Measuring the origins of macroeconomic uncertainty

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Abstract

This paper extends the procedure developed by Jurado *et al.* (2015) to allow the estimation of measures of uncertainty that can be attributed to specific structural shocks. This enables researchers to investigate the 'origin' of a change in overall macroeconomic uncertainty. To demonstrate the proposed method we consider two applications. First, we estimate UK macroeconomic uncertainty due to external shocks and show that this component has become increasingly important over time for overall uncertainty. Second, we estimate US macroeconomic uncertainty conditioned on monetary policy shocks with the results suggesting that while policy uncertainty was important during early 1980s, recent contributions are estimated to be modest.

Key words: FAVAR, Stochastic volatility, Proxy VAR, Uncertainty measurement.

JEL codes: C2,C11, E3

1 Introduction

One of the key aims of the growing literature on uncertainty has been to provide a general method of measuring this variable at the macroeconomic level. Measurement of uncertainty is of paramount importance for policy makers in order to ensure an effective policy reaction. For researchers, a reliable measure of uncertainty can aid in the investigation of the effects of uncertainty shocks.

For these reasons, a number of papers have proposed methods to construct indices of uncertainty. A prominent contribution in this literature is by Jurado *et al.* (2015) who devise a procedure to estimate a

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measure of macroeconomic uncertainty. They define this object as a weighted average of the forecast error variance (FEV) of large number of macroeconomic and financial data series where the FEV is obtained using factor augmented VARs (FAVARs) that allow for time-varying residual volatility. Jurado *et al.* (2015) argue that their method is distinct from other proposals as it explicitly removes the forecastable component from each series and constructs a macro measure by averaging the FEV across a large cross-section of data covering various sectors.[1]

In this paper we propose an extension of Jurado *et al.* (2015) procedure which allows the estimation of macroeconomic uncertainty that is due to an identified structural shock. In other words, by considering the contribution of shocks of interest to the FEV of each series rather than the total FEV, we isolate a measure of uncertainty originating from this shock. A comparison of this measure with the estimate of total macroeconomic uncertainty can then provide an indication of the importance of uncertainty associated with the shock of interest.

The shock-specific measures of macroeconomic uncertainty delivered by our procedure can be useful for the purposes of policy as they provide an indication of the source of uncertainty. For example, in the case of a small open economy like the United Kingdom, the proposed method can be used to estimate uncertainty associated with external shocks. Similarly, a measure of uncertainty associated with financial shocks may be useful in the case of an economy with a large financial sector. By identifying shocks to policy, the role of policy uncertainty can be investigated.

This procedure is related to papers such as Mumtaz and Zanetti (2013), JO (2014), Mumtaz and Surico (n.d.) that estimate the dynamic impact of innovations to the stochastic volatility of an identified shock. However, these papers employ small scale VARs, while the use of larger data sets in our procedure allows the interpretation of the estimated measure at a macroeconomic level. Similarly, while Berger *et al.* (2014), Mumtaz and Theodoridis (2017) and Mumtaz and Musso (2018) decompose uncertainty into components that are common across countries or regions, our analysis focuses on the origins of uncertainty in terms of structural shocks.

We show two applications of the proposed method in the empirical analysis below. First we estimate a

[1] Scotti (2016) also proposes an index built using forecast errors. However, the focus of the index on real activity measures.

measure of UK macroeconomic uncertainty that is associated with external or foreign shocks. As a proportion of total UK macroeconomic uncertainty, 'foreign shock' uncertainty has become increasingly important over time reaching its peak during the financial crisis of 2007. Second, we use the US data set employed by Jurado *et al.* (2015) and estimate uncertainty due to monetary policy. The estimates suggest that monetary policy uncertainty was extremely important during the early 1980s. However, over the remaining sample, uncertainty due to this shock has only played a modest role.

The paper is organised as follows: Section 2 describes the proposed method for estimating uncertainty. Two empirical examples are shown in section 3 while section 4 concludes.

2 Empirical method

2.1 The Jurado *et al.* (2015) method to measure uncertainty

Before describing the extension proposed in this paper, it is instructive to consider the procedure in Jurado *et al.* (2015). Jurado *et al.* (2015) consider a panel of M economic and financial time series $y_t = \{y_{1,t}, y_{2,t}, .., y_{M,t}\}$. The uncertainty associated with ith series at horizon k is defined as the conditional volatility of its unforecastable component:

$$U_{i,t}(k) = \sqrt{E\left[\left(y_{i,t+k} - E\left(y_{i,t+k}|I_t\right)\right)^2|I_t\right]} \tag{1}$$

where I_t denotes information available to agents at time t. The measure of macroeconomic uncertainty is then constructed by taking a (weighted) average of $U_{i,t}(k)$ across the M series. To construct the forecast $E(y_{i,t+h}|I_t)$, Jurado *et al.* (2015) use a factor augmented forecasting regression with stochastic volatility:

$$y_{i,t} = c_i + \sum_{p=1}^{P}\rho_{i,p}y_{i,t-p} + \sum_{q=1}^{Q}b_{i,q}Z_{t-q} + \sigma_{i,t}e_{i,t}, e_{i,t}\tilde{}N(0,1) \tag{2}$$

where Z_t denotes a set of regressors that includes common factors F_t and any additional relevant predictors z_t. The common factors are estimated as principal components (PC) from a large panel of data $X_t = [y_t, x_t]$ where x_t is an additional set of series that is thought to provide useful information in constructing the forecast. Jurado *et al.* (2015) assume that each column of $Z_t = \{Z_{1,t}, Z_{2,t}, .., Z_{K,t}\}$ follows an AR process with stochastic volatility:

$$Z_t = C + \sum_{l=1}^{H} d_l Z_{t-l} + h_t v_t, v_t \tilde{} N(0,1) \tag{3}$$

where $C = [C_1, .., C_K]'$, $d_l = diag([d_{1,l}, .., d_{K,l}])$ and $h_t = diag([h_{1,t}, .., h_{K,t}])$. Note that the log of the volatilities $\ln(\sigma_{i,t})^2$ and $\ln(h_{j,t})^2$ are described by AR(1) processes:

$$\ln(\sigma_{i,t})^2 = \alpha_i + \delta_i \ln(\sigma_{i,t-1})^2 + \tau_i \varepsilon_{i,t} \tag{4}$$

$$\ln(h_{j,t})^2 = \tilde{\alpha}_j + \tilde{\delta}_j \ln(h_{j,t-1})^2 + \tilde{\tau}_j \varepsilon_{j,t} \tag{5}$$

for $j = 1, 2, .., K$. In order to construct the FEV, Jurado *et al.* (2015) write equations 2 and 3 as a FAVAR model with stochastic volatility:

$$\begin{pmatrix} y_{i,t} \\ Z_t \end{pmatrix} = \begin{pmatrix} c_i \\ C \end{pmatrix} + \begin{pmatrix} \rho(L) & b(L) \\ 0 & d(L) \end{pmatrix} \begin{pmatrix} y_{i,t} \\ Z_t \end{pmatrix} + \begin{pmatrix} \sigma_{i,t} e_{i,t} \\ h_t v_t \end{pmatrix} \tag{6}$$

where $\rho(L), b(L)$ are lag polynomials of order P, Q, $d(L)$ denotes the matrix $diag([d_1(L), .., d_K(L)])$ with $d_j(L)$ representing a lag polynomal of order H. Note that, the error terms in equation 6 are heteroscedastic but contemporaneously uncorrelated. Let $Y_{i,t}$ denote $\begin{pmatrix} y_{i,t} & Z_t & y_{i,t-1} & Z_{t-1} & . & . & y_{i,t-\tilde{P}+1} & Z_{t-\tilde{P}+1} \end{pmatrix}'$ with $\tilde{P} = \max(P, Q, H)$. Then, in companion form, this FAVAR can be represented as:

$$Y_{i,t} = \Phi_i Y_{i,t-1} + V_{i,t} \tag{7}$$

where Φ is a function of the lag polynomials$\rho(L), b(L)$ and $d(L)$ and $E\left(V_{i,t} V_{i,t}'\right) = Q_{i,t} = diag\left(\left[\sigma_{i,t}^2, h_t^2, 0_{1\times((K+1)\times(\tilde{P}-1))}\right]\right)$. The k-period ahead forecast from the FAVAR is thus given by:

$$E_t(Y_{i,t+k}) = \Phi_i^k Y_{i,t} \tag{8}$$

The FEV is defined as $\Omega_i(k) = E_t\left[\left(Y_{i,t+k} - E_t\left(Y_{i,t+k}\right)\right)\left(Y_{i,t+k} - E_t\left(Y_{i,t+k}\right)\right)'\right]$ and evolves as the recursion:

$$\begin{aligned}\Omega_i(1) &= Q_{i,t+1} \\ \Omega_i(k) &= \Phi_i \Omega_i(k-1)\Phi_i' + Q_{i,t+k}\end{aligned} \tag{9}$$

Equation 9 requires an estimate of $Q_{i,t}$ over the forecast horizon. Given that the stochastic volatilities $\ln\left(\sigma_{i,t}\right)^2$ and $\ln\left(h_{j,t}\right)^2$ follow an AR(1) process, analytical expressions for $E\left(\sigma_{i,t+k}\right)^2$ and $E\left(h_{j,t+k}\right)^2$ can be easily derived making recursion 9 operational.[2] The uncertainty measure for the *ith* series at horizon k is the square root of the diagonal element in $\Omega_i(k)$ corresponding to $y_{i,t}$. As noted above, the macroeconomic uncertainty measure is constructed as a weighted average of the series specific uncertainty estimates.

2.2 The proposed method to measure uncertainty conditional on a shock

We modify this procedure to allow the estimation of the FEV in equation 9 conditional on an identified shock. To that end, we start from a FAVAR with stochastic volatility:

$$\begin{pmatrix} y_{i,t} \\ Z_t \end{pmatrix} = \begin{pmatrix} c_i \\ C \end{pmatrix} + \begin{pmatrix} \tilde{\rho}(L) & \tilde{b}(L) \\ \tilde{d}(L) & \bar{d}(L) \end{pmatrix}\begin{pmatrix} y_{i,t} \\ Z_t \end{pmatrix} + A^{-1}\begin{pmatrix} \sigma_{i,t} & 0 \\ 0 & h_t \end{pmatrix}\begin{pmatrix} e_{i,t} \\ v_t \end{pmatrix} \tag{10}$$

where $\tilde{\rho}(L), \tilde{b}(L), \tilde{d}(L)$ and $\bar{d}(L)$ denote lag polynomials of order P, A is a lower triangular matrix and $E_t = \begin{pmatrix} e_{i,t} \\ v_t \end{pmatrix} \tilde{} N(0, I)$. Denoting the residuals of the FAVAR by U_t, it is easy to see that $cov\left(U_t\right) = \Sigma_t = A^{-1}\begin{pmatrix} \sigma_{i,t} & 0 \\ 0 & h_t \end{pmatrix} A^{-1\prime}$. This formulation for the error covariance Σ_t is used in most studies that employ VARs with time-varying volatility (see for e.g. Cogley and Sargent (2005) for a prominent example). As we explain below, we estimate the system in equation 10 using a Gibbs sampling algorithm.

From our perspective, the key feature of the specification is the ability to decompose Σ_t as $\Sigma_t = A_{0,t}A_{0t}'$. The voluminous literature on structural VARs (SVARs) has led to numerous methods that can be used to calculate the contemporaneous impact matrix $A_{0,t}$ in a manner that imparts an economic interpretation on

[2] For example, $E\left(\sigma_{i,t+k}\right)^2 = \exp\left(\alpha_i \sum_{s=0}^{k-1}\left(\delta_i\right)^s + \frac{\tau_i^2}{2}\sum_{s=0}^{k-1}\left(\delta_i\right)^{2s} + \left(\delta_i\right)^k \ln\left(\sigma_{i,t}\right)^2\right)$. See Jurado *et al.* (2015) pp 1187.

the orthogonal shocks $\Upsilon_t = A_{0,t}^{-1}U_t$. For example, if the first column of $A_{0,t}$ satisfies the restriction that the associated responses of output and inflation are negative and of the short-term interest rate are positive, then one can interpret the first shock in Υ_t as a monetary policy shock. Similarly, as we show below, $A_{0,t}$ can be calculated via external proxies for shocks of interest.

Denote the companion form of the FAVAR as:

$$\begin{aligned} Y_{i,t} &= \Phi_i Y_{i,t-1} + \tilde{V}_{i,t} \\ E\left(\tilde{V}_{i,t}\tilde{V}_{i,t}'\right) &= \tilde{Q}_{it} = blkdiag\left[\Sigma_t, 0_{(N\times(P-1))\times(N\times(P-1))}\right] \end{aligned}$$

where $N = K + 1$ denotes the number of endogenous variables. Note that, as before, $E\left(\sigma_{i,t+k}\right)^2$ and $E\left(h_{j,t+k}\right)^2$ can be calculated by exploiting the assumption that the volatilties follow AR(1) processes thus allowing the calculation of Σ_t (and $\tilde{Q}_{it}$) over the forecast horizon. The total FEV is then given by the recursion:

$$\begin{aligned} \Omega_i\left(1\right) &= \tilde{Q}_{i,t+1} \\ \Omega_i\left(k\right) &= \Phi_i\Omega_i\left(k-1\right)\Phi_i' + \tilde{Q}_{i,t+k} \end{aligned} \tag{11}$$

The estimated uncertainty associated with series i is the square root of its FEV:

$$U_{i,t}\left(k\right) = \sqrt{e_1\Omega_i\left(k\right)}e_1' \tag{12}$$

where e_1 is a selection vector that extracts the FEV of $y_{i,t}$. The measure of total macroeconomic uncertainty can be calculated as a weighted average of $U_{i,t}\left(k\right)$:

$$U_t(k) = \sum_{i=1}^{M} \varpi_i U_{i,t}\left(k\right) \tag{13}$$

where ϖ_i denote weights.

Now suppose that interest centers on the uncertainty associated with the j_{th} shock, i.e. the shock identified by the j_{th} column of $A_{0,t}$ (denoted by $A_{0,t}^{(j)}$). The FEV conditional on this shock can be calculated using the recursion:

$$\begin{aligned}\Omega_i^{(j)}(1) &= \tilde{Q}_{i,t+1}^{(j)} \\ \Omega_i^{(j)}(k) &= \Phi_i \Omega_i^{(j)}(k-1)\Phi_i' + \tilde{Q}_{i,t+k}^{(j)}\end{aligned} \tag{14}$$

where $\tilde{Q}_{i,t}^{(j)} = blkdiag\left[A_{0,t}^{(j)}A_{0,t}^{(j)\prime}, 0_{((K+1)\times(P-1))\times((K+1)\times(P-1))}\right]$ and $A_{0,t}$ at a particular horizon is calculated using the estimate of Σ_t at that horizon. In other words, this estimate of the FEV differs from the total FEV in equations 9 and 11 only in that it uses the column of the $A_{0,t}$ matrix associated with the shock of interest. The measure of uncertainty conditioned on the j_{th} shock at horizon k is given by

$$U_{i,t}^{(j)}(k) = \sqrt{e_1 \Omega_i^{(j)}(k) e_1'} \tag{15}$$

In other words, $U_{i,t}^{(j)}(k)$ measures the variance of the forecast error of series i driven by the jth shock. The measure of macroeconomic uncertainty conditioned on shock j is then calculated as:

$$U_t^{(j)}(k) = \sum_{i=1}^{M} \varpi_i U_{i,t}^{(j)}(k) \tag{16}$$

$U_t^{(j)}(k)$ can be interpreted as a measure of uncertainty in the economy arising from shock j. A comparison of $U_t^{(j)}(k)$ and $U_t(k)$ over time provides information on periods when uncertainty arising from a specific set of shocks was of primary importance.

