gourio, 2012; Basu and Bundick, 2012), Real-option channel (Bloom et al., 2012; Bachmann and Bayer, 2013) and financials friction channel (Gilchrist, 2012). Moreover, this model adds to the existing literature that monetary policy uncertainty can bring contractionary effect to the real sector through the credit risk channel. Secondly, the main idea of this paper is in line with a large strand of literature focusing on the credit risks in macroeconomics fluctuations after the financial crisis in 2008 (Miao and Wang, 2010; Gilchrist, 2012). This paper is also associated with some literature on China’s policy issues. The core finding of this paper that China’s monetary policy uncertainty can lead to the increase of credit risk, provides direct evidence to support the analysis of Song and Xiong (2018). Besides, we complement those literatures by constructing a specific measure for China’s monetary policy uncertainty and its credit risk.

3 The Model

Following Bernanke et al. (1999) and Christiano et al. (2014), we incorporated the credit risk based on the costly state verification of debt contract, and additionally we introduce stochastic volatility into the monetary policy rule to capture China’s monetary policy uncertainty. In the meanwhile, we assume that the economy is characterized by different types of nominal and real rigidities: price stickiness, capital adjustment costs, habit formation and financial market frictions. On this basis, the impact of monetary policy uncertainty shock on credit risk and macroeconomic fluctuations is investigated.
3.1 Model set-up

3.1.1 Household

Suppose the representative household chooses consumption $C_t$ and labor input $N_t$ to maximize its lifetime expected utility function:

$$\text{max } E_t \sum_{t=0}^{\infty} \beta^t \left( \frac{(C_t - bC_{t-1} - \frac{\psi N_{t+1}^{1+\eta}}{1+\eta})^{1-\sigma} - 1}{1-\sigma} \right)$$ (1)

Where $E_t$ refers to the expectation operator, which indicates the expected value for economic variables based on the information set in the period $t$, $\beta$ is the inter-temporal discount factor and $0 < \beta_t < 1$. $\eta$ is the Frisch elasticity of the household’s labor supply, $\psi$ is the utility weight for leisure, $\sigma$ is the relative risk-aversion coefficient. $b$ refers to habit formation parameter that reflects the persistence of consumption habit of household, $0 < b < 1$. The representative household enters the economy by holding $B_t$ units of nominal deposits in a financial intermediary which pay the interest rate $R_t$ that the household takes as given. During period $t$, the representative household supply the labor to the entrepreneur and earn wages incomes $W_tN_t$. Additionally, the household pay the lump-sum tax $T_t$ to the government and receive the dividends $\Pi_t$ from the retailer firms since we assume that all the firms are ultimately owned by the household. The household choose to allocate those revenues to the current consumption and deposit holding for next periods. The inter-temporal budget constraint of the household is as follows:

$$P_tC_t + B_{t+1} = W_tN_t + R_tB_t + \Pi_t - T_t$$ (2)

Subjected to the budget constraints, the household choose the consumption, labor input and deposit holding to maximize its life utility function as shown in (1). We can derive the following first-order conditions in (3)-(5), where $\lambda_t$ is the Lagrangian multipliers associated with budget constraint (1).

$$\lambda_t = \left( C_t - bC_{t-1} - \frac{\psi N_{t+1}^{1+\eta}}{1+\eta} \right)^{-\sigma} - \beta b \left( C_{t+1} - bC_t - \frac{\psi N_{t+1}^{1+\eta}}{1+\eta} \right)^{-\sigma}$$ (3)

$$\lambda_t = \beta E_t \left( \lambda_{t+1}R_{t+1}P_{t+1} \right)$$ (4)

$$\lambda_t \frac{W_t}{P_t} = \left( C_t - bC_{t-1} - \frac{\psi N_{t+1}^{1+\eta}}{1+\eta} \right)^{-\sigma} \psi N_t^\eta$$ (5)

3.1.2 Entrepreneurs

According to Bernanke et al.(1999), entrepreneurs manage the production sector that produces wholesale goods and sell it to the retailer firms. Entrepreneurs are risk neutral and are assumed to have a finite expected horizon, the probability that an entrepreneur will survive into the next period is $\gamma$. Entrepreneurs purchase capital from the capital producer and employ labor force from the household for production in each period, where the production function is set in the form of the
following C-D production function:

\[ Y_t = A_t K_t^\alpha N_t^{1-\alpha} \]  \hspace{1cm} (6)

Where \( A_t \) refers to total factor productivity, \( Y_t \) is the gross output, and \( \alpha \) is the share of capital in output. Suppose that the entrepreneur sells the goods to the retailer at wholesale price \( P_t^{W} \) after completing the production, and the retailer further packages the wholesale goods and sells them to the household and capital goods manufacturer at the retail price \( P_t \). We define the markup percentage of the retailer as \( X_t \), which means if the price of the final products is 1, the relative price of the wholesale goods produced by the entrepreneur is \( \frac{1}{X_t} \).

At the end of the period \( t \), entrepreneurs purchase capital used in the next period at the price of \( Q_t \). The total fund needed for the new capital purchasing is \( Q_t K_{t+1} \), which will be partly financed by the entrepreneur’s net worth. However, the net worth (the firm equity) of the entrepreneur will never be enough to fully cover the total fund for new capital acquisition due to its limited lifetime. Thus, entrepreneurs have to issue debt contracts and seek funding from financial institution. If the entrepreneur’s net worth is \( V_t \), the external financing that the entrepreneur needs to obtain from the financial institution at the end of period \( t \) is:

\[ B_t^c = Q_t K_{t+1} - V_t \]  \hspace{1cm} (7)

The entrepreneur’s demand for capital is determined by the expected marginal return of the capital, and the expected marginal cost of the funding at period \( t+1 \), that is \( E_t R^{k}_{t+1} \).

\[ E_t R^{k}_{t+1} = E_t \left( \frac{1}{X_t} X_t Y_{t+1}^\alpha + Q_{t+1} (1-\delta) \right) \]  \hspace{1cm} (8)

Where \( \delta \) is the capital depreciation rate. In the meanwhile, the demand for labor force depends on the marginal output of labor and the wage, the optimal demand for labor input can be determined by:

\[ \frac{W_t}{P_t} = 1 - \alpha \frac{Y_t}{X_t N_t} \]  \hspace{1cm} (9)

### 3.1.3 Financial Intermediaries

According to Christiano et al.(2014), we assume the entrepreneurs suffer from the idiosyncratic productivity shock \( \omega_t \), such that in each period \( t \), the entrepreneur’s marginal return of capital becomes stochastic \( \omega_{t+1} R^k_{t+1} \). Following Christiano et al.(2014) and Bernanke et al.(1999), we assume that \( \omega_t \) are mutually independent and follow the logarithmic normal distribution, the cumulative distribution function and density function of \( \omega_t \) are respectively given by \( F(\omega_t) \) and \( f(\omega_t) \), and \( E(\omega_t) = 1 \). Due to asymmetric information in the credit market, entrepreneurs themselves can observe the state of \( \omega_t \), while financial intermediaries have to pay an extra monitoring cost to verify the state of \( \omega_t \). Suppose that monitoring costs are proportional to capital gains of next period \( \mu \omega_{t+1} R^k_{t+1} Q_t K_{t+1} \). This set-up is the so-called costly state verification (CSV). According to the analysis of Townsend(1978), the optimal contract is the standard debt contract. That is to say, the entrepreneur receives a contact from the financial intermediary which specifies the loan rate \( R^b_{t+1} \) and the
loan amount $B_{t+1}^b$. If the contract matures, the entrepreneur will repay the principal and interest, while if the entrepreneur goes into bankruptcy and fail to pay back the loan, the bank will pay a monitoring cost and take everything left. Therefore, we define the default threshold value of $\omega_{t+1}$ for entrepreneurs as $\omega_{t+1}$:

$$\omega_{t+1} R_{t+1}^k Q_t K_{t+1} = R_{t+1}^b B_{t+1}^b$$  \hspace{1cm} (10)

