

School of Economics and Finance

What do VARs Tell Us about the Impact of a Credit Supply Shock? An Empirical Analysis

Haroon Mumtaz, Gabor Pinter and Konstantinos Theodoridis

Working Paper No. 716

April 2014

ISSN 1473-0278



Queen Mary
University of London

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

Haroon Mumtaz
Queen Mary College

Gabor Pinter
Bank of England

Konstantinos Theodoridis
Bank of England

March 2014

Abstract

This paper evaluates the performance of structural VAR models in estimating the impact of credit supply shocks. In a simple Monte-Carlo experiment, we generate data from a DSGE model that features bank lending and credit supply shocks and use SVARs to try and recover the impulse responses to these shocks. The experiment suggests that a proxy VAR that uses an instrumental variable procedure to estimate the impact of the credit shock performs well and is relatively robust to measurement error in the instrument. A structural VAR with sign restrictions also performs well under some circumstances. In contrast, VARs of the narrative variety, i.e. VAR models that include measures of the credit shock as endogenous variables are highly sensitive to ordering and measurement error. An application of the proxy VAR model and the VAR with sign restrictions to US data suggests, however, that the credit supply shock is hard to identify in practice.

JEL Classification: C15, C32, E32. *Keywords:* Credit supply Shocks, Proxy SVAR, Sign restrictions, 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 banking and debt crisis in the Euro-Area. For example Peersman (2011), uses a structural VAR (SVAR) with sign restrictions to identify loan supply shocks and finds that these explain a large proportion of the variation in Euro-Area industrial production. Peersman (2011)'s work builds on a number of papers that have used SVARs with sign restrictions to identify

credit shocks— see for e.g. Eickmeier and Ng (2011) and Gambetti and Musso (2012) for recent applications of this approach. 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 establish how well SVARs perform in identifying this shock and to establish the relative merits of different identification strategies in this context.

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 three 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 Peersman (2011) and Gambetti and Musso (2012). The second SVAR treats (functions of) the simulated credit shock as a proxy variable and adds it to the VAR as an endogenous variable and mimics the approach taken for e.g. in Lown and Morgan (2006) and Gilchrist and Zakrajsek (2012). Finally, we estimate a proxy SVAR model (as proposed in Stock and Watson (2008) and Mertens and Ravn (2012)) where the simulated proxy is used as an instrument to estimate the credit supply shock. The results of this Monte-Carlo experiment suggest that the proxy SVAR model delivers the best performance producing impulse responses that match those from the DSGE model. The SVAR with sign restrictions is found to deliver accurate results under certain conditions. In contrast, the recursive SVAR is sensitive to ordering and measurement error and can produce estimates that are very mis-leading.

Given that the results of this Monte-Carlo experiment point to the superior performance of the proxy SVAR model and the VAR with sign restrictions, we use these models to estimate the impact of credit supply shocks for the US economy. The empirical results are disappointing and suggest that it is very difficult to identify the impact of this shock in practice. In particular, the VAR with sign restrictions produces a wide range for the possible impact of this shock and appears unable to pinpoint its effect. The proxy SVAR that uses the 'strongest' instrument for credit supply leads to an estimate of the credit supply shock that is highly correlated with estimated productivity and uncertainty shocks and thus makes it less likely that the estimates from the model can be used to discern the impact of credit supply.

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.

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 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 $VAR(u_t) = \Omega = A_0 A_0'$.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 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. We find in our monte-carlo experiments that this set of admissible responses can be quite wide thus complicating inference.

2.2 Proxy Variables

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 $\hat{\varepsilon}_t^c$ 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. (2012a) refine this measure further by removing the component associated with macro-economic 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

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.

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 introduced 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 the instrument $\hat{\varepsilon}_t^c$ is correlated with the structural shock to be estimated, while the second expression rules out a 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 (2012) and Mertens and Ravn (2011), 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 $A_0^{(3)} \varepsilon_t = u_t$ 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 $E(u_t \hat{\varepsilon}_t^c) = E(\tilde{A}_0 \varepsilon_t \hat{\varepsilon}_t^c) = [\tilde{A}_{0,1} \dots \tilde{A}_{0,N}] \begin{bmatrix} E(\varepsilon_{1t} \hat{\varepsilon}_t^c) \\ \cdot \\ \cdot \\ E(\varepsilon_{Nt} \hat{\varepsilon}_t^c) \end{bmatrix} = \tilde{A}_{0,1} \alpha$. Let Π denote the coefficient on u_t . Then the fitted value Πu_t equals the structural shock of interest up to sign and scale:

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

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.

3 Identifying Credit Supply shocks: A Monte-Carlo experiment

In this section we consider the performance of the three structural VAR models in the estimation of the credit supply shock via a Monte-Carlo experiment. In particular we generate data from a DSGE model. We then use the generated data to estimate a VAR model and identify the shock to credit supply using the three identification schemes discussed above.

3.1 The Data Generating process and empirical models

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_t of available funds from the project, and transfer them back to the household, in which case depositors would recover the remaining $1 - \theta_t$ 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 explore exogenous changes in θ_t , which lead to a fall (rise) in the quantity of credit, a reduction (expansion) in economic activity and an increase (decrease) in the spread between the lending rate and the deposit rate. This type of collateral shock has been recently studied by Liu et al. (2013). As an alternative proxy for credit supply shocks, we separately investigate 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 3 in appendix A 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, except that of the credit shocks. For these shocks we consider two values for the standard deviation: a benchmark value of 0.01 and an alternative calibration of 0.05 that mimics the magnitude of the 2007-2008 financial crisis. The autoregressive coefficient for the collateral shock is set to 0.9.²The details of the model equations are provided in the appendixA.

We generate 1000 artificial datasets from this model for 1000 periods with the first 800 observations discarded to remove the impact of starting values. The final 200 observations are used to estimate the following VAR models:

First we estimate the following SVAR:

$$Y_t^{(1)} = c + \sum_{j=1}^P B_j Y_{t-j}^{(1)} + A_0^{(1)} \varepsilon_t^{(1)} \quad (5)$$

²In different models of collateral constraints, θ -type shocks have been estimated to have a persistence value between 0.85 (Iacoviello and Pavan (2013)) and 0.98 (Liu et al. (2013)).

where the matrix of endogenous variables $Y_t^{(1)} = \{y_t, \pi_t, R_t, S_t, C_t\}$. 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 and C_t denotes the quantity of credit. The credit supply shock (ordered first for notational convenience) is identified by imposing the following model-implied sign restrictions on $A_0^{(1)}$

$$A_0^{(1)} = \begin{pmatrix} - & \times & \times & \times & \times \\ - & \times & \times & \times & \times \\ - & \times & \times & \times & \times \\ + & \times & \times & \times & \times \\ - & \times & \times & \times & \times \end{pmatrix} \quad (6)$$

where \times denotes an unrestricted element. A negative credit supply shock, therefore, 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.

The second VAR model is given by

$$Y_t^{(2)} = c + \sum_{j=1}^P B_j Y_{t-j}^{(2)} + A_0^{(2)} \varepsilon_t^{(2)} \quad (7)$$

where $Y_t^{(2)} = \{M_t, y_t, \pi_t, R_t, S_t, C_t\}$. Note that $M_t = CS(M_t)$ where $M_t = \varepsilon_t^{c,DSGE} + v_t$, $v_t \sim N(0, \sigma_v^2)$ and CS denotes the cumulated sum across t . $\varepsilon_t^{c,DSGE}$ is the simulated credit supply shock from the DSGE model and v_t is measurement error. This mimics the kind of SVAR models considered for example in Lown and Morgan (2006) where a measure of the credit supply shock enters the VAR system directly. In the Monte-Carlo experiment, we assume three possible values for σ_v^2 such that: $\frac{\sigma_v^2}{\sigma_c^2} = 0$, $\frac{\sigma_v^2}{\sigma_c^2} = 0.5$ and $\frac{\sigma_v^2}{\sigma_c^2} = 2$ where σ_c^2 is the variance of the credit shock under consideration.