2.2.1 Estimation of the FAVAR with stochastic volatility

As our proposed method relies on a structural model, we depart from the estimation methodology of Jurado *et al.* (2015) where the forecasting regression 2 and the predictor regression 3 are estimated seperately, with the estimated residuals used to estimate the stochastic volatilities in an additional step. Instead, we follow the literature on VARs with stochastic volatility and use a well known Gibbs algorithm to approximate the posterior distribution of the parameters of the model in equation 10. The algorithm is set out in detail in the technical appendix and borrows heavily from the seminal contribution of Cogley and Sargent (2005).[3] However, there are two features worth highlighting. First, we use a principal component estimator to calculate the factors F_t before including them in the FAVAR. While, in principal, it is possible to treat F_t as additional latent states this increases the computational burden substantially. The main reason for this is that the FAVAR is estimated M times for each $y_{i,t}$ in the panel where M is typically large. Using a PC estimate of F_t reduces computational time rendering the procedure practical for the applied researcher. In addition, studies such as Bernanke *et al.* (2005) find that a two step approach whereby the factors are estimated via PC performs well in a structural setting. Second, as the number of endogenous variables in the FAVAR can be large, we use the computationally efficient method developed in Clark *et al.* (2016) to sample from the conditional posterior distribution of the VAR coefficients.

3 Empirical Results

In this section, we apply the proposed method to estimate uncertainty measures for the UK and the US. In the former case, we estimate an uncertainty measure that is associated with foreign shocks. In the latter case we consider macroeconomic uncertainty due to monetary policy shocks.

3.1 Foreign shocks and UK macroeconomic uncertainty

We first consider the role of foreign shocks in driving macroeconomic uncertainty in the UK. This question is of crucial importance for a small open economy like the UK, especially in the light of the financial crisis in 2007/2008.

To estimate uncertainty, we use the following FAVAR model

$$Y_t = c + \sum_{p=1}^{P} B_p Y_{t-p} + A^{-1} H_t e_t \tag{17}$$

[3] The model in equation 10 is simpler than the VAR considered in Cogley and Sargent (2005) as it allows for stochastic volatility but keeps the VAR coefficients fixed over time. Jurado *et al.* (2015) argue that the inclusion of factors in the model alleviates the possible impact of structural breaks.

where $Y_t = \begin{pmatrix} F_t^F \\ y_{i,t} \\ F_t^{UK} \end{pmatrix}$. F_t^F denote the N_F 'foreign' factors, i.e. principal components extracted from a data set comprising macroeconomic and financial data from a set of OECD countries excluding the UK (described below). Each series included for the UK is denoted by $y_{i,t}$ while F_t^{UK} is a set of N_{UK} 'UK factors', i.e. principal components extracted from the set of UK data series. As described above, the matrix A is lower triangular while H_t is a diagonal matrix with stochastic volatilities on the main diagonal:

$$H_t = \begin{pmatrix} H_t^F & 0 & 0 \\ 0 & \sigma_{i,t} & 0 \\ 0 & 0 & H_t^{UK} \end{pmatrix} \tag{18}$$

where $H_t^F = \left[h_{1,t}^F, .., h_{N_F,t}^F\right]$ are the time-varying standard deviations corresponding to the equations for F_t^F, $\sigma_{i,t}$ is the standard deviation of the residuals to the equations to $y_{i,t}$ while $H_t^{UK} = \left[h_{1,t}^{UK}, .., h_{N_F,t}^{UK}\right]$ is the standard deviations of the residuals to F_t^{UK}. The stochastic volatilities follow AR(1) processes:

$$\ln\left(h_{j,t}^F\right)^2 = \alpha_j + \delta_j \ln\left(h_{j,t-1}^F\right)^2 + \tau_j v_{j,t} \tag{19}$$

$$\ln\left(\sigma_{i,t}\right)^2 = \tilde{\alpha}_i + \tilde{\delta}_i \ln\left(\sigma_{i,t-1}\right)^2 + \tilde{\tau}_i \tilde{v}_{i,t} \tag{20}$$

$$\ln\left(h_{s,t}^{UK}\right)^2 = \bar{\alpha}_s + \bar{\delta}_s \ln\left(h_{s,t-1}^{UK}\right)^2 + \bar{\tau}_s \bar{v}_{i,t} \tag{21}$$

for $j = 1, .., N_F$, $i = 1, .., N$, $s = 1, .., N_{UK}$ and with $v_{j,t}, \tilde{v}_{i,t}, \bar{v}_{i,t}\tilde{\ } N(0,1)$.

3.1.1 Data

Our data set for this analysis comprises 22 OECD countries and is obtained from Mumtaz and Musso (2018). The list of countries includes Germany, France, Italy, Spain, the Netherlands, Belgium, Austria, Finland, Greece, Ireland, Portugal, Sweden, Denmark, Switzerland, Norway, US, Canada, Japan, South Korea and the UK. As described in Mumtaz and Musso (2018), 20 series are included for each country comprising real activity, inflation, labour market variables, asset prices, interest rates and money supply and series related to the trade position. The data is quarterly and runs from 1960Q1 to 2015Q4 with the first five years of data used as a training sample to initialise the Gibbs sampling algorithm. Before estimation, all non-stationary series are log-differenced.

3.1.2 Model specification and identification of foreign shocks

The foreign factors F_t^F are estimated via a PC estimator using the series for all countries except the UK. Based on the Bai and Ng (2002) criteria, we set $N_F = 6$. The UK factors are estimated using the $N = 20$ UK series $y_{i,t}$ with the Bai and Ng (2002) criteria suggesting that the number of factors $N_{UK} = 4$. The lag length in the FAVAR is set to 4.

In order to calculate the contemporaneous impact matrix $A_{0,t}$ we use a simple recursive scheme. Given that UK is a small open economy, we order F_t^F before $y_{i,t}$ and F_t^{UK}, thus assuming that UK shocks have no contemporaneous impact on common economic conditions in the rest of the OECD. We label the first 6 shocks as foreign shocks and interpret the FEV based on these shocks as a measure of uncertainty orginating from abroad.

The FAVAR in equation 17 is estimated for each $y_{i,t}$ with $i = 1, 2, .., 20$ to obtain the total FEV $U_{i,t}(k)$ and the FEV conditional on the first 6 structural shocks, (i.e. the foreign disturbances) $U_{i,t}^F(k)$. The measures of macroeconomic uncertainty and macroeconomic uncertainty due to the foreign shocks are calculated as cross-section averages of these variances. As shown in the technical appendix, similar results are obtained using the first PC as the aggregate measure.

