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Measuring financial fragility in China

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Abstract

This paper proposes a metric for a financial fragility index for the Chinese banking sector. This metric is a weighted average of two variables: bank profitability and multiple probability of undercapitalization. The weights of the two variables are assigned based on their effects on real output, estimated by a vector autoregressive model. The main contribution is two-fold: incorporating a capital adequacy ratio into a quantitative measure and aggregating insolvency risk through a multiple probability measure. We confirm that our metric successfully identifies three periods of financial turmoil accompanied by economic downturns and rules out one minor perturbation caused by side effect of the policy between 2007 and 2014. In particular, this study provides an economic rationale for the relationship among financial instability, policy, and economic activity.

Keywords: Chinese economy, financial fragility, insolvency risk

JEL Classification: E30, E44, G18, G28

1 Introduction

The global financial crisis that began in the US and led to a downturn in advanced and developing economies highlighted the importance of understanding financial fragility. An essential concern is how financial instability affects macroeconomic activity and produces real economic costs. Thus policy makers, such as central banks, start to go beyond maintaining price stability and make an effort to reduce the economic consequences of financial fragility.

This paper aims to propose a measure for financial fragility in the Chinese banking sector. China is the world's second largest economy, and since projections made in 2014 it may surpass the US as the world's largest based on estimates by the IMF (2014 and 2015). In particular, the impact of China's growing influence in addressing the global financial crisis cannot be overlooked (Overholt, 2010). While China maintained growth above international averages, its growth rate was substantially lowered by the crisis (Li et al., 2012). Indeed, the Chinese financial system has been relatively fragile, as brought to light by several episodes of financial turmoil such as the global financial crisis, European sovereign debt crisis, real estate crash, and cash crunch since 2007. Further, the recent stock market crash is noteworthy in that it not only resulted in decreased purchasing power but also heightened instability in the entire financial market and the contingent financial contagion across global markets. Thus it is important to look for an appropriate metric to capture the feature of financial fragility for the Chinese banking sector, which has dominated the entire financial system as the main resource for funding firms' growth (Allen et al., 2012b).

Many studies indicate that there is no general consensus on the definition of financial stability. Crockett (1997) noted that financial stability requires key institutions and key markets to be stable. Mishkin (1994) explained that financial instability occurs when shocks to the financial system interfere with information flows so that the financial system can no longer do its job of channeling funds to those with productive investment opportunities. Haldane et al. (2004) have stated that financial instability is any deviation from the optimal saving-investment plan of the economy that is due to imperfections in the financial sector. Issing (2003) and Foot (2003) have said that financial instability is linked to financial market bubbles, or more generally, volatility in financial markets. Further, none of these studies appropriately defines a measure to analyze financial stability. Cevik et al. (2013) and Illing and Liu (2006) conducted a general survey and mention that financial stability indices typically aggregate some variables, indicating different author-defined risks, (e.g. if values of these variables deteriorate within a certain period, then financial instability arises). However, there should be more of an economic rationale than a natural conclusion supported by economic theory; a cogent measure should be based on theory.

Thus, we follow the definition of financial instability provided by Tsomocos (2003a and b), where financial fragility is characterized by reduced bank profitability and increased insolvency risk. To put it differently, whenever bank insolvency risk increases and bank profitability decreases, i.e. when the economy is financially more fragile, real output falls, which is based on simulations and calibrations of the model developed in Goodhart et al. (2005 and 2006).[1] We follow Aspachs et al. (2006) and Lee et al. (2013) to use a weighted two-factor model to compose a financial fragility index (FIX) for China. We then use a vector autoregressive (VAR) model to determine the weights assigned to these two variables based on their effect on real output.

We extend Aspachs et al. (2006) and Lee et al. (2013) by incorporating the capital adequacy ratio (CAR) into a quantitative measure for FIX. This modification is essential for the analysis of the insolvency risk of banks (Chan-Lau and Sy, 2007). First, the financial regulator imposes pre-default interventions on banks once they become undercapitalized. Therefore, in the view of regulators, the probability of undercapitalization (PoU), which measures the risk that banks fail to meet a CAR and consequently trigger pre-default actions, is more relevant than probability of default (PoD). Second, the theoretical study (Tsomocos, 2003a and b) on which we based the FIX construct takes CAR into consideration, as well. Thus, we substitute PoU for PoD as one of the components of our FIX. We calculate PoU following Chan-Lau and Sy (2007).

It is challenging to consider the Chinese banking sector typically because it is mainly domi-

[1] The theoretical modeling in Goodhart et al. (2005 and 2006) illuminates problems relating to individual bank behavior, to possible contagious inter-relationships between banks, and to the capital adequacy ratio. Financial instability emerges naturally as an equilibrium phenomenon in their model. The effects of shocks on the stability of the overall banking system can reasonably be represented by two factors, i.e. bank profitability and default probability of the banking sector.

nated by a few large commercial banks. Five banks held approximately 43-55 percent of the total assets of the entire banking sector from 2007 to 2013, according to the China Banking Regulatory Commission (CBRC, 2013). Consequently, we question the previous literature's use of a joint aggregation scheme for banks' insolvency risk, i.e. the probability that all banks fall into default. This underestimates the systemic insolvency risk, especially when only a few banks, which dominate the whole banking sector, fail. Thus instead of the joint aggregation method, we use a multiple probability measure —the probability that at least one bank will fail— to analyze financial fragility in China.

Some may question the existence of insolvency risk in the Chinese banking sector, over which government holds major control, given government protection to rescue banks from insolvency. However, even assuming that the government, indeed, provides external support, the *ex-ante* insolvency risk should be still considered due to the cost of *ex-post* bailout. In fact, the government in China should care about the insolvency risk more than other countries with less government ownership. As Demirgüç-Kunt and Detragiache (2002) argued, government ownership tends to be associated with higher risk-taking by shareholders, so excessive risk is borne by the government. Thus, insolvency risk needs to be monitored either for reducing the cost of bailout or for avoiding high risk-taking behavior.

Using FIX, we analyze the mechanism through which financial instability affects economic cycles. Many people are under the impression that China did not experience serious financial damage during the global financial crisis or European sovereign debt crisis, because China was not seriously engaged in subprime mortgages and had limited exposure to European banks. However, we find that, indeed, China went through financial instability in these periods. This study provides an analysis of how the financial instability spreads from the advanced economies to China. In addition to these two worldwide episodes, another event of turmoil in China, called a cash crunch, had a huge impact on the Chinese financial market. All of the above events are captured by our FIX, and we provide the channels through which financial fragility is linked to economic activity.

To limit the financial instability and banking crisis, the People's Bank of China (PBoC) implemented a series of macroeconomic policies over the past few years. Our results show that in the short term, the policy worked well in terms of stabilizing the economy, whereas it was questionable in the long term. A discussion about the effects of policy on the real economy and financial fragility is provided, as well.

The rest of the paper is organized as follows. Section 2 describes the components of FIX and the aggregation method. Section 3 reports the data and empirical results. Section 4 discusses the relationship among financial fragility, economic activity and macroeconomic policy, and Section 5 concludes.

2 Construction of the financial fragility index

2.1 Selecting variables

According to our definition of financial fragility, we need to choose variables that would give a good measure of banking profitability and insolvency risk. The possible proxies for these two variables might be taken from balance sheet accounts, e.g. net income and non-performing loans. But these accounting data do not work well possibly due to the existence of accounting manipulation and the long delays between the current effect of events on banks and their appearance in the accounts (Aspachs et al., 2006). Thus, we switch from an accounting measure to a market measure.

