Cardiff Economics Working Papers

Working Paper No. E2012/22

How important is the credit channel? An empirical study of the US banking crisis

Chunping Liu and Patrick Minford

August 2012, updated December 2013

Cardiff Business School
Aberconway Building
Colum Drive
Cardiff CF10 3EU
United Kingdom
t: +44 (0)29 2087 4000
f: +44 (0)29 2087 4419
business.cardiff.ac.uk

How important is the credit channel? An empirical study of the US banking crisis*

Chunping Liu Nottingham Trent University
Patrick Minford Cardiff University and CEPR

December 17, 2013

Abstract

We examine whether by adding a credit channel to the standard New Keynesian model we can account better for the behaviour of US macroeconomic data up to and including the banking crisis. We use the method of indirect inference which evaluates statistically how far a model's simulated behaviour mimics the behaviour of the data. We find that the model with credit dominates the standard model by a substantial margin. Credit shocks are the main contributor to the variation in the output gap during the crisis.

Key words: financial frictions, credit channel, bank crisis, indirect inference

JEL codes: C12, C52, E12, G01, G1

1 Introduction

The banking crisis that erupted in 2007 and triggered the Great Recession of 2009 has led many economists and policy-makers to question the standard New Keynesian model of the economy on the grounds that it can neither account for the crisis nor shed any light on banking behaviour since it has no banking sector. In its defence it can be said that it has been shown to give a good account of the US economy's business cycle behaviour in recent years, including the crisis period- Liu and Minford (2012); furthermore if shifts in the trend of potential output are added to the model, it can give a good account of the overall behaviour since the crisis, including the permanent effects of such shifts in trend - Le, Meenagh and Minford (2012). However, the absence of a banking sector remains a serious gap since clearly banking shocks contributed to the recent crisis in a material way. Accordingly, in this paper we explore how far

*We are grateful to Huw Dixon and Paul de Grauwe for helpful comments; and also to an anonymous referee for productive suggestions.

adding a banking sector, based on recent work of De Fiore and Tristani (2012), can improve the standard model's fit to the US data and also how this extended model accounts for the recent behaviour of the US economy. Our approach, which uses small aggregated DSGE models, parallels recent work on the US that uses large-scale DSGE models with an added banking sector to account for the crisis-Christiano, Motto & Rostagno (2010), Gilchrist et al. (2009), Jermann and Quadrini (2012) amd Le, Meenagh and Minford (2012).

To anticipate, we find that the model with the banking extension improves on the standard model substantially and also attributes the bulk of the output recession to banking. This result, as we have already said, applies to the business cycle part of the data- to give an overall account of the crisis one must also add in the effects of trend output shifts which we do not deal with here.

In the rest of this paper, we first set out the standard and extended models; in the third section we explain our testing procedures which are based on indirect inference, whereby a model is judged by its ability in simulation to replicate behaviour found in the data; in the fourth we set out our results for the usual calibrated versions of these models; in the fifth section we reestimate the models to get them as close as possible to the data and test these reestimated versions. In the sixth section we interpret the model results for the crisis episode and compare them with other recent work on the crisis origins. The last section concludes.

2 The Models

The standard New Keynesian model includes a standard aggregate demand equation, an aggregate supply function, and a policy rule equation, as follows:

$$\tilde{Y}_t = E_t\tilde{Y}_{t+1} - a_1(R_t - E_t\pi_{t+1}) + \varepsilon_{1t} \tag{1}$$

$$\pi_t = b_1\tilde{Y}_t + \beta E_t\pi_{t+1} + k\varepsilon_{2t} \tag{2}$$

$$R_t = (1 - c_1)(c_2\pi_t + c_3\tilde{Y}_t) + c_1 R_{t-1} + u_t \tag{3}$$

where $\tilde{Y}_t$ is the output gap, π_t is the rate of inflation, R_t is the nominal interest rate, and ε_{1t}, ε_{2t}, and u_t are respectively the demand, supply and policy errors. These errors are assumed to be autoregressive processes with the coefficients calculated from the sample estimates. Equation 1 is the aggregate demand equation, determined by the expectation of output gap in the next period and real interest rate. Equation 2 is the New Keynesian Phillips Curve. Equation 3 is the Taylor Rule (1993) but with the lagged interest rate added to allow for smoothing of interest rate reactions over time. This rational expectations model is solved by Dynare (Juillard 2001).

2.1 A Model with Credit: Adding a Banking Sector

We follow De Fiore and Tristani (2012) in their adaptation of this model to include a credit channel. They assume that firms producing homogeneous goods for the wholesale market consist of risk-neutral entrepreneurs who produce with inputs of labour and idiosyncratic productivity shocks. They have to pay workers in advance of production by raising external finance from banks. It is assumed that the financial market is imperfect, with asymmetric information and costly state verification (see Townsend, 1979; Gale and Hellwig, 1985); there is a risk of default on their debts because of their idiosyncratic shocks. Perfectly competitive banks lend to them on debt contracts that are optimal under this set-up.

The timing of the economy is as follows. At the beginning of the period, the financial market opens with the aggregate shocks. Households then make their portfolio decisions by allocating their wealth (including existing assets, bond and deposits). The banks keep these deposits, which are used to finance the production of firms. Each wholesale firm stipulates a contract with a bank in order to pay its labour costs. In the second period, the goods market opens. Wholesale firms produce homogeneous goods, which are then sold to the retail sector. If profits are adequate to repay the debt, then the firms will place the remaining revenues into the financing of entrepreneurial consumption. If the revenues are not sufficient to repay the debt, then they will default and their production is seized by the banks. Firms in the retail sector buy the homogeneous goods from wholesale entrepreneurs in a competitive market and they use them to produce differentiated goods at no cost. Retail firms have some market power due to the differentiation of their goods. However, they are not free to change their price because prices are subject to Calvo contracts. The retail goods are then purchased both by households and wholesale entrepreneurs for their own consumption.

Everything in this model is standard to the New Keynesian model apart from the banking contract. In the wholesale sector, the firms (indexed by i) are owned by entrepreneurs, who face a linear technology production function that is specified as:

$$y_{i,t} = A_t \omega_{i,t} l_{i,t} \tag{4}$$

where A_t is an aggregate productivity shock and $\omega_{i,t}$ is an idiosyncratic productivity shock with log-normal distribution function Φ and density function ϕ. This production function can be seen as an abstraction from capital accumulation which forms the basis of the credit need in the Bernanke, Gertler and Gilchrist (1999) model. In De Fiore and Tristani's model, it is assumed that each firm receives a constant endowment of internal funds τ at the beginning of each period; but these funds are insufficient to finance their desired level of production so that they must borrow from the banks. These charge an interest rate spread over the risk-free rate, reflecting the resulting default risk.

Firms pay wages by raising external finance before profiting from the sale of retail goods. The financial contract is stipulated with the banks before observing the idiosyncratic productivity shock but after observing aggregate shocks. The amount of external finance is $P_t(x_{i,t} - \tau)$, which means that the total funds at hand are $P_t x_{i,t} = P_t x_t$ since all firms are identical. Since these wholesale firms are perfectly competitive and operate under constant returns to scale, they make zero profits in equilibrium and borrow the full amount of their wage bill as dictated by aggregate demand.

The terms on which they can do this are dictated by the bank contract. The banks, also perfectly competitive, will lend at a spread that gives them an expected return equal to their cost of deposits, R_t. This must compensate for the risk of default which rises with the size of the loan (=the wage bill) and the risk-free rate. As the wage bill (i.e. the value of employment) rises, the size of possible bankruptcy rises and with it the credit spread. As the risk-free rate rises, the banks' cost of funds rises and this is passed on to firms; because this higher cost makes it harder for the firms to pay back the funds, default probabilities rise. Unlike the credit contract of Bernanke et al. (1999), which is for investment, the contract here is for working capital, ie for production itself. Bank funding is therefore a cost of production that affects inflation.

The logic of the bank contract works as follows. The firm needs enough funds to pay for its wage bill, i.e. its direct production costs, for producing the goods required for equilibrium aggregate demand. Since it has limited funds, the total funds it needs defines its required leverage. For the bank to supply this leverage it requires, for a given profit rate of the firm, a certain bankruptcy threshold, which rises with rising leverage; this threshold is given by the incentive compatibility constraint on the firm- namely that at this threshold it must be just in the interest of the firm not to default, so that the loan service it has to pay is just equal to its expected return on its assets. The combination of this leverage and the threshold define for this rate of profit what the bank must charge as a risk-spread on top of the risk-free interest rate, so that it (as a perfectly competitive bank) earns an expected return on its loans just equal to the risk-free deposit rate it pays on its deposits.