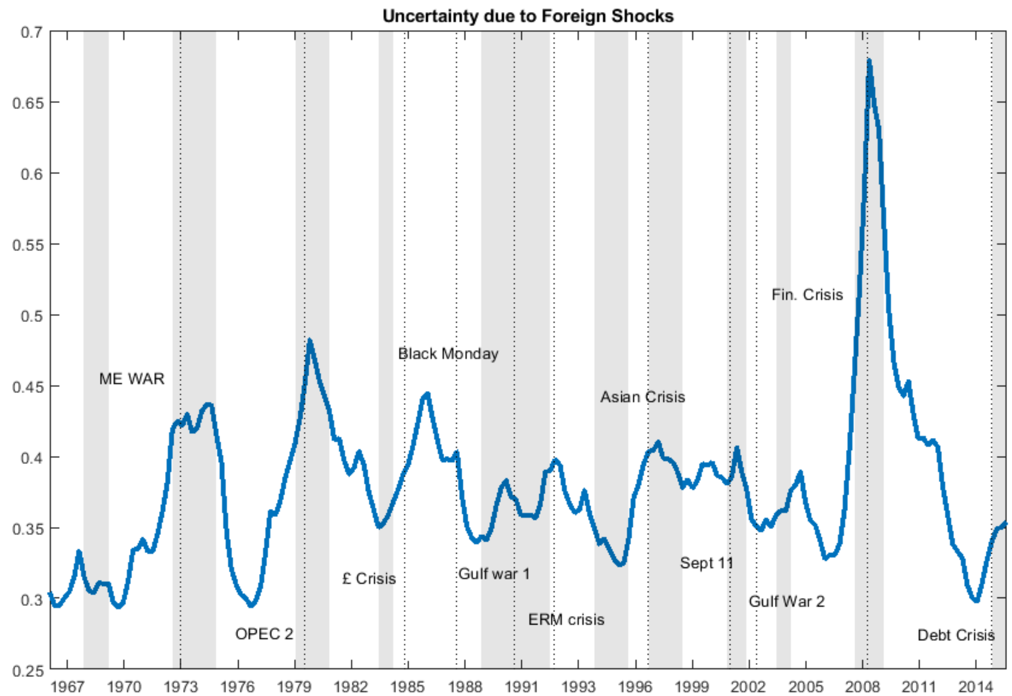

Figure 1: Macroeconomic uncertainty in the UK due to foreign shocks. 'ME WAR' denotes the Arab Israeli conflict while the sterling crisis of 1985 is denoted by '£ crisis'. The shaded areas denote recessions dates for the UK as indicated by the OECD.

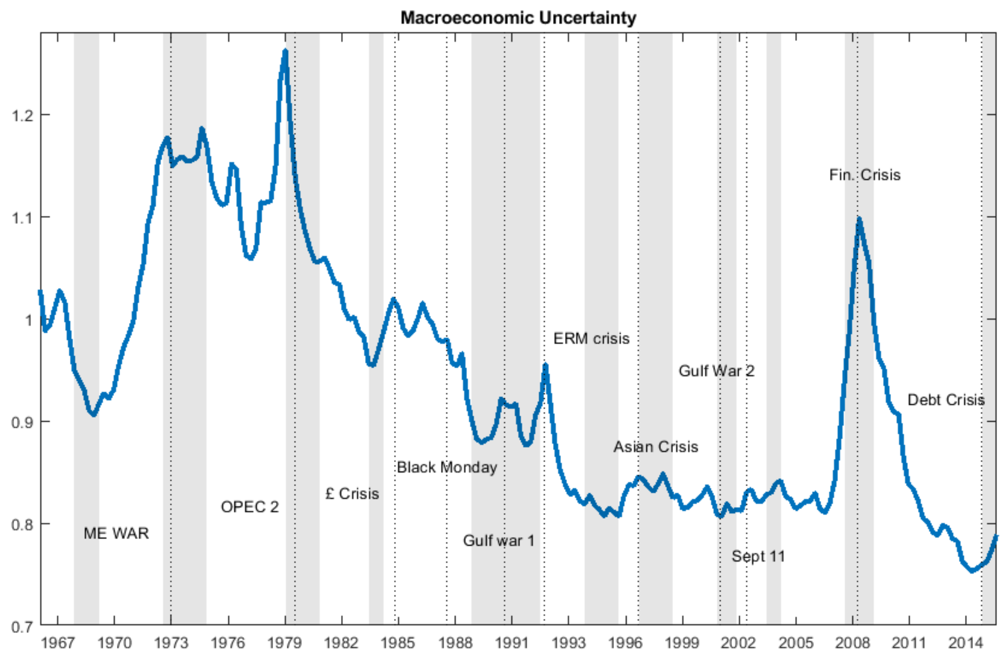

Figure 2: Macroeconomic uncertainty in the UK. 'ME WAR' denotes the Arab Israeli conflict while the sterling crisis of 1985 is denoted by '£ crisis'. The shaded areas denote recessions dates for the UK as indicated by the OECD.

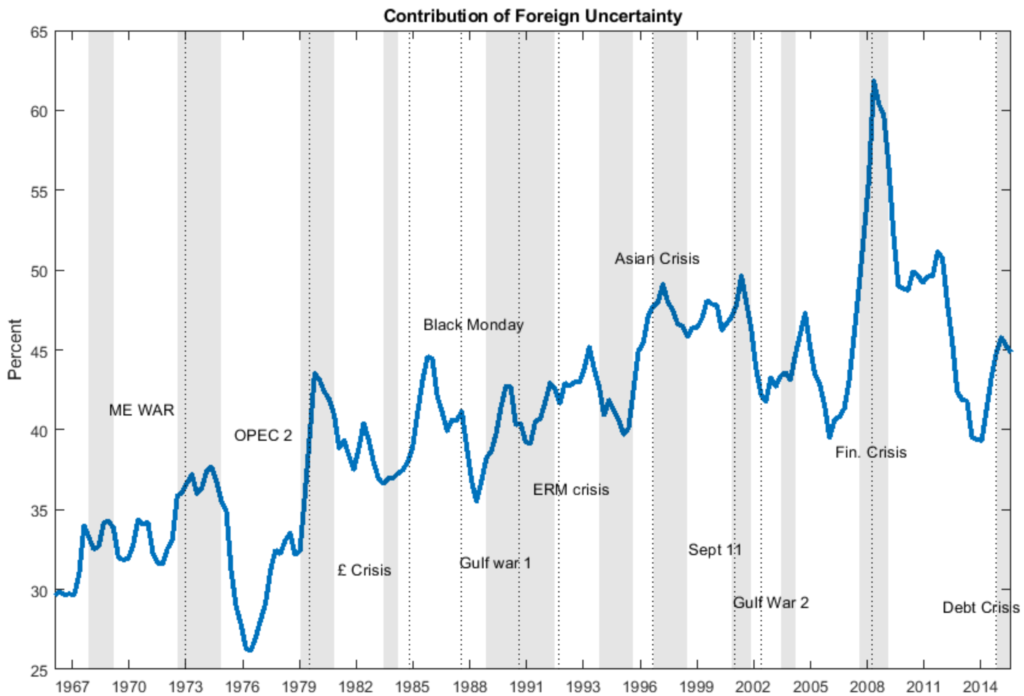

Figure 3: Contribution of foreign uncertainty. ‘ME WAR’ denotes the Arab Israeli conflict while the sterling crisis of 1985 is denoted by ‘£ crisis’. The shaded areas denote recessions dates for the UK as indicated by the OECD.

3.1.3 Results

Figure 1 displays the estimated macroeconomic uncertainty, 4 quarters ahead, conditioned on the foriegn shocks. Foreign uncertainty was high during the Arab Israeli conflict and then during the oil shocks at the end of the 1970s. During the 1980s, this measure rose after the Sterling crisis in 1985 and remained elevated up to 1988. There was an increase in foreign uncertainty during the ERM crisis in 1992 with the measure rising again towards the end of this decade as the Asian financial crisis hit. The measure reached its peak during the financial crisis of 2007 and 2008 indicating the importance of foreign shocks at this time.