The final VAR model is the proxy SVAR defined as:

$$Y_t^{(3)} = c + \sum_{j=1}^P B_j Y_{t-j}^{(3)} + A_0^{(3)} \varepsilon_t^{(3)} \quad (8)$$

where $Y_t^{(3)} = \{y_t, \pi_t, R_t, S_t, C_t\}$. The first shock in $\varepsilon_t^{(3)}$ is the credit supply shock and is identified using the moment restrictions

$$\begin{aligned} E\left(M_t, \varepsilon_{1,t}^{(3)}\right) &= \alpha \neq 0 \\ E\left(M_t, \varepsilon_{i,t}^{(3)}\right) &= 0, i = 2, 3, 4 \end{aligned} \quad (9)$$

The lag length P for all VAR models is selected via the Schwarz Information criterion at each Monte-Carlo replication.

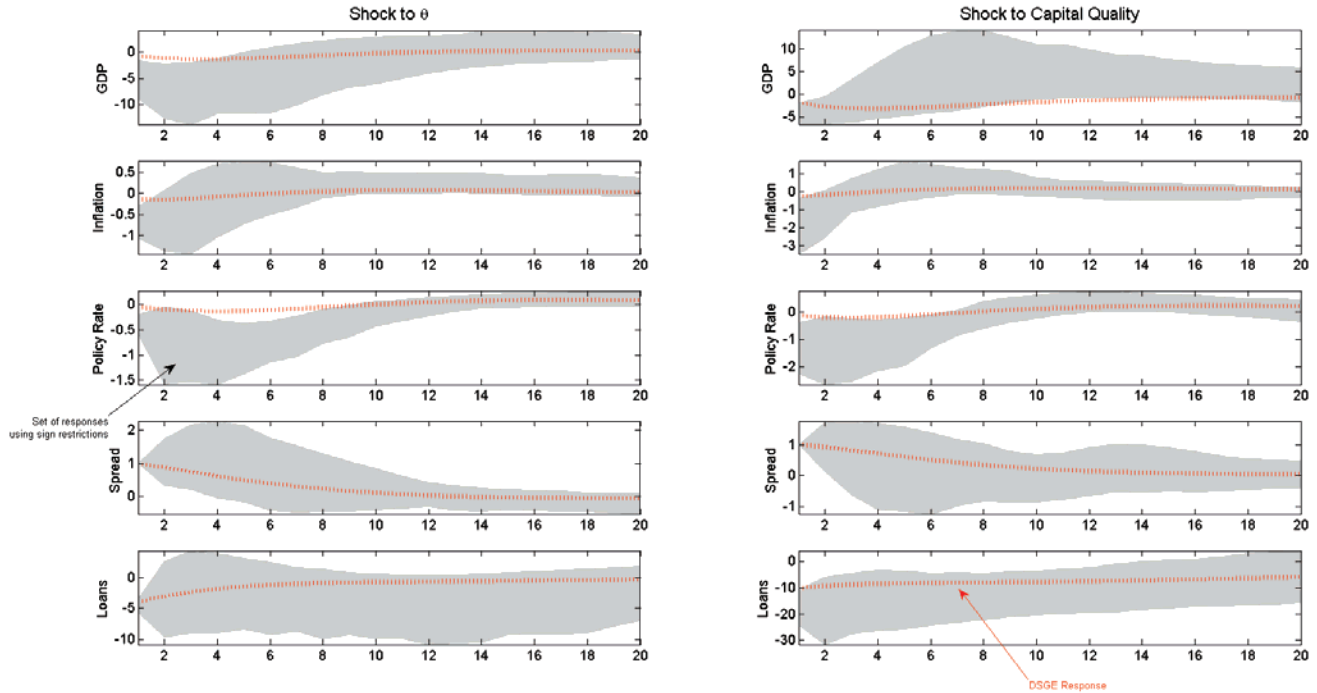


Figure 1: A comparison of DSGE and SVAR responses. Identification via sign restrictions. The standard deviation of credit shocks is calibrated to equal 0.01.

3.2 Results

3.2.1 SVAR with Sign restrictions

For each simulated dataset the VAR model (equation 5) is estimated via OLS. We then use the algorithm described in Rubio-Ramírez et al. (2010) to generate 10,000 estimates of $A_0^{(1)}$ that satisfy the sign restrictions in 6. The impulse response to the credit shock is computed for each of these draws and the resulting distribution is compared to the underlying DSGE response in figure 1. The left panel considers the simulation when the shock to θ_t is active, while the right panel shows the simulation from the model when the capital quality shock is used. Note that both shocks imply the same sign restrictions in the DSGE model as apparent from the model impulse responses shown as the red dotted lines.

Consider the left panel. The grey shaded area represents the distribution of the impulse response obtained using the VAR model.³It is interesting to note that the estimated distribution is fairly wide. The distribution of the VAR estimate of the response of output lies below the DSGE response over the first four periods, with the VAR estimates suggesting a much larger movement by GDP in response to this shock. Focussing on the contemporane-

³We discard the 1st and the 99th percentile in order to remove extreme outliers.

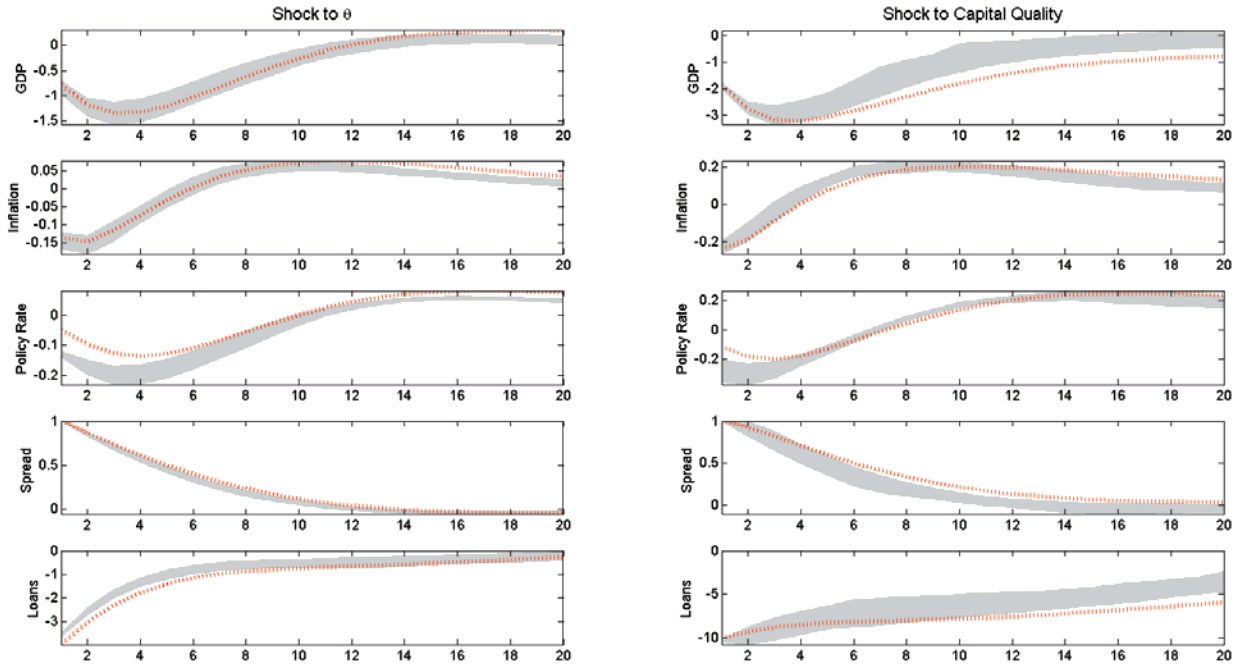


Figure 2: A comparison of DSGE and SVAR responses. Identification via sign restrictions. The standard deviation of credit shocks is calibrated to equal 0.05.

ous response, the VAR estimates include magnitudes that more than double the true value. A similar pattern can be observed for inflation and the policy rate, the the VAR estimates over-estimating the response and the estimated set pointing to a large range of possible values. The right panel of the figure suggests that a similar conclusion can be reached for all variables when the capital quality shock is the active credit supply shock.