The full derivation of the optimal contract is complex- see De Fiore and Tristani (op. cit.). The key details are as follows: the threshold $\overline{\omega}$ is given by the equation for the bank's zero profit conditions as $g(\overline{\omega}, \mu)$ [the bank's expected share of firm profits net of bankruptcy monitoring costs] $= (\frac{x-\tau}{x})\frac{R}{q}$ where the threshold rises with required funds, x, the risk-free rate, R, and it falls with the profit rate the firm makes, q. The interest rate the firm will pay on its loan, z, relative to its profit rate, q, is in turn given by $\frac{z}{q} = \overline{\omega}(\frac{x}{x-\tau})$, which can be thought of as measuring the burden of funding costs on the firm. For the firm to be willing to pay these costs the burden must be lowered sufficiently by a rise in the profit rate, which lowers $\overline{\omega}$. The optimal contract is set where q is large enough to optimise the firm's expected profits after paying the funding costs- as firms have free entry under perfect competition this will in the long run (ie steady state) also be the zero net profit point where the firm's costs including funding just equal its revenues.

After successive substitutions to reduce it to a small compact form, the credit model can be written in loglinearised form as:

$$\tilde{Y}_t = E_t\tilde{Y}_{t+1} - a_1(R_t - E_t\pi_{t+1}) - a_2(\hat{\Delta}_t - E_t\hat{\Delta}_{t+1}) + a_3(R_t - E_tR_{t+1}) + \epsilon_{1t} \quad (5)$$

$$\pi_t = b_1\tilde{Y}_t + \bar{\kappa}R_t + b_2\hat{\Delta}_t + \beta E_t\pi_{t+1} - \bar{\kappa}\epsilon_{2t} \quad (6)$$

$$\hat{\Delta}_t = c_1\tilde{Y}_t - c_2R_t + c_3\epsilon_{3t} \quad (7)$$

$$R_t = (1 - d_1)(d_2\pi_t + d_3\tilde{Y}_t) + d_1R_{t-1} + u_t \quad (8)$$

where each variable is linearised around its steady state. $\hat{}$ denotes log-deviations from steady states. $\tilde{Y}_t$ is the output gap, defined as output in deviation from potential output; π_t is the rate of inflation; R_t is the nominal interest rate; Δ_t is the credit spread; ϵ_{1t}, ϵ_{2t} and ϵ_{3t} represent the demand, supply, and credit market shocks, respectively, and u_t the policy shock. It is assumed that the four errors are AR(1) processes.

Equation 5 is the new version of the IS curve; it now also depends on the credit spread and the nominal interest rate (the latter reflecting entrepreneurial profits which are correlated positively with the cost of finance). Equation 6 is the extended Phillips Curve: here the nominal interest rate and credit spread now enter as cost factors. Equation 7 is the reduced form for the credit spread. This increases with aggregate demand as this raises the funds requirement. It falls with the nominal interest rate because for a given funds requirement this makes funds more expensive; given firms' capacity to pay is set by aggregate demand conditions, the spread has to fall for them to be able to afford the same amount of credit. Equation 8 is the policy rule that is used in this model, unchanged from the standard model. The model's coefficients from Equation 5 to 7are functions of the structural coefficients as in the Table 1.

Reduced form Coefficients	**Definitions**
$a_1 = \sigma\frac{1+\sigma^{-1}\frac{e}{c}}{1-\varphi\frac{e}{c}}$	interest rate elasticity on output gap
$a_2 = \frac{\alpha_1-\alpha_2\frac{e}{c}}{1-\varphi\frac{e}{c}}$	credit spread coefficients on output gap
$a_3 = \frac{\frac{e}{c}}{1-\varphi\frac{e}{c}}$	interest surprise coefficient on output gap
$\beta = 0.99$	discount factor
$\kappa = (1-\theta)(1-\beta\beta\theta)/\theta$	coefficient of interest rate on inflation
$b_1 = \kappa(\sigma^{-1}+\varphi)$	coefficient of output gap on inflation
$b_2 = \kappa(\sigma^{-1}\alpha_1+\alpha_2)$	coefficient of credit spread on inflation
$c_1 = \frac{1+\varphi+\sigma^{-1}\frac{Y}{c}}{\delta_1}$	coefficient of output gap on spread
$c_2 = \frac{\sigma^{-1}\frac{e}{c}}{\delta_1}$	coefficient of interest rate on spread
$c_3 = \frac{1}{\delta_1}$	financial market shock parameter

Table 1: Reduced Form Coefficients

As this reveals there are 10 structural coefficients determining 12 model coefficients (excluding β which is fixed); this enables us to test the model in terms of the structural coefficients, which in turn determine the model coefficients uniquely.

The model is written here in terms of the four shocks to the IS, Phillips Curve, credit spread and interest rate rule. These are the familiar ones from such reductions of New Keynesian models to a few equations; as is well-known while the interest rate rule shock is structural, the result of central bank choice, the other three are linear combinations of the structural shocks in the underlying DSGE model and so reduced form shocks. Thus the IS shock is the 'demand effect' of these structural shocks, while the PP shock is their 'supply effect'; and in this model the credit spread shock is their effect on the credit premium. At the aggregated level of this model these shocks are the ones we observe and accordingly the ones we use to evaluate the model empirically. They are also comparable with shocks discussed in relation to other such New Keynesian aggregated models and so we continue our account of the model in terms of them at this stage. In the model here the underlying shocks are two: a technology shock and a 'loan monitoring' shock, which is a shock to banks' lending costs; once the model is tested and estimated, we can also calculate best estimates of what these underlying shocks are; and then compute the way these have affected the economy. We do this below, once we have completed the testing and estimation in terms of the observed data and errors. Thus for now we will continue to refer to the observed errors when we refer to 'shocks'.

To illustrate the workings of this model, we show the impulse response functions (IRF) for the four shocks, using the estimated parameters from section 5 below. A financial shock (ϵ_{3t}), by directly raising the credit premium, also raises costs and so inflation; this in turn leads to a rise in the risk-free rate as policy reacts. Output falls in response to this general tightening of monetary conditions (see Figure 1).

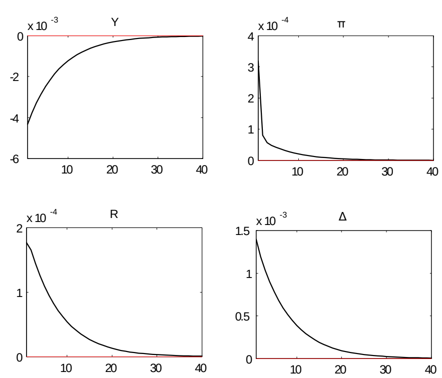

Figure 1: IRF to a Financial Shock

A monetary policy shock (u_t) in Figure 2 raises the real interest rate sharply: this in turn depresses output and inflation, and lowers the credit premium as lending drops with the lower wage bill. Though the real rate rises, the nominal risk-free rate falls with the fall in inflation.

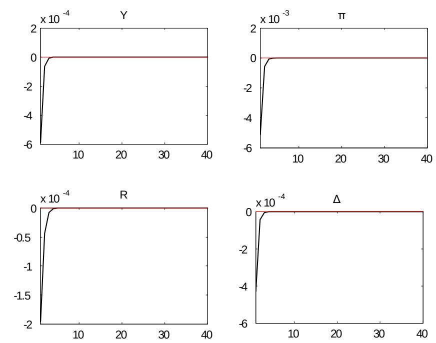

Figure 2: IRF to a Monetary Policy Shock

The demand shock (ϵ_{1t}) illustrates the way that higher inflation and output cause a rise in interest rates and this in turn reduces the credit premium with the reduction in firms' capacity to pay the credit margin (see Figure 3).

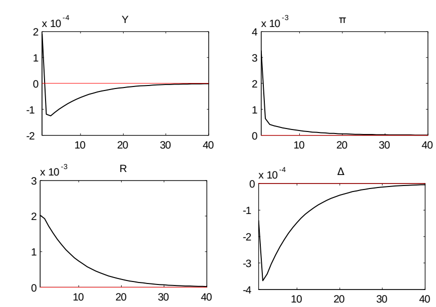

Figure 3: IRF to a Demand Shock

Finally, in Figure 4, the supply shock (ϵ_{2t}), raising productivity, lowers inflation and boosts output, so also the credit premium, but lowers interest rates as money is loosened.

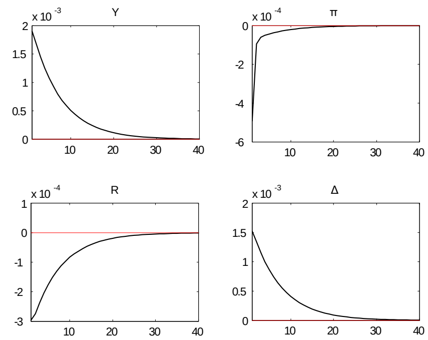

Figure 4: IRF to a Supply Shock

3 The Testing Procedure

Indirect Inference provides a framework for judging whether a model with a particular set of parameters could have generated the behaviour found in a set of data. The procedure provides a statistical criterion for rejecting the model as the data generating mechanism.

