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Haroon Mumtaz, Gabor Pinter and Konstantinos Theodoridis

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Queen Mary
University of London

What do VARs tell us about the impact of a credit supply shock?*

Haroon Mumtaz
Queen Mary College

Gabor Pinter
Bank of England

Konstantinos Theodoridis
Bank of England

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Abstract

This paper evaluates the performance of a variety of structural VAR models in estimating the impact of credit supply shocks. Using a Monte-Carlo experiment, we show that identification based on sign and quantity restrictions and via external instruments is effective in recovering the underlying shock. In contrast, identification based on recursive schemes and heteroscedasticity suffer from a number of biases. When applied to US data, the estimates from the best performing VAR models indicate, on average, that credit supply shocks that raise spreads by 10 basis points reduce GDP growth and inflation by 1% after one year. These shocks were important during the Great Recession, accounting for about half the decline in GDP growth.

JEL Classification: C15, C32, E32. *Keywords:* Credit supply Shocks, Proxy SVAR, Sign restrictions, identification via heteroscedasticity, DSGE models.

1 Introduction

A large number of recent empirical studies have focussed on identifying and estimating the impact of credit supply shocks. This issue has gained renewed prominence in the face of the great recession and the banking and debt crisis in the Euro-Area. For example, Gambetti and Musso (2012) use sign restrictions to identify credit supply shocks for a number of countries

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with a similar identification approach adopted in Eickmeier and Ng (2011), Peersman (2011), Furlanetto et al. (2014) and Bijsterbosch and Falagiarda (2014) amongst others. Gilchrist and Zakrajsek (2012), instead, adopt an alternative approach. The authors use firm level data to build an index of credit spreads and show that a component of this index (that is not related to countercyclical movements in expected defaults) can be interpreted as a proxy for credit supply. Gilchrist and Zakrajsek (2012) is related to a large body of work that has proposed different indicator variables that may provide information about credit supply, with prominent papers including Kashyap et al. (1993) and Gertler and Gilchrist (1994). Lown and Morgan (2006) uses the Federal Reserves' senior loan officers survey to build a proxy for credit supply and finds that negative shocks to this measure have a significant negative impact on GDP.

In this paper we re-examine the identification of the credit supply shock using SVARs. The aim is to investigate how SVARs perform in identifying this shock and to establish whether the estimated importance of the credit supply shock varies substantially with the identification scheme. This question is important both from a methodological and economic point of view. From the former perspective, this exercise can be seen as an attempt to shed light on the relative performance of the SVAR models used in the papers cited above. More importantly, our work attempts to estimate the impact of this shock while accounting for the uncertainty associated with identification. In other words, this paper tries to provide *general* results on the role played by this shock in driving recent fluctuations in economic activity—a question that is vital for policy-makers.

With this aim in mind, the paper considers a Monte-Carlo experiment where the data is generated from a DSGE model featuring credit supply. The artificial data is used to estimate five types of structural VAR models with the aim of identifying credit supply shocks. The first SVAR model uses DSGE based sign restrictions to identify the credit supply shock à la Gambetti and Musso (2012). We also consider an augmented sign restriction scheme where restrictions on the forecast error variance (FEV) decomposition are also added in addition to the sign restrictions. The third SVAR treats the simulated credit shock as a proxy variable and adds it to the VAR as an endogenous variable, and mimics the recursive approach to identification adopted in Lown and Morgan (2006) and Gilchrist and Zakrajsek (2012) for example. In addition, we estimate a proxy SVAR model (as proposed in Stock and Watson (2008) and Mertens and Ravn (2012)) where the simulated proxy is used an instrument to estimate the credit supply shock. The final SVAR model is based on the data driven approach based on Rigobon (2003) and Lanne et al. (2010), and identifies the credit supply shock via heteroscedasticity. The results of this Monte-Carlo experiment suggest that the SVAR with sign and FEV restrictions and the proxy SVAR model deliver the best performance producing impulse responses that match those from the DSGE model. The scheme based on heteroscedasticity works well under certain conditions. In contrast, the recursive SVAR is sensitive to ordering and measurement error and can produce estimates that are very mis-leading.

We then estimate these SVAR models using US data. While there is some dispersion

of the results across models, the SVARs that perform well in the Monte-Carlo experiment lead to fairly similar empirical results. On average across models, a credit supply shock that leads to a rise in the credit spread by 10 basis points, is estimated to reduce annualised GDP growth by 1% after one year on a cumulative basis. The cumulative impact of this shock on annual inflation at this horizon is similar with this variable declining by 1%. The credit supply shock explains about 13% of the FEV of GDP and 18% of the FEV of inflation at the one year horizon. We find strong evidence that this shock made a large contribution to the decline in GDP growth and inflation over the Great Recession. The estimates suggest that the decline in GDP growth in 2009 would have been reduced by 50% if the negative credit supply shock at that time was absent. These results, therefore, re-enforce the message of DSGE papers such as Christiano et al. (2014) that frictions associated with financial intermediation play a key role in propagating shocks that drive macroeconomic fluctuations.

The paper is organised as follows. Section 2 introduces the various approaches to estimating the impact of credit supply shocks via SVARs. The Monte-Carlo experiment is presented in section 3, while section 4 presents the empirical results for the US. Section 5 concludes.

2 The SVAR approach to estimating the impact of credit supply shocks

2.1 Sign Restrictions

As mentioned, above a number of recent papers have used sign restrictions in an attempt to identify credit supply shocks. For example, Gambetti and Musso (2012) estimate the following type of SVAR model:

$$Y_t = c + \sum_{j=1}^P B_j Y_{t-p} + A_0 \varepsilon_t \quad (1)$$

where Y_t is a matrix of endogenous variables. The structural shocks ε_t are related to the VAR residuals u_t via the relation $A_0 \varepsilon_t = u_t$ where A_0 is a matrix such that $VAR(u_t) = \Omega = A_0 A_0'$.¹

Gambetti and Musso (2012) include five variables in the VAR model: Real GDP, CPI, volume of loans, a lending rate and a short-term interest rate. The credit supply shock ε_t^c is identified via the assumption that an expansionary shock leads to an increase in real GDP and the volume of loans and a reduction in the lending rate. Peersman (2011) uses a more general sign restrictions scheme to identify a lending multiplier shock, where data on lending net of the monetary base is utilised to distinguish this shock from a monetary easing.

The algorithm to find A_0 proceeds by first calculating \tilde{A}_0 an arbitrary matrix square root of Ω . Then a candidate A_0 is found by multiplying \tilde{A}_0 with a rotation matrix and

¹Note that Gambetti and Musso (2012) allow for time-varying parameters which is an important extension but not the primary focus of the analysis in the current paper. Bijsterbosch and Falagiarda (2014) apply this methodology to a set of euro area countries.

checking if the impulse responses using this candidate structural impact matrix satisfy the sign restrictions. Note that this algorithm delivers a *set* of A_0 matrices and impulse responses that are admissible under the identification scheme. Given that the set of admissible A_0 matrices can be fairly wide, we also consider a scheme that augments the sign restrictions with the requirement that the identified shock also maximises the FEV contribution to the quantity of credit up to a horizon of 40 quarters (see Uhlig (2004)). This augmented scheme is similar in spirit to the ‘plausibility restriction’ approach adopted in Kilian and Murphy (2012). In our application we rule out A_0 matrices that deliver credit supply shocks that contribute little to fluctuations in the quantity of credit. From an economic point of view, this additional restriction is motivated by the observation that the monetary authority can use its policy instruments to mitigate the impact of credit demand shocks. In contrast, credit technology shocks that disrupt supply are harder to deal with and are likely to affect credit quantity over a longer period of time.

2.2 Proxy Variables

The VAR analysis in Lown and Morgan (2006), Bassett et al. (2012) and Gilchrist and Zakrajsek (2012) relies on building a proxy for credit supply $\hat{\varepsilon}_t^c$ and adding it to the VAR model as an endogenous variable. For example, Lown and Morgan (2006) use net percentage tightening of credit standards from the US senior loan officers’ survey as a proxy and show that shocks to this variable result in a decline in output and the quantity of lending. Bassett et al. (2012) refine this measure further by removing the component associated with macroeconomic factors influencing loan demand. Increases in their residual measure are associated with a fall in output and widening of credit spreads. Gilchrist and Zakrajsek (2012) use a firm level dataset on corporate bond prices to build an aggregate spread index. They then decompose this aggregate corporate bond spread into a component explained by firm specific expected default and firm specific bond characteristics and a residual component—i.e. the excess bond premium. The authors argue that this residual component represents: ‘(the) *average price of bearing exposure to U.S. corporate credit risk, above and beyond the compensation for expected defaults*’. Gilchrist and Zakrajsek (2012) interpret the excess bond premium as a proxy for credit supply and show that it is highly correlated with measures of supply derived from the senior loan officers survey. When added to a VAR model (positive) shocks to the excess bond premium lead to a significant reduction in GDP growth, consumption growth and investment in the US.

Given that $\hat{\varepsilon}_t^c$ is a proxy for true underlying value of the credit supply shock, it is reasonable to assume a degree of measurement error. For example, the relationship between the constructed measure of credit supply and its underlying value may be defined as $\hat{\varepsilon}_t^c = \varepsilon_t^c + \sigma_v v_t$ where v_t is standard normal. It is easy to see that the presence of measurement error would bias the estimate of the structural shock of interest. In addition, it is well known that OLS estimates of the VAR coefficients would suffer from attenuation bias due to the correlation between the RHS variables and the residuals introduced by the measurement error.

2.3 Proxy SVAR

Stock and Watson (2008) and Mertens and Ravn (2012) have recently proposed a structural VAR approach that uses proxy variables as instruments rather than additional endogenous variables. The underlying VAR model is given by the following equation:

$$\tilde{Y}_t = c + \sum_{j=1}^P B_j \tilde{Y}_{t-p} + \tilde{A}_0 \tilde{\varepsilon}_t \quad (2)$$

The matrix of endogenous variables \tilde{Y}_t does not contain the constructed measure of credit supply directly but, instead, this is used as an instrument to estimate the structural shock of interest, i.e. ε_t^c . Denoting the remaining shocks by $\tilde{\varepsilon}_t^\bullet$, this approach requires the proxy for credit supply $\hat{\varepsilon}_t^c$ to satisfy the following conditions

$$\begin{aligned} E(\hat{\varepsilon}_t^c, \varepsilon_t^c) &= \alpha \neq 0 \\ E(\hat{\varepsilon}_t^c, \tilde{\varepsilon}_t^\bullet) &= 0 \\ VAR(\tilde{\varepsilon}_t) &= D = \text{diag}(\sigma_{\varepsilon_{1t}}, \dots, \sigma_{\varepsilon_{Nt}}) \end{aligned} \quad (3)$$

The first expression in equation 3 states that the instrument $\hat{\varepsilon}_t^c$ is correlated with the structural shock to be estimated, while the second expression rules out any correlation between $\hat{\varepsilon}_t^c$ and the remaining structural shocks and establishes exogeneity of the instrument. The final condition ensures that the shocks are contemporaneously uncorrelated. As shown in Stock and Watson (2008), Mertens and Ravn (2011) and Mertens and Ravn (2012), these conditions along with the requirement that the structural shocks $\tilde{\varepsilon}_t$ are contemporaneously uncorrelated can be used to derive a GMM estimator for the column of \tilde{A}_0 that corresponds to $\hat{\varepsilon}_t^c$. Letting $\tilde{A}_0 = [\tilde{A}_{0,1} \dots \tilde{A}_{0,N}]$ and $\tilde{A}_0 \tilde{\varepsilon}_t = u_t$ where $VAR(u_t) = \Omega$. Then Stock and Watson (2008) show that that ε_{1t} can be estimated via a regression of $\hat{\varepsilon}_t^c$ on u_t . Note that

$$E(u_t \hat{\varepsilon}_t^c) = E(\tilde{A}_0 \varepsilon_t \hat{\varepsilon}_t^c) = [\tilde{A}_{0,1} \dots \tilde{A}_{0,N}] \begin{bmatrix} E(\varepsilon_{1t} \hat{\varepsilon}_t^c) \\ \vdots \\ E(\varepsilon_{Nt} \hat{\varepsilon}_t^c) \end{bmatrix} = \tilde{A}_{0,1} \alpha. \text{ Let } \Pi \text{ denote the coefficient}$$

on u_t . Then the fitted value Πu_t equals the structural shock of interest up to sign and scale:

$$\begin{aligned} \Pi u_t &= E(\hat{\varepsilon}_t^c u_t') \Omega^{-1} u_t \\ &= \alpha \tilde{A}'_{0,1} \left(\tilde{A}_0 D \tilde{A}'_0 \right)^{-1} u_t \\ &= \alpha \left(\tilde{A}'_{0,1} \tilde{A}_0^{-1'} \right) D^{-1} \left(\tilde{A}_0^{-1} u_t \right) \\ &= \frac{\alpha \varepsilon_{1t}}{D_{11}} \end{aligned} \quad (4)$$

where going from the third to the final line uses the fact that $(\tilde{A}'_{0,1} \tilde{A}_0^{-1'}) = [1, 0, \dots, 0]$ and $\tilde{A}_0^{-1} u_t = \varepsilon_t$. Note that equation 3 imposes less stringent conditions on the quality of $\hat{\varepsilon}_t^c$

than those required for unbiased estimation when the proxy variable is added directly to the VAR model. In particular, the only requirements are that $\hat{\varepsilon}_t^c$ is correlated with the shock of interest and uncorrelated with other shocks. These conditions can be satisfied even if $\hat{\varepsilon}_t^c$ is measured with error.

2.4 Identification through heteroscedasticity

Building on Rigobon (2003), Lanne et al. (2010) describe how heteroscedasticity in the structural shocks can be used to estimate the contemporaneous impact matrix in equation 1. In particular, Lanne et al. (2010) consider the following parameterisation for the variance of u_t .

$$\text{var}(u_t) = \Omega_{s_t}$$

where $s_t = 1, 2, \dots, M$ follows a Markov process with transition probabilities $p_{ij} = \Pr(s_t = j | s_{t-1} = i)$. The covariance matrix Ω_{s_t} is defined as:

$$\begin{aligned} \Omega_1 &= BB' \\ \Omega_i &= B\Lambda_i B' \end{aligned} \tag{5}$$

where $i = 2, \dots, M$ and Λ_i is a diagonal matrix that represents the volatility of the structural shocks relative to the first regime. Lanne et al. (2010) show that expression 5 provides enough equations to estimate the unknown elements of B uniquely (up to sign changes and column permutations) provided that there exists a state where the diagonal elements of Λ are distinct. There are two noteworthy features of this set-up. First, it assumes that the contemporaneous and lagged impact of the shocks is time-invariant and temporal changes are fully captured by Λ_i . Second, the estimate of the contemporaneous impact matrix from this procedure is purely statistical and the impulse responses have to be given an economic interpretation ex-post.

3 A Monte-Carlo experiment

In order to assess the performance of these identification schemes, we simulate data from a DSGE model featuring credit. The SVAR models are estimated using this artificial data and the estimated impulse responses to credit supply shocks are compared with those implied by the model.

3.1 The design of the experiment

We simulate data from the monetary DSGE model developed by Gertler and Karadi (2011) where financial intermediaries take centre stage. The economy is populated by five agents: households, financial intermediaries, intermediate goods producers, retailers, and capital goods producers. By assumption, households are limited to saving via the banking system

owing to prohibitively large costs associated with direct intermediation to firms. Intermediate goods producers, in turn, are reliant on bank loans to finance the physical capital, which they purchase from capital producers, who are subject to investment adjustment costs. Intermediate goods producers combine capital with labour, provided by households, to produce wholesale goods, which are bought and repackaged by monopolistically competitive retailers. Retailers are subject to Calvo-type pricing and backward indexation rules. All profits in the economy are ultimately repaid to households.

The representative household consists of “workers” and “bankers”. Workers supply labour and return their wages to the household. Bankers manage financial intermediaries and return non-negative dividends to the household. The fraction of the household who save do not directly provide funds to producers, but supply savings to banks other than the ones they own. Savings take the form of riskless short term deposits. Household deposits together with banker’s own net worth form banks’ liabilities, which finances the purchase of financial claims on producers.

The heart of the model is a moral hazard problem between depositors and banks. At the beginning of each period the banker can choose to divert a fraction θ of available funds from the project and transfer them back to the household, in which case depositors would recover the remaining $1 - \theta$ fraction of assets. In order for depositors to continue to supply funds, the bank’s franchise value must be sufficiently large to satisfy the incentive constraint. The bank’s optimality condition pins down the optimal leverage ratio, at which point the banker’s incentive to divert assets is exactly offset by the cost of bankruptcy. To model credit shocks, we consider the capital quality shock, originally studied by Gertler and Karadi (2011). This shock destroys a fraction of the productive capital stock, which, since claims on capital are held on the balance sheets of banks, imposes losses directly on financial intermediaries leading to a fall in credit supply and a rise in spreads.

We follow Gertler and Karadi (2011) in setting both the conventional parameters and the parameters specific to the credit friction of the model. The standard deviation of the shocks is set to 0.01. Note that a switching version of this model is also simulated in order to evaluate the SVAR with heteroscedasticity. In this case, we allow the volatility of shocks to switch between two regimes, where the second regime is assumed to be the high volatility state. The shock volatilities in the second regime are chosen such that they are distinct thus ensuring that the identification conditions for the SVAR with heteroscedasticity are met in the generated data. For this simulation, in the benchmark case we assume that the variance of the credit supply shock in the second regime is five times larger relative to the first regime and that this shock is the most volatile compared to the other shocks. The on-line appendix lists the model equations, the parameter values used and provides additional technical details on the model simulations.

We generate 1000 datasets that include the following variables: $y_t, \pi_t, R_t, S_t, C_t, \varepsilon_t^{C,DSGE}$. Here y_t denotes real output, π_t is the inflation rate, R_t is the policy interest rate, S_t is the spread between the lending rate and the policy rate, C_t denotes the quantity of credit and $\varepsilon_t^{C,DSGE}$ is the credit supply shock. The length of the time-series is set to 1000, with the first

800 observations discarded to remove the influence of initial conditions.

The generated data is used to estimate 5 SVAR models described above: (1) a SVAR that identifies the credit supply shocks via sign restrictions implied by the Gertler and Karadi (2011) model – a negative credit supply shock is assumed to reduce output, inflation, the quantity of loans and the policy rate on impact and increase the spread between lending rates and the policy rate. (2) the SVAR with sign restrictions and the constraint that the credit supply shock maximises its contribution to the FEV of C_t over a horizon of 40 quarters. (3) A recursive SVAR where the cumulated shock $\varepsilon_t^{c,DSGE}$ is included as a variable in the model. Following standard practice, the shock is ordered after output, inflation and the credit quantity but before the policy rate and the spread and thus has a contemporaneous impact on the latter two variables. (4) A proxy SVAR model that uses $\varepsilon_t^{c,DSGE}$ as an instrument to identify the shock. (5) A switching SVAR that uses heteroscedasticity to estimate the contemporaneous impact matrix.