Figure 2 shows that that the VAR estimated impulse response distribution is much tighter when the variance of the credit shock is calibrated to 0.05. Consider the left panel. The response of output is precisely estimated by the VAR model with most of the distribution concentrated close to the DSGE response. In contrast, the VAR model under-estimates the response of lending especially over the earlier part of the horizon. The largest discrepancy, however, is in the response of the policy rate. The distribution of the contemporaneous SVAR response is substantially larger in magnitude than the DSGE response and erroneously suggests a substantial and immediate monetary easing in response to the credit shock. The right panel of the figure shows that the estimated impulse response distribution is slightly wider when the artificial data is generated using the capital quality shock. The response of output estimated via the SVAR model is centered on the DSGE response. Note, however, that over the first few periods, the distribution is skewed to the right with more probability

attached to magnitudes smaller than the DSGE response. The response of inflation displays a similar pattern. For the policy rate and the credit quantity, the bulk of the estimated distribution is below the DSGE response over the first 2 to 3 periods, while the reverse appears to hold over longer horizons.

Overall, these results suggest that the VAR with sign restrictions delivers a mixed performance. If the volatility of the credit shock is assumed to be the same as that of other shocks, then this method appears unable to pin down the impact of this shock. In contrast, when the credit shock is more volatile, most VAR responses are good approximations of the true ones. There are exceptions, however, and for some variables, the VAR responses diverge from the true responses substantially. In addition, the set of responses consistent with the sign restrictions can be quite large and include outcomes that are very different from the true responses. This latter feature of the sign restriction methodology has been examined in detail by Fry and Pagan (2011), Canova and Paustian (2011) and Kilian and Murphy (2012). Fry and Pagan (2011) suggest summarizing the distribution by presenting the response closest to the median. However, Kilian and Murphy (2012) argue that this rule for picking the point estimate does not necessarily result in an impulse response that is economically plausible as the underlying estimate of the median is affected by regions of the impulse response distribution that are not meaningful from an economic point of view. They instead suggest incorporating ‘plausibility restrictions’ by restricting the values of some impulse responses to lie within a pre-specified range. Canova and Paustian (2011) also argue that incorporating additional restrictions can help to narrow the set of estimated responses. We follow their suggestion in the empirical analysis below.

3.2.2 Recursive SVAR

In order to mimic the methodology of studies like Lown and Morgan (2006), we estimate the VAR model in equation 7 and calculate the structural impact matrix using a Cholesky decomposition. In the benchmark model the credit supply shock measure M_t is ordered first thus allowing it to have a contemporaneous impact on all variables. This ordering is consistent with the underlying DSGE model.

In figures 3 and 4 we present the monte-carlo results using 0.01 and 0.05 as the two different calibrations for the standard deviation of the credit supply shock. Note that the shock is normalised as a one unit increase in M_t . In the DSGE model, this corresponds to a negative shock when using θ_t and a positive shock when considering the capital quality shock. The VAR responses appear to be almost identical across the two calibrations. When M_t is measured without error, the VAR model performs reasonably well, with the estimated response close to the DSGE response, especially at short horizons. However, it is clear that as the variance of the measurement error increases, there is an attenuation bias. In our simulation, the bias can be substantial even when $\frac{\sigma_v^2}{\sigma_c^2} = 0.5$. For example, for this value of the measurement error, the impulse response of output is biased downwards by a factor of about 50%.

In figure 5 we present the results from the simulation where M_t is ordered in the VAR after

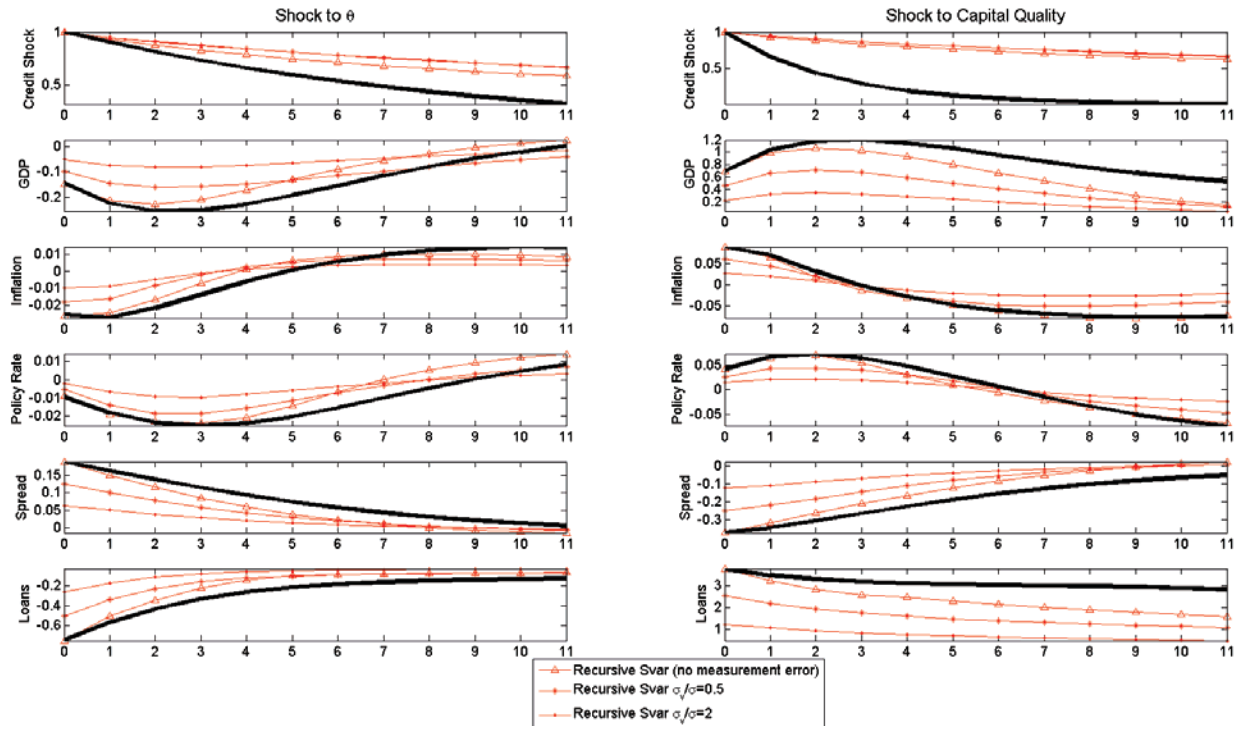


Figure 3: A comparison of DSGE and SVAR responses. Identification via a Cholesky decomposition. The standard deviation of credit shocks is calibrated to equal 0.01.