Indirect inference has been well known in the estimation literature, since being introduced by Smith (1993); see also Gregory and Smith (1991, 1993), Gourieroux *et al.* (1993), Gourieroux and Montfort (1995) and Canova (2005). In indirect estimation the behaviour of the data is first described by some atheoretical time-series model such as a Vector Auto Regression, the 'auxiliary model'; then the parameters of the structural model are chosen so that this model when simulated generates estimates of the auxiliary model as close as possible to those obtained from actual data. It chooses the structural parameters that can minimise the distance between some function of these two sets of estimates. Indirect estimation was introduced largely in order to estimate models, such as ones with nonlinearity, that could not be estimated directly, for example by FIML. However, our use of indirect inference is for the purpose of testing a model, however constructed, whether for example by calibration, Bayesian estimation, or ordinary estimation. We use indirect estimation also, but as a means of ensuring that the model is tested across the full potential range of its parameter values. In what follows we give a brief account of this testing method; a full account, together with Monte Carlo experiments checking its accuracy and power and comparing it with other methods in use for evaluating DSGE models, can be found in Le, Meenagh, Minford and Wickens (LMMW, 2011 and 2012).

The test is based on the comparison of the actual data with the data simulated from the structural model through an auxiliary model. We choose a VAR as our auxiliary model and base our tests on the VAR coefficients and also the variances (of the variables in the VAR). The reason for choosing a VAR as the auxiliary model is that a DSGE model like the ones here have as their solution a restricted vector autoregressive-moving-average (VARMA), which can be closely represented by a VAR. The VAR captures the dynamic inter-relationships found in the data between the variables of the model. The test statistic is based on the joint distribution of the chosen descriptors- here the VAR coefficients and the variances. The null hypothesis is that the macroeconomic model is the data generating mechanism.

The test statistic for this joint distribution is a Wald statistic Following the notation of Canova (2005), y_t is defined as an $m \times 1$ vector of observed data $(t = 1, ..., T)$ and $x_t(\theta)$ is an $m \times 1$ vector of simulated data with S observations from the model, θ is a $k \times 1$ vector of structural parameters from the model. We set $S = T$, because we want to compare simulated data and actual data using the same size of sample. y_t and $x_t(\theta)$ are assumed to be stationary and ergodic. The auxiliary model is $f[y_t, \alpha]$, where α is the vector of descriptors. Under the null hypothesis $H_0 : \theta = \theta_0$, the auxiliary model is then $f[x_t(\theta_0), (\theta_0)] = f[y_t, \alpha]$. The null hypothesis is tested through the $q \times 1$ vector of continuous functions $g(\alpha)$. Under the null hypothesis, $g(\alpha) = g(\alpha(\theta_0))$. a_T is defined as the estimator of α using actual data and $\alpha_S(\theta_0)$ as the estimator of based on simulated data for θ_0. Then we have $g(a_T)$ and $g(\alpha_S(\theta_0))$.The simulated data is obtained by bootstrapping N times of structural errors, so there are N sets of simulated data. We can calculate the bootstrapped mean by $\overline{g(\alpha_S(\theta_0))} = \frac{1}{N}\sum_{k=1}^{N} g_k(\alpha_S(\theta_0))$. The Wald statistic ($WS$) using the bootstrapped distribution of $g(a_S) - \overline{g(\alpha_S(\theta_0))}$ can be specified as

$$WS = (g(a_T) - \overline{g(\alpha_S(\theta_0))})' W^{-1}(\theta_0)(g(a_T) - \overline{g(\alpha_S(\theta_0))}) \tag{9}$$

where $W(\theta_0)$ is the variance-covariance matrix of the bootstrapped distribution of $g(a_S) - \overline{g(\alpha_S(\theta_0))}$. Here we use a, the descriptors themselves, as $g(a)$.

The testing procedure involves three steps. The first step is to back out the structural errors from the observed data and parameters of the model. If the model equations have no future expectations, the structural errors can be simply calculated using the actual data and structural parameters. If there are expectations in the model equations, we calculate the rational expectation terms using the robust instrumental variables methods of McCallum (1976) and Wickens (1982); we use the lagged endogenous data as instruments and hence use the auxiliary VAR model as the instrumental variables regression. The errors are treated as autoregressive processes; their autoregressive coefficients and innovations are estimated by OLS. [1]

[1] The idea of using these backed-out errors is that they should be consistent with the model and the data: otherwise the model being tested could be considered rejected by the data at the structural stage. As noted by LMMW (2012), an alternative way to estimate the errors in equations with rational expectations terms is to use the model (including the lagged errors)

Secondly, these innovations are then bootstrapped and the model is solved by Dynare. The innovations are repeatedly drawn by time vector to preserve any contemporaneous correlations between them. By this method we obtain N (usually set at 1000) sets of simulated data, or bootstrap samples. These represent the sampling variation of the data implied by the structural model.

Finally, we compute the Wald statistic. By estimating the VAR on each bootstrap sample, the distribution of the VAR coefficients and data variances is obtained, the α. Thus, the estimates of α from the data and the model estimates can be compared. We examine separately the model's ability to encompass the dynamics (the VAR coefficients) and the volatility (the variances) of the data. We show where in the Wald bootstrap distribution the Wald based on the data lies (the Wald percentile).

We use a VAR(1) as the auxiliary model. With a VAR(1), α contains 12 elements, the 9 VAR coefficients and the 3 data variances. This number of descriptors provides a strong requirement for the structural model to match. Raising the VAR order would increase the number of VAR coefficients (eg with a VAR(2) the number would double to 18, making 21 elements in α in total); the requirement of the test arguably becomes excessive, since we do not expect our structural models to replicate data dynamics at such a high level of refinement.

The steps above detail how a given model, with particular parameter values, is tested. These values would typically be obtained in the first place by calibration. However, the power of the test is high and the model will be rejected if the numerical values chosen for the parameters are inaccurate. Therefore, to test a model fully one needs to examine its performance for all (theoretically permissible) values of these parameters. This is where we introduce indirect estimation; in this we search for the numerical parameter values that minimise the Wald statistic. For this purpose we use a powerful algorithm due to Ingber (1996) based on Simulated Annealing in which search takes place over a wide range around the initial values, with optimising search accompanied by random jumps around the space. After reestimating the model in this way, we then test it on these values. If it is rejected on these, then the model itself is rejected, as opposed merely to its calibrated parameter values.

---

to generate the expectations and iterate to convergence but in Monte Carlo experiments the LIML method is slightly more accurate (if we knew the true model including the true ρ_s, then we could back out the exact errors by using the model to solve for the expectations; but of course we do not).

Once the errors and their autoregressive coefficients (ρ) are estimated, they become part of θ_0 and are fixed for the testing process therefore. In indirect estimation the search algorithm finds the structural parameters, the backed-out errors and the ρs that jointly get closest to the α found in the data. If they are also not rejected by these α, then we may treat this model as the data generating mechanism.

4 Data, Calibration and Results for Calibrated Models

4.1 Data

We apply the models to quarterly US data from 1981Q4 to 2010Q4 on the output gap ($\tilde{Y}_t$), the inflation rate (π_t), the interest rate (R_t) and the bank loan rate (R_{lt}), collected from Federal Reserve Bank of St. Louis. The data include the recent financial crisis as far availability permits.

The output gap ($\tilde{Y}_t$) is defined as the percentage gap between real GDP and potential GDP, for which we use the HP filter. Inflation (π_t) is defined as the quarterly change in the log of the CPI. The interest rate is the federal funds rate, expressed as a fraction per quarter. π_t, R_t,and R_{lt} are linearly detrended, because they have a significant deterministic trend (see Table 2). The credit spread is the difference between the detrended bank prime loan rate (R_{lt}) and risk free rate (R_t).

Table 2[2] gives the stationarity property for each variable, which confirms that the inflation and interest rate are trend-stationary. Figure 5 displays the time paths of the four variables in the sample period after necessary detrending has been made. It is notably volatile in the early 1980s, a turbulent period. With inflation in double digits, Paul Volcker was appointed as Fed chairman in 1979 to bring it under control. With the resulting policies, which included spells of both monetary base control and credit restriction, interest rate volatility reached a peak, not exceeded even in the recent bank crisis. This usefully puts into a longer term context the extent to which the banking shocks in the recent crisis were not pathologically extreme.

Variable	**Coeff on the Trend**	**P-Value**	**Implication**
$\tilde{Y}$	-9.97E-15	0.0000	stationary
π	-5.61E-05**	0.0000	trend-stationary
R	-0.000203**	0.0000	trend-stationary
R_l	-0.000171**	0.0002	trend-stationary
$\hat{\Delta}$	7.83E-20	0.0052	stationary

Table 2: ADF Test Results

Our auxiliary model is the VAR(1), Equation 10,

$$\begin{bmatrix} \tilde{Y}_t \\ \pi_t \\ R_t \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ \beta_{12} & \beta_{22} & \beta_{32} \\ \beta_{13} & \beta_{23} & \beta_{33} \end{bmatrix} \begin{bmatrix} \tilde{Y}_{t-1} \\ \pi_{t-1} \\ R_{t-1} \end{bmatrix} + \Omega_t \tag{10}$$

The VAR's nine coefficients represent the dynamic properties found in the data. We also look at the volatility properties as indicated by the variances. We

[2]* represents 5% significance level. ** denotes 1% significance level.