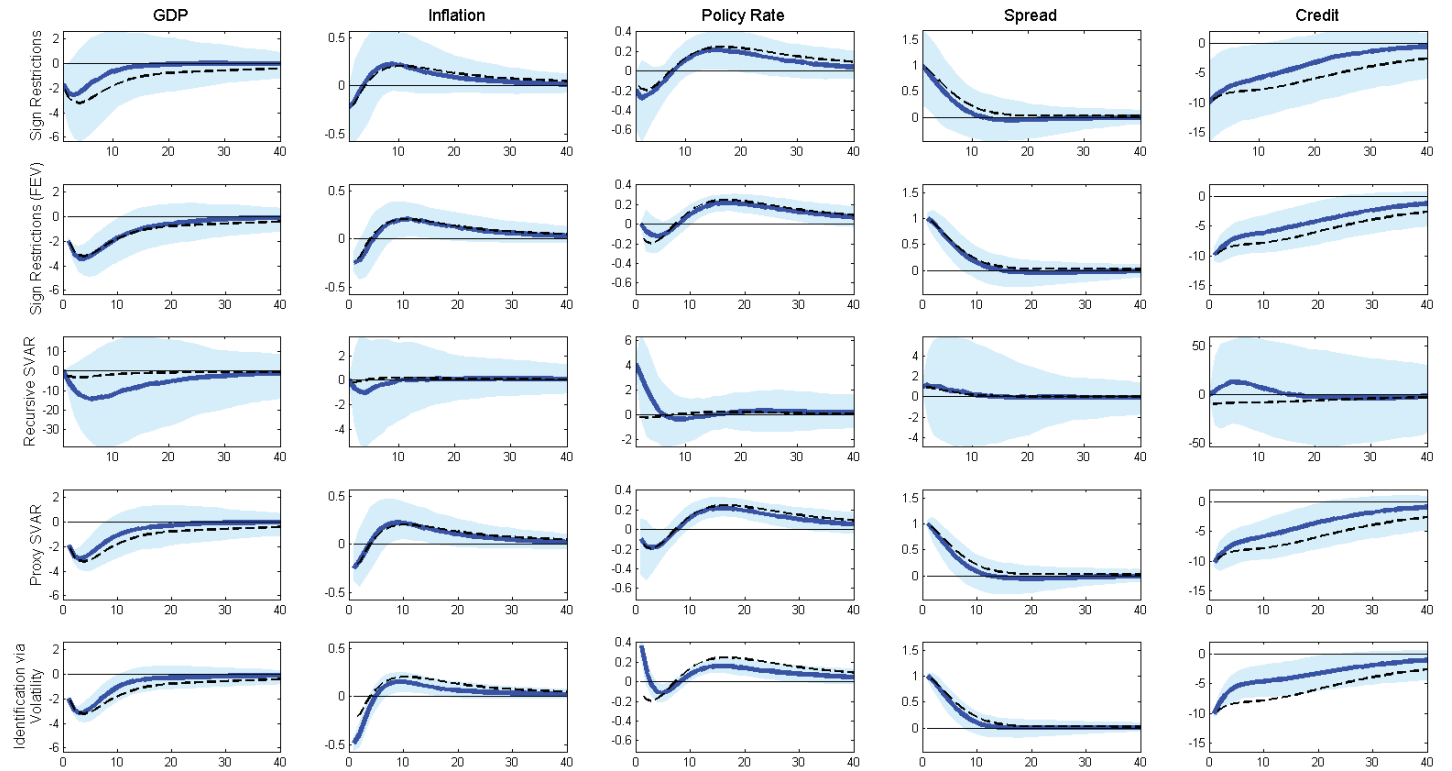


Figure 1: Comparison of SVAR and DSGE responses to a credit supply shock. The shock is normalised to increase the spread by 1 unit. The black dotted line represents, the DSGE response. The blue line is the median estimate from the SVAR with the shaded area is the 90% error band from the Monte-Carlo experiment. Sign restrictions (FEV) refer to the VAR with sign restrictions and the constraint on the contribution of the credit supply shock to the FEV.

3.2 Results

Figure 1 compares the impulse responses obtained from each SVAR model with those implied by the DSGE model. The top two rows of the figure consider the performance of the SVAR with sign restrictions, without and with the constraint on the FEV, respectively. The median estimate from the pure sign restriction scheme is close to the true response for inflation and the interest rates. The estimated response of output and the credit quantity displays a bias at the medium and long horizons. More importantly, the uncertainty surrounding the median estimates is quite large suggesting that the set of admissible models is wide. This appears to be a practical problem in this setting as the wide error bands prevent meaningful inference on key variables such as output. For example, at the one year horizon the response of output ranges from -6.4 percent to 1.2 percent, with each of these estimates admissible under the contemporaneous sign restrictions. The estimated response of the other variables shares this feature and highlights the point raised in Kilian and Murphy (2012) that additional restrictions may be required to pin down the results when using sign restrictions. This point is further re-enforced by the results presented in the second row of the figure. When the restriction on the FEV is added to the sign restrictions, the median estimate of the response improves and the error bands shrink. Note that for each variable, the median impulse response is close to the DSGE response and the bias in the estimate for output and credit is smaller. The restriction on the FEV reduces the set of admissible models and leads to a narrower range of estimates. For example, the output response at the 4 quarter horizon ranges now from -5% to -2% and, in contrast, to the pure sign restriction scheme leads one to infer correctly that the effect of this negative shock is unambiguously contractionary at this horizon.

The third and the fourth rows of the figure presents the estimates from the recursive and proxy SVARs, respectively. The recursive VAR performs poorly with the median response very different from the DSGE response. The poor performance of this model is directly related to the fact that the zero restrictions imposed by this scheme are not consistent with the DSGE model. As a consequence, the response of output and inflation is severely biased and the estimated sign of the credit and the short-rate response is incorrect. In contrast, the Proxy SVAR performs well. At short horizons, the median estimated responses are close to theoretical responses, with a slight bias in the output and credit response at longer horizons. Note also that the error bands are fairly narrow indicating that the responses are estimated with precision.

In sections 2.4 and 2.5 in the on-line appendix, we consider an additional experiment featuring the recursive and proxy SVAR where the proxy variable $\varepsilon_t^{c,DSGE}$ is assumed to be measured with error. In particular, in these experiments we define the proxy variable as $\varepsilon_t^{c,DSGE} + v_t$, $v_t \sim N(0, \sigma_v^2)$ where we consider scenarios under which σ_v^2 is half and twice as large as the variance of credit shock. In both cases, the responses from the recursive VAR display a large attenuation bias with the bias increasing in σ_v^2 . In contrast, the measurement error has little effect on the performance of the proxy SVAR. This is because, in the proxy VAR model, the instrument does not enter the VAR directly as an endogenous variable and

therefore the estimates of the VAR parameters are unaffected by measurement error bias.

The final row of the figure presents the results for switching VAR model. The VAR response for output is fairly close to the theoretical response. The sign of the inflation response matches that of the DSGE response. However, the VAR estimate is biased upwards. The estimated response of the policy rate displays the largest divergence from theory. The VAR response of this variable is positive over short horizons while the DSGE response is negative. This suggests that when using this identification scheme it is difficult to distinguish between the credit supply shock and a monetary policy shock, where the latter would imply a positive short-rate response. Note that this occurs despite the fact that we assume in the DGP that the credit supply shock has the largest variance in the high volatility regime and label the columns of the estimated B matrix accordingly.² In section 2.3 in the on-line appendix we show that the performance of this identification method improves as the magnitude of the switch in the variance of the credit supply shock increases. However, for our DGP, the magnitude of the regime change required for this scheme to perform well appears to be unrealistically large – this model performs well if it is assumed that the variance of the credit supply shock becomes 50 times larger in the second regime. Such a change in volatility is difficult to reconcile with the data for countries such as the US.

Overall, the Monte-Carlo experiment suggests that the VAR with sign and FEV restrictions and the proxy VAR display the best performance in identifying the credit supply shock. Identification via heteroscedasticity appears to be sensitive to the degree of the volatility shift. Finally, the recursive scheme performs poorly and appears to be strongly affected by measurement error bias.

With these simulation results in hand, we take these SVAR models to the data and attempt to gauge the importance of the credit supply shock for the US economy.

4 The impact of credit supply shocks in the US

In this section of the paper we use the structural VAR models discussed above to estimate the impact of credit supply shocks for the US. The basic data for the VAR models runs from 1973Q1 to 2013Q2 and, unless otherwise noted, includes the following variables: (1) Real private investment, (2) Real consumption expenditure growth, (3) Real GDP growth, (4) CPI inflation, (5) Growth of total lending to households and private non-financial corporations, (6) the spread of a composite lending rate over the 3-month treasury bill rate, (7) the 3-month treasury bill rate, (8) the Chicago Fed financial conditions index and (9) the measure of economic uncertainty developed by Jurado et al. (2013).³ The variables included in the VAR model cover the real and monetary sectors of the economy and also try to account for the role played by shocks to the financial sector and uncertainty, both of which have been identified as being important for economic fluctuations (see Bloom (2009) and Alessandri

²In other words, the estimated shock with the largest relative variance in the second regime is labelled as the credit supply shock in each iteration of the experiment. This labelling is consistent with the DGP.

³Appendix A provides details on data sources and construction.

	GDP growth	CPI Inflation	Lending growth	Spread	3mth T-Bill
Credit Supply	\leq	\leq	\leq	\geq	\leq

Table 1: Sign Restrictions in the benchmark model

and Mumtaz (2014) amongst others). The lag length for all VAR models is chosen via the Schwarz criteria using a maximum lag of 4 and all growth rates are defined in quarterly annualised terms.

4.1 Impulse responses and variance decomposition

4.1.1 A VAR with sign restrictions and constraints on the FEV

The sign restrictions that we use to identify the credit supply shock are summarised in table 1. These restrictions are implied by Gertler and Karadi (2011) model are robust across different calibrations.⁴

Given the superior performance of the sign restriction algorithm *with* restrictions on the forecast error variance in the Monte-Carlo experiment described above, we also impose the condition that the credit supply shock maximises its contribution to the forecast error variance of lending growth over a horizon of 40 quarters.

The top row of figure 2 plots the impulse responses obtained from this model. The shock is normalised to increase the credit spread by 10 basis points on impact. The figure shows that this shock has a large and persistent negative impact on the economy. Credit growth declines by 0.8%, the uncertainty index increases and the FCI rises on impact signalling a deterioration of financial conditions. Investment declines by about 2%, with consumption and GDP growth falling by about 0.4% to 0.5%. Note that it takes about 3 to 5 quarters for the impact on these variables to dissipate. The decline in inflation and the short-term interest rate in response to this shock is estimated to be more persistent.

Table 2 shows that the contribution of the credit supply shock to the FEV of GDP and consumption growth and inflation is estimated to be about 20% at the one year horizon, while the estimates suggest that this shock was less important for investment fluctuations.

⁴A figure that shows the range of impulse responses from the Gertler and Karadi (2011) model obtained by using a grid for the calibrated parameters is available in the on-line appendix.

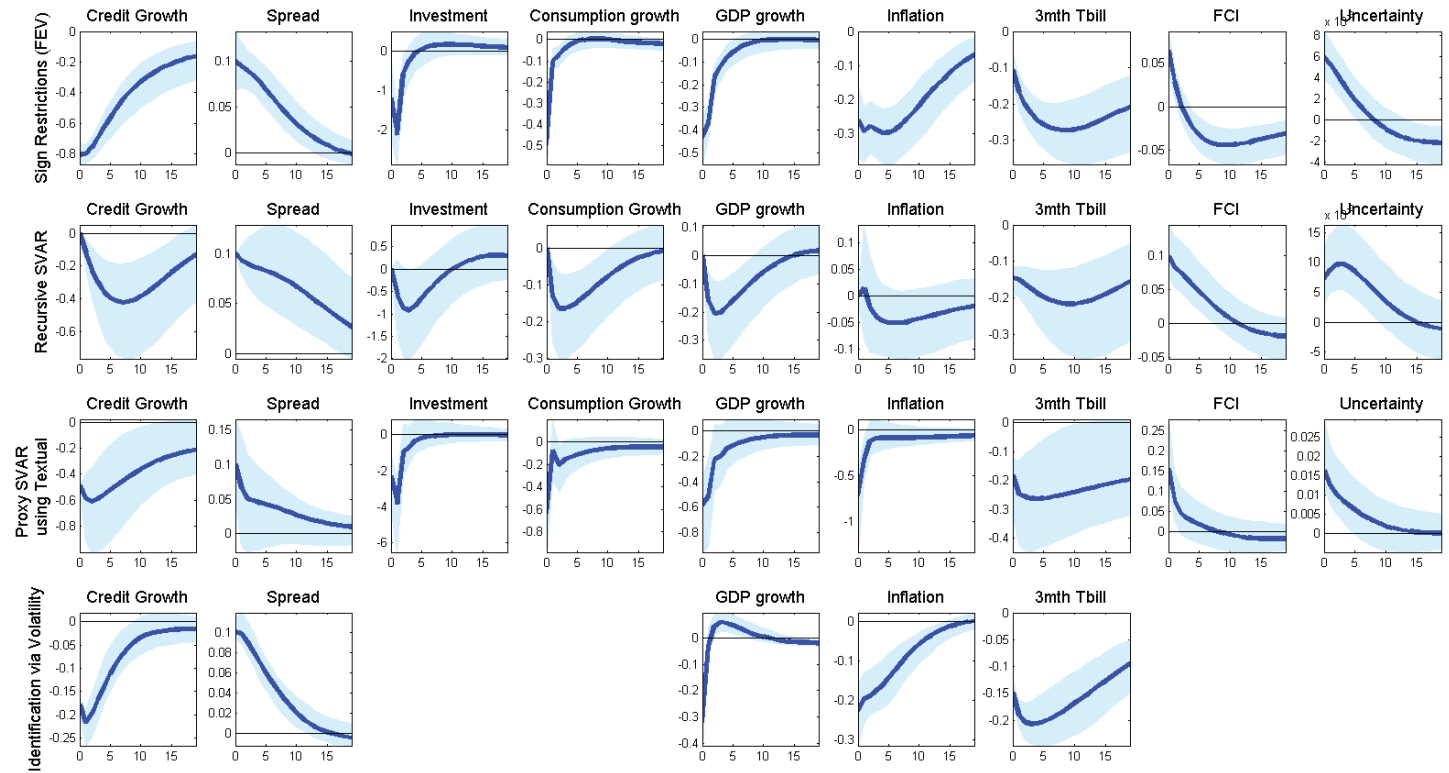


Figure 2: Impulse response to a credit supply shock from SVAR models. The shock is normalised to increase the spread by 0.1% on impact. The responses for all variables except FCI and the uncertainty index are in percentages. The responses for FCI and the uncertainty index are in the units of these variables. Sign restrictions (FEV) refer to the VAR with sign restrictions and the constraint on the contribution of the credit supply shock to the FEV.

	Credit	Spread	Investment	Consumption	GDP	Inflation	3mth Tbill	FCI	Uncertainty	
1 Q Ahead										
Sign Rest. (FEV)	80.3	16.1	1.4	24.8	13.2	8.6	9.4	11.3	15.1	
Recursive VAR	0.0	8.6	0.0	0.0	0.0	0.0	7.5	10.9	8.0	
Proxy VAR	10.2	5.7	7.2	18.7	10.9	23.5	10.2	36.1	49.0	
Heteroscedasticity	31.0	68.8			15.2	14.7	67.7			
Average	30.4	24.8	2.9	14.5	9.8	11.7	23.7	19.4	24.0	
4 Q Ahead										
Sign Rest. (FEV)	91.0	25.2	5.4	22.9	19.3	19.2	23.2	7.4	13.3	
Recursive VAR	2.0	9.0	0.5	1.6	1.7	0.9	7.8	10.9	9.0	
Proxy VAR	21.0	5.9	17.9	17.2	16.2	22.4	18.1	22.6	32.6	
Heteroscedasticity	33.5	73.1			14.3	26.4	77.8			
Average	36.9	28.3	8.0	13.9	12.9	17.2	31.7	13.6	18.3	
5 Y ahead										
Sign Rest. (FEV)	85.6	33.4	6.5	21.5	18.9	37.0	50.8	20.6	11.6	
Recursive VAR	7.4	10.6	1.6	3.3	3.2	2.0	12.1	9.1	8.0	
Proxy VAR	33.0	8.6	16.7	17.4	15.9	23.4	30.7	14.6	19.2	
Heteroscedasticity	29.1	64.8			15.5	35.5	76.9			
Average	38.8	29.3	8.3	14.1	13.4	24.5	42.6	14.8	12.9	

Table 2: Contribution of the credit supply shock to the forecast error variance

4.1.2 Recursive SVAR models

A number of proxies for credit supply shocks have been proposed in a growing empirical literature. As discussed above, a common approach is to include these proxies in a VAR and treat the orthogonalised shock to the proxy variable equation as an approximation of the credit supply shock. Prominent recent examples of such proxy variables include: (1) the excess bond premium (EBP) proposed in Gilchrist and Zakrajsek (2012), (2) the measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2012), (3) innovations to the financial conditions index calculated by Jermann and Quadrini (2012) and (4) the risk shock (CMR) from the DSGE model of Christiano et al. (2014).⁵ In addition to using these proxies, we propose a textual measure of credit supply shocks in the spirit of similar measures developed to estimate changes in uncertainty (see Baker et al. (2012)). This measure is based on a search for the words ‘credit crunch’ and ‘tight credit’ using 9 US newspapers.⁶ An index is then built by counting the number of occurrences of the words of interest. Note that as discussed in appendix B, these proxies are available for different periods over our main sample.

Figure 3 plots the credit shock proxies that described above. The temporal evolution of the proxies is similar with each pointing to tight credit conditions during the early and the mid-1980s, the early 1990s and 2000s and during the recent recession in 2009. We include each of these proxies in our VAR model and identify the credit supply shock via a Cholesky decomposition. We use a standard ordering of the variables following studies like Gilchrist and Zakrajsek (2012) – the shock proxy is ordered after investment, consumption growth, GDP growth, inflation and credit growth and before the spread, the short-term rate, FCI and uncertainty index. This ordering assumes, therefore, that the credit supply shock can have an immediate impact on financial variables and uncertainty but affects macroeconomic variables with a lag.

