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China's financial crisis — the role of banks and monetary policy*

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Abstract

This paper develops a model of the Chinese economy using a DSGE framework that accommodates a banking sector and money. The model is used to shed light on the period of the recent period of financial crisis. It differs from other applications in the use of indirect inference to estimate and test the fitted model. We find that the main shocks that hit China in the crisis were international and that domestic banking shocks were unimportant. Officially mandated bank lending and government spending were used to supplement monetary policy to aggressively offset shocks to demand. An analysis of the frequency of crises shows that crises occur on average about every half-century, with about a third accompanied by financial crises. We find that monetary policy can be used more vigorously to stabilise the economy, making direct banking controls and fiscal activism unnecessary.

Keywords: DSGE model; Financial Frictions; China; Crises; Indirect Inference; Money; Credit

JEL classification: E3; E44; E52; C1;

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1 Introduction

The rapid development of the Chinese economy since the 1980s has attracted the attention of numerous scholars — some positive about its future[1] and others less so[2]. Research on the modelling of the Chinese macro-economy has also grown with a number of papers also available to the non-Chinese reader. These models are the familiar demand led, and data generated type vintage[3]. While a few of studies utilising the DSGE framework have emerged in recent years there has been no effort to model the Chinese business cycle including a banking sector. In an earlier paper (Le, Meenagh, Matthews, Minford and Xiao, 2014, LMMMX) we explored such an approach and reported some success. In this paper we take matters further by adding a fuller monetary sector. In the previous paper we incorporated the Bernanke et al. (1999, BGG) model of the banking system but paid no explicit attention to balance sheets, the quantity of money and bank credit. Here we try to develop a framework that allows us to comment on policy relating monetary quantities and bank credit (including the activity of the shadow banking system) as opposed to just interest rates.

This paper employs a variant of the Smets and Wouters (2003, 2007, SW) model due to Le et al. (2011). The model is augmented with the quantity of credit and money, in a way we explain in detail below. The basic idea is that the monetary base acts as collateral for loans because it is entirely liquid and riskless. Hence it is a powerful agent of credit growth in a way that has hitherto been relatively neglected in DSGE models.

The focus of this paper is empirical. We apply a powerful testing procedure to this theoretical set-up, and check whether China's business cycle behaviour can be explained by this theory[4].

[1] Notably Chow (2007) and more recently Coase and Wang (2012)

[2] See Huang (2008)

[3] See for example Chow (2011), Qin et al. (2007), Sun et al. (2009), the CQMM (Xiamen University China Quarterly Macroeconomic Model) and the CUFEM (Central University of Finance and Economics Model).

[4] We are treading to some extent in the footsteps of earlier work done for China without banking by Dai (2012) which managed to fit a model of this type on stationary data to the joint behaviour of output, inflation and interest rates.

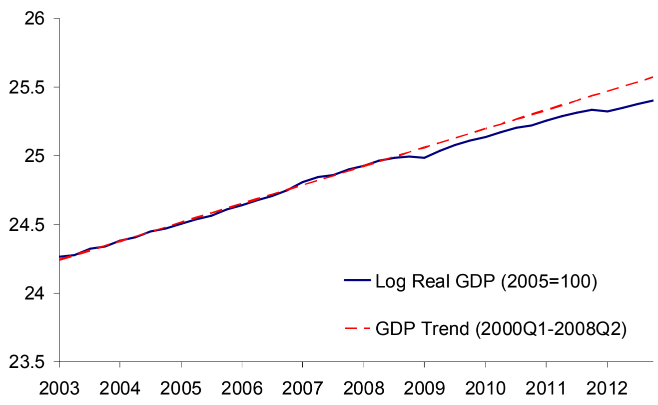


Figure 1: China Log Real GDP and Pre-Crisis Trend

China was not immune to the global financial crisis. As LMMMX (2014) show, China (Figure 1) too experienced a severe loss of output in the crisis and suffered a strong growth slowdown and like most Western economies has not recouped this loss nor reached its previous trend growth rate. The purpose of this paper is to see whether the evolution of the Chinese economy during this period can be plausibly explained within our set up.

To anticipate our results, we estimate a version of this model to fit the Chinese economy covering this crisis period. The model tells us that the main shocks hitting China in the crisis were international and that Chinese banking shocks were a modest contributor. However the state banking system together with direct government spending was used to supplement monetary policy in aggressively offsetting the crisis on GDP. It seems that while Chinese capitalism is as vulnerable as any to crises, such is the importance of growth to the Chinese leadership's strategy that the state retains powerful instruments to mitigate the effects of crises on growth. Nevertheless, their use has the potential to destabilise the economy.

In our empirical procedures we use the indirect inference (II) procedure to test the model on some initial parameter values, mainly based on US data, and then allow the parameters to be moved flexibly to the values that maximise the criterion of replicating the data behaviour — indirect estimation. This allows us to test the model itself rather than a particular set of parameter values that could be at fault. The basic reason for using II over the now-popular

Bayesian ML is that it tests the overall ability of the model to replicate key aspects of data behaviour — there is no guarantee that Bayesian estimates will pass this test.

The rest of this paper is as follows: in the next section we set out the model in outline, incorporating the modified BGG framework to the SW model. In the third section, we review the current state of DSGE modelling of the Chinese economy and describe the state of the banking sector. In the fourth section we explain our testing procedure, based on the method of II whereby the model's simulated behaviour is compared statistically with the behaviour found in the data; we also explain the method of indirect estimation. In the fifth section, we set out the empirical results for the model. The model is used to analyse the banking crisis and to speculate on the causes of future crises. In the penultimate section we consider how monetary policy could be reformed to minimise the occurrence of crises, independently of the regulative solutions now widely being suggested. Our final section concludes, with some reflections on the implications for China's banking.

2 The SW and BGG models

2.1 The Models in Brief

One of the main faults of the first type of calibrated DSGE model, the real business cycle (RBC) model, was its failure to capture the stylised features of the labour market observed in actual data. Employment was found to be not nearly volatile enough in the RBC model compared with observed data, and the correlation between real wages and output was found to be much too high (see, for example, King, Plosser and Rebelo, 1988). In the New-Keynesian tradition, the SW marks a major development in macroeconometric modelling based on the DSGE framework. Its main aim is to construct and estimate a DSGE model in which prices and wages, and hence real wages, are sticky due to nominal and real frictions in both the goods and labour markets, and to examine the consequent effects of monetary policy which is set through a Taylor rule. SW combine both calibration and Bayesian estimation methods.

The SW model contains a full range of structural shocks. In the euro-area version — Smets and Wouters (2003) — on which the US version is based, there are ten structural shocks. These are reduced to seven in the US version: for total factor productivity, the risk premium, investment-specific technology, the wage mark-up, the price mark-up, exogenous spending and monetary policy. These shocks are generally assumed to have an autoregressive structure. The model finds that aggregate demand has hump-shaped responses to nominal and real shocks.

Smets and Wouters made various tests of their model and subsequently Del Negro, Schorfheide, Smets and Wouters (2007) examined the model by considering the extent to which its restrictions help to explain the data. Estimating the SW model using Bayesian methods, they approximate it by a VAR in vector error-correction form and compare this with an unrestricted VAR fitted to actual data that ignores cross-equation restrictions. A hyperparameter λ to measure the relative weights of the two VARs is chosen to maximise the marginal likelihood of the combined models. However, none of these exercises in evaluating the SW model were a test of specification in the classical sense. Le et al. (2011) proposed such a test, a Wald test based on indirect inference which compares the model's VAR representation with the VAR estimated from the data, and showed that over the full post-war sample the original SW New Keynesian (NK) model was rejected. In addition, they examined an alternative 'New Classical' (NC) version in which prices and wages were fully flexible but there was a simple one-period information delay for labour suppliers. This NC version was also rejected by the test. A hybrid version that was a weighted average of the corresponding NK and NC equations got much closer to the data for the full sample.

Essentially, the NK model generated too little nominal variation while the NC model delivered too much. However the hybrid model was able to reproduce the variances of the data; and it is this key feature that enables it to match the data overall more closely. It is this version that we use here, adding to it the BGG model of banking.

The BGG financial sector produces certain changes in this model but much remains unchanged. Production is divided into three distinct participants: as previously, retailers and intermediate goods producers (now called entrepreneurs for a reason described later) and in addition, capital producers. Retailers function in the same way as before, operating in perfect competition to produce final goods by aggregating differentiated intermediate products using the Dixit-Stiglitz technology. With the assumption that retail output is made up of a fixed proportion of intermediate goods in an imperfectly competitive market and intermediate goods sold competitively, the aggregate price is a weighted average of prices received in the two types of market. As a result, the aggregate price equation is unchanged. Capital producers operate in a competitive market and take prices as given. They buy final consumption goods and transform them into capital to be sold on to entrepreneurs.

The difference in BGG lies in the nature of entrepreneurs. They still produce intermediate goods, but now they do not rent capital from households (who do not buy capital but only buy bonds or deposits) but must buy it from capital producers and in order to buy this capital they have to borrow from a bank which converts household savings into lending. On the production side, entrepreneurs face the same situation as in Le et al. (2011). They hire labour from households for wages that are partly set in monopolistic, and partly in competitive labour markets. Similarly they buy capital from capital producers at prices of goods also set in a mixture of monopolistic and competitive goods markets. Thus the production function, the labour demand and real marginal cost equations are unchanged. It is on their financing side that there are major changes.

Entrepreneurs buy capital using their own net worth, pledged against loans from the bank, which thus intermediates household savings deposited with it at the risk-free rate of return. The net worth of entrepreneurs is kept below the demand for capital by a fixed death rate of these firms $(1-\theta)$; the stock of firms is kept constant by an equal birth rate of new firms. Entrepreneurial net worth n_t therefore is given by the past net worth of surviving firms plus their total return on capital cy_t minus the expected return (which is paid out in borrowing costs to the bank) on the externally financed part of their capital stock — equivalent to

$$n_t = \theta n_{t-1} + \frac{K}{N}(cy_t - E_{t-1}cy_t) + E_{t-1}cy_t + enw_t \tag{1}$$

where $\frac{K}{N}$ is the steady state ratio of capital expenditures to entrepreneurial net worth, θ is the survival rate of entrepreneurs and enw_t is a net worth shock. Those who die will consume their net worth, so that entrepreneurial consumption c_t^e is equal to $(1-\theta)$ times net worth. In logs this implies that this consumption varies in proportion to net worth so that:

$$c_t^e = n_t \tag{2}$$

In order to borrow, entrepreneurs sign a debt contract prior to the realisation of idiosyncratic shocks on the return to capital: they choose their total capital and the associated borrowing before the shock realisation. The optimal debt contract takes a state-contigent form to ensure that the expected gross return on the bank's lending is equal to the bank opportunity cost of lending. When the idiosyncratic shock hits, there is a critical threshold for it such that for shock values above the threshold, the entrepreneur repays the loan and keeps the surplus, while for values below it, he would default, with the bank keeping whatever is available. From the first order conditions of the optimal contract, the external finance premium is equated with the expected marginal product of capital which under constant returns to scale is exogenous to the individual firm (and given by the exogenous technology parameter); hence the capital stock of each entrepreneur is proportional to his net worth, with this proportion increasing as the expected marginal product rises, driving up the external finance premium. Thus the external finance premium increases with the amount of the firm's capital investment that is financed by borrowing:

$$E_t cy_{t+1} - (r_t - E_t \pi_{t+1}) = \chi \left(qq_t + k_t - n_t \right) + epr_t \tag{3}$$

where the coefficient $\chi > 0$ measures the elasticity of the premium with respect to leverage. Entrepreneurs leverage up to the point where the expected return on capital equals the cost of borrowing from financial intermediaries. The external finance premium also depends on an exogenous premium shock, epr_t. This can be thought of as a shock to the supply of credit: that is, a change in the efficiency of the financial intermediation process, or a shock to the financial sector that alters the premium beyond what is dictated by the current economic and policy conditions.

Entrepreneurs buy capital k_t at price qq_t in period t and uses it in $(t+1)$ production. At $(t+1)$ entrepreneurs receive the marginal product of capital rk_{t+1} and the ex-post aggregate return to capital is cy_{t+1}. The capital arbitrage equation (Tobin's Q equation) becomes:

$$qq_t = \frac{1-\delta}{1-\delta+R_*^K} E_t qq_{t+1} + \frac{R_*^K}{1-\delta+R_*^K} E_t rk_{t+1} - E_t cy_{t+1} \tag{4}$$

The resulting investment by entrepreneurs is therefore reacting to a Q-ratio that includes the effect of the risk-premium. There are as before investment adjustment costs. Thus, the investment Euler equation and capital accumulation equations are unchanged from Le et al. (2011). The output market-clearing condition becomes:

$$y_t = \frac{C}{Y} c_t + \frac{I}{Y} inn_t + R_*^K k_y \frac{1-\psi}{\psi} rk_t + c_y^e c_t^e + eg_t \tag{5}$$

where y_t is output, c_t is consumption, inn_t is investment and eg_t is the exogenous demand shock.

2.2 Modifications to the BGG model to allow effects of Quantitative Easing and Bank Regulation:

In the years since the crisis there have been key developments in the monetary scene. The first has been the zero bound on official interest rates in developed economies, as central banks have driven the rate at which they will lend to banks down virtually to zero; however, this has not occurred in China. The second development has been aggressive open market operations ('Quantitative Easing'), intended to inject liquidity into the banking system and spur greater credit creation. The third has been more intrusive regulation of banks, via increased capital and liquidity ratios. Both these last two elements have occurred in China and it seems important to us to introduce into the model here a tool to deal with each of these developments.