We use the annual percentage change in the China Mainland Banks Index (CMI) as a proxy for bank profitability, named Equity; this index reflects the performance of 16 listed banks in China. As the 16 banks' aggregate share of the total assets of banking institutions is within the range of 0.60-0.66 from 2003 to 2013 (CBRC, 2013), the performance can adequately represent the profitability of the Chinese banking sector. Table 1 lists the names of the banks and the beginning of the data period, as well as the rank in terms of total assets.[2,3]

[2]The banking institutions analyzed by CBRC (2013) include policy banks, the China Development Bank, large commercial banks, joint-stock commercial banks, city commercial banks, rural commercial banks, rural cooperative banks, urban credit cooperatives, rural credit cooperatives, non-bank financial institutions, foreign banks, new-type rural financial institutions, and the Postal Savings Bank.

[3]All 16 banks can be traded in mainland China and nine of them in Hong Kong, as well. Chongqing Rural Commercial Bank (CQRCB) is traded only in Hong Kong. CMI does not include CQRCB as CQRCB's share of the total assets of banking institutions is no more than 0.34 percent from 2008 to 2013.

$$Equity_t = \frac{CMI_t - CMI_{t-12}}{CMI_t}$$

<Insert Table 1 here>

There are two steps to calculate the insolvency risk of the Chinese banking sector, i.e. multiple probability of undercapitalization (MPoU). First, we calculate PoU based on the methodology of Chan-Lau and Sy (2007). They modify Merton's (1974) model, which can measure corporate insolvency risk, to create a proper framework of insolvency risk for banks. Second, we aggregate PoU of banks with multiple probability measure following Cathcart and El-Jahel (2004).

PoU has a similar theoretical framework to PoD derived from Merton's model. The value of assets is assumed to follow the geometric Brownian motion. The value of equity can be considered a call option on the value of assets, with the strike price equal to the face value of the liability. At the maturity of liability, if the value of the assets is less than the value of the liability, the bank will default. The PoD is defined as follows:

$$PoD = \Pr(V < L) = N(-DD)$$

$$DD = \frac{\ln\left(\frac{V}{L}\right) + \left(\mu - \frac{1}{2}\sigma_V^2\right) T}{\sigma_V \sqrt{T}}$$

where $N(\cdot)$ stands for the cumulative normal distribution function and DD is the distance to default, V is the market value of the bank's assets, L is the debt level of the bank with time to maturity T, μ is the continuously compounded expected return on V and σ_V is the volatility of the bank's assets.

PoD is widely used for corporate distress measure. However, it may understate the risk of bank interventions and bank closures prompted by regulators when banks cannot fulfill certain requirements, in particular maintaining CAR. Based on Merton's framework, in order to incorporate the effect of CAR, DD can be modified into distance to capital (DC). As a result, PoU would be a better measurement of banks' insolvency risk. The PoU can be written as follows:

$$PoU = \Pr(V - L < CAR \cdot V) = N(-DC)$$

$$DC = \frac{\ln\left(\frac{V}{\lambda L}\right) + \left(\mu - \frac{1}{2}\sigma_V^2\right) T}{\sigma_V \sqrt{T}}$$

$$DD - DC = \frac{\ln(\lambda)}{\sigma_V \sqrt{T}} \tag{1}$$

λ is a correction factor for DC, where $\lambda = \frac{1}{1-CAR}$. CAR is the capital adequacy ratio threshold set by the supervisory authority. The most commonly used CAR is the statutory minimum capital adequacy ratio.[4]

In order to calculate MPoU, the financial contagion is modeled following Cathcart and El-Jahel (2004), in which asset correlation is taken into consideration, as well as Acharya (2009), Allen et al. (2012a) and Gornall and Strebulaev (2013). As Allen et al. (2012a) point out, asset commonality is a source of systemic insolvency risk. Upon borrowing, banks invest in risky and safe assets. In addition, they choose the industry in which they undertake risky investments. Although diversification reduces the individual default probabilities, it can lead to greater systemic insolvency risk as banks' investments become increasingly similar (Wagner, 2010; Ibragimov et al., 2011). Since banks' assets are opaque (Morgan, 2002; Flannery et al., 2013), the market receives information on the banking sector's overall solvency rather than on the precise value of banks' asset fundamental values, which leads to information contagion among financial institutions. The extent of contagion depends on the composition of the asset structure, that is, on the degree of overlap of banks' portfolios.

The aggregation methodology through asset correlation proposed by Cathcart and El-Jahel (2004) is as follows:[5]

$$\begin{aligned} MPoU\,(1 \cup \cdots \cup n) &= \textstyle\sum_{i=1}^{n} PoU\,(i) - \sum_{i \neq j} PoU\,(i \cap j) + \\ &\quad \cdots + (-1)^{n-1}\, PoU\,(1 \cap \cdots \cap n) \end{aligned}$$

$$PoU\,(1 \cap \cdots \cap k) = N_k\left(-DC_1, \cdots, -DC_k; \rho_{i,j}\right)$$

where k is the number of banks, $N_k(\cdot)$ stands for the k-dimensional cumulative normal distribution function, and $\rho_{i,j}$ is the asset correlation between bank i and bank j.

[4]On June 7, 2012, CBRC issued administrative measures for the capital of commercial banks. The capital measures came into force on 1 January 2013. Commercial banks are required to have minimum capital adequacy ratios of 8 percent.

[5]See the detailed calculation method in Appendix A.

2.2 Aggregation of variables

Financial instability matters in that it impairs the real economy in such a way that output and general welfare suffer materially (De Bandt and Hartmann, 2000; ECB, 2009). Thus, financial fragility, measured as values of bank profitability and insolvency risk, would have an impact on real output proxied by industrial production index (IPI).[6] In this paper FIX is a weighted-sum metric of these variables. The weights are assigned based on their effects on real output. We investigate their relationship with output using a VAR model following Aspachs et al. (2007) and Lee et al. (2013). The model can be specified as follows:

$$X_t = \Phi_1 X_{t-1} + \ldots + \Phi_p X_{t-p} + \epsilon_t$$

where X_t represents a 3-dimensional vector $(IPI_t, Equity_t, MPoU_t)'$.

To measure the effects of Equity and MPoU on IPI, we then derive the weights of two indicators through variance decomposition. The FIX is defined as follows:

$$FIX = w_A * MPoU - w_B * [Equity' + av(MPoU_t) - av(Equity')] \tag{2}$$

where $Equity'$ is the transformed equity growth rate series which has the same mean absolute value and standard deviation as $MPoU$. $av(MPoU)$ denotes the average of $MPoU$ and $av(Equity')$ denotes the average of $Equity'$.

3 Empirical analysis

3.1 Data

We construct a monthly FIX for November 2007 through April 2014. Data on the China Mainland Banks Index (CMI), number of shares (N), equity price (P), debt level of banks (D), risk-free rate (R) and real interest rate (RIR) are taken from the Wind database. IPI and consumer price index (CPI) are obtained from the National Bureau of Statistics of China (NBS). In addition, property prices (PRP) is obtained from Bank for International Settlements (BIS).

[6]IPI is a measure of aggregate output (Fama, 1981; Chen et al., 1986). There are monthly data for IPI, but not for GDP (only quarterly). Due to sample size, IPI is used instead of GDP.

The sample size is limited by the availability for N and P. This limitation, however, does not prevent us from investigating financially fragile periods, which rarely happened before our sample period. A description of the variables is given in Table 2 and in Appendix B.

