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HOW IMPORTANT IS THE CREDIT CHANNEL? AN EMPIRICAL STUDY OF THE US BANKING CRISIS

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ABSTRACT

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JEL Classification: C12, C52, E12, G01 and G1
Keywords: bank crisis, credit channel, financial frictions and indirect inference

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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. The credit channel is the main contributor to the variation in the output gap during the crisis.

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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 adding a banking sector, based on recent work of De Fiore and Tristani (2009),

*We are grateful to Huw Dixon and Paul de Grauwe for helpful comments.

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.

To anticipate, we find that this extended model improves on the standard model substantially and also attributes around two thirds 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 shifts which we do not deal with here. Nevertheless, the empirical result is striking, even if perhaps it should not be surprising to policy-makers.

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. The last section concludes, relating our work to other work of this type and drawing some policy implications.

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:

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

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

$$R_t = (1 - c_1)(c_2\pi_t + c_3\tilde{Y}_t) + c_1R_{t-1} + u_t \tag{3}$$

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 the demand error, supply error and policy error respectively. 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 (2009) 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 the 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 their 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, ie 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; 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.

The 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 relative to its profit rate 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 π_t, R_t, $\hat{\Delta}_t$ represent inflation, nominal interest rate, and credit spread, respectively; 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.

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. In what follows we give a brief account of the 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) 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 ρs, 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.

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.

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), and the interest rate (R_t), collected from Federal Reserve Bank of St. Louis. The data include the recent financial crisis as far availability permits.

The output gap ($\tilde{Y}$) is defined as the percentage gap between real GDP and potential GDP, for which we use the HP filter. Inflation (π) 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 and R_t are linearly detrended. The credit spread is the difference between the bank prime loan rate (R_l) and risk free rate (R). 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 and credit controls, 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.

Figure 1 displays the time paths of the four variables in the sample period after detrending. Table 1 gives the ADF test results, which also confirm they are all strictly stationary after detrending.

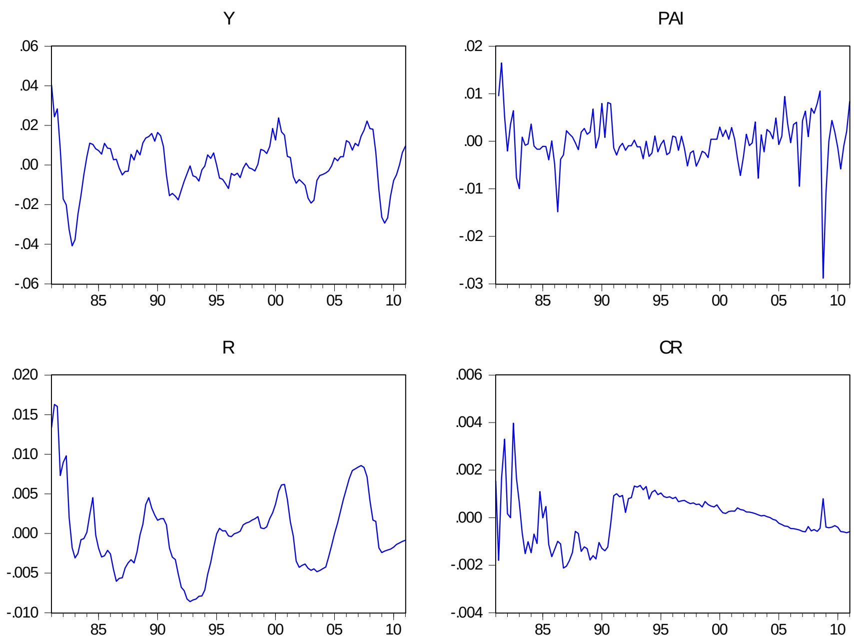

Figure 1: Time Paths of $\tilde{Y}, \pi, R, \hat{\Delta}$

Variable	ADF statistics	Implication
$\tilde{Y}$	-2.137881	stationary
π	-8.313042	stationary
R	-4.300952	stationary
$\hat{\Delta}$	-2.816015	stationary

Table 1: 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 consider these two properties both separately and together, calculating Wald statistics for each. We show these as the percentile where the data Wald lies in the Wald bootstrap distribution.