We show in section 3.1 of the on-line appendix that the median responses are similar in magnitude when the proxy is assumed to be EBP, CMR or BCDZ. Shocks to JQ and the textual proxy suggest a much smaller response of key variables like GDP growth. In addition, the model with EBP and the textual proxy produce large error bands and the null hypothesis of a zero response for all variables cannot be rejected. In the second row of figure 2, we show the average response from the models that produce non-zero responses over, at least, some of the horizon – i.e. the VAR that includes JQ, BCDZ and CMR. On average, the recursive VAR suggests that the decline in credit growth, inflation and real variables is smaller than suggested by the SVAR with sign restrictions. For example, the magnitude of the fall in investment, consumption and GDP growth is estimated to be about half of the decline suggested by the SVAR with sign restrictions. Note also that in the recursive model that the trough in the responses occurs after a year, a feature that is different from

⁵Of course, there are numerous other measures proposed in this literature. Our aim is to present results based on the most recent contributions.

⁶The newspapers included in the search are the Boston Globe, Chicago Tribune, Dallas Morning News, LA Times, Miami Herald, New York Times, San Francisco Herald, USA Today and the Washington post.

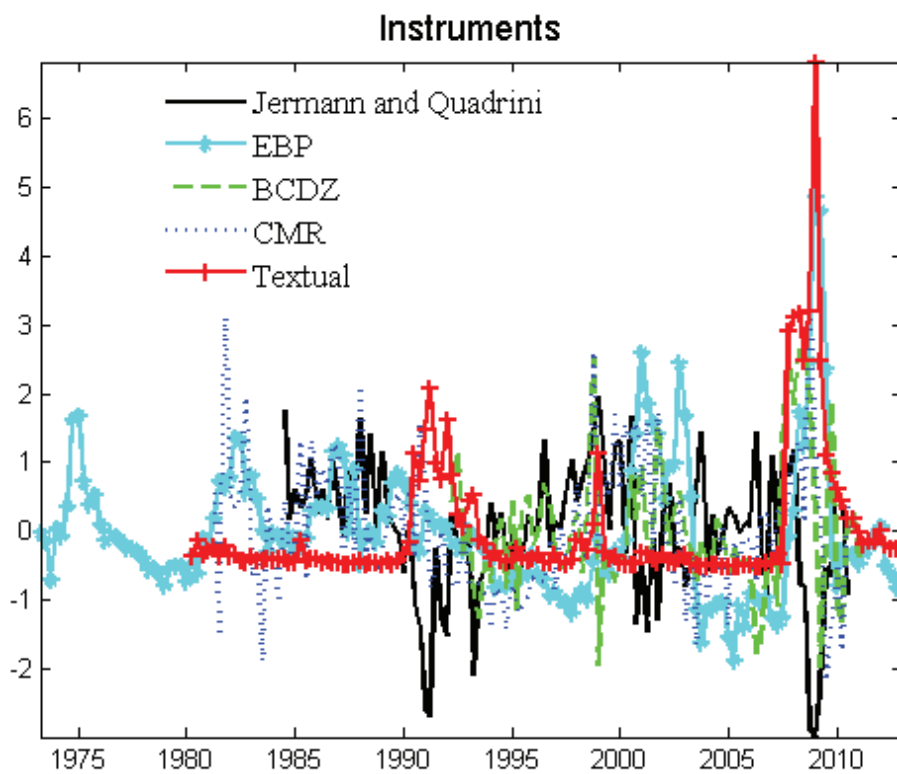


Figure 3: Proxies for credit supply shocks. Apart from the Jermann and Quadrini (2012) measure, higher values represent an adverse shock.

	R_M	F
JQ	0.50	13.1
EBP	0.10	2.36
BCDZ	0.15	3.5
CMR	0.2	3.82
Textual	0.18	5.5

Table 3: Reliability Statistic and the first stage F statistic for proxy variables

the results obtained via sign restrictions. This delayed effect appears to be the result of the zero restrictions imposed on impact on these variables. Note that variables that react contemporaneously to the credit shock (the short-term interest rate, FCI and the uncertainty index) have responses comparable in magnitude to those obtained from the SVAR with sign restrictions. This suggests that the assumptions inherent in the recursive identification scheme can have important implications for the magnitude and dynamics of the resulting responses. In addition, table 2 shows that the one year contribution of the credit supply shock to the FEV calculated using the recursive SVAR is substantially smaller for investment, consumption and GDP growth compared to other SVAR models.

4.1.3 Proxy SVAR models

Including these proxies directly in an SVAR can result in biased responses if the proxy is mis-measured. Given that the credit supply shock is unobserved, a degree of measurement error is inevitable. Therefore, we also consider proxy SVAR models that use these measures as instruments to identify the credit supply shock rather than endogenous variables in the VAR. In theory, one can use each of these as an instrument to estimate the proxy VAR model. However, these proxies differ in their ‘reliability’ as an instrument. We therefore proceed in two steps: we first analyse the suitability of each instrument and then use the best performing proxy in the final SVAR model.

We check the reliability of the instrument using two statistics. First, following Stock and Watson (2012), we consider the F-statistic in the ‘first-stage’ regression in equation 4. A large estimated value of the F-statistic is associated with a strong instrument. In addition we calculate the reliability statistic proposed by Mertens and Ravn (2012). The authors define reliability R_m as the squared correlation between the proxy variable and the underlying structural shock of interest. Their proposed estimator takes values between 0 and 1 with larger values indicating higher reliability.

Table 3 shows the estimated F statistic and the value of R_m for each instrument. The F-statistic and the reliability measure are estimated to be the highest for the measure proposed in Jermann and Quadrini (2012). The textual measure also appears to be a moderately strong instrument on the basis of the F-statistic but has a relatively low R_M .

It is interesting to consider the sample correlation between the shocks identified by each instrument. As discussed in Stock and Watson (2012), if two instruments are identifying

the same underlying shock, then the correlation of the estimated shock will be one in the population. A correlation matrix reported in section 3.2 of the on-line appendix shows that the credit shock estimated using the Jermann and Quadrini (2012) proxy is highly correlated with those obtained using the EBP and moderately correlated with the shock estimated using the textual measure. In contrast, this shock has a near-zero correlation with the innovation estimated using the BCDZ measure. This suggests that these two instruments potentially identify very different shocks. In contrast, the shock estimated using the textual measure displays a correlation of 0.4 to 0.8 with the remaining three estimates of this shock. This indicates the the shock identified using the textual measure shares common features with the shocks identified using the remaining proxies and is less likely to be related to a different economic concept.

As pointed out in Stock and Watson (2012), the possible correlation between the identified shock and other shocks (i.e. those identified using a different set of instruments) provides additional information on the strength of the identification of the shock of interest. In section 3.2 of the on-line appendix we consider the correlation between the credit shocks and estimates of a productivity shock, a monetary policy shock and an uncertainty shock, respectively. The productivity shock is identified by using the estimated productivity shock from the Smets and Wouters (2007) model. The monetary policy shock is estimated using the measure proposed in Romer and Romer (2004). Finally, innovations to the Baker et al. (2012) index (calculated as residuals to an AR(2) model) are used to identify the uncertainty shock. The estimated correlations suggest that the credit shock identified via the Jermann and Quadrini (2012) instrument has a correlation of 0.7 with the productivity and uncertainty shock. This suggests that this shock is not exclusively an innovation to credit supply, but instead is a composite of different economic innovations. In contrast, the credit supply shock estimated using the textual measure (which ranks second in terms of instrument strength) has a low correlation with the productivity and monetary policy shock and appears only moderately associated with the uncertainty shock.

In summary, the analysis of instrument strength in conjunction with the correlations described above suggest that the textual measure is a potential instrument to be used in the final SVAR model. While this instrument is not ranked the highest in terms of the F-statistic, there appears to be less evidence that the identified shock is related strongly to shocks other than credit supply. The same claim cannot be made about the shock identified via the Jermann and Quadrini (2012) instrument. We therefore use the textual proxy in the final model.

The third row of figure 2 presents the impulse responses obtained from the proxy SVAR using the textual proxy. The estimated decrease in inflation, investment, consumption and GDP growth is estimated to be larger than the estimates from the recursive SVAR and the SVAR with sign restrictions. The comparison with the recursive SVAR is especially interesting. Recall that when this proxy is added directly to the model and the shock identified via a Cholesky decomposition, the resulting responses are indistinguishable from zero. This again highlights the potential biases that may arise by using proxies directly and

the impact of assuming a recursive identification scheme.

The contribution of this shock to the FEV of GDP growth one year ahead (see table 2) matches the estimates obtained from the SVAR with sign restrictions but is substantially larger than the estimate from the recursive SVAR. Notice also that in this model the credit supply shock makes a sizeable contribution to the FEV of investment, FCI and the uncertainty measure, with these estimates larger than those obtained via the SVAR with sign restrictions.

4.1.4 Identification through heteroscedasticity

Due to computational constraints, we estimate a parsimonious version of the model containing only the key variables when considering identification of the credit supply shock through changes in the variance. The benchmark 9-variable VAR model has a large number of parameters and, given the limited time-series available, this makes it difficult to obtain reliable maximum likelihood estimates of the parameters. In particular, the error bands around the estimated impulse responses are very large. This latter problem makes it difficult to distinguish among impulse responses to different shocks and thus makes it harder to assign an economic interpretation to them. Given these concerns, we consider a five-variable VAR model that contains GDP growth, CPI inflation, credit growth, spread and the short-term interest rate and allow for the possibility of up to three regimes.

The number of regimes is an important specification choice for this model. As shown in section 3.3 of the on-line appendix, model selection criteria such as Akaike, Schwarz and the deviance information criteria clearly reject a linear VAR model, and suggest that a three regime model fits the data best. There is also some evidence that the assumption of a state-invariant contemporaneous impact matrix is supported by the data. After estimating the three-regime VAR model, we investigate if the diagonal elements of Λ_2 or Λ_3 are distinct, i.e. we check the condition for identification. As shown in the on-line appendix (section 3.3), there is fairly strong evidence that this condition is satisfied. Next, we examine the impulse responses to the five shocks in the model in order to label them from an economic point of view. It is clear that the shock to the spread equation produces responses that are consistent with those obtained from the DSGE model. The responses to other shocks, on the other hand, are not consistent with theory. With this evidence in mind, we label this shock the credit supply shock.

The bottom row of figure 2 plots the estimated responses to the credit supply shock. The GDP growth, inflation and T-Bill response displays persistence similar to that obtained from SVAR with sign restrictions, but appears less persistent than the estimates from the recursive and proxy SVARs. In terms of magnitude, the contemporaneous estimates are close to the peak estimates from the recursive SVAR and the VAR with sign restrictions, but generally smaller than those obtained from the proxy SVAR model. The bounce-back in GDP growth two quarters after the shock implies that the cumulative impact of the shock is estimated to be much smaller in this model.

While the contribution of this shock to the FEV of GDP growth and inflation is broadly

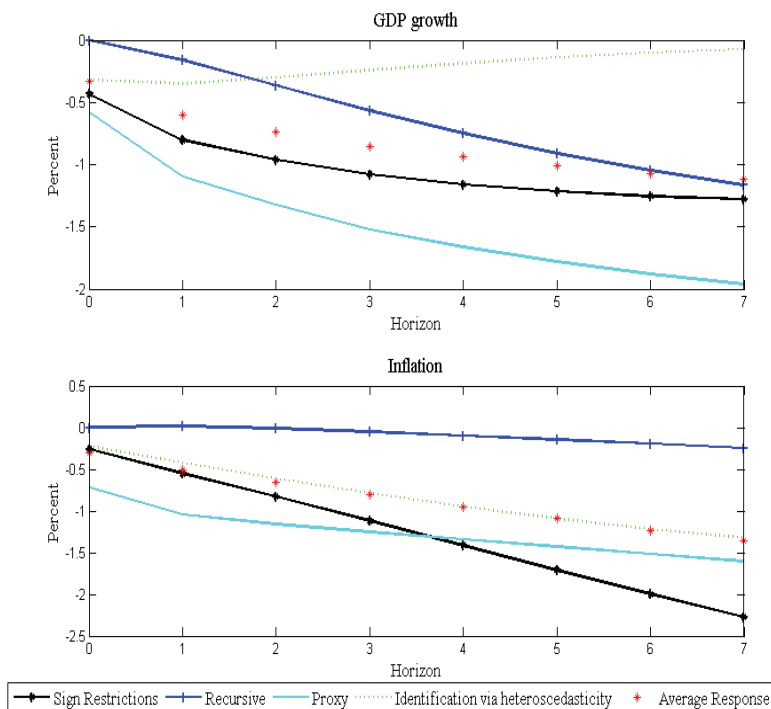


Figure 4: The cumulated impulse response of GDP and inflation a credit supply shock. The shock is normalised to increase the credit spread at the one year horizon.

similar to the VAR with sign restrictions and the proxy SVAR, the shock estimated from the switching VAR appears to be substantially more important for the spread and the short-term interest rate (see table 2).

4.2 How big is the impact of the credit supply shock?

Figure 4 shows a comparison of the cumulated responses of GDP growth and inflation to a credit supply shock obtained from the four SVAR models. We focus on these two variables as these are of primary interest to policy makers. Consider the response of GDP growth. It is clear that at the one year horizon, the proxy SVAR and VAR with sign restrictions suggest a fairly similar total response of GDP of around -1.2% to -1.7%. The average response from the recursive SVARs suggests a smaller decline in GDP at this horizon, estimated at 0.75%. As noted above, this may reflect the zero restriction on the contemporaneous response imposed under this scheme or a possible attenuation bias resulting from errors in variables. Finally, notice that the VAR identified via heteroscedasticity indicates the smallest response of GDP growth at this horizon, estimated at -0.2%. Given that the initial response of GDP from this model is broadly in line with estimate from the SVAR with sign restrictions, the difference at longer horizons appears to be driven by the fact that the estimated response from the

switching VAR is much less persistent than suggested by the other models.

At the one year horizon, the cumulated response of inflation from the proxy SVAR and the VAR with sign restrictions is the largest suggesting a decline in inflation of about 1.4%. As in the case of GDP growth, the recursive and the heteroscedastic VAR, indicate a smaller response ranging from -0.1% in the former case to -0.9% in the latter.

On average across models, a credit supply shock that raises the spread by 10 basis points leads to a cumulative decline of 0.94% in annualised GDP growth one year after the shock. The average decline in inflation at this horizon is similar and estimated at 0.95%. The FEV decomposition in table 2 suggests that, on average, the credit supply shock explains about 13% of the FEV of GDP growth and 17% of the FEV of inflation at the one year horizon.

While the uncertainty around these estimates is large, these average results are largely driven by the impulse responses from VAR models that perform well in the Monte-Carlo experiment conducted above. Therefore, on balance, we can conclude that , ceteris paribus, the credit supply shock can have large effects on the macroeconomy.⁷

⁷When the main models are estimated using pre-Great Recession data, the average impact of the credit supply shock on GDP growth and inflation is fairly similar to the benchmark. See section 4 in the online appendix.

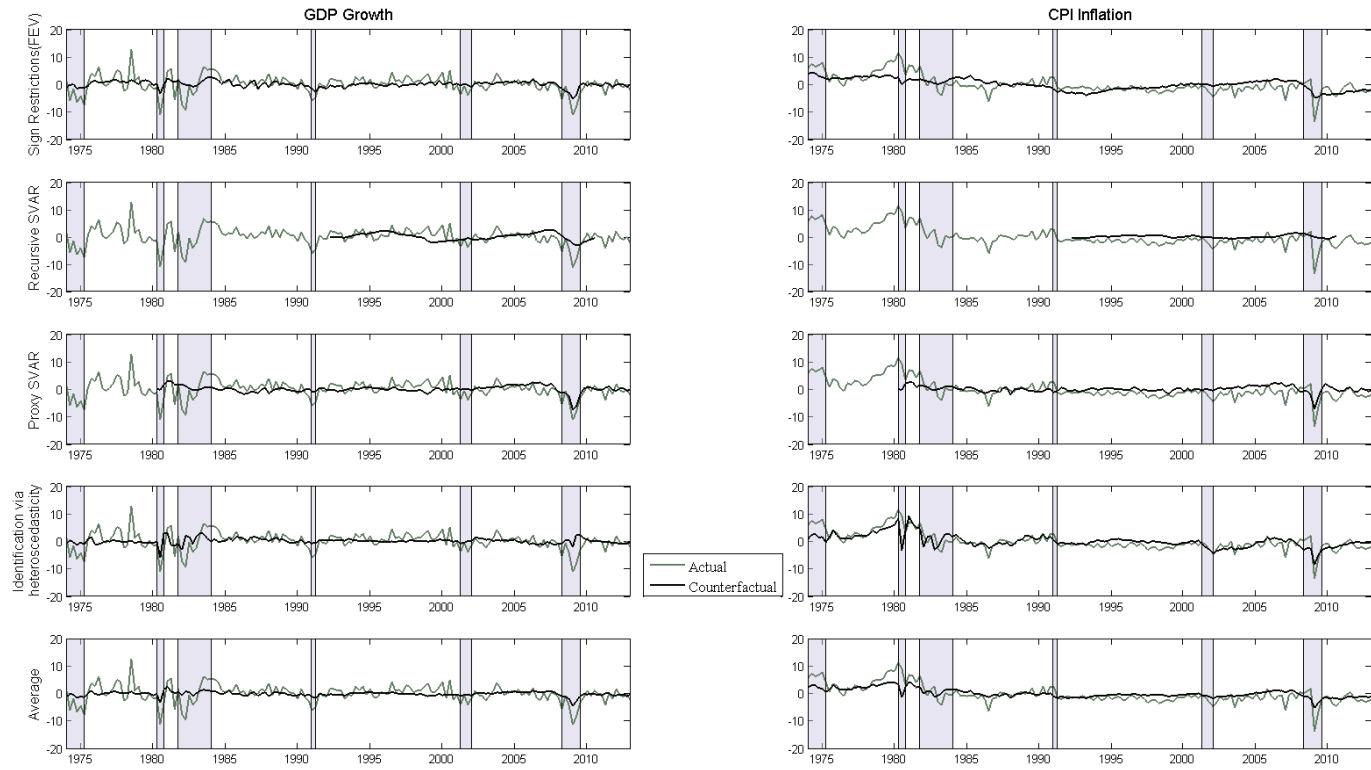


Figure 5: Historical decomposition of GDP growth and inflation using the SVAR models. Shaded areas represent NBER recession dates.