<Insert Table 2 here>

3.2 Components of FIX

First of all, we calculated MPoU and Equity in Figure 1(a) and (b), along with MPoD as a comparison with MPoU. MPoD stays high before 2009 and keeps decaying later on, even when the Chinese economy suffered recessions. They responded actively to the global financial crisis (end-2007 to mid-2009) during which period China's annual growth of real GDP fell from 14.2% in 2007 to 9.6% in 2008. There was a sharp fall in the stock market in 2007 and 2008, and exposure of Chinese banks to subprime-related assets was estimated to be up to 3.7% of their total assets (Sun and Zhang, 2009). This finding is in line with Milne (2014), who analyzed DD for the 41 largest global banking institutions and found that DD fell from end-2006 through to end-2008, and Harada et al. (2013), who examined the movements of DD of eight failed Japanese banks and found that DD became smaller in anticipation of failure in many cases.

However, MPoD does not responsively capture the downturn of the European sovereign debt crisis in 2011 and the cash crunch in 2013 that caused a mounted risk for the banking sector. This observation might be due to the fact that Merton's model needs large enough implied volatility to generate thick tail distribution of $V(T)$ to capture the growing risk, while the implied volatilities of assets are dragged down by the decreasing equity volatilities of banks over time. Both MPoD and MPoU indicate a high systemic insolvency risk in the first recession. However, only MPoU captures the dynamics of Chinese economic episodes in the second recession, demonstrating the significance of the incorporation of CAR in FIX.

<Insert Figure 1 here>

To illustrate the effect of CAR, we took the differences between DD and DC, i.e. DD - DC, for 16 banks in Figure 2 which are the components of MPoD and MPoU. If DC is close to DD, then the regulatory action has limited influence on lowering banks' insolvency risk. The larger the difference between DD and DC, the stronger effect the regulatory action has on controlling insolvency risk in each bank. Since the measure of DC is supposed to correct the understated likelihood of regulations prior to default, unsurprisingly, DD - DC is always positive. The dynamics of DD - DC are the mirror image of the asset volatility according to equation (1): the lower the asset volatility, the higher DD - DC.

<Insert Figure 2 here>

In a tranquil period, low asset volatility enables banks to take on high debt safely, leading to credit expansion, which is one of the sources of insolvency risk (Gornall and Strebulaev, 2013). This is the time when CAR, supposed to reduce bank insolvency risk, is more necessary and is more effective in intervening in a bank's lending behavior. Chan-Lau and Sy's framework (2007) refers to this negative correlation between asset volatility and the effectiveness of CAR, which is proxied by DD - DC. Similarly, bank leverage decreases with high volatility. This behavior is well documented in capital structure literature both theoretically and empirically (Leland, 1994; Adrian and Shin, 2010). As loan portfolios become more volatile, banks decrease their leverage to protect themselves against default (Gornall and Strebulaev, 2013). Banks execute credit contraction and stick to maintaining CAR on their own initiative, not to passively meet CAR. Thus, the role of regulatory actions seems to be reduced, resulting in the lower DD - DC.

Further, we can see that there are similar systematic patterns for the 16 banks in the dynamics of asset volatility and DD - DC, which is mainly driven by equity volatility.[7] Chen et al. (2012) divide the asset volatility in Merton's model into systematic and idiosyncratic asset volatilities. As we can see from Figure 2, in the last quarter of 2008, there was an obvious regime shift, with an increasing asset volatility for most banks. There was another regime shift, with a decreasing asset volatility in the third quarter of 2009. These two time periods correspond

[7]However, Ping An Bank, one of the 16 banks, had an opposite trend to that of the other 15 banks between January 2013 and April 2014. It experienced an upward trend during that time period. In 2013, the price of gold in the global market was extremely volatile, with a downswing. Ping An Bank pursued an aggressive gold investment in 2013. The annual report of Ping An Bank shows that by the end of December 2013, the gold assets had achieved RMB 21.28 billion, with a 776 percent growth rate from 2012 (RMB 2.43 billion). This resulted in higher asset volatility in 2013.

to two important monetary policy adjustments in China.[8] This finding is also in line with Zhang et al. (2011), which captures the nature of China's stock market volatility in the period of 2003-2009 with the Marrkov regime switching to a GARCH model.[9] The loose monetary policy, to a large extent, lowered the real cost of investment and encouraged investors with a preference for high risk investments to invest in capital assets and to add more risks to the market. This was followed by monetary policy concerns about the credit expansion and the credit risk underneath. Given the reduction of lendable funds in the banking sector, risk prevention awareness has been enhanced, and loans were examined more carefully, thus making the asset less volatile (Chen, 2012).

3.3 VAR

As mentioned, to compose the FIX, we measure the impact of Equity and MPoU on real output. We use the VAR methodology, which treats all the variables as endogenous, to estimate the weights of two variables by variance decomposition of the VAR model. Our baseline model is {IPI, Equity, MPoU}. IPI is the annual growth rate of real IPI, and Equity is the annual growth rate of the bank equity index. MPoU is the measure of the banking sector's insolvency risk. The optimal lags are selected by Akaike Information Criterion (AIC).

Before we estimate the VAR model, we investigate whether variables are stationary or not. We conduct the unit root tests, i.e. Augmented Dickey–Fuller (ADF) and Phillips-Perron (PP), as in Table 3. Both ADF and PP tests consistently show that we reject the null hypothesis (the variable has a unit root) for IPI and cannot reject for Equity at 5 percent significance level. Yet these two tests provide conflicting results for MPoU, i.e. the null hypothesis is rejected for MPoU by PP but not by ADF test at 5 percent significance level. After taking first-order difference for the three variables, the null hypothesis is rejected at 1 percent significance level

[8] In order to alleviate the negative impact of the financial crisis, from September to December 2008, the PBoC lowered the benchmark interest rates on deposits and loans five times and the reserve requirement ratio four times, which led to extraordinary growth in domestic credit and money supply. Faced with continuously rising inflation and a real estate bubble, the PBoC issued 1.3 trillion yuan worth of central bank bills and sold 870 billion repurchase agreements in open market operations in the third quarter of 2009. At the end of 2009, the net withdrawal of currency from circulation reached up 0.5 trillion yuan. The PBoC began to tighten the monetary policy in January 2010 and raised the required reserve ratio 12 times by June 2011 (Source: PBoC, 2009a, 2009d, 2010a-d and 2011a-b).

[9] Equity volatility is a common proxy for asset volatility (Beaton, 2010; Wagner, 2012), which is also implied by the equation (5).

for all three variables. However, the results of conventional ADF and PP tests are dubious due to ignoring the possible structural breaks of variables, which may lead to a bias that fails to reject a false unit root null hypothesis. Therefore, we re-examine the nonstationarity of Equity and MPoU using one-break unit root tests as in Table 3, which allows for additive outlier (AO) scheme and the innovational outlier (IO) scheme proposed by Perron and Vogelsang (1992).[10] The results show that we can reject the unit root null hypothesis for these two variables at the 5 percent significance level as well.

<Insert Table 3 here>

Given that IPI, Equity and MPoU are stationary, we derive the weights of two indicators by variance decomposition of the VAR model.[11] The ordering of variables is IPI, Equity, and MPoU, determined by the variables' degrees of linkage to external factors. Table 4 shows the responses of one standard deviation shock to the other variables. The results show that a positive shock to MPoU or a negative shock to Equity has a negative impact on IPI. These results support our metric of a FIX with MPoU and Equity, along with the signs assigned to them (Aspachs et al., 2006 and 2007; Lee et al., 2013).

<Insert Table 4 here>

We check the robustness of the baseline model's result by adding more variables to the VAR model: RIR, CPI and PRP. These variables are representative macroeconomic variables that may have significant effects on output (Goodhart and Hofmann, 2008; Rudebusch, 2005). Therefore, we conduct estimations with the models {IPI, RIR, Equity, MPoU}, {IPI, CPI, RIR, Equity, MPoU} and {IPI, PRP, CPI, RIR, Equity, MPoU}. The results of these models show that the direction and significance of the responses of IPI to Equity and MPoU remain as shown in Table 4.