4.2 Calibrating and Testing the Standard New Keynesian Model

Table 2 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 2: Calibration of Standard Model

The Table 3 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
$\text{var}(\tilde{Y})$	0.1584	0.0595	0.2265	IN
$\text{var}(\pi)$	0.0238	0.0150	0.0349	IN
$\text{var}(R)$	0.0183	0.0108	0.0443	IN
Wald (Dynamics)	95.6%			
Wald (Volatility)	26.6%			
Overall Wald	90.4%			

Table 3: Test Results for Standard Model with Calibration

4.3 Calibrating and Testing the Credit Model

Table 4 lists the calibrated values in the credit model, as in De Fiore and Tristani (2009). 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 5 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.[2]

[2] 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 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.

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 4: 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 5: Test Results for Credit Model with Calibration

It does however get closer to the data overall than the standard model. The table 6 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 6: Comparison of Credit and Non-credit Model Using Calibration

5 Reestimating and Retesting the Models

5.1 Indirect Estimation of the Two Models

Tables 7 and 8 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 flatter and the Taylor Rule stronger on inflation. For the credit model 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 either model is there much change in the persistence parameters whether in the Taylor Rule or on the errors.

	Definitions	**Est.**	**Cali.**	**Variation**
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 7: Estimates of Standard Model

	Definitions	Est.	Cali.	Variation
a_1	interest rate elasticity on output gap	1.6055	1.54	4%
a_2	credit spread coefficients on output gap	1.9145	3.82	-50%
a_3	interest surprise coefficient on output gap	0.7968	0.54	48%
b_1	coefficient of output gap on inflation	0.8454	1.49	-43%
κ	coefficient of interest rate on inflation	1.7292	1.49	16%
b_2	coefficient of credit spread on inflation	14.1591	9.45	50%
c_1	coefficient of output gap on spread	0.2829	0.19	49%
c_2	coefficient of interest rate on spread	0.0603	0.04	51%
c_3	financial market shock parameter	0.0390	0.075	-48%
d_1	interest rate persistence parameter	0.7123	0.8	-11%
d_2	policy preference on inflation	2.6123	2.0	31%
d_3	policy preference on output gap	0.0570	0.1	43%
ρ_1	autoregressive coefficient for demand error	0.8681	0.85	2%
ρ_2	autoregressive coefficient for supply error	0.7881	0.84	-6%
ρ_3	autoregressive coefficient for financial error	0.8667	0.86	1%
ρ_4	autoregressive coefficient for policy error	0.1549	0.18	-14%

Table 8: Estimates of Credit Model

5.2 Testing the Reestimated Models

Tables 9 and 10 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.

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Nevertheless it is also clear that the credit model now dominates the standard model by a substantial margin in all aspects. Table 11 shows the comparative p-values of the two reestimated models. Overall, the credit model is roughly three times more probable.

6 Using The Credit Model to analyse the Banking Crisis

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

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 9: Test Results of Standard Model with reestimated Parameters

Auxiliary model	Actual	95% Lower	95% Upper	IN/OUT
β_{11}	0.9145	0.7164	0.9220	IN
β_{21}	0.0205	-0.3510	0.1124	IN
β_{31}	-0.2214	-0.2516	0.3140	IN
β_{12}	0.0554	-0.0933	0.0726	IN
β_{22}	0.1214	-0.0716	0.3144	IN
β_{32}	0.1413	-0.0486	0.3972	IN
β_{13}	0.0336	-0.0334	0.0411	IN
β_{23}	-0.0073	-0.0718	0.0909	IN
β_{33}	0.8849	0.7897	0.9658	IN
var($\tilde{Y}$)	0.1584	0.0687	0.2429	IN
var(π)	0.0238	0.0155	0.0318	IN
var(R)	0.0183	0.0108	0.0427	IN
Wald (Dynamics)	63.8%			
Wald (Volatility)	12.3%			
Overall Wald	45.4%			