Let us begin with bank regulation: what this does is to raise the cost of lending to firms (the credit friction). The regulators insist banks hold as counterpart funds for the credit assets they hold, not purely deposits that have low cost but also in particular capital; the latter is more expensive because shareholders putting up such equity require an appropriate premium to compensate them for the risk the banks' losses will lose this capital. We do not model the regulations explicitly through these balance sheet quantities but for simplicity put into the model an addition to the credit friction, ξ, reflecting these requirements — and also the costs of other regulative intrusions[5].

Next, we consider the role of QE. To deal with this, we note that in BGG firms put up no collateral. Net worth by construction is all invested in plant, machinery and other capital. However, once so invested, this amount cannot be recovered at original value plainly: it will have less value as second hand sales when the firm goes bankrupt because it has become specialised to the firm's activities. The cost of bankruptcy recovery (costly state verification) applies to the valuation of the activity this capital still allows.

It is in fact normal for banks to request an amount of collateral from the firms to which

[5] Such as 'ringfencing' different activities and imposing high liquidity ratios

they lend. This gives firms more 'skin in the game' and so more incentive to avoid bankruptcy[6]. We therefore supplement the BGG model by the assumption that banks require firms to put up the amount of collateral, c, as a fraction of their net worth. We also assume that recovery of this typical collateral costs a proportion δ of its original value when posted — we can think of the example of a house being put up and it costing this proportion in fees and forced-sale losses to sell the house and recover its value in cash. We modify the workings of the model according to these two assumptions — these modifications are shown in an appendix.[7]

It is at this point we introduce the idea of cash as collateral. If a firm holds some cash on its balance sheet, this can be recovered directly with no loss of value and no verification cost; thus it eliminates the cost δ. We show in the appendix that the elimination of this cost lowers the credit premium for given leverage; it therefore permits firms to increase leverage and so raise their expected returns. We therefore assume that banks and firms have an interest in firms holding as much cash as can be acquired for collateral. Thus as M0 is issued we assume that it is acquired by firms from banks to be held as collateral. This effect of the monetary base on collateral echoes Williamson (2013) in a search model.

The government/central bank issues this cash through open market operations (QE) to households in exchange for government bonds (GB) they hold. They deposit this cash with the banks. Firms wish to acquire as much of this cash as possible for their collateral needs. We can think of them as investing their net worth in cash (to the maximum available), with the rest going into other collateral and capital. In practice of course their profits (which create their net worth) are continuously paid out as dividends to the banks which provide

[6]Some models underpin bank contracting entirely on the basis that banks will only lend against collateral — Kiyotaki and Moore (1997) — however we do not adopt this extreme position here.

[7]The posting of collateral actually lowers firms' profits from borrowing for given net worth and leverage; this is because collateral has no yield and could be sold for higher profitable investment. Hence it seems to be puzzling that banks demand collateral in a contract designed to maximise firms' profits subject to the constraints of truth-telling and bank zero net profits due to competition. However, undoubtedly collateral is a routine precaution taken by banks engaged in arm's length lending. The natural interpretation of collateral in this context is that it ensures that the borrower does not abscond; in the event of absconding the collateral is directly seizable. Equivalent amounts are taken in numerous financial transactions as 'deposits', 'margin' and so on.

them with credit, so they have nothing with which to acquire these assets if they do not collaborate with banks. So they achieve this balance sheet outcome by agreeing with the banks that, as a minimum counterpart to the credit advanced they will hold the maximum cash collateral available, which is M0. Thus all of M0 at once finds its way into firms' balance sheets, where it is securely pledged to the banks in the event of bankruptcy (for example by being actually lodged with them).[8]

Finally, we model the rate on official lending to the banks by the central bank as now: it is exogenously chosen according to some rule, such as the Taylor Rule. We assume that in normal times the central bank enforces this rule via discount window operations so that M0 is endogenous — supporting the lending implied by the Taylor Rule. It does so in a manner that keeps δ within some normal range (reflecting the normal share of M0 in collateral and also the normal cost of acquiring M0 via the Bank discount window). However, at the zero bound the Taylor Rule is suspended and the central bank is creating M0 independently via open market operations and in such a way as to bring down δ sufficiently to absorb the supply, which is in excess of what is required to support lending at a normal δ. It thus operates to expand lending beyond what would normally be associated with the bounded interest rate, by driving down the cost of collateral. In effect under QE it is providing M0 at less expense to the banks since it is not providing it through the discount window on

[8] One might ask: could not bank deposits be held as collateral? Consider first whether a firm collaborating with bank A could hold deposits in bank B as collateral for its bank A credit. The problem for bank A would be that it would know bank B would lend out these deposits to other firms against those firms' collateral. Thus the average bank deposit has as its counterpart asset bank credit, which is leveraged on firms' collateral. If firms could hold other banks' deposits as collateral, the banks as a whole would have no collateral at all since effectively the 'collateral' would be lending to firms. Thus while an individual firm deposit with another bank, on its own, could provide some collateral, the practice if allowed by a bank could open the system, and so it too, to abuse. So it is plain that banks will not agree for bank deposits with other banks to be collateral.

Consider second whether a deposit of a firm with its own bank could be collateral. We can see that this is exactly equivalent to the firm holding M0 (which is then held for it by the bank). Imagine firms hold the same part of their Net Worth as they held M0 before, but now in the form of deposits with their own banks; it is agreed that this amount will not be invested but held as collateral. Lending then goes ahead in the same amount as before but this part is held by the banks unlent, in a form that can be fully seized. To do so the banks must hold M0 on their balance sheets, as this is the only asset that is fully seizable — just as before when they held it on behalf of firms. In effect they invest the firms' Net Worth in M0.

Thus in general we can think of M0 as the only available monetary collateral.

the usual terms but lodging it with the banks via bank deposits created by its purchases of government debt on the open market.

This now gives our monetary authorities three instruments: ξ, $M0$ and r. Accordingly they will need three operating rules for these instruments. We will discuss these shortly.

First, we set out the balance sheets of the agents in the economy and discuss how they are altered by acts of policy.

Firms		Banks		Households		Govt/central bank	
A	L	A	L	A	L	A	L
$\begin{pmatrix} COLL - exM0- \\ COLL - M0+ \\ K+ \end{pmatrix}$	$\begin{pmatrix} NW \\ CR+ \end{pmatrix}$	$\begin{pmatrix} CR+ \end{pmatrix}$	$\begin{pmatrix} DEP+ \end{pmatrix}$	$\begin{pmatrix} DEP+ \\ GB- \end{pmatrix}$	$\begin{pmatrix} CUMSAV \end{pmatrix}$	$\begin{pmatrix} CUMDEF \end{pmatrix}$	$\begin{pmatrix} GB- \\ M0+ \end{pmatrix}$

Table 1: Balance Sheets of the Agents of the Economy

Consider now how an open market operation (QE) by buying GB for M0 would change these balance sheets — as indicated by + and − . Households place the extra cash on deposit; the banks then lend it to firms who are able to use it as collateral in a future lending deal with the banks, so that a larger part of collateral (COLL) is held as M0. With collateral cheaper (δ falls) the bank credit premium falls, inducing a rise in investment and leverage; the other collateral is thus disposed of so that the proceeds can be invested directly in capital.

To adjust the model for these additional features, we need to introduce the effect of M0 on the credit premium via its effect on the cost of liquidating collateral, δ; and we need to add ξ, the macro-prudential instrument directly raising the credit friction, into the credit premium equation. This equation now has additional terms in m (=ln $M0$) and ξ, as follows:

$$E_t cy_{t+1} - (r_t - E_t \pi_{t+1}) = \chi \left(qq_t + k_t - n_t \right) - \psi m_t + \xi_t + epr_t \tag{6}$$

where ψ is the elasticity of the premium to M0 via its collateral role. This effect comes about, conditional on leverage $(k - n)$, through the willingness of banks (under their zero profit condition) to reduce credit premium for given leverage. Now that they will recover more in the event of bankruptcy, the equilibrium contract, for given leverage, now has a lower bankruptcy threshold and a lower required rate of return on firm assets. Both produce a lower credit premium for given leverage.

We now need equations for the supply of M0 and for the setting of ξ. In China M0 seems to have been set to moderate the growth of credit/broad money. We find a small negative coefficient of M0 on the latter. We write the equation for M0 as:

$$\Delta m_t = \phi \Delta M_t + errm1t \tag{7}$$

where M_t is money and we expect ϕ to be negative.

Macro-prudential measures have been built on the Basel Agreements nos 1 and 2; clearly they have been made more harsh over this period in response to the crisis, which was unpredicted by officials. Before that there was a gradual tightening of regulation at least in the Agreements, if not always in practical application by individual countries. This suggests that macro-prudential measures have evolved as an exogenous I(1) time-series process, with the crisis acting as an exogenous shock to the process. We write the equation for the macro-prudential instrument as:

$$\Delta \xi_t = errxi_t \tag{8}$$

Given that we have very poor data on these macro-prudential measures we have to this point simply included these in the error epr_t.

Finally, we need an equation now additionally for the supply of money, which we define as equal to deposits (= credit) +M0. Here we simply use the firms' balance sheet ($M = CR + M0 = K + COLL - NW + M0$) which can be written in loglinearised form as:

$$M_t = (1 + \nu - c - \mu)K_t + \mu m_t - \nu n_t$$

where M, K, m, n are respectively the logs of Money, capital, M0 and net worth, we have omitted the constant (which includes collateral, assumed fixed as a proportion of money); ν, μ, c are respectively the ratios of net worth, M0 and collateral to money.[9]

3 DSGE, Banking and the Chinese Economy

It can be argued that the model, developed out of the Smets and Wouters (2003, 2007) is only suitable for a large closed economy as characterised by the USA. It might be thought that since China has a large export sector (26% of GDP) and a similarly large import sector, it cannot be modelled as a closed economy. However, China's export and import sector has developed rapidly as a result of decisions to invest in new infrastructure in cities and transportation; once these decisions were taken, the resulting output of goods was sold on world markets at the prices needed to absorb it. Nevertheless as there is some degree of price and wage rigidity in China, there will be effects of world demand in the short run. Because the industrial structure is largely dominated by multi-national companies, imports too are closely related to the export volumes. Thus we would argue that net imports can reasonably be modelled as exogenous processes in China; this is how they enter in the Smets-Wouters model, as an exogenous error process in the goods market-clearing equation whereby output equals demand for goods.

An alternative argument is that the Chinese economy does not function fully as a developed market economy and that the modelling of the economy must include the distortions of a dominant state sector (Zheng, Storesletten and Zilibotti, 2011) that stifles the growth of private enterprise through state-capitalism (Huang, 2008) and distortions in the labour market (Dollar and Jones, 2013) and a controlled banking system (Chen et al. 2012). While there is merit in this argument, we argue that it misses the point of using a model as an analytical aid to thinking about the determinants of the business cycle. In reality no economy developed or otherwise behaves fully as the SW framework describes. The purpose of using

[9] Notice that in this model the demand for money is simply the demand for deposits as a savings vehicle. Savings in the model are equal to investment by market-clearing, so that any additional investment requiring additional bank supply of leverage is equal to the additional supply of savings.

a DSGE model of a variant of the SW framework is to use it to isolate the principal factors that drive the business cycle in China even with distorted markets.

Indeed DSGE models have been increasingly utilised in modelling the Chinese economy. Zhang (2009) calibrate a DSGE model for China to examine welfare implications of a money supply rule versus an interest rate rule. Mehrotra et al. (2013) use a partially estimated (GMM) and calibrated DSGE model based on Christiano et al. (2005) to evaluate a re-balancing of the Chinese economy from investment-led to consumption-led growth. The labour market is assumed to be frictionless but rigidities arise from staggered price setting by firms, habit formation in consumption and capital adjustment costs. Technology shocks have a damped effect on output in a re-balanced economy. Wan and Xu (2010) use Bayesian methods to estimate an open economy DSGE model based on Fernandez-Villaverde and Rubio-Ramirez (2004). They find the standard result that technology shocks are the main driver of the business cycle and that they dominate monetary shocks. Counter-cyclical credit policy is examined by Peng (2012), in a New-Keynesian DSGE model based on Iacoviello (2005). Firms are credit constrained and the Peoples Bank of China controls credit growth through its hold on the banking system. While as expected, technology shocks dominate the variance of output, credit shocks are also a strong driver. Counter-cyclical credit policy is effective in reducing output volatility. In contrast, Sun and Sen (2012), develop a Bayesian estimated modified Smets-Wouters DSGE model to examine the business cycle and find that technology shocks play a subsidiary role. The dominant drivers of output are investment and preference shocks.

A number of studies using the New Keynesian DSGE framework have been published by Chinese scholars (in Chinese). Xu and Chen (2009) incorporate a bank lending channel into a DSGE model with price stickiness. They find that technology shocks explain the majority of the variations of output, investment and long-term consumption, and the fluctuations of short-term consumption, loan and real money balance are mainly attributed to credit shocks. Xi and He (2010) evaluate the welfare losses of China's monetary policy with a

New Keynesian DSGE model and find that the welfare losses are negatively correlated with nominal interest rate-inflation sensitivity and positively correlated with nominal interest rate-output sensitivity. They recommend using interest rate policy to stabilize the price level but not to adjust economic growth rate. They also find that the welfare losses caused by fluctuations in money supply are larger than caused by fluctuations in interest rate; hence the appropriate intermediate target of monetary policy should be interest rate instead of money supply. Yuan, Chen and Liu (2011) investigate the existence of the financial accelerator within a small open economy. While the financial accelerator amplifies the impacts of shocks to the marginal efficiency of investment and monetary policy, its amplification effect on the technology and preference shocks is subsidiary. Similar results are reported in Liu and Yuan (2012). Overall, the Chinese publications are in line with the results of those in the international arena[10].