Where $\omega_{t+1}$ is cutoff value for the entrepreneurs’ default, below this value, the entrepreneur suffers from a bad productivity and fails to repay the loan since it’s total assets now are less than the loan principal and its interest, when $\omega$ is higher than this cutoff value, the entrepreneur will be able to earn a positive profit after paying back to the bank. The contract arrangements between entrepreneurs and financial intermediaries are as follows: when $\omega_{t+1} > \omega_{t+1}$, the enterprise will pay the principal and interests of the loan $R_{t+1}^b Q_t K_{t+1}$; when $\omega_{t+1} < \omega_{t+1}$, the enterprise will go bankrupt and all the assets $\omega_{t+1} R_{t+1}^b Q_t K_{t+1}$ of the enterprise will be taken over by the bank. After deducting the monitoring costs, the net incomes of the bank in this case will be $(1 - \mu) \omega_{t+1} R_{t+1}^k Q_t K_{t+1}$. Since financial intermediaries obtain zero profit in equilibrium under the assumption of fully competitive market with free entry and exit, we can get:

$$[1 - F(\omega_{t+1})] R_{t+1}^b B_{t+1}^b + (1 - \mu) \int_{\omega_{t+1}}^{\omega_{t+1}} \omega_{t+1} R_{t+1}^k Q_t K_{t+1} dF(\omega_{t+1}) = R_t B_{t+1}$$  \hspace{1cm} (11)

The left-hand side is financial intermediaries’ expected incomes from the loan contract, which should be equal to the opportunity cost of their fund in the right-hand side. And equation (11) can be further rewritten as:

$$\Gamma(\omega_{t+1}) = \mu \Theta(\omega_{t+1}) = \frac{R_t}{E_t R_{t+1}^k} \frac{Q_t K_{t+1} - V_{t+1}}{Q_t K_{t+1}} = \frac{R_t}{E_t R_{t+1}^k} \frac{L_t - 1}{L_t}$$  \hspace{1cm} (12)

Where $\Gamma(\omega_{t+1}) = \int_{\omega_{t+1}}^{\omega_{t+1}} \omega_{t+1} dF(\omega_{t+1}) + \omega_{t+1} \int_{\omega_{t+1}}^{\infty} dF(\omega_{t+1}), \Theta(\omega_{t+1}) = \int_{\omega_{t+1}}^{\omega_{t+1}} \omega_{t+1} dF(\omega_{t+1})$, and $\Gamma(\omega_{t+1}) = \Theta(\omega_{t+1}) + \omega_{t+1} (1 - F(\omega_{t+1}))$ can be interpreted as the profit share of the total capital return $R_{t+1}^F Q_t K_{t+1}$ that goes into the financial institution including the monitoring cost. If we deduct the monitoring cost, we can get the net profit share of the financial intermediary as $\Gamma(\omega_{t+1}) = \mu \Theta(\omega_{t+1})$. $L_t = \frac{Q_t K_{t+1}}{V_{t+1}}$ is the leverage ratio of the entrepreneurs. Higher $L_t$ means higher debt ratio and lower net worth of entrepreneurs. We can define the entrepreneur’s utility function as the expected return over opportunity cost of funds:

$$max \hspace{0.5cm} U = \frac{\int_{\omega_{t+1}}^{\infty} (\omega_{t+1} R_{t+1}^k Q_t K_{t+1} - R_{t+1}^b B_{t+1}^b) dF(\omega_{t+1})}{V_t R_t}$$  \hspace{1cm} (13)

Where the denominator is the opportunity cost of entrepreneur in the form of bank deposit return, and the nominator is the expected incomes of entrepreneur. The optimal contract is a combination of $(\omega_{t+1}, L_t)$ which maximizes the entrepreneur’s utility (11). By substituting (12) into (13) and taking logarithm, the first order condition can be written as:

$$\frac{1 - F(\omega_{t+1})}{1 - \Gamma(\omega_{t+1})} = \frac{E_t R_{t+1}^k}{R_t} \frac{(1 - F(\omega_{t+1}) - \mu \omega_{t+1} \Theta(\omega_{t+1})}{1 - \frac{E_t R_{t+1}^k}{R_t} (\Gamma(\omega_{t+1}) - \mu \Theta(\omega_{t+1}))}$$  \hspace{1cm} (14)
Suppose that the probability for survival entrepreneurs in each period is $\gamma$, then the transition path of entrepreneur’s net value $V_t$ can be given by:

$$V_t = \gamma(1 - \Gamma(\bar{\omega}_{t+1}))E_t R_{t+1}^k Q_t K_{t+1}$$ (15)

It is worth noting that when $\bar{\omega}_{t+1} < \bar{\omega}_{t+1}$, the entrepreneur would go bankrupt and fail to repay the bank’s loans, we define the credit risk of this system as the default probability of entrepreneur:

$$Bankrupt_t = \int_{-\infty}^{\bar{\omega}_{t+1}} dF(\bar{\omega}_{t+1})$$ (16)

A larger $Bankrupt_t$ suggests higher default rate caused by firm bankruptcy and greater non-performing loan, thus inducing larger credit risk in the whole economy. According to Bernanke et al. (1999), the values of $\omega_t$ are independent of each other and follow logarithmic normal distribution. In order to ensure that $E(\omega_t) = 1$, we set $\mu_t = -\frac{\sigma^2_t}{2}$, that is $F(\omega_t) = logcdf(\omega_t, \mu_t, \sigma^2_t)$. $\sigma^2_t$ denote the period $t$ standard deviation of $log\omega_t$, and $\sigma^2_t$ is supposed to follow the following logarithmic AR(1) process:

$$log\left(\frac{\sigma_t}{\sigma}\right) = \rho_s log\left(\frac{\sigma_{t-1}}{\sigma}\right) + \epsilon_{st}$$ (17)

Since $\omega_t$ reflect the idiosyncratic risk in real production activities of entrepreneur, $\sigma_t$ characterizes the extent of cross-sectional dispersion in $\omega_t$. The greater $\sigma_t$ means more dispersion in the distributions $\omega_t$. According to Christiano et al. (2014), the time-varying $\sigma_t$ was interpreted as the risk shocks.

### 3.1.4 Capital Producers

Capital producers purchase the final goods from retailer firms and use them to produce the capital for next period with a linear technology. At each period $t$, capital producer is subject to an investment-specific shock $u_t$. They use a fraction of final goods purchased from retailers as investment goods $I_t$, and produce efficient investment goods $u_t I_t$, which together with the existing capital after depreciation generate new capital for next period and then were sold to entrepreneur for production. Following Christensen and Dib (2008), we suppose that capital producer is faced with the quadratic capital adjustment costs specified as $\frac{1}{2}(\frac{I_t}{K_t} - \delta)^2$, and the evolution path of capital goods is:

$$K_{t+1} = u_t I_t + (1 - \delta)K_t$$ (18)

Where $u_t$ follows the logarithmic AR(1) process, $logu_t = \rho_s logu_{t-1} + \epsilon_{ut}$, $\epsilon_{ut} \sim N(0, \sigma^2_u)$. The optimization problem of capital producer is to choose the quantity of the investment to maximize expected profit:

$$max E_t [Q_t u_t I_t - I_t - \frac{\chi}{2}(\frac{I_t}{K_t} - \delta)^2]$$ (19)

Thus, the optimal condition is:

$$Q_t = \frac{1}{u_t} \left[1 + \chi(\frac{I_t}{K_t} - \delta)\right]$$ (20)
Which is the Tobin’s Q equation that relates the price of capital to the marginal investment adjustment costs.

### 3.1.5 Retailers

Retailers are introduced to produce price stickiness. Suppose that retailers are continuously distributed in the interval \([0, 1]\), and each retailer buys the good \(Y_t\) from entrepreneurs at the wholesale price \(P^W_t\) at period \(t\), and differentiates them at no cost. They sell these differentiated retail goods in a monopolistically competitive market after repackaging. The retailer employs a Dixit-Stiglitz aggregator \(Y_t\) for final good production:

\[
Y_t = \left( \int_0^1 Y_i(i) \frac{\epsilon_p^p - 1}{\epsilon_p^p} \, di \right)^\frac{\epsilon_p^p}{\epsilon_p - 1}\tag{21}
\]

Where \(\epsilon_p\) is the elasticity of substitution between different wholesale goods.

