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The impact of uncertainty shocks in the United Kingdom

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Abstract

This paper uses a data-rich environment to produce direct econometric estimates of macroeconomic and financial uncertainty in the United Kingdom for the period 1991–2016. These indices exhibit significant independent variation from popular proxies for macroeconomic and financial uncertainty. We identify the impact of uncertainty shocks using narrative sign restrictions, which allow us to exploit individual historic events to separate the impact of macroeconomic, financial and credit shocks on real variables. Using only traditional sign restrictions, we find that the real effects of macroeconomic uncertainty shocks are generally weaker than proxies suggest and that the effects depend on a subsequent rise in financial uncertainty and credit spreads to have a negative impact on GDP. Exploiting narrative events such as the disorderly exit from the Exchange Rate Mechanism, the dot-com recession and the financial crisis support this finding. However, conditioning on narrative events more closely associated with political uncertainty, ie tight general elections, suggests a stronger impact response of GDP to macro uncertainty shocks. We find these results are robust to controlling for both financial and global uncertainty.

Key words: Economic uncertainty, business cycles, United Kingdom.

JEL classification: D80, E32.

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1 Introduction

Macroeconomic uncertainty as a source of business cycle fluctuations has received renewed attention after the financial crisis of 2007-09. Both the Federal Open Market Committee (FOMC) and the Bank of England Monetary Policy Committee (MPC) cited increased uncertainty as an important force behind reduced household and business spending during the financial crisis. Stock and Watson (2012) find support for this claim, citing liquidity risk and uncertainty shocks as accounting for two thirds of the decline in U.S. GDP over this time. Similarly, Dendy et al. (2013) find evidence for the role of macro uncertainty in driving unemployment and industrial production during this time for the U.K. Moreover, uncertainty shocks remain pertinent for policy decisions after the crisis, with the December 2016 FOMC minutes citing considerable uncertainty around the Trump administration's fiscal stimulus plans and the Bank of England MPC forecasting large declines in consumption and investment due to increased uncertainty in August 2016 following the vote to exit the European Union in the U.K.

Despite this influence on policy makers, there remains considerable debate on how uncertainty should be measured. The majority of the proxies for uncertainty draw on the influential work of Bloom (2009) and Baker et al. (2016). The latter employs realised volatility in financial markets (stock market) and the former measures uncertainty more broadly using media citations of fiscal and monetary policy, forecaster disagreement, and data on expiring federal taxes. For example, the Bank of England measure uncertainty using the methodology of Haddow et al. (2013) which is the first principal component drawn from a swathe of uncertainty proxies: three month option implied stock market volatility (FTSE 100), implied volatility of the trade weighted exchange rate index, forecast disagreement on GDP growth, consumer confidence survey responses on unemployment expectations and their financial situation over the next 12 months and media citations of uncertainty. However, these approaches can suffer from a number of problems. Firstly, they do not explicitly control for a deterioration in expectations of the mean economic outcome when volatility increases, potentially conflating uncertainty shocks and confidence shocks. Secondly, they focus on measuring variability when what ought to matter for economic decision making is a deterioration in agents' ability to predict economic outcomes, as emphasised by Jurado et al. (2015). Thirdly, the use of a small number of proxies for uncertainty can lead to a misleading relationship between uncertainty and the real economy when, for example, one of those proxies is unusually volatile (Forbes (2016))[1].

This paper addresses these concerns by producing a new measure of macroeconomic and financial uncertainty for the U.K. for 1991-2017 following the methodology of Jurado et al. (2015) - hereafter JLN. The latter measures macroeconomic and financial uncertainty as the conditional variance of the unforecastable component common to a large number of macroeconomic and financial variables. This measure systematically removes a forecast of the mean from the uncertainty measure, captures a deterioration in predictability rather than just volatility and defines uncertainty as common to a large set of time series, avoiding disproportionate influence of any one series. This methodology allows us to construct measures of both financial and macroeconomic uncertainty which are useful in trying to separate the real effects of different types of uncertainty shocks.

Across a variety of measures of uncertainty, the major uncertainty shock in the sample is the global financial crisis of 2007-09. This poses significant challenges to identifying the effect of macroeconomic uncertainty shocks. It is difficult to separate the effect of a macroeconomic uncertainty shock from the financial shocks that took place at that time. A number of studies have suggested that once credit

[1]For example, media citations are highly volatile yet have a relatively weak correlation with real variables, which can generate misleading signals about the real effects of rises in uncertainty. The Bank of England's benchmark uncertainty index has arguably suffered from just this sort of problem after the Brexit vote, see Forbes (2016)

and financial shocks are accounted for the real effects of macroeconomic uncertainty shocks is greatly reduced (Popescu and Smets (2010), Caldara et al. (2016) and Ludvigson et al. (2015)). Similarly, the financial crisis was a global recession with large spillovers in trade flows, output and elevated risk aversion in many countries. Thus the real effects of macro uncertainty shocks are likely to be conflated with the effects of these global shocks (Cesa-Bianchi et al. (2014), Mumtaz and Theodoridis (2015) and Berger et al. (2016)). To address these concerns we construct separate uncertainty measures for macroeconomic, financial and global uncertainty using the JLN methodology and employ narrative sign restrictions, as recently proposed by Antolin-Diaz and Rubio-Ramirez (2016), to better separate macro uncertainty shocks from other uncertainty shocks.

Our estimates for uncertainty show significant independent variation from popular proxies such as those based on implied volatility and the Baker et al. (2016) methodology. We compare the results from our new measure of macro uncertainty to those based on the paper by Haddow et al. (2013). Using only traditional sign restrictions, we find that the real effects of macroeconomic uncertainty shocks is generally weaker than proxies suggest and that the effects depend on a subsequent rises in financial uncertainty and credit spreads to have a negative impact on GDP. Exploiting narrative events such as the disorderly exit from the Exchange Rate Mechanism, the dot-com recession and the financial crisis support this finding. However, conditioning on narrative events more closely associated with political uncertainty, i.e. tight general elections, suggests a stronger impact response of GDP to macro uncertainty shocks.

The remainder of this paper is structured as follows: section 2 reviews the literature on uncertainty shocks, section 3 outlines the econometric framework used to measure macro and financial uncertainty following JLN; section 4 describes the data set used in estimation; section 5 describes the estimates of uncertainty we find and compares these to popular proxies; section 6 describes the macroeconomic impact of uncertainty shocks and section 7 concludes.

2 Literature

A variety of approaches exist on measuring uncertainty. Bloom (2009) initiated the literature developing proxies for uncertainty using large changes in realised stock market volatility as exogenous changes in uncertainty. Baker et al. (2016) develop an economic policy uncertainty index for the U.S. comprised of a frequency count of news stories on uncertainty about the economy or fiscal and monetary policy, the number and revenue impact of scheduled federal taxes set to expire, and the extent of disagreement among economic forecasters over future government purchases and future inflation. Dendy et al. (2013) pursue a similar methodology for the U.K. focusing on economic rather than policy uncertainty, with an index composed of a newspaper searches, variation in forecasts of economic variables and mentions of uncertainty in the Bank of England Monetary Policy Committee (MPC) minutes and Financial Stability Reports (FSRs). Other proxies have focused on forecaster disagreement as the most compelling component of the above proxies, these studies include Dovern et al. (2012); Leduc and Liu (2012) and Bachmann and Bayer (2013). Other studies aim to measure the role of uncertainty through econometric techniques to estimate the time varying volatility of macroeconomic time series.Fernandez-Villaverde et al. (2011) study time-varying volatility in the real interest rates of four emerging small open economies: Argentina, Ecuador, Venezuela, and Brazil. They find that real interest rate volatility leads to a fall in output, consumption, investment, and hours worked. Fernandez-Villaverde et al. (2015) estimate volatility of government spending and taxes and feed this series of volatility estimates into a general equilibrium model, finding similar contractionary patters for real variables similar to previous studies. Mumtaz and Zanetti (2013),Mumtaz and Surico (2013) and Mumtaz and Theodoridis (2015) augment a standard SVAR model to allow for time variation in the volatility of identified monetary policy shocks where the level of endogenous variable included in the VAR and this time varying volatility dynamically interact. A recent alternative econometric approach, pursued by Jurado et al. (2015), measures macroeconomic and financial uncertainty as the conditional variance of the unforecastable component common to a large number of firm-level, macroeconomic and financial variables. JLN aim to deliver an uncertainty proxy that captures (1) when the economy has become less predictable and (2) where that decline in predictability applies to many macroeconomic time series. This approach is outlined in more detail in section 2 below.

Even if uncertainty is appropriately measured it remains difficult to separate the effects of macroeconomic uncertainty shocks from those of financial and global shocks. A number of studies have found common co-movement between domestic uncertainty (especially as measured using financial variables) across countries and that, once global uncertainty shocks are accounted for, domestic uncertainty has relatively modest effects real effects (Cesa-Bianchi et al. (2014); Berger et al. (2016) and Mumtaz and Theodoridis (2017)).

The literature on the conflation of uncertainty and financial shocks is more developed and addresses two key issues. Firstly, the largest uncertainty shock identified in most studies coincides with the financial crisis, when credit and other financial shocks also took place. Secondly, its not clear whether uncertainty is primarily an endogenous response to financial shocks or if it is an independent forcing variable in its own right. Popescu and Smets (2010), studying German data, use a VAR with forecaster dispersion as a proxy for uncertainty and credit spreads (corporate and mortgage bond rates to government bonds rates) as a measure of financial stress. They show that the real effects of financial stress are much larger and persistent than those of uncertainty with lower inflation and GDP, and higher unemployment. Caldara et al. (2016)seek to discriminate between the role of financial and uncertainty shocks in the business cycle. Their identification procedure uses the penalty function method of Uhlig (2005) to (1) extract the shock explaining the largest forecast error variance of corporate credit spreads (adjusted for predictable default) then (2) do the same for an uncertainty proxy (realised volatility of cross-sectional stock market returns) conditional on the financial shock identified in the first step. They then repeat this procedure but reversing the order of shocks. The first identification strategy makes it hard for uncertainty shocks to matter, but it extracts the most powerful financial shock in the system and the second strategy delivers the most powerful uncertainty shock by minimizing the role played by financial shocks. They find that both financial and uncertainty shocks matter for real fluctuations but that uncertainty shocks matter significantly more when they coincide with a tightening of credit spreads.

Ludvigson et al. (2015) address the above question by focusing on the impact of macro vs. financial uncertainty shocks. First, they build on JLN by using the latter methodology to produce separate measures of macroeconomic and financial uncertainty. Second, they identify the impact of uncertainty shocks on GDP by constructing a synthetic external instrumental variable that is correlated with macro and financial uncertainty but contemporaneously uncorrelated with real activity shocks. They find that macro uncertainty is fully an endogenous response to other shocks that cause business cycles but that financial uncertainty shocks have negative effects on a variety of real variables.

Our approach follows JLN in that we study the impact of both financial and macro uncertainty shocks and we acknowledge the problems of recursive identification in this context. The approach of synthetic external instruments is innovative but it is complex and consequently opaque to many applied users and policymakers. Moreover, as highlighted by Terry (2016), independent financial shocks can cause the synthetic external variable approach to fail as they create independent correlation between that variable and real variables, invalidating the instrument. Instead we adopt the combination of flexible sign restrictions and narrative restrictions on historical events, as pioneered by Antolin-Diaz and Rubio-Ramirez (2016). This methodology allows us to place weak sign restrictions on the shocks and then sharpen inference by placing restrictions on the historical decomposition of the variables in the SVAR. These restrictions are simple, transparent and relatively easy to motivate based on historical episodes.

We place narrative restrictions on two types of historical event: economic events associated with high uncertainty and general elections when that election outcome was highly uncertain. The former include well known periods of economic uncertainty such as the disorderly departure of the U.K. from the Exchange Rate Mechanism in September 1992 and the collapse of Lehman Brothers in late 2008. The latter draws on the literature finding that uncertainty shocks take place around general elections. In particular the evidence that tight election races tend to lead to higher uncertainty. Li and Born (2006) find that realised U.S. stock market volatility rises prior to the election date if there is no clear leader in election polls. Bialkowski et al. (2008) find that realised stock market volatility is 23% higher within a two month window around elections using data on 27 OECD countries. They find evidence that a small margin of victory is a significant determinant of that rise in volatility. Goodell and Vahamaa (2013) find similar evidence of increased implied volatility around elections using the VIX. Kelly et al. (2016) find evidence of a 5% permuim on options that cover political events (national elections and global summits) relative to those that do not and that this premuim is higher during a downturn. Julio and Yook (2012) and Canes-Wrone and Park (2014) document uncertainty induced declines in investment around general elections across a variety of developed and developing countries.

3 Measuring Uncertainty: Econometric Framework

We measure uncertainty following JLN; the reader is directed to their paper for full details of their approach. That methodology ensures that measured uncertainty captures when the economy has become less predictable (rather than just more volatile) and also reduces dependencies on one (or a small number of) observable series. Following Ludvigson et al. (2015), let $y^C_{jt} \in Y^C_t = (y^C_{1t}, y^C_{2t}, ..., y^C_{N_C t})$ be a variable in category C. A forecast, $E\left[y^C_{jt+h}|I_t\right]$, is taken from a factor augmented forecasting model:

$$y^C_{jt+1} = \phi^y_j(L)y^C_{jt} + \gamma^F_j(L)\hat{\mathbf{F}}_t + \gamma^G_j(L)\hat{\mathbf{G}}_t + \gamma^W_j(L)\mathbf{W}_t + v^y_{jt+1} \tag{1}$$

Where $\phi^y_j(L)$, $\gamma^F_j(L)$ and $\gamma^W_j(L)$ are finite order lag polynomials. The factors, $\hat{\mathbf{F}}_t$, are drawn from the information set of agents, I_t, comprised of the full data set of macro and financial variables described below. $\hat{\mathbf{G}}_t$ is drawn in the same way except that the squares of the original data are used to capture potential non-linearities. The prediction errors for y^C_{jt+1}, $\hat{\mathbf{F}}_t$,$\hat{\mathbf{G}}_t$ and $\mathbf{W}_t$ are permitted to have time-varying volatility[2]. Uncertainty is then the conditional expectation of this time-varying

[2]JLN allow for stochastic volatility in both the estimates of the factors used to augment the VAR and the variables included in the VAR. This results in four sources of time variation in the forecast errors due to the stochastic volatility of the VAR shocks, the factors, the covariance between these two, and an autoregressive term due persistence in the

squared forecast error, which is computed using a stochastic volatility model[3]. That model allows for shocks to the second moment of a variable to be independent of the first moment ensuring that these estimates capture a mean preserving increase in volatility rather than a rise in volatility that accompanies a deterioration in the mean (as is often seen in survey forecasts used widely in uncertainty proxies). The forecasting model can be cast as FAVAR in first order companion form with $\mathbf{Z}_t = (\hat{\mathbf{F}}'_t, \hat{\mathbf{G}}'_\mathbf{t}, \mathbf{W}'_t)$, $Y^C_{jt} = (y^C_{jt}, y^C_{jt-1}, ..., y^C_{jt-q+1})'$ and $\mathcal{Z}_t = (\mathbf{Z}'_t, ..., \mathbf{Z}_{t-q+1})'$:

$$\begin{pmatrix} \mathcal{Z}_t \\ Y^C_{jt} \end{pmatrix} = \begin{bmatrix} \Phi^Z & \mathbf{0} \\ \Lambda'_j & \Phi^Y_j \end{bmatrix} \begin{pmatrix} \mathcal{Z}_{t-1} \\ Y^C_{jt-1} \end{pmatrix} + \begin{pmatrix} \mathcal{V}^Z_t \\ \mathcal{V}^Y_{jt} \end{pmatrix} \tag{2}$$

The mean squared forecast error varies over time due to the fact that shocks in y^C_{jt+1} and $\mathbf{Z}_t$ have time varying variances, defined by

$$\Omega_{jt}(h) = \Phi^Y_j \Omega_{jt}(h-1) \left(\Phi^Y_j\right)' + E_t \left(\mathcal{V}^Y_{jt+h} \left(\mathcal{V}^Y_{jt+h}\right)'\right) \tag{3}$$

Uncertainty about the variable y^C_{jt}, $\mathcal{U}^C_{jt}(h)$, at forecast horizon h, is the conditional volatility of the purely unforecastable component of the future value of the series, conditional on all information known at time t:

$$\mathcal{U}^C_{jt}(h) = \sqrt{1'_j \Omega_{jt}(h) 1_j} = \sqrt{E\left[\left(y^C_{jt+h} - E\left[y^C_{jt+h}|I_t\right]\right)^2 |I_t\right]} \tag{4}$$

This procedure results in an uncertainty measure for each series in Y^C_t. To arrive at an aggregate measure of uncertainty in that category we use the average of those indices:

$$\mathcal{U}_{Ct}(h) \equiv \text{plim}_{N_C \to \infty} \sum_{j=1}^{N_C} \frac{1}{N_c} \mathcal{U}^C_{jt}(h) \tag{5}$$

We consider two types of uncertainty, macro and financial based on which series we use to estimate the aggregate uncertainty measure[4].