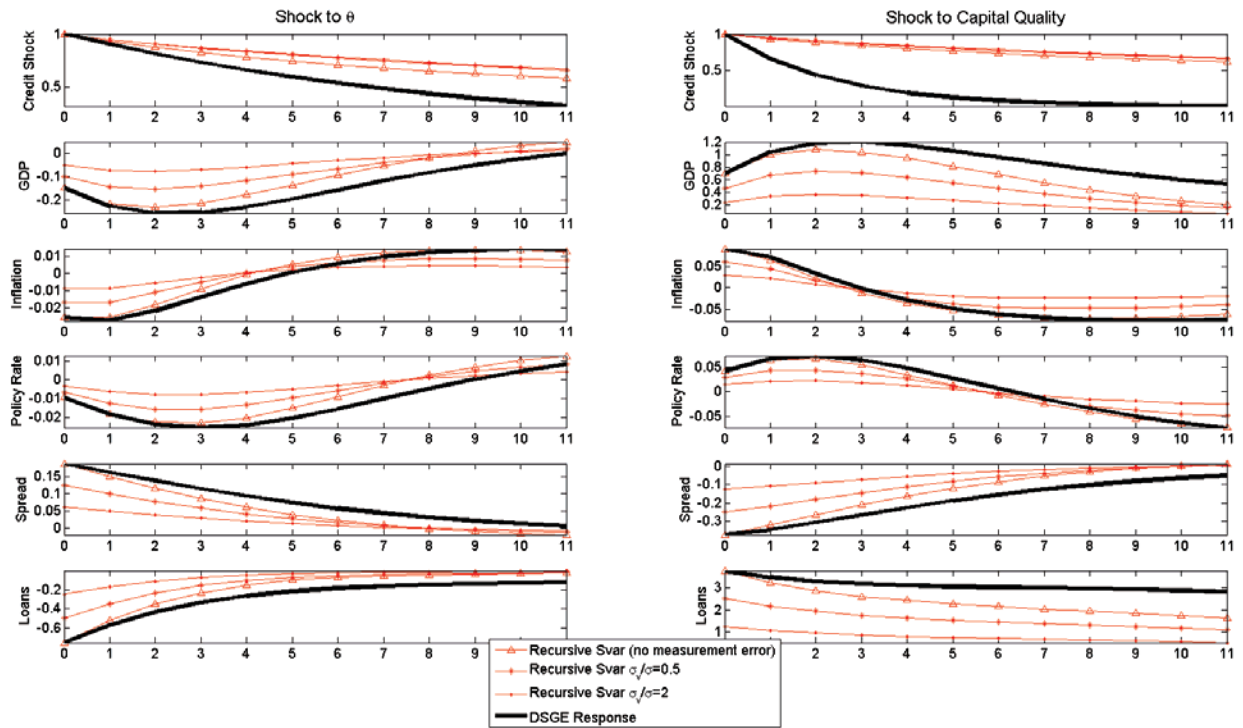


Figure 4: A comparison of DSGE and SVAR responses. Identification via a Cholesky decomposition. The standard deviation of credit shocks is calibrated to equal 0.05.

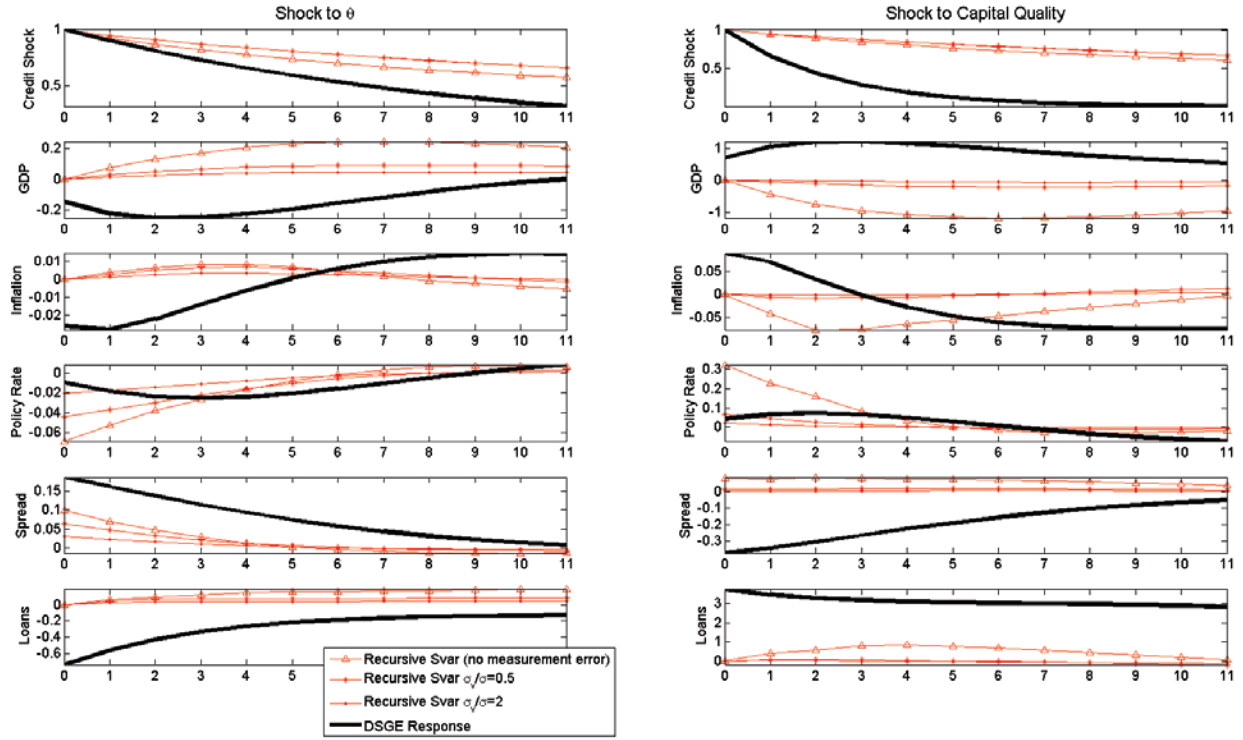


Figure 5: A comparison of DSGE and SVAR responses. Identification via a Cholesky decomposition with M_t after GDP, inflation and lending but before the interest rate and the spread. The standard deviation of credit shocks is calibrated to equal 0.01.

output, inflation and credit quantity. This kind of ordering is used for example in Gilchrist and Zakrajsek (2012) and can be justified on the grounds that a credit shock should take at least one quarter to have an impact on non-financial variables.⁴ The results, however, suggest that restricting the response of output, inflation and credit quantity to be zero on impact leads to large downward biases in their impulse response functions. In fact, the response of GDP consistently moves in the opposite direction to DSGE response, with similar results apparent for other variables.

These results suggest that if the proxy for ‘credit-supply’ is measured with error, the resulting impulse responses from the simple recursive SVAR can suffer from attenuation bias that is large in magnitude. In addition, it appears that the recursive VAR approach is highly sensitive to the ordering of the variables.

3.2.3 Proxy SVAR

The final VAR model considered in the simulation is the Proxy SVAR given in equation 8. 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 shown in equation 9.

Figures 6 and 7 compare the DSGE responses to a negative credit shock with those obtained using the proxy SVAR. The shock is normalised to increase spreads by 1%. Consider the left panel of these figures. When the instrument is assumed to be measured perfectly, the VAR responses are close to the DSGE ones. It is interesting to note that when the volatility of the credit shock is assumed to be low, there is a small discrepancy between the VAR and DSGE responses, with the estimates from the latter biased downwards in the case of GDP and inflation. This bias rises as the measurement error variance increases. Focussing on a key variable like GDP, the results from the proxy SVAR for this simulation are marginally better than those from the recursive SVAR presented in the left panel of figure 3, with the attenuation bias smaller in the former case. When a more volatile θ shock is considered (left panel of figure 7), the proxy VAR responses are very close to the DSGE responses for all values of the measurement error variance. When the capital quality shock is considered in this experiment, the results are more uniform across the two calibrations for the credit shock volatility. In particular, the right panel of figures 6 and 7 shows that the proxy VAR performs well in recovering the true responses especially over short horizons. The impact of measurement error bias appears to be small for this simulation.

3.3 Evaluation of the Monte-Carlo results

Overall, the results from the simulations presented above suggest that the proxy SVAR performs well relative to the competing SVAR models. When it is assumed that the volatility of the credit shock in the DSGE model matches the variance of the other shocks, the VAR

⁴The results are very similar when the credit shock in the DSGE model is calibrated with a standard deviation equal to 0.05. These results are available on request.