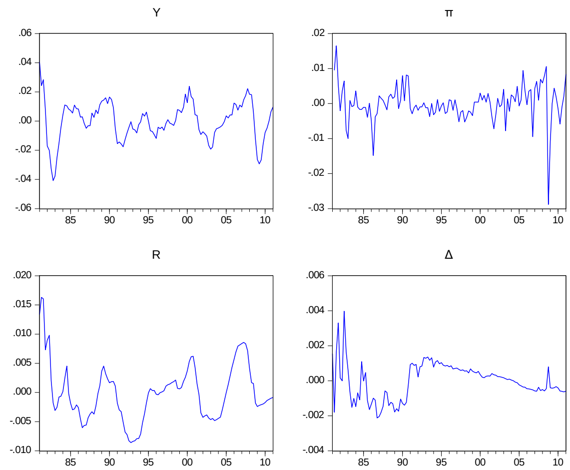

Figure 5: Time Paths of $\tilde{Y}, \pi, R, \hat{\Delta}$

consider these two properties both separately and together, calculating Wald statistics for each. We show these as the percentile on which the data Wald lies in the Wald bootstrap distribution.

4.2 Calibrating and Testing the Standard New Keynesian Model

Table 3 shows the calibrated values for this model, taken from Minford and Ou (2010).

Parameters	**Definitions**	**Values**
a_1	real interest rate elasticity on output gap	0.50
b_1	coefficient of output gap on inflation	2.36
β	inflation expectation on inflation	0.99
k	coefficient of supply shock on inflation	0.42
d_1	Interest rate persistence parameter	0.8
d_2	policy preference on inflation	2.0
d_3	policy preference on output gap	0.1
ρ_1	autoregressive coefficient for demand error	0.89
ρ_2	autoregressive coefficient for supply error	0.86
ρ_3	autoregressive coefficient for policy error	0.18

Table 3: Calibration of Standard Model

Table 4 shows the results for the standard model. The first column lists the parameters of the VAR (which represent the dynamic inter-relationships in the data) in the upper part, the data variances (representing the volatility in the data) in the second part and overall Wald percentiles for each aspect, dynamics, volatility, and overall for both together in the third part. The second column shows the values in the data, the third and fourth show the 95% bounds implied by the DSGE model, the fifth recording whether the data values are inside or outside these bounds. What can be seen is that the standard model is on the borderline of rejection for the dynamics, easily accepted on the volatility, and accepted overall.

Categories	**Actual**	**95% Lower**	**95% Upper**	**IN/OUT**
β_{11}	0.9145	0.7143	0.9197	IN
β_{21}	0.0205	-0.3961	0.0963	IN
β_{31}	-0.2214	-0.2133	0.3020	OUT
β_{12}	0.0554	-0.0748	0.0779	IN
β_{22}	0.1214	0.1187	0.4813	IN
β_{32}	0.1413	-0.0620	0.3252	IN
β_{13}	0.0336	-0.0249	0.0471	IN
β_{23}	-0.0073	-0.0221	0.1614	IN
β_{33}	0.8849	0.7916	0.9481	IN
$\mathrm{var}(\tilde{Y})$	0.1584	0.0595	0.2265	IN
$\mathrm{var}(\pi)$	0.0238	0.0150	0.0349	IN
$\mathrm{var}(R)$	0.0183	0.0108	0.0443	IN
Wald (Dynamics)	95.6%			
Wald (Volatility)	26.6%			
Overall Wald	90.4%			

Table 4: Test Results for Standard Model with Calibration

4.3 Calibrating and Testing the Credit Model

Table 5 lists the calibrated values in the credit model, as in De Fiore and Tristani (2012). The firm's idiosyncratic shock has a log-normal distribution with mean and standard deviation calibrated so as to ensure the quarterly steady state credit spread is equal to 0.5% and 1% bankruptcy rate for each quarter.

Table 6 shows for the credit model the equivalent test results shown above for the standard model. It can be seen that the credit model is easily accepted on the dynamics, not so easily accepted as the standard model on the volatility, and somewhat more easily accepted overall. Thus, like the standard model, the credit model is accepted by the data overall.[3]

[3] Several of the VAR coefficients and one out of the three data variances lie outside their individual 95% bounds, which might suggest that both on the dynamics and on the volatility the model should be rejected. However, the joint distribution only coincides with the collected individual distributions when the model-implied covariances are zero; this is generally not the case with these models which imply substantial covariances between variables and also between

Parameters	**Definitions**	**Values**
β	discount factor	0.99
a_1	interest rate elasticity on output gap	1.54
a_2	credit spread coefficients on output gap	3.82
a_3	interest surprise coefficient on output gap	0.54
b_1	coefficient of output gap on inflation	1.49
κ	coefficient of interest rate on inflation	1.49
b_2	coefficient of credit spread on inflation	9.45
c_1	coefficient of output gap on spread	0.19
c_2	coefficient of interest rate on spread	0.04
c_3	financial market shock parameter	0.075
d_1	interest rate persistence parameter	0.8
d_2	policy preference on inflation	2.0
d_3	policy preference on output gap	0.1
ρ_1	autoregressive coefficient for demand error	0.85
ρ_2	autoregressive coefficient for supply error	0.84
ρ_3	autoregressive coefficient for financial error	0.86
ρ_4	autoregressive coefficient for policy error	0.18

Table 5: Calibration of Credit Model

Categories	**Actual**	**95% Lower**	**95% Upper**	**IN/OUT**
β_{11}	0.9145	0.7221	0.9134	OUT
β_{21}	0.0205	-0.3485	0.0076	OUT
β_{31}	-0.2214	-0.2152	0.3704	OUT
β_{12}	0.0554	-0.1444	0.0754	IN
β_{22}	0.1214	0.0032	0.3855	IN
β_{32}	0.1413	-0.3940	0.3138	IN
β_{13}	0.0336	-0.0354	0.0363	IN
β_{23}	-0.0073	-0.0273	0.0865	IN
β_{33}	0.8849	0.7384	0.9327	IN
var($\tilde{Y}$)	0.1584	0.0680	0.2602	IN
var(π)	0.0238	0.0245	0.0875	OUT
var(R)	0.0183	0.0085	0.0336	IN
Wald (Dynamics)	85.5%			
Wald (Volatility)	79.0%			
Overall Wald	83.4%			

Table 6: Test Results for Credit Model with Calibration

It does however get closer to the data overall than the standard model. The table 7 presents the comparison of the two models in terms of their p-values, which measure the probability that each model gets as close as it does to the data (in percent they are simply 100 minus the Wald percentiles). It can be seen that except on volatility the credit model is closer than the standard model to the behaviour of the data.

P-values (%)	**Credit Model**	**Non-Credit Model**
Dynamics	14.5	4.4
Volatility	21.0	73.4
Overall	16.6	9.6

Table 7: Comparison of Credit and Non-credit Model Using Calibration

5 Reestimating and Retesting the Models

5.1 Indirect Estimation of the Two Models

Tables 8 and 9 show the results of reestimation for each model. All parameters are allowed to change (except for sign) apart from β, time preference, which is held fixed on theoretical grounds. For the standard model, the main changes are that the Phillips Curve becomes steeper and the Taylor Rule stronger on inflation. For the credit model the real interest rate elasticity is much higher. The Phillips Curve becomes steeper while again the Taylor Rule becomes stronger on inflation; but what is most striking is that all the credit coefficients need to change substantially. In neither model is there much change in the persistence parameters whether in the Taylor Rule or on the errors.

5.2 Testing the Reestimated Models

Tables 10 and 11 show the equivalent test results with reestimated parameters. Both models get substantially closer to the data behaviour in all aspects, dynamics, volatility and overall; all individual VAR coefficients and data variances lie within their model 95% bounds. Thus the data behaviour cannot now reject either model either on dynamics or volatility or overall.

.

the VAR coefficients and the variable variances. Consider as an illustration the high positive covariance between inflation and interest rates induced by the Taylor Rule in these models; this will also imply that for example the autocorrelations of these two variables will positively covary- a sample in which inflation is highly persistent will also be one in which interest rates are highly persistent, whereas one in which inflation is barely autocorrelated will also be one in which interest rates mimic it closely, with low autocorrelation too.