4 Data

The forecasts above are formed on the basis of two data sets, one capturing macroeconomic series and one capturing financial variables. Both data sets are monthly ranging from January 1991 to July 2016 for the United Kingdom. The macro data set comprises 33 series, covering real output, international trade, the labour market, inflation, house prices, retail sales, capacity utilisation, business and household expectations. The financial data set comprises 29 financial time series, covering U.K. credit extension, interest rates, bond yields, share prices, credit spreads, exchange rates, a variety of Fama-French portfolio returns (based on size and book-to-market), money supply, oil prices and

volatility of the VAR shocks. Without stochastic volatility the forecast error would not vary with t but only with h. See JLN, p1188.

[3]Using the STOCHVOL package in R as per JLN, which uses Markov Chain Monte Carlo (MCMC) methods to estimate the volatilties. The forecasting residuals are estimated with least squares and those residuals are used to estimate stochastic volatility model where volatility follows an AR(1) process with an intercept term.

[4]See the robustness section below where this method is applied to global macro and financial data to produce a global uncertainty index

option implied volatilities for the currency and oil prices[5]. The appendix provides a full description of the data used as well as relevant transformations. After transformations and taking lags for the forecasting model we estimate uncertainty over the time period June 1991 to June 2016. The two data sets are combined to form the information set in the forecasting model where the forecasting factors are drawn from. The forecasting model uses a large set of potential predictors in the factors, $\mathbf{F}_t$, and $\mathbf{W}_t$ which are comprised of squares of the first component in $\mathbf{F}_t$ and $\mathbf{G}_t$ a further set of factors drawn from the squares of the original data set. From the potential factors, $\mathbf{F}_t$ and $\mathbf{G}_t$, a subset, $\hat{\mathbf{F}}_t$ and $\hat{\mathbf{G}}_t$, are chosen based on the information criterion in Bai and Ng (2002), which indicates that 8 factors is an optimal number to explain the 62 series in macro and financial variables. These explain 55% of the variation in the original data set, with the first factor weighting predominantly on share prices and portfolio returns explaining 11%, the second which weights most on consumer confidence and labour market variables explaining 10%, and the third factor which is dominated by the Bank of England policy rate and corporate bond spreads explaining 8%. The set of predictors, $\{\mathbf{F}_t, \mathbf{G}_t, \mathbf{W}_t\}$, are selected for inclusion in the forecasting model based on their incremental predictive power using a t-test (with the threshold set at $t = 2.575$) for each y_{jt}^{C}[6].

5 Estimates of Uncertainty

Figure (1) compares the resulting macro uncertainty indicator, referred to as UK macro uncertainty, to two other proxies, the Bank of England uncertainty index and the news based version of the index of Baker et al. (2016)[7], hereafter BBD. The Bank of England measure is the principal component drawn from a swathe of uncertainty proxies: three month option implied stock market volatility (FTSE 100), implied volatility of the exchange rate index, forecast disagreement on GDP growth, consumer confidence survey responses on unemployment expectations and their financial situation over the next 12 months and media citations of uncertainty. The measures disagree significantly over certain episodes: the BBD news index, surprisingly, measures almost no rise in uncertainty around the financial crisis whereas it explodes during the vote to leave the EU (Brexit) in June 2016. While the UK and the BoE measures indicate that the financial crisis was by far the largest uncertainty shock in the sample period, they disagree on the uncertainty levels during the dot-com bust around 2002, the Euro-crisis of 2011/12 and the Brexit vote. The UK index indicates that the 2002 dot-com bust was a time where the economy was highly unpredictable despite relatively strong performance for GDP and while there was a small uptick in macro uncertainty leading up to the Brexit vote, the vote itself did not lead to any significant increase in uncertainty.

[5]It might seem inappropriate to feed a forecasting model a volatility series, and then estimate its time varying volatility, however market participants care about and forecast these volatilities in a similar way to how they forecast the other financial variables included in the data set and thus this information forms part of the information set that is relevant for them (and their uncertainty about the economy).

[6]The equations each contain four lags of their own series. While, the factors selected differ for each series, the first factor of is selected $\hat{\mathbf{F}}_t$ most often. The nonlinear factors are relatively unimportant across all series.

[7]available from policyuncertainty.com

Figure 1: Macro Uncertainty

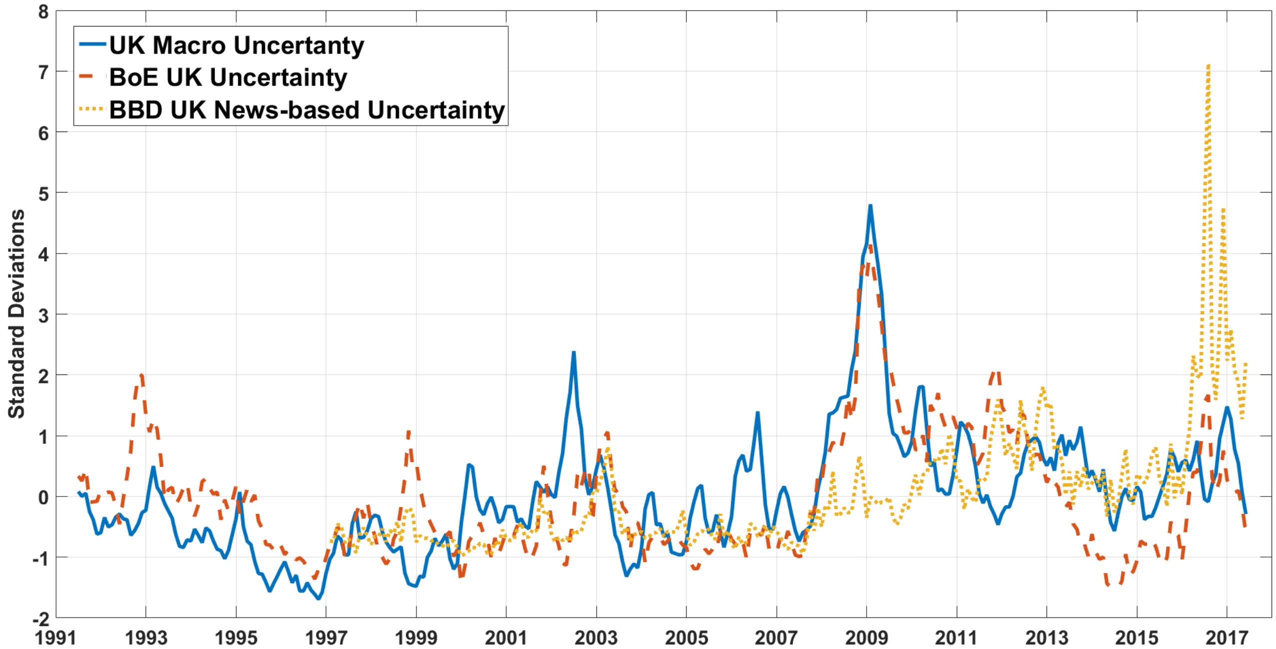


Figure 2: Financial Uncertainty

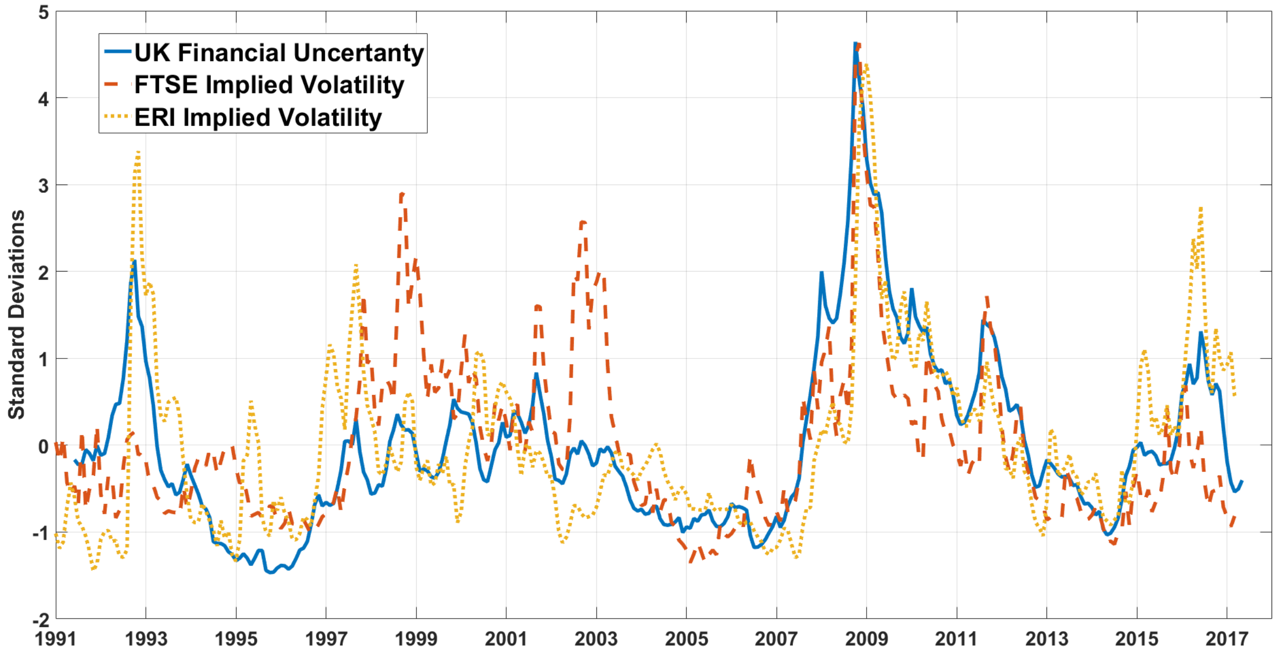


Table 1: Micro uncertainty during selected periods

Macro Uncertainty		***Financial Uncertainty***	
Series	*Share (%)*	*Series*	*Share (%)*
Dot-com bust (June 2002)			
Manufacturing Production	6.84	FTSE all share	6.52
Industrial Production	6.63	FTSE 250 INDEX	5.92
Imports Volume (Goods)	4.93	FF: SMALL LoBM†	5.31
BOP Total Exports (Goods)	4.85	FF: ME1 BM3†	5.24
Financial Crisis (February 2009)			
Weekly wage earnings	6.84	3m LIBOR	6.52
Public Sector Net Cash Requirement	6.63	5 year real implied forward rate	5.92
Industrial Production	4.93	FTSE All Share	5.31
Manufacturing Production	4.85	FTSE 250 Index	5.24
Brexit Vote (July 2016)			
Exports (Value)	4.88	Sterling implied volatility	10.1
Imports (Volume)	4.58	Sterling exchange rate index	5.43
Exports (Volume)	4.36	10 year real implied forward rate	4.67
Manufacturing Production	4.26	5 year real implied forward rate	4.58

†Fama-French portfolios returns based on size and book-to-market combinations.

Uncertainty during the Dot-com bust was concentrated on manufacturing and trade. Although U.K. GDP was largely unaffected by this (mostly U.S. focused shock), manufacturing did experience a significant decline in output (see table 1). The financial crisis lead to uncertainty more broadly in the labour market, fiscal capacity and real production. Brexit uncertainty, which did not lead to a large increase in uncertainty, is driven by uncertainty in similar sectors to the Dot-com episode with effects on trade and manufacturing dominating.

Figure (2) compares the UK financial uncertainty measure, derived from the above JLN methodology, to alternative proxies of financial uncertainty, the 3-month implied volatility of the FTSE 100 stock market index and the implied volatility of a trade-weighted index of nominal sterling exchange rates (ERI). Again, substantial independent variation is evident across the 3 indices. The ERI and JLN measures identify the 1992 Exchange Rate Mechanism crisis, the financial crisis and Brexit as periods of elevated uncertainty. However, FTSE implied volatility is more moderate during ERM and the Brexit vote but sees a significant spike in the 1998 potentially due to the failure of Long-Term Capital Management and the Russian debt crisis and again in 2002 in a global equities slump linked to the sharp revaluation of many internet companies (Dot-com bust). Table (1) reveals the individual series that experienced the greatest degree of uncertainty in the JLN measure over some of these periods. The financial crisis was driven by credit and stock price uncertainty while the Dot-com bust was primarily uncertainty around equity prices. Brexit related financial uncertainty is primarily around the value of Sterling and the yield curve.

6 Macroeconomic Impact of Uncertainty Shocks

The benchmark VAR model estimated below is:

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{B}(\mathbf{L})\mathbf{Y}_{t-1} + \mathbf{u}_t \tag{6}$$

Where $\mathbf{B(L)}$ is a matrix of lag polynomial coefficients and $\mathbf{u}_t \sim \mathcal{N}(0, \mathbf{\Sigma})$. This reduced form VAR is estimated using Bayesian methods using a Normal inverse Wishart Prior[8]. The variables included in the matrix $\mathbf{Y}_t$ are the Bank of England Bank Rate, Consumer Price Index, hours, investment, consumption, GDP, credit spreads and a measure of uncertainty. All variables are the cyclical component from a HP Filter except for credit spreads, bank rate and the uncertainty measure. We vary the uncertainty measure between the BoE, UK macro and UK financial indices. The sample is quarterly and runs from 1991Q3 to 2016Q2. The model includes 2 lags following the Schwartz and Hannan-Quinn information criteria. Structural shocks, $\epsilon_t = A_0\mathbf{u}_t$ are defined by identifying restrictions on the matrix A_0. Below we pursue a variety of a variety of identifying assumptions and study the impact of the implied structural uncertainty shocks.