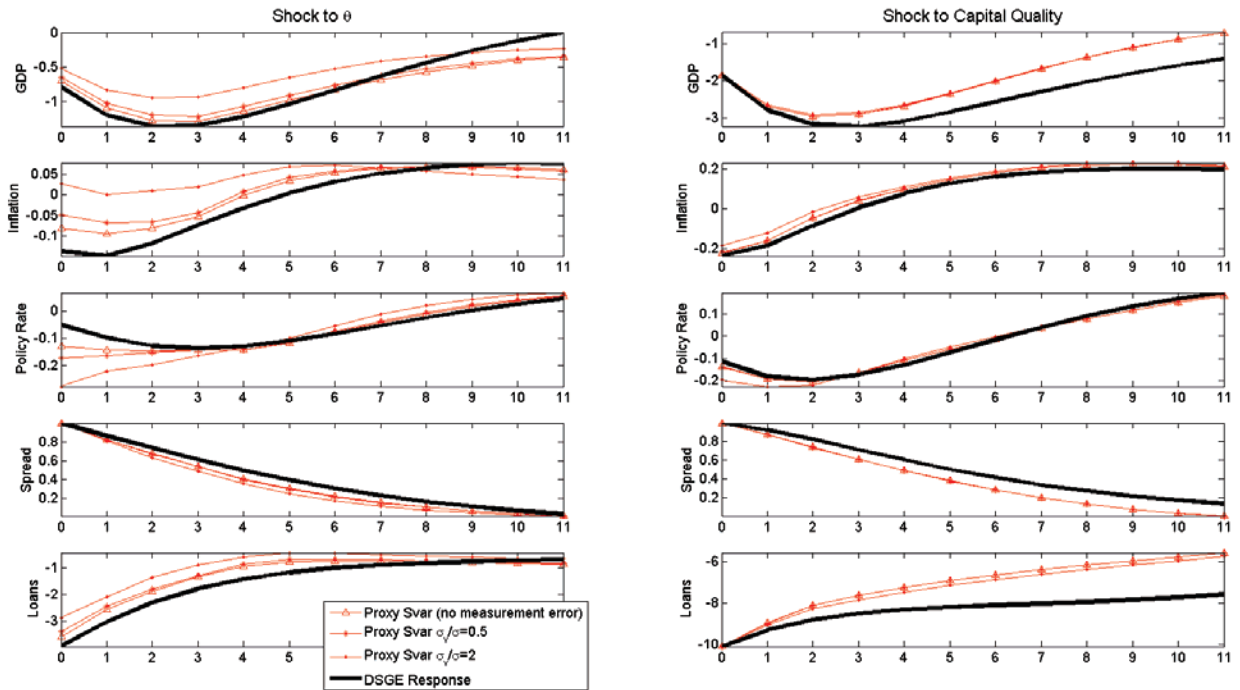


Figure 6: A comparison of DSGE and SVAR responses. Identification via the Proxy VAR method. The standard deviation of credit shocks is calibrated to equal 0.01.

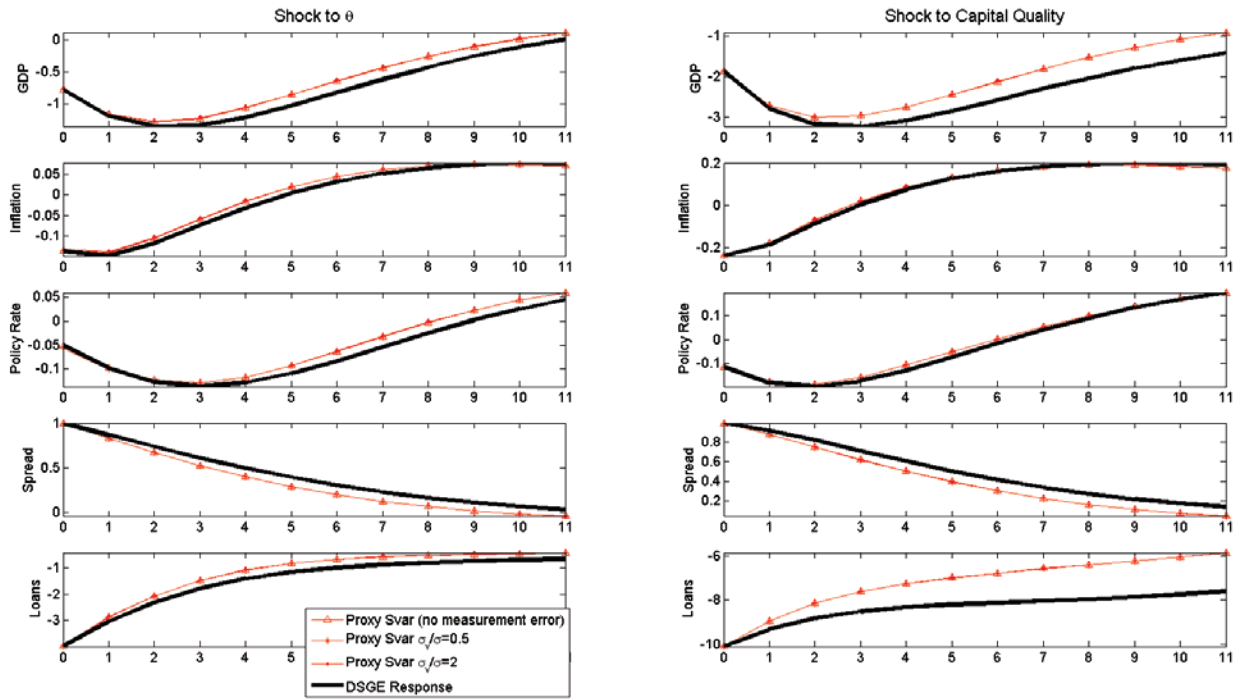


Figure 7: A comparison of DSGE and SVAR responses. Identification via the Proxy VAR method. The standard deviation of credit shocks is calibrated to equal 0.05.

with sign restrictions produces such a wide range of responses that the results are of little use from a practical perspective. Similarly, the recursive VAR model is very sensitive to ordering and the presence of measurement error. While measurement error also has an affect on the Proxy VAR estimates, the estimated impulse responses appear less sensitive to this problem.

When the credit shock is assumed to be more volatile than the other shocks in the DSGE model, both the sign restriction scheme and the proxy SVAR perform well in recovering the DSGE responses. A comparison of figures 2 and 7 suggest, however, that the proxy SVAR may offer an improvement over the VAR with sign restrictions in the case of the response of the policy rate.

In summary, the Monte-carlo results point to the Proxy VAR as a reliable model vis a vis the estimation of the credit supply shock. The simulations also suggest that if the credit shock is volatile enough, the sign restriction scheme delivers reasonable results.

4 The impact of credit supply shocks in the US. An examination of SVAR evidence

In this section of the paper we apply the proxy VAR and the SVAR with sign restrictions to US data. In both cases, we estimate the following basic reduced form VAR

$$Y_t = c + \sum_{j=1}^P B_j Y_{t-j} + A_0 \varepsilon_t \quad (10)$$

where Y_t contains the following variables: (1) real GDP growth, (2) CPI inflation, (3) the growth of loans to the non-financial private sector, (4) the spread of the composite lending rate over the three month treasury bill rate, (5) the three month treasury bill rate and (6) consumer confidence index. The data is quarterly and available from 1971Q2 to 2011Q4.⁵ The lag length P is chosen via the Schwarz criteria using a maximum lag of 4. Note that we include the consumer confidence index to control for agents' expectations.

4.1 A VAR with sign restrictions

We identify two shocks: (1) monetary policy and (2) credit supply. The sign restrictions that we use are summarised in table 1. These restrictions are implied by Gertler and Karadi (2011) model are robust across different calibrations.⁶

⁵See the data appendix for details on data sources and construction. Note that the period 1971Q2 to 2011Q4 represents the largest available sample of data. Some of the credit supply proxies described below are only available over a sub-sample.

⁶A 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 on request.