How important was the credit supply shock in driving GDP growth and inflation over the recent past? Figure 5 plots the data on these variables, together with the counterfactual estimates of the data from the four SVAR models under the assumption that only the identified credit supply shock is operational. The SVAR with sign restrictions and the heteroscedastic VAR suggest that the credit supply shock played a role in the decline of GDP during the two recessions of the early 1980s, with the latter model also indicating that this shock was important in driving inflation over that period. Similarly, there is some indication that during the recession following the savings and the loans crisis during the late 1980s, the credit supply shock makes a contribution to the downturn in GDP growth. However, it is during the Great Recession that the contribution of this shock appears to be largest as indicated by all models. In fact, the average estimates in the last row of the figure suggest that the trough of the decline in GDP growth in 2009 would have been halved if the credit supply shock was absent. Similarly, the sharp decline in inflation over this period would have been ameliorated, if the impact of this shock was absent.

It is interesting to note that the estimated magnitude of the effects on key variables are fairly similar to those obtained by recent DSGE based studies (see for example Gerali et al. (2010), Del Negro et al. (2013), Christiano et al. (2014) and Del Negro et al. (ress) among others).⁸ The average dynamic effect of the credit supply shock on GDP growth implied by the SVAR analysis seems to lie well within the range of estimates implied by the above DSGE studies. However, the SVAR inflation response is higher than what it is implied by DSGE models. The theoretical inflation response to a credit supply shock tends to depend crucially on the specification of the model. For instance, the absence of financially constrained households reduces the demand effect on inflation (as consumption is the largest GDP component) and, consequently, leads to a smaller inflation reaction relative to the case where these agents exist in the model (see(Pinter et al., 2013)). The analysis of Del Negro et al. (ress) illustrates that the slope of the price Philips curve also influences the inflation response after a shock. Furthermore, in the presence of working capital type frictions (see (Gerali et al., 2010)) inflation can increase after a negative credit supply shock. Christiano et al. (2014) show that credit supply shocks have played a significant role in explaining GDP historically. Interestingly, the importance of the shock rises during the recessions and this is also supported by the analysis in Gerali et al. (2010) for the great recession. Clearly, these results are in line with the SVAR inference.

5 Conclusions

A growing empirical literature has proposed several SVAR models to estimate the impact of innovations in credit supply. In this paper we examine the performance of these SVAR models and try to establish a consensus view of the importance of credit supply shocks. Using a Monte-Carlo experiment, we find that the SVAR with sign and FEV restrictions

⁸By a credit supply shock we refer only to the unanticipated component of the ‘risk’ shock in Christiano et al. (2014)

and the Proxy SVAR model can recover the true impulse responses to credit supply fairly accurately. Identification through heteroscedasticity is found to work well when the credit supply shock is sufficiently volatile. In contrast, the recursive identification scheme suffers from a myriad of inaccuracies and biases.

When applied to a US dataset, the SVAR models that perform well in the Monte-Carlo experiment suggest, on average, that the impact of credit supply shocks is fairly large and in line with DSGE based evidence. A shock that raises the spread by 10 basis points is found to have a cumulated negative impact of about 1% on GDP growth and inflation at the one year horizon. At this horizon, the shock explains about 13% of the FEV of GDP growth and 17% of the FEV of inflation on average across the SVAR models. The historical decomposition suggests that the credit supply shock was responsible for a large proportion of the decline in GDP growth and inflation during the great recession.

These results have important implications for policy makers. If the use of interest rates is less effective in mitigating the impact of credit supply changes, then, given the large estimated impact of this shock, monetary authorities may need to develop policy tools that specifically address this problem. There has been some progress on this front, with central banks like the Bank of England introducing direct schemes to encourage bank lending. One interesting avenue of future research is to model the transmission mechanism of such policies and investigate their effectiveness in stimulating credit supply.

6 Appendix A: Data

- Loans to nonfinancial private sector Source: Flow of Funds Accounts of the United States: www.federalreserve.gov/releases/z1/current/

This is constructed as the sum of nominal outstanding amounts of loans to households (flow of funds series FL154104005.q minus flow of funds series FL163162005.q) and loans to non-financial corporations (flow of funds series FL144104005.q minus sum of FL103169100.q, FL103163003.q and FL103162005.q).

- Composite lending rate This is constructed using the data sources and method described in appendix b of Gambetti and Musso (2012).
- Macroeconomic and financial data: This data is obtained from Federal Reserve economic data (FRED). The FRED codes are as follows: (1) Real GDP GDPC96, (2) CPI: CPIAUCSL, (3) 3-Month Treasury Bill Rate: TB3MS, (4) Real Private Investment : GDPIC96, (5) Real consumption expenditure (PCECC96), (6) Chicago Fed National Financial Conditions Index, (7) The Uncertainty index is taken from Jurado et al. (2013).
- Instruments for the proxy VAR: (1) The excess bond premium (EBP) is taken from Gilchrist and Zakrajsek (2012) (data periods 1973Q1 to 2012Q4), (2) the measure of

bank lending shocks (BCDZ) is defined in Bassett et al. (2012) (data periods 1992Q1 to 2010Q4), (3) innovations to the financial conditions index (JQ) is calculated by Jermann and Quadrini (2012) (data periods 1984Q2 to 2010Q2) and the risk shock (CMR) is taken from the DSGE model of Christiano et al. (2014) (1981Q1 to 2010Q1). In addition, we calculate a textual measure of credit supply shocks in the spirit of similar measures developed to estimate changes in uncertainty (see Baker et al. (2012)) (data periods 1980Q1 to 2012Q4).

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What do VARs tell us about the impact of a credit supply shock? An empirical analysis (Technical Appendix)

Haroon Mumtaz
Queen Mary College

Gabor Pinter
Bank of England

Konstantinos Theodoridis
Bank of England

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Contents

1	DSGE Model	1
2	Detailed Monte-Carlo results	2
2.1	Sign Restrictions	2
2.2	Sign Plus Forecast Variance Restrictions	5
2.3	Identification Through Heteroscedasticity	7
2.4	Recursive Identification	10
2.5	Proxy SVAR	12
3	Detailed SVAR results	13
3.1	Recursive VAR	13
3.2	Proxy VAR	16
3.3	Identification via heteroscedasticity	20
3.3.1	Estimation	20
3.3.2	Model Selection	20
4	Estimation before the great recession	29

1 DSGE Model

We use a medium-scale monetary DSGE model developed by Gertler and Karadi (2011) where financial intermediaries take a centre stage. The economy is populated by five agents: households, financial intermediaries, intermediate goods producers, retailers, and capital goods producers. By assumption, households are limited to saving via the banking system owing to prohibitively large costs associated with direct intermediation to firms. Intermediate goods producers, in turn, are reliant on bank loans to finance the physical capital, which they purchase from capital producers,

who are subject to investment adjustment costs. Intermediate goods producers combine capital with labour, provided by households, to produce wholesale goods, which are bought and repackaged by monopolistically competitive retailers. Retailers are subject to Calvo-type pricing and backward indexation rules. All profits in the economy are ultimately repaid to households.

The representative household consists of “workers” and “bankers”. Workers supply labour and return their wages to the household. Bankers manage financial intermediaries and return non-negative dividends to the household. The fraction of the household who save, do not directly provide funds to producers, but they supply savings to banks other than the ones they own. Savings take the form of riskless short term deposits. Household deposits together with banker’s own net worth form banks’ liabilities, which finances the purchase of financial claims on producers.

The heart of the model is a moral hazard problem between depositors and banks, which means that at the beginning of the period the banker can choose to divert a fraction θ of available funds from the project, and transfer them back to the household, in which case depositors would recover the remaining $1 - \theta$ fraction of assets. In order for depositors to continue to supply funds, the bank’s franchise value must be sufficiently large to satisfy the incentive constraint. The bank’s optimality condition pins down the optimal leverage ratio, at which point the banker’s incentive to divert assets is exactly offset by the cost of bankruptcy. To model credit shock is the capital quality shock, originally studied by Gertler and Karadi (2011). This shock destroys a fraction of the productive capital stock, which, since claims on capital are held on the balance sheets of banks, imposes losses directly on financial intermediaries leading to a fall in credit supply and a rise in spreads.

Table 1 lists the set of parameters values for the baseline simulation. We follow Gertler and Karadi (2011) in setting both the conventional parameters and the parameters specific to the credit friction of the model. The standard deviation of the shocks is set to 0.01. Tables 2 and 3 report the first order conditions of agents’ optimisation problems.

To check whether the sign restrictions implied by the Gertler and Karadi (2011) model are robust to different parameterisation, we compute the impulse responses for 34992 number of models using the following parameter grids: $h = [0.1, 0.4, 0.815]$, $\varphi = [0.276, 1.2, 2.2]$, $\zeta = [3.2, 5.2, 7.2]$, $\theta = [0.87, 0.97]$, $\eta_i = [0.728, 1.728, 2.728]$, $\gamma = [0.35, 0.779]$, $\psi = [0.1, 0.241, 0.5]$, $\phi^{\Pi} = [1.1, 1.5, 1.9]$, $\phi^X = [0, -0.25]$, $\rho_i = [0, 0.4, 0.8]$, $\rho_{\xi} = [0, 0.66]$. Figure 1 plots the 20-80 (dark gray) and 10-90 (light gray) percentiles of the set of impulse responses together with the median (circled line).

2 Detailed Monte-Carlo results

2.1 Sign Restrictions

As mentioned, above a number of recent papers have used sign restrictions in an attempt to identify credit supply shocks. For example, Gambetti and Musso (2012) estimate the following type of VAR model

$$Y_t = c + \sum_{j=1}^P B_j Y_{t-p} + A_0 \varepsilon_t \quad (1)$$

where Y_t is a matrix of endogenous variables. The structural shocks ε_t are related to the VAR residuals u_t via the relation $A_0 \varepsilon_t = u_t$ where A_0 is a matrix such that $VAR(u_t) = \Omega = A_0 A_0'$.

The algorithm to find A_0 proceeds by first calculating \hat{A}_0 an arbitrary matrix square root of Ω . Then a candidate A_0 is found by multiplying \hat{A}_0 with a rotation matrix and checking if the

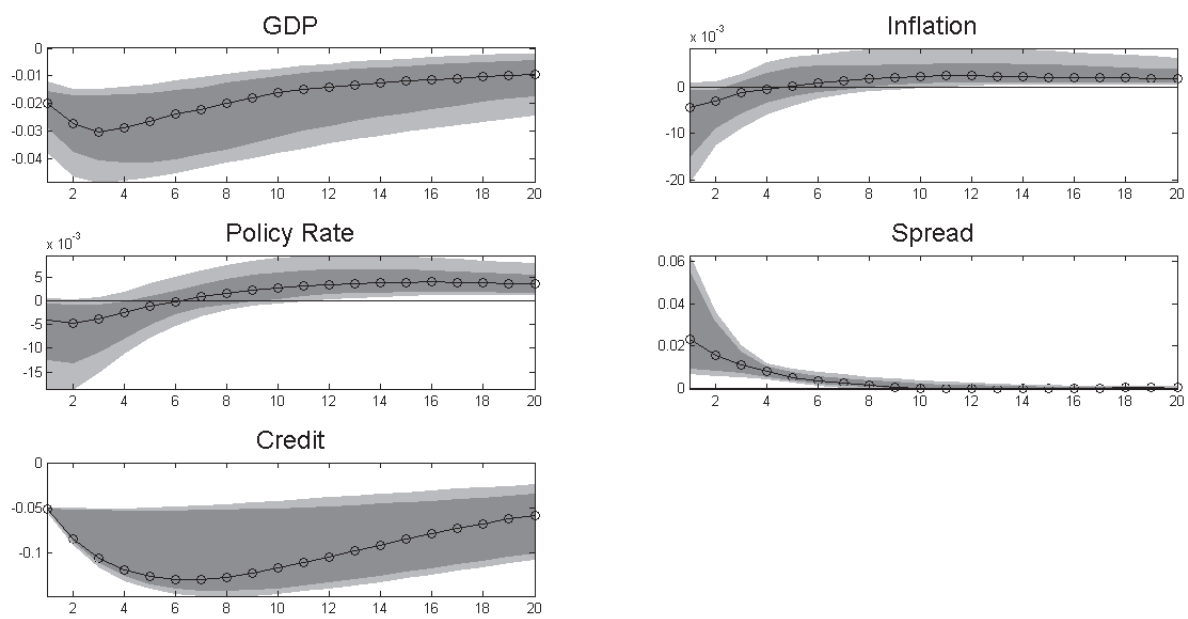


Figure 1: Robustness of sign restrictions

Table 1: DSGE Model Parameters

Parameters	Description	Value
β	Discount rate	0.990
σ	Intertemporal elasticity of substitution	1.000
h	Consumption habit parameter	0.815
χ	Relative utility weight of labor	3.410
φ	Inverse Frisch elasticity of labor supply	0.276
θ	SS fraction of capital that can be diverted by the bank	0.381
ω	Proportional transfer to the entering local bankers	0.002
λ	Survival rate of bankers	0.972
α	Capital share	0.330
δ	Depreciation rate	0.020
η_i	Inverse elasticity of net investment to the price of capital	1.728
ζ	Elasticity of depreciation wrt. utilization	7.200
b	Relative utilisation weight	0.037
G_{ss}	Steady state government consumption	0.169
ε	Elasticity of substitution between final goods	4.167
γ	Calvo parameter	0.779
ψ	Price indexation parameter	0.241
ρ_m	Interest rate smoothing parameter	0.800
ϕ^Π	Inflation coefficient in the monetary policy rule	1.500
ϕ^X	Mark-up coefficient in the monetary policy rule	-0.125
ρ_k	Persistence: capital quality shock	0.660
ρ_a	Persistence: TFP shock	0.950
ρ_g	Persistence: government spending shock	0.950
σ_k	SD: capital quality shock	0.010
σ_a	SD: TFP shock	0.010
σ_g	SD: government spending shock	0.010
σ_b	SD: bank net worth shock	0.010
σ_m	SD: monetary policy shock	0.010

impulse responses using this candidate structural impact matrix satisfy the sign restrictions. Note that this algorithm delivers a *set* of A_0 matrices and impulse responses that are admissible under the identification scheme. The sign restrictions used in the simulations here are given by Table 4 and they are ‘robust’ based on Canova and Paustian (2011) methodology.

Figure 2 illustrates that sign restrictions are able to identify the true structural shock on average. However, the set of admissible responses is quite wide and thus complicating inference. This is a well known problem in the applied literature (Paustian, 2007; Uhlig, 2005; Fry and Pagan, 2011) and several approaches have been suggested to overcome this problem (such as the use of *i*) a penalty function Uhlig (2005); Liu and Theodoridis (2012) or/and *ii*) quantity type restrictions Kilian and Murphy (2012)).

Table 2: DSGE Model Equations

Description	Equation
Marginal Utility of Consumption	$\lambda_t = (C_t - hC_{t-1})^{-\sigma} + \beta h \mathbb{E}_t (C_{t+1} - hC_t)^{-\sigma}$
Marginal Disutility of Labour	$u_t^L = \chi L_t^\varphi$
Euler-equation	$\mathbb{E}_t \Lambda_{t,t+1} R_t = 1$
Labour-supply condition	$W_t = u_t^L / \lambda_t$
Stochastic Discount Factor	$\Lambda_{t,t+1} = \mathbb{E}_t \beta \lambda_{t+1} / \lambda_t$
Production Function	$Y_{m,t} = A_t (U_t \xi_t K_t)^\alpha L_t^{1-\alpha}$
Optimal Capacity Utilisation	$P_{m,t} \alpha \frac{Y_{m,t}}{U_t} = \delta' (U_t) \xi_t K_t$
Labour Demand	$P_{m,t} (1 - \alpha) \frac{Y_{m,t}}{L_t} = W_t$
Investment Demand	$Q_t = 1 + \frac{\eta_i}{2} \left(\frac{I_t^n + I_{ss}}{I_{t-1}^n + I_{ss}} - 1 \right)^2 + \eta_i \left(\frac{I_t^n + I_{ss}}{I_{t-1}^n + I_{ss}} - 1 \right) \frac{I_t^n + I_{ss}}{I_{t-1}^n + I_{ss}}$ $- \mathbb{E}_t \Lambda_{t,t+1} \eta_i \left(\frac{I_{t+1}^n + I_{ss}}{I_t^n + I_{ss}} - 1 \right) \left(\frac{I_{t+1}^n + I_{ss}}{I_t^n + I_{ss}} \right)^2$
Return on Capital	$R_{t+1}^K = \mathbb{E}_t \left[P_{m,t} \alpha \frac{Y_{m,t+1}}{\xi_{t+1} K_{t+1}} + Q_{t+1} - \delta (U_{t+1}) \right] \xi_{t+1} / Q_t$
Spread	$S_t = \frac{R_{t+1}^K}{R_t}$
Deposit	$D_t = Q_t K_t - N_t$
Capital Accumulation	$K_{t+1} = \xi_t K_t + I_t^n$
Depreciation Rate	$\delta (U_t) = \delta_c + \frac{b}{1+\zeta} U_t^{1+\zeta}$
Net Investment	$I_t^n = I_t - \delta (U_t) \xi_t K_t$
Aggregate Resource Constraint	$Y_t = C_t + I_t + \frac{\eta_i}{2} \left(\frac{I_t^n + I_{ss}}{I_{t-1}^n + I_{ss}} - 1 \right)^2 (I_t^n + I_{ss}) + G_t$
Value of Firms' Capital	$\nu_t = \mathbb{E}_t \left\{ (1 - \lambda) \Lambda_{t,t+1} (R_{t+1}^K - R_t) + \Lambda_{t,t+1} \lambda x_{t+1} \nu_{t+1} \right\}$
Value of Firms' Net Worth	$\eta_t = \mathbb{E}_t \left\{ (1 - \lambda) + \mathbb{E}_t \Lambda_{t,t+1} \lambda z_{t+1} \eta_{t+1} \right\}$
Optimal Leverage	$\phi_t = \frac{\eta_t}{\theta - \nu_t}$
Growth Rate of Bank Net Worth	$z_t = N_t / N_{t-1} = (R_t^K - R_{t-1}) \phi_{t-1} + R_{t-1}$
Growth Rate of Bank Capital	$x_t = \frac{\phi_t}{\phi_{t-1}} z_t$

2.2 Sign Plus Forecast Variance Restrictions

In this section we show that when the sign restrictions from the previous section are combined with quantity – forecast variance decomposition – restrictions then the process of identifying the structural shock from the set of VAR residuals improves dramatically. To be precise, in addition to the sign restrictions employed in the previous exercise (Table 4) we further impose in this case that the first column of A_0 maximises its forecast variance contribution on the credit variable over the horizon between 0 to 40 quarters.