6.1 Recursive restrictions

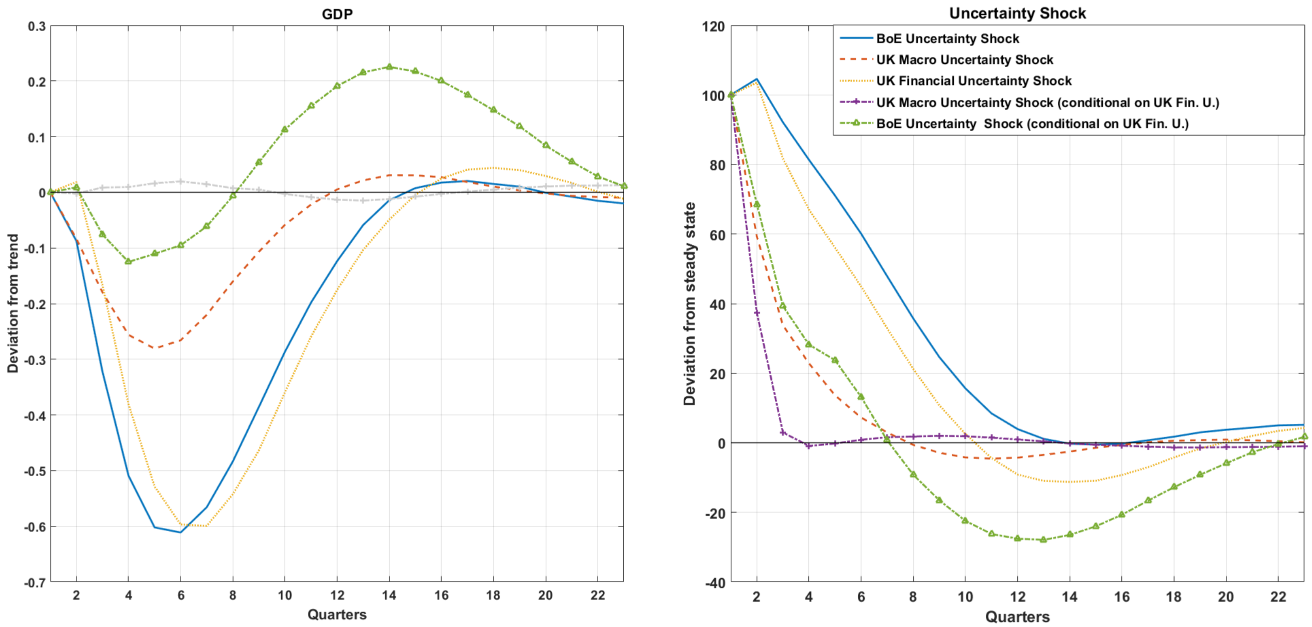
A variety of identification schemes are pursued: recursive (Cholesky), sign restrictions and narrative sign restrictions. The first set of results use a recursive ordering following the order the variables are listed above (i.e. all other variables respond to uncertainty shocks with a lag). The full results are available in the appendix; here I will focus on the impact on GDP. The response of GDP is approximately 0.6% deviation from (HP filtered) trend using the BoE and UK financial uncertainty - see figure (3). However, there is a noteworthy difference in the response of consumption and inflation under the two shocks with the BoE uncertainty shock resulting in a large drop in consumption after 1 quarter and a positive response of inflation. The majority of empirical studies find that precautionary motives dominate following an uncertainty shock leading to effects similar to a negative demand shock with lower inflation and a slowly building negative impact of real variables (Leduc and Liu (2012); Mumtaz and Zanetti (2013); Dendy et al. (2013); Baker et al. (2016)[9]). This is the case for the financial uncertainty shock. The construction of the BoE index suggests why this might be the case, namely the inclusion of consumer confidence measures which are primarily about expectations of the mean outcome for unemployment and the households financial situation. Indeed, removing these terms from the BoE index and using an equally weighted index of the remaining components reduces the impact effect on consumption by around half, however the inflationary response remains (and is brought forward) - see figure (16). Aside from inflation and consumption, the response of the economy to a financial and BoE uncertainty shock are similar, especially for the GDP and the uncertainty measure itself. This is at least suggestive that both measures capture a similar shock to the economy - one where the role of financial shocks may be predominant. The impact of an uncertainty shock as measured by the UK macro measure is broadly similar to a financial uncertainty shock however the real effects are around half the size. Both UK uncertainty measures are supportive of the evidence that uncertainty shocks are demand shocks, as advocated by Leduc and Liu (2012). However, once the UK financial uncertainty measure is added to the VAR, and ordered so that no contemporaneous rise in financial uncertainty accompanies a macro uncertainty shock, the real effects on GDP change substantially: neither measure indicates a recession and the BoE measure actually suggests a rise in GDP after around 3 years (see figure (18)). The finding that macro uncertainty has much weaker real effects once financial shocks (in this case financial uncertainty) are controlled for echos the findings of Popescu and Smets (2010); Caldara et al. (2016), who note that uncertainty acts to propagate financial shocks. The finding of potentially positive effects of macro uncertainty

[8] The Normal inverse Wishart prior assumes a normal prior for the VAR coefficients and a inverse Wishart prior for the covariance matrix, see Blake and Mumtaz (2012).

[9] However, there are some studies that find an inflationary response e.g. Popescu and Smets (2010); Mumtaz and Theodoridis (2015); Jurado et al. (2015)

are more unusual. The logic of such a result relates to growth options, where equity holders have limited losses (their entire investment) but unlimited upside when a greater variety of outcomes is likely, these are sometimes called Oi-Hartmann-Abel effects (see Bloom (2014)). Recent empirical evidence of such effects is found by Ludvigson et al. (2015) controlling for financial uncertainty using synthetic external instrumental variables.

Figure 3: Response of GDP under recursive identification



Median impulse responses. Response in grey are not significant.

6.2 Sign restrictions

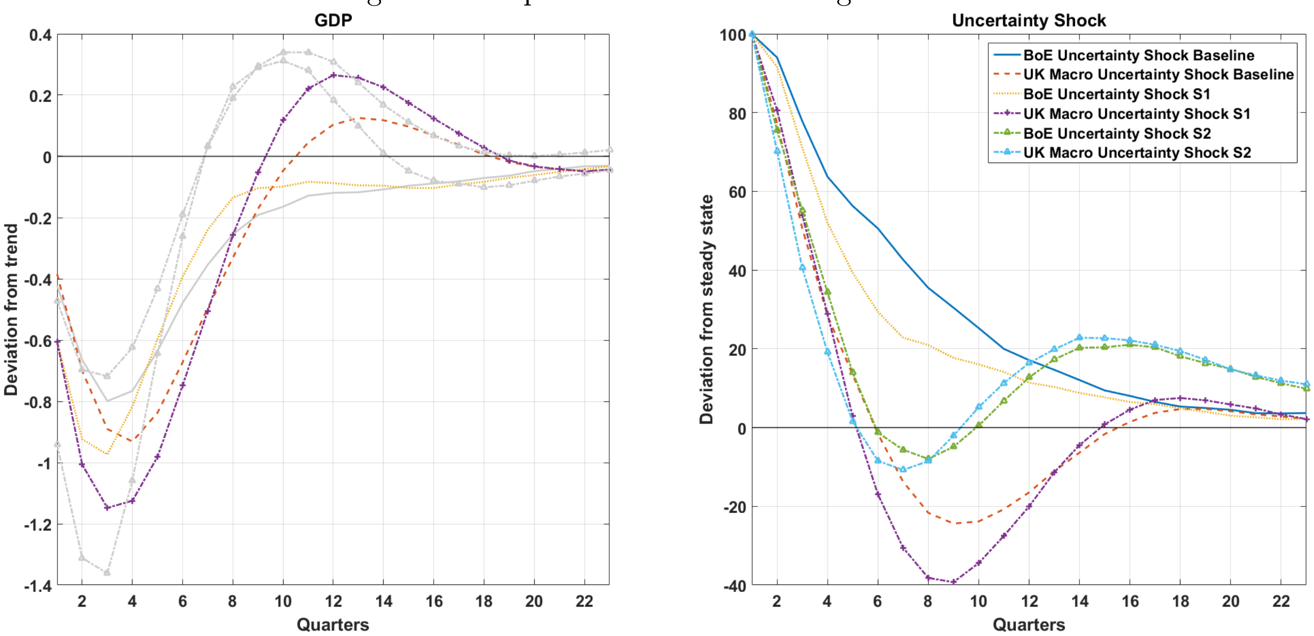
6.2.1 Temporary uncertainty shock

Using recursive ordering for identification imposes a rigid structure on the response of the VAR system to a shock. Sign restrictions offer identification with more flexibility in the assumptions around the timing of variables responses to shocks. This results in set identified responses to the shocks. As a baseline we use the restrictions outlined in table (2). These restrictions are weaker than recursive restrictions above and the results indicate that the effects on GDP are less robust in that only the uncertainty shocks measured by the UK macro uncertainty index are significant under the Baseline and S1, and the BoE uncertainty measure under S1 identification - see Figure 4 where insignificant GDP responses appear in grey. However, uncertainty shocks that ensure a decline in investment (i.e. shocks identified under S1 and S2) have, somewhat unsurprisingly, significantly stronger real effects close to double that found under the recursive identification. Identification S2 attempts to capture a situation where rises in credit spreads don't reinforce the real effects on the uncertainty shock. Under this assumption macro uncertainty shocks have no significant effects on GDP. The same holds if we add UK financial uncertainty to the VAR and require that financial uncertainty doesn't spike during a macro uncertainty shock. In short, the real effects of macro shocks are far less robust when identified with sign restrictions but the theme that increases in credit spreads and financial uncertainty are important to find real effects on GDP, remains.

Table 2: Sign restrictions for 2 quarters

	Bank rate	*CPI*	*Hours*	*Investment*	*Consumption*	*GDP*	*Credit Spreads*	*Macro Uncertainty*
Baseline	-	?	-	?	?	?	+	+
S1	-	?	-	-	?	?	+	+
S2	-	?	-	-	?	?	-	+

Figure 4: Response of GDP under sign restrictions

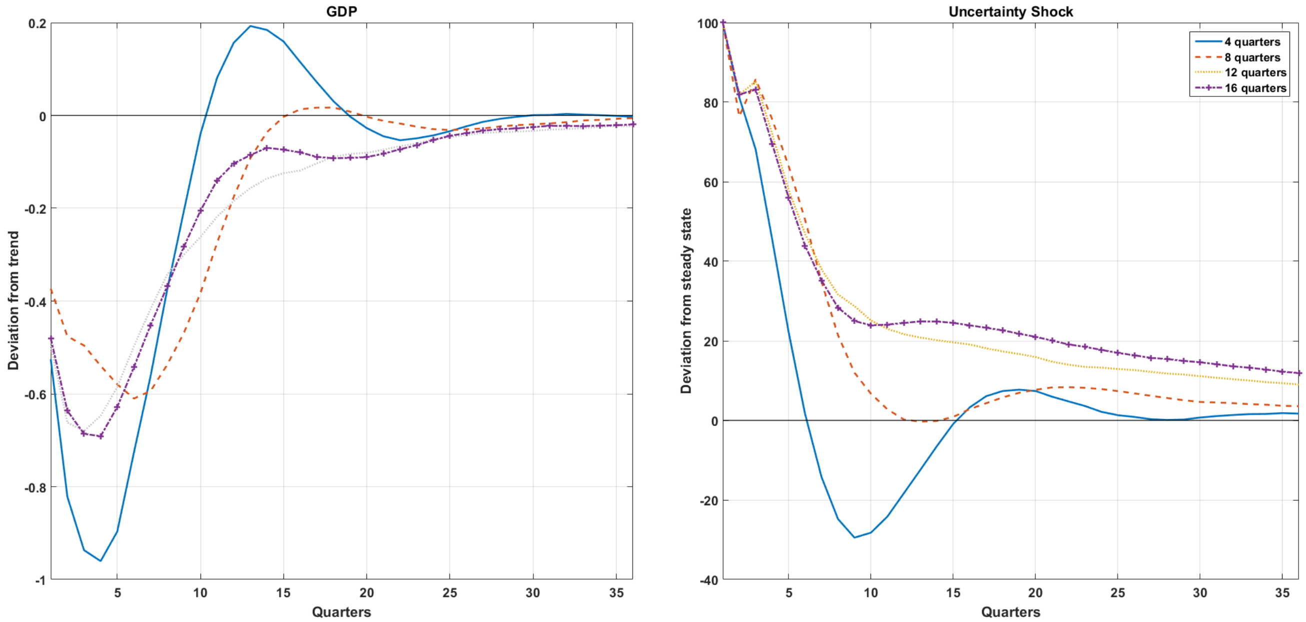


Median impulse responses. Response in grey are not significant.

6.2.2 Persistent uncertainty shock

Sign restrictions provide sufficient flexibility to examine the impact of prolonged periods of macro uncertainty. It is common to think of an uncertainty shock as a temporary shock contributing to a recession, however uncertainty that is set off due to deep structural shifts (such as Brexit) or substantial changes in policy (the Trump administration in the U.S.) may be prolonged and the behavioural response may differ simply due to the persistence of these shocks. For example, if it is difficult to discern whether an uncertainty shock is permanent or temporary, the initial response to a permanent shock may be muted but grow as it becomes clear that uncertainty will remain for some time. The majority of empirical and theoretical work studies temporary rather than persistent uncertainty shocks, however exceptions include Haddow et al. (2013) and Bloom (2009). The latter examines the impact of increased persistence of an uncertainty shock in a model with fixed and variable costs leading to changes in the optimal level of inaction by firms, he finds that the response to a persistent shock is qualitatively the same as a temporary shock, output simply responds as if a larger temporary shock has occurred. Haddow et al. (2013) employs a VAR that is very similar to the one employed in this paper except that they use the BoE uncertainty measure throughout and recursive identification. To examine a persistent shock they simply impose that the shock remains at 1 standard deviation for 4 years and apply that shock to the Impulse Response Functions derived from the SVAR (the same IRFs that apply for a temporary shock). This method will not capture any behavioural change across temporary and persistent shocks since the estimated regression coefficients and identification is identical for both. They find a result similar in spirit to Bloom (2009) in that the response to a permanent shock is much like a large temporary shock.

Figure 5: Response of GDP under sign restriction S1, UK Macro Uncertainty



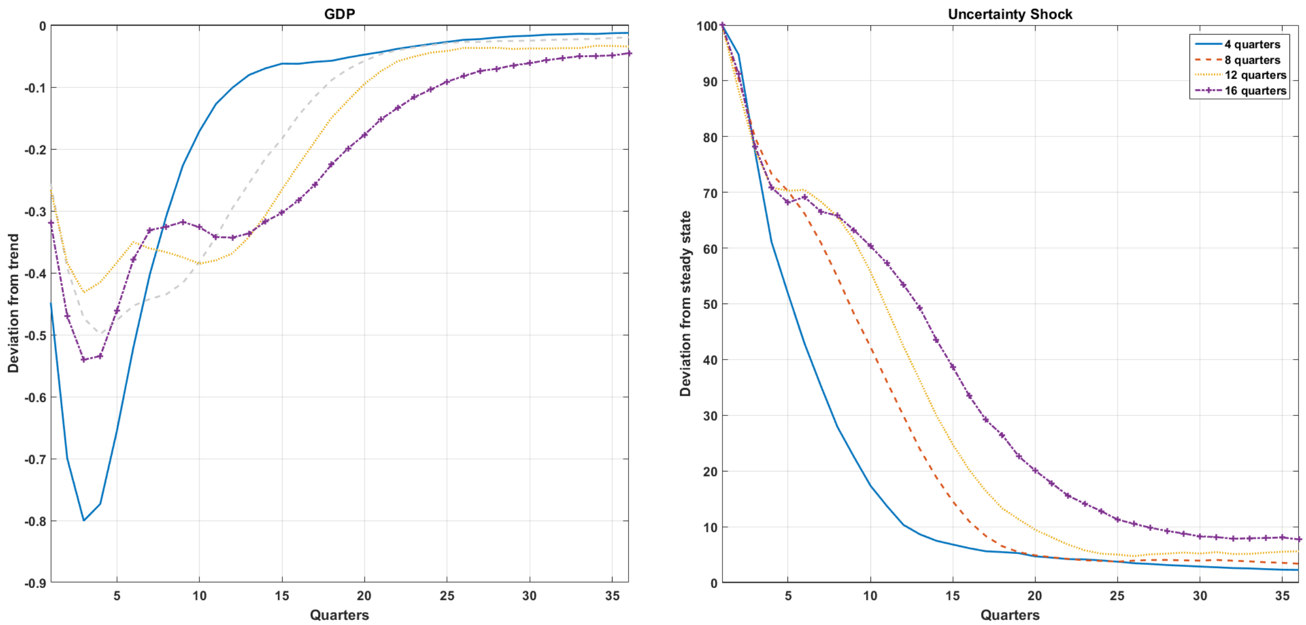
Median impulse responses. Response in grey are not significant.