The evolution of the Chinese banking system illustrates the broader evolution of its capitalism with Chinese characteristics. Traditionally banking like the rest of the economy has been dominated by the state: state-owned banks provide credit to state-owned firms. But more recently the non-state owned banks have grown in parallel with the private production sector. Because the state banks are closely supported by the government on favourable terms, credit from them finds its way also to the private sector via a round-about route, to the shadow banking system through the sale of wealth management products. Thus emerges the peculiarly Chinese feature of two parallel systems, separate but connected. In our model here we have treated the system as an integrated unit in which market forces work in a similar, connected way — see LMMMX (2014) for details of the Chinese banking system and monetary instruments.

It is clear that the Chinese banking system, state, non-state and shadow, is complex and that its operations are intervened in by the government in many ways. Here we necessarily abstract from these complexities partly because there is little relevant data and partly

[10]Among all existing DSGE modelling of Chinese economy, to our knowledge, only two have incorporated a banking sector: Chen et al. (2012) and Xu and Chen (2009).

because their interactions are hard to model. Instead we model it as if it behaves like an ordinary banking system, facing idiosyncratic risk and costs of bankruptcy, the result of which is a credit premium that rises with investment needs. Essentially one can think of this as what the marginal investor in the private sector faces as the outcome of the banking system in China.

4 The method of indirect inference

We evaluate the model's capacity in fitting the data using the method of II originally proposed in Minford, Theodoridis and Meenagh (2009) and subsequently with a number of refinements by Le et al. (2011) who evaluate the method using Monte Carlo experiments. The approach employs an auxiliary model that is completely independent of the theoretical one to produce a description of the data against which the performance of the theory is evaluated indirectly. Such a description can be summarised either by the estimated parameters of the auxiliary model or by functions of these; we will call these the descriptors of the data. While these are treated as the 'reality', the theoretical model being evaluated is simulated to find its implied values for them.

II has been widely used in the estimation of structural models (e.g., Smith, 1993, Gregory and Smith, 1991, 1993, Gourieroux et al., 1993, Gourieroux and Monfort, 1995 and Canova, 2005). Here we make a further use of indirect inference, to evaluate an already estimated or calibrated structural model. The common element is the use of an auxiliary time series model. In estimation the parameters of the structural model are chosen such that when this model is simulated it generates estimates of the auxiliary model similar to those obtained from the actual data. The optimal choices of parameters for the structural model are those that minimise the distance between a given function of the two sets of estimated coefficients of the auxiliary model. Common choices of this function are the actual coefficients, the scores or the impulse response functions. In model evaluation the parameters of the structural model are taken as given. The aim is to compare the performance of the auxiliary model estimated on simulated data derived from the given estimates of a structural model — which is taken as a true model of the economy, the null hypothesis — with the performance of the auxiliary model when estimated from the actual data. If the structural model is correct then its predictions about the impulse responses, moments and time series properties of the data should statistically match those based on the actual data. The comparison is based on the distributions of the two sets of parameter estimates of the auxiliary model, or of functions of these estimates.

The testing procedure thus involves first constructing the errors implied by the previously estimated/calibrated structural model and the data. These are called the structural errors and are backed out directly from the equations and the data[11]. These errors are then bootstrapped and used to generate for each bootstrap new data based on the structural model. An auxiliary time series model is then fitted to each set of data and the sampling distribution of the coefficients of the auxiliary time series model is obtained from these estimates of the auxiliary model. A Wald statistic is computed to determine whether functions of the parameters of the time series model estimated on the actual data lie in some confidence interval implied by this sampling distribution.

Following Meenagh et al. (2012) we use as the auxiliary model a VECM which we reexpress as a VAR(1) for the three macro variables (interest rate, output gap and inflation) with a time trend and with the productivity residual entered as an exogenous non-stationary process (these two elements having the effect of achieving cointegration)[12]. Thus our auxiliary model in practice is given by:

$y_t = [I-K]y_{t-1} + \gamma\overline{x}_{t-1} + gt + v_t$ where $\overline{x}_{t-1}$ is the stochastic trend in productivity, gt are the deterministic trends, and v_t are the VECM innovations. We treat as the descriptors of

[11] Some equations may involve calculation of expectations. The method we use here is the robust instrumental variables estimation suggested by McCallum (1976) and Wickens (1982): we set the lagged endogenous data as instruments and calculate the fitted values from a VAR(1) — this also being the auxiliary model chosen in what follows.

[12] See Le et al. (2013).

the data the VAR coefficients (on the endogenous variables only, $I-K$) and the VAR error variances ($var[v]$). The Wald statistic is computed from these[13]. Thus effectively we are testing whether the observed dynamics and volatility of the chosen variables are explained by the simulated joint distribution of these at a given confidence level. The Wald statistic is given by:

$$(\Phi-\overline{\Phi})'\sum\nolimits_{(\Phi\Phi)}^{-1}(\Phi-\overline{\Phi}) \tag{9}$$

where Φ is the vector of VAR estimates of the chosen descriptors yielded in each simulation, with $\overline{\Phi}$ and $\sum_{(\Phi\Phi)}$ representing the corresponding sample means and variance-covariance matrix of these calculated across simulations, respectively.

The joint distribution of the Φ is obtained by bootstrapping the innovations implied by the data and the theoretical model; it is therefore an estimate of the small sample distribution[14]. Such a distribution is generally more accurate for small samples than the asymptotic distribution; it is also shown to be consistent by Le et al. (2011) given that the Wald statistic is 'asymptotically pivotal'; they also showed it had quite good accuracy in small sample Monte Carlo experiments[15].

This testing procedure is applied to a set of (structural) parameters put forward as the true ones (H_0, the null hypothesis); they can be derived from calibration, estimation, or both. However derived, the test then asks: could these coefficients within this model structure be the true (numerical) model generating the data? Of course only one true model with one set of coefficients is possible. Nevertheless we may have chosen coefficients that are not

[13]We do not attempt to match the time trends and the coefficients on non-stationary trend productivity; we assume that the model coefficients yielding these balanced growth paths and effects of trend productivity on the steady state are chosen accurately. However, we are not interested for our exercise here in any effects on the balanced growth path, as this is fixed. As for the effects of productivity shocks on the steady state we assume that any inaccuracy in this will not importantly affect the business cycle analysis we are doing here — any inaccuracy would be important in assessing the effect on the steady state which is not our focus. Thus our assessment of the model is as if we were filtering the data into stationary form by regressing it on the time trends and trend productivity.

[14]The bootstraps in our tests are all drawn as time vectors so contemporaneous correlations between the innovations are preserved.

[15]Specifically, they found on stationary data that the bias due to bootstrapping was just over 2% at the 95% confidence level and 0.6% at the 99% level. Meenagh et al. (2012) found even greater accuracy in Monte Carlo experiments on nonstationary data.

exactly right numerically, so that the same model with other coefficient values could be correct. Only when we have examined the model with all coefficient values that are feasible within the model theory will we have properly tested it. For this reason we later extend our procedure by a further search algorithm, in which we seek other coefficient sets that could do better in the test.

Thus we calculate the minimum-value full Wald statistic for each period using a powerful algorithm based on Simulated Annealing (SA) in which search takes place over a wide range around the initial values, with optimising search accompanied by random jumps around the space[16]. In effect this is Indirect Inference estimation of the model; however here this estimation is being done to find whether the model can be rejected *in itself* and not for the sake of finding the most satisfactory estimates of the model parameters. Nevertheless of course the method does this latter task as a by-product so that we can use the resulting unrejected model as representing the best available estimated version. The merit of this extended procedure is that we are comparing the best possible versions of each model type when finally doing our comparison of model compatibility with the data.

Before we proceed to carry out our tests and estimation, we should explain why we do not use the much more familiar 'direct inference' estimation and testing procedures here. In direct inference one fits a structural model directly to the data, either by classical 'frequentist' FIML or by the now popular Bayesian ML. The likelihood that is maximised in FIML is derived from the size of the reduced form errors. In Bayesian ML it is derived from this plus the priors — effectively the resulting ML parameters are a weighted average of the FIML values and the priors, where the weights depend on the prior distributions and the extent to

[16] We use a Simulated Annealing algorithm due to Ingber (1996). This mimics the behaviour of the steel cooling process in which steel is cooled, with a degree of reheating at randomly chosen moments in the cooling process — this ensuring that the defects are minimised globally. Similarly the algorithm searches in the chosen range and as points that improve the objective are found it also accepts points that do not improve the objective. This helps to stop the algorithm being caught in local minima. We find this algorithm improves substantially here on a standard optimisation algorithm. Our method used our standard testing method: we take a set of model parameters (excluding error processes), extract the resulting residuals from the data using the LIML method, find their implied autoregressive coefficients ($AR(1)$ here) and then bootstrap the implied innovations with this full set of parameters to find the implied Wald value. This is then minimised by the SA algorithm.

which the FIML values differ from the priors. The FIML values are essentially those that give the best current forecasting performance for the model (i.e. minimising the size of the reduced form errors). One can develop overall tests of the model specification under direct inference by creating, in the FIML case, a Likelihood Ratio against some benchmark model, a natural one being an unrestricted VAR; in the Bayesian case Del Negro and Schorfheide have proposed the DSGE-VAR weight as a measure of model closeness to the data (this is the weight on the prior model's implied VAR, as combined with the unrestricted VAR, that maximises the likelihood). This can also be treated as a specification test of the overall model, even though usually Bayesians are reluctant to talk about 'testing' the model as whole.

Such tests are compared with the indirect inference tests using Monte Carlo experiments with an SW model, in Le et al. (2014).They find that the tests compare quite different features of model performance. The direct ones check (in-sample) forecasting ability, while the indirect one checks the model's causal structure. For policy purposes we are most interested in using DSGE models for simulation of the effects of policy changes and hence in their causal structure. Typically forecasting is done by other means.

Both tests can still be used to test a model's specification and hence its causal structure, even if the direct method checks it via forecasting performance. But Le et al. also find that, viewed as test of model specification, the power of direct inference tests in small samples is much lower than that of indirect inference. In other words they discriminate rather weakly against false models. This is presumably because forecasting is only weakly related to good specification; bad models with a lot of ad hoc lags and added exogenous variables forecast better than models based on good theory, which are restricted to having only structural shock processes as their exogenous variables. Furthermore false models will generate false structural shock processes which may well partly compensate for the specification error in the model's forecasting performance. Meanwhile the indirect inference test's power against false models allows one to discover rather accurately what features of the data behaviour a model can replicate and what not; this in turn can be helpful in thinking about respecification.

In estimation both FIML and Indirect estimators are consistent and asymptotically normal. But as we have seen the latter's power is greater in small samples so that it should also give more reliable results from estimation in small samples. For these reasons we use the indirect inference procedure here both to estimate the model on our available small samples and to test its specification.

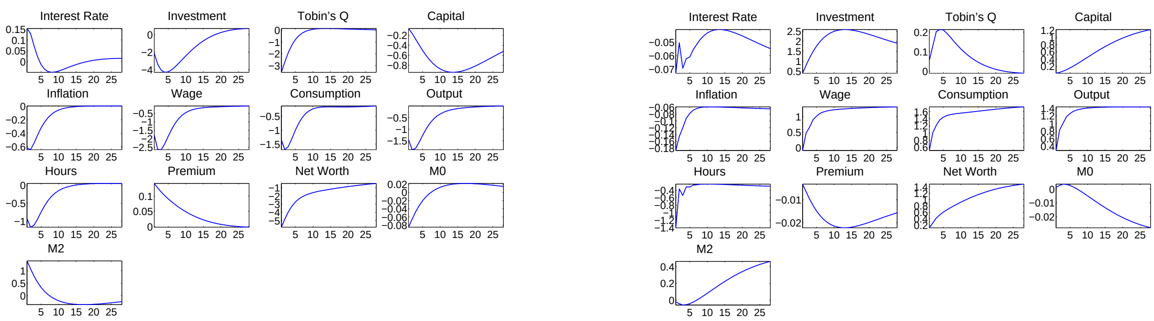
5 Model decomposition and the origins of the banking crisis

5.1 Estimation and model fit

The model that integrates the banking sector and money is estimated using the method of II as set out in Le et al. (2011) for the 1991–2011 period. The estimated model is tested against the data using the main macroeconomic variables, output, inflation and the interest rate. We use a test of whether the model can match the time series properties of the data jointly. The model is found to fit the data well according to the Wald statistic with a p-value of 0.0901. The estimated parameters can be found in Table 2. Impulse response functions to key variables when the model is applied to non-stationary data are shown in Figure 2. Note that the second set of IRFs in Figure 2 are due to a non-stationary productivity shock. Figure 3 shows that the model generates 95% confidence intervals for the implied VAR responses that easily encompasses the data-based VAR responses to a monetary shock — see Appendix 2 for the VAR responses to other shocks.

Table 2 presents four columns of parameter estimates. The first column is for the US economy by Le, Meenagh and Minford (2012a) and the second column shows the same model for China. The comparison reveals that in China the competitive structure of labour and product markets is more competitive than that in the US; about 64% of the labour market is imperfectly competitive but 93% of the product market is competitive. In the imperfectly competitive labour market wages are less rigid in China and there is less wage indexation. Chinese labour supply is about twice as responsive to real wages as in the US. In China there is about a third less habit persistence in consumption. Capital adjustment costs are about twice as great and it is four times as costly to vary capacity utilisation. In money and banking the response of the credit spread to Tobin's Q is twice as large; and the Taylor Rule is roughly twice as responsive both to inflation and output gaps, and has similar persistence. If one had to place China along the New Keynesian-New Classical spectrum it would therefore be closer to the New Classical end, with less nominal rigidity. This should mean that in response to a similar-sized shock prices are more volatile than in the US. This is what we find in for example the IRF to a monetary contraction; inflation falls about three times as much as it does for an equivalent shock in the US. The third column of parameters is for the modified model that incorporates the banking sector with the money supply added as discussed above.