	GDP growth	CPI Inflation	Lending growth	Spread	3mth T-Bill	Cons. Confid
Monetary Policy	\leq	\leq	\leq	\cdot	\geq	\cdot
Credit Supply	\leq	\leq	\leq	\geq	\leq	\cdot

Table 1: Sign Restrictions in the benchmark model

In addition to the sign restrictions, we follow Kilian and Murphy (2012) and impose plausibility bounds on the response of GDP growth and CPI inflation to the monetary policy shock. In particular we require the contemporaneous response of these variables (to a policy shock scaled to increase the interest by 100 basis points) to be less than 0.1%. This plausibility restriction is motivated by the large body of existing empirical evidence on the effects of monetary policy shocks that strongly suggests that the *contemporaneous* response of these variables is close to zero. For example, classic papers on the monetary transmission mechanism (see for e.g. Christiano et al. (1996)) actually impose a zero contemporaneous response for real activity and inflation to policy shocks in order to accommodate policy lags. Papers that allow for a contemporaneous response (see Romer and Romer (2004a)) find that the *initial* impact of monetary policy is small and sometimes statistically insignificant. By imposing the plausibility restriction, we are able to narrow the range of admissible responses considerably.

A numerical bayesian approach (Gibbs sampling) is well suited to the estimating this structural VAR model.⁷ We employ 5200 Gibbs iterations using the first 5000 as burn-in. For each of the remaining 200 iterations, we generate 50,000 rotations of the contemporaneous impact matrix and retain those that satisfy the sign restrictions in table 1 and the plausibility restriction on the impact of monetary policy shocks.⁸

In figure 8 we present the 68% highest posterior density interval (HPDI) of the impulse response to the credit supply shock (normalised to increase the growth of credit by 0.6% on impact, the magnitude considered in Gambetti and Musso (2012)) and the contribution of this shock to the forecast error variance (FEV) of the endogenous variables.

Consider the impulse responses in the left panel. The estimated HPDI of the impact of the shock is wide, especially on impact. For example, the impact on GDP growth ranges from 0.5% to greater than 3% with the response close to zero within two quarters. The response of CPI inflation is more persistent, but the estimated magnitude covers a large range especially over the first few quarters. The response of the spread, consumer confidence and the short-term interest rate displays similar characteristics.

The right panel of the figure shows the 68% HPDI of the contribution of this shock to the FEV. The estimated HPDI covers such a large range that it is difficult to reach firm conclusions about the importance of this shock. For example, the estimated contribution to the FEV of GDP growth and CPI inflation ranges from around zero to over 50%. A similar

⁷We use a Normal inverse Wishart prior for the VAR parameters. This is described in the appendix.

⁸Note that out of a possible $200 \times 50000 = 10\,000\,000$ contemporaneous impact matrices 27543 satisfy the sign and the plausibility restrictions.

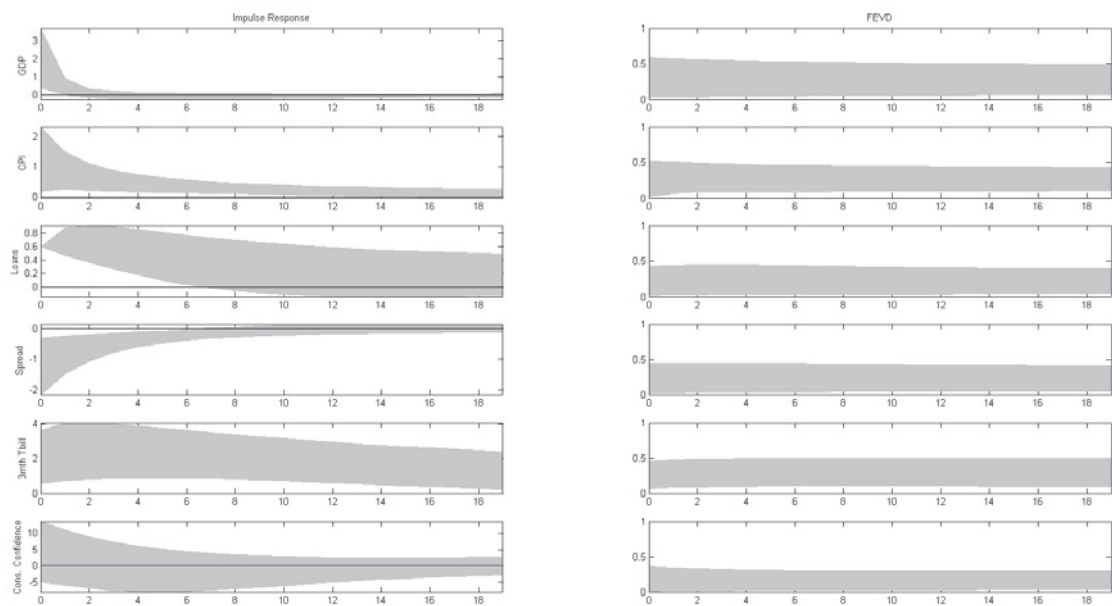


Figure 8: The impact of credit supply easing in the US using a VAR with sign restrictions. The grey shaded area represents the 68% HPDI.

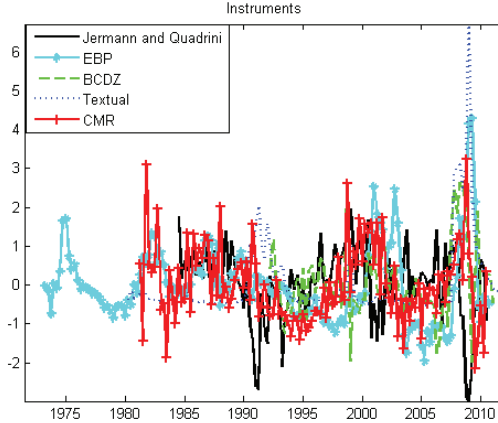


Figure 9: Instruments considered for the proxy VAR model.

pattern is apparent for the other variables.

To summarise, the results from the SVAR with sign restrictions appear to encompass admissible models that produce a large range for the impact of this shock. This occurs even after identifying an additional shock and placing tight plausibility restrictions on the response to this additional shock. Thus for our dataset, the sign restriction scheme appears unable to pin down the impact of credit supply shocks.

5 Proxy SVAR models

A number of proxies for credit supply shocks have been considered in a growing empirical literature. Prominent examples 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. (2012b), (3) 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).⁹ 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)). This measure is based on a search for the words ‘credit crunch’ and ‘tight credit’ using 9 US newspapers¹⁰ An index is then built by counting the number of occurrences of the words of interest.

Figure 9 plots the credit shock proxies that we consider. The temporal evolution of the proxies is similar with each pointing to tight credit conditions during the early and the

⁹Of course, there are numerous other measures proposed in this literature. Our aim is to present results based on the most recent contributions.

¹⁰The 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.

	R_M	F
Jermann and Quadrini	0.53	18.32
EBP	0.10	3.00
BCDZ	0.17	2.68
CMR	0.11	2.67
Textual	0.14	5.96

Table 2: Reliability Statistic and the first stage F statistic for proxy variables

mid-1980s, the early 1990s and 2000s and during the recent recession in 2009.

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 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 of 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 2 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 (see figure 10). 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. The scatter plots in the first column of figure 10 show that the credit shock estimated using the Jermann and Quadrini (2012) proxy is highly correlated with those obtained using the EBP and the textual measure. In contrast, this shock has a low correlation with the estimated shock using the BCDZ measure. This suggests that these instruments potentially identify very different shocks.