In contrast we approach this question by imposing sign restrictions on the duration of the positive response of uncertainty to an uncertainty shock while holding fixed the duration of the sign restrictions on other variables. This method identifies a different shock to the temporary case examined above and provides the potential to find delayed response behaviour. This is done under identification S1 for both the UK macro and BoE uncertainty indices and we vary the restriction on how long the uncertainty index must be positive from 1 to 4 years to estimate the relative effects of persistence. The results under both indices suggest a weaker impact effect and a greater proportion of the total response taking place at a later date (see figure 5 and figure 6). This is arguably inconsistent with an imperfect information argument, mentioned above, where this would predict a similar impact effect but a stronger long run effect. However, looking at the sum of the deviations from trend for GDP under the different persistence assumptions we do see slightly larger long run effects for more persistent shocks but this is not proportional to the increase in uncertainty that results, as measured by the ratio of the sum of the GDP response to the sum of the uncertainty index response to the uncertainty shock see table 3. Under the imperfect information hypothesis we would expect this ratio to be stable over time rather than falling. Moreover, the larger long run effect is much stronger for the BoE measure (consistent with imperfect information), but this measure also indicates a significantly weaker impact response (inconsistent with imperfect information). Alternatively, it may be that wait-and-see effects are curtailed under a persistent uncertainty shock, as under a temporary shock it makes sense to wait as you expect the uncertainty to dissipate relatively soon, however when you expect uncertainty to last for years, agents continue in a business-as-usual mode until that uncertainty resolves later. However, it is worth noting that persistent macro uncertainty shocks also require rising credit spreads to have real effects on GDP, as found for temporary uncertainty shocks (i.e. impact on GDP was not significant with identification S2).

Table 3: Long run effects of persistent uncertainty shocks

	UK Macro Uncertainty		*BoE Uncertainty*	
Uncertainty shock restriction:	$\sum IRF_{GDP}$	$\frac{\sum IRF_{GDP}}{\sum IRF_{Uncertainty}}$	$\sum IRF_{GDP}$	$\frac{\sum IRF_{GDP}}{\sum IRF_{Uncertainty}}$
4 Quarters	-5.38	-0.0237	-6.15	-0.0092
8 Quarters	-5.91	-0.0089	-6.53	-0.0072
12 Quarters	-6.92	-0.007	-7.00	-0.0064
16 Quarters	-6.56	-0.0061	-8.26	-0.0063

Figure 6: Response of GDP under sign restriction S1, BoE Uncertainty



Median impulse responses. Response in grey are not significant.

6.3 Narrative sign restrictions

The results above point to a general conclusion that macro uncertainty shocks matter little if not accompanied by a rise in credit spreads and financial uncertainty. Here we test the robustness of the above result using a new method to identify uncertainty shocks: narrative sign restrictions following Antolin-Diaz and Rubio-Ramirez (2016). Whereas traditional sign restrictions place restrictions only on the prior assumed for the VAR, narrative sign restrictions since they are a function of the actual data (rather than just the parameters of the model) place restrictions on the likelihood of the VAR model. This means that the posterior is no longer a function of the prior times the likelihood but rather, as Antolin-Diaz and Rubio-Ramirez (2016) show, a function of the prior times a re weighted likelihood where the reweighting is proportional to the probability of the restrictions being satisfied.

Their method allows us to use historical events, by imposing that a macro uncertainty shock occurred at a certain date to identify the shocks. We consider two types of events for narrative restrictions that a priori should raise macro uncertainty: economic events and tight general elections.

6.3.1 Economic events

We impose that a positive macro uncertainty shock takes place on the following dates:

1. *Exchange Rate Mechanism (ERM) crisis - 1992Q3*

   After initially rejecting the options of joining, Margaret Thatcher's government entered the Exchange Rate Mechanism in October 1990. The ERM pegged the value of the pound to the German Deutschmark within a band of 6%. With U.K. inflation approximately three times that of Germany and significant current account pressures brought on by dollar depreciation, the rejection of the Maastricht Treaty by Denmark in Spring 1992 and the prospect of another referendum vote in France pushed the pound toward the lower bound of the ERM band. Despite an effort to defend the currency the pound was forced off the ERM on 16 September 1992.

2. *Dot-com bust - 2000Q1*

   Following a period of over optimistic valuations of technology and internet focused companies, where investors ignored traditional valuation metrics (all time high for cyclically adjusted Price-Earnings ratio at 44 of almost 3 times the long run average of 17[10]), and supported by a number of bankruptcies in communication and technology firms over the period 2000-2002, there was a large global stock market decline and subsequent recession in the U.S. The real effects were relatively mild for the U.K. with the exception of the manufacturing industry.

3. *Lehman Brothers Bankruptcy - 2008Q3*

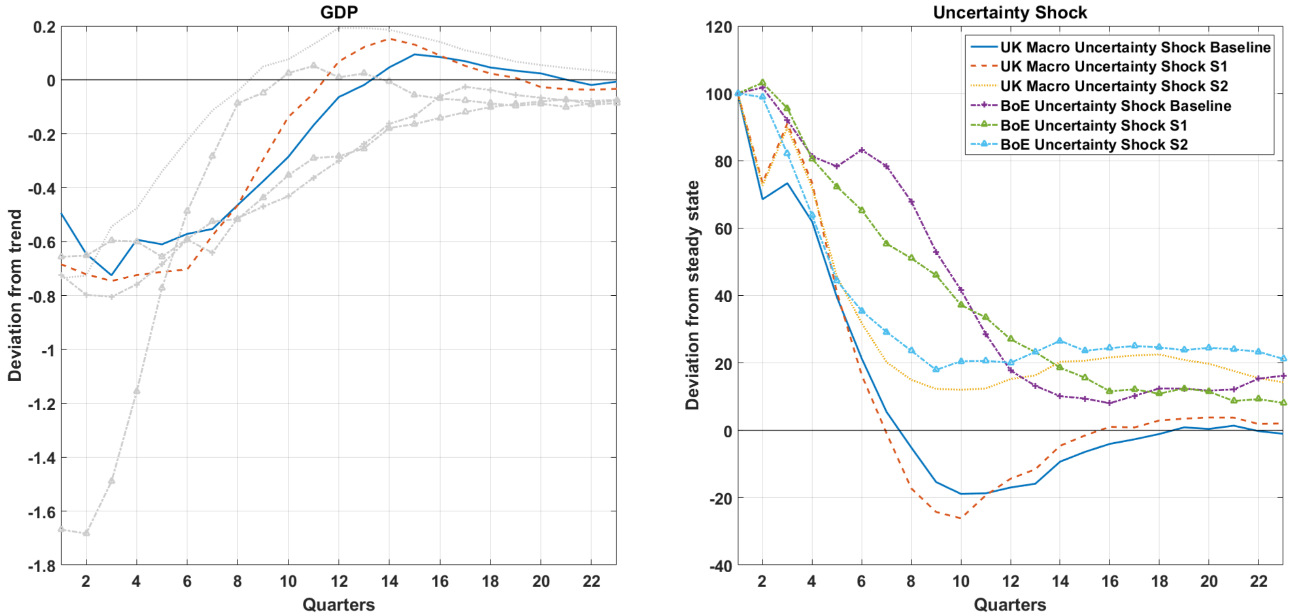
   The collapse of Lehman Brothers marks the start of the financial crisis in 2007-09 when significant uncertainty around the impact on the real economy of a freeze in lending and potential bankruptcy of many large and systematically important banks accompanied a large and protracted recession.

4. *U.K. votes to leave E.U. - 2016Q2*

   On 23 June 2016 the referendum on E.U. membership resulted in the surprise result of a vote to leave. This lead to a change of Prime Minister and Cabinet, a protracted period of uncertainty surrounding future immigration and trading arrangements with the E.U. (the U.K.'s largest trading partner) as well as many legal precedents created through E.U. law.

[10] see http://www.econ.yale.edu/~shiller/data/ie_data.xls

Figure 7: Response of GDP under narrative sign restrictions for economic events



Median impulse responses. Response in grey are not significant.

Imposing these narrative restrictions results in a similar impact effect of macro uncertainty shocks found with general sign restrictions, however the peak effect on GDP is weaker. Under general sign restrictions the peak effect was around -1% deviation from trend - however this falls to around -0.7%. The two most important narrative restrictions for the weaker response of GDP are (2) The Dot-com bust and (4) the Brexit vote where whatever uncertainty took place it wasn't accompanied by large declines in GDP. In particular, the effect on consumption is much less, with only a brief period of significant contraction occuring after 1.5 years (see figures 36 and 37). These particular narrative restrictions based on economic events provide a way to characterize the real effects of uncertainty shocks during periods when measured uncertainty and credit spreads are less highly correlated than during the dominant uncertainty shock of the sample, the financial crisis.[11] Nevertheless, for macro uncertainty shocks to have real effects they must be accompanied by rising credit spreads - sign restrictions S2 were credit spreads don't rise lead to an insignificant impact on GDP. The results found using narrative sign restrictions indicate that the conclusions reached using recursive and simple sign restrictions are robust. Next we examine alternative narrative restriction, closely contested general elections where the policies of the resultant government are uncertain and uncertainty ought to rise around these events, a priori.

6.3.2 Tight general elections

We impose a positive rise in uncertainty in the quarter prior to the election date following the findings in the literature that uncertainty tends to be higher leading to up to the event - seeLi and Born (2006); Bialkowski et al. (2008); Goodell and Vahamaa (2013). Since we are using end of quarter values this also more closely aligns with the election date itself[12]. We impose that a macro uncertainty shock

[11] Credit spreads were elevated and rising in 2008Q3 at around 5.5% but were far below the levels seen during the 2009-2012 period where they averaged near 8%

[12] For example, the 1992 election took place on 9 April which is 10 days away from the end of Q1 value but 82 days away from the end of Q2 value on 30 June 1992.

takes place on the following general dates:

1. *1992Q1*

   Under increasing political pressure and the high profile resignations from her cabinet (Nigel Lawson in 1989 and Geoffrey Howe in 1990), Margaret Thatcher lost a leadership battle for the Conservative Party with John Major succeeding her. The general election of 1992 was extremely close with a majority of polls predicting a hung parliament (including voting day exit polls). However, the Conservatives won outright for the fourth time in succession.

2. *2010Q1*

   A tightly contested election that lead to only the second hang parliament in post-war Britain (the first was in 1974). Polling results in the run up to the election were volatile with a significant rise in support for the Liberal Democrats one month prior to the vote. The Conservatives took 306 seats, Labour 258 and the Liberal Democrats 57 with 326 needed to form a majority government. Coalition talks lasted five days and concluded with a Conservatives-Liberal Democrats coalition government.

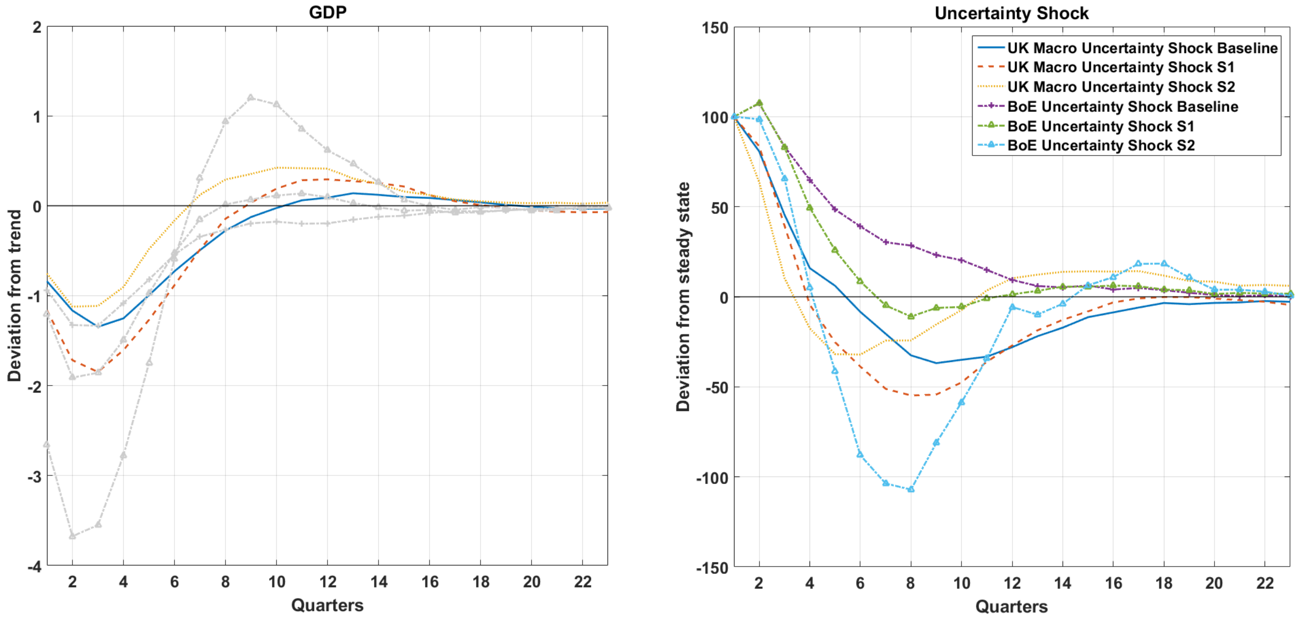
3. *2015Q1*

   Similar to the 2010 result a large number of polls and professional forecasters expected a hang parliament and the need to form a coalition government[13]. However, the Conservative Party won a surprise majority while Labour and the Liberal Democrats saw significant losses in support in Scotland due to the rise of the Scottish National Party following the 2014 Scottish Independence Referendum.

Unlike the case of narrative restrictions based on economic events, narrative restrictions placed on uncertain elections indicates a significant impact of macro uncertainty shocks across all three sets of sign restrictions (all BoE uncertainty index shocks remain not significant) - see figure 8. We examine this result more closely by further requiring no increase in financial uncertainty and applying the narrative restrictions one by one. The result of a significant GDP response is robust (except for the case of narrative restrictions around the 2015 election where the response is insignificant). The additional information captured in the narrative sign restrictions using tight elections has sharpened the inference around the findings using standard sign restrictions (where these all found a negative but insignificant response of GDP to a macro uncertainty shock). What can we infer from the fact that the same does not hold for narrative restrictions based on economic events?

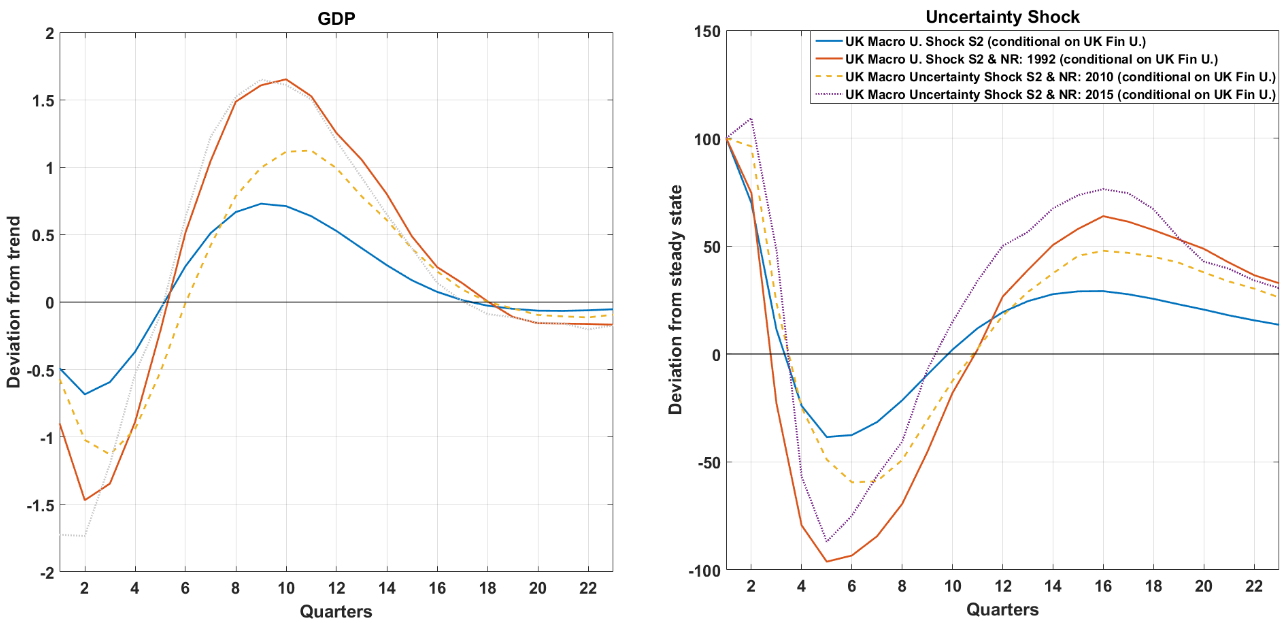
[13] For a summary of the pre-election poll results see https://en.wikipedia.org/wiki/Opinion_polling_for_the_2015_United_Kir
see http://electionforecast.co.uk/2015/index.html for an example of the election forecast predicting a hang parliament.