When we turn to the comparison of the China model with money supply added, we can see that its coefficients are little different from those of the previous China model. The difference comes basically through the substitution of M0-based collateral in place of net worth. The feedback coefficient on M0 from the credit/money supply is set very small in estimation because otherwise it tends to destabilise the model.



IRFs for a monetary shock IRFs for a non-stationary productivity shock

Figure 2: IRFs for key variables

Model Coefficients: 1991Q1-2011Q4				
		Est US	Est China	Est China + money
Steady-state elasticity of capital adjustment	φ	7.5744	4.0445	4.2960
Elasticity of consumption	σ_c	1.2716	1.3329	1.4676
External habit formation	λ	0.6512	0.4718	0.4423
Probability of not changing wages	ξ_w	0.7533	0.6034	0.6691
Elasticity of labour supply	σ_L	2.8327	1.3139	1.4569
Probability of not changing prices	ξ_p	0.8398	0.8417	0.8835
Wage indexation	ι_w	0.9404	0.6163	0.6934
Price indexation	ι_p	0.1213	0.1648	0.1558
Elasticity of capital utilisation	ψ	0.1988	0.5308	0.4922
Share of fixed costs in production (+1)	Φ	1.6841	1.6211	1.4468
Taylor Rule response to inflation	r_p	1.8886	2.6671	2.9436
Interest rate smoothing	ρ	0.7742	0.7680	0.7716
Taylor Rule response to output	r_y	0.0381	0.1001	0.0917
Taylor Rule response to change in output	$r_{\Delta y}$	0.1133	0.1466	0.1618
Share of capital in production	α	0.1435	0.1832	0.1647
Proportion of sticky wages	ω^w	0.5624	0.6376	0.6930
Proportion of sticky prices	ω^r	0.0874	0.0708	0.0607
Elasticity of the premium with respect to leverage	χ	0.0279	0.0554	0.0619
Quarterly steady-state inflation†	$\bar{\pi}$	0.7800	0.7800	0.7800
Discount factor†	β	0.9984	0.9984	0.9984
Steady-state hours worked†	$\overline{L}$	0.5300	0.5300	0.5300
Quarterly steady-state output growth†	$\bar{\gamma}$	0.4300	0.4300	0.4300
Ratio of M0 to credit	ν			0.0731
Ratio of net worth to credit	μ			0.2459
M0 response to broad money	ϕ			-0.0607
Elasticity of the premium to M0	ϕ_1			-0.0668
WALD (Y, π, R)		20.9734	19.6967	20.4425
†Fixed parameters p-value		0.0736	0.1084	0.0901

Table 2: Coefficient Estimates (1984Q3-2009Q2)

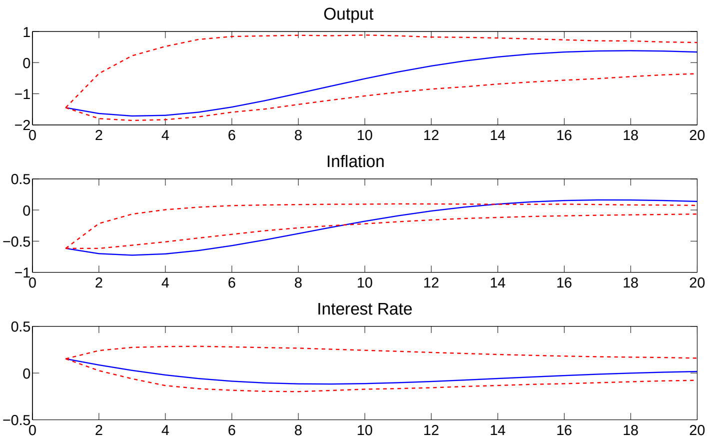


Figure 3: VAR IRFs for a monetary shock

5.2 Error properties on unfiltered data

Having established that the model that integrates the banking sector and money is not rejected by the data, we now go on to apply it to the recent crisis episode in China. To do this we extract the model shocks from the unfiltered data and fit to each an AR time-series process over the period. Table 3 shows the status of each shock and also the AR parameters that emerge from the estimation process. We find that productivity unambiguously has a unit root and we specify it in first differences. The other shocks we treat as either stationary or trend-stationary, because theoretically the model implies that they should be; for example 'government spending' (which includes net exports) is bounded by taxable capacity/the balance of payments, and the credit spread by collateral and limits on Tobin's Q. We then allow the error data to determine the AR parameters, with the results reported in this Table. Even though the AR coefficients do not closely approach the unit root, many of them show high persistence. Though the ADF and KPSS tests are consistent in several cases with unit roots, the fact that the model as a whole fits the data behaviour with the AR coefficients used here is evidence in their favour; had unit roots given a better fit, we would observe AR coefficients negligibly different from unity.

Clearly the crisis had international ramifications but we cannot identify the causality

	ADF p-value+	KPSS statistic	Conclusion	Coefficient AR
Exogenous Demand	0.2317	0.2817***	Trend Stationary‡	0.8369
Preferences	0.0019	0.1413	Stationary	0.6422
Private Investment	0.3275	0.5026**	Stationary‡	0.8806
Taylor Rule	0.0458	0.7030**	Stationary‡	0.6665
Productivity	0.9964	1.2011***	Nonstationary	−0.4237
Price Mark-up	0.0132	0.1814	Stationary	0.1912
Wage Mark-up	0.0000	0.4311	Stationary	0.3203
Labour Supply	0.6326	0.1537**	Trend Stationary‡	0.9219
Premium	0.0402	0.1717**	Trend Stationary‡	0.8428
Net Worth	0.0002	0.4837	Stationary	0.4660
M0	0.0170	0.0573	Stationary	0.7496

+ p-value of 0.05 is the 5% confidence limit for rejecting the unit root.
**(***) KPSS rejects stationarity at 5%(1%).
‡ After detrending the series are stationary with a AR coefficient less than 1

Table 3: Stationarity of Shocks and AR Parameters

of these in a China-only model. The shocks that show up in the model are partly coming from these international effects. Thus commodity price shocks that enter through the 'price mark-up' here are themselves responding to the crisis. Also the exogenous demand shock, which consists of government spending and net exports, contains the international downturn in world trade.

A further, similar limitation of our account is our inability to analyse connections between the shocks to the model. No doubt the banking shocks we identify had simultaneous and lagged effects on the non-banking shocks; but also vice versa, the non-banking on the banking. The sample episode is too short to establish which way such effects might go or even if they exist, tempting as it might be to run some regressions to detect them. The model assumes that each shock is separate from the others and only related to its own past. The model then disentangles how each shock works through the economy to affect final outcomes. Anyone that wished to take matters further would have to model the interactions of the shocks themselves through a wider model, such as one of political economy.

5.3 The errors driving the episode

We begin by showing the behaviour of the main model errors (i.e. the total cumulated innovations) during the crisis episode, which we treat as 2006Q1 to 2011Q4.

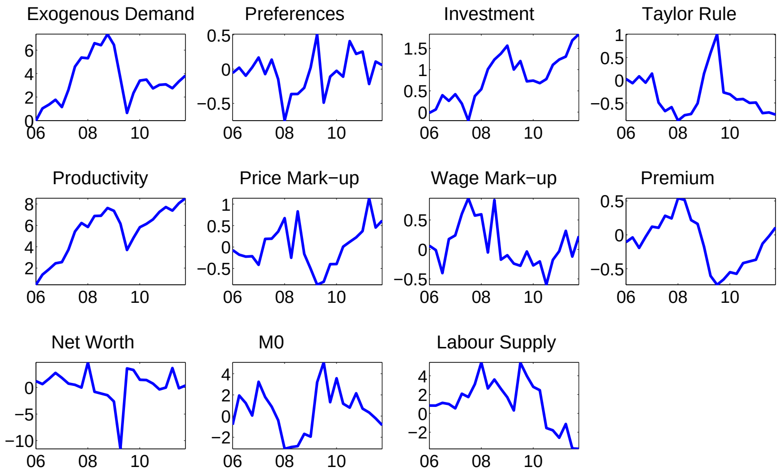


Figure 4: Accumulated Shocks from 2006Q1–2011Q4

We can see from Figure 4 that there was turbulence over the crisis in many of these shocks. We can single out ones where this was greatest. Exogenous demand shows the collapse of world trade at the end of 2008. There are parallel falls in consumption and investment. The price mark-up fluctuated with world commodity price movements. The Taylor Rule error appears to be associated with these and with world trade movements; there was no zero bound problem in China such as we find in the US as both interest rates and inflation remained fairly high during the episode.

Productivity fell after the crisis hit[17]; and the labour supply error (a measure of 'wage push' from workers) rose and then fell as workers responded to the crisis by cutting wages unusually.

Finally there is a strong shock coming via M0, which fell sharply during the crisis but

[17] Jian et al. (2010) use a standard sticky-price DSGE, to identify the effects of oil price shocks on productivity. They confirm that oil price shocks have permanent negative effects on output.

was then greatly boosted during 2009 by Bank policy.

Overall, we can see that there was a wide set of shocks hitting the Chinese economy during the crisis period, the major ones coming from abroad but in turn triggering domestic counterpart shocks. The Chinese authorities' response was, as we know, to give orders to banks to lend for investment projects, mainly infrastructure. We can see this response in the investment error, which turns sharply positive from the end of 2009. We can also see a strong reaction to the crisis in government spending which with net exports constitutes the exogenous demand shock; this is revealed by the available annual data shown in Figure 5 (there is quarterly data only for the two combined).

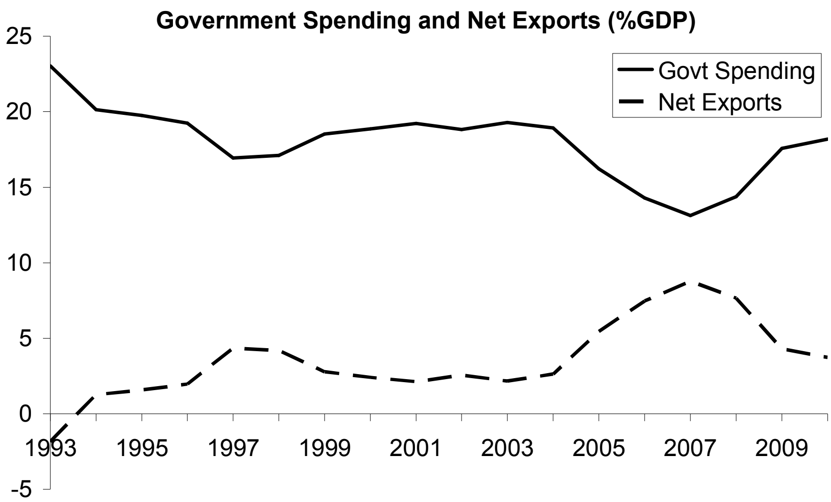


Figure 5: Government Spending and Net Exports (%GDP)

5.4 A stochastic variance decomposition of the episode

We next look at the variance decomposition of such episodes. Again, we are using unfiltered data when performing this analysis which treats the episode stochastically — that is, we take the shocks in the episode and replay them by redrawing them randomly and repeatedly with replacement to see what a typical crisis episode would be like. Our variance decomposition is therefore for such a typical episode.

	Int. rate	Inv.	Inf.	Real Wages	Cons.	Output	Emp.
Exogenous Demand	17.6	0.1	1.1	1.1	6.0	13.5	17.0
Preferences	27.5	0.3	5.0	15.1	14.2	7.2	6.4
Investment	1.8	1.9	0.2	0.4	0.5	0.6	0.2
Taylor Rule	2.1	2.5	54.0	49.1	25.1	26.9	23.0
Productivity	0.6	0.3	3.3	7.2	18.3	10.7	21.3
Price Mark-up	15.4	0.6	31.9	16.8	5.9	6.5	5.2
Wage Mark-up	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Labour Supply	2.8	0.7	2.8	4.3	18.5	11.8	16.0
Premium	0.5	0.6	0.0	0.1	0.1	0.2	0.1
Net Worth	12.8	32.9	0.6	2.1	4.8	9.2	4.6
M0	18.8	60.2	1.0	3.3	6.5	13.5	5.9
TOTAL	100	100	100	100	100	100	100
Banking Shocks	32.1	93.7	1.7	5.5	11.4	22.9	10.6
Non-Banking Shocks	67.9	6.3	98.3	94.5	88.6	77.1	89.4

Table 4: Variance Decomposition for Crisis Period

What we see from Table 4 is that only 23% of the output variance is due to financial shocks (here essentially the M0 shock[18]); and the rest is due to the usual non-banking shocks. The M0 shock operates by disturbing the supply of credit and so investment; thus for investment the share of financial shocks is very high (94%); but this gets dampened in its effect on GDP because interest rates react to them. Accordingly we see that interest rates are also quite highly affected (32%) by the financial shocks.

Thus there is a distinct role for financial shocks in such Chinese episodes. However, the bulk of the variation comes from the other shocks: exogenous demand, labour supply, productivity, monetary policy and the price mark-up.

[18]It may seem strange to include the M0 error among financial/banking shocks when its rise at the end of the period reflects a strong policy response. However, in this is parallels the behaviour of the credit premium shock in the US which was clearly a financial shock but also later embodied a strong policy response in the form of bank bailout. In China the credit premium shock was small because the banks are largely state banks with little perceived credit risk.

5.5 Accounting for this particular banking crisis episode

We can also decompose what actually happened in the precise episode that occurred according to the model as a result of these shocks. We do this in the charts that follow for the main macro variables.