This means that we solve the following optimisation problem

$$\omega^* = \arg \max_{h=0}^{40} \Omega_{i,j}(h) = \arg \max_{h=0}^{40} \frac{e_i' \left(\sum_{\tau=0}^h B_\tau \tilde{A}_0 Q(\omega) e_j e_j' Q(\omega)' \tilde{A}_0' B_\tau \right) e_i}{e_i' \left(\sum_{\tau=0}^h B_\tau \Sigma B_\tau \right) e_i}, \quad (2)$$

Table 3: DSGE Model Equations (continues)

Description	Equation
Aggregate Capital	$Q_t K_t = \phi_t N_t$
Banks' Net Worth	$N_t = N_t^E + N_t^N$
Existing Banks' Net worth	$N_t^E = \lambda N_{t-1} z_t \varepsilon_t^b$
New Banks' Net Worth	$N_t^N = \omega Q_t \xi_t K_{t-1}$
Wholesale Output	$Y_t = Y_{m,t} J_t$
Price Dispersion	$J_t = \gamma J_{t-1} \Pi_{t-1}^{-\psi \varepsilon} \Pi_t^\varepsilon + (1 - \gamma) \left(\frac{1 - \gamma \Pi_{t-1}^{\psi(1-\gamma)} \Pi_t^{\gamma-1}}{1 - \gamma} \right)^{-\frac{\varepsilon}{1-\gamma}}$
Mark-up	$X_t = 1/P_{m,t}$
CPI Inflation	$\Pi_t^{1-\varepsilon} = (1 - \gamma) (\Pi_t^*)^{1-\varepsilon} + \gamma \left(\Pi_{t-1}^\psi \right)^{1-\varepsilon}$
Inflation I	$f_{1,t} = Y_t P_{m,t} + \mathbb{E}_t \Lambda_{t,t+1} \gamma \left(\Pi_t^{-\psi \varepsilon} / \Pi_{t+1}^{-\varepsilon} \right) f_{1,t+1}$
Inflation II	$f_{2,t} = Y_t + \mathbb{E}_t \Lambda_{t,t+1} \gamma \left(\Pi_t^{\psi(1-\varepsilon)} / \Pi_{t+1}^{1-\varepsilon} \right) f_{2,t+1}$
Inflation III	$\Pi_t^* = \frac{\varepsilon}{\varepsilon-1} \frac{f_{1,t}}{f_{2,t}} \Pi_t$
Fisher-equation	$R_t^n = R_t \mathbb{E}_t \Pi_{t+1}$
Monetary Policy Rule	$R_t^n = [R_{t-1}^n]^{\rho_i} \left[\frac{1}{\beta} (\Pi_t)^{\phi^\pi} \left(\frac{\varepsilon-1}{\varepsilon} X_t \right)^{\phi^X} \right]^{1-\rho_i} \varepsilon_t^m$
Government Spending Shock	$G_t = G^{SS} e^{g_t}, \quad g_t = \rho_g g_{t-1} + \varepsilon_t^g$
TFP Shock	$A_t = e^{a_t}, \quad a_t = \rho_a a_{t-1} + \varepsilon_t^a$
Capital Quality Shock	$\xi_t = e^{s_t}, \quad s_t = \rho_\xi s_{t-1} + \varepsilon_t^\xi$

Table 4: Sign Restrictions

	GDP	Inflation	Policy Rate	Spread	Credit
Credit Supply Shock	+	+	+	-	+

subject to

$$Q(\omega) Q(\omega)' = I, \quad (3)$$

$$\text{sign}(S \tilde{A}_0 Q(\omega)) = \Upsilon \text{ or } \text{sign}(S \tilde{A}_0 Q(\omega)) = -\Upsilon \quad (4)$$

where ω is a vector of angles ($\omega \in (0, \pi]$) and S is a selector matrix that has 1s in elements corresponding to restricted elements, and 0s elsewhere, sign refers to the signum function, which maps real positive elements to 1s, and real negatives to -1s, Υ is a matrix that has -1s where the IRF is restricted to be negative, 1s for elements restricted to be positive, and 0s elsewhere. The Matlab built in *fminsearch* function is used to carry out the minimisations. For each minimisation we find first – via random draws – 100 $Q(\omega)$ matrices that satisfy the sign restrictions and from these 100 matrices we use as a starting point for the minimisation the one that maximises the objective function.

Figure 3 shows that the the set of admissible responses decreases dramatically and, therefore, makes the inference more useful. The intuition of what drives this improvement is simple, from

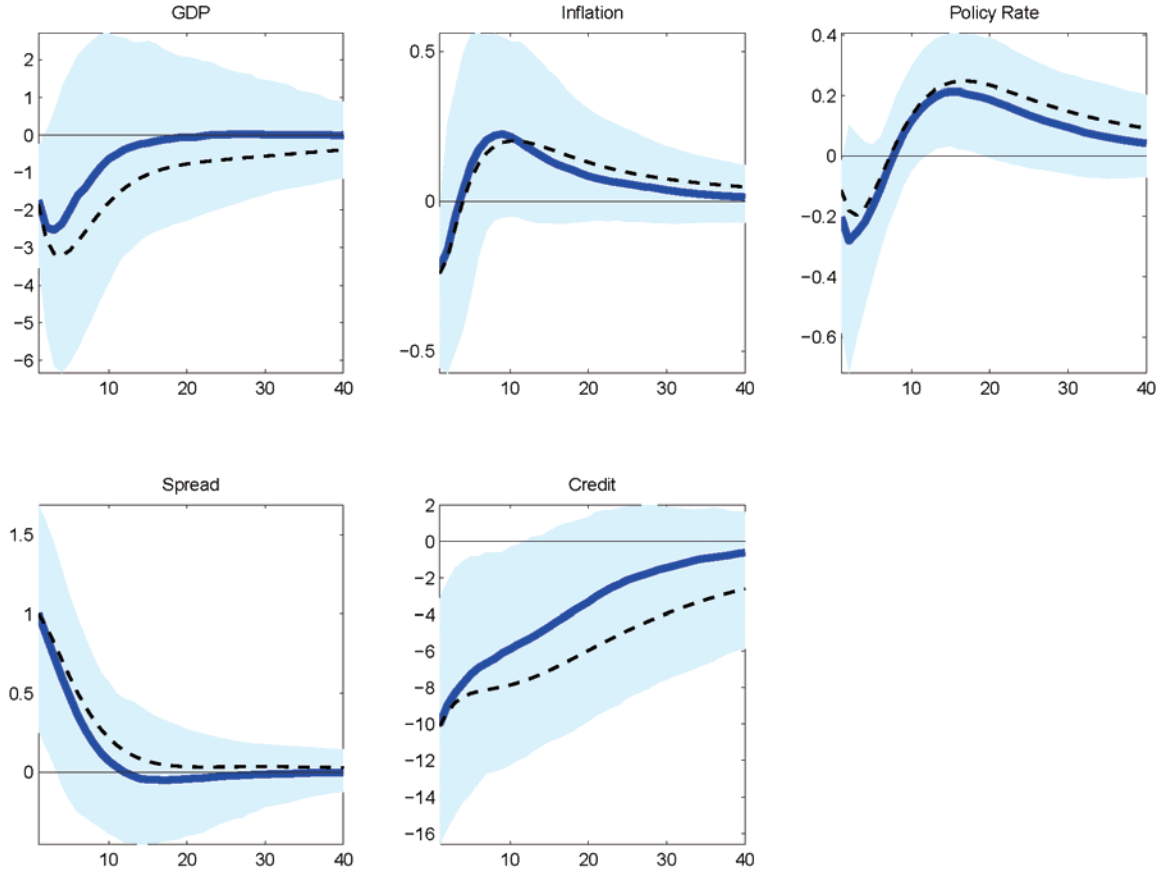


Figure 2: The shadow area and the blue solid thick line reflect the 90% simulation interval and the median, respectively. The black dashed line illustrates the DSGE model response. The shock is normalised to increase the spread by 1% on impact.

this large set of credit supply shocks we only ‘care’ for those exogenous disturbances that could be viewed as the main drivers of credit.

2.3 Identification Through Heteroscedasticity

Lanne et al. (2010) argue that when the structural shocks are heteroscedastic but structural parameters (including the persistence of structural shocks) are invariant (the study of Sims and Zha (2006) provides significant empirical support for this hypothesis) then there exist sufficient restrictions to uniquely identify A_0 . For instance, let us assume that there are two – a low and a high – uncertainty regimes

$$\Omega_L = A_0 \Lambda_L A_0' \quad (5)$$

$$\Omega_H = A_0 \Lambda_H A_0' \quad (6)$$

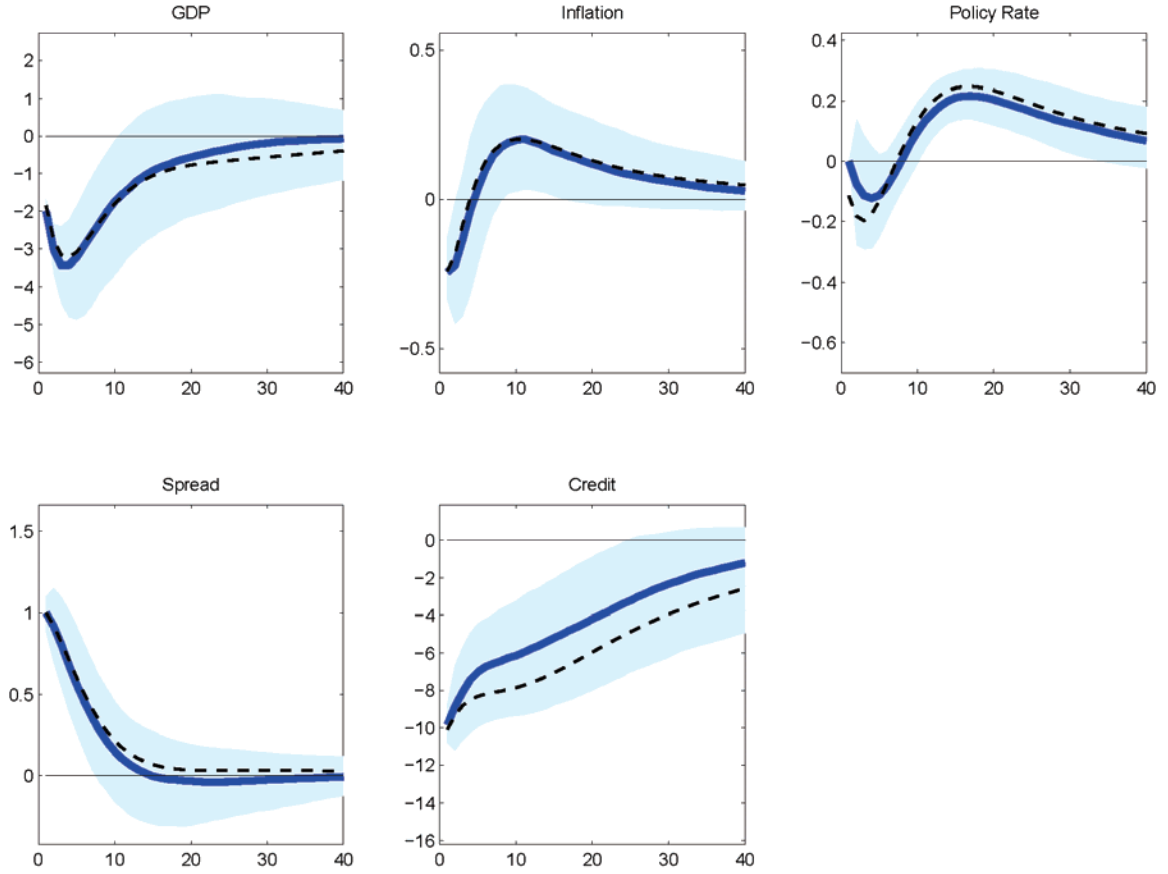


Figure 3: The shadow area and the blue solid thick line reflect the 90% simulation interval and the median, respectively. The black dashed line illustrates the DSGE model response. The shock is normalised to increase the spread by 1% on impact.

where Λ_j ($j = L, H$) is a diagonal matrix, we assume further that Λ_L is the identity matrix (normalised) and the diagonal elements of Λ_H are larger than the diagonal elements of Λ_L and that these elements are distinct ($\Lambda_H(i, i) \neq \Lambda_H(k, k)$).

$$\Omega_L = A_0 A_0' \quad (7)$$

$$\Omega_H = A_0 \Lambda_H A_0' \quad (8)$$

The system in this case consists of $K(K+1)$ equations that it can be uniquely solved for the K^2 elements of A_0 and the K diagonal elements of Λ_H .

To assess the performance of this scheme we simulate data from a Markov Switching version of the DSGE model and we use for this purpose RISE; a toolkit for Markov Switching DSGE models developed by J. Maih (Maih, 2015). The variances of the structural shocks are allowed to follow a Markov Switching of order 1 process. In other words, there are two – a low and a high uncertainty

– regimes that evolve stochastically and the probability switching from the low to high uncertainty regime is 15% and vice versa.

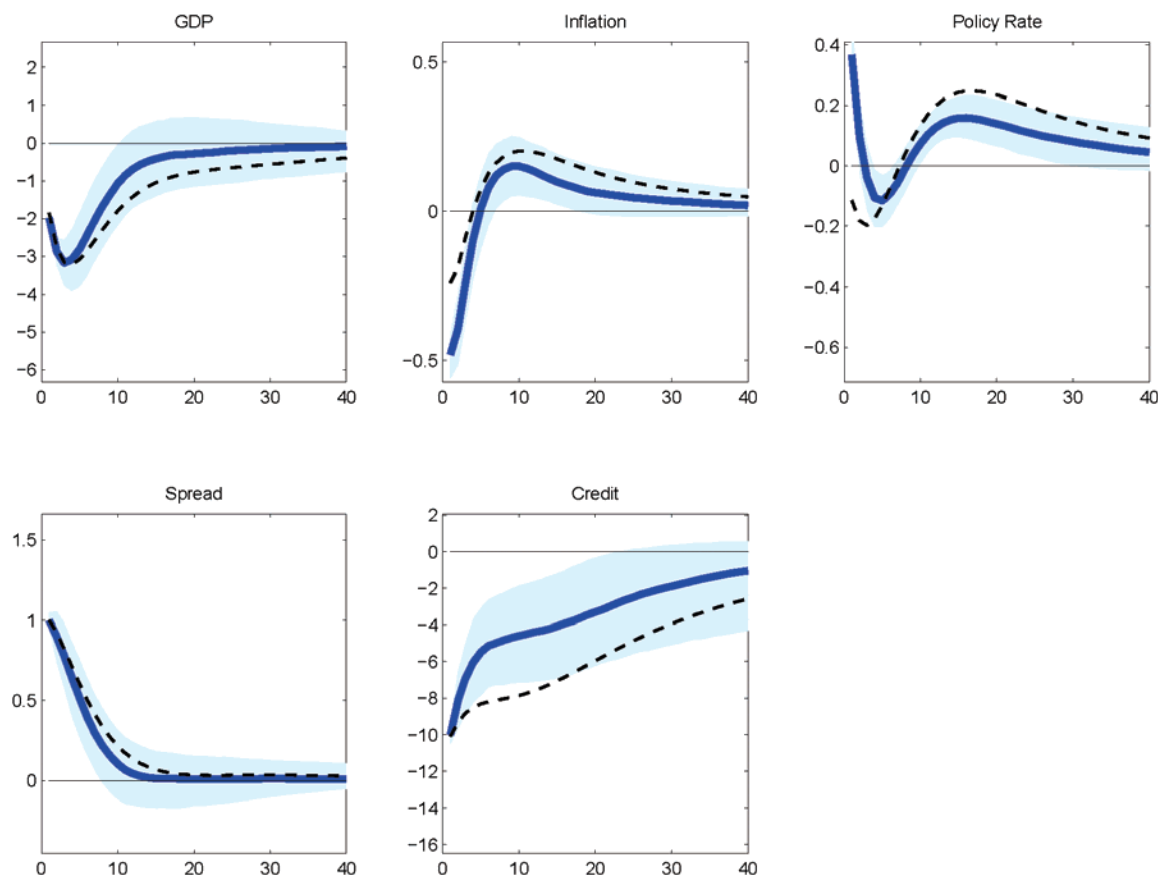


Figure 4: The shadow area and the blue solid thick line reflect the 90% simulation interval and the median, respectively. The black dashed line illustrates the DSGE model response. The shock is normalised to increase the spread by 1% on impact.

Figure 4 reveals the performance of the identification scheme when the standard deviation of the credit supply shock in the high uncertainty regime (σ_H) is 5 times the standard deviation of the shock in the low uncertainty regime (σ_L). In terms of estimation precision, this methodology seems to deliver more precise estimates than the identification process discussed in the previous section. However, procedure faces difficulties to correctly identify the shock. At the moment, the VAR identified shock looks more like an ‘interest rate/policy’ than a credit supply shock. Figure 5 provides evidence regarding the source of this bias. To be precise, in a second exercise we investigate what happens to the identified impulse responses as we increase the standard deviation of the credit supply shock in the high uncertainty regime ($\sigma_H = 2\sigma_L, 10\sigma_L, 50\sigma_L$). Clearly, the experiment suggests that this bias goes away as the size of the shock increases, however, the shock

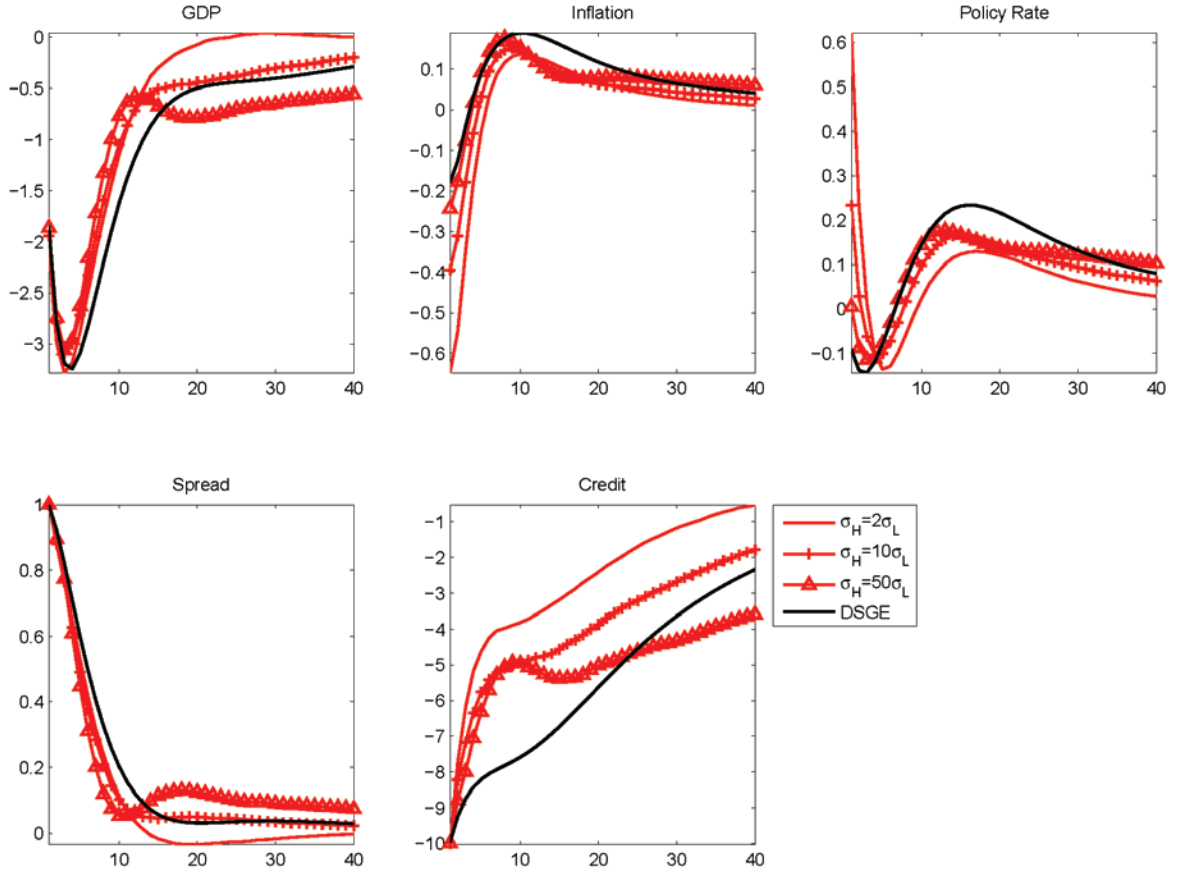


Figure 5: The red line represents the median from the 1000 simulations for different sizes of the credit supply shock in the high uncertainty regime. The shock is normalised to increase the spread by 1% on impact.

needs to be unrealistically large in order for the scheme to correctly identify the shock.