Figure 8: Response of GDP under narrative sign restrictions for tight general elections



Median impulse responses. Response in grey are not significant.

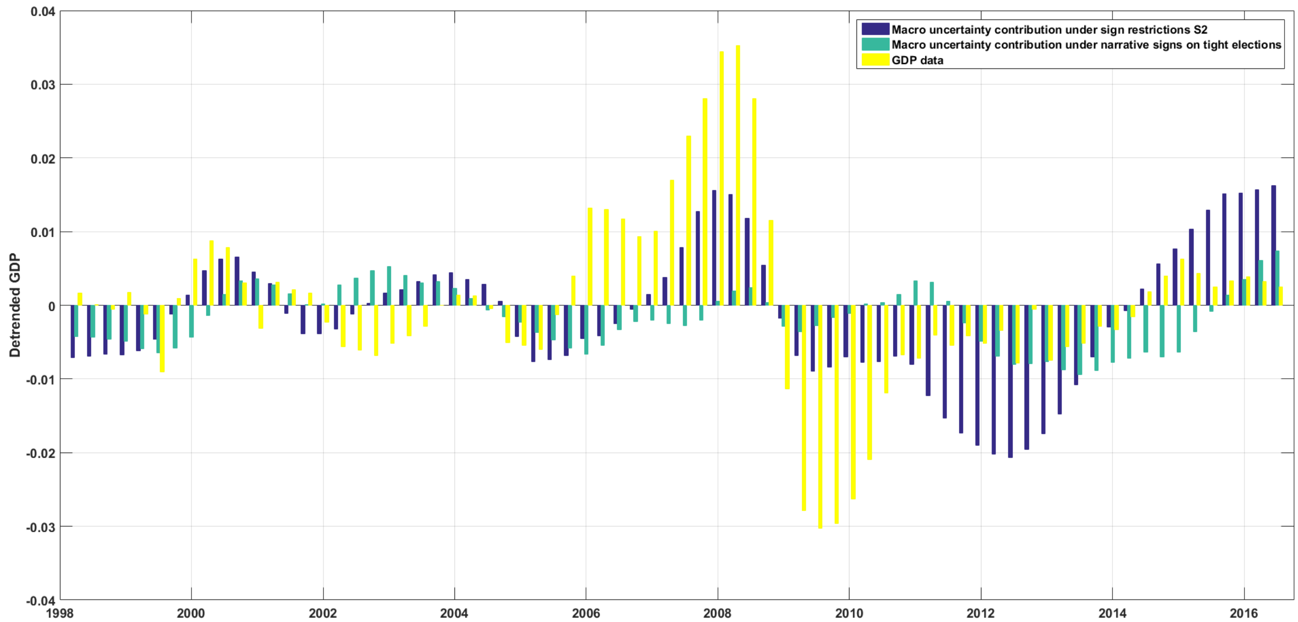
Figure 9: Response of GDP under narrative sign restrictions for tight general elections



Median impulse responses. Response in grey are not significant.

Linking identification to economic events where macro uncertainty has risen are also times where its more likely that credit and financial uncertainty shocks play a bigger role, thus when we condition on neither an increase in credit spreads nor any rise in financial uncertainty its harder to find any significant drop in GDP linked to macro uncertainty. However, linking identification to uncertainty around elections is more likely to capture periods where macro uncertainty has risen due to fiscal and regulatory policy uncertainty and less on occasions when macro uncertainty is potentially acting as a propagation mechanism for financial shocks. The historical decomposition of GDP indicates that the role of macro uncertainty shocks changes considerably under identification based on tight election events during and after the financial crisis. Narrative restrictions significantly reduce the role of macro shocks in general and specifically during the financial crisis of 2008/9 as well as reducing its role during the euro crisis period of 2011/12 but extending the drag out to around 2015. This is evidence of a decoupling of the shocks around financial crisis and macro uncertainty shocks. This allows macro uncertainty shocks to have a significant impact on GDP even when the channels of financial uncertainty and credit spreads are shut down.

Figure 10: Historical Decomposition of Detrended GDP under sign restrictions S2



6.4 Robustness checks: the role of global uncertainty shocks

A number of studies have found common co-movement between domestic uncertainty (especially as measured using financial variables) across countries and that once global uncertainty shocks are accounted for, domestic uncertainty has relatively modest real effects (Cesa-Bianchi et al. (2014); Berger et al. (2016) and Mumtaz and Theodoridis (2017)). To address this concern we build a global uncertainty index in a similar manner to the U.K. macro and financial uncertainty indices above, following Jurado et al. (2015). The index uses global macro and financial data covering stock market returns, sovereign bonds yields, exchange rates, commodity prices, trade volumes, retail sales, consumer and business confidence from emerging and advanced economies (full description of variables used is in the appendix). U.K. variables are removed from this data set to capture global uncertainty not measured in the U.K. indices.

Figure (11) compares the JLN based global uncertainty measure to Baker, Bloom and Davis' Global Economic Policy index which is a PPP weighted average of national uncertainty indices produced broadly following the methodology of Baker et al. (2016)[14]. We also include the UK financial index for comparison. The BBD and global measures agree early in the sample: spikes occur in 1998 (Asian and Russian financial crises), late 2001 (9/11) and late 2002 (invasion of Iraq). However, they disagree substantially from 2008 onwards. The Global Index puts a very large weight on the financial crisis and much less on the Euro crisis in 2011/12 as well as Brexit (which is the most

[14] Available at http://www.policyuncertainty.com/global_monthly.html

uncertain time globally according to the BBD index). This difference seems to be driven, at least in part, due to the Global index capturing a greater amount of global financial uncertainty which can be seen by the fairly strong correlation between the UK financial uncertainty index and the Global measure. Below we show that this high correlation between U.K. financial uncertainty and global uncertainty implies that it is sufficient to control only for domestic financial uncertainty in assessing the impact of U.K. macro uncertainty shocks.

Figure 11: Global Uncertainty

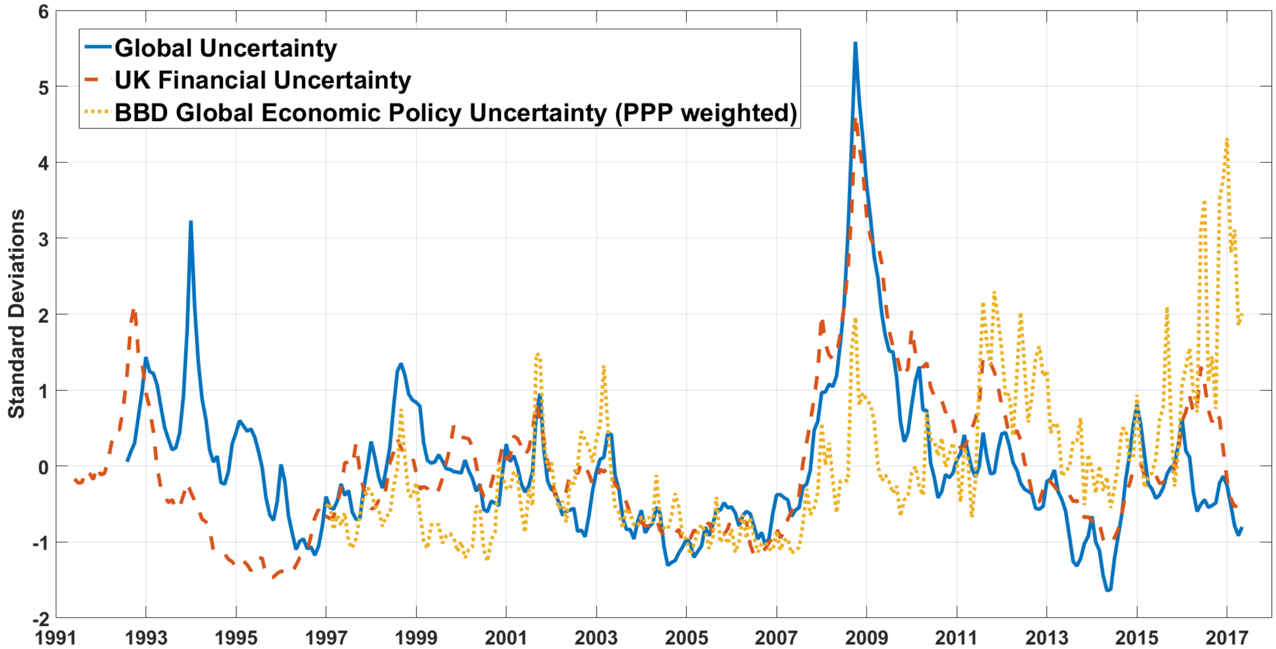
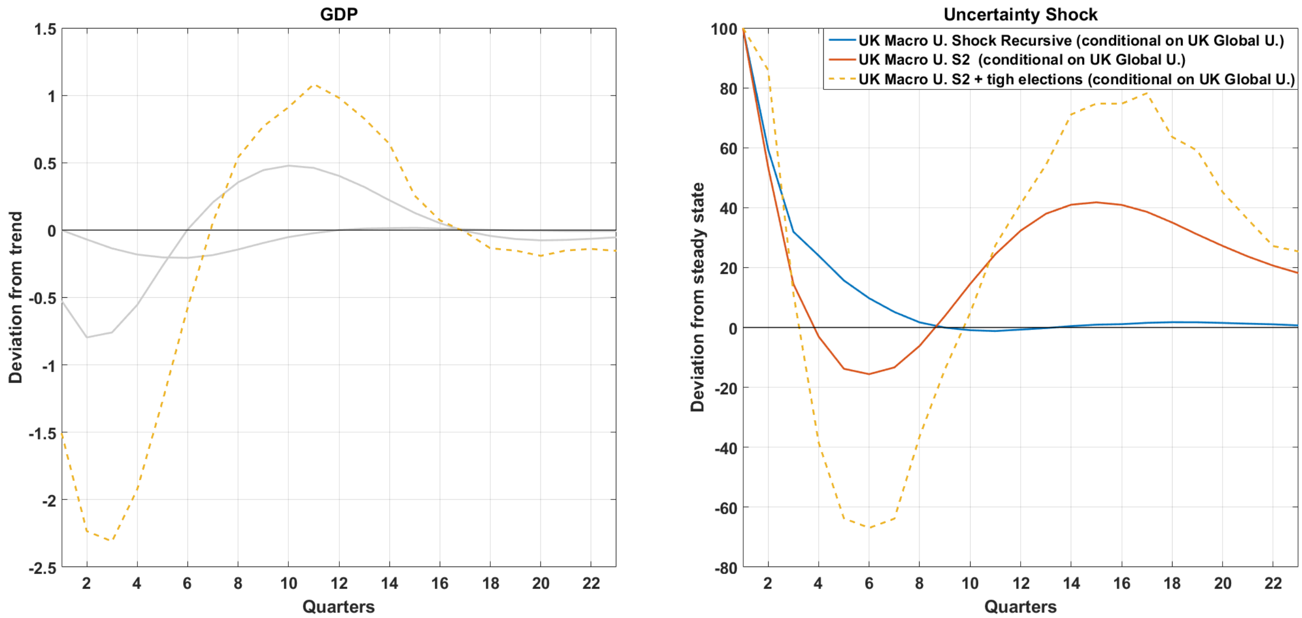


Figure (12) shows the response of GDP to a UK macro uncertainty shock under recursive, traditional sign and narrative sign restrictions, conditional on no rise in JLN global uncertainty. The results broadly accord with those found above conditioning on UK financial uncertainty. Under the recursive scheme the GDP impact becomes smaller and less robust (only significant for 68% credible set, see figure 45). For identification with sign restrictions we focus on the S2 identification where credit spreads don't rise for the first two periods. Similar to the case discussed above the GDP imapct is not significant. However, under narrative sign restrictions around tight general elections we continue to find a significant response (somewhat larger) when conditioning on no global uncertainty.

Figure 12: Response of GDP under narrative sign restrictions for tight general elections



Median impulse responses. Response in grey are not significant.

7 Conclusion

This paper uses a data rich environment to produces new econometric measures of macroeconomic and financial uncertainty for the U.K. as well as a new index of global uncertainty following Jurado et al. (2015). We find that global and financial uncertainty are highly correlated as would be expected for a financially developed open economy like the U.K. Our measure of macroeconomic uncertainty exhibits significant independent variation from a number of popular uncertainty proxies typically used to assess the real effects of uncertainty shocks. We study the impact of macroeconomic uncertainty shocks using a variety of identification schemes and conditional on both financial and global uncertainty. Using recursive and traditional sign restrictions, we find that real effects of macroeconomic uncertainty shocks are generally weaker than popular proxies suggest and that the effect depends on a subsequent rise in financial uncertainty and credit spreads to have a negative impact on GDP. The inclusion of narrative information on events, such as the disorderly exit from the Exchange Rate Mechanism, dot-com recession and financial crisis, into the analysis supports this finding. However, conditioning on narrative events more closely associated with political uncertainty, i.e. tight general elections, suggests a stronger impact response of GDP to macro uncertainty shocks. This result stems from narrative restrictions reducing the role of macro uncertainty shocks during the financial crisis, which our results without narrative restrictions indicate identifies cases where macro uncertainty acts mainly as a propagation mechanism for financial shocks. This result is also robust to controlling for global uncertainty, suggesting that macro uncertainty associated with events that are primarily about economic policy uncertainty may have a significant impact on GDP, even without increases in financial stress or global uncertainty.