If we focus first on output (Figure 6), we see that the economy overall contracts about 8% due to the crisis between the peak in 2008 and the trough in 2009. There are two main elements in this: exogenous demand and Taylor Rule tightening. It may seem surprising that tightening money reinforced the crisis downturn, but to understand this one must turn to the inflation chart (Figure 7, in % per quarter) which shows the inflation upsurge just prior to the Lehman collapse; the upward swing in inflation by mid-2008 from 2006 was 8% per annum. This would have fuelled alarm in the central bank over and above the normal counter-inflation response in the Taylor Rule. Accordingly we see that the main drivers of the inflation fluctuations are the price mark-up and the Taylor Rule shocks.

Thus when we turn to interest rates (Figure 8), we see that they do decline after Lehman but not as fast as one might expect. They remain surprisingly flat until the middle of 2009 when finally they plunge, assisted by the collapse of the price mark-up with falling commodity prices. Interest rates are affected by most of the shocks to some degree.

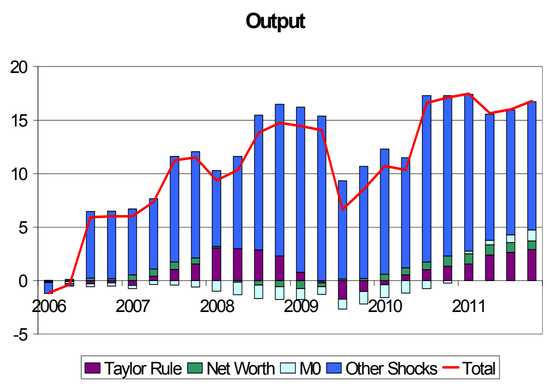


Figure 6: Shock decomposition for output for the period 2006-2011

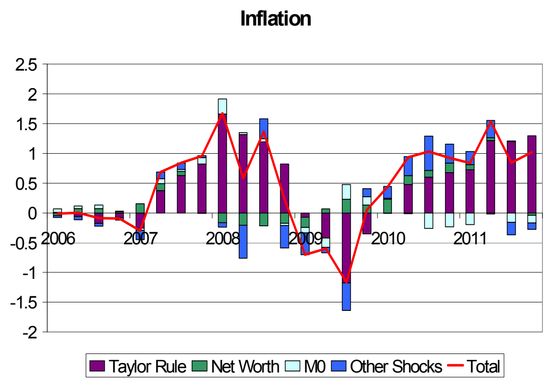


Figure 7: Shock decomposition for inflation for the period 2006-2011

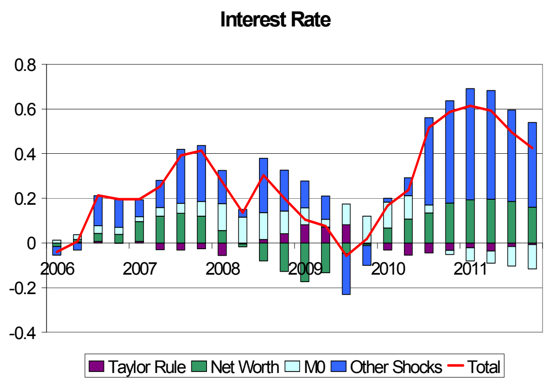


Figure 8: Shock decomposition for interest rate for the period 2006-2011

The overall interpretation coming from this analysis is of a crisis in China triggered by a large exogenous demand shock, mainly external, and by large shocks to inflation from world commodity prices; these in turn probably triggered the sharp monetary policy shocks which also contributed. Financial shocks seem to have played a modest part in the swings at the heart of the crisis period, though they did contribute to general variation over the whole period. Notice that this is not a crisis 'created by the (Chinese) financial system'[19].

[19]Chinese banks had only a limited exposure to the sub-prime market. The Bank of China, ICBC and China Construction Bank together held RMB11.9bn in sub-price mortgage backed securities and CDOs.

5.6 What is and what causes a (financial) crisis in China?

If we take a longer perspective than just this crisis, we can ask: what is the nature of a crisis in China and what causes it, according to our analysis of this sample? Let us define a 'crisis' as a severe interruption in output growth, a large part of which is permanent; and a financial crisis as a crisis in which there is also a financial collapse of some sort. What does this model have to say in general about the causes of these? We examine this question by inspecting the bootstrap experience (potential scenarios over the period) from the model and its normal shocks; for this we use the shocks from the period 1991–2007 so that we do not reuse the shocks from this crisis period itself. Again, this analysis is done on unfiltered data. Plainly we know that these shocks generate crisis; and we want to discover whether this experience is unique. We also look at the full period including the crisis, 1991–2011; as it turns out the two periods are not that different, because China's crisis was not particularly severe.

We find the following regularities:

a) Crisis is a normal part of Chinese capitalism: this economy will generate crises regularly from 'standard' shock sequences. In Figures 9 and 10 we illustrate this from some of the bootstrap simulations/scenarios produced from the shocks of the 1991–2007 period (i.e. sans crisis). In around one third of them there were quite serious interruptions of activity, which satisfy the definition of crisis. If we define a crisis as an interruption of GDP growth such that output falls and does not recover to its past peak for at least 3 years (which for a China accustomed to regular 7% plus growth is a severe interruption), then we find that a crisis on average will occur about every 47 years; this figure does not change materially when the period is extended to include the crisis period, i.e. 1991–2011. This reflects the fact that shocks during the crisis period were not as large as for some earlier periods.

Clearly these figures are affected by the nature of the sample shocks; here we have used the experience of the last two decades, which apart from the crisis itself was the period of the Great Moderation in the world economy. As we know that the variance of shocks in this period was markedly lower than in earlier post-war history, extending our sample backwards in time would no doubt change our estimates in detail.

b) When there is a crisis, about 41% of the time there is also a financial crisis; we measure this here by the appearance of an abnormal premium rise accompanying a crisis fall in output. This is shown for the same scenarios by showing the corresponding external premium behaviour.

c) A financial shock is not sufficient to produce a crisis. To check this point we redid these scenarios with just the three financial shocks including the crisis period values; thus this shock series includes both normal and extreme financial shocks. If financial crisis can be the result of extreme financial shocks, we should obtain a few at least. However what we find is that even though our financial shock series is effectively non-stationary it does not cause a crisis; we obtained none by our measure above.

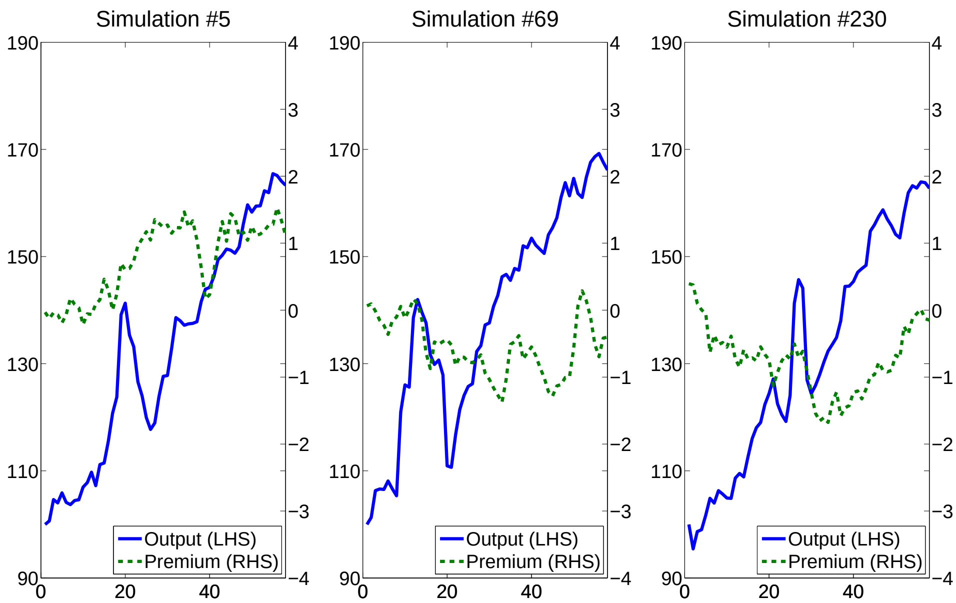


Figure 9: Crises Not Accompanied by Financial Crisis

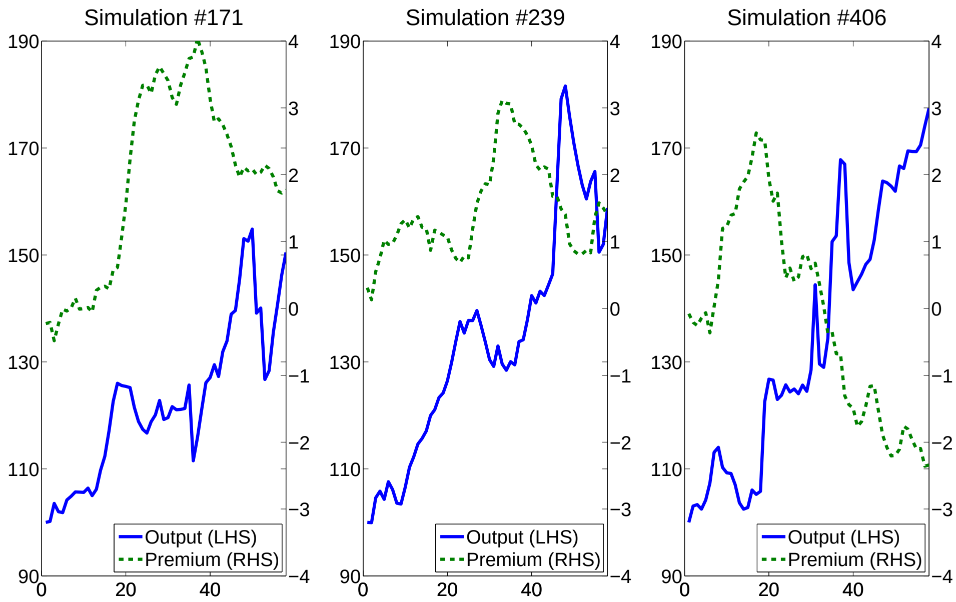


Figure 10: Crises Accompanied by Financial Crisis

6 Policy Reforms

During the crisis the Chinese government used both a direct fiscal response in the form of higher government spending and a credit-direction response in which banks were directed to lend for investment. While the fiscal response was effective and when we simulated it in repeated samples caused a dampening of output fluctuations, the credit/investment response caused dangerous instability in the form of rising excess capacity — this was the major finding of LMMMX (2014). We now look, using our model with both money and credit, at whether the Chinese authorities could have made more effective use of monetary policy to dampen the crisis.

The model endows the authorities with two instruments, apart from regulation which we leave on one side as a last resort, given the distortionary impacts that it has. These instruments are M0 (Quantitative Easing, Open Market Operations) and interest-rate setting via a Taylor Rule. We assume in this model that the instruments can be independently chosen. Open market operations supply M0 in exchange for government onds of all types, so setting the credit premium by affecting the supply of collateral. Interest rates are set by selling or buying short government bonds for long.

As we have seen the Chinese economy according to our model is capable of generating frequent crises in the absence of policy feedback — about one every half-century on average. From the point of view of maintaining consensus behind the government's policies for growth and market liberalisation the avoidance of crisis is of key importance, as clearly revealed in the Chinese government's strong response to the financial crisis. Thus an average frequency of crisis of this order, implying a good chance of more frequent occurrence, is plainly unacceptable to Chinese policymakers.

6.1 Changes in the monetary regime

The Great Recession showed that an economy with inflation targeting alone struggled to cope with big shocks to the economy and might even contribute to instability (Beckworth, 2014) because monetary policy was too tight (and may have been too loose in the boom that led up to it). In this section, we discuss some possible changes to the monetary regime that could improve economic stability, compared with the baseline regime (embedded in the model) of inflation targeting, minimal regulation and an accommodative M0 response to the money supply. Our focus with these alternative regimes is their capacity to reduce the number of crises.

6.1.1 Monetary reform

One of the features of the run-up to the Great Recession was a substantial expansion of money and credit, permitted by the inflation targeting regime. This came about because inflation did not respond much to this expansion, anchored as it was by expectations that the inflation target would be effective. Yet since monetary expansion has a stimulative effect on the economy, supplementing the interest rate rule with a money supply rule could be helpful to stability. We now investigate how a monetary reform regime of this type might work. Here we supplement the Taylor Rule with a powerful M0 rule responding strongly to the output gap.

The optimal monetary reform takes the following form

$$\Delta m_t = 100\left(y_{t-1} - y^*_{t-1}\right) \tag{10}$$

To measure its effect in stabilising the economy we perform a large number of bootstrap simulations over the sample period and compute the average frequency of crisis as defined above, namely a drop in output where output does not recover to its previous peak for 3 years. This M0 rule brings down the frequency of crisis per 1000 years from 16.9 (a crisis on average every 48 years) in the baseline case to 2.2 (one on average every 450 years) (see Table 5).[20]

	Base case	Monetary Reform	PLT	NGDPT
Frequency of crisis (crises per 1000 years)	16.9	2.2	1.2	3.0

Table 5: Frequency of crisis and stability under different monetary regimes

6.1.2 Price-level targeting regime

The zero lower bound situation in most developed economies and the recession associated with it has renewed interest in price level targeting (PLT) as a better alternative monetary policy that can achieve price stability while also reducing the impact of the zero lower bound (Wolman, 2005; Vestin, 2006; Nakov, 2008; and Dib et al, 2008; for a recent survey see Hatcher and Minford, 2013). Under PLT, inflation expectations adjust to stabilise the economy: if an unanticipated shock pushes the price level below the target, people will expect higher than average inflation in the future to bring the price level back to the target.

[20]The coefficient in the M0 rule is 100, which may seem high. Nevertheless it needs to be seen in the context of the experience of Quantitative Easing in the recent crisis, such as in the US and the UK, where the monetary base was expanded by large multiples (around 8-fold in the case of the UK) in order to stimulate financial recovery.