2.4 Recursive Identification

The VAR analysis in Lown and Morgan (2006), Bassett et al. (2012a) and Gilchrist and Zakrajsek (2012) relies on building a proxy for credit supply shock ($\hat{\varepsilon}_t^c$) and adding it to the VAR model as an endogenous variable. The shock is then identified using recursive restrictions, to be precise in Gilchrist and Zakrajsek (2012) $\hat{\varepsilon}_t^c$ is ordered in the VAR after output, inflation and credit quantity and before the spread and the policy rate. This kind of ordering can be justified on the grounds that a credit shock should take at least one quarter to have an impact on non-financial variables.

Figure 6 summarises the results from the simulations where the credit supply shock is identified via recursive restrictions. The scheme does not appear to be able to identify the credit supply

shock successfully. As it is discussed in Canova (2005) and shown – via simulations – in Carlstrom et al. (2009) this ‘failure’ is because the zero type restrictions implied by the Choleski factor of the covariance matrix are not consistent with the DSGE model.

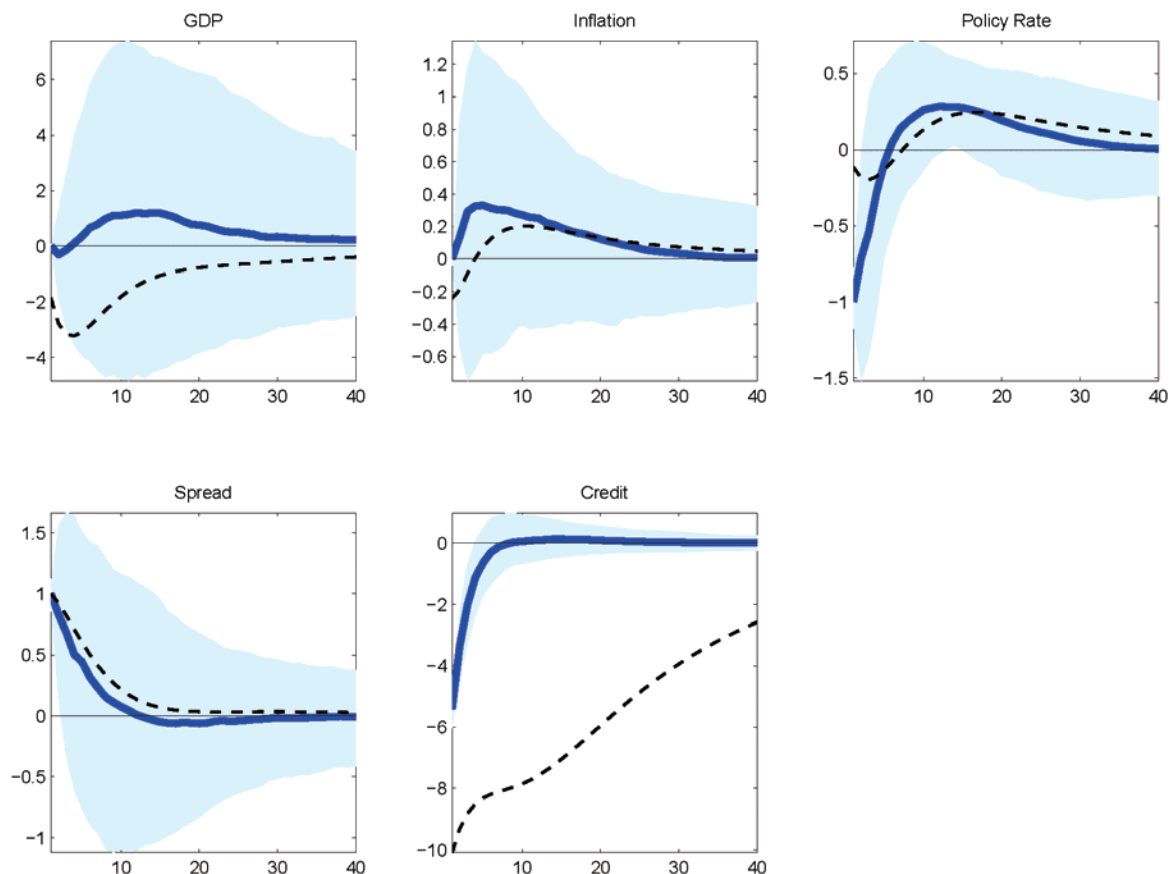


Figure 6: The shadow area and the blue solid thick line reflect the 90% simulation interval and the median, respectively. The black dashed line illustrates the DSGE model response. The shock is normalised to increase the spread by 1% on impact.

Given that $\hat{\varepsilon}_t^c$ is a proxy for true underlying value of the credit supply shock, it is reasonable to assume a degree of measurement error. For example, the relationship between the constructed measure of credit supply and its underlying value may be defined as

$$\hat{\varepsilon}_t^c = \varepsilon_t^c + \sigma_v v_t \quad (9)$$

where v_t is a standard normal variable. It is easy to see that the presence of measurement error would bias the estimate of the structural shock of interest. In addition, it is well known that OLS estimates of the VAR coefficients would suffer from attenuation bias due to the correlation between the RHS variables and the residuals introduced by the measurement error. Figure 7 illustrates what

happens to the VAR responses as the noise to signal ratio increases from 0 to 0.5 and, finally, to 2. The performance of the scheme deteriorates further and this raises concerns about the dangers of employing recursive identification schemes when the practitioner is not absolutely confident whether the zero type restrictions imposed by the procedure are consistent with the true Data Generation Process.

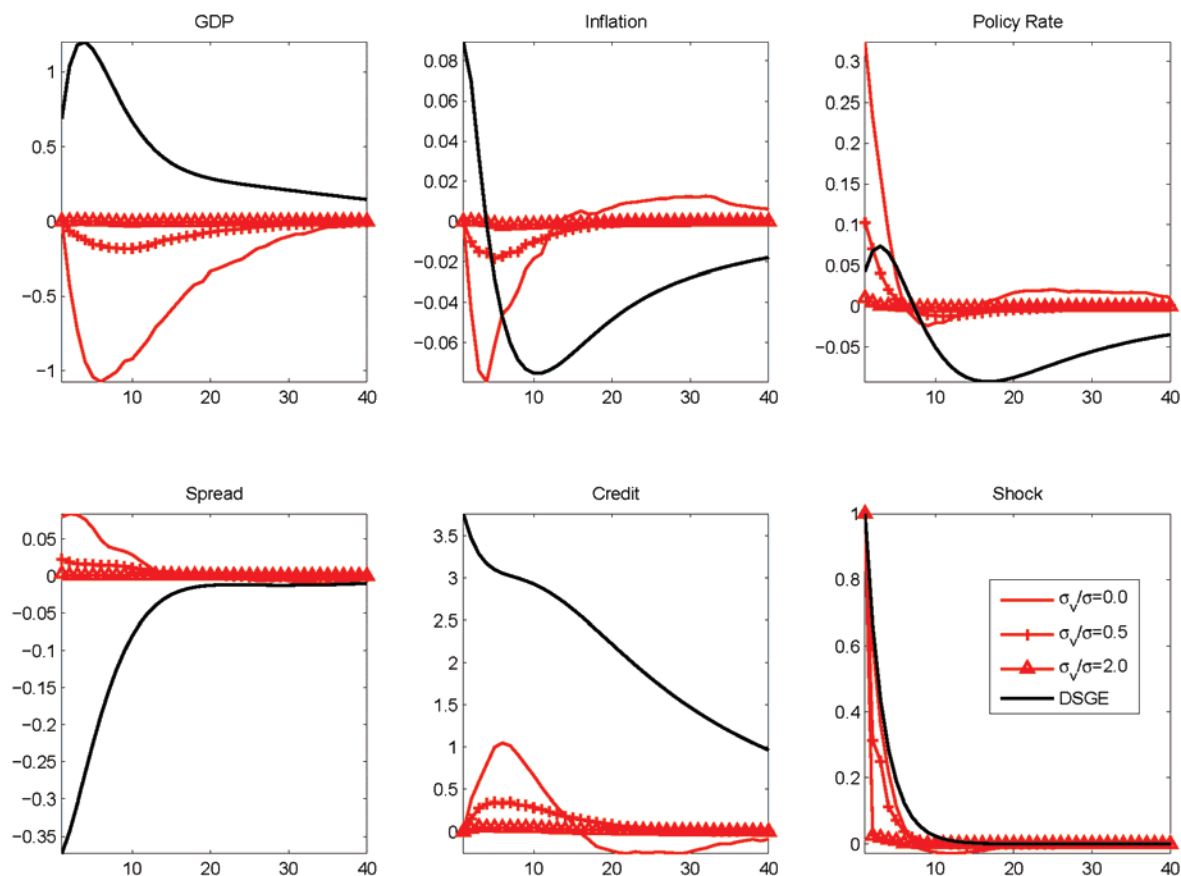


Figure 7: The red line represents the median from the 1000 simulations for different degrees of noise to signal ratio. The shock has been normalised to increase by 1%.

2.5 Proxy SVAR

The final VAR model considered in the simulation is the Proxy SVAR, as mentioned above, this model differs from the recursive SVAR in that it does not require the proxy variable to enter the VAR directly. In contrast, the proxy is used as an instrument to estimate the structural impact matrix using the moment conditions.

Figure 8 illustrates the overall performance of the identification scheme, while 9 shows what

happens when the instrument is measured with an error.

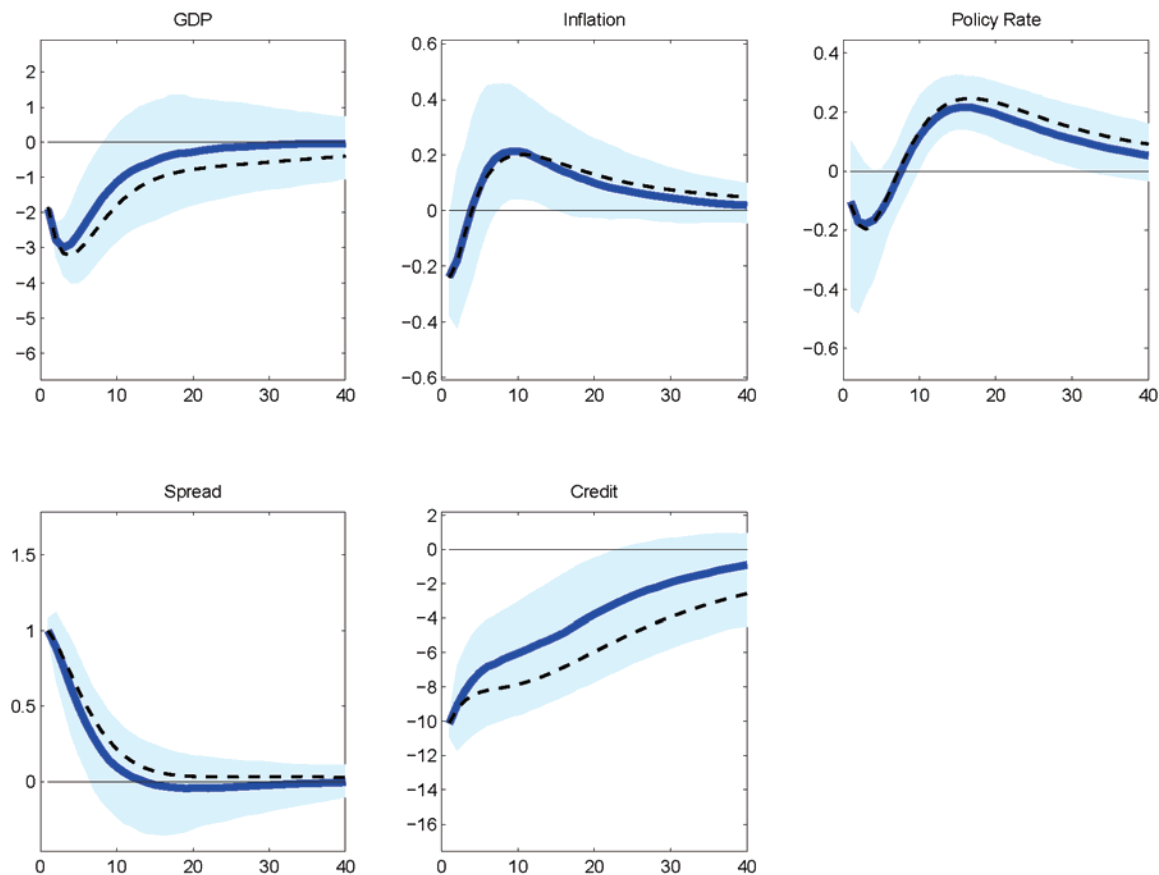


Figure 8: The shadow area and the blue solid thick line reflect the 90% simulation interval and the median, respectively. The black dashed line illustrates the DSGE model response. The shock is normalised to increase the spread by 1% on impact.

The results suggest that the Proxy SVAR model not only correctly identifies the true shock but also it is robust to measurement error issues.

This is in sharp contrast with the simulation evidence from the recursive identification scheme.

3 Detailed SVAR results

3.1 Recursive VAR

Figure 10 presents impulse responses using each of the credit supply proxies. The proxies are (1) the excess bond premium (EBP) proposed in Gilchrist and Zakrajsek (2012), (2) the measure of bank

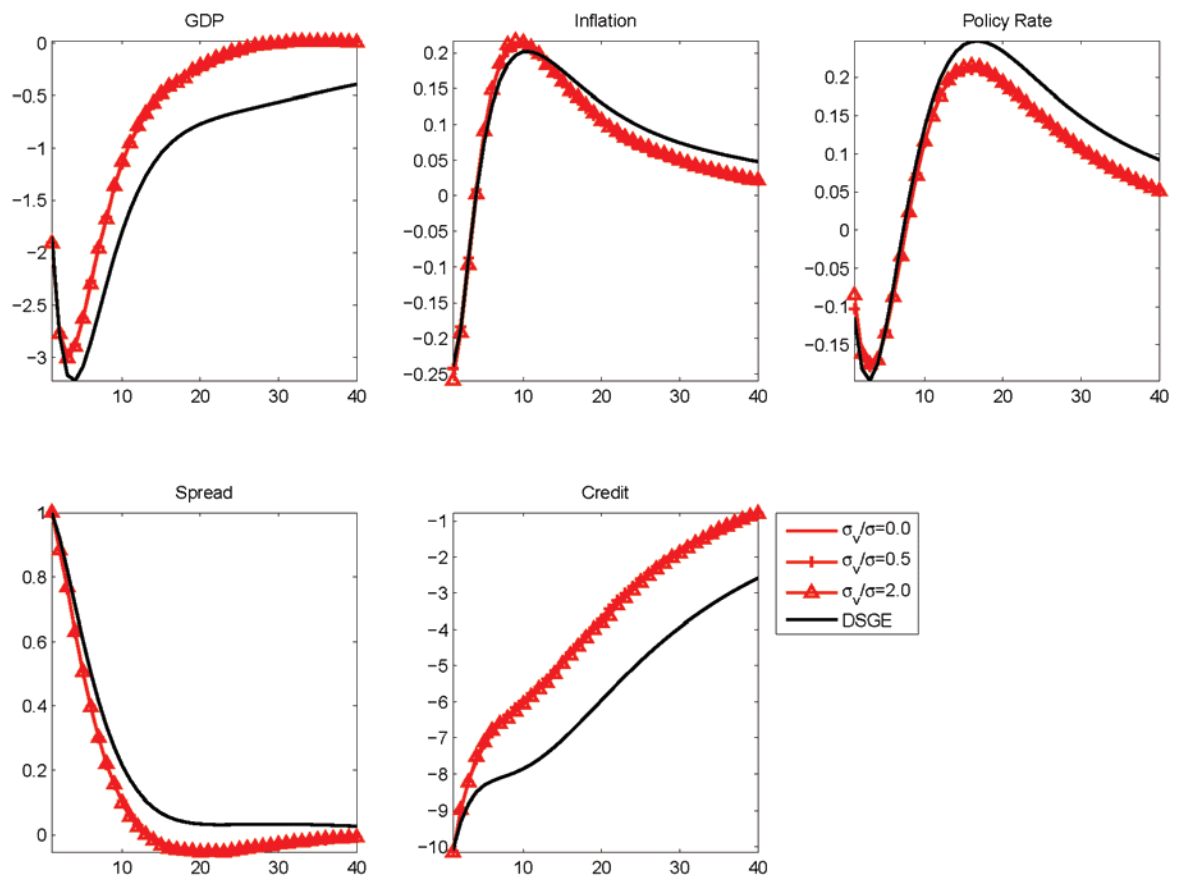


Figure 9: The red line represents the median from the 1000 simulations for different degrees of noise to signal ratio. The shock is normalised to increase the spread by 1% on impact.

lending shocks (BCDZ) calculated by Bassett et al. (2012b), (3) (JQ) innovations to the financial conditions index calculated by Jermann and Quadrini (2012) and the risk shock (CMR) from the DSGE model of Christiano et al. (2012). In addition, we calculate a textual measure of credit supply shocks in the spirit of similar measures developed to estimate changes in uncertainty (see Baker et al. (2012)).