Figure 2 shows the estimated measure of UK macroeconomic uncertainty. The profile of the uncertainty measure is very similar to that reported in Theophilopoulou (2018). Unlike the measure conditioned only on foreign shocks, total uncertainty was substantially higher during the 1970s and then displayed a downward trend over the next two decades. As shown in Figure 3, this implies that the contribution of foreign uncertainty to the total increased from an average of about 30% during the 1970s to an average of 40% to 45% in the subsequent period. Events such as the second oil shock of the 1970s, the Sterling and the Asian crisis and the September 11th terrorist attacks were associated with sharp rises in this contribution. However, Figure 3 clearly shows that the largest increase in the contribution occurred during the financial crisis of 2007/2008.

3.2 Monetary Policy uncertainty in the US

In our second application, we consider the role of macroeconomic uncertainty in the US associated with monetary policy shocks. The FAVAR model used to estimate uncertainty for each US series $y_{i,t}$ is given by:

$$Y_t = c + \sum_{j=1}^{P} b_j Y_{t-j} + e_t \tag{22}$$

$$m_t = c_m + v_t \tag{23}$$

where $Y_t = \begin{pmatrix} R_t \\ y_{i,t} \\ F_t \end{pmatrix}$. R_t is the policy interest rate while F_t denotes the factors extracted via PC from the large US data set described below. Following Mertens and Ravn (2013) and Stock and Watson (2012) our identification strategy uses an external instrument m_t. The instrument for the monetary policy shock satisfies the conditions:

$$cov\left(m_t, \varepsilon_{1,t}\right) = \alpha \tag{24}$$

$$cov\left(m_t, \varepsilon_{\cdot,t}\right) = 0 \tag{25}$$

In other words, the instrument is assumed to be correlated with the monetary policy shock $\varepsilon_{1,t}$ and uncorrelated with all remaining shocks $\varepsilon_{\cdot,t}$. As in Drautzburg (2016), the instrument is described by equation 23. The error terms $U_t = \begin{pmatrix} e_t \\ v_t \end{pmatrix}$ have the covariance matrix Ω_t:

$$\Omega_t = A^{-1} H_t A^{-1'} \tag{26}$$

where A is a lower triangular matrix and H_t is a diagonal matrix:

$$H_t = \begin{pmatrix} h_t^2 & 0 \\ 0 & \sigma_m^2 \end{pmatrix} \tag{27}$$

The vector h_t^2 contain the stochastic volatilities of the orthogonalised error terms of the FAVAR in equation 22.

3.2.1 Identification of the monetary policy shock

The first column of the contemporaneous impact matrix, i.e. corresponding to the monetary policy shock can be calculated by considering the following partition of Ω_t:

$$\Omega_t = \begin{pmatrix} \Omega_{ee} & \Omega_{ev}' \\ \Omega_{ev} & \Omega_{vv} \end{pmatrix} \tag{28}$$

where $\Omega_{ev} = E\left(\underbrace{(m_t - c_m)}_{v_t} e_t\right) = cov\left(m_t e_t\right)$.

The contemporaneous impact matrix $A_{0,t}$ can be expressed as:

$$e_t = A_{0,t}^{(1)} \varepsilon_{1,t} + A_{0,t}^{(\cdot)} \varepsilon_{\cdot,t} \tag{29}$$

where $A_{0,t}^{(1)} = \begin{pmatrix} A_{11,t} \\ A_{21,t} \\ . \\ A_{J1,t} \end{pmatrix}$ is the first column while $A_{0,t}^{(\cdot)} \varepsilon_{\cdot,t}$ denotes the product of each of the remaining J columns with the remaining J shocks, i.e. $A_{0,t}(\cdot)\varepsilon_{\cdot,t} = A_{0,t}^{(2)} \varepsilon_{2,t} + A_{0,t}^{(3)} \varepsilon_{3,t}.. + A_{0,t}^{(J)} \varepsilon_{J,t}$. Given equation 29, the covariance $cov\,(m_t e_t)$ can be written as:

$$E\left(\left(m_t - c_m\right) e_t\right) = E\left[v_t \left(A_{0,t}^{(1)} \varepsilon_{1,t} + A_{0,t}^{(\cdot)} \varepsilon_{\cdot,t}\right)\right] \tag{30}$$

Using the assumptions in equation 24 and 25 this equals:

$$cov\,(m_t e_t) = A_{0,t}^{(1)} \alpha$$

Therefore each element of the vector $A_{0,t}^{(1)} = \begin{pmatrix} A_{11,t} \\ A_{21,t} \\ . \\ A_{J1,t} \end{pmatrix}$ can be expressed as a function of the covariance of m_t with the residuals e_t and α:

$$\begin{pmatrix} A_{11,t} \\ A_{21,t} \\ . \\ A_{J1,t} \end{pmatrix} = \begin{pmatrix} \frac{cov(m_t, e_{1,t})}{\alpha} \\ \frac{cov(m_t, e_{2,t})}{\alpha} \\ . \\ \frac{cov(m_t, e_{J,t})}{\alpha} \end{pmatrix} \tag{31}$$

As α is unknown, this cannot be estimated directly. However, it is possible to estimate the relative impulse vector $\frac{A_{0,t}^{(1)}}{A_{11,t}}$ directly. In other words, the relative impulse vector $\frac{A_{0,t}^{(1)}}{A_{11,t}}$ is:

$$\begin{pmatrix} \frac{A_{21,t}}{A_{11,t}} \\ . \\ \frac{A_{J1,t}}{A_{11,t}} \end{pmatrix} = \begin{pmatrix} \frac{cov(m_t, e_{2,t})}{cov(m_t, e_{1,t})} \\ . \\ \frac{cov(m_t, e_{J,t})}{cov(m_t, e_{1,t})} \end{pmatrix} \tag{32}$$

As $cov(m_t, e_t)$ can be obtained at each point in time using the posterior estimate of Ω_t, equation 32 provides extra moment conditions to estimate the contemporaneous impact matrix at each point in time. In fact, Mertens and Ravn (2013) show that a solution for $A_{0,t}^{(1)}$ can be obtained by using the conditions in equation 32 along with the covariance restrictions $A_{0,t}A_{0,t}' = cov\,(e_t)$.

With an estimate of $A_{0,t}^{(1)}$ in hand, the FEV of $y_{i,t}$ conditioned on the monetary policy shock is obtained by using the recursion in equation 14.

We follow Gertler and Karadi (2015) and use the 1 year government bond yield as the policy instrument R_t. Our instrument for the monetary policy shock is the benchmark instrument in Gertler and Karadi (2015), i.e. the change in the 3 month ahead Fed Funds futures. Gertler and Karadi (2015) provide evidence supporting the strength of this instrument. Note that this instrument is only available after 1992 m1. However, following Drautzburg (2016), the missing data for m_t are treated as parameters and a step is added in the Gibbs sampler to sample from its conditional posterior. The technical appendix describes the estimation algorithm in detail.

3.2.2 Data and model specification

We use the monthly data set of Jurado *et al.* (2015) which spans the period 1960m1 to 2011m12 with the first 60 observations used as a training sample to initialise the Gibbs sampling algorithm. As discussed in Jurado *et al.* (2015), the data set consists of 132 macro series ($y_t = \{y_{1,t}, .., y_{132,t}\}$) used to calculate the uncertainty measures. These series include data on real activity, inflation, interest rates and asset prices. However, to estimate the factors F_t Jurado *et al.* (2015) combine y_t with an additional 146 financial time series. The series are transformed to induce stationarity.