PLT has two advantages over inflation targeting. First, due to the automatic adjustment in inflation expectations, the central bank does not need to move interest rates aggressively in response to shocks (Cover and Pecorino, 2005), thus it reduces the likelihood of hitting the zero bound. Second, PLT can generate positive inflation expectations in a deflationary situation, lowering real interest rates even at the zero bound and so stengthen recovery. While China has not experienced a zero bound, similar mechanisms work outside the zero bound: when the economy grows strongly pushing up the price level, inflation expectations fall sharply, so powerfully raising real interest rates; and when the econoy is weak, pushing prices down, inflation expectations rise sharply, lowering real interest rates and promoting recovery.

The PLT rule is specified as follows:

$$r_t = \rho_1 r_{t-1} + (1-\rho_1)\left\{\rho_\pi\left(p_t - \overline{p}\right) + \rho_y(y_t - y^*)\right\} + \rho_{\Delta y}\left[(y_t - y^*) - (y_{t-1} - y^*)\right] + er_t \quad (11)$$

Under the zero inflation steady state, the steady state price level is assumed constant here and normalised as $\overline{p} = 0$.

We are looking for an optimal PLT specification that provides the least frequency of crisis under our bootstrap simulations. The following PLT

$$r_t = 0.99 r_{t-1} + (1-0.99)\left\{1.027 p_t + 0.963(y_t - y^*)\right\} + 0.857\left(y_t - y_{t-1}\right) + er_t \quad (12)$$

reduces crisis frequency per 1000 years to 1.2 from the baseline 16.9 (Table 5).

6.1.3 Nominal GDP targeting

A group known as Market Monetarists who run a widely-accessed blog on monetary policy, have been calling for monetary policy to target the level of nominal GDP (NGDP), rather than either a monetary aggregate or inflation (Sumner 2011, Nunes and Cole 2013). A similar proposal was made some time ago in a series of papers by McCallum (1988) and McCallum and Nelson (1999) who suggested a rule setting interest rates in response to deviations of nominal GDP growth from a target rate. McCallum argued that this rule would be superior to monetary targeting because of the large and unpredictable changes in payments technology and financial regulations. Compared with the later Taylor Rule McCallum's rule has interest rates responding as strongly to output growth deviations as to inflation deviations. However, Market Monetarists argue for targeting the level of NGDP rather than its growth rate; the reasons are similar to those for PLT, except that in this case a expected future interest rate stimulus is triggered also by output falling below its trend (McCallum, 2011). A concern about this is that with a stochastic productivity trend monetary policy would be affected by permanent shifts in productivity; thus the NGDP rule we use here allows for changes in the model's productivity trend — since this is hard for the central bank to estimate, the results for the NGDP rule shown here are 'best case'. Nevertheless, if this best case can be assumed, the NGDP rule generates expectations of very strong monetary responses in conditions of prolonged recession — analogous to Roosevelt's 1930s abandonment of the Gold Standard (Carney, 2012 and Woodford, 2012).

Implementing the NGDP target, the central bank would specify an intermediate target for the official interest rate. The rule might be written as follows:

$$r_t = \rho_1 r_{t-1} + \rho_y (y_t + p_t - \overline{y_t} - \overline{p}) + er_t \tag{13}$$

where $\overline{y} + \overline{p}$ is the target for NGDP, where $\overline{p} = 0$ and $\overline{y_t}$ follows the trend path in real output generated by productivity.

Given this general rule, we bootstrap our model and implied shocks to see whether implementing the NGDP targeting regime could help to stabilise the economy. We found that the rule in of form of

$$r_t = 0.309 r_{t-1} + 0.990(p_t + y_t - \overline{y_t}) + er_t \tag{14}$$

also dramatically reduces the frequency of crisis from the baselibne 16.9 per 1000 years to 3 (Table 5).

We give two examples below in Figures 11 and 12 of simulated samples over the period in which there were substantial crisis in the baseline; the figures show how the three rules would have smoothed out real GDP. It can be seen clearly how powerful the rules are even in these two volatile episodes.

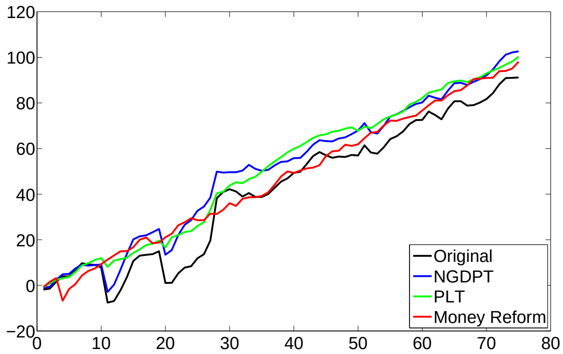


Figure 11: Simulated output under different rules (example 1)

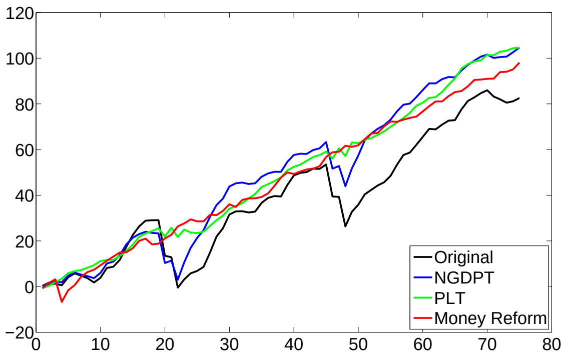


Figure 12: Simulated output under different rules (example 2)

What we see from implementing these reforms either to the Taylor Rule or to the M0 reaction function is that they are capable of reducing the frequency of crises to negligible levels. Our illustrative bootstrap samples reveal that they smooth output fluctuations markedly, both moderating the boom and counteracting the slump. By doing so they also effectively eliminate financial crises also, since as we have seen these have their entire origin in macroeconomic fluctuations due to real shocks. There is therefore no need for the authorities to use heavy-handed and distortionary regulative controls on banks to avoid financial crisis. Of course financial shocks will occur but as we have seen these alone are incapable of producing financial crisis; we can regard these as requiring simply and on occasion the normal central bank response of lender of last resort.

7 Conclusions

This paper presents the results of an investigation into the behaviour of the Chinese economy over the period of the recent crisis with the aid of the well-known Smets-Wouters DSGE model, as modified by Le et al. (2011) to allow for greater heterogeneity in price/wage behaviour and including the banking/financial accelerator model of Bernanke et al. (1999). Furthermore, we have modified the BGG model to allow for the role of money, replacing net worth as collateral with the firm's holding of cash (M0) and the cash-conversion. A value of its capital stock. This allows the model to generate monetary behaviour.

The method of indirect inference was used to estimate the model which was then used to carry out an accounting exercise in the shocks causing the crisis episode. The estimation was done on unfiltered data, allowing for non-stationary shocks. The model was not rejected by the data and a variance decomposition was conducted to establish what a typical crisis generated by these shocks if redrawn randomly would be caused by. The decomposition focussed specifically on the crisis period. A variety of simulations bootstrapped from different sets of the shocks in the sample (over the last three decades, on the grounds that this is of most relevance today) was conducted to shed light on the causes of crisis and the banking crisis in particular. The conclusion of the exercise is perhaps not very surprising: the crisis in China was not a crisis in the conventional sense, in that it was a growth slowdown rather than a precipitous drop in output as in the rest of the world. The cause was mainly the result of external shocks from world trade and commodity prices, which in turn triggered responses from the Chinese authorities in the form of monetary policy shocks and shocks to investment (via targeted loans from state banks). Banking shocks as identified by the model played only a minor role in the main crisis period of 2008–9 though they added to fluctuations over the whole period to date. Thus the crisis in China was not a crisis of Chinese banking, as is well known.

The model also tells us that crises are regular occurrences in capitalist economies, such as China now is moving towards, and that they frequently will have as their by-product financial crisis in the sense that the premium rises sharply. These crises will occur in spite of there being no extreme financial shocks such as occurred in the recent episode; so serious financial shocks are not required for crises to happen. Furthermore, extreme financial shocks on their own of the type identified in this sample do not cause crises; all they do is cause temporary recessions. Thus both crises and financial crises result from non-financial shocks; naturally financial shocks if extreme enough will add an extra layer of recession.

We built on the results of an earlier paper where we found that the Chinese government's response to the crisis in the form of mandated credit provision across the economy risked generating severe excess capacity and consequent instability. In this paper we looked at alternative monetary responses to those in the prevailing regime. We found that a strong M0 reponse to the output gap, or an interest rate rule with either a price level target or a nominal GDP target would have greatly stabilised the Chinese economy, reducing crises to a minimum.

The policy conclusion of this paper is that regulative responses to the instability of the economy, money and credit are mis-placed because they cause market distortions and are also unnecessary, since monetary policy can do the job, if properly calibrated. This echoes the policy conclusion of Le et al. (2014) for the US. In this respect, as in many others, the behaviour of the Chinese economy does not appear to be qualitatively different from that of the US economy.

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8 Appendix 1: Model Listing

Consumption Euler equation

$$c_t = \frac{\frac{\lambda}{\gamma}}{1+\frac{\lambda}{\gamma}} c_{t-1} + \frac{1}{1+\frac{\lambda}{\gamma}} E_t c_{t+1} + \frac{(\sigma_c - 1)\frac{W_* L_*}{C_*}}{\left(1+\frac{\lambda}{\gamma}\right)\sigma_c}(l_t - E_t l_{t+1}) - \left(\frac{1-\frac{\lambda}{\gamma}}{\left(1+\frac{\lambda}{\gamma}\right)\sigma_c}\right)(r_t - E_t p_{t+1}) + eb_t \tag{15}$$

Investment Euler equation

$$inn_t = \frac{1}{1+\beta\gamma^{(1-\sigma_c)}} inn_{t-1} + \frac{\beta\gamma^{(1-\sigma_c)}}{1+\beta\gamma^{(1-\sigma_c)}} E_t inn_{t+1} + \frac{1}{\left(1+\beta\gamma^{(1-\sigma_c)}\right)\gamma^2\varphi} qq_t + einn_t \tag{16}$$

Tobin Q equation

$$qq_t = \frac{1-\delta}{1-\delta+R_*^K} E_t qq_{t+1} + \frac{R_*^K}{1-\delta+R_*^K} E_t rk_{t+1} - E_t cy_{t+1} \tag{17}$$

Capital Accumulation equation

$$k_t = \left(\frac{1-\delta}{\gamma}\right) k_{t-1} + \left(1-\frac{1-\delta}{\gamma}\right) inn_t + \left(1-\frac{1-\delta}{\gamma}\right)\left(1+\beta\gamma^{(1-\sigma_c)}\right)\left(\gamma^2\right)(\varphi)(einn_t) \tag{18}$$

Price Setting equation

$$\begin{aligned} rk_t \;=\; & \omega^r \left[\frac{1}{\alpha\left(\frac{1}{1+\beta\gamma^{(1-\sigma_c)}\iota_P}\right)\left(\frac{\left(1-\beta\gamma^{(1-\sigma_c)}\xi_p\right)(1-\xi_p)}{\xi_p((\phi_p-1)\epsilon_p+1)}\right)} \left\{ \begin{array}{c} p_t - \frac{\beta\gamma^{(1-\sigma_c)}\iota_P}{1+\beta\gamma^{(1-\sigma_c)}\iota_P} E_t p_{t+1} - \frac{\iota_P}{1+\beta\gamma^{(1-\sigma_c)}\iota_P} p_{t-1} + \left(\frac{1}{1+\beta\gamma^{(1-\sigma_c)}\iota_P}\right) \\ \left(\frac{\left(1-\beta\gamma^{(1-\sigma_c)}\xi_p\right)\left(1-\xi_p\right)}{\xi_p\left(\left(\phi_p-1\right)\epsilon_p+1\right)}\right)((1-\alpha)w_t - ea_t) - ep_t \end{array} \right\} \right] \\ & + (1-\omega^r)\left[\frac{ea_t}{\alpha} - \frac{1-\alpha}{\alpha} w_t\right] \end{aligned} \tag{19}$$

Wage Setting equation

$$w_t = \omega^w \left[\begin{array}{c} \frac{\beta\gamma^{(1-\sigma_c)}}{1+\beta\gamma^{(1-\sigma_c)}} E_t w_{t+1} + \frac{1}{1+\beta\gamma^{(1-\sigma_c)}} w_{t-1} + \frac{\beta\gamma^{(1-\sigma_c)}}{1+\beta\gamma^{(1-\sigma_c)}} E_t p_{t+1} - \frac{1+\beta\gamma^{(1-\sigma_c)}\iota_w}{1+\beta\gamma^{(1-\sigma_c)}} p_t \\ + \frac{\iota_w}{1+\beta\gamma^{(1-\sigma_c)}} p_{t-1} - \frac{1}{1+\beta\gamma^{(1-\sigma_c)}} \left(\frac{\left(1-\beta\gamma^{(1-\sigma_c)}\xi_w\right)(1-\xi_w)}{(1+\epsilon_w(\phi_w-1))\xi_w} \right) \\ \left(w_t - \sigma_l l_t - \left(\frac{1}{1-\frac{\lambda}{\gamma}}\right)\left(c_t - \frac{\lambda}{\gamma} c_{t-1}\right)\right) + ew_t \end{array} \right] +$$

$$(1-\omega^w)\left[\sigma_l l_t + \left(\frac{1}{1-\frac{\lambda}{\gamma}}\right)\left(c_t - \frac{\lambda}{\gamma} c_{t-1}\right) - (\pi_t - E_{t-1}\pi_t) + ew_t^S \right] \tag{20}$$

Labour demand

$$l_t = -w_t + \left(1 + \frac{1-\psi}{\psi}\right) rk_t + k_{t-1} \tag{21}$$

Market Clearing condition in goods market

$$y_t = \frac{C}{Y} c_t + \frac{I}{Y} inn_t + R_*^K k_y \frac{1-\psi}{\psi} rk_t + c_y^e c_t^e + eg_t \tag{22}$$