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. Figure 11 shows the correlation between the credit shock identified using the Jermann and Quadrini (2012) proxy 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 (2004b). 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 first column of figure 11 shows that the credit shock is highly

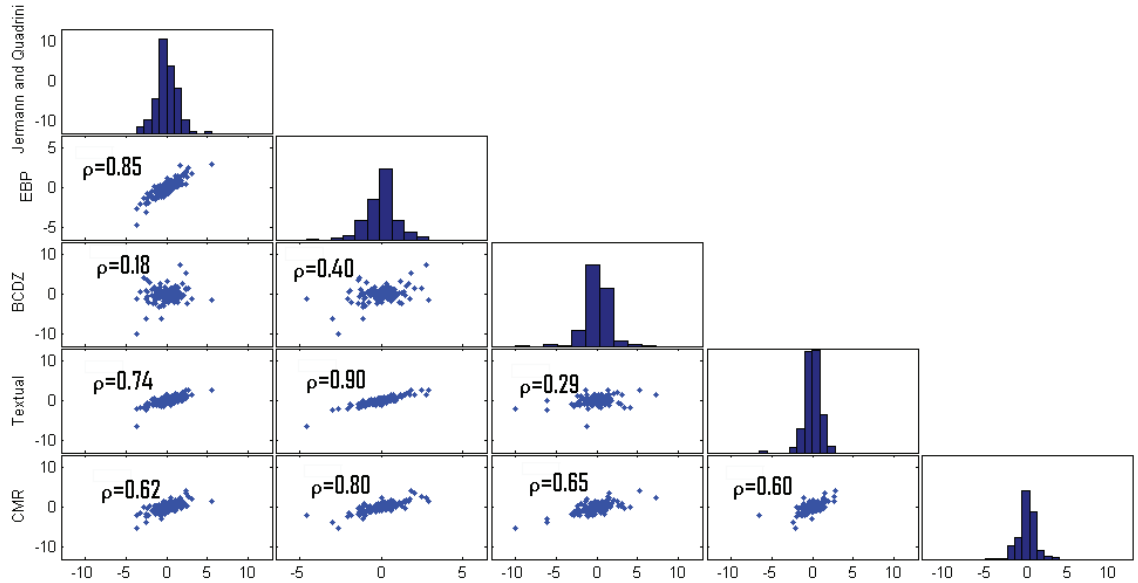


Figure 10: Sample correlation amongst the estimated shocks

correlated with the productivity and the uncertainty shock. This suggests that the Jermann and Quadrini (2012) instrument is not exclusively identifying a shock to credit supply. In contrast the identified shock is a composite of different economic innovations. While figure 11 focusses on the credit shock identified using the ‘strongest’ instrument, similar results hold for the credit shock estimates using the remaining instruments in table 2. The credit shocks identified via EBP, the textual index and the CMR measure are highly correlated with the productivity and uncertainty shocks, while the credit shock obtained using the BCDZ proxy has a correlation of over 0.9 with the monetary policy shock.

The estimated impulse response to and forecast error variance (FEV) decomposition of the credit supply shock (see figure 12) highlight this issue further. The estimated response of GDP is large, with the contemporaneous impact at around 2%. Similarly, the contribution of the credit supply shock to the FEV of GDP growth is estimated to be substantial, with the point estimate close to 0.8 over the entire horizon.¹¹ This suggests again that the shock identified using the Jermann and Quadrini (2012) proxy is perhaps a convolution of credit, productivity and uncertainty shocks. In short, it appears that it is not possible to directly infer the importance of credit supply shocks using the proxy variables in our data set.

¹¹These results do not change if the system is expanded to include fiscal variables, oil prices and measures of uncertainty. The results from the extended VAR are available on request.

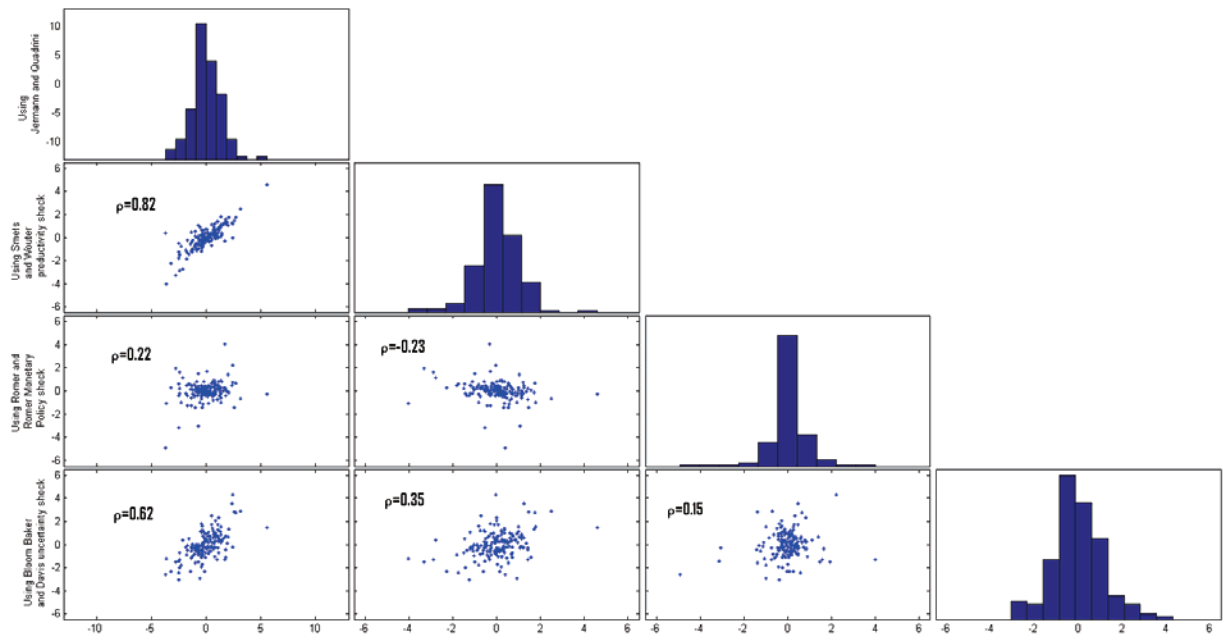


Figure 11: Correlation between the estimated credit shock and shocks to productivity, uncertainty and monetary policy.

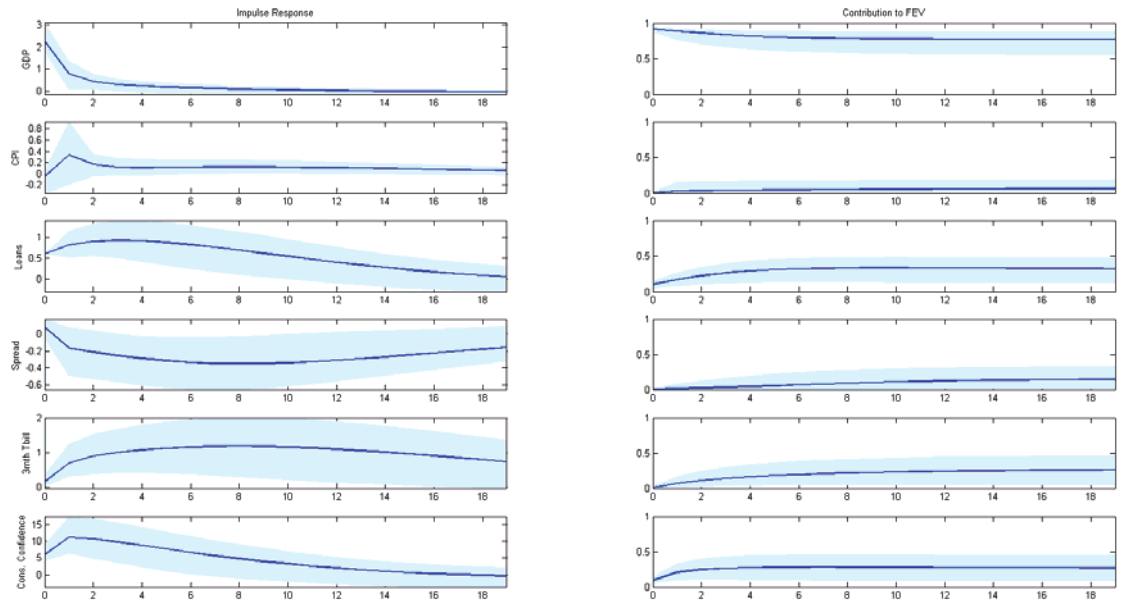


Figure 12: The impact of credit supply easing in the US using a proxy VAR with the Jermann and Quadrini (2012) proxy as an instrument. The impulse responses are normalised to increase lending growth by 0.6% The blue shaded area represents the 95% confidence interval obtained using the wild bootstrap described in Goncalves and Kilian (2004)..