	Definitions	Est.	Cali.	Change
a_1	real interest rate elasticity on output gap	0.4307	0.50	-14%
b_1	coefficient of output gap on inflation	3.5046	2.36	49%
k	coefficient of supply shock on inflation	0.2935	0.42	-30%
d_1	Interest rate persistence parameter	0.8190	0.8	2%
d_2	policy preference on inflation	2.8641	2.0	43%
d_3	policy preference on output gap	0.0804	0.1	-20%
ρ_1	autoregressive coefficient for demand error	0.8849	0.89	-1%
ρ_2	autoregressive coefficient for supply error	0.8677	0.86	1%
ρ_3	autoregressive coefficient for policy error	0.1736	0.18	-4%

Table 8: Estimates of Standard Model

	Definitions	Est.	Cali.	Change
a_1	real interest rate elasticity on output gap	2.5151	1.54	63%
a_2	credit spread coefficients on output gap	1.4988	3.82	-61%
a_3	interest surprise coefficient on output gap	0.8879	0.54	64%
b_1	coefficient of output gap on inflation	2.2262	1.49	49%
κ	coefficient of interest rate on inflation	1.5595	1.49	5%
b_2	coefficient of credit spread on inflation	6.8382	9.45	-28%
c_1	coefficient of output gap on spread	0.7767	0.19	309%
c_2	coefficient of interest rate on spread	0.1426	0.04	257%
c_3	financial market shock parameter	0.2612	0.075	248%
d_1	interest rate persistence parameter	0.7553	0.8	-6%
d_2	policy preference on inflation	2.5316	2.0	27%
d_3	policy preference on output gap	0.0192	0.1	-81%
ρ_1	autoregressive coefficient for demand error	0.8860	0.85	4%
ρ_2	autoregressive coefficient for supply error	0.8611	0.84	3%
ρ_3	autoregressive coefficient for financial error	0.8693	0.86	1%
ρ_4	autoregressive coefficient for policy error	0.1557	0.18	-14%

Table 9: Estimates of Credit Model

Auxiliary model	**Actual**	**95% Lower**	**95% Upper**	**IN/OUT**
β_{11}	0.9145	0.7277	0.9316	IN
β_{21}	0.0205	-0.3817	0.1688	IN
β_{31}	-0.2214	-0.2566	0.3016	IN
β_{12}	0.0554	-0.0772	0.0756	IN
β_{22}	0.1214	0.0892	0.4276	IN
β_{32}	0.1413	-0.1136	0.2630	IN
β_{13}	0.0336	-0.0252	0.0420	IN
β_{23}	-0.0073	-0.0266	0.1429	IN
β_{33}	0.8849	0.8027	0.9525	IN
var($\tilde{Y}$)	0.1584	0.0613	0.2514	IN
var(π)	0.0238	0.0119	0.0320	IN
var(R)	0.0183	0.0100	0.0408	IN
Wald (Dynamics)	90.0%			
Wald (Volatility)	24.2%			
Overall Wald	79.8%			

Table 10: Test Results of Standard Model with reestimated Parameters

Auxiliary model	**Actual**	**95% Lower**	**95% Upper**	**IN/OUT**
β_{11}	0.9145	0.7101	0.9284	IN
β_{21}	0.0205	-0.3284	0.1303	IN
β_{31}	-0.2214	-0.2800	0.2834	IN
β_{12}	0.0554	-0.0831	0.0904	IN
β_{22}	0.1214	-0.0840	0.2903	IN
β_{32}	0.1413	-0.0190	0.4259	IN
β_{13}	0.0336	-0.0276	0.0384	IN
β_{23}	-0.0073	-0.0812	0.0566	IN
β_{33}	0.8849	0.8354	0.9724	IN
var($\tilde{Y}$)	0.1584	0.0628	0.2317	IN
var(π)	0.0238	0.0177	0.0408	IN
var(R)	0.0183	0.0116	0.0427	IN
Wald (Dynamics)	39.8%			
Wald (Volatility)	43.9%			
Overall Wald	33.3%			

Table 11: Test Results for Credit Model with Reestimated Parameters

Nevertheless it is also clear that the credit model now dominates the standard model by a substantial margin in dynamics and overall. Table 12 shows the comparative p-values of the two reestimated models. Overall, the credit model is roughly three times more probable.

P-values %	**Credit Model**	**Non-credit Model**	**Ratio**
Dynamics	60.2	10.0	6.0
Volatility	56.1	75.8	0.7
Overall	66.7	20.2	3.3

Table 12: Comparison of Credit and Non-credit Model Using Estimated Parameters

6 Using the Credit Model to Analyse the Banking Crisis

6.1 The model in reduced form

We have seen that the credit model brings considerable extra insight into our analysis of the US data. We now use it to examine the role of financial shocks and transmission in the banking crisis period, from 2006Q1 to 2010Q4. We will do this in two ways: first, looking at the variance decomposition the model implies for the period and second, looking at the contribution of the actual estimated shocks to the real-time evolution of the economy. We begin with the reduced form shocks, whose interpretation is as the residuals of the reduced form equations of the model- that is, they are the overall effect of these errors on the basic New Keynesian equations extended by the credit equation. These, as we have seen, are according to the structural model, linear combinations of the underlying structural shocks. We will examine these structural shocks in the next subsection. But the reduced form shocks are of interest in themselves because they extend the usual New Keynesian analysis.

The following charts show the shocks that are backed out of the model and the data, first for the whole sample period (Figure 6) and secondly for the crisis period part in clearer detail (Figure 7).

It can be seen that the financial shock forces up the premium savagely in the third quarter of 2008 (with the Lehman collapse in September) and does not fade until late in 2009, under the impact of the large-scale bail-out of the banking system and the start of Quantitative Easing. Accompanying it in the next quarter (2008Q4) are a sharp demand contraction, as business confidence fell with the freezing of credit conditions; a supply contraction (reflecting a fall in productivity as output fell faster than employment could be cut); and a strong positive policy shock, reflecting the Fed's inability to cut rates below the zero bound. Of all these shocks the thing to note is the large scale of the financial shock- 0.06 at its peak, or 6% per quarter. Not surprisingly we will find that

Figure 6: Shocks for the Whole Sample

this exerts a substantial impact on the economy according to the model.

6.1.1 A Stochastic Variance Decomposition of the Crisis Period

Table 13 shows the variance decomposition for each variable in the credit model during the crisis period. It can be seen that the financial shock plays an important part in explaining the variance of the output gap, though a minor part for inflation and interest rates.

Variances	$\tilde{Y}$	$\boldsymbol{\pi}$	R
Demand Shock	5.1%	21.2%	86.4%
Supply Shock	19.6%	3.3%	5.2%
Financial Shock	69.8%	2.6%	4.3%
Policy Shock	5.5%	72.9%	4.1%

Table 13: Variance Decomposition: 2006Q1-2010Q4

This shows how each shock individually contributes to each variable's variance, assuming that they are independent. However, in the case of the crisis the shocks' high correlations mean that we cannot allocate overall shares without assumptions to identify the causal ordering. As we have seen and discuss further below, the demand, supply and credit shocks are all combinations of the same two underlying structural shocks and therefore they cannot be causally ordered. As for the policy shock it in principle reflects the policymaker's judgement of how the Taylor Rule needs to be supplemented in each period; this judgement is also likely to be responding, in some unknown way reflecting the policymaker's varying judgements, to the underlying structural shocks of the model. Thus again it cannot be ordered causally.

It follows that our assessment of the importance of financial shocks in re-

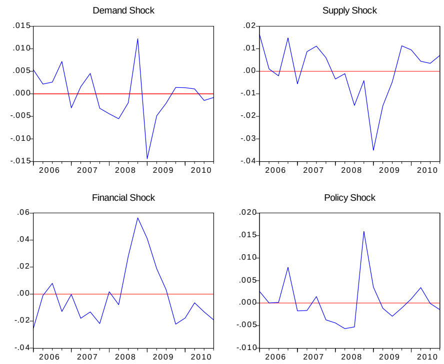

Figure 7: Shocks for the Crisis Period

peated stochastic simulation can only be done conditional on the assumption of independence. This conditionality makes it ultimately not very informative, in the obvious sense that the financial shocks themselves may really be dependent on the non-financial underlying shock. We will revisit this issue when we consider the structural shocks below.

What we can do unambiguously is determine the decomposition of actual events in the episode in terms of these four shocks as they actually occurred. Here we can ignore all correlations because we know exactly the shocks' values in each quarter and so events simply are the adding up of these shocks' effects. We turn to this 'time-line' exercise next.

6.1.2 Accounting for the Shocks in the Crisis Episode

We now turn to how the actual shocks we estimate to have occurred shaped the actual events of the crisis period. For the output gap, Figure 8, we see that the credit channel has a small but distinct effect; and that the financial shocks have a large effect- also shown here in green. After the financial shock, the main effect comes from the supply shock in red.

When we turn to inflation, Figure 9, we find that the financial shock had little effect. The main effects are coming from the demand and the policy shocks, with almost all the rest coming from the supply shock (including movements in commodity prices). Notice that in so far as the financial shock affects inflation it raises it in 2008.4-2009.3, because in the model it acts as a cost push factor.

For interest rates, Figure 10, the shock decomposition tells a story in which the demand shock's effect on output pulls rates down from 2009.1 very sharply, but this effect is counteracted by the upward push to inflation imparted by the financial and supply shocks, which cause interest rates to rise. The fact that the financial shock raises interest rates seems puzzling until one notes that in this model higher financing charges act to raise production costs.