The profit maximization problem of retailer which takes the final good price \(P_t\) and wholesale price \(P^W_t(i)\) can be written as:

\[
\max P_t Y_t - \int_0^1 P_t(i) Y_t(i) \, di
\]

This will produce a downward sloping demand curve for each retailer \(i\):

\[
Y_t(i) = \left( \frac{P_t(i)}{P_t} \right)^{-\epsilon_p} Y_t
\]

We suppose that all retailers’ price adjustment strategies follow Calvo (1983) and only a proportion of \(1 - \phi_p\) retailers can readjust their prices at each period while the rest of retailers keep their price unchanged. Therefore, the evolution equation of the price \(P_t\) is:

\[
P_t = (P_{t-1})^{\phi_p} (P^W_{t-1})^{1-\phi_p}\tag{24}
\]

The optimal pricing strategy of retailers is to choose \(\overline{P}_t(i)\) to maximize their expected profits:

\[
\max E_t \sum_{k=0}^{\infty} \phi_p^k \Lambda_{t,t+k} \left[ \frac{\overline{P}_t(i)}{P_{t+k}} - \frac{P^W_{t+k}(i)}{P_{t+k}} \right] Y_{t+k}(i)
\]

Where \(\Lambda_{t,t+k} = \beta^k u(C_{t+k}) u(C_t)\) refers to stochastic discount factor. By substituting the expression of demand curve \(Y_{t+k}(i)\) into the formula and defining \(\kappa = \frac{\epsilon_p}{\epsilon_p - 1}\), the expression of optimal price \(\overline{P}_t\) can be obtained as follows:

\[
\overline{P}_t = \kappa \prod_{k=0}^{\infty} (P^W_{t+k})^{(1-\beta\phi_p)(\beta\phi_p)^k}\tag{26}
\]

### 3.1.6 Central Bank and Government

The task of center bank is to implement monetary policy to regulate the economy and financial system. A large strand of literature documents that there does exist some uncertainties in the monetary policies of central bank (Davig and Leeper, 2007; Mumtaz and Zanetti, 2013; Born and Pfeifer, 2014; Bianchi and Melosi, 2017). On the other hand, related literature has emphasized the importance of allowing
for time-varying volatility in macroeconomic time series models, where the het-
eroskedastic errors are typically modeled by introducing stochastic volatility (see,
e.g., Cogley and Sargent, 2005; Primiceri, 2005). Sims and Zha(2006) also found
that monetary policy rules with regime-switching in the disturbance variances can
best fit US’s data. Recently, a growing literature introduces the time-varying volatil-
ity to model the uncertainty shocks. Following Fernández-Villaverde et al.(2011),
we add stochastic volatility into the monetary policy rule:

\[ i_t = i_0 + \gamma_0 i_{t-1} + \gamma_1 \pi_t + \gamma_2 y_t + \sqrt{h_t} \zeta_t \quad \zeta_t \sim N(0, \sigma_1^2) \] (27)

\[ \ln h_t = \alpha_0 + \rho_1 \ln h_{t-1} + \nu_t \quad \nu_t \sim N(0, \sigma_2^2) \] (28)

Where \( i_t \) is the nominal interest rate, \( \pi_t \) and \( y_t \) are inflation rate and output gap
respectively, \( \gamma_0 \) is the interest rate smoothing coefficient, \( \gamma_1 \) and \( \gamma_2 \) are the reaction
coefficients of the interest rate to the inflation rate and output gap respectively. Note
that \( h_t \) represents the time-varying volatility of monetary policies rule, capturing the
uncertainty of monetary policy, which is assumed to follow the logarithmic AR(1)
process as shown in (28). \( \zeta_t \) and \( \nu_t \) are supposed to be independent from each other
and follow the standard normal distribution. Where \( \zeta_t \) refers to level shock of
monetary policies, that is, the first moment shock, while \( \nu_t \) reflects the uncertainty
shocks of monetary policies, namely, the second moment shock of monetary policies.

In the meanwhile, we also set the fiscal policy rules as shown in (29),and \( \omega_t^g \) is the
ratio of government’s expenditure to GDP. \( \omega_t^g \) follows AR (1) process with steady-
state value \( \omega_g^* \), and \( \epsilon_t \) refers to fiscal policies shock.

\[ G_t = \omega_t^g Y_t \] (29)

\[ \omega_t^g = (1 - \rho_g) \omega_g^* + \rho_g \omega_{t-1}^g + \epsilon_t \quad \epsilon_t \sim N(0, \sigma_g^2) \] (30)

Finally, in order to ensure the balance of government budget, we assume that
the government’s fiscal expenditures should be equal to its tax revenues, namely:

\[ G_t = T_t \] (31)

3.1.7 Market Clearing

The market clearing conditions for products can be expressed as (32),\( C_t \) is the
total consumption,\( I_t \) is the total investment,\( G_t \) is the government expenditure, while
\( \mu \int_0^{\omega_{t+1}^k} \omega_{t+1}^k R^k_{t+1} Q_t K_{t+1} dF \omega_{t+1}^k \) refers to the monitoring costs resulted from financial
frictions.

\[ Y_t = C_t + I_t + G_t + \mu \int_0^{\omega_{t+1}^k} \omega_{t+1}^k R^k_{t+1} Q_t K_{t+1} dF \omega_{t+1}^k \] (32)

3.1.8 Symmetric Equilibrium

In the symmetric equilibrium, all entrepreneurs and retailers are identical, so
they make the same decision. Given the fiscal policies \( \{G_t, T_t\}_{t=0}^\infty \) chosen by the gov-
ernment and the monetary policies \( \{R_t\}_{t=0}^\infty \) chosen by the central bank, the symmet-
ric equilibrium consists of a price sequence \( \Delta = \{P_t, P^W_t, R^k_t, W_t, Q_t, \pi_t, \lambda_t\}_{t=0}^\infty \)
and an allocation sequence \( \Xi = \{C_t, N_t, Y_t, K_t, B_t, I_t, V_t, L_t, \omega_t\}_{t=0}^\infty \) so that allocation
\( \Xi \) solves the problems of utility maximization of household (1), utility maximization
of entrepreneurs (13), profit maximization of capital producer (19) and profit maximization of retailers (25) respectively, and the price sequence ∆ clears the product market and bond market.

### 3.2 Calibration and Estimation

#### 3.2.1 Calibrated parameters

Following most existing literatures on DSGE model, the steady state values of technological level $A_t$ and asset price $Q_t$ are standardized as 1, the quarterly depreciation rate $\delta$ is set to 0.025. The price stickiness parameter $\phi_p$ is set to 0.75, which means the duration period of product price is 1 year. The elasticity of substitution of wholesale goods $\epsilon_p$ is set as 10, indicating the retail markup and the markup in steady state are 11.11%. The subjective discount rate $\beta$ is set as 0.993, and this is line with the annual average one-year deposit interest rate level of 0.418% from 2013-2017. The habit formation parameter $b$ and labor supply elasticity $\eta$ are respectively calibrated as 0.7 and 2. Following the most literatures on China's DSGE model, the capital output share $\alpha$ is set as 0.5, the first-order autoregressive coefficient $\rho$ is calibrated as 0.78. According to Bernanke et al. (1999), the monitoring cost coefficient $\mu$ is calibrated as 0.2.

The steady value of quarterly capital return $R_{t+1}^k$ is calibrated to 1.0125, which is align with 5% of the annual loan rate in China from 2016-2017. According to the nonperforming loan rates of Chinese banks from 2006 to 2017, we calibrate the quarterly steady state default rate $F(\Omega)$ as 0.4%. The steady state value of labor input $N$ is set to 0.33. $\omega_g$ is calibrated to 0.178 to match the quarterly average ratio of China’s government expenditure to GDP from 1996 to 2017. Table 1 shows the meaning and calibration of the major parameters in this paper.