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Appendix I - Data Sources

Transformations:

1. Levels
2. First difference.
3. Second difference.
4. Natural log
5. Log first difference
6. Log second difference.

Macroeconomic Data

Variable	*Transformation*
'Manufacturing Production'	5
'Real Retail Sales ex Fuel'	5
'Real Retail Sales ex Food'	5
'BOP Total Exports (Goods)'	5
'Exports Volume (Goods)'	5
'BOP Total Imports (Goods)'	5
'Imports Volume (Goods)'	5
UK CBI Survey- below capacity'	2
'CBI Industrial Trends: Current Total Order Book'	2
'CBI - vol of stocks bal'	2
'New Cars Registrations'	5
'LFS Unemployment Rate'	1
'LFS Number of Employees (Total)'	5
'Claimant Count Rate'	1
UK LFS: Total Hours'	5
UK Weekly wages in private sector'	5
'PPI'	5
'CPI all items'	5
'RPI all items'	5
'UK PSNCR Public Sector Net Cash Requirement'	5
'New Cars Registrations'	5
'GfK Consumer Confidence'	1
'European Commission Consumer Confidence'	1
'CBI Distributive Trades: Retail Volume of Sales vs Year Ago'	1
'CBI Industrial Trends: Current Total Order Book'	1
'CBI Industrial Trend: Expected Selling Prices'	1
'Gfk/EC consumer conf, current financial situation of HH'	1
'Gfk/EC consumer conf, current financial situation of HH over next 12m'	1
'CBI MT expectations'	1

Financial Data

Variable	*Transformation*
'10yr nom implied fwd'	2
Fama French Portfolio	2
'5yr nom implied fwd'	2
'5yr real implied fwd'	2
'FTSE all share'	5
'SHORT STERLING IMPLIED VOL 12 MO'	2
'OIL (WTI) 12mo implied vol'	2
'Sterling exchange rate index'	5
'FTSE 250 INDEX'	5
UK Laons and advances to the private sector'	1
UK MONEY SUPPLY M4 '	5
UK UK MONEY SUPPLY M3 '	5
UK MONEY SUPPLY M1'	5
UK MONEY SUPPLY M2 '	5
'GBP TO USD (BOE) - EXCHANGE RATE'	5
'GBP TO EUR (BOE) - EXCHANGE RATE'	5
'Moody''s Aaa'	1
'Moody''s Baa'	1
Fama French Portfolio 'SMALL LoBM'	1
Fama French Portfolio 'ME1 BM2'	1
Fama French Portfolio 'ME1 BM3'	1
Fama French Portfolio 'ME1 BM4'	1
Fama French Portfolio 'SMALL HiBM'	1
UK BANK OF ENGLAND BASE RATE '	1
'bank rate libor spread'	1
'bank rate 5yr spread'	1
'bank rate 10 yr spread'	1
'Oil Brent'	5

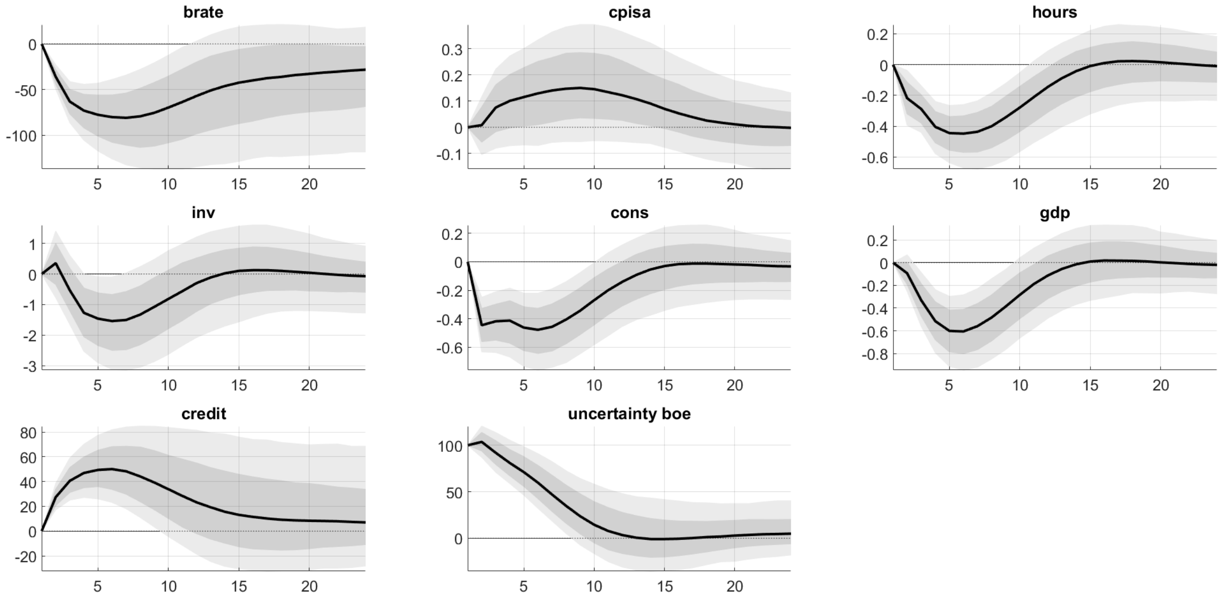
Global Data

Variable	*Transformation*
Global composite leading indicator (OECD)	4
US economic policy uncertainty index	4
VIX	5
MSCI WORLD	5
MSCI EM	5
S&P 500	5
S&P GSCI Industrial Metals Spot	5
Crude Oil Brent spot	5
S&P GSCI Gold Spot	5
S&P GSCI Copper Spot	5
Baltic Exchange Dry Index	4
JPY TO USD	5
EUR TO USD	5
AUD TO USD	5
YUAN TO USD	5
Japan	5
Eurozone	5
Australia	5
US	5
China	5
US CPI	5
EM HICP	5
US benchmark 10 year index	5
Japan benchmark 10 year index	5
Italy benchmark 10 year index	5
Germany benchmark 10 year index	5
Personal consumption expenditures (ar) cura	5
Employed - nonfarm industries total (payroll survey) vola	5
Ism purchasing managers index (mfg survey) sadj	5
Industrial production - total index vola	5
Retail sales & food services, total cura	5
Retail sales - autombile & other motor vehicle dealers cura	5
Shipments - mfg, nondefense capital goods, excl aircraft cura	5
New orders - mfg, nondefense capital goods cura	5
Private construction expenditures - total (ar) cura	5
Government bond yield - 10 year	5
New passenger car registrations (wda) vola	5
Economic sentiment indicator (ea) vola	1
Industrial production excluding construction (ea19) vola	5
Ifo business climate index (pan germany) vola	5
Retail sales: consumer goods (unrevised) curn	5
Consumer confidence index nadj	2
Macroeconomic climate index - leading index sadj	5
Industrial production % change yoy	4
Macroeconomic climate index - coincident index sadj	5
Brazil industrial production vola	5
Russia retail trade turnover curn	5

Appendix II - Full Impulse Response Functions

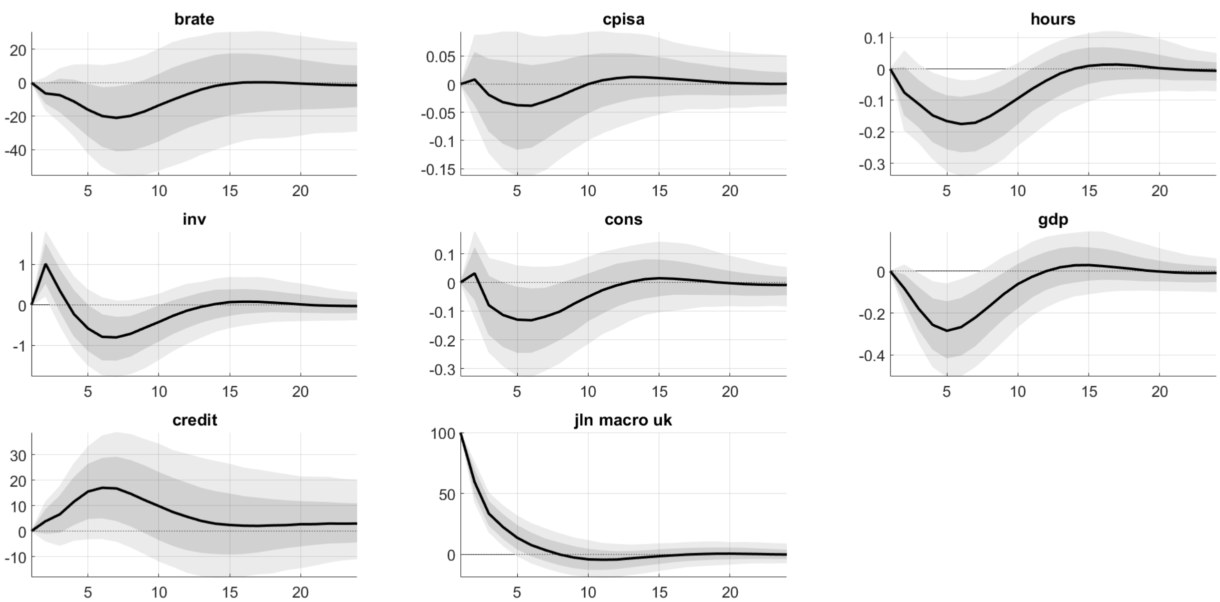
Recursive restrictions

Figure 13: BoE uncertainty shocks with recursive identification



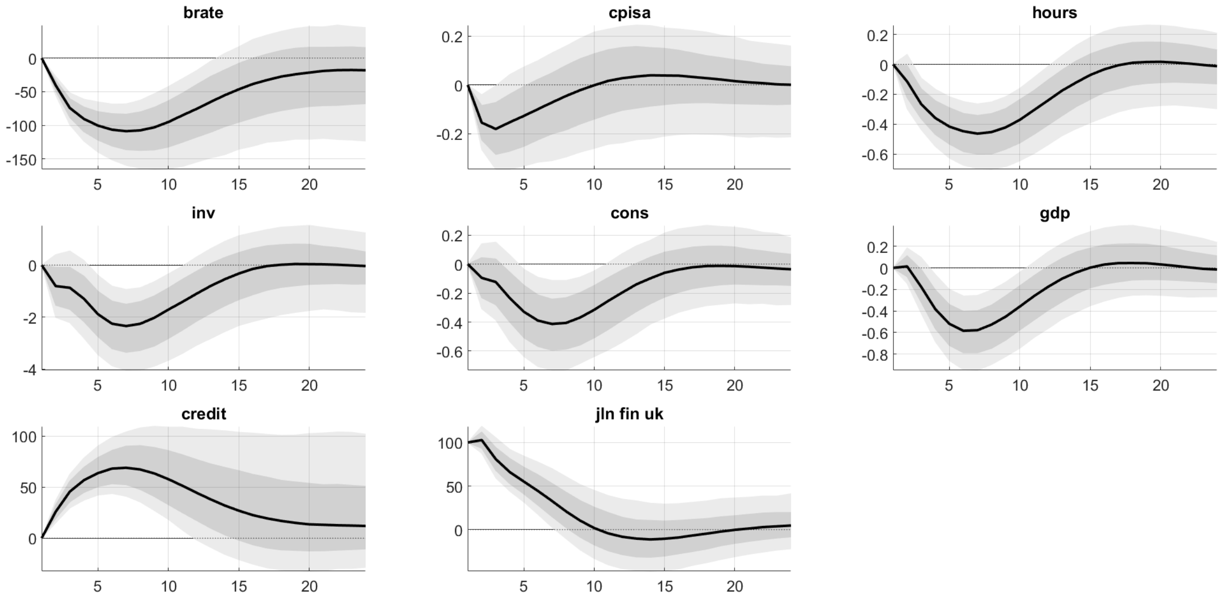
Response to Cholesky one s.d. innovations with 68% and 90% credible intervals.

Figure 14: UK macro uncertainty shocks with recursive identification



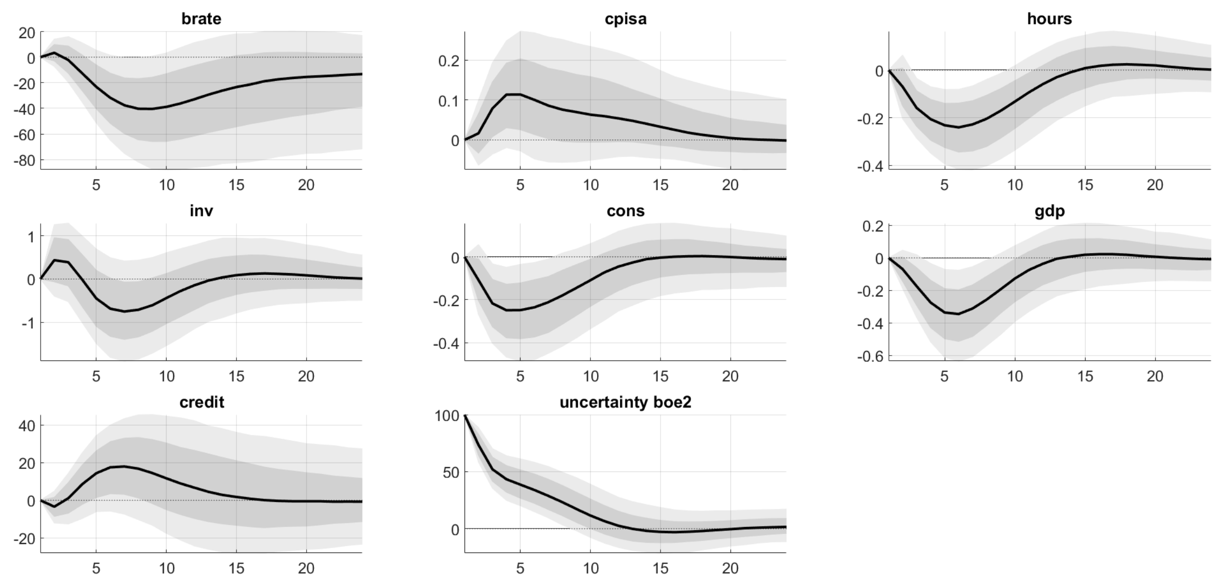
Response to Cholesky one s.d. innovations with 68% and 90% credible intervals.

Figure 15: UK financial uncertainty shocks with recursive identification



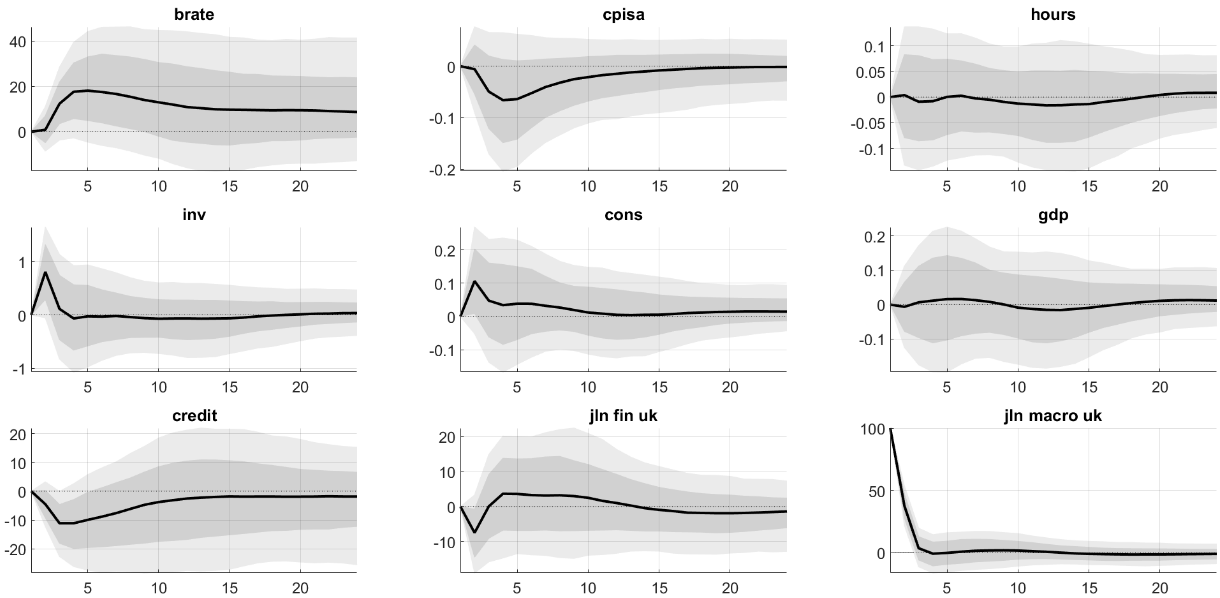
Response to Cholesky one s.d. innovations with 68% and 90% credible intervals.

Figure 16: BoE uncertainty shocks (No consumer confidence measures in uncertainty measure) with recursive identification



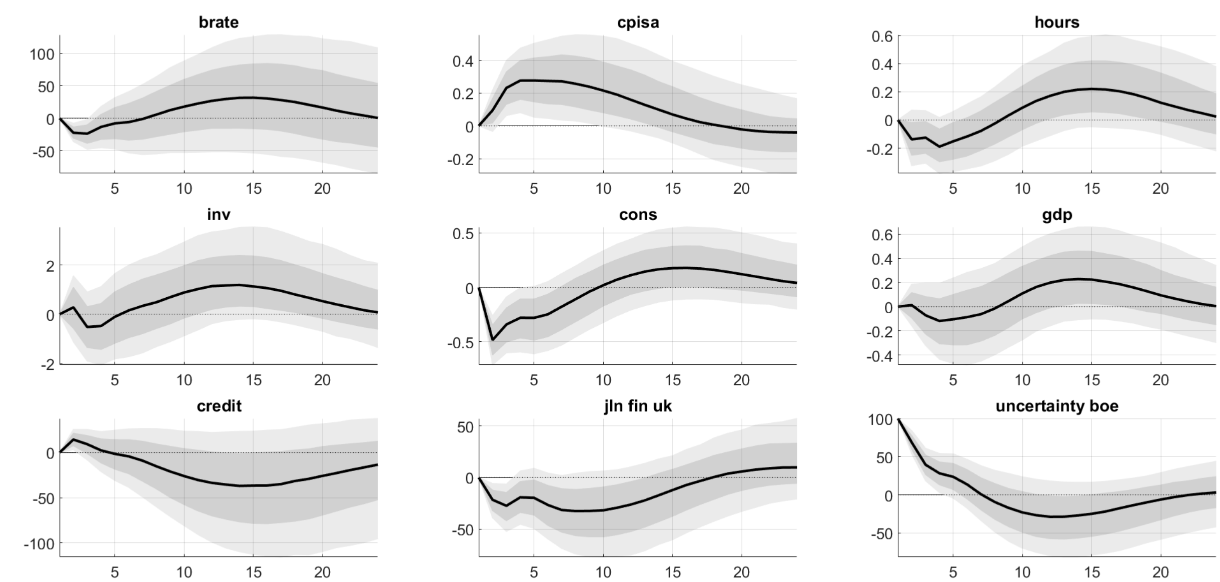
Response to Cholesky one s.d. innovations with 68% and 90% credible intervals.