Table 10: Test Results for Credit Model with Reestimated Parameters

P-values %	**Credit Model**	**Non-credit Model**	**Ratio**
Dynamics	36.2	10.0	3.6
Volatility	87.7	75.8	1.2
Overall	54.6	20.2	2.7

Table 11: Comparison of Credit and Non-credit Model Using Estimated Parameters

6.1 A Stochastic Variance Decomposition of Crisis Period

Table 12 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	2.3%	13.4%	84.6%
Supply Shock	17.4%	4.7%	8.1%
Financial Shock	75.3%	4.6%	6.9%
Policy Shock	5.0%	77.3%	0.4%

Table 12: Variance Decompsition: 2006Q1-2010Q4

This shows how each shock individually contributes to each variable's variance, assuming that they are independent. However, our bootstraps draw shocks in time vectors, to preserve any mutual dependence; the shocks' resulting interaction means that we cannot allocate overall shares exactly but can obtain a range, depending on which order we draw them. Furthermore, we would like to know the part played by financial transmission as well as financial shocks. The Tables that follow examine the share of financial shocks and transmission ('financial factors') in the overall variances under two orderings of non-financial and other shocks.

Variances	**No Real Shocks**	**Total Incl. Real Shocks**	**Contribution of Financial Factors**
var($\tilde{Y}$)	0.0436	0.1174	37.1%
var(π)	0.0026	0.0401	6.5%
var(R)	0.0022	0.0175	11.4%

Table 13: Variance Share of Financial Factors When They Are Ordered First

Variances	**No Financial Factors**	**Total Incl. Financial Factors**	**Non-financial Contribution**	**Financial Contribution**
var($\tilde{Y}$)	0.0307	0.1174	26.1%	73.9%
var(π)	0.0284	0.0401	70.8%	29.2%
var(R)	0.0164	0.0175	93.7%	6.3%

Table 14: Variance Share of Financial Factors When They Are Ordered Second

We get a range of variance contributions of financial factors to the output gap variance of 37-74%; for inflation of 6-29% and for interest rates of 6-11%. Summarising, we can say that typical crisis financial factors are an important source of output gap variance but less important for inflation and interest rates.

6.2 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. Apart from showing the effect of each individual shock, we show the separate effects of a) non-financial shocks only, with the credit channel blocked out (zero values for all credit parameters, $a_2 = a_3 = k = b_2 = 0$)- the red line b) non-financial shocks including the credit channel- the green line c) the whole model and all shocks - the blue line. b), green, minus a), red, shows the effect of the credit channel working on the non-financial shocks alone; c), blue, minus b), green, shows the effects of the financial shocks alone.

For the output gap, Figure 2, 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 deep blue. After the financial shock, the main effect comes from the supply shock in brown.

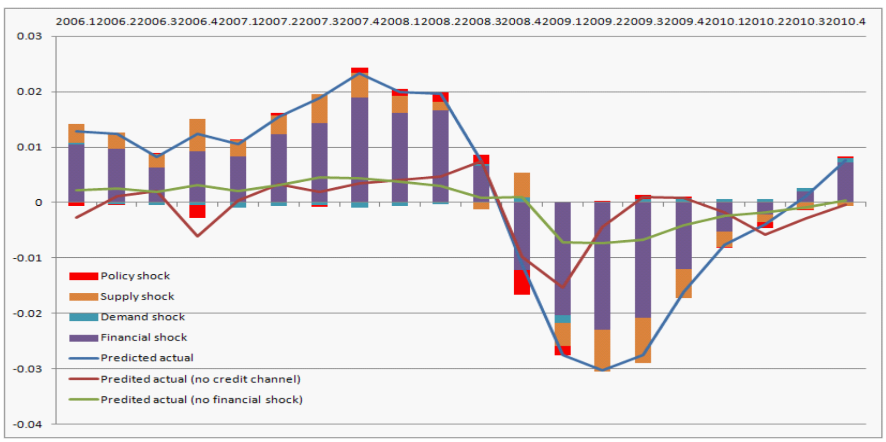

Figure 2: Shock Decomposition for Output During Crisis Period

When we turn to inflation, Figure 3, we find that neither the credit channel nor the financial shocks had much 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 4, 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.