#### 3.2.2 Estimation of Monetary Policy Uncertainty

When it comes to the coefficients in the monetary policy rules, we select the seven-days inter-bank interest rate, the inflation rate and GDP data ranging from 1996 to 2017. After the seasonal adjustment and HP filter to the quarterly GDP sequences, we get the output gap. According to Jacque and Rossi (2004), we adopt the Gibbs Sampling with Metropolis-Hastings algorithms to estimate the monetary policy rule with stochastic volatility. Estimation result is shown in Table 2, according to the estimated mean equation of monetary policy rules above, the smoothing coefficient of interest rate $\gamma_0$ is calibrated as 0.89; the reaction coefficient $\gamma_1$ and $\gamma_2$ to output gap and inflation are respectively calibrated as 0.32 and 0.09. According to the estimated volatility equation of the monetary policy rule above, $\alpha_0$, $\rho_h$, $\sigma_u$ are respectively calibrated as -0.716, 0.595 and 0.019.

Fig.1 and Fig.2 show the posterior distribution of estimated parameters in the monetary policy with stochastic volatility. According to the estimation result in Table 1, $\rho_1$ is significantly not equal to 0, which indicates the existence of China’s monetary policy uncertainty. Fig.3 depicts the evolution patterns of uncertainty of China’s monetary policy.

As shown in Fig.3, China’s monetary policy uncertainties were at high during the Asian financial crisis from 1997 to 1998 and then declined gradually and remained stable. In 2007, The Chinese economy experienced astonishing growth, the PBC
raised interest rates six times in 2017 to cool down the overheated economy. In 2008, the global financial crisis has led to a severe depression to the global economy including China. In the second half of 2008, the PBC strengthened its support for economic growth, lowering the benchmark deposit and loan rates five times and reducing the reserve requirement, those frequent policy operations pushed China’s monetary policy to a new high. During the 'cash crunch' in 2013 China’s monetary policy rose significantly, the recurrent cash squeezes as banks scrambled for fresh funds highlighted the policy dilemma the PBC faced and increased China’s monetary policy uncertainty. In 2015, the PBC expanded China’s money supply, so called "expansionary monetary policy", and cut interest rate several times. During the 2015 stock market crash, China’s monetary policy uncertainty reached a new high.

According to Schmitt-Grohé and Uribe(2004), the first-order Taylor approximation to DSGE model could yield to certainty equivalence, which means stochastic system and deterministic system will be mutually equivalent and the volatility shock has no influence on the economic activities. To carry out the welfare analysis, at least the second-order Taylor approximation will be needed. According to Fernández-Villaverde et. al.(2011), the third-order Taylor approximation is required in order to obtain the uncertainty shocks. According to Lan and Meyer(2013), the solution method firstly maps our nonlinear DSGE model to the following expressions:

$$E_t f(x_{t+1}, x_t, x_{t-1}, e_t) = 0$$  (33)

Where $x_t$ is the endogenous variable while $e_t$ is the exogenous shocks. The policy function for model solution can be obtained through the perturbation method:

$$x_t = h(\tau, e_t, e_{t-1})$$  (34)

Where $\tau \in [0, 1]$ denotes a scaling parameter for the distribution of the stochastic shock $e_t$. $\tau = 1$ represents the original stochastic system; while $\tau = 0$ refers to the non-stochastic case. According to Fernández-Villaverde et al. (2011), third-order Taylor approximation to (34) must be carried out to get the uncertainty shocks:

$$x_t = \tau + \frac{1}{2} y_{t, 2} + \frac{1}{2} \sum_{i=0}^{\infty} (x_i + x_{t, 2, i}) e_{t-i} + \frac{1}{2} \sum_{j=0}^{\infty} \sum_{i=0}^{\infty} x_{j, i} (e_{t-j} \otimes e_{t-i}) + \frac{1}{6} \sum_{k=0}^{\infty} \sum_{j=0}^{\infty} \sum_{i=0}^{\infty} x_{k, j, i} (e_{t-k} \otimes e_{t-j} \otimes e_{t-i})$$  (35)

### 3.3 Model dynamics

A common problem when simulating time series with higher-order solutions is that the impulse response function of the model might diverge rapidly due to the existence of high-order term, so it often leads to explosive paths. To solve this problem, we have to "pruning" out the unstable higher-order terms. Andreasen et al.(2017) provided the pruning algorithm and related MATLAB toolbox. Based on the model and algorithms introduced above, we examine the influences of policy uncertainties on China’s financial risks and macroeconomic fluctuations. We impose one standard deviation shock to disturbance term of the risk shock $\sigma_t$. The impulse response results are shown in the following figures.
3.3.1 Risk shock

Fig. 4 shows the impulse response function for one-unit standard deviation risk shock $\sigma_t$. As shown in Fig. 2, the increase of risk shocks leads to a significant decline of output, investment and consumption, namely, the increase of financial risks can spillover to the real economy and bring about the contractionary effects on the economic activities. It can be seen from Fig. 2 that the risk shocks can reduce the labor supply and depress the asset price, which further amplify the deflationary effect of the risks shocks on the real economy. As can be seen in the Fig. 4, the net worth of entrepreneur also shrinks after the risk shocks. The declined asset prices further pull the net worth of the borrowers down, tightening the borrowing constraint and depressing investment due to financial fiction in the credit market. Thus, it becomes more difficult for entrepreneur to get external financing since the external financing premium increases, and so do the probability of default bankruptcy and the overall financial risks of economic system.

3.3.2 Monetary policy uncertainty shock

Fig. 5 illustrates the dynamic of output, consumption and investment and other macroeconomic variable after imposing one standard unit of monetary policy uncertainty shocks. As shown in Fig. 3, the rise of monetary policy uncertainty results in the persistent decline of output and consumption. This is in line with numerous researches on uncertainty shocks. According to Gourio (2012), when the monetary policy uncertainty increases, the risk-averse households tend to increase their precautionary saving and reduce consumption. According to the real option theory of investment proposed by Bloom et al. (2012), entrepreneurs choose to delay their investment and to wait for the new information until the future uncertainty dies off. Consequently, the stock of total capital declined dramatically. As a result, the increased monetary policy uncertainties will bring forth remarkable contractionary effects on the real economy.

From Fig. 5, we can also discover that the monetary policy uncertainties also bring negative effects to the labor supply and asset price, which worsen the balance-sheet of the entrepreneurs. A fall in entrepreneur’s net worth along with the tightening of its balance-sheet conditions drive up the external funding cost. On the other hand, the increase of bankruptcy rate means that the monetary policy uncertainty shocks directly leads to the increase of credit risk in the entire economy. Based on those results, we can put forward two propositions:

Proposition 1: The rise of monetary policy uncertainty directly leads to the increase of credit risk and the decline of the output

Proposition 2: Credit risk can amplify the monetary policy uncertainty shock, which further aggravates negative impacts on the real economic activities.

3.4 Additional analysis

Uncertainty shocks can depress the business activities through various channels. For instance, Basu and Bundick (2017) emphasize the role of household’s incentive for precautionary saving. The uncertainty shocks will increase the precautionary saving of the risk-averse household and lead to the fall of the current consumption. In the
meanwhile, according to the real option theory, owing to the irreversible costs of investment, the uncertainty shocks enable the enterprenuers to "wait and see", and thus postpone their investment. Gourio (2012) believes that financial friction is the main mechanism behind the uncertainty shocks. We adjust the consumer’s habit formation parameter  \( b \) and calibrate it respectively as 0.6, 0.7 and 0.8 while keeping other parameters unchanged. The results are as shown in Fig.6.

We can link the habit formation introduced in household’s utility function with household’s incentives for precautionary saving. Since habit formation itself leads to prudent behavior, with larger habit formation parameter, the household are more prudent and more affected more by previous consumption patterns, therefore stronger motive for saving. In Fig.6,we shift the value of the habit formation parameter to 0.6,0.7,0.8 respectively while keeping the other parameters unchanged, we can discover that the larger of the parameter  \( b \),the larger the negative shocks of the monetary policy uncertainty shocks on the output and investment. It implies that the household’s precautionary saving incentive can propagate the impacts of uncertainty shocks.