Figure 17: UK Macro uncertainty shocks (conditional on no contempoaneous UK fin uncertainty shock) with recursive identification



Response to Cholesky one s.d. innovations with 68% and 90% credible intervals.

Figure 18: BoE uncertainty shocks (conditional on no contempoaneous UK fin uncertainty shock) with recursive identification

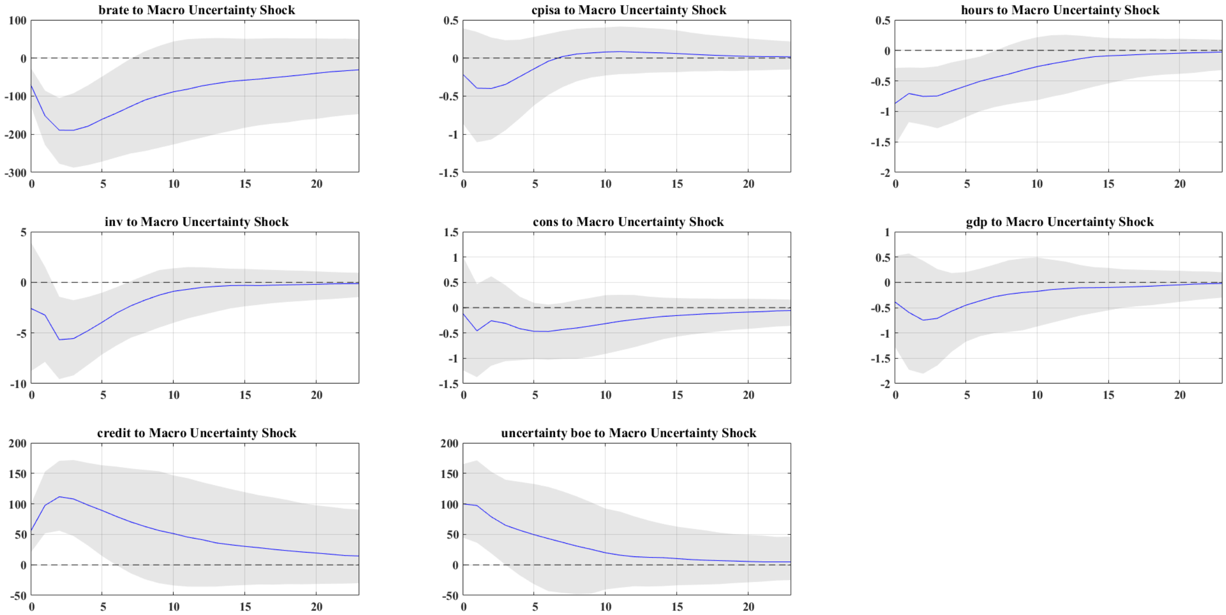


Response to Cholesky one s.d. innovations with 68% and 90% credible intervals.

Sign restrictions

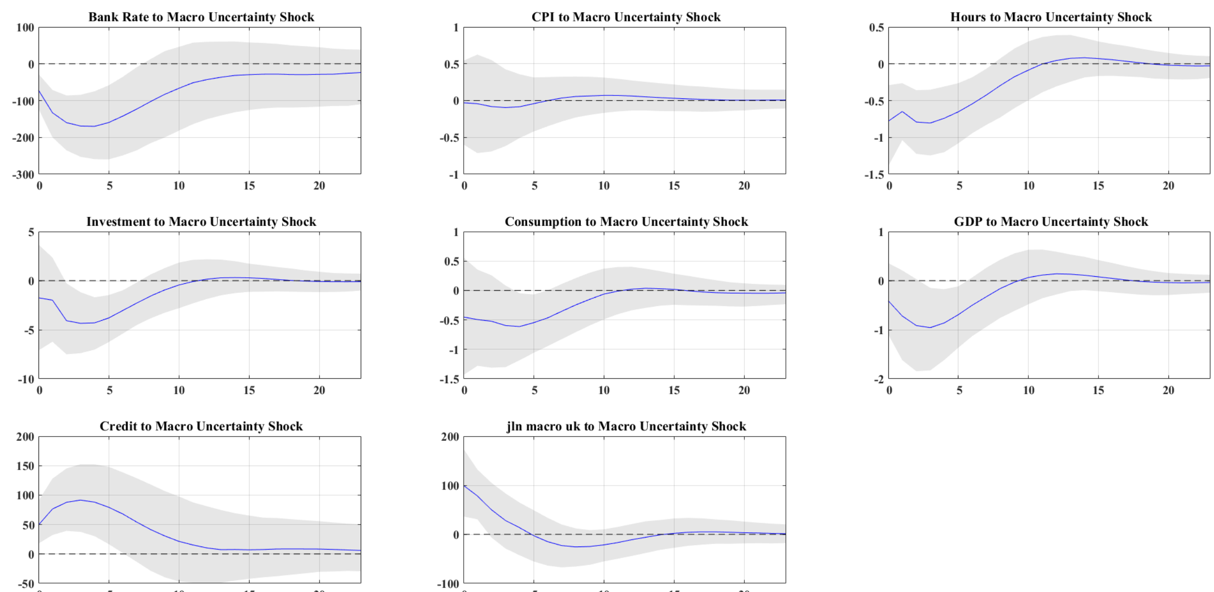
Temporary uncertainty shock

Figure 19: BoE uncertainty shocks with sign restrictions



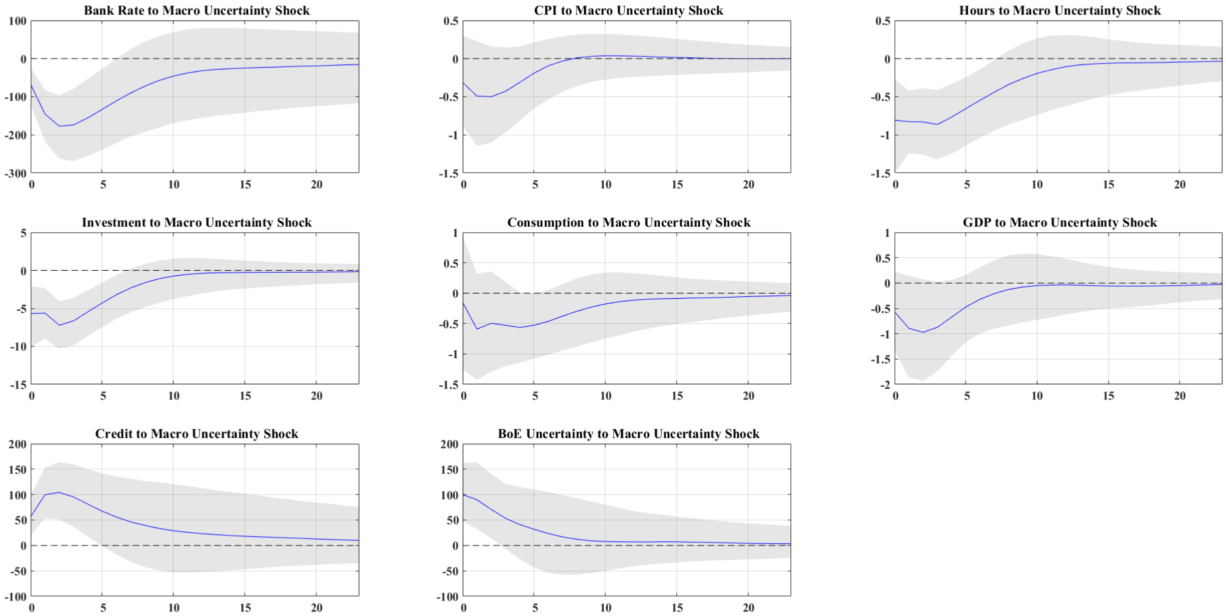
Response to one s.d. innovations with 68% credible intervals.

Figure 20: UK macro uncertainty shocks with sign restrictions



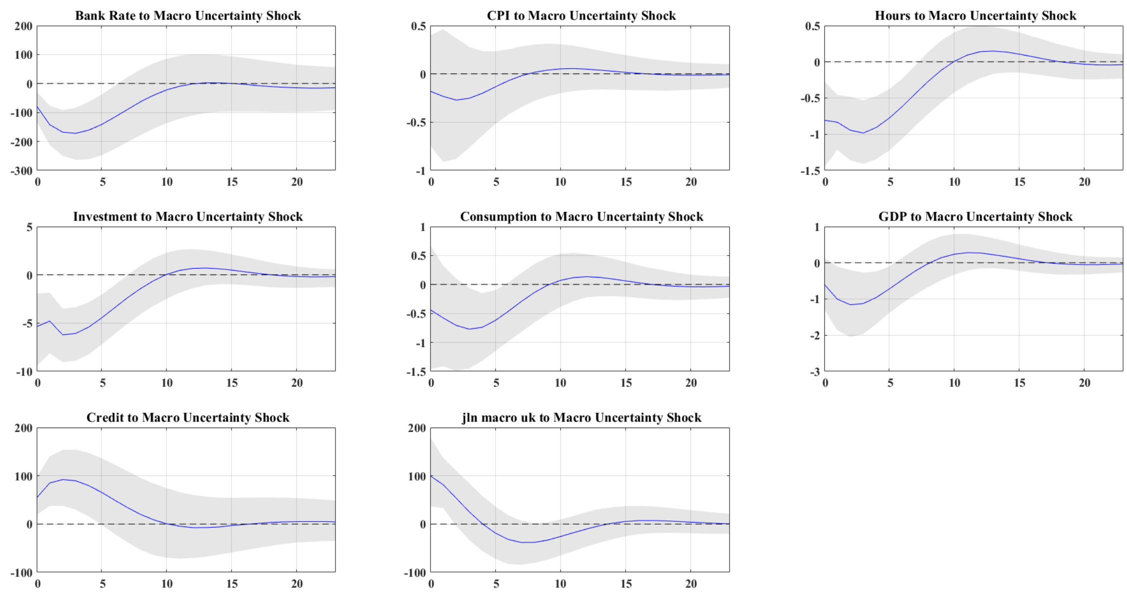
Response to one s.d. innovations with 68% credible intervals.

Figure 21: BoE uncertainty shocks with sign restrictions S1



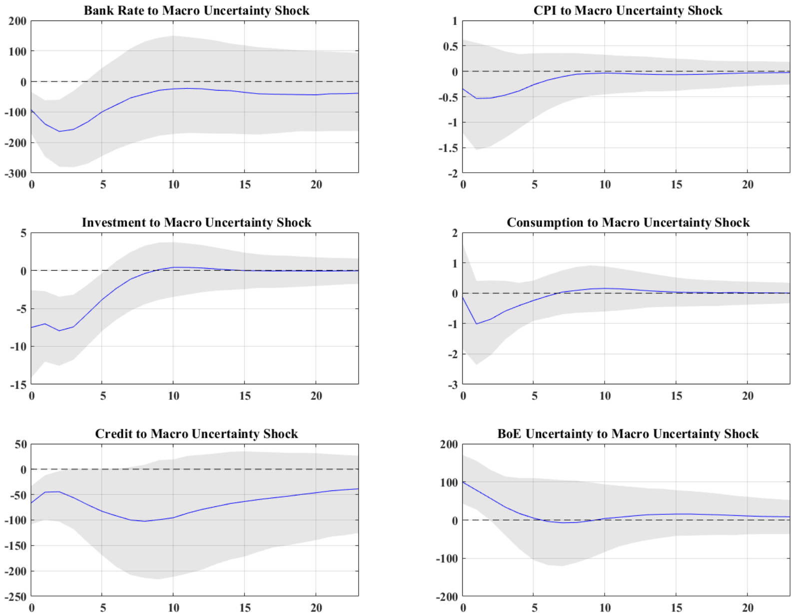
Response to one s.d. innovations with 68% credible intervals.

Figure 22: UK macro uncertainty shocks with sign restrictions S1



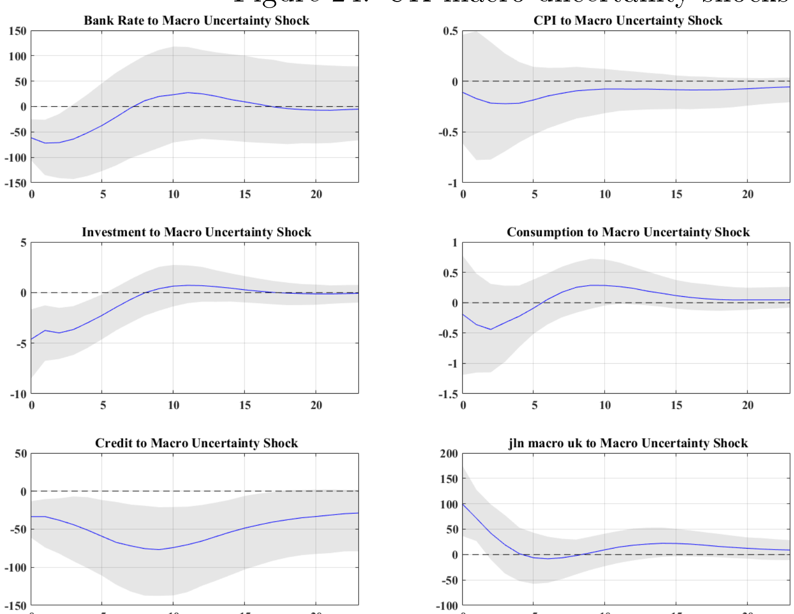
Response to one s.d. innovations with 68% credible intervals.

Figure 23: BoE uncertainty shocks with sign restrictions S2



Response to one s.d. innovations with 68% credible intervals.

Figure 24: UK macro uncertainty shocks with sign restrictions S1

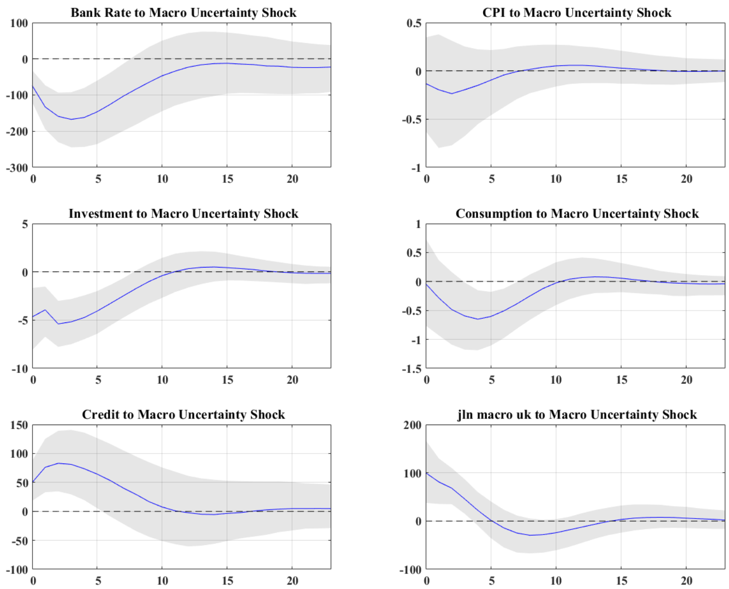


Response to one s.d. innovations with 68% credible intervals.