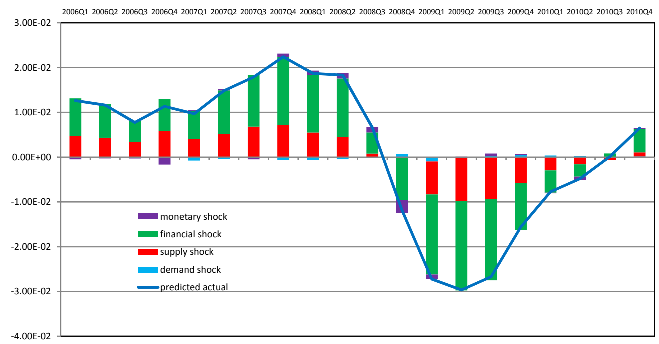

Figure 8: Shock Decomposition for Output during Crisis Period

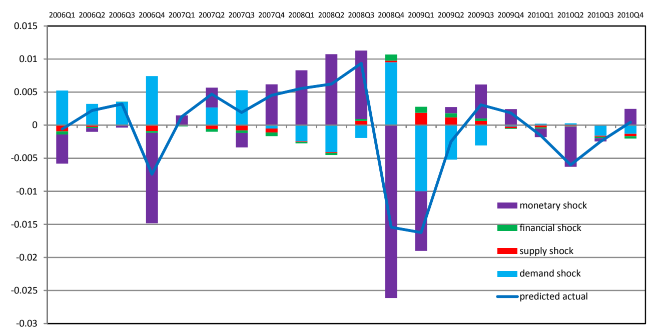

Figure 9: Shock Decomposition for Inflation during Crisis Period

6.2 Understanding the economy in terms of the model's structural shocks

As noted above, this model specifies two underlying or structural shocks: to technology (a_t) and to bank costs (μ_t). In this subsection we extract the implied structural shocks from the observed reduced form shocks found in our estimation procedure; we then repeat the exercise we have just carried out, but this time with these implied structural shocks.

Using our shock notation and assuming that these underlying shocks are like our estimated reduced form shocks AR(1) (so that for example $E_t a_{t+1} = \rho_a a_t$ where ρ_a is the AR coefficient of a_t), then we can write the three reduced form shocks in terms of these underlying shocks. The coefficients are in several cases determined by the model's structural coefficients.

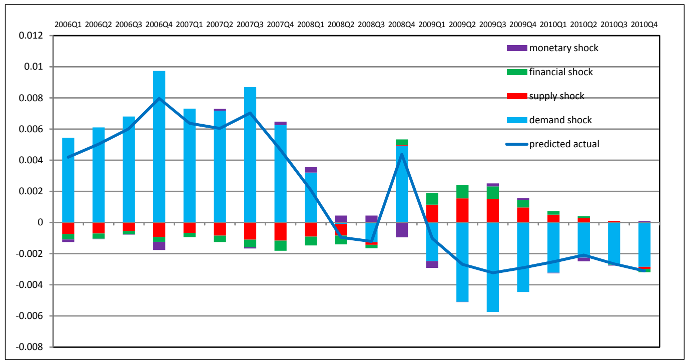

Figure 10: Shock Decomposition for Interest Rate during Crisis Period

$$\epsilon_{1t} = \frac{\frac{e}{c}}{1-\varphi\frac{e}{c}} E_t(\epsilon_{2t+1} - \epsilon_{2t}) + \delta_1 E_t(\mu_{t+1} - \mu_t) \tag{11}$$

$$= \frac{-\frac{e}{c}}{1-\varphi\frac{e}{c}}(1-\rho_{\epsilon 2})\epsilon_{2t} - \delta_1(1-\rho_\mu)\mu_t \tag{12}$$

$$\epsilon_{2t} = -\sigma^{-1}\frac{1+\varphi}{\sigma^{-1}+\varphi} E_t(a_{t+1} - a_t) + \delta_2\mu_t + s_t \tag{13}$$

$$= \sigma^{-1}\frac{1+\varphi}{\sigma^{-1}+\varphi}(1-\rho_a)a_t + \delta_2\mu_t + s_t \tag{14}$$

$$\epsilon_{3t} = -\frac{\sigma^{-2}\frac{e}{c}(1+\varphi)}{\sigma^{-1}+\varphi} E_t(a_{t+1} - a_t) + \frac{(1+\sigma^{-1}\frac{e}{c})(1+\varphi)}{\sigma^{-1}+\varphi} a_t - \delta_2\mu_t + c_t \tag{15}$$

$$= \{\frac{\sigma^{-2}\frac{e}{c}(1+\varphi)}{\sigma^{-1}+\varphi}(1-\rho_a) + \frac{(1+\sigma^{-1}\frac{e}{c})(1+\varphi)}{\sigma^{-1}+\varphi}\} a_t - \delta_2\mu_t + c_t \tag{16}$$

We now search for the time-series processes $a_t = \rho_a a_{t-1} + \varepsilon_{at}$ and $\mu_t = \rho_\mu \mu_{t-1} + \varepsilon_{\mu t}$ that give the best fit to our observed shocks. Given the structural parameters we have estimated the search is heavily constrained. Thus since we know the demand and supply error and the coefficient $\frac{-\frac{e}{c}}{1-\varphi\frac{e}{c}}(1-\rho_{\epsilon 2})$,we can find $\delta_1(1-\rho_\mu)\mu_t$ directly from the demand error equation and from that estimate ρ_μ, thus obtaining $\delta_1\mu_{t'}$; we normalise $\delta_1 = 1$ so obtaining our estimate of the monitoring shock μ_t. Now we minimise the sum of squared errors, s_t and c_t, of the other two error equations, (subject to the known coefficient constraints) with respect to the unknowns, a_t, δ_2, ρ_a; to find the minimum we use the simulated annealing algorithm to search across the parameter space (see appendix for more details). Figure 11 shows the structural shocks and shock parameters that achieve this minimisation, as well as the two estimation errors; Table shows the estimated error coefficients. What we see is that the underlying productivity and monitoring shocks are very highly correlated; and also that the two extra (estimation) shocks, needed to track the reduced form errors exactly, are inversely and also highly correlated. Thus in effect where we had three reduced form shocks, we now have four underlying shocks, productivity and the (extra) supply shock, monitoring and the (extra) credit shock.

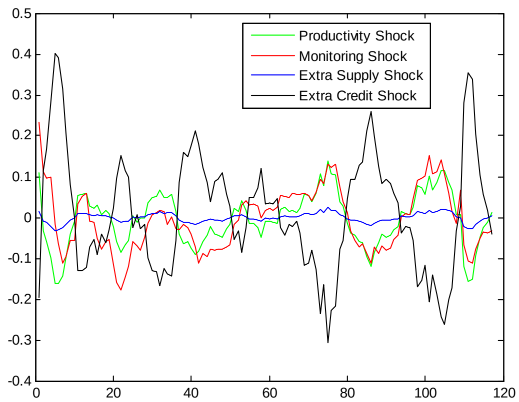

Figure 11: Structural Shocks

Parameters	**Estimates**
$\frac{e}{c}$	0.6053
φ	0.5260
σ	1.1092
δ_1	1
δ_2	0.000
ρ_a	0.8776
ρ_μ	0.8558

Table 14: Estimates of Shock Errors

We can think of this credit shock as a measure of how well the structural model is specifying the overall credit shock, since it reflects what is *not* in the structural model. Another point to note is that the credit shock only affects the credit premium shock, whereas the monitoring shock only affects the demand shock, having a negligible effect on both supply and credit premium shocks in the constrained estimates ($\widehat{\delta_2} = 0$[4]). The supply shock is quite small, suggesting the

[4]The reason for this apparently strange result is that by the model constraint δ_2 must

structural model is specifying the supply shocks more accurately; if we ignored it, we could think of the structural model as requiring one extra shock, the credit shock, to account exactly for the model's errors. It is clear that this would always be needed since otherwise there would only be three errors for a four-variable model, implying stochastic singularity. Here we add the supply shock as a further shock to achieve the best fit.

Turning to the IRFs with these structural shocks, we can see in Figure12 that a shock rise in productivity (a_t) raises output and lowers inflation and interest rates, but raises real interest rates and so lowers the credit premium. A rise in the extra supply shock (which only enters the Phillips Curve) lowers inflation and so interest rates, and also lowers real interest rates which raises output and the credit premium. A shock rise in the monitoring cost (μ_t) only has an effect on demand; it lowers demand initially, and this lowers interest rates and inflation, also real interest rates. These in turn create a subsequent upturn in output which raises the credit premium. A rise in the extra credit shock also raises the credit premium (directly) and this feeds into inflation; this in turn pushes up interest rates, both nominal and real output falls.