We use a two-year average of the impact in the variance decomposition in Table 5 to estimate the weights of two factors. Based on a two-year average value of variance decomposition, Equity explains 14.8% of the variation of IPI, while MPoU of the banking sector explains

[10] AO scheme allows for a sudden change in mean while IO scheme is for more gradual changes.

[11] The result of VAR shows that our model is stable and the impulse response functions do not explode, which satisfies our purpose of using VAR, i.e. to investigate the impact of Equity and MPoU on real output.

6.1%. Hence, we assign the weight of Equity as 0.71 [14.8/(14.8+6.1)] and that of MPoU as 0.29 [6.1/(14.8+6.1)]. As the weight of Equity is higher than that of MPoU, we consider bank profitability a more significant variable than MPoU, which contrasts with the conclusion of Lee et al. (2013) in relation to the case of Korea.

<Insert Table 5 here>

The robustness results show that the relative weights of Equity and MPoU are 0.62-0.78 and 0.22-0.38, respectively. Our baseline model shows that the weights fall in these intervals, which means the baseline model predictions are reasonable. In addition, we change the ordering of variables in the baseline model and confirm that the weights of Equity and MPoU vary within 0.71-0.77 and 0.23-0.29, which indicates the weights of two variables are not sensitive to the ordering.

3.4 Financial fragility index

According to the metric of FIX in equation (2), with weights of Equity (0.71) and MPoU (0.29), we compose FIX as reported in Figure 3. The increase in the value of FIX indicates the instability of the banking sector. Following Cardarelli et al. (2011), we identify the episodes of financial fragility as those periods when FIX is more than one standard deviation above its trend estimated by Hodrick-Prescott (HP) filter. During our sample periods, three episodes are identified as financial fragility: (1) global financial crisis, (2) European sovereign debt crisis, and (3) cash crunch in China. All of them capture the recessions that echo the character of FIX, i.e. the financial instability impairs real output.

<Insert Figure 3 here>

Other than these three cases, the real estate crash in 2010 was broadly perceived as a turmoil event in China. However, the value of FIX during that time is below the threshold. In fact, the crash was a consequence of strict government control of real estate policy as a precaution against a serious crisis due to the real estate market, such as the Asian financial crisis and the US subprime mortgage crisis. In other words, the real estate crash does not correlate to economic downturn. Instead, it results from precautionary policy intervention for potential financial instability. Overall, our FIX is a good indicator in the sense that it not only captures the fragile financial events but also correctly measures the degree of instability which can be overestimated.

The reason FIX works well as a measurement of financial fragility is that the two components of FIX, i.e. Equity and MPoU, characterize the effects of shocks on the financial system. These two factors reveal the real economic activity. In the following section we will provide an analysis of the transmission mechanism through which financial instability affects economic activity.

Moreover, financial fragility is highly affected by macroeconomic policy, in particular fiscal and monetary policies. The sharp decline of FIX in November 2008 and the cash crunch also relate to these policies. We will discuss more details about the influence of policy on financial fragility and economy in the following section.

4 Financial fragility, policy and economic activity

The global financial crisis and European sovereign debt crisis, which started in the external markets, hit the Chinese economy with a decline in foreign demand for Chinese goods and a drop-off in foreign direct investment (Morrison, 2012; Wong, 2011; Li et al., 2012; Wang et al. 2010; Guo and N'Diaye, 2009; Mezo and Udavari, 2012). The capital outflows from China and the loss of confidence hit the Chinese stock market, as well. Although the default loss of the Chinese banking system directly due to subprime mortgages or European sovereign debt was limited, there was a significant decline in banking repayment capacity (increase of insolvency risk) due to the reduction of the banks' capital. Thus it was likely that banks would reduce lending in order to shore up their capital. Reductions in bank lending reduced investment and lowered growth further. Indeed, the bank profitability subsequently declined dramatically in 2008 and remained negative for a year.

However, deeper consideration should be given to the effect of the European debt crisis on China. In a crisis situation, the developed countries deviated from free trade to protectionist measures, so as to fuel domestic demand. The European Union has increasingly focused on China as a target of antidumping policies, particularly in the photovoltaic solar industry, which contributed to the first default of corporate bonds in China as a result of a sharp decrease of demand for targeted products.

In response to the financial instability that spread from western countries, e.g. the global financial crisis, in November 2008 Chinese policymakers introduced a massive stimulus program. This served as a major factor in persistent growth during the following two years, against the background of the global financial crisis.[12] The new purchasing power was allocated to public infrastructure, industries, and household consumption. On the supply side, the additional investments contributed to capital accumulation as well as technological innovation, which acted as growth factors. Banks' profits were improved as a result of their involvement in industrial investment. Moreover, the substantial increase in equity growth increased banks' capital, lowering MPoU.

Overall, this series of fiscal and monetary policies has helped sustain a healthy pace of economic growth in China, while much of the world fell into recession. Yet most of the stimulus came not in the form of direct fiscal outlays but through an explosion in new lending (Borst, 2014).[13] As a consequence of policies, huge amounts of capital were injected into the economy through investment leading to overcapacity in some industries such as solar energy and real estate, which gave rise to the first default of corporate bonds due to supply far outstripping demand with the antidumping policies of the European Union and the real estate bubble in China.

In order to remedy these side effects of policies, the central bank required banks to slow down the growth rate of loans and to improve the overall quality of credit assets by tightening monetary policy, along with enhancing risk prevention awareness.[14] As a result, commercial banks' non-performing loans (NPLs) ratio in real estate decreased significantly, in spite of the

[12] The stimulus program comprised an investment program, accommodative monetary policies, tax cuts, and easing of the burden on state-owned enterprises totaling RMB 4 trillion (US$ 586.68 billion).

[13] From 2008 to 2014, the amount of debt in China increased from around 7 trillion to 22 trillion. The total credit to GDP grew from 120 percent to above 200 percent (Source: National Bureau of Statistics of China and Bank for International Settlements).

[14] From January 2010 to June 2011, the PBoC raised the required reserve ratio 12 times, and benchmark rates three times. See more detail in PBoC (2010a-d).

collapse of real estate.[15,16] In the short-term, these remedial measures stabilized the financial system after the turmoil in the real estate industry. However, it may prove problematic in the longer term. The excessive liquidity squeeze brought about the cash crunch in China. First, the rigid reserve requirements could be one of the reasons for the banks' low profitability, as it reduced the amount of loans provided and subsequently the interest from loans. Second, there exists a serious liquidity mismatch in China because banks massively finance their long-term asset holdings with short maturity liabilities (Chen et al., 2015; Borst, 2014). The reduced money supply puts pressure on the finance of the long-term and medium-term loans, which increases the insolvency risk. Moreover, the central bank's restrictive monetary policy has forced smaller enterprises, which cannot compete with the large state-owned companies in obtaining loans from banks, to seek finance from shadow banks. The rapid credit growth in the shadow banking system in China, which lacks oversight and market disclosure (IMF, 2013), has been one of the economy's key vulnerabilities.

In summary, we claim that the global financial crisis, the sovereign debt crisis, and the cash crunch are fragile financial events in China based on our FIX. The instability comes from the shocks to the real economy characterized by lower bank profitability and high insolvency risk. The macroeconomic policies created in response to a recession or the overheating of the economy successfully stabilized the economy in the short-term. However, in the long-term, the effectiveness of these restrictive policies is doubtful, as is partly revealed by the first bond default and cash crunch in China.

[15]The NPLs ratio serves as a proxy of ex-post quality for credit risk. The NPLs dropped to 1.26 percent at the end of 2010, from 1.93 percent at the end of 2009 (CBRC, 2010).