Based on the Bai and Ng (2002) criteria, we set the number of factors to 10. The lag length of the FAVAR in 22 is set to 12. The system in equations 22 and 23 is estimated for $y_{1,t}, .., y_{132,t}$ and the posterior mean estimate of the parameters and volatilties is used to estimate uncertainty measures $U_{i,t}^{(j)}(k)$ and $U_{i,t}(k)$ for each series . The average across these 132 series specific uncertainty measures is used as the estimate of uncertainty due to monetary policy and total macroeconomic uncertainty, respectively.

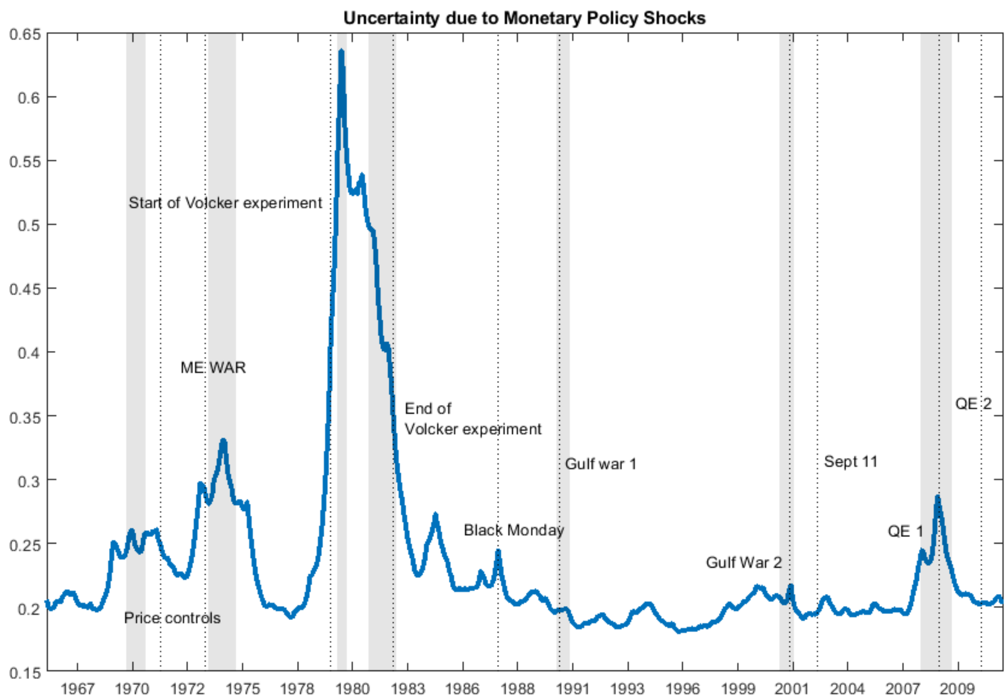

Figure 4: Macroeconomic uncertainty 12 months ahead in the US due to monetary policy shocks. The shaded areas denote NBER recessions dates.

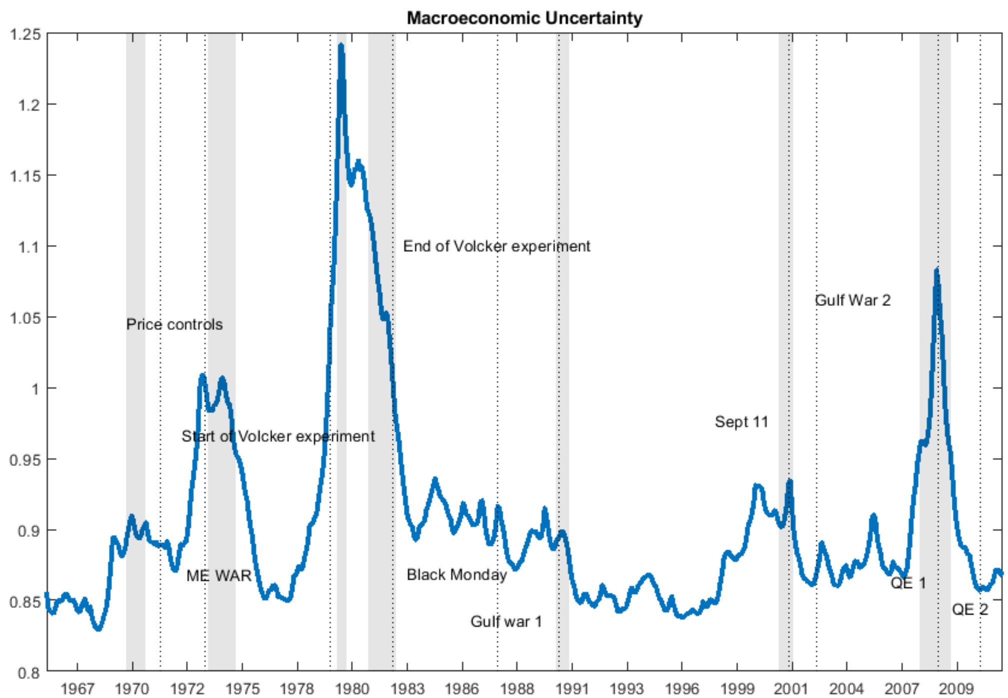

Figure 5: Macroeconomic uncertainty 12 months ahead in the US. The shaded areas denote NBER recessions dates.

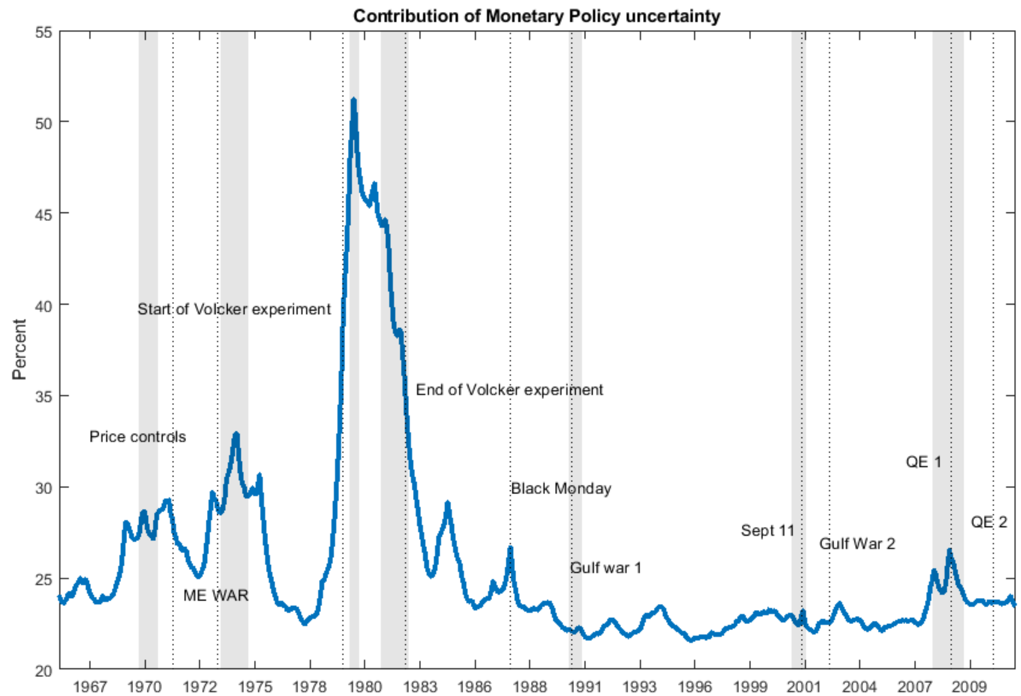

Figure 6: Contribution of monetary policy uncertainty to macroeconomic uncertainty 12 months ahead in the US. The shaded areas denote NBER recessions dates.