Our model can also document the real option channel of uncertainty shocks put forward by Bloom (2009). When uncertainty shocks hit the economy, the entrepreneurs tend to delay their investment since they are uncertain about the future economic environment. As some investment projects are irreversible,i.e.,once invested, they are less redeployable and less likely to be transferred in the second-hand market. Because less redeployable capital tends to have lower liquidation values, the entrepreneur with less redeployable assets would more concern about potential uncertainty. Therefore, after an increase in uncertainty, which increases the possibility of bad times, the entrepreneurs with less redeployable asset would retreat more investment. Due to the existence of investment adjusting cost, the larger the adjustment cost  \( \chi \), the more irreversible the entrepreneurs’ investment are. As shown in Fig.7, given the other parameters, we calibrate the value of  \( \chi \) to 0.1,0.5,5 respectively. We can find that the larger the adjustment cost parameter of investment, the larger the negative response of investment and output when hit by monetary policy uncertainty shocks. It means that the monetary policy uncertainty shocks will amplify the economic fluctuations through the real option mechanism. The higher the asset’s irreversibility, the greater the negative shocks of the monetary policy uncertainties on the economic activities.

On the other hand, we calibrate the risk premium in the steady state to 1.4%, 1.8% and 2.2% respectively to illustrate the financial friction channel emphasized by Gilchrist et al.(2014). Higher risk premium means more severe financial frictions in the credit market. Fig.8 shows that the higher the risk premium in the steady state, the greater negative effects of the monetary policy uncertainty shocks on the economy, which also means that the existence of financial friction will further aggravate the monetary policy uncertainty shocks on the real economy.

4 Measuring China’s Credit risk

The 2007–08 global financial crisis remind us that the financial market not only transmit and propagate the adverse shocks to the real economy, but it also can be the origin of business fluctuations. As a result, massive literature emphasizes the role of financial sector in macroeconomic models after the crisis. Christiano et al.(2014)
incorporate the financial market into the standard monetary DSGE model and they find that risk shock originates from the financial institution plays a significant role in business cycle fluctuations. Gertler and Kiyotaki(2010), Gertler and Karadi(2011) develop a new framework with endogenous bank risk exposure and quantitatively assess the relation between financial intermediaries and the real economy. Another strand of empirical literature focuses on the measure of financial risks (Engle et al.,2012; Adrian and Brunnermeier,2016). Recently, large-dimensional dynamic factor models have become popular in measuring financial risk or financial conditions in macroeconomics. Hatzius et al.(2010) construct a financial conditions index from a large set of US financial data by principal components analysis. Furthermore, Lucchetta and Nicolò(2015) measure and forecast the real and systemic financial risks of G-7 economies by using the dynamic factor model.

Large scale factor models are more advantageous than other methods in various aspects. Factor models ultimately utilize the information contained in the large data set, and they also free from imposing tight assumptions as is sometimes the case in structural models. Additionally, there is growing literature in favor of structural instabilities in the coefficients or loadings of macroeconomic and financial factor models(Bates et al.,2013). Therefore, we use the time-varying DFM based on Koop and Korobilis(2014) to measure China’s financial risk factors from a large financial and macro data set.

4.1 Dynamic factor model

Let $y_t$ be an $n_1$ vector of macroeconomic variables. And let $x_t$ be an $m_1$ vector of financial variables. We build the $p$-lag time-varying DFM (dynamic factor model) to construct the financial risk factors, written as

$$\begin{bmatrix} f_t \\ y_t \end{bmatrix} = c_t + B_{1t} \begin{bmatrix} f_{t-1} \\ y_{t-1} \end{bmatrix} + \ldots + B_{pt} \begin{bmatrix} f_{t-p} \\ y_{t-p} \end{bmatrix} + v_t$$

(36)

$$x_t = \Lambda^f f_t + \Lambda^y y_t + e_t$$

(37)

Where $f_t$ are the latent financial risk factors, $c_t$ is the intercept, $(B_{1t}, B_{2t} \ldots B_{pt})$ are time-varying VAR coefficients, $\Lambda^f$ are time-varying factor loadings and $\Lambda^y$ are time-varying regression coefficients. We assume that $v_t$ and $e_t$ are zero-mean Gaussian disturbances with time-varying covariances $a_t = (c_t', vec(B_{1t})', \ldots, vec(B_{pt})')$ and $b_t = ((\Lambda^f)'', (\Lambda^y)''$)’ evolve as:

$$a_t = a_{t-1} + \mu^a_t$$

(38)

$$b_t = b_{t-1} + \mu^b_t$$

(39)

Where $\mu^a_t \sim N(0, \Sigma^a_t), \mu^b_t \sim N(0, \Sigma^b_t)$, $\Sigma^a_t$ and $\Sigma^b_t$ are time-varying covariances matrix.

4.2 Data

We select data mainly from Chinese interbank market, bond market and stock market, and use VIX (CBOT Volatility Index) to measure global financial condition. All series which are nonstationary are transformed to stationary sequence by log
difference, and then all series are normalized by the z-score method, with range from 2006Q1 to 2017Q3. Table 3. provides the details. All the data except VIX are from CEIC while VIX is from FRED database.

4.3 Financial risk factors

Following Koop and Korobilis(2014), we use Bayesian method with Markov Chain Monte Carlo(MCMC) algorithm to estimate the time-varying DFM. We ad hoc choose the number of factors equal to 3 following Bernanke et al. (2005). Based on the estimated model, we get three Chinese financial risk factors shown in Fig.9.

Fig.9 shows three estimated Chinese financial risk factors, named as FRF1, FRF2, FRF3 respectively. Factor loading matrices before and after Varimax rotation are listed in Table 4. We can see that FRF1 mainly displays positive loadings on government bond yield spread and long-term corporate bond yield spread. FRF1 fluctuates up and down frequently, and peaks after the 2008 financial crisis, then has a downswing. Thus, FRF1 mainly represents the risk condition of bond market and the maturity risk premium, which shows a strong correlation with the business cycle.

FRF2 primarily features positive loadings on consumer loan rate and corporate bonds yield spread, which can be interpreted as the credit risk in credit market. During the 2007 subprime crisis, credit spread rises significantly because of the bankruptcy and financial difficulty of enterprises. After the global financial crisis, China’s government put forward the 4-Trillion-Yuan Stimulus Package to boost the economy, China’s debt problem became much more pressing. Hence the FRF2 stays at high level in 2009. Recently, the booming shadow banking system and the large local government debt raises the worry about the debt risk in China, as can be shown in the Fig.2., the FRF2 climbed to a new high while the other two factors declined slightly, which implies credit risk currently makes the greatest contribution to China’s whole financial risks.

While FRF3 mainly has positive loadings on stock market volatility and turnover rate, which represents the volatility risk of stock market. In 2007, Chinese stock market experiences a roller-coaster process and leads to large volatility. During the bull market 2013M02-2013M06, and the huge turbulence period of in 2015, the FRF3 also remains at relative high level.