[16]The banking system experienced high exposure to the real estate sector through direct or indirect investment and real estate loans. Mei and Saunder (1995), He et al. (1996), Ghosh et al. (1997), Lu and So (2005), and Li and Cao (2009) find a positive relationship between bank stock returns and real estate stock returns in the US and some Asian countries, including mainland China. The influence of the real estate market on bank stock returns might be that the unfavorable information about the real estate market lowers the markets' expectations regarding real estate, as well as the quality of banks' asset holdings in real estate. As a result, investors will ask for more risk compensation or will switch from banking stocks to other holdings, and the bank stock price will therefore decrease (Ghosh et al. 1997; Lu and So, 2005).

5 Conclusion

China has a significant and growing influence in the global economy, but few studies have focused on China's financial fragility. This paper proposes a FIX for the Chinese banking sector using an aggregate weighting technique. The variables used for the construction of the FIX include growth rate on banking equity index and MPoU, which are the proxies for bank profitability and insolvency risk, respectively. We assigned the weights of two variables on FIX based on the effects on real output by analyzing the impulse response functions and variance decompositions of a VAR model.

We extend the existing literature on financial fragility in several ways. First, in choosing a measurement of systemic insolvency risk, we resolve the problem faced by a banking sector like that of China, which is dominated by a few banks, by way of substituting a multiple measure for a joint measure of probability of default. Second, we incorporated the effect of bank regulation, i.e. CAR, into the framework of the FIX by focusing on PoU instead of PoD following Chan-Lau and Sy (2007). Our results show that the incorporation of CAR is significant, especially during the tranquil periods of low asset volatility. In addition, we provide not only the empirical analysis of the relationship between the financial fragility and economic activity with VAR model, but also offer an economic rationale for the mechanism through which financial instability affects economic cycles.

According to our FIX with its threshold, we have identified three relatively fragile episodes during the five years: (1) the global financial crisis, (2) the European sovereign debt crisis, and (3) the cash crunch in China, with slowdowns of the growth rate, accompanied by a decrease of bank profitability and an increase of insolvency risk. Meanwhile, the Chinese government implemented a series of macroeconomic policies to boost or stabilize the economy. The policies took effect promptly but brought about several side effects in the longer term, such as overcapacity of industries, serious shadow banking risk and heavy dependence on investment.

In future, instead of using asset correlation, which only captures linear dependence, we could apply copula functions to characterize the whole dependence structure of default, i.e. linear and non-linear dependence (Goodhart and Segoviano, 2009). Moreover, the study could be further extended to investigate Hong Kong's financial fragility because of its close interaction and integration with mainland China. We could compare and contrast the financial fragility of the two and see how they interact with each other.

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Appendices

Appendix A. Systemic insolvency risk

In Merton (1974), the following stochastic process describes the dynamics of value of assets

$$dV = \mu V dt + \sigma_V V dW \tag{3}$$

where V is the market value of the firm's assets, μ is the continuously compounded expected return on V, σ_V is the volatility of firm value and dW is a standard Wiener process.

It can be shown that

$$E = VN(d_1) - Le^{-rT}N(d_2) \tag{4}$$

$$\sigma_E = \left(\frac{V}{E}\right) N\left(d_1\right) \sigma_V \tag{5}$$

$$d_1 = \frac{\ln(\frac{V}{L}) + (r + \frac{1}{2}\sigma_V^2)T}{\sigma_V \sqrt{T}}$$

$$d_2 = d_1 - \sigma_V \sqrt{T}$$

where r is the risk-free rate, and L is the debt level with time to maturity T.

From equations (4) and (5), we can calculate V and σ_V

$$V = \frac{E + Le^{-rT} N\left(d_2\right)}{N\left(d_1\right)}$$

$$\sigma_V = \frac{E}{N\left(d_1\right) V} \sigma_E$$

PoD can be written by

$$PoD = Prob(\ln(V_T) \leq \ln(L))$$

Since the value of assets follows the geometric Brownian motion of equation (3), the value of the assets at time T is given by

$$\ln\left(V_T\right) = \ln\left(V_0\right) + \left(\mu - \frac{1}{2}\sigma_V^2\right) T + \sigma_V \sqrt{T} \varepsilon_T$$

$$\varepsilon_T = \frac{W(T) - W(0)}{\sqrt{T}} \sim N(0,1)$$

Therefore, we can rewrite *PoD* as follows:

$$PoD = N(-DD)$$

$$DD = \frac{\ln\left(\frac{V}{L}\right) + \left(\mu - \frac{1}{2}\sigma_V^2\right) T}{\sigma_V \sqrt{T}}$$

In this paper, σ_E^2 is estimated for each month by the Exponential Weighted Moving Average (*EWMA*), as proposed by J.P. Morgan (1996)

$$\sigma_{E,t}^2 = (1-\theta)(R_t - \mu)^2 + \theta\sigma_{E,t-1}^2$$

where R is the monthly return of equity, and θ is the decay factor, which is set equal to 0.97 for the monthly data.[17] The initial value of σ_E^2 is set equal to the variance of the first 12 observations. Value of equity, E, is equal to the product of the outstanding number of shares and stock prices.

We use the methodology proposed by Cathcart and El-Jahel (2004) to estimate multiple default probability with asset correlation, the probability that at least one bank in a portfolio will fail. Consider the case of two banks, $n = 2$, where n is the number of banks. $PoD\,(1 \cap 2)$ is the probability that the two banks default at the same time

$$PoD\,(1 \cap 2) = Prob(\ln(V_T^1) \leq \ln(L^1), \ln(V_T^2) \leq \ln(L^2))$$

As the default probability of a single bank is assumed to follow a standard normal distribution, for the case of two banks, $PoD\,(1 \cap 2)$ is equal to a standard bivariate normal density,

$$N_2\,(-DD_1, -DD_2; \rho_{1,2})$$

DD_1 and DD_2 are given in the above calculations, and $\rho_{1,2}$ is the pairwise correlation between the assets of bank 1 and bank 2. The probability that at least one bank defaults, i.e. MPoD, can be written by

[17] The *EWMA* method is a standard to estimate volatility. J.P. Morgan (1996) provides this model to estimate time-varying variance and covariance. In that paper, the decay factor, θ, is determined as 0.94 for daily data and 0.97 for monthly data.

$$
\begin{aligned}
MPoD\,(1\cup 2) &= PoD\,(1) + PoD\,(2) - PoD\,(1\cap 2) \\
&= N\,(-DD_1) + N\,(-DD_2) - N_2\,(-DD_1, -DD_2; \rho_{1,2})
\end{aligned}
$$

Consider the probability of at least one default in a portfolio of $n \geq 2$:

$$
\begin{aligned}
MPoD\,(1\cup\cdots\cup n) &= \textstyle\sum_{i=1}^{n} PoD\,(i) - \sum_{i\neq j} PoD\,(i\cap j) + \\
&\quad \cdots + (-1)^{n-1}\, PoD\,(1\cap\cdots\cap n)
\end{aligned}
$$

$$
PoD\,(1\cap\cdots\cap k) = N_k\left(-DD_1, \cdots, -DD_k; \rho_{i,j}\right)
$$

where MPoU can be calculated in the same way as MPoD.