3.2.3 Results

Figure 4 plots the estimate of US macroeconomic uncertainty 12 months ahead that originates from the identified monetary policy shocks. During the mid-1970s, this measure of uncertainty peaked in the aftermath of first oil price shock. The period of monetary targeting by the Fed during the chairmanship of the Paul Volcker coincided with the largest increase in monetary uncertainty. Smaller increases in this measure can be seen during the stock market crash of 1987 and after the September 11th terrorist attacks. Uncertainty rose during the financial crisis before recording a decline after the introduction of quantitative easing.

Note that the estimated measure of *macroeconomic* uncertainty (shown in Figure 5) has a correlation of 0.95 with the original uncertainty index of Jurado *et al.* (2015). This is reassuring given that the specification of our FAVAR and the estimation sample is different from the forecasting regressions in Jurado *et al.* (2015). In Figure 6 we show the contribution of uncertainty due to monetary policy shocks to the total measure. On average across the sample, the contribution is estimated at a modest 25 percent. However, during the 1970s, the contribution exceeds this average a number of times, most noticeably during the Volcker experiment. It is interesting to note that during the recent financial crisis, the contribution of monetary policy increased, albeit by a modest amount.

4 Conclusions

This paper extends the methodology of Jurado *et al.* (2015) to allow the estimation of uncertainty that can be traced back to an identified shock. The procedure may be useful if the objective of the researcher is to investigate the factors behind a change in aggregate uncertainty measures. For example, information on the origins of uncertainty may help in the formulation of appropriate policy measures.

To demonstrate this method we estimate UK macroeconomic uncertainty due to external shocks and US macroeconomic uncertainty associated with monetary policy shocks. In future work, it may be interesting to consider the role played by uncertainty in financial markets in bringing about changes in uncertainty at the macroeconomic level.

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Measuring the origins of macroeconomic uncertainty

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August 15, 2018

Abstract

Technical Appendix

Key words: FAVAR, Stochastic volatility, Proxy VAR, Uncertainty measurement.

JEL codes: C2,C11, E3

1 Gibbs Sampling algorithm

We define the algorithm for the general model with an equation for an instrument with missing data. Without the instrument, the algorithm simplifies with steps 3 and 7 redundant.

The model is defined as:

$$Y_t = c + \sum_{p=1}^{P} b_p Y_{t-p} + e_t \tag{1}$$

$$m_t = c_m + v_t \tag{2}$$

$$cov\begin{pmatrix} e_t \\ v_t \end{pmatrix} = \Omega_t \tag{3}$$

$$\Omega_t = A^{-1} H_t A^{-1\prime} \tag{4}$$

$$H_t = \begin{pmatrix} h_t^2 & 0 \\ 0 & \sigma_m^2 \end{pmatrix} \tag{5}$$

$$\ln\left(h_t^2\right) = a + d \ln\left(h_{t-1}^2\right) + g\varepsilon_t \tag{6}$$

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Note that some of the data for the instrument m_t may be missing. The missing data is denoted by m_{-t}. Note that the stochastic volatilties are in the vector $h_t = [h_{1,t}, .., h_{J-1,t}]$ where equation 2 is indexed by J.

1.1 Priors

1. The priors for the VAR coefficients $B = vec([c, b_1, .., b_P])$ are set equation by equation. For the jth equation the priors are normal $P(B_j)\tilde{}N(B_{j,0}, \Sigma_{j,0})$ and set in the spirit of the Minnesota procedure with coefficients on the lagged dependent variables shrunk towards an AR(1) model. The tightness of the prior is set to a level that is standard for Bayesian VARs estimated for US data.

2. The prior for the intercept c_m is assumed to be uninformative. The prior is normal: $P(c_m)\tilde{}N(c_0, V_0)$ where $c_0 = 0$ and $V_0 = 1000$.

3. The prior for the non-zero, non-one elements of A is normal: $P(\alpha_j)\tilde{}N(\alpha_{j,0}, W_{j,0})$ where α_j denotes the non-zero, non-one elements in the jth row of A. $\alpha_{j,0}$ is set equal to a vector of zeros and $W_{j,0}$ is a diagonal matrix with diagonal elements equal to 1000.

4. The prior for σ_m^2 is inverse Gamma: $IG(\sigma_0^2, t_0)$ where $\sigma_0^2 = 0.01$ and $t_0 = 1$.

5. The prior for g^2 is inverse Gamma: $IG(g_0^2, t_0)$ where $g_0^2 = 0.01$ and $t_0 = 1$.

6. The prior for $\delta = [a, d]$ is normal: $N(\delta_0, V_\delta)$ where $\delta_0 = \begin{pmatrix} 0 \\ 0.9 \end{pmatrix}, V_\delta = \begin{pmatrix} 1 & 0 \\ 0 & 0.1 \end{pmatrix}$.

7. The prior for the initial condition for the volatility $\ln h_0$ is normal $N(\mu_0, s_0).\mu_0$ is set equal to the diagonal of variance covariance matrix obtained via OLS estimation of a VAR using a training sample of T_0 observations.

8. The initial conditions for the missing data m_{-t} are assumed to be normal $N(m_0, v_m)$ where m_0 is a vector of zeros and v_m is an identity matrix.

1.2 Conditional Posteriors

The Gibbs sampling algorithm samples from the following conditional posterior distributions:

1. $H\left(\bar{B}|\Xi\right)$ where $\bar{B}=[B,c_m]$ and Ξ denotes all the remaining parameters. We use the algorithm of Clark *et al.* (2016) to sample from the conditional posterior of the coefficients of each equation of the system in 1 and 2. Given the lower triangular nature of A, the model can be written equation by equation as:

$$\begin{aligned}
Y_{1,t} &= c_1+\sum_{p=1}^{P}b_{1,p}Y_{t-p}+h_{1,t}E_{1,t}\\
Y_{2,t}-h_{1,t}E_{1,t}\alpha_2' &= c_2+\sum_{p=1}^{P}b_{2,p}Y_{t-p}+h_{2,t}E_{2,t}\\
&.\\
&.\\
Y_{J-1,t}-h_{1:J-2,t}E_{1:J-2,t}\alpha_{J-1}' &= c_{J-1}+\sum_{p=1}^{P}b_{J-1,p}Y_{t-p}+h_{J-1,t}E_{J-1,t}\\
m_t-h_{1:J-1,t}E_{1:J-1,t}\alpha_J' &= c_m+\sigma_m E_{J,t}
\end{aligned}$$

where $Y_{j,t}$ denotes the dependent variable of the jth equation of the VAR in equation 1. The orthogonal residuals are denoted by $E_{j,t}$. $h_{1:j,t}$ and $E_{1:j,t}$ refer to the stochastic volatilities and orthogonal residuals in equations 1 to j. Note that when dealing with each equation, the terms on the left hand side involving $h_{j,t}$ and $E_{j,t}$ are observed and therefore the dependent variable can be constructed. The residuals of each equation are uncorrelated with the remaining residuals but are heteroscedastic. Denoting the constructed dependent variable for the jth equation as y_t and the regressors as x_t, the conditional posterior is normal $N(M,V)$ where:

$$V = \left(\Sigma_{j,0}^{-1}+x_t^{*'}x_t^*\right)^{-1} \tag{7}$$

$$M = V\left(\Sigma_{j,0}^{-1}B_{j,0}+x_t^{*'}y_t^*\right) \tag{8}$$

with $y_t^*=\frac{y_t}{h_{j,t}}$ and $x_t^*=\frac{x_t}{h_{j,t}}$ for the equations of the VAR 1 and $y_t^*=\frac{y_t}{\sigma_m}$ and $x_t^*=\frac{x_t}{\sigma_m}$ for the final equation 2.