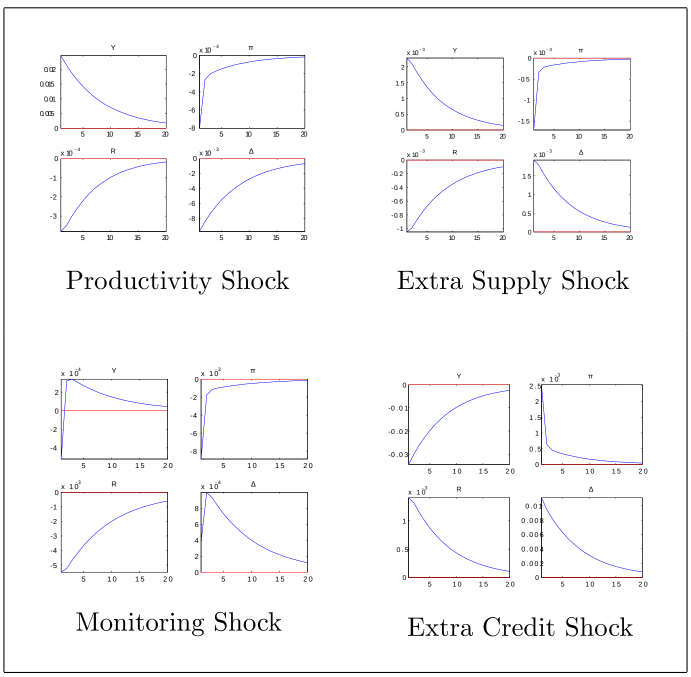

Figure 12: IRF to the Structural Shocks

be negative (implying that a rise in monitoring costs raises inflation and also credit costs). However the monitoring cost error is found to be highly and positively correlated with productivity which is in turn positively correlated with the supply error. So a negative coefficient on the monitoring error in the supply error equation worsens its fit. As for the credit error, this is negatively correlated with the supply error and so also with the monitoring error; so a positive δ_2 worsens this equation fit also. Thus the estimation forces this coefficient to zero.

A monetary policy shock (u_t) in Figure 13 raises the real interest rate sharply: this in turn depresses output and inflation, and lowers the credit premium as lending drops with the lower wage bill. Though the real rate rises, the nominal risk-free rate falls with the fall in inflation.

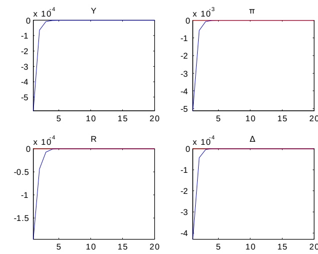

Figure 13: IRF to a Policy Shock

When we redo the variance decomposition of the crisis episode using these structural shocks and assuming that they are independent we find quite a similar share for financial shocks on the output gap, but much larger for interest rates and inflation. Again it would be impossible to allocate the share reliably if we regarded the shocks are highly correlated, in line with their sample behaviour seen from the charts above. However according to the structural model they are in truth independent and simply show correlation in this sample by chance. In this case the Table 15 shows the true decomposition, with financial shocks contributing 62% of output, 32% of inflation, and 89% of interest rate variance.

Variances Decomposition	$\tilde{Y}$	$\boldsymbol{\pi}$	R
Productivity Shock	36.9%	1.6%	2.9%
Monitoring Shock	0.3%	26.0%	81.3%
Extra Supply Shock	0.6%	4.0%	5.5%
Extra Credit Shock	62.0%	6.0%	7.5%
Policy Shock	0.3%	62.3%	2.7%
Total	100%	100%	100%
Financial Shocks	62.3%	32.0%	88.8%
Non-Financial Shocks	37.7%	68.0%	11.2%

Table 15: Variance Decomposition: 2006Q1-2010Q4

This finding from the structural model fits well into the existing literature. We can say that typical crisis financial factors are an important source of output gap and interest rate variance but less important for inflation. What we have found here for output variance is similar to findings of other recent work using stationarised data, where it has been found that financial shocks were dominant in the crisis period- Jermann and Quadrini (2012), Gilchrist et al. (2009), and Christiano et al. (2010). This is in contrast to the findings of Le, Meenagh and Minford (2012) who use raw, non-stationary data; with this they find that the productivity shock is non-stationary, while some other non-financial shocks are highly persistent, and these shocks dominate the crisis. They report that moving from stationary to nonstationary data reduces the share of financial shocks in output volatility sharply, from 52.3% to 8.5%. This is also in line with the findings of Stock and Walson (2012) using a dynamic factor VAR; they find that the contribution of financial shocks to the crisis period is not significantly different from its contribution in previous periods. Thus our finding here, like those of other recent authors using stationary data, that it is financial shocks dominating output variance, most likely reflects our abstraction from the shocks contributing to the trends in the data.

If we turn to the time-lines generated by the structural shocks, we see that the output gap (Figure 14) is dominated by the credit shock and the productivity shock which pull in opposite directions. The other shocks have small or imperceptible effects; as we have seen the monitoring shock only works through the demand error. If we compare this with the timeline in terms of the reduced form shocks where both supply and financial shocks worked in the same direction, we can see that the model is saying (if we allow the credit shock to supplement it) that financial shocks were dominant in reducing output a) by raising the credit premium b) by raising financial costs more than an opposite rise in productivity lowered production costs (the negative supply shock).

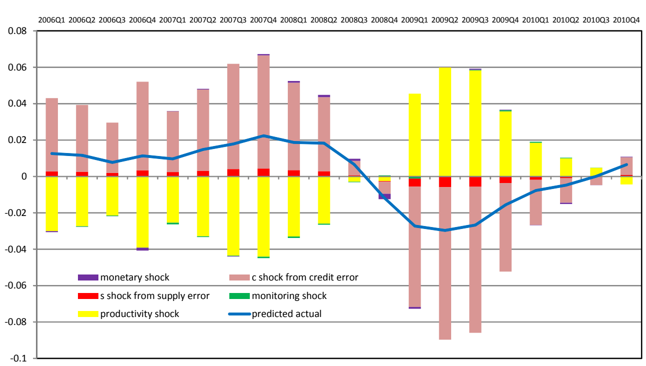

Figure 14: Shock Decomposition for Output during Crisis Period

Turning to the inflation time-line (Figure 15) we see that the dominant shock is monetary but that all the other shocks contribute to some degree, in line with our variance decomposition. In 2008Q4, when Lehman failed, the quarter of greatest volatility, monetary policy was tightened compared with the Taylor Rule due to the zero lower bound; this is partially offset here by a cost-raising credit shock.

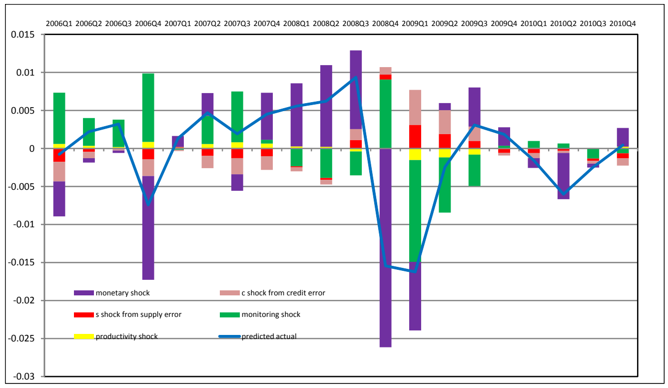

Figure 15: Shock Decomposition for Inflation during Crisis Period

If we turn to the interest rate time-line (Figure 16) we find the monitoring shock playing an overwhelming role, as in our stochastic decomposition above (Table 15). Otherwise small effects come from the credit and supply shocks. The monetary policy shock hardly enters, being absorbed almost entirely in its inflation effect; nor does the productivity shock, which in its turn is absorbed mainly by its output effect.

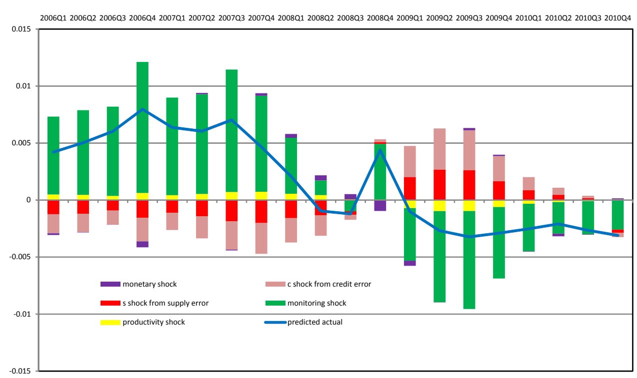

Figure 16: Shock Decomposition for Interest Rate during Crisis Period

The examination of the structural model thus yields some additional information about the sources of volatility in this crisis episode, provided we allow the model to be supplemented with additional credit and supply shocks, whose interpretation is that, unlike the productivity and monitoring shocks, they each contribute *solely* to the credit premium and supply equations respectively. Nevertheless, this necessity to add, at least, one very large (credit) shock inevitably casts doubt on the model's structural interpretation of the reduced form shocks. If we believe a 'monitoring' shock to be the driver of credit costs, what then exactly is the credit shock? Or vice versa, if the credit shock is driving the credit premium alone, what exactly is the 'monitoring' cost? Thus in the end the reduced form shocks remain the limit of our hard empirical knowledge, while the structural model can be regarded as a useful means to construct a viable 4-equation aggregate model with credit as well as a source of suggestions for the interpretation of the underlying shocks.