To calculate this probability, we need to know multivariate standard normal distribution. So $\rho_{i,j}\left(=\sigma_{i,j}^2(\sigma_i\sigma_j)^{-1}\right)$ should be estimated, where $\sigma_{i,j}^2$ is the covariance between bank i and bank j's asset returns. σ_i and σ_j are the volatilities of bank i and bank j's asset returns. σ_i and σ_j are the same as the case of individual default. We also follow J.P. Morgan (1996) to estimate $\sigma_{i,j}^2$ by *EWMA:*

$$
\sigma_{i,j,t}^2 = (1-\theta)\,(R_{i,t}-\mu_i)\left(R_{j,t}-\mu_j\right) + \theta\sigma_{i,j,t-1}^2
$$

where R_i and R_j are asset returns of bank i and bank j. The initial value of $\sigma_{i,j}^2$ is set equal to the covariance of the first 12 observations.

Appendix B. Data set details

- *N & P:* In China, some banks' stocks are traded not only on the mainland but also in Hong Kong. There are also some restricted shares on the mainland, which are not traded within the market. However, they do have value. We follow Peng et al. (2007) in estimating the price of restricted shares as equal to 58% of stock prices on the mainland.

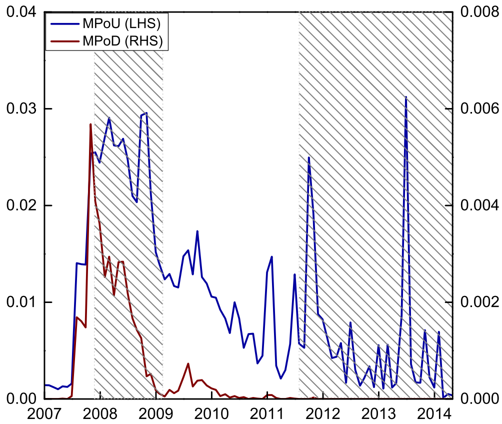
- *D*: We follow Vassalou and Xing (2004) in dealing with liability. We assume the liability to be due in one year, i.e. $T = 1$. L is equal to short-term debt plus half of long-term debt. As the balance sheet data is available annually at the end of the year, monthly data is estimated using cubic splines interpolation. It is available in three to four month lags compared to the equity price, so we use lagged four-month debt data in our calculation. For example, the debt level we used for 31 May is the reported debt level on 31 January of the same year.

- Shanghai Interbank Offered Overnight Rate (*SHIBOR*): This is the first interest rate to be largely liberalized in China, while deposit rates remain heavily controlled by PBoC. Therefore we use *SHIBOR* as our risk-free rate, which is determined more by market forces than other interest rates. PBoC (2009b) has confirmed the function of *SHIBOR* as a benchmark rate in the money market. From 2007, all corporate bonds have been quoted with *SHIBOR.*

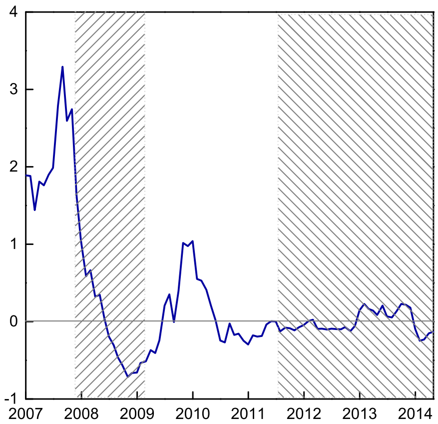
- *IPI*: The National Bureau of Statistics of the People's Republic of China publishes the annual growth rate of real *IPI.*

- China's 16 listed banks: see in Table 2.

Appendix C. Figures and tables



(a) MPoD vs. MPoU



(b) Equity index growth

Figure 1: Insolvency risk and bank profitability

In Figure 1(a), the blue line is MPoU (LHS) and the red line is MPoD (RHS). Figure 1(b) explains the quarter on quarter percentage change of the equity index of the Chinese banking sector. The shaded areas show the recessionary periods according to the *OECD*-based recession indicators for China offered by *FRED*.

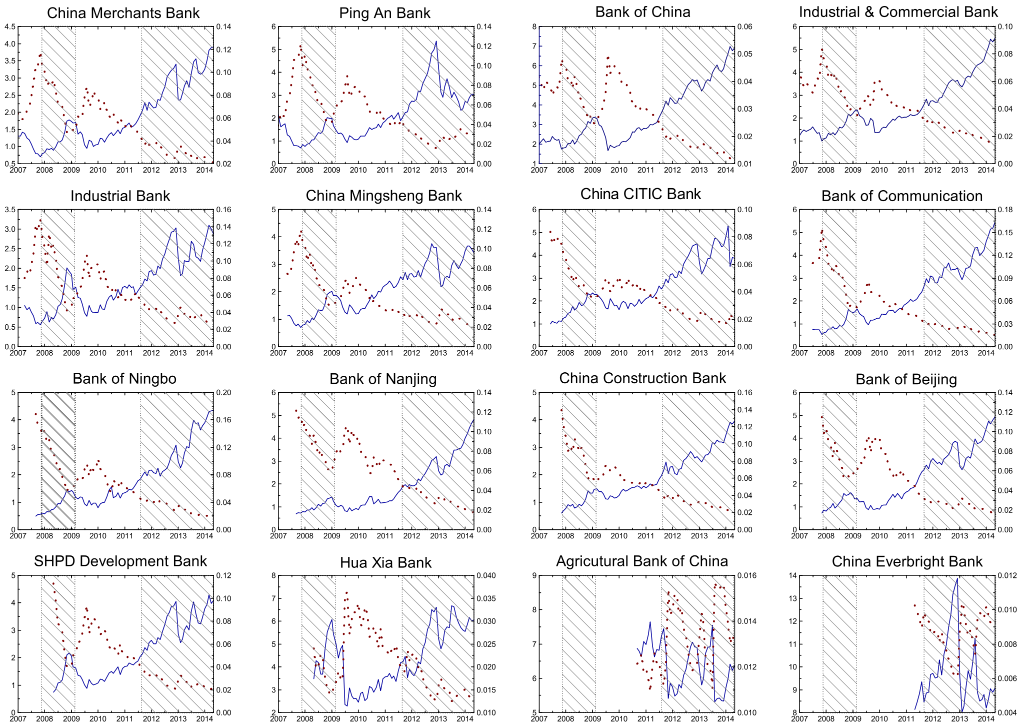


Figure 2: The effects of CAR and asset volatility

In Figure 2, The solid lines are the effect of CAR (LHS) and the dotted lines are the asset volatility of 16 banks (RHS). The shaded areas show the recessionary periods according to the *OECD*-based recession indicators for China offered by *FRED*.

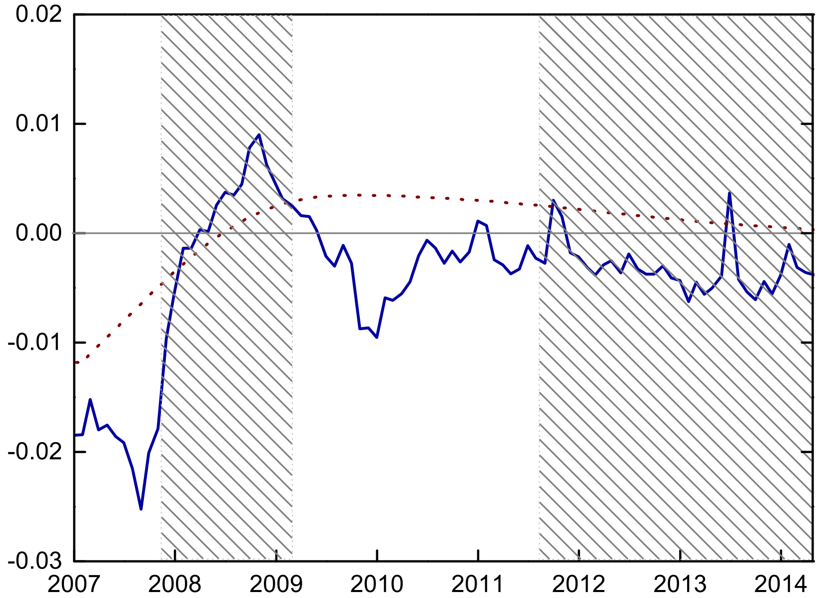


Figure 3: Financial fragility index

The solid line is the *FIX* and the dotted line is the threshold of FIX. The shaded areas show the recessionary periods according to the *OECD*-based recession indicators for China offered by *FRED*.