Aggregate Production equation

$$y_t = \phi \left[\alpha \frac{1-\psi}{\psi} rk_t + \alpha k_{t-1} + (1-\alpha)\, l_t + ea_t\right] \tag{23}$$

Taylor Rule

$$r_t = \rho r_{t-1} + (1-\rho)\left(r_p p_t + r_y y_t\right) + r_{\Delta y}\left(y_t - y_{t-1}\right) + er_t \tag{24}$$

Premium

$$E_t cy_{t+1} - (r_t - E_t p_{t+1}) = \chi\left(qq_t + k_t - n_t\right) + \phi_1 m_t + epr_t \tag{25}$$

Net worth

$$n_t = \frac{K}{N}\left(cy_t - E_{t-1}cy_t\right) + E_{t-1}cy_t + \theta n_{t-1} + enw_t \tag{26}$$

Entrepreneurial consumption

$$c_t^e = n_t \tag{27}$$

M0

$$m_t = m_{t-1} + \phi\left(M_t - M_{t-1}\right) + em_t \tag{28}$$

M2

$$M_t = (1 + \nu - \mu)k_t + \mu m_t - \nu n_t \tag{29}$$

8.1 Augmenting the BGG model for collateral and money

The assumptions added to BGG are that the banks demand collateral as a proportion of net worth of c; and that liquidating this collateral costs δ per unit of collateral. The BGG model consists of three parts:

a) a bankruptcy threshold at which firms will choose to default

b) banks' zero profit condition (free entry drives profits to zero) — this condition gives us the banks' leverage offer curve.

c) firms' maximisation of utility subject to a) and b); this gives us the overall contract.

a) the bankruptcy threshold ($\overline{\omega}$; ω is the return obtained per unit of assets, distributed as a random variable with a mean of unity): this is such that the firm is indifferent between defaulting and staying in business. If it goes bankrupt, it loses $(1 + R^K)\overline{\omega}A + cN$ and it gains ZB. Here Z=1+credit rate and B= bank borrowing; A is total investment, R^K = the firms' return on investment, and N= net worth of the firm. Thus at the threshold $ZB = (1 + R^K)\overline{\omega}A + cN$. Note also that the firms' balance sheet is $B = A - N + cN$; thus when this condition holds:$(1 + R^K)\overline{\omega}A + cN = Z(A - N + cN)$. Let $L = A/N$= Leverage. Divide the condition by N and obtain: $Z = \frac{(1+R^K)\overline{\omega}L+c}{L-1+c}$

b) banks' zero profit condition is given by

$[1-F(\overline{\omega})]ZB+(1-\mu)G(\overline{\omega})(1+R^K)A+cNF(\overline{\omega})(1-\delta)=(1+R)B$

On the left hand side the first term is the probability of obtaining the loan proceeds (ZB), where $F(\overline{\omega})$ is the probability of going bankrupt. In the second term $G(\overline{\omega})$ is the expected value of the returns per unit asset to be made if the firm goes bankrupt times the probability of bankruptcy; this is reduced by the cost of collection, μ. Finally, there is the recovery of collateral in the event of bankruptcy minus its liquidation cost δ. On the right hand side is the cost of the funds the bank has received from depositors at the riskless rate, R.

Substitute from the bankruptcy threshold $ZB=(1+R^K)\overline{\omega}A+cN$ in the first term of the LHS and on the RHS for B from firms' balance sheet $B=A-N+cN$.This gives:

$[1-F(\overline{\omega})](1+R^K)\overline{\omega}A+(1-\mu)G(\overline{\omega})(1+R^K)A+cN(1-\delta F(\overline{\omega}))=(1+R)(A-N+cN)$

Let $\Gamma(\overline{\omega})=[1-F(\overline{\omega})]\overline{\omega}+G(\overline{\omega})$. Divide by N to obtain:

$[\Gamma(\overline{\omega})-\mu G(\overline{\omega})](1+R^K)L=(1+R)(L-1)+c(1+R-1+\delta F(\overline{\omega}))$ so that we obtain:

$L=\frac{1+R-c[R+\delta F(\overline{\omega})]}{1+R-\Psi(\overline{\omega})(1+R^K)}$ where $\Psi(\overline{\omega})=\Gamma(\overline{\omega})-\mu G(\overline{\omega})$

This is the banks' leverage offer curve. It can be readily verified that it slopes upward and is convex in $[1-\Gamma(\overline{\omega})]$ space- as shown in the diagram below.

Note that $dL/d\overline{\omega}>0, dL/dR^K>0, dl/d\delta<0$

c) To obtain the overall contract firms' utility (returns), relative to their cost of funds, are maximised. These are given by:

$\int_{\overline{\omega}}^{\infty}\frac{\{(1+R^K)\omega A+cN-ZB\}dF(\omega)}{N(1+R)}$; now also note that from the bankruptcy threshold $ZB=(1+R^K)\overline{\omega}A+cN$. So it can be seen that the firms' returns are unaffected by the existence of collateral, essentially because it remains as part of their gross return if they do not go bankrupt but also, for given total assets A, the borrowing costs at which they will choose to go bankrupt rise by the amount of this collateral.

Substituting into the returns from the bankruptcy threshold gives the overall returns as:

$\int_{\overline{\omega}}^{\infty}\frac{\{(1+R^K)(\omega-\overline{\omega})A\}dF(\omega)}{N(1+R)}=\frac{(1+R^K)}{(1+R)}L[1-\Gamma(\overline{\omega})]$ where the first two terms give the total expected return to the firm from its invested capital (A) as a proportion of its funds, N(1+R) and the last term $[1-\Gamma(\overline{\omega})]$ is the share of this that goes to the firm (the bank takes the loan costs if the firm survives and the returns below $\overline{\omega}$ if it does not).

This utility function gives indifference curves in $(\overline{\omega}, L)$ space, that are concave. An interior optimum is reached.

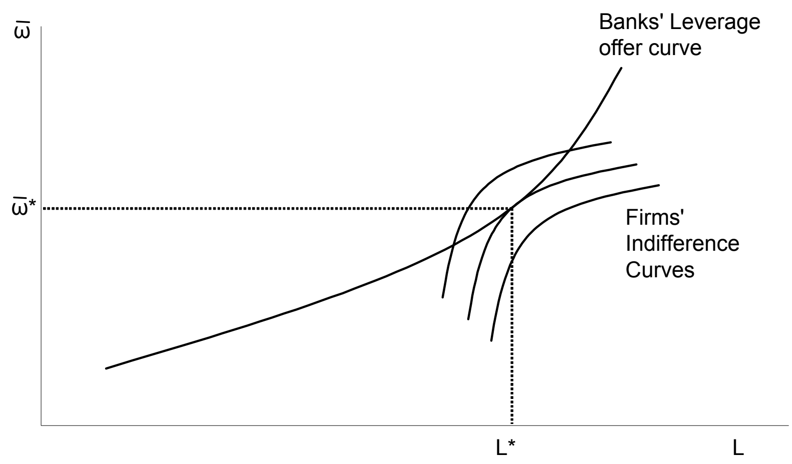

Figure 13: The optimum contract for $(\bar{\omega}^{*}, L^{*})$ for given R^{k}, R, δ

We can compute this optimum by maximising $\frac{(1+R^K)}{(1+R)}L[1-\Gamma(\overline{\omega})]$ wrt $(\overline{\omega}, L)$ subject to the leverage offer curve from the banks $L = \frac{1+R-c[R+\delta F(\overline{\omega})]}{1+R-\Psi(\overline{\omega})(1+R^K)}$(from b above). Solving for the implicit function this gives in $\overline{\omega}$ gives us finally the firm's optimum choice of $\overline{\omega}$ as the solution of:

$$\{1+R-c[R+\delta F(\overline{\omega})]\}\{1+R-\Phi'(1+R^K)\} = \{\frac{-c\delta F'(\overline{\omega})[1-\Gamma(\overline{\omega})]}{\Gamma'(\overline{\omega})}\}\{1+R-\Psi(\overline{\omega})(1+R^K)\}$$

where $\Phi' = \frac{\Psi'(\overline{\omega})}{\Gamma'(\overline{\omega})} + (1-\frac{\Psi'(\overline{\omega})}{\Gamma'(\overline{\omega})})\Psi(\overline{\omega}) \approx 1$

In addition we have the leverage offer curve defining L in terms of $\overline{\omega}$ and so giving us the total $(\overline{\omega}, L)$ solution.

We can now create two equations in $(\overline{\omega}, L)$ from the firm's optimum and the banks' leverage offer. We can rewrite the firm's optimum choice using the banks' leverage offer as:

1) $L\{1+R-\Phi'(1+R^K)\} = \{\frac{-c\delta F'(\overline{\omega})[1-\Gamma(\overline{\omega})]}{\Gamma'(\overline{\omega})}\}$

and then we can add the banks' leverage offer:

2) $L = \frac{1+R-c[R+\delta F(\overline{\omega})]}{1+R-\Psi(\overline{\omega})(1+R^K)}$

We now investigate the comparative static properties of changes around the equilibrium by taking the total differential of this two-equation system in $dL, d\overline{\omega}, d\delta$ and dR^K. We will evaluate the derivatives at an equilibrium where $\delta = 0$; we do this for convenience because we will be dealing with a heavily monetised collateral set-up where it is close to zero. Note that in the rest of the DSGE model $\ln L_t{=}k_t - n_t$ is determined while δ is determined by the provision of M0 as an alternative to illiquid collateral. Thus we can regard these as exogenous to this banking model subsector which then solves for $\overline{\omega}$ and R^K (the return on capital required to make the needed leverage possible). These two elements are internal to the bank contract decision and unobservable in the public domain but in turn from these we can solve for the observable cost of the bank credit, Z, from the bankruptcy threshold as $Z = \frac{((1+R^K)\overline{\omega}L+c}{L-1+c}$.

We write the total differential as:

1) $\{1+R-\Phi'(1+R^K)\}dL + L(-\Phi')dR^K = (derivative = 0)d\overline{\omega} + \{\frac{-cF'(\overline{\omega})[1-\Gamma(\overline{\omega})]}{\Gamma'(\overline{\omega})}\}d\delta$

and

2) $dL = L\{\frac{\Psi^{'}(\overline{\omega})(1+R^K)}{1+R-\Psi(\overline{\omega})(1+R^K)}\}d\overline{\omega} + L\{\frac{\Psi(\overline{\omega})}{1+R-\Psi(\overline{\omega})(1+R^K)}\}dR^K + \{\frac{-cF(\overline{\omega})]}{1+R-\Psi(\overline{\omega})(1+R^K)}\}d\delta$

Our interest lies in the effect of δ on the equilibrium value s of R^K and $\overline{\omega}$, and thus on Z. We begin by noting from 1) that

$\frac{dR^K}{d\delta} = \{\frac{cF^{'}(\overline{\omega})[1-\Gamma(\overline{\omega})]}{L\Phi^{'}\Gamma^{'}(\overline{\omega})}\} = \{\frac{cF^{'}(\overline{\omega})[1-\Gamma(\overline{\omega})]}{L\Phi^{'}[1-F(\overline{\omega})]}\} \succ 0$

and from 2) that:

$\frac{d\overline{\omega}}{d\delta} = \frac{d\overline{\omega}}{dR^K}.\frac{dR^K}{d\delta} + \frac{d\overline{\omega}}{d\delta} = \{\frac{-\Psi(\overline{\omega})}{\Psi^{'}(\overline{\omega})(1+R^K)}\}\{\frac{cF^{'}(\overline{\omega})[1-\Gamma(\overline{\omega})]}{L\Phi^{'}\Gamma^{'}(\overline{\omega})}\} + \frac{cF(\overline{\omega})}{L\Psi^{'}(\overline{\omega})(1+R^K)} = \frac{cF(\overline{\omega})}{L\Psi^{'}(\overline{\omega})(1+R^K)}\{1 - \frac{F^{'}(\overline{\omega})}{F(\overline{\omega})}\frac{\Psi(\overline{\omega})[1-\Gamma(\overline{\omega})]}{\Phi^{'}\Gamma^{'}(\overline{\omega})}\}$

$= \frac{cF(\overline{\omega})}{L\Psi^{'}(\overline{\omega})(1+R^K)}\{1 - \frac{F^{'}(\overline{\omega})}{F(\overline{\omega})}\frac{\Psi(\overline{\omega})[1-\Gamma(\overline{\omega})]}{\Phi^{'}[1-F(\overline{\omega})]}\}$ since we note that $\Gamma^{'}(\overline{\omega}) = [1 - F(\overline{\omega})]$.

The sign of the last total derivative is strictly ambiguous and needs to be computed numerically. Consider a bankruptcy rate around 2.3% and a standard normal distribution of $ln\omega$ (i.e. with a standard deviation of unity, so that the bankruptcy threshold will be exactly two standard deviations below the mean). $\overline{\omega}$ will then take the value of 0.135 (=e^{-2}); $F(\overline{\omega}) = 0.023$; $\frac{F^{'}(\overline{\omega})}{F(\overline{\omega})} = 2.3$; $\Psi(\overline{\omega}) \simeq \Gamma(\overline{\omega}) = [1 - F(\overline{\omega})]\overline{\omega} = 0.13x0.977 = 0.127$ since $G(\overline{\omega}) \simeq 0$; it also follows as noted above that $\Phi^{'} = \frac{\Psi^{'}(\overline{\omega})}{\Gamma^{'}(\overline{\omega})}$thus $\{1 - \frac{F^{'}(\overline{\omega})}{F(\overline{\omega})}\frac{\Psi(\overline{\omega})[1-\Gamma(\overline{\omega})]}{\Phi^{'}[1-F(\overline{\omega})]}\} = 0.73$ and so is clearly positive for any values around that size of bankruptcy rate and standard deviation. The reason essentially is that the banks' share of returns,$\Gamma(\overline{\omega})$, is under the assumed competitive nature of banks quite modest; and so a rise in the rate of return has only a modest effect on profits while a rise in the bankruptcy threshold has a much larger effect. Hence at zero profits with given leverage the trade-off of threshold given up for extra required rate of return is small.