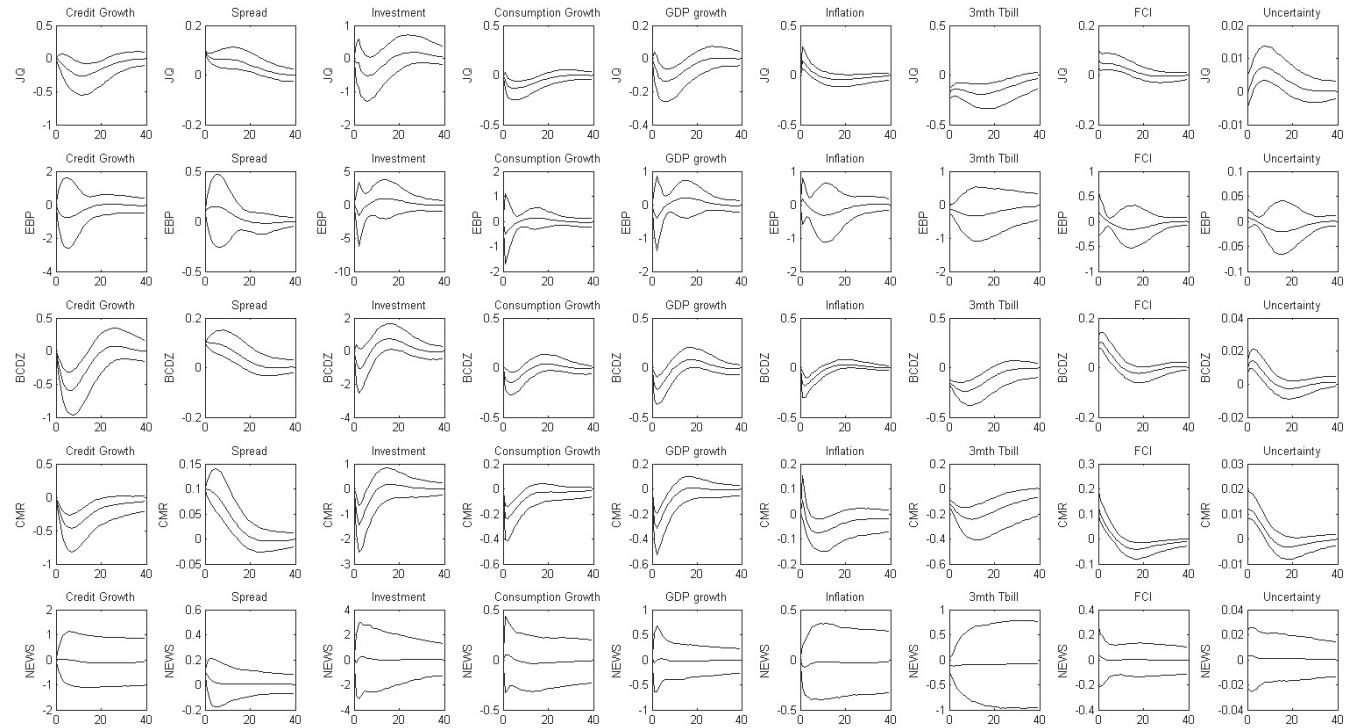


Figure 10: Impulse response to a credit supply shock using a recursive SVAR

3.2 Proxy VAR

Figures 11, 12 and 13 show the correlation amongst the estimated credit shocks and the correlation of the shock identified using the JQ instrument and the textual measure with monetary policy, productivity and uncertainty shocks. The numbers shown in each panel represent the Pearson Correlation Coefficient.

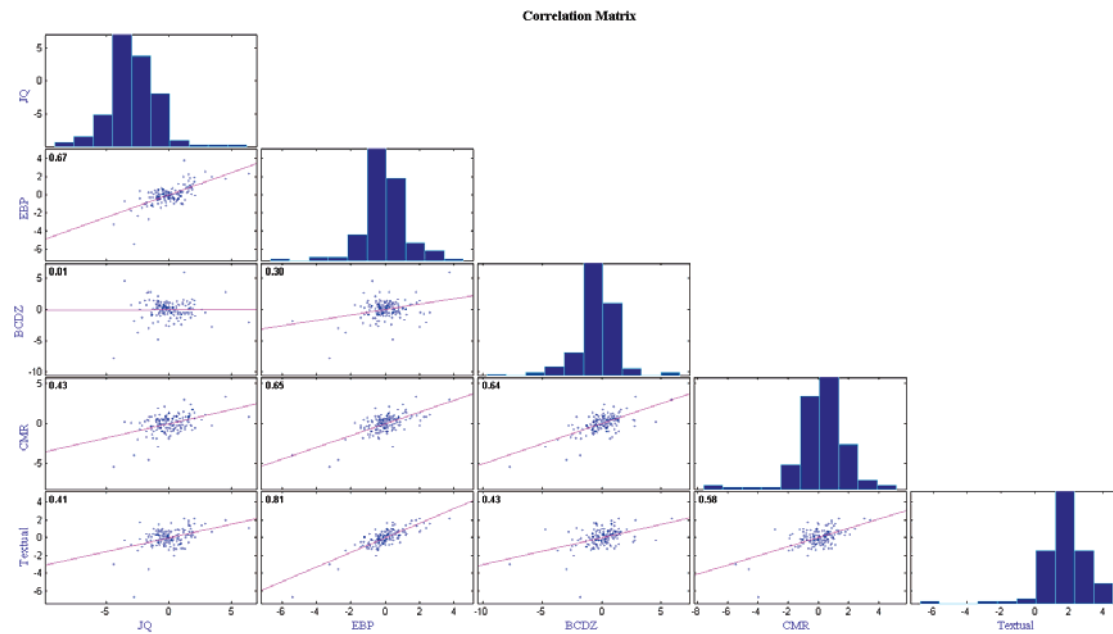


Figure 11: Correlation between the credit supply shocks identified using different instruments. The instruments are (1) the excess bond premium (EBP) proposed in Gilchrist and Zakrajsek (2012), (2) the measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2012b), (3) (JQ) innovations to the financial conditions index calculated by Jermann and Quadrini (2012) and the risk shock (CMR) from the DSGE model of Christiano et al. (2012). In addition, we calculate a textual measure of credit supply shocks in the spirit of similar measures developed to estimate changes in uncertainty (see Baker et al. (2012)).

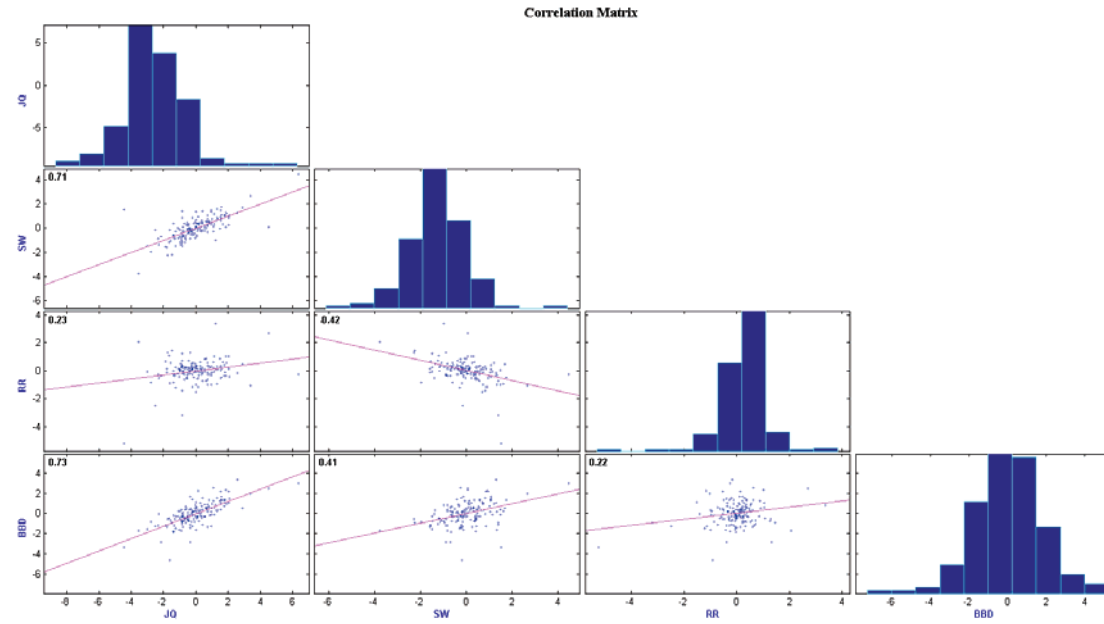


Figure 12: Correlation between the credit supply shock estimated using the JQ instrument and other shocks. These include: (1) a productivity shock identified by using the estimated productivity shock from the Smets and Wouters (2007) model (SW). (2) A monetary policy shock (RR) is estimated using the measure proposed in Romer and Romer (2004). Finally, innovations to the Baker et al. (2012) index (calculated as residuals to an AR(2) model) are used to identify the uncertainty shock (BBD).

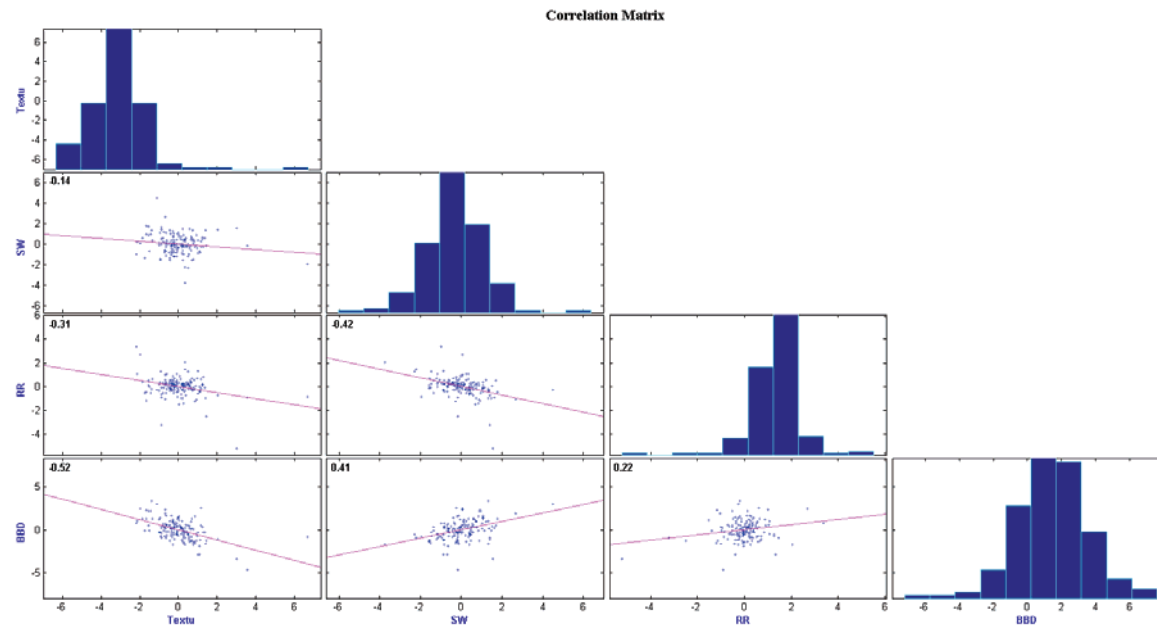


Figure 13: Correlation between the credit supply shock estimated using the textual instrument and other shocks. These include: (1) a productivity shock identified by using the estimated productivity shock from the Smets and Wouters (2007) model (SW). (2) A monetary policy shock (RR) is estimated using the measure proposed in Romer and Romer (2004). Finally, innovations to the Baker et al. (2012) index (calculated as residuals to an AR(2) model) are used to identify the uncertainty shock (BBD).

3.3 Identification via heteroscedasticity

3.3.1 Estimation

Consider the VAR model given by

$$Y_t = c + \sum_{j=1}^P B_j Y_{t-p} + u_t$$

where

$$\text{var}(u_t) = \Omega_{s_t}$$

where $s_t = 1, 2, \dots, M$ follows a Markov process with transition probabilities $p_{ij} = \Pr(s_t = j | s_{t-1} = i)$. The covariance matrix Ω_{s_t} is defined as

$$\begin{aligned} \Omega_1 &= BB' \\ \Omega_i &= B\Lambda_i B' \end{aligned} \tag{10}$$

The likelihood function of this Markov Switching VAR can be calculated using the Hamilton (1989) filter. Following Chernozhukov and Hong (2003), we use an MCMC algorithm to approximate the posterior distribution of the model parameters. This numerical approach is particularly suited to our application where the VAR is relatively large and the available time-series is small. See Lanne et al. (2010) for a classical estimation approach. Note, however, that we do not employ prior distributions so the posterior estimates are proportional to likelihood based results. Collecting the VAR parameters in a vector Ξ , the MCMC algorithm is a random walk Metropolis Hastings algorithm that contains the following steps:

1. Draw from the proposal density for iteration i

$$\Xi_i = \Xi_{i-1} + \alpha$$

where $\alpha \sim N(0, \Psi)$ and $\Psi = \Psi_{MLE} \times k$. The starting value for the recursion Ξ_0 is obtained by maximising the likelihood function of the model. The covariance matrix of the maximum likelihood parameters Ψ_{MLE} is used to calibrate the variance of the shock α .

2. Accept the draw Ξ_i with probability $\min\left[\frac{L(\Xi_i)}{L(\Xi_{i-1})}, 1\right]$ otherwise retain Ξ_{i-1} . The scalar k is chosen to maintain an acceptance rate between 20% and 40%.

We use 100,000 iterations and retain the last 10000 draws for inference. Recursive means of the retained draws (see figure 14) are fairly stable indicating evidence in favour of convergence of the algorithm.

3.3.2 Model Selection

Table 1 presents model selection criteria for various MSVAR models. In practical terms, the Deviance information criterion DIC can be calculated as: $DIC = \bar{D} + p_D$. The first term is defined as $\bar{D} = E(-2 \ln L(\Xi_i)) = \frac{1}{M} \sum_i (-2 \ln L(\Xi_i))$ where $L(\Xi_i)$ is the likelihood evaluated at the draws of all of the parameters Ξ_i in the MCMC chain. This term measures goodness of fit. The second term p_D is defined as a measure of the number of effective parameters in the model (or model

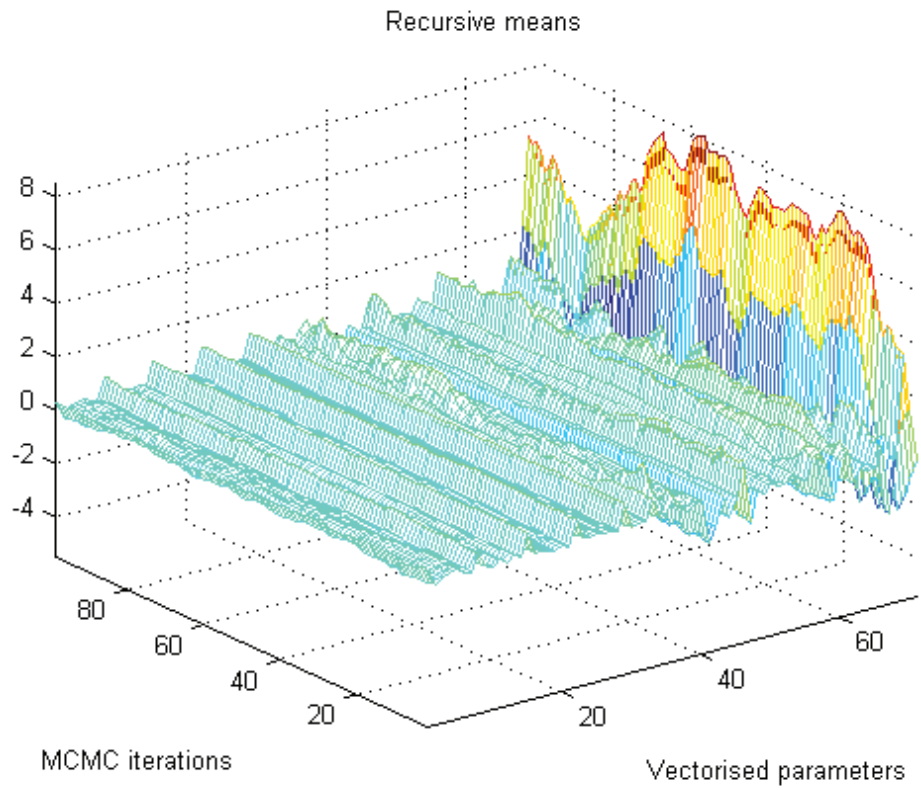


Figure 14: Recursive means of retained draws

Table 5: Model Selection for the MSVAR models

	DIC	SC	AIC
Linear	-461.777	-1.4055	-2.5636
2 regimes unrestricted	-723.799	-2.4918	-4.171
2 regimes State invariant B	-712.377	-3.2888	-4.4854
3 regimes unrestricted	-751.209	-1.7892	-4.1247
3 regimes state invariant B	-738.71	-3.3123	-4.6827

complexity). This is defined as $p_D = E(-2 \ln L(\Xi_i)) - (-2 \ln L(E(\Xi_i)))$ and can be approximated as $p_D = \frac{1}{M} \sum_i (-2 \ln L(\Xi_i)) - \left(-2 \ln L\left(\frac{1}{M} \sum_i \Xi_i\right) \right)$.

The Schwarz criteria (SC) is defined as $SC = -2l/T + n \ln T/T$ where l is the log likelihood at the maximum and n denotes the total number of parameters. The Akaike criteria (AIC) is defined as $AIC = -2l/T + 2n/T$ where l is the log likelihood at the maximum and n denotes the total number of parameters. In each case, the minimum value indicates the best fitting model. The table considers 5 different models. It compares the linear VAR model with 2 and 3 regime VARs where the B matrix is either kept constant or allowed to switch. The AIC and SC criteria clearly favour a 3-regime VAR with fixed B . The DIC provides some evidence in favour of a 3-regime model with switching B . On balance, we take this as evidence in favour of the 3-regime VAR with fixed B . The smoothed regime probability for this model is shown in figure 15. The regime switches are concentrated around the mid-1970s, the early 1980s and during the recent financial crisis of 2009.