Table 1: 16 listed banks in China

RANK	BANK	Start
1	Industrial and Commercial Bank of China	10/31/2006
2	China Construction Bank	9/28/2007
3	Agricutural Bank of China	7/30/2010
4	Bank of China	7/31/2006
5	Bank of Communication	5/31/2007
6	China Merchants Bank	9/30/2005
7	Industrial Bank	2/28/2007
8	China Mingsheng Banking Corp	3/31/2006
9	Shanghai Pudong Development Bank of China	3/30/2007
10	China CITIC Bank	4/30/2007
11	China Everbright Bank	8/31/2010
12	Ping An Bank	9/30/2005
13	Hua Xia Bank	3/30/2007
14	Bank of Beijing	9/28/2007
15	Bank of Ningbo	7/31/2007
16	Bank of Nanjing	7/31/2007

Table 2: Description of dataset

Name	Components	Source
CMI	Shares in all 16 banks listed on the mainland	Wind database
N&P	Shares in mainland China, Hong Kong and under restriction	
D	Short-term debt plus half of long-term debt	
R	*SHIBOR*	
RIR	*SHIBOR* minus expected inflation	
IPI	Output of manufacturing, mining and utilities	NBS
CPI	Relative cost of a basket of consumer goods and services	
PRP	The average residential property price in China	BIS

Table 3: Statistics of unit root tests

Variables	ADF	PP	AO	IO
IPI	-3.444*	-3.284*	-	-
Equity	-2.362	-1.817	-4.473*	-6.380*
MPoU	-2.815	-3.264*	-4.347*	-4.283*
$\triangle$IPI	-9.321**	-8.953**	-	-
$\triangle$Equity	-5.366**	-8.214**	-	-
$\triangle$MPoU	-9.935**	-11.543**	-	-

In the test equation, the intercept term is included and the trend term is not included. "**" and "*" indicate that the null hypothesis that the variable has a unit root can be rejected at the 1% and 5% significance level respectively.

Table 4: Impulse responses of VAR

Model	Equity $\rightarrow$ IPI	MPoU $\rightarrow$ IPI
{IPI, Equity, MPoU}	+	-
{IPI, RIR, Equity, MPoU}	+	-
{IPI, CPI, RIR, Equity, MPoU}	+	-
{IPI, PRP, CPI, RIR, Equity, MPoU}	+	-

Appendix D. Supplementary information

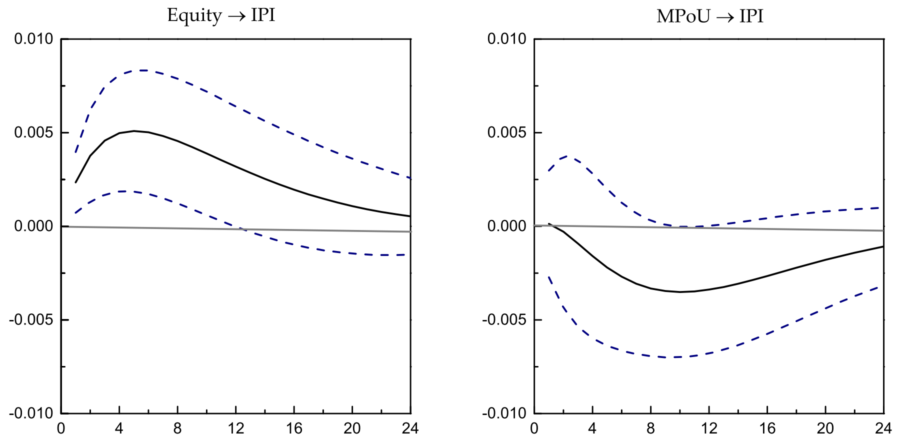


Figure 4: IRFs of VAR model {IPI, Equity, MPoU}

The solid lines indicate the impulse responses of one standard deviation shock and the dotted lines indicate 95% confidence intervals.

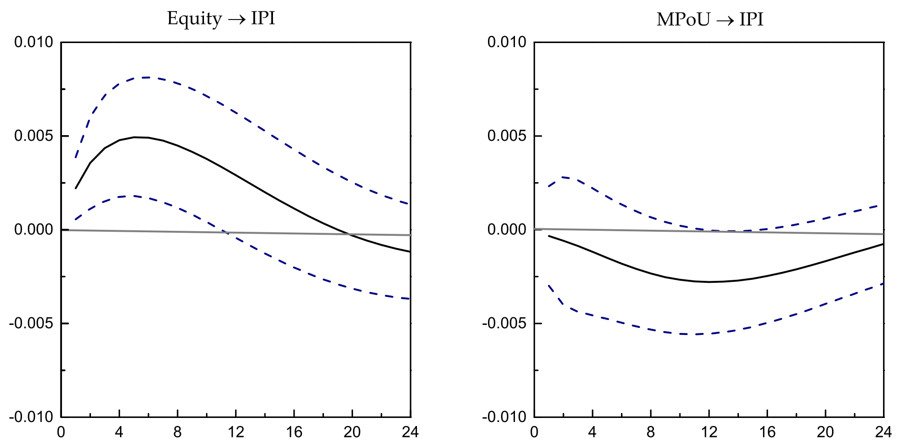


Figure 5: IRFs of VAR model {IPI, RIR, Equity, MPoU}

The solid lines indicate the impulse responses of one standard deviation shock and the dotted lines indicate 95% confidence intervals.

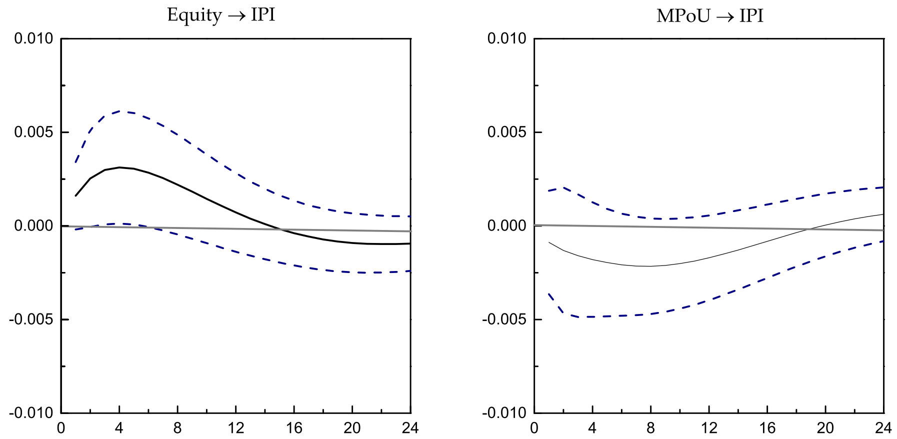


Figure 6: IRFs of VAR model {IPI, CPI, RIR, Equity, MPoU}

The solid lines indicate the impulse responses of one standard deviation shock and the dotted lines indicate 95% confidence intervals.