Finally, we find

$\frac{dZ}{d\delta} = \frac{L}{L-1+c}\{[1+R^K]\frac{d\overline{\omega}}{d\delta}+\overline{\omega}\frac{dR^K}{d\delta}\} = \frac{c}{L-1+c}\left\{\frac{F(\overline{\omega})}{\Psi^{'}(\overline{\omega})}\{1 - \frac{F^{'}(\overline{\omega})}{F(\overline{\omega})}\frac{\Psi(\overline{\omega})[1-\Gamma(\overline{\omega})]}{\Phi^{'}[1-F(\overline{\omega})]}\} + \{\frac{\overline{\omega}F^{'}(\overline{\omega})[1-\Gamma(\overline{\omega})]}{\Phi^{'}[1-F(\overline{\omega})]}\}\right\} > 0$, on the assumption that $\frac{d\overline{\omega}}{d\delta} > 0$ as above.

Thus finally since δ is reduced by M0 injections we can conclude that a rise in M0 will reduce the required return on capital and also the credit premium.

9 Appendix 2: VAR IRFs

In this appendix we show how the model, given that it jointly predicts (within 95% bounds) the VAR coefficients that determine the IRFs of shocks on the three key macro variables, thereby also broadly predicts these IRFs. Because the Wald test is of the joint behaviour of the VAR coefficients and on the variances of the three variable residuals, there is not a perfect correspondence with the individual IRFs. However, it can be seen, as expected, that most of the IRfs lie mostly within the bounds.

It is the IRFs that policymakers are interested in, as pointed out by Christiano et al. (2005). They need to be assured that empirically the IRFs the model implies should appear in the data actually do so within statistical bounds (of course the IRFs implied for data behaviour reflect both the model structural IRFs and sample shock variations). Then they feel able to use the model's (structural) IRFs to determine the effect of shocks and of policies to offset shocks.

The VAR innovations are identified throughout by the model; we have no independent way of identifying the VAR innovations (any such ways suggested are based on some 'non-controversial' model restrictions; however, the model here is non-controversial in its current innovation structure and so we use it.) The testing kicks in on the variances of the VAR innovations and on the lagged effects of each variable (the VAR coefficients).

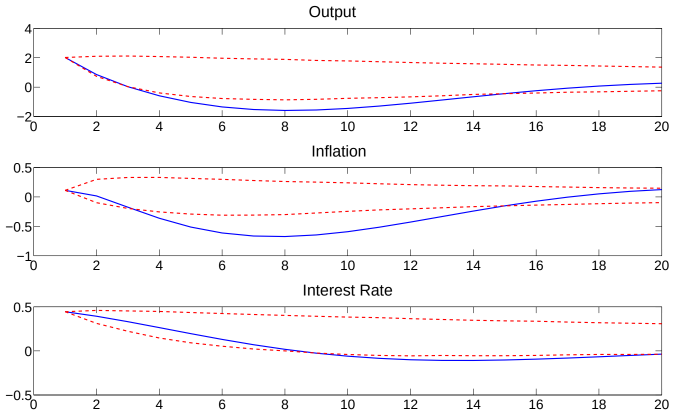

Figure 14: VAR IRFs for an exogenous demand shock

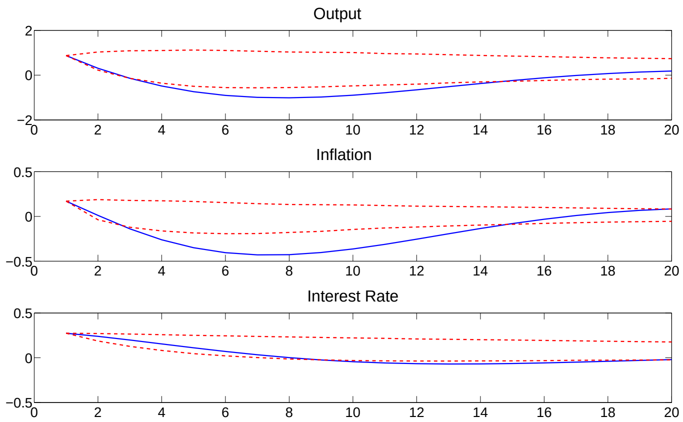

Figure 15: VAR IRFs for a consumer preference shock

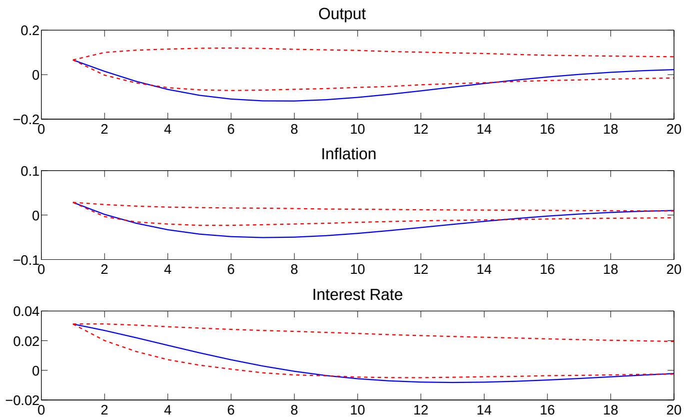

Figure 16: VAR IRFs for a investment shock

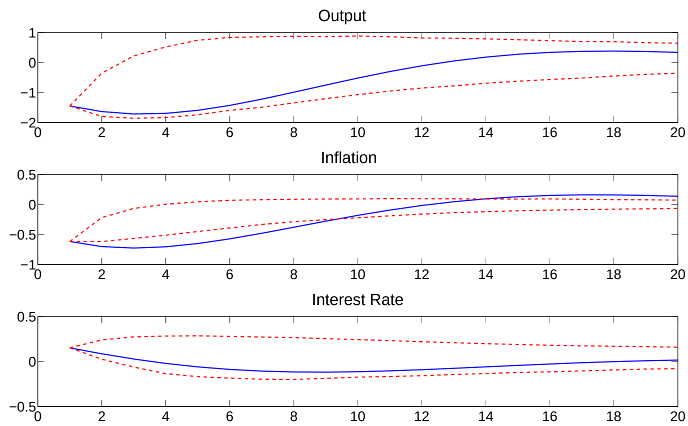

Figure 17: VAR IRFs for a monetary shock

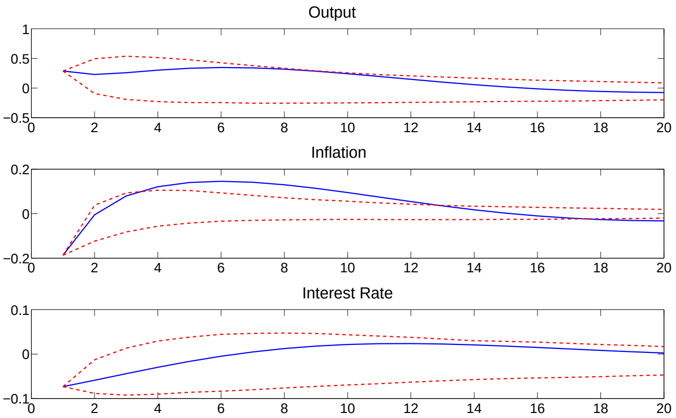

Figure 18: VAR IRFs for a productivity shock

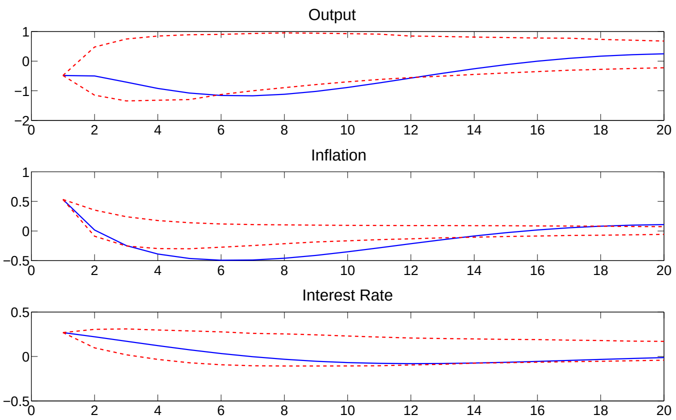

Figure 19: VAR IRFs for a price mark-up shock

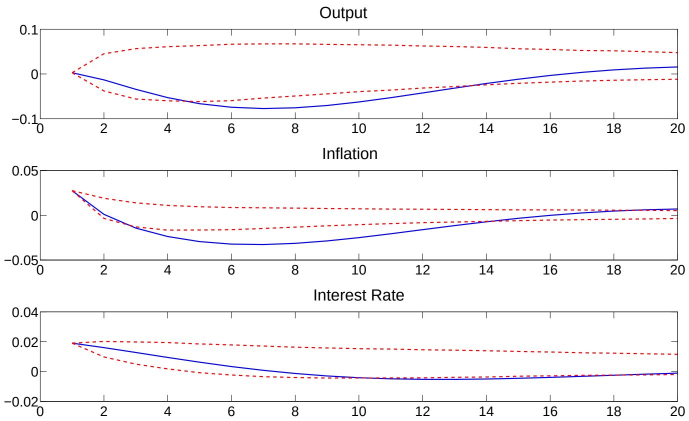

Figure 20: VAR IRFs for a wage mark-up shock

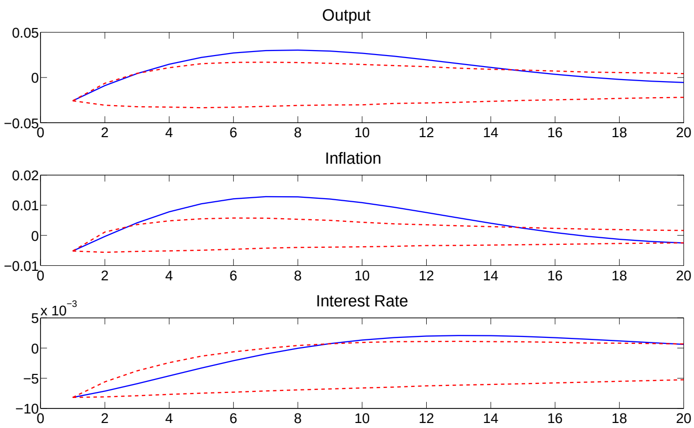

Figure 21: VAR IRFs for a labour supply shock

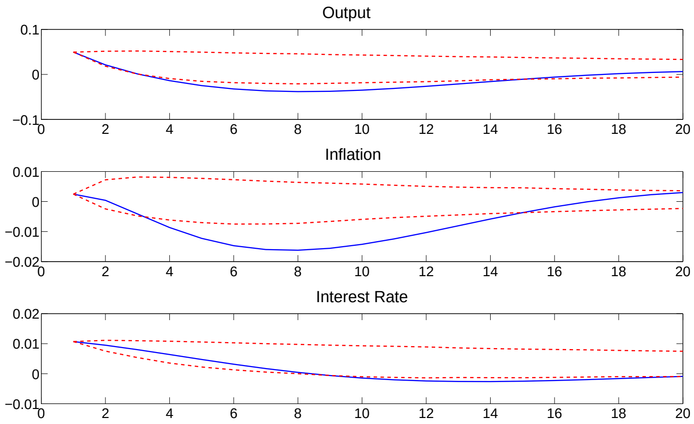

Figure 22: VAR IRFs for a premium shock

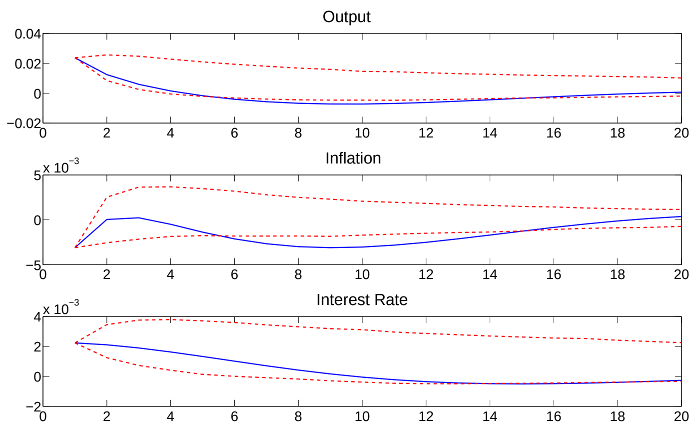

Figure 23: VAR IRFs for a networth shock

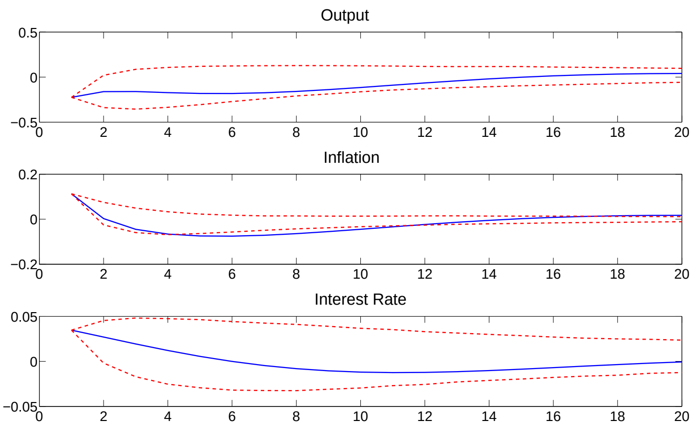

Figure 24: VAR IRFs for an M0 shock