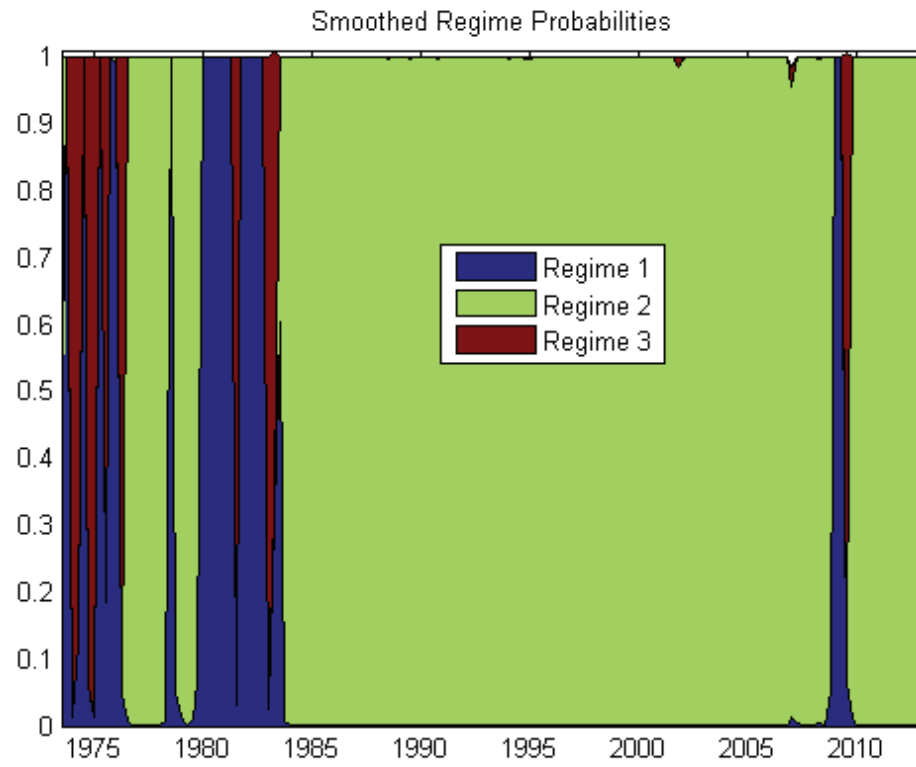
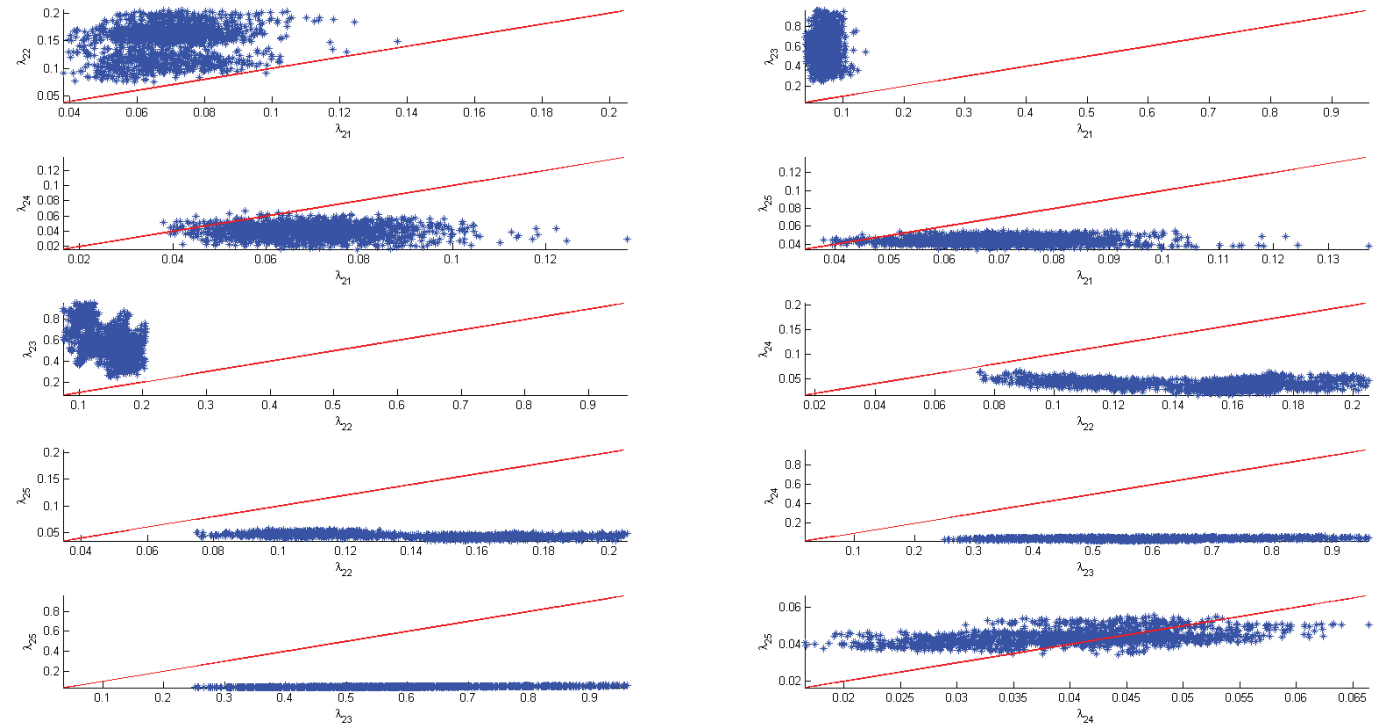
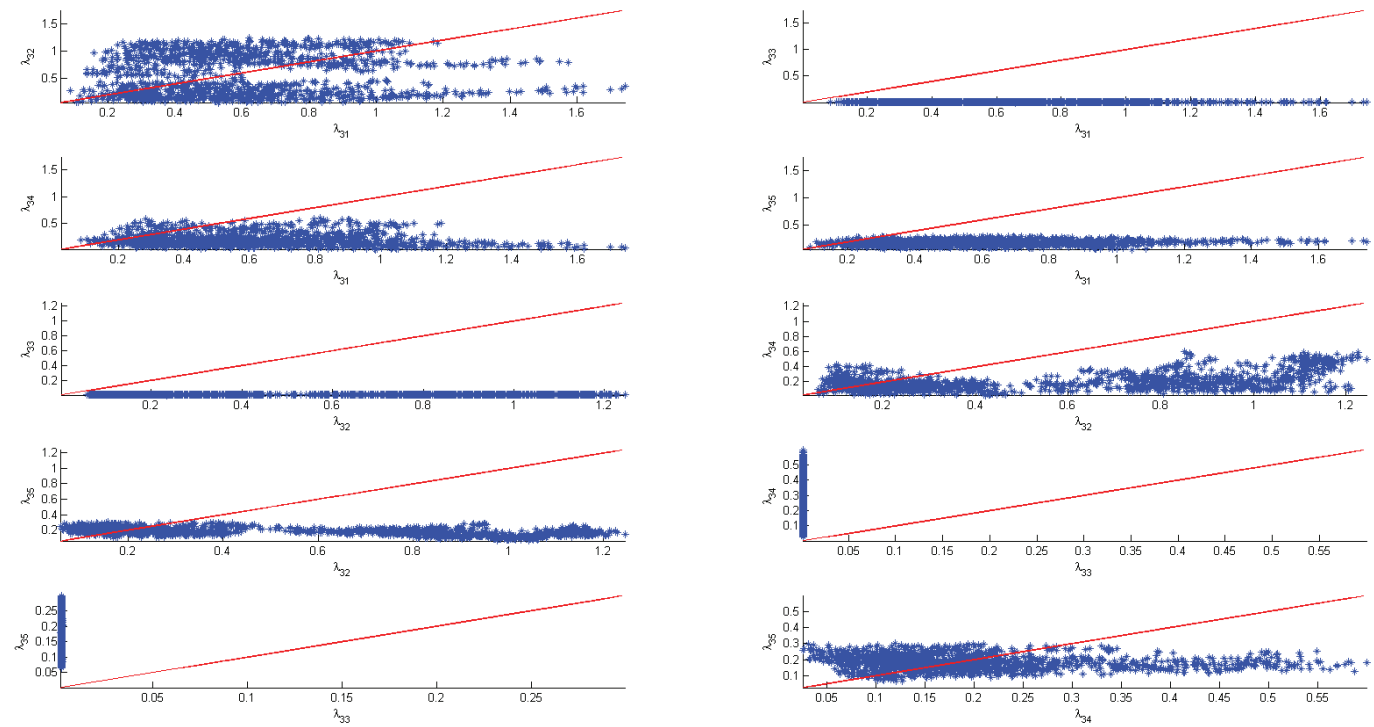


Figure 15: Smoothed probability of regimes

Figure 16: Joint distribution for elements of Λ_2

Figure 17: Joint distribution for elements of Λ_3

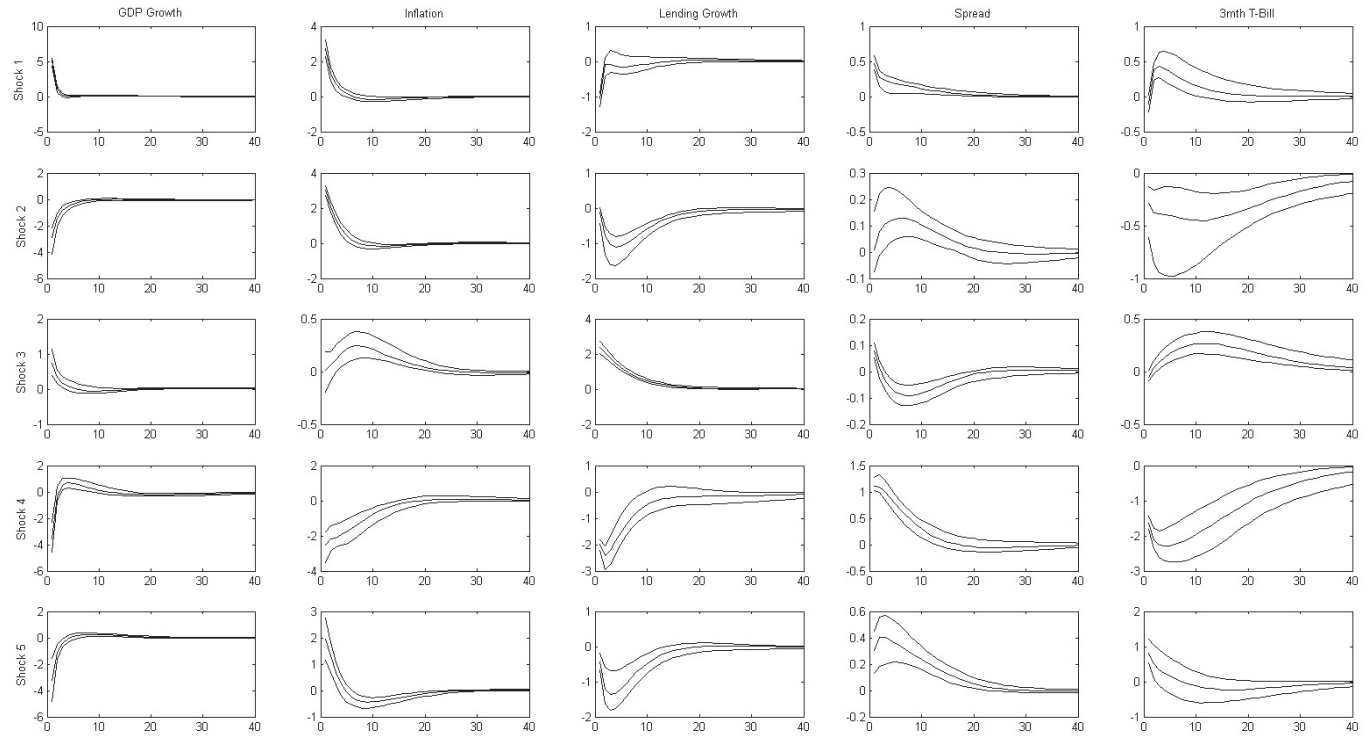


Figure 18: Impulse response to 5 shocks

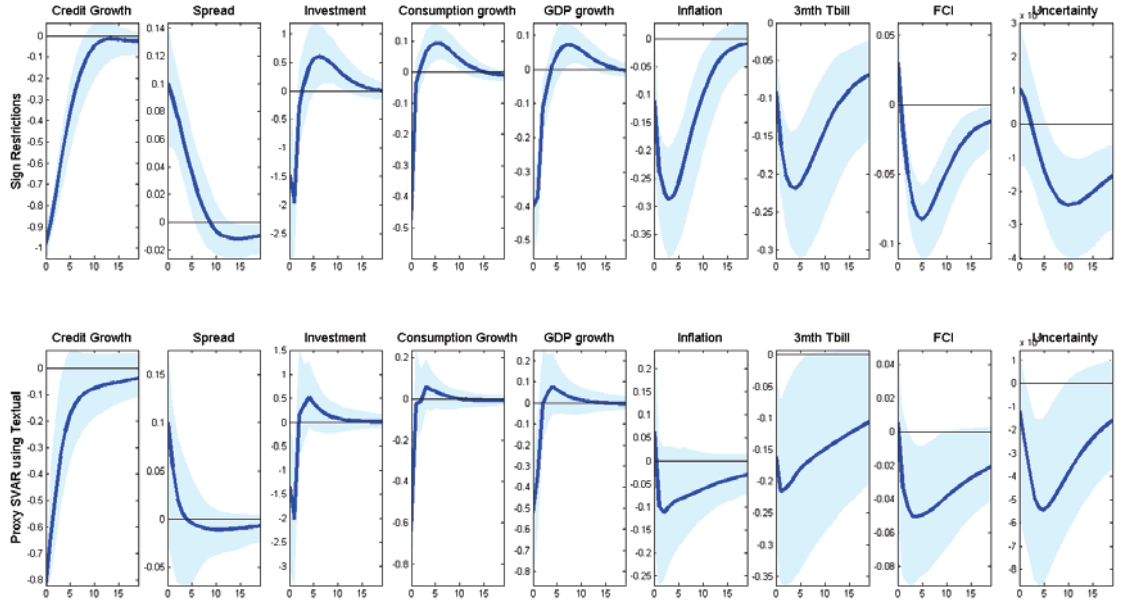


Figure 19: Estimates using data up to 2006Q4.

As described in Lanne et al. (2010), expression 10 provides enough equations to estimate the unknown elements of B uniquely (up to sign changes and column permutations) provided that there exists a state where the diagonal elements of Λ are distinct. Figures 16 and 17 consider the joint distribution of the diagonal elements of Λ_2 and Λ_3 respectively. The scatter plots compare the joint distribution with the 45-degree line. If the elements are distinct, then the joint distribution should lie on the 45-degree line. Consider figure 16 which shows the analysis for the diagonal elements of Λ_2 denoted by $\lambda_{21}, \dots, \lambda_{25}$. The top four panels of the figure clearly show that λ_{21} is systematically different from the remaining elements. The middle 4 panels suggest a similar conclusion for λ_{22} . Similarly, it is clearly the case that λ_{23} is distinct from λ_{25} and λ_{24} . The final panel shows that while part of the joint distribution of λ_{24} and λ_{25} lies on the 45-degree line, there is some evidence of a difference between these elements. Overall, the results indicate provide evidence that in state 2, the diagonal elements of Λ are distinct.

The impulse responses to the 5 shocks obtained from the VAR model are shown in figure 18. Note lending growth and the spread have an opposite short-horizon response in the case of shock 1, shock 4 and shock 5. This suggests the possibility that these three shocks are candidates for the credit supply shock. Note that the response to shock 4 is closest to the impulse responses implied by the theoretical model: GDP growth and CPI inflation, Lending growth and the short-term interest rate move in the opposite direction to the spread. We therefore label shock 4 as the credit supply shock.

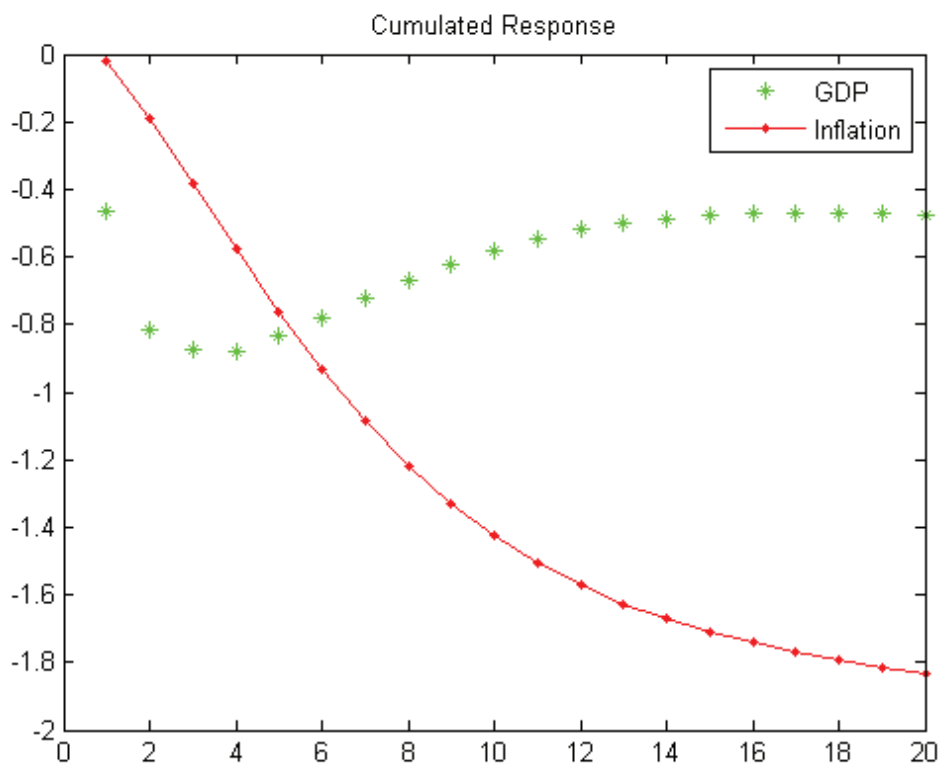


Figure 20: Cumulated Average Response

4 Estimation before the great recession

Figure 19 presents the estimated responses from the two main VAR models estimated using data upto 2006Q4. The responses of real variables from the VAR with sign and FEV restrictions (top row) are very similar to those obtained using the full sample. The magnitude of the response of these variables using the Proxy VAR is also close to the benchmark. However, the FCI and uncertainty response from both models is different. The pre-crisis response suggests a fall in these variables indicating the data on the Great Recession period is important in driving these variables. Note also that the proxy VAR response of inflation is smaller over this sub-sample.

On average, the cumulated impact of the credit supply shock leads to a decline in GDP and inflation that is very similar to the benchmark. This can be seen in figure 20 which shows that these variables decline by about 1% at the 4 quarter horizon.

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**School of Economics and Finance
Queen Mary University of London
Mile End Road
London E1 4NS
Tel: +44 (0)20 7882 7356
Fax: +44 (0)20 8983 3580
Web: www.econ.qmul.ac.uk/research/workingpapers/**