6 Conclusions

This paper evaluates the performance of structural VAR models in estimating the impact of credit supply shocks. A monte-carlo experiment using a DSGE model as a DGP suggests that the proxy VAR model performs this task well while the VAR with sign restrictions is reliable under certain circumstances.

When applied to US data the results from these two structural VAR methods are disappointing. The VAR with sign restrictions produces inconclusive results. The proxy SVAR that uses the Jermann and Quadrini (2012) financial shock as an instrument indicates that credit supply shocks have a large and significant impact on the US economy – However, this estimated shock appears to be highly correlated with productivity and supply shocks.

7 Appendix A

8 Appendix B: 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) Oil Prices: OILPRICE
- Fiscal data: (1) Government Consumption expenditures and gross investment (BEA Table 1.15 line 21) divided by nominal GDP (FRED series: GDP). (2) Net Taxes: Current Receipts (BEA Table 3.1 Line 1) minus current transfer payments (BEA Table 3.1 line 17) and interest payments (BEA Table 3.1 line 22) divided by nominal GDP.

BEA is the bureau of economic analysis. FRED is the federal reserve economic data.

References

Baker, S. R., N. Bloom, and S. J. Davis (2012). Measuring economic policy uncertainty. Technical report.

- Bassett, W. F., M. B. Chosak, J. C. Driscoll, and E. Zakrajsek (2012a). Changes in bank lending standards and the macroeconomy. Technical report.
- Bassett, W. F., M. B. Chosak, J. C. Driscoll, and E. Zakrajsek (2012b). Changes in bank lending standards and the macroeconomy. Technical report.
- Canova, F. and M. Paustian (2011). Business cycle measurement with some theory. *Journal of Monetary Economics* 58(4), 345–361.
- Christiano, L., R. Motto, and M. Rostagno (2012). Risk shock. Mimeo.
- Christiano, L. J., M. Eichenbaum, and C. Evans (1996). The effects of monetary policy shocks: Evidence from the flow of funds. *Review of Economics and Statistics* 78, 16–34.
- Eickmeier, S. and T. Ng (2011). How do credit supply shocks propagate internationally? a gvar approach. Technical report.
- Fry, R. and A. Pagan (2011, December). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature* 49(4), 938–60.
- Gambetti, L. and A. Musso (2012). Loan supply shocks and the business cycle. Working papers, Universitat Autònoma de Barcelona.
- Gertler, M. and S. Gilchrist (1994, May). Monetary policy, business cycles, and the behavior of small manufacturing firms. *The Quarterly Journal of Economics* 109(2), 309–40.
- Gertler, M. and P. Karadi (2011, January). A model of unconventional monetary policy. *Journal of Monetary Economics* 58(1), 17–34.
- Gilchrist, S. and E. Zakrajsek (2012, June). Credit spreads and business cycle fluctuations. *American Economic Review* 102(4), 1692–1720.
- Goncalves, S. and L. Kilian (2004, November). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics* 123(1), 89–120.
- Iacoviello, M. and M. Pavan (2013). Housing and debt over the life cycle and over the business cycle. *Journal of Monetary Economics* 60(2), 221–238.
- Jermann, U. and V. Quadrini (2012, February). Macroeconomic effects of financial shocks. *American Economic Review* 102(1), 238–71.
- Kashyap, A. K., J. C. Stein, and D. W. Wilcox (1993, March). Monetary policy and credit conditions: Evidence from the composition of external finance. *American Economic Review* 83(1), 78–98.

- Kilian, L. and D. P. Murphy (2012, October). Why agnostic sign restrictions are not enough: Understanding the dynamics of oil market var models. *Journal of the European Economic Association* 10(5), 1166–1188.
- Liu, Z., P. Wang, and T. Zha (2013, 05). Land price dynamics and macroeconomic fluctuations. *Econometrica* 81(3), 1147–1184.
- Lown, C. and D. P. Morgan (2006, September). The credit cycle and the business cycle: New findings using the loan officer opinion survey. *Journal of Money, Credit and Banking* 38(6), 1575–1597.
- Mertens, K. and M. O. Ravn (2011, September). The dynamic effects of personal and corporate income tax changes in the united states. CEPR Discussion Papers 8554, C.E.P.R. Discussion Papers.
- Mertens, K. and M. O. Ravn (2012, May). A reconciliation of svar and narrative estimates of tax multipliers. CEPR Discussion Papers 8973, C.E.P.R. Discussion Papers.
- Peersman, G. (2011, December). Bank lending shocks and the euro area business cycle. Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium 11/766, Ghent University, Faculty of Economics and Business Administration.
- Romer, C. D. and D. H. Romer (2004a). A new measure of monetary shocks: Derivation and implications. *American Economic Review* 94(4), 1055–1084.
- Romer, C. D. and D. H. Romer (2004b, September). A new measure of monetary shocks: Derivation and implications. *American Economic Review* 94(4), 1055–1084.
- Rubio-Ramírez, J. F., D. F. Waggoner, and T. Zha (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *Review of Economic Studies* 77(2), 665–696.
- Smets, F. and R. Wouters (2007). Shocks and frictions in US business cycles: a Bayesian DSGE approach. *American Economic Review* 97, 586–606.
- Stock, J. H. and M. W. Watson (2008). What’s new in econometrics- time series. Lecture 7, National Bureau of Economic Research, Inc.
- Stock, J. H. and M. W. Watson (2012, May). Disentangling the Channels of the 2007-2009 Recession. NBER Working Papers 18094, National Bureau of Economic Research, Inc.

Table 3: 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	0.80
ϕ^Π	Inflation coefficient in the monetary policy rule	1.50
ϕ^X	Mark-up coefficient in the monetary policy rule	-0.125
ρ_k	Persistence: capital quality shock	0.66
ρ_θ	Persistence: shock to the credit constraint	0.9
ρ_a	Persistence: TFP shock	0.95
ρ_g	Persistence: government spending shock	0.95
σ_k	SD: capital quality shock	0.05
σ_θ	SD: shock to the credit constraint	0.05
σ_a	SD: TFP shock	0.01
σ_g	SD: government spending shock	0.01
σ_b	SD: bank net worth shock	0.01
σ_m	SD: monetary policy shock	0.01

Table 4: 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	$\phi_t = \frac{\eta_t}{\theta_t - \nu_t}$
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	$x_t = \frac{\phi_t}{\phi_{t-1}} z_t$

Table 5: 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	$\Pi_t^{1-\varepsilon} = (1 - \gamma) (\Pi_t^*)^{1-\varepsilon} + \gamma (\Pi_{t-1}^\psi)^{1-\varepsilon}$
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	$A_t = e^{a_t}, \quad a_t = \rho_a a_{t-1} + \varepsilon_t^a$
Collateral Constraint Shock	$\theta_t = \theta e^{\Theta_t}, \quad \Theta_t = \rho_\theta \Theta_{t-1} + \varepsilon_t^\theta$
Capital Quality Shock	$\xi_t = e^{s_t}, \quad s_t = \rho_\xi s_{t-1} + \varepsilon_t^\xi$

**This working paper has been produced by
the School of Economics and Finance at
Queen Mary, University of London**

**Copyright © 2014 Haroon Mumtaz, Gabor Pinter
and Konstantinos Theodoridis. All rights reserved**

**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/papers/wp.htm