Persistent uncertainty shock

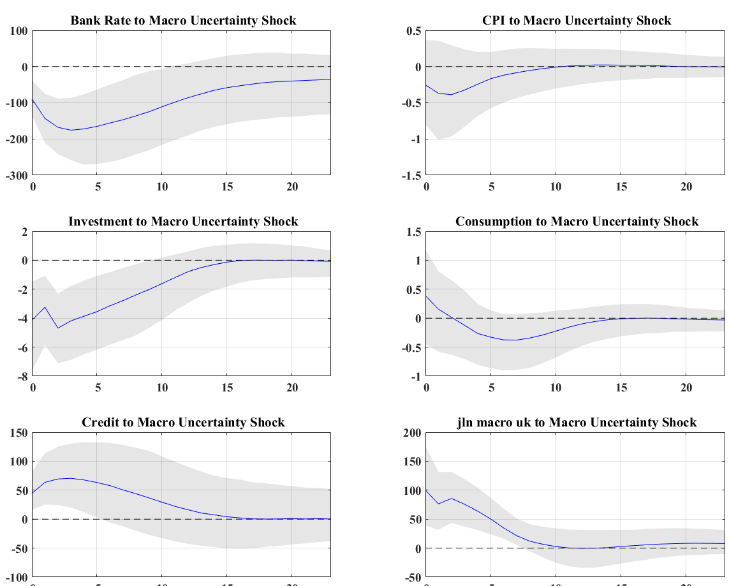
UK Macro Uncertainty

Figure 25: UK macro uncertainty shocks with sign restrictions S1, 4 Quarters



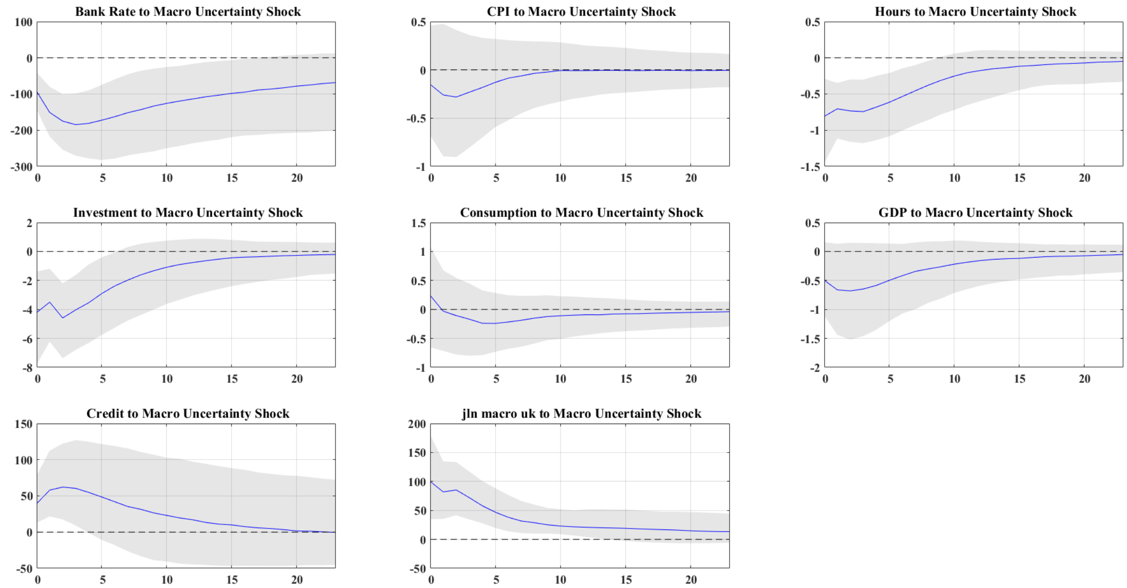
Response to one s.d. innovations with 68% credible intervals.

Figure 26: UK macro uncertainty shocks with sign restrictions S1, 8 Quarters



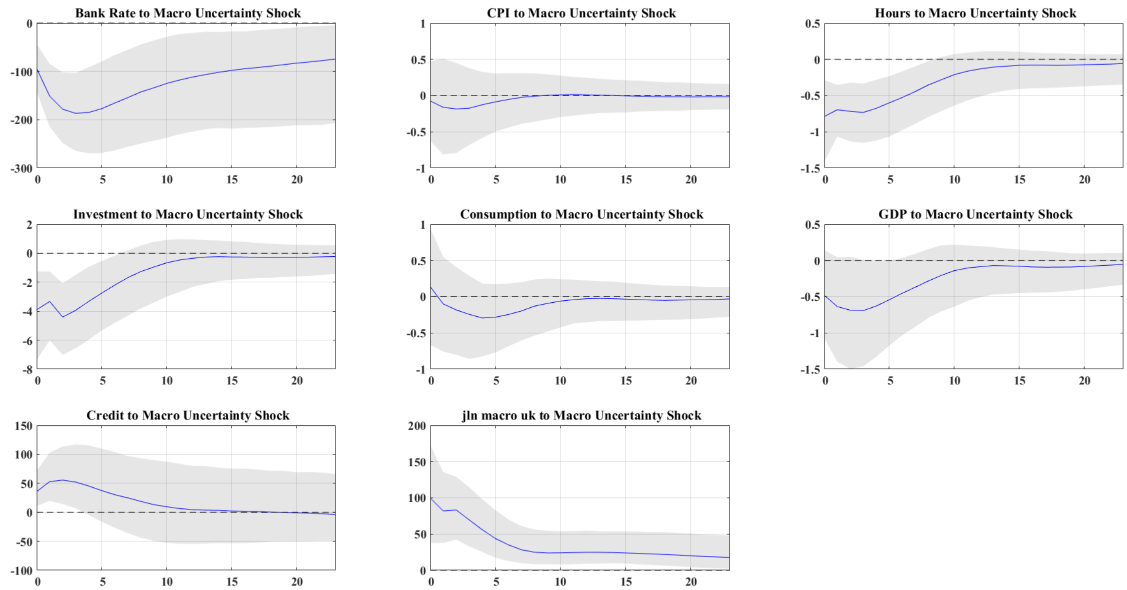
Response to one s.d. innovations with 68% credible intervals.

Figure 27: UK macro uncertainty shocks with sign restrictions S1, 12 Quarters



Response to one s.d. innovations with 68% credible intervals.

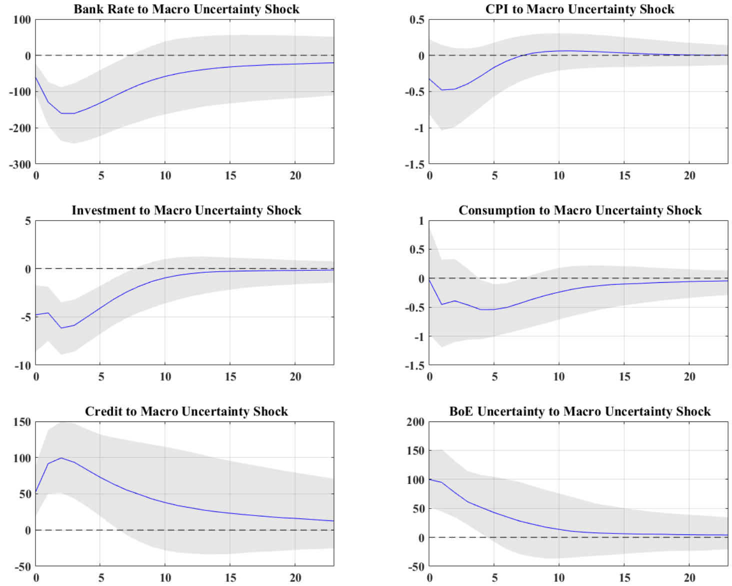
Figure 28: UK macro uncertainty shocks with sign restrictions S1, 16 Quarters



Response to one s.d. innovations with 68% credible intervals.

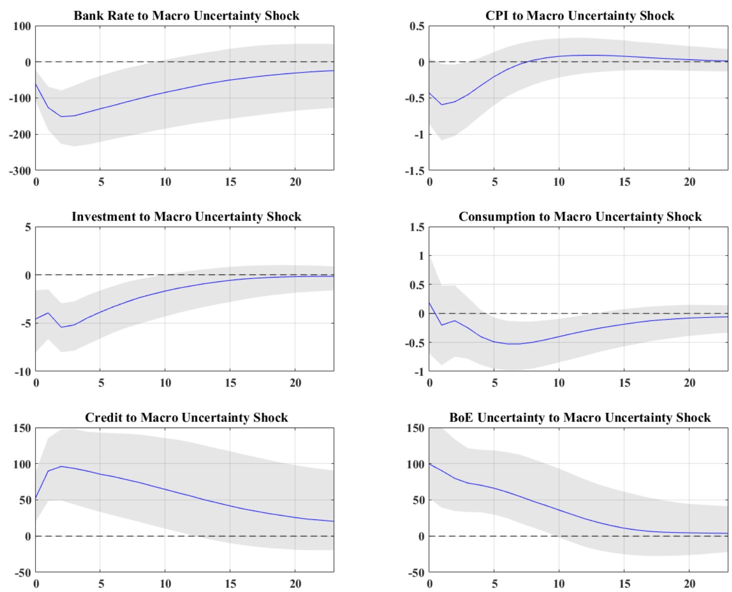
BoE Uncertainty

Figure 29: BoE uncertainty shocks with sign restriction S1, 4 Quarters



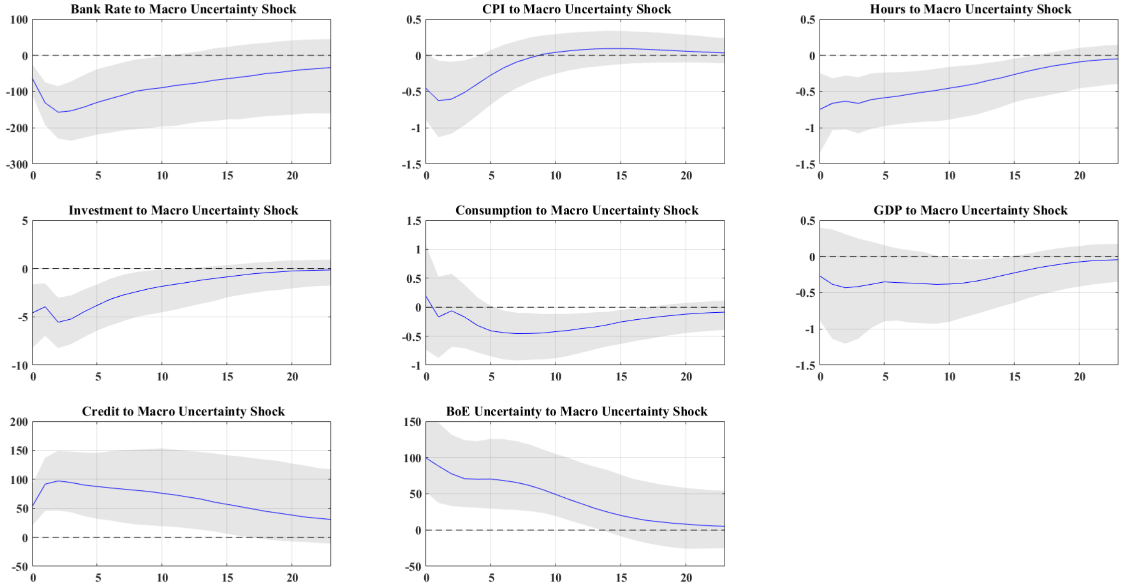
Response to one s.d. innovations with 68% credible intervals.

Figure 30: BoE uncertainty shocks with sign restriction S1, 8 Quarters



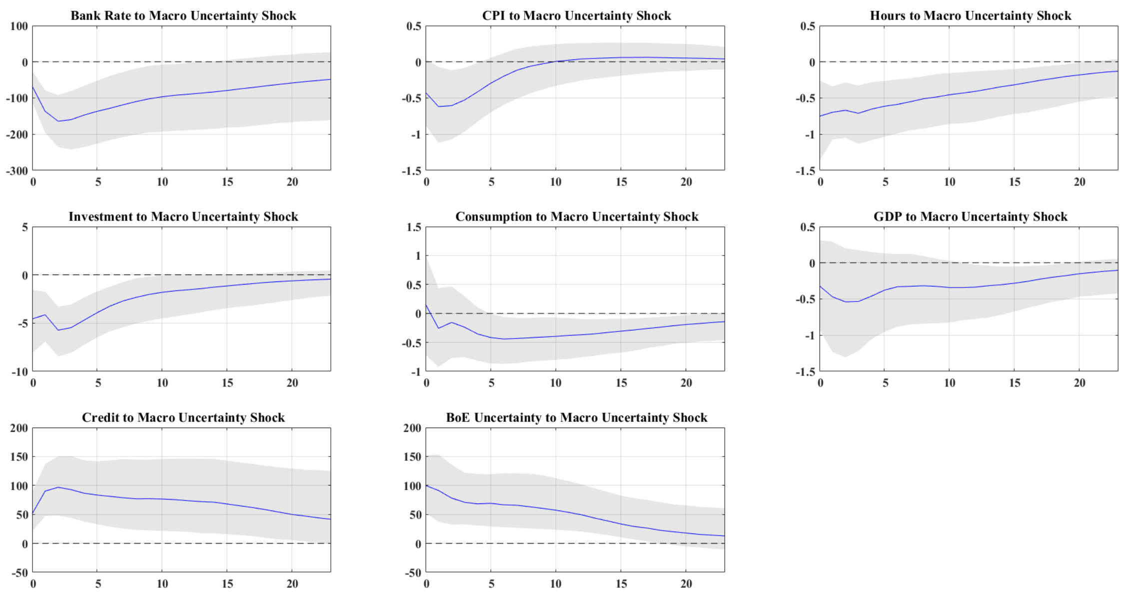
Response to one s.d. innovations with 68% credible intervals.

Figure 31: BoE uncertainty shocks with sign restriction S1, 12 Quarters



Response to one s.d. innovations with 68% credible intervals.

Figure 32: BoE uncertainty shocks with sign restriction S1, 16 Quarters

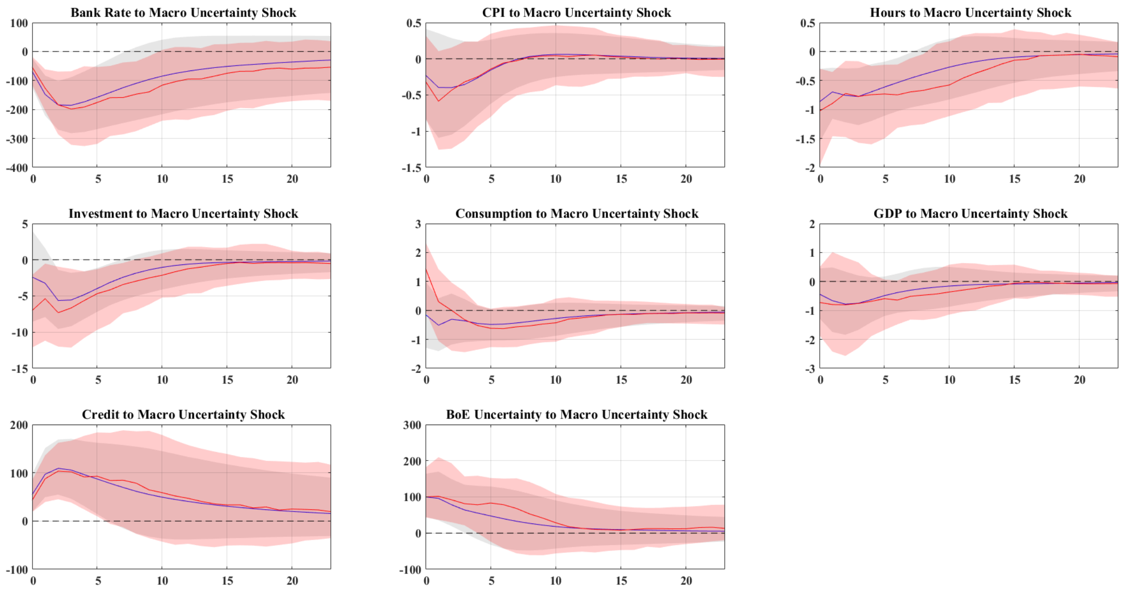


Response to one s.d. innovations with 68% credible intervals.

Narrative sign restrictions