5 Bayesian VAR evidence

The DSGE model has analyzed the impact of monetary policy uncertainty shocks on China’s credit risk and macroeconomic fluctuations. Furthermore, we get the monetary policy uncertainty through the Bayesian MCMC and obtained financial risk factors with the time-varying dynamic factor model. To give more empirical evidence to support the DSGE model, we further build the Bayesian VAR model including the data of monetary policy uncertainties, financial risk factors and the quarterly data of actual GDP growth rate ranging from 2006Q1 and 2017Q3.
5.1 Bayesian VAR model

Considering the following VAR model with lag $p$:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots + B_p Y_{t-p} + v_t$$  \hspace{1cm} (40)

Where $Y_t$ is the matrix of $T \times N$ composed of all observed values of $N$ endogenous variables in $T$ period. $c$ is the intercept term, $B_1, B_2, \ldots, B_p$ is the corresponding coefficient matrix, $v_t$ is the error term satisfying $E(v_t); if t = s, then E(v'_s v_t) = \Sigma; if t \neq s, then E(v'_s v_t) = 0$. If we define $X_t = \{c, Y_{i,t-1}, Y_{i,t-2}, \ldots, Y_{i,t-p}\}$, VAR model can be written down in the following form:

$$Y_t = X_t B + v_t$$  \hspace{1cm} (41)

If all equations have the same regressor, (41) can be written in the following vectoring compressed forms:

$$y_t = (I_N \otimes X)b + V$$  \hspace{1cm} (42)

Where $y_t = vec(Y_t), b = vec(B)$ and $V = vec(v_t)$. According to Bańbura et al. (2010), we set the prior using dummy observations:

$$b_0 = (X'_D X_D)^{-1} (X'_D Y_D)$$  \hspace{1cm} (43)

$$S = (Y_D - X Db_0)'(Y_D - X Db_0)$$  \hspace{1cm} (44)

Where $Y_D, X_D$ are the artificial data produced according to Bańbura et al. (2010), $T_D$ is the length of artificial data and $k$ is the number of regressors in each equation. Set $\tilde{b}_0 = vec(b_0)$. A regression of $Y_D$ on $X_D$ gives the prior mean for the VAR coefficients and the sum of squared residuals give the prior scale matrix for the error covariance matrix. The prior of coefficient $b$ is normal distribution while the prior of covariance matrix of VAR model is Inverse Wishart distribution:

$$p(b|\Sigma) \sim N(\tilde{b}_0, \Sigma \otimes (X'_D X_D)^{-1})$$  \hspace{1cm} (45)

$$p(\Sigma) \sim IW(S, T_D - K)$$  \hspace{1cm} (46)

Accordingly, the conditional posterior distribution of the coefficient $b$ and covariance matrix of the VAR model can be expressed as:

$$p(b|\Sigma, Y_t) \sim N(vecB^*, \Sigma \otimes (X'^* X^*)^{-1})$$  \hspace{1cm} (47)

$$p(\Sigma|Y_t) \sim IW(S^*, T^*)$$  \hspace{1cm} (48)

Where $Y^* = [Y; Y_D], X^* = [X; X_D]$ and $T^*$ is the number of rows in $Y^*$; the expressions of $B^*$ and $S^*$ are respectively obtained from the following:

$$B^* = (X'^* X^*)^{-1}(X'^* Y^*)$$  \hspace{1cm} (49)

$$S^* = (Y^* - X^* b)'(Y^* - X^* b)$$  \hspace{1cm} (50)

According to the conditional posterior distribution in (48) and (49), the Gibbs sampling algorithm can be adopted to carry out the Bayesian estimation on the
VAR model.

5.2 ADF test and Cointegration test

The China’s monetary policy uncertainty MPU estimated through Bayesian MCMC method, the three financial risk factors FRF1, FRF2, FRF3 constructed from the dynamic factor model, and the quarterly data of the Chinese actual GDP growth rate GDP, are selected to construct the Bayesian VAR model for empirical test. All the data ranges from 2006Q1 to 2017Q3. Before modelling, we carry out the ADF test and cointegration test of the related time series, except for the second and third risk factors, the other three series are stationary at the 5% significance level. Those nonstationary factors are the I(1) process and can be transformed to stationary sequence after the first-order difference. According to cointegration test result, both the trace statistic and the maximum eigenvalue statistic can reject the null hypothesis at the significance level of 5%. It means that there is at least one cointegration relationship between those several series and thus the VAR modelling analysis is feasible.

5.3 Impulse response analysis

The lag order is selected as 3 according to the relevant information criterion such as AIC; then the Gibbs sampling is adopted to conduct the Bayesians simulations to the above VAR model. We set simulation period equals to 5000 while the first 3000 periods are called the “Burn in” periods. Fig.10 to Fig.13 show the impulse response function.

According to Fig.10, when the monetary policy uncertainties rise, the three financial risk factors show a continuous upward trend, indicating the increase of monetary policy uncertainty will exacerbate the risks of bond market, credit market and stock market. Of the three sectors, the credit market is mostly severe affected. The growth rate of output has obvious negative response; the negative response reaches its lowest at about -0.16% after eighth quarter and then restore to the steady state gradually. This is in line with the proposition 2 concluded in the theoretical model.

The rise of monetary policy uncertainty drives up credit risk and depresses the real economy activities such as output, investment and consumption etc.

Fig.11 shows the impulse response functions of the risk factor1. According to Fig.11, when the financial risks in the bond market rise, the other two risk factors will also exhibit positive response. This give evidences to support the conclusion that the financial risks can spillover across different markets. Meanwhile, the output has negative response as well; and the negative response reach the lowest in the second quarter at about -0.12%. This is also in line with the conclusion of the proposition 1 about the impact of risk shocks in the DSGE model.

Fig.12 shows the impulse response function of the credit risk shocks in credit market. According to Fig.12, an increase of credit risk resulted in the persistent positive responses of the financial risks in bond market and stock market, and bring persistent adverse effect to output. The duration is about three years. The is also consistent with the results in DSGE model.

Fig.13 is the impulse response function of the risk shocks in stock market. It can be seen from Fig.13 that compared with other two sector, the shocks of financial risks in Chinese stock have weaker negative
impact on the output, which corroborates that China’s financial risks currently are mainly concentrated in the credit market.

6 Conclusion

In this paper, we examined the impact of monetary policy uncertainty on China’s credit risks and real economy both theoretically and empirically. Following Bernanke et al. (1999) and Christiano et al. (2014), we introduce the credit risk into DSGE model, and augmented monetary policy rule with stochastic volatilities to capture monetary policy uncertainty. Using the Bayesian MCMC method, we gave a specific measure for China’s monetary policy uncertainty, then we adopted the time-varying dynamic factor model to indentify the credit risk from the overall financial risks in China based on a large data set ranging from 2006Q1 to 2017Q3. Lastly, we further used Bayesian VAR model to study the impact of China’s monetary policy uncertainty empirically. The main conclusion can be summarized as follows: (1) The rise of the China’s monetary policy uncertainty can directly lead to the increase of credit risk and the shrinkage of output. (2) credit risk can spillover to the real economy and further aggravate contractionary effect of the monetary policy uncertainty shocks. (3) China’s financial risk currently is most concentrated in the credit market.

The conclusion implies that the rise of monetary policy uncertainties will threaten China’s macroeconomic and financial stability. One important policy implication of this paper is that, other than guarding against systemic financial risks, Chinese government should also give the top priority to reduce its policy uncertainty, since increased economic policy uncertainty has been shown to have negative effects on economic activity and exacerbate the financial risks. China face a sharp increase of economic uncertainty recent years especially when the US-China trade war broke out, Chinese policymakers are supposed to reduce policy uncertainty and unnecessary intervention to the economy, and adhere to well-defined, transparent and rules-based policy frameworks. In addition, Chinese government should take stronger initiative to monitor, warn against and deal with risks in the credit market since currently credit risk poses the most stressing pressure to the financial stability.

7 References


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8 Appendix

8.1 Bayesian MCMC method for the Taylor rule with stochastic volatility

The Gibbs Sampling and Metropolis-Hastings for the following stochastic volatility model:

\[ i_t = i_0 + \gamma_0 i_{t-1} + \gamma_1 \pi_t + \gamma_2 y_t + \sqrt{h_t} \zeta_t \quad \zeta_t \sim N(0, \sigma_1^2) \]  \quad (51)

\[ \ln h_t = \alpha_0 + \rho_1 \ln h_{t-1} + \nu_t \quad \nu_t \sim N(0, \sigma_2^2) \]  \quad (52)

Divide the parameter into five groups: \( B_1 = [i_0, \gamma_0, \gamma_1, \gamma_2], B_2 = [\alpha_0, \rho_1], \sigma_1, \sigma_2, \) and \( \{h_t\} \).