7 Conclusion

We have compared the ability of the standard New Keynesian model and a version augmented with a credit channel to account for the behaviour of the US data over a sample period extending from the start of the 1980s up to and including the recent crisis period to the end of 2010. We found that both models could match this behaviour reasonably well even in their calibrated form; and once reestimated could do so quite easily. Of the two the credit-augmented version came much the closer to the data. When accordingly we used this credit model to account for the crisis period, we found that financial shocks played a dominant role in the banking crisis, accounting for some two thirds of output gap variation, whether we use the reduced from or the structural shocks. This is much in line with other work on the banking crisis that examines the business cycle variation over the crisis; these studies, like ours here, abstract from the trend movements in output and other variables which some other recent work has found to contribute the dominant source of output variation in the crisis.

Clearly much work remains to be done on exactly what caused these, here exogenous, financial shocks. Nevertheless, the fact that such shocks can occur and that they can contribute to recessions should not be a surprise; nor is there necessarily any means to suppress such shocks, as seems to be the intention of such legislation as Dodd-Frank. The model here at least helps to establish the quantitative role of these shocks in the economy's behaviour during the crisis.

8 Appendix

In order to estimate the parameters in Equation 11 to 15, we assume $a_t = \rho_a a_{t-1} + \varepsilon_{at}$ and $\mu_t = \rho_\mu \mu_{t-1} + \varepsilon_{\mu t}$. The shock equations can be written as follows:

$$\epsilon_{1t} = \alpha_{11}(1 - \rho_{\epsilon_2})\epsilon_{2t} - \delta_1(1 - \rho_\mu)\mu_t \tag{17}$$

$$\epsilon_{2t} = \alpha_{21}(1 - \rho_a)a_t + \delta_2\mu_t \tag{18}$$

$$\epsilon_{3t} = \alpha_{31}(1 - \rho_a)a_t + \alpha_{32}a_t - \delta_2\mu_t \tag{19}$$

where $\alpha_{11} = -\frac{\frac{\varepsilon}{c}}{1-\varphi\frac{\varepsilon}{c}}, \alpha_{21} = \sigma^{-1}\frac{1+\varphi}{\sigma^{-1}+\varphi}, \alpha_{31} = \frac{\sigma^{-2}\frac{\varepsilon}{c}(1+\varphi)}{\sigma^{-1}+\varphi}$,and $\alpha_{32} = \frac{(1+\sigma^{-1}\frac{\varepsilon}{c})(1+\varphi)}{\sigma^{-1}+\varphi}$. When we estimate the above, these parameters $(\alpha_{11}, \alpha_{21}, \alpha_{31}, \alpha_{32})$ are restricted to the values calculated by the estimated parameters in Table 9. We normalised the shock μ_t by setting δ_1 equal to one. δ_2 is a function of microfounded parameters that need to be estimated using Simulated Annealing approach with initial values of the calibrated ones (the model theory makes it negative). We estimate δ_2 using the following steps:

Step 1: Starting from Equation 17, estimate ϵ_{2t} in an AR(1) process to obtain ρ_{ϵ_2}. Given $\alpha_{11}, \rho_{\epsilon_2}$ and data ϵ_{2t}, extract $\delta_1(1-\rho_\mu)\mu_t$ and estimate $\delta_1(1-\rho_\mu)\mu_t$ in an AR(1) process to get ρ_μ. Then we can solve for μ_t. The model actually tells us exactly what μ_t is. So there is no error on this equation.

Step 2: Plug μ_t into Equation 18 and 19. Iterate using Simulated Annealing procedure. Starting from the initial value of δ_2, generate from Equation 18 the data $a_{1t} = \alpha_{21}(1-\rho_a)a_t$; then generate from 19 a value for $a_{2t} = [\alpha_{31}(1-\rho_a) + \alpha_{32}]a_t$. Calculate the AR(1) coefficients on each of these two expressions in a_{1t} and a_{2t} and use the average as ρ_α. Knowing α_{21}, α_{31}, α_{32} and with this estimate of ρ_a, create $a_t = 0.5(a_{1t} + a_{2t})$. This gives equal weight to the two equations in estimating a_t and ρ_a.

Step 3: This creates two errors (s_t and c_t) in the Equation 18 and 19. Now choose δ_2 by Simulated Annealing to minimise sum of squared two errors (again giving equal weight to the two equations), iterating over Steps 2 and 3 until the minimum is reached.

References

[1] Bernanke, B., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. In Taylor, J.B., Woodford, M. (Eds.), Handbook of Macroeconomics, Amsterdam: North-Holland.

[2] Canova, F., 2005. Methods for Applied Macroeconomic Research, Princeton University Press, Princeton.

[3] Christiano, L.J, Motto, R. & Rostagno, M., 2010. Financial factors in economic fluctuations. Working Paper Series 1192, European Central Bank.

[4] De Fiore, F., Tristani, O., 2013. Optimal monetary policy in a model of the credit channel. The Economic Journal, 123(571), 906-931.

[5] Gale, D., Hellwig, M., 1985. Incentive-compatible debt contracts: the one-period Problem. The Review of Economic Studies, 52(4), 647-663.

[6] Gertler, M., Kiyotaki, N., 2010. Financial intermediation and credit policy in business cycle analysis. In Friedman, B., Woodford, M. (Eds.), Handbook of Monetary Economics. Amsterdam: Elsevier.

[7] Gertler, M., Karadi, P., 2011. A model of unconventional monetary policy. Journal of Monetary Economics, January.

[8] Gilchrist, S., Ortiz, A. Zakrajsek, E., 2009. Credit Risk and the Macroeconomy: Evidence from an Estimated DSGE Model. Unpublished manuscript, Boston University.

[9] Gourieroux, C., Monfort, A., Renault, E., 1993. Indirect inference. Journal of Applied Econometrics, 8, 85-118.

[10] Gourieroux, C., Monfort, A., 1995. Simulation Based Econometric Methods. CORE Lectures Series, Louvain-la-Neuve.

[11] Gregory, A., Smith, G., 1991. Calibration as testing: Inference in simulated macro models. Journal of Business and Economic Statistics, 9, 293-303.

[12] Gregory, A., Smith, G., 1993. Calibration in macroeconomics. In Maddala, G. (Edd.), Handbook of Statistics, 11, Elsevier, St. Louis, Mo., 703-719.

[13] Jermann, U., Quadrini, V., 2012. Macroeconomic Effects of Financial Shocks. American Economic Review, 102(1), 238–71.

[14] Juillard, M., 2001. DYNARE: a program for the simulation of rational expectations models. Computing in Economics and Finance. 213. Society for Computational Economics.

[15] Le, V.P.M., Meenagh, D., Minford, P., Wickens, M., 2011. How much nominal rigidity is there in the US economy? testing a New Keynesian DSGE Model using indirect inference. Journal of Economic Dynamics and Control, 35(12), 2078-2104.

[16] Le, V.P.M., Meenagh, D., Minford, P. Wickens, M., 2012. Testing DSGE models by Indirect inference and other methods: some Monte Carlo experiments, Cardiff Economics working paper E2012/15, also CEPR discussion paper 9056.

[17] Le, V.P.M., Meenagh, D., Minford, P., 2012. What causes banking crises? An empirical investigation.Cardiff Economics working paper E2012/14, also CEPR discussion paper 9057.

[18] Liu, C., Minford, P., 2012. Comparing behavioural and rational expectations for the US post-war economy, Cardiff Economics Working Papers E2012/22, Cardiff University, Cardiff Business School, Economics Section.

[19] McCallum, B.T., 1976. Rational expectations and the natural rate hypothesis: some consistent estimates. Econometrica, 44, 43-52.

[20] Minford, P., Ou, Z., 2010. Testing the monetary policy rule in US: a reconsideration of Fed's behaviour, Cardiff University Working Paper Series, E2009/12, October 2009, updated in 2010.

[21] Smith, A., 1993. Estimating nonlinear time-series models using simulated vector autoregressions. Journal of Applied Econometrics, 8, 63-84.

[22] Stock, J. H. and Watson, M. W., 2012. Disentangling the Channels of the 2007-2009 Recession, Brookings Papers on Economic Activity.

[23] Taylor, J.B., 1993. Discretion versus policy rules in practice. Carnegie-Rochester Conference Series on Public Policy, 39, 195-214.

[24] Townsend, R., 1979. Optimal contracts and competitive markets with costly verification. Journal of Economic Theory, 22, 265-293.

[25] Wickens, M., 1982. The efficient estimation of econometric models with rational expectations. Review of Economic Studies, 49, 55-67.