2. $H\left(A|\Xi\right)$. Given a draw for the VAR coefficients and stochastic volatilties, the system can be written

in terms of the residuals

$$AU_t = H_t^{1/2} E_t$$

where $U_t = \begin{pmatrix} e_t \\ v_t \end{pmatrix}$ and $E_t \tilde{} N(0, I)$. Because A is lower triangular, the first equation in this system is an identity. The jth equation is defined as:

$$U_{j,t} = -U_{1:j-1,t}\alpha_{j'} + h_{j,t}E_{j,t}$$

This is a linear regression with heteroscedasticity. As in step 1, the conditional posterior is normal with mean and variance as in equations 8 and 7.

3. $H\left(\sigma_m^2|\Xi\right)$. The conditional posterior is inverse Gamma: $IG\left(\tilde{E}'_{J,t}\tilde{E}_{J,t} + \sigma_0, T + t_0\right)$ where $\tilde{E}_{J,t}$ is the orthogonalised residual of equation 2 and T is the sample size.

4. $H\left(g_j^2|\Xi\right)$. Given the stochastic volatilities and the coefficients of jth transition equation δ_j, the conditional posterior of g_j^2 is inverse Gamma: $IG\left(\varepsilon_t'\varepsilon_t + g_0^2, t_0 + T\right)$.

5. $H\left(\delta_j|\Xi\right)$. Given the stochastic volatilties and g_j^2, the transition equations 6 are linear regressions. The conditional posterior is normal $N(m, v)$:

$$v = \left(V_\delta^{-1} + \frac{1}{g_j^2}h'_{j,t-1}h_{j,t-1}\right)^{-1} \quad (9)$$

$$m = v\left(V_\delta^{-1}\delta_0 + \frac{1}{g_j^2}h'_{j,t-1}h_{j,t}\right) \quad (10)$$

6. $H\left(h_t|\Xi\right)$. Following Cogley and Sargent (2005), the stochastic volatilities are sampled using the Metropolis Hastings algorithm in Jacquier *et al.* (1994). Given a draw for the VAR coefficients and A the orthogonal residuals are defined as $AU_t = \tilde{E}_t$ and $VAR\left(\tilde{E}_t\right) = H_t$ where the first $J-1$ diagonal elements are the stochastic volatilities $h_{j,t}$. Jacquier *et al.* (1994) note that conditional on other VAR parameters, the distribution $h_{j,t}$, is given by $f\left(h_{j,t}|h_{j,t-1}, h_{j,t+1}, \tilde{E}_{j,t}\right) = f\left(\tilde{E}_{j,t}|h_{j,t}\right) \times f\left(h_{j,t}|h_{j,t-1}\right) \times f\left(h_{j,t+1}|h_{j,t}\right) = h_{j,t}^{-0.5}\exp\left(\frac{-\tilde{E}_{j,t}^2}{2h_{j,t}}\right) \times h_{j,t}^{-1}\exp\left(\frac{-(\ln h_{j,t}-\mu)^2}{2\sigma_h}\right)$ where μ and σ_h denote the mean and the variance of the log-normal density $h_{j,t}^{-1}\exp\left(\frac{-(\ln h_{j,t}-\mu)^2}{2\sigma_h}\right)$. Jacquier

et al. (1994) suggest using $h_{j,t}^{-1}\exp\left(\frac{-(\ln h_{j,t}-\mu)^2}{2\sigma_h}\right)$ as the candidate generating density with the acceptance probability defined as the ratio of the conditional likelihood $h_{j,t}^{-0.5}\exp\left(\frac{-\tilde{E}_{j,t}^2}{2h_{j,t}}\right)$ at the old and the new draw. This algorithm is applied at each period in the sample.

7. $H\left(m_{-t}|\Xi\right)$. We treat the missing data for the instrument as an unobserved state and write the problem in state-space form. For periods when m_t is unobserved, the observation equation is given by

$$\begin{pmatrix} Y_t & m_{-t} \end{pmatrix} = \begin{pmatrix} I_{J-1,NS} \\ 0_{1,NS} \end{pmatrix} \beta_t + V_t$$

where $\beta_t = \begin{pmatrix} Y_t \\ \hat{m}_t \\ Y_{t-1} \\ \hat{m}_{t-1} \\ . \\ . \\ Y_{t-P+1} \\ \hat{m}_{t-P+1} \end{pmatrix}$, $\hat{m}_t$ is the estimate of m_t, I denotes an identity matrix, 0 denotes a matrix of zeros and NS denotes the rows of the state vector, i.e. the number of states. The error term V_t is zero for the equations corresponding to the observed data Y_t. In contrast, the element of V_t corresponding to m_{-t} is assumed to have a very large variance. When data on m_t is observed, the observation equation changes to:

$$\begin{pmatrix} Y_t & m_{-t} \end{pmatrix} = \left(I_{J,NS}\right)\beta_t$$

The transition equation is:

$$\beta_t = \mu + F\beta_{t-1} + L_t, var\left(L_t\right) = Q_t$$

where μ, F denote the constants and coefficients of the system 1 and 2 in companion form. Similarly, Q_t denotes the error covariance Ω_t in companion form. With the model in state space form, the Carter and Kohn (1994) algorithm is then used to draw β_t. The distribution of the state vector is Gaussian: $\beta_T|\Xi \sim$

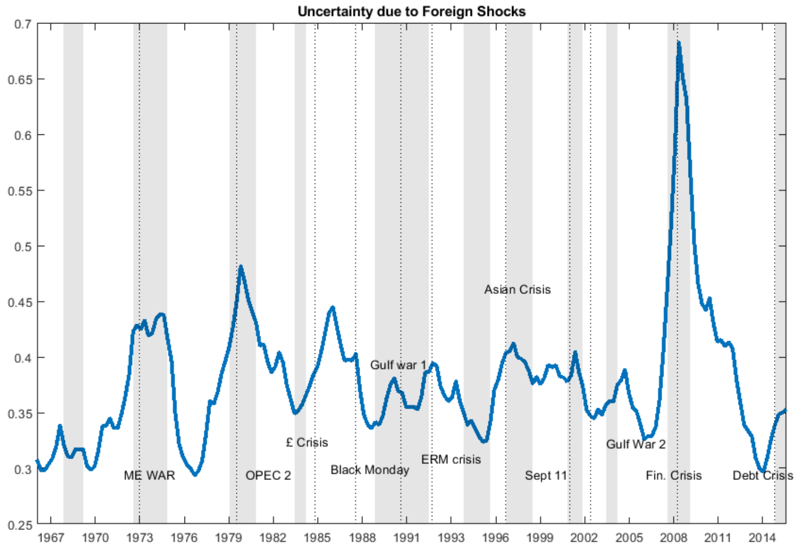

Figure 1: Uncertainty due to external shocks.

$N\left(\beta_{T\backslash T}, P_{T\backslash T}\right)$ and $\beta_t|\beta_{t+1}, \Xi \sim N\left(\beta_{t|t+1,\beta_{t+1}}, P_{t|t+1,\beta_{t+1}}\right)$. As shown by Carter and Kohn (1994) the simulation proceeds as follows. First we use the Kalman filter to draw $\beta_{T|T}$ and $P_{T|T}$ and then proceed backwards in time using $\beta_{t|t+1,\beta_{t+1}} = \beta_{t|t} + P_{t|t}F'\left(FP_{t|t}F' + Q_{t+1}\right)^{-1}\left(\beta_{t+1} - \mu - F\beta_{t|t}\right)$ and $P_{t|t+1,\beta_{t+1}} = P_{t|t} - P_{t|t-1}F'\left(FP_{t|t}F' + Q\right)^{-1}FP_{t|t}$.

2 Additional Results

Figure 1 uses the first PC to construct UK macroeconomic uncertainty due to external shocks.

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