1. Set prior
Run the weighted least square to (1.1), and the weight is given by
\[ \frac{1}{\sqrt{h}}. \]
Given \( B_1, B_2, \sigma_1, \sigma_2 \) sampling \( h_t \sim f(h_t|B_1, B_2, \sigma_1, \sigma_2) \)

Step 1: when \( t = 1 \) to \( T \), according to Jacquier and Rossi (2004), sampling \( h_{t,new} \) from:

\[
q(\Phi^{G+1}) = h_t^{-1} \exp \left( -\frac{(\ln h_t - \mu)^2}{2\sigma_h^2} \right) \\
\mu = (\alpha_0 + \rho_1 \ln h_1 + v_t) \\
\sigma_h = \frac{\sigma_2}{1 + \rho_1^2}
\]

Calculate the accept-reject ratio:

\[
\alpha = \min \left( \frac{h_{t,new}^{-1} \exp \left( -\frac{m_t^2}{2\sigma_{h,new}^2} \right)}{h_{t,old}^{-1} \exp \left( -\frac{m_t^2}{2\sigma_{h,old}^2} \right)}, 1 \right)
\]

Where \( m_t = i_t - \hat{i}_0 - \hat{\gamma}_0 h_{t-1} - \hat{\gamma}_1 t - \hat{\gamma}_2 y_t \). Draw \( u \) from the uniform distribution \( u \sim U(0,1) \), if \( u < \alpha \) then \( h_t = h_{t,new} \), otherwise retain \( h_{t,old} \).

Step 2: when \( t = T \), sampling \( h_T \) from:

\[
q(\Phi^{G+1}) = h_t^{-1} \exp \left( -\frac{(\ln h_t - \mu)^2}{2\sigma_h^2} \right) \\
\mu = \ln h_{t-1} \\
\sigma_h = \sigma_2
\]

Step 3: when \( t = 0 \), sampling \( v_t \sim N(0, \Sigma_2) \), and set \( h_0 = \exp(\alpha_0 + \rho_1 \ln h_1 + v_t) \).

3. Given the \( h_t \), sampling \( B_2, \sigma_2 \sim f(B_2, \sigma_2|h_t, B_1, \sigma_1) \)

Run OLS to (1.2), where \( Y_t = \ln h_t, X_t = \{1, \ln h_{t-1}\} \), get the OLS estimator \( \hat{B}_2 = \{\hat{\alpha}_0, \hat{\rho}_1\} \) and sum of residual square \( \hat{\sigma}_2^2 = (Y_t - \hat{B}_2X_t)'(Y_t - \hat{B}_2X_t) \).

Sampling \( B_2 \) from:

\[
B_2 \sim N(B_2^*, \Sigma_2^*) \\
\Sigma_2^* = (\Sigma_2^{-1} + \hat{\sigma}_2^{-2}X_t'X_t)^{-1}
\]

Sampling \( \hat{\sigma}_2^2 \) from:

\[
\hat{\sigma}_2^2 \sim IG \left( \frac{T_2}{2}, \frac{v_2}{2} \right)
\]

4. Given the \( h_t \), sampling \( B_1, \sigma_1 \sim f(B_1, \sigma_1|h_t, B_2, \sigma_2) \)

Run the weighted least square to (1.1), and the weight is given by \( \frac{1}{\sqrt{h_t}} \), where \( Y_t = \{\frac{y_t}{\sqrt{h_t}}\} \)

Get the WLS estimator \( \hat{B}_1 = \{\hat{i}_0, \hat{\gamma}_0, \hat{\gamma}_1, \hat{\gamma}_2\} \) and sum of residual square \( \hat{\sigma}_1^2 = (Y_t - \hat{B}_1X_t)'(Y_t - \hat{B}_1X_t) \).

Sampling \( B_1 \) from:

\[
B_1 \sim N(B_1^*, \Sigma_1^*) \\
\Sigma_1^* = (\Sigma_1^{-1} + \hat{\sigma}_1^{-2}X_t'X_t)^{-1}
\]

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Sampling $\sigma_1^2$ from

$$\sigma_1^2 \sim IG(\frac{T_1^*}{2}, \frac{v_1^*}{2})$$

$$T_1^* = T_1 + T, v_1^* = v_1 + (Y_t - \hat{B}_1X_t)'(Y_t - \hat{B}_1X_t)$$

5. Repeat (2) to (4) 10000 draws while discard the initial 5000 draws, the last 5000 draws provide an approximation to the marginal posterior distributions.
8.2 First order conditions

We have 24 variables and 24 equations:
\{C_t, N_t, Y_t, K_t, B_t, I_t, V_t, L_t, \varpi_{t+1}, R_{t+1}^k, r_t, R_t, W_t, Q_t, \lambda_t, \pi_t, mc_t, sp_t, G_t, \sigma_t, A_t, u_t, \omega_t^2, h_t\}.

The first order condition are as follows:
\[ \lambda_t = \left(C_t - bC_{t-1} - \frac{\psi N_{t+1} \lambda}{1+\eta}\right)^{-\sigma} - \beta \left(C_{t+1} - bC_t - \frac{\psi N_{t+1} \lambda}{1+\eta}\right)^{-\sigma} \]
\[ \lambda_t = \beta E_t \left(\frac{\lambda_{t+1} R_{t+1} P_t}{P_{t+1}}\right) \]
\[ \lambda_t \varpi_t = \left(C_t - bC_{t-1} - \frac{\psi N_{t+1} \lambda}{1+\eta}\right)^{-\sigma} \psi N_t^\sigma \]
\[ Y_t = A_t K_t^\alpha N_t^{1-\alpha} \]
\[ B_t^c = Q_t K_{t+1} - V_t \]
\[ E_t R_{t+1}^k = E_t \left(\frac{\alpha_{t+1} + Q_{t+1}(1-\delta)}{Q_t}\right) \]
\[ \frac{W_t}{P_t} = 1 - \frac{1}{\varpi_t} \frac{Y_t}{N_t} \]
\[ V_t = \gamma \left(1 - \Gamma(\varpi_{t+1})\right) E_t R_{t+1}^k Q_t K_{t+1} \]
\[ Bankrupt_t = f_0^{\varpi_{t+1}} dF(\varpi_{t+1}) \]
\[ sp_t = 1 - \frac{E_t R_{t+1}^k}{E_t R_{t+1}^k + 1} \]
\[ 1 - F(\varpi_{t+1}) = \frac{E_t R_{t+1}^k}{1 - F(\varpi_{t+1}) - \mu \varpi_{t+1} \Theta(\varpi_{t+1})} \]
\[ \Gamma(\varpi_{t+1}) - \mu \Theta(\varpi_{t+1}) = \frac{R_t}{E_t R_{t+1}^k} \frac{Q_t K_{t+1} - V_{t+1}}{Q_t K_{t+1}} = \frac{R_t}{E_t R_{t+1}^k} \frac{L_{t-1}}{L_t} \]
\[ K_{t+1} = u_t I_t + (1 - \delta) K_t \]
\[ Q_t = \frac{1}{u_t} \left[1 + \chi \left(\frac{K_t}{K_t - \delta}\right)\right] \]
\[ \varpi_t = \frac{\epsilon_p}{\epsilon_p - 1} \sum_{k=0}^{\infty} \phi \beta^k u'(C_{t+k}) mc_{t+k} P_{t+k}^\rho Y_{t+k} \]
\[ i_t = i_0 + \gamma \omega_{t-1} + \gamma I_t + \gamma_2 Y_t + \sqrt{\omega_t} \zeta_t \quad \zeta_t \sim N(0, \sigma_2^2) \]
\[ G_t = \omega_t^\rho Y_t \]
\[ Y_t = C_t + I_t + G_t + \mu \int_0^{\varpi_{t+1}} \omega_{t+1} R_{t+1}^k Q_t K_{t+1} dF(\omega_{t+1}) \]
\[ lnh_t = \alpha_0 + \rho lnh_{t-1} + u_t \quad u_t \sim N(0, \sigma_2^2) \]
\[ \omega_t^\rho = (1 - \rho_g) \omega_y + \rho_g \omega_t^\rho + \epsilon_{gt} \quad \epsilon_{gt} \sim N(0, \sigma_2^2) \]
\[ lnA_t = \rho_a lnA_{t-1} + \epsilon_{at} \quad \epsilon_{at} \sim N(0, \sigma_2^2) \]
\[ ln\omega_t = \rho_a ln\omega_{t-1} + \epsilon_{ut} \quad \epsilon_{ut} \sim N(0, \sigma_2^2) \]

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9 Tables and Figures

<table>
<thead>
<tr>
<th>Para</th>
<th>Comment</th>
<th>Value</th>
<th>Para</th>
<th>Comment</th>
<th>Value</th>
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<td>β</td>
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<td>b</td>
<td>Habit formation parameter</td>
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<td>δ</td>
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<td>0.025</td>
<td>η</td>
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<td>φₚ</td>
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<td>σ</td>
<td>Risk-aversion coefficient</td>
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<tr>
<td>μ</td>
<td>Monitoring cost</td>
<td>0.2</td>
<td>ω₉</td>
<td>Gov.expenditure ratio</td>
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<td>N</td>
<td>Steady state labor supply</td>
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<td>F(ϖ)</td>
<td>Steady state default rate</td>
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Table 1: Calibrated parameters

<table>
<thead>
<tr>
<th>Para</th>
<th>Mean</th>
<th>Std</th>
<th>5% and 95%</th>
<th>Para</th>
<th>Mean</th>
<th>Std</th>
<th>5% and 95%</th>
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<tbody>
<tr>
<td>i₀</td>
<td>0.4849</td>
<td>0.0887</td>
<td>(0.3394 0.6311)</td>
<td>α₀</td>
<td>-0.7159</td>
<td>0.3778</td>
<td>(-1.4241 -0.1809)</td>
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<tr>
<td>γ₀</td>
<td>0.8907</td>
<td>0.0167</td>
<td>(0.8636 0.9185)</td>
<td>ρ₁</td>
<td>0.5946</td>
<td>0.2151</td>
<td>(0.1917 0.9014)</td>
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<tr>
<td>γ₁</td>
<td>0.3204</td>
<td>0.1694</td>
<td>(0.0411 0.5934)</td>
<td>σ₁</td>
<td>4.3985</td>
<td>1.0670</td>
<td>(2.9059 6.2774)</td>
</tr>
<tr>
<td>γ₂</td>
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<td>0.0218</td>
<td>(0.0483 0.1213)</td>
<td>σ₂</td>
<td>0.0192</td>
<td>0.0219</td>
<td>(0.0023 0.0632)</td>
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</table>

Table 2: Calibrated parameters
<table>
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<th>#</th>
<th>Abbreviation</th>
<th>Description</th>
<th>Unit</th>
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<tr>
<td>1</td>
<td>3mTED</td>
<td>3m SHIBOR/3m Household Savings Deposits Rate Spread</td>
<td>%</td>
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<tr>
<td>2</td>
<td>6mTED</td>
<td>6m SHIBOR/6m Household Savings Deposits Rate Spread</td>
<td>%</td>
</tr>
<tr>
<td>3</td>
<td>3mTED</td>
<td>1y SHIBOR/1y Household Savings Deposits Rate Spread</td>
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<tr>
<td>4</td>
<td>1-5yHRate</td>
<td>Individual Housing Provident Fund loan rate: 5 Year or Less</td>
<td>%</td>
</tr>
<tr>
<td>5</td>
<td>05yHRate</td>
<td>Individual Housing Provident Fund loan rate: Over 5 Year</td>
<td>%</td>
</tr>
<tr>
<td>6</td>
<td>CLoans</td>
<td>Consume Loan: Short Term/VAI</td>
<td>%</td>
</tr>
<tr>
<td>7</td>
<td>CLoanl</td>
<td>Consume Loan: Medium &amp; Long Term/VAI</td>
<td>%</td>
</tr>
<tr>
<td>8</td>
<td>Loans</td>
<td>Financial Inst: Use: Loan: Domestic: Short &amp; Term/VAI</td>
<td>%</td>
</tr>
<tr>
<td>9</td>
<td>Loanl</td>
<td>Financial Inst: Use: Loan: Domestic: Medium &amp; Long Term/VAI</td>
<td>%</td>
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<td>Beta</td>
<td>CAPM Beta Value of Banks Stock</td>
<td>Level</td>
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<td>11</td>
<td>1y3mTS</td>
<td>1y Treasury Bond Yield/3m Treasury Bond Yield Spread</td>
<td>%</td>
</tr>
<tr>
<td>12</td>
<td>3y3mTS</td>
<td>3y Treasury Bond Yield/3m Treasury Bond Yield Spread</td>
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</tr>
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<td>13</td>
<td>5y3mTS</td>
<td>5y Treasury Bond Yield/3m Treasury Bond Yield Spread</td>
<td>%</td>
</tr>
<tr>
<td>14</td>
<td>7y3mTS</td>
<td>7y Treasury Bond Yield/3m Treasury Bond Yield Spread</td>
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</tr>
<tr>
<td>15</td>
<td>10y3ms</td>
<td>10y Treasury Bond Yield/3m Treasury Bond Yield Spread</td>
<td>%</td>
</tr>
<tr>
<td>16</td>
<td>1y3mCS</td>
<td>1y Enterprise Bond(AAA)Yield/3m Treasury Bond Yield Spread</td>
<td>%</td>
</tr>
<tr>
<td>17</td>
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<td>3y Enterprise Bond(AAA)Yield/3m Treasury Bond Yield Spread</td>
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</tr>
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<td>18</td>
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<td>19</td>
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<td>7y Enterprise Bond(AAA)Yield/3m Treasury Bond Yield Spread</td>
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<td>20</td>
<td>10y3mCS</td>
<td>10y Enterprise Bond(AAA)Yield/3m Treasury Bond Yield Spread</td>
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<tr>
<td>21</td>
<td>SVOLSH</td>
<td>Volatility of Shanghai Stock Exchange Composite Index Return</td>
<td>%</td>
</tr>
<tr>
<td>22</td>
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<td>Volatility of Shenzhen Stock Exchange Composite Index Return</td>
<td>%</td>
</tr>
<tr>
<td>23</td>
<td>TOSH</td>
<td>Turnover Rate of Shanghai Stock Exchange Composite Index</td>
<td>%</td>
</tr>
<tr>
<td>24</td>
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<td>%</td>
</tr>
<tr>
<td>25</td>
<td>VIX</td>
<td>Volatility Index</td>
<td>Index</td>
</tr>
<tr>
<td>26</td>
<td>M2VAI</td>
<td>M2/VAI</td>
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</tr>
<tr>
<td>27</td>
<td>FAIVAI</td>
<td>Fixed Asset Investment/VAI</td>
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<tr>
<td>28</td>
<td>RSVAI</td>
<td>Retail Sales of Consumer Goods /VAI</td>
<td>%</td>
</tr>
<tr>
<td>29</td>
<td>PMI</td>
<td>Purchasing Managers’ Index</td>
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<tr>
<td>30</td>
<td>ECI</td>
<td>Economic Climate Indicator</td>
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</table>

Note: 1-25 are financial variables, and 26-30 are macroeconomic variables. VAI is Value Added of Industry

Table 3: Data Description
<table>
<thead>
<tr>
<th>Variable</th>
<th>Factor loading before rotation</th>
<th>Factor loading after rotation</th>
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<tbody>
<tr>
<td></td>
<td>Factor 1</td>
<td>Factor 2</td>
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<tr>
<td>TED</td>
<td>-0.67</td>
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</tr>
<tr>
<td>1-5HRate</td>
<td>0.52</td>
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<tr>
<td>O5yHRate</td>
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<tr>
<td>CLoans</td>
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<tr>
<td>CLoanl</td>
<td>-1.20</td>
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<tr>
<td>Loans</td>
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<td>0.93</td>
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<td>Loanl</td>
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<tr>
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Table 4: Factor loading matrix
Figure 1: Posterior of parameter in mean equation
Figure 2: Posterior of parameter in volatility equation

Figure 3: Estimated monetary policy uncertainty
Figure 4: Risk shock

Figure 5: Monetary policy uncertainty shock
Figure 6: Sensitivity analysis I

Figure 7: Sensitivity analysis II
Figure 8: Sensitivity analysis III

Figure 9: Financial risk factors
Figure 10: Monetary policy uncertainty shock
Figure 11: Shock of risk factor in bond market
Figure 12: Shock of risk factor in credit market
Figure 13: Shock of risk factor in stock market