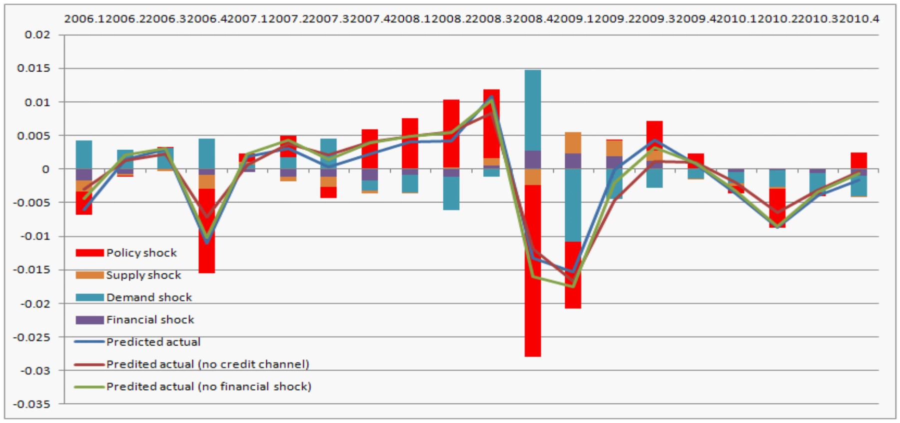

Figure 3: Shock Decomposition for Inflation During Crisis Period

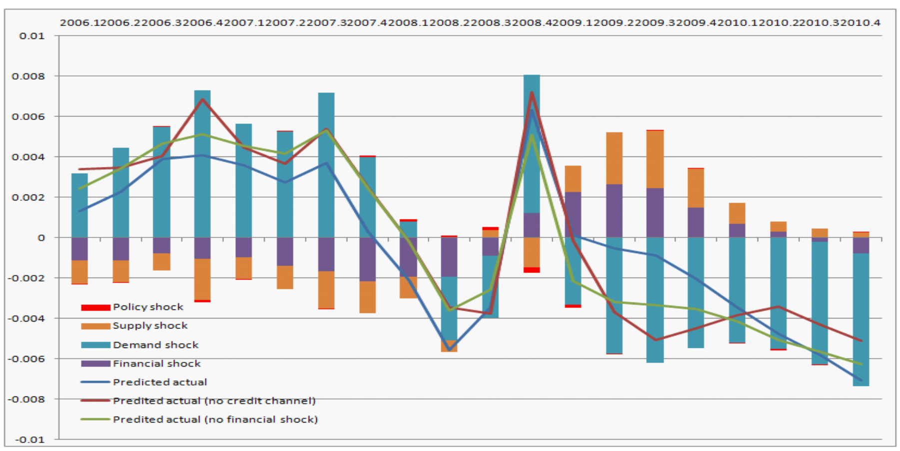

Figure 4: Shock Decomposition for Interest Rate During Crisis Period

We can set these results alongside those of Le, Meenagh and Minford (2012) who studied much the same US data using a version of the Smets-Wouters model with a credit channel of the Bernanke et al type and a flex-price sector. They too found a large role for financial shocks and little for credit transmission on output. The role was proportionately smaller in theirs than here, because they also included non-stationary productivity shocks which dominate the movement of output in the crisis period. In their model financial shocks had a negative effect on interest rates and this was balanced by a 'policy shock' due to the zero bound preventing rates from going as low as the Taylor Rule would have suggested; this difference arises from funding costs not being part of production costs but rather being part of investment costs. Since the empirical performances of the Le et al model and the one here are similarly good, it is hard to distinguish these two causal transmission processes empirically, at least without further investigation. Otherwise the two models give broadly consistent accounts of the crisis.

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 an important role in the banking crisis, accounting for up to two thirds of output gap variation. In other work on the banking crisis using a full DSGE model with a credit sector non-stationary productivity shocks were included, and these, with no connection to banking, acquired an equally important role in accounting for total output behaviour during the crisis. However, given that the model here excludes such non-stationary elements, it appears to be broadly in line with this other work. 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.

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