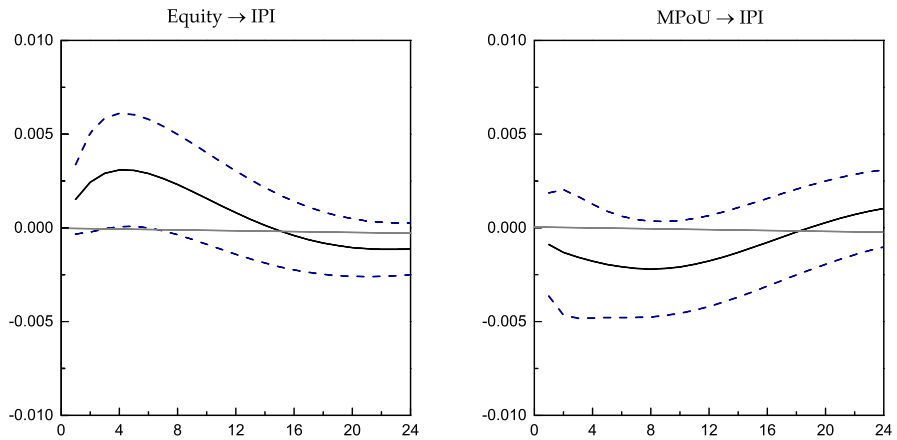


Figure 7: IRFs of VAR model {IPI, PRP, CPI, RIR, Equity, MPoU}

The solid lines indicate the impulse responses of one standard deviation shock and the dotted lines indicate 95% confidence intervals.

Table 5: Variance decomposition of *IPI* with *Equity* and *MPoU*

Step	*IPI*	*Equity*	*MPoU*
1	100.0000	0.0000	0.0000
2	99.1918	0.8057	0.0025
3	97.5005	2.4872	0.0124
4	95.1469	4.7433	0.1098
5	92.3807	7.2361	0.3832
6	89.4369	9.6849	0.8782
7	86.5073	11.9056	1.5871
8	83.7297	13.8072	2.4631
9	81.1904	15.3673	3.4423
10	78.9331	16.6060	4.4609
11	76.9703	17.5640	5.4658
12	75.2939	18.2886	6.4175
13	73.8835	18.8261	7.2904
14	72.7122	19.2173	8.0705
15	71.7506	19.4967	8.7527
16	70.9697	19.6920	9.3383
17	70.3420	19.8252	9.8328
18	69.8423	19.9135	10.2442
19	69.4485	19.9698	10.5818
20	69.1411	20.0038	10.8552
21	68.9036	20.0226	11.0738
22	68.7219	20.0315	11.2466
23	68.5844	20.0341	11.3815
24	68.4814	20.0330	11.4856

Table 6: Variance decomposition of *IPI* with *RIR*, *Equity* and *MPoU*

Step	*IPI*	*RIR*	*Equity*	*MPoU*
1	100.0000	0.0000	0.0000	0.0000
2	98.9803	0.2621	0.7412	0.0164
3	97.0553	0.5840	2.3012	0.0596
4	94.6253	0.8239	4.4051	0.1457
5	91.9967	0.9521	6.7561	0.2951
6	89.3691	0.9915	9.1135	0.5259
7	86.8600	0.9793	11.3114	0.8492
8	84.5330	0.9500	13.2502	1.2667
9	82.4193	0.9292	14.8813	1.7702
10	80.5304	0.9335	16.1922	2.3439
11	78.8664	0.9713	17.1956	2.9667
12	77.4198	1.0453	17.9198	3.6151
13	76.1785	1.1533	18.4026	4.2655
14	75.1270	1.2904	18.6866	4.8960
15	74.2476	1.4495	18.8150	5.4878
16	73.5209	1.6230	18.8297	6.0264
17	72.9274	1.8028	18.7687	6.5011
18	72.4470	1.9815	18.6653	6.9061
19	72.0607	2.1527	18.5471	7.2395
20	71.7504	2.3110	18.4355	7.5031
21	71.4996	2.4526	18.3461	7.7018
22	71.2937	2.5749	18.2889	7.8425
23	71.1203	2.6768	18.2689	7.9339
24	70.9694	2.7584	18.2867	7.9855

Table 7: Variance decomposition of *IPI* with *CPI, RIR, Equity* and *MPoU*

Step	*IPI*	*CPI*	*RIR*	*Equity*	*MPoU*
1	100.0000	0.0000	0.0000	0.0000	0.0000
2	99.1068	0.0017	0.3676	0.4039	0.1199
3	97.6185	0.0022	0.8163	1.2241	0.3390
4	95.9031	0.0188	1.1646	2.2767	0.6369
5	94.1636	0.0762	1.3755	3.3794	1.0052
6	92.5005	0.1948	1.4732	4.3977	1.4338
7	90.9588	0.3853	1.4977	5.2522	1.9060
8	89.5564	0.6481	1.4857	5.9107	2.3991
9	88.2985	0.9749	1.4647	6.3747	2.8872
10	87.1837	1.3517	1.4520	6.6669	3.3457
11	86.2068	1.7615	1.4565	6.8212	3.7541
12	85.3598	2.1865	1.4805	6.8748	4.0984
13	84.6322	2.6103	1.5223	6.8635	4.3718
14	84.0118	3.0189	1.5772	6.8180	4.5741
15	83.4854	3.4015	1.6398	6.7623	4.7110
16	83.0392	3.7506	1.7046	6.7138	4.7918
17	82.6598	4.0618	1.7667	6.6830	4.8286
18	82.3348	4.3333	1.8226	6.6751	4.8341
19	82.0530	4.5658	1.8698	6.6909	4.8204
20	81.8049	4.7614	1.9071	6.7280	4.7986
21	81.5828	4.9233	1.9345	6.7820	4.7774
22	81.3805	5.0556	1.9528	6.8476	4.7636
23	81.1937	5.1623	1.9632	6.9194	4.7614
24	81.0193	5.2477	1.9674	6.9924	4.7732

Table 8: Variance decomposition of *IPI* with *PRP, CPI, RIR, Equity* and *MPoU*

Step	*IPI*	*PRP*	*CPI*	*RIR*	*Equity*	*MPoU*
1	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	99.1175	0.0114	0.0002	0.3863	0.3616	0.1230
3	97.6446	0.0303	0.0104	0.8508	1.1223	0.3416
4	95.9273	0.0499	0.0521	1.2041	2.1312	0.6354
5	94.1591	0.0654	0.1438	1.4112	3.2212	0.9994
6	92.4458	0.0748	0.2937	1.5008	4.2574	1.4275
7	90.8460	0.0786	0.4990	1.5173	5.1526	1.9064
8	89.3934	0.0786	0.7487	1.5005	5.8638	2.4150
9	88.1065	0.0774	1.0267	1.4788	6.3831	2.9275
10	86.9932	0.0781	1.3156	1.4694	6.7264	3.4173
11	86.0526	0.0833	1.5993	1.4801	6.9237	3.8610
12	85.2762	0.0951	1.8645	1.5118	7.0113	4.2410
13	84.6497	0.1151	2.1016	1.5608	7.0257	4.5471
14	84.1539	0.1438	2.3046	1.6210	7.0002	4.7765
15	83.7665	0.1815	2.4713	1.6857	6.9619	4.9332
16	83.4640	0.2273	2.6022	1.7484	6.9315	5.0267
17	83.2232	0.2801	2.7000	1.8041	6.9223	5.0703
18	83.0225	0.3383	2.7689	1.8492	6.9416	5.0794
19	82.8429	0.4003	2.8141	1.8821	6.9908	5.0698
20	82.6692	0.4640	2.8405	1.9028	7.0671	5.0564
21	82.4897	0.5276	2.8532	1.9127	7.1650	5.0517
22	82.2970	0.5896	2.8564	1.9144	7.2769	5.0657
23	82.0873	0.6485	2.8534	1.9109	7.3950	5.1049
24	81.8600	0.7031	2.847	1.9055	7.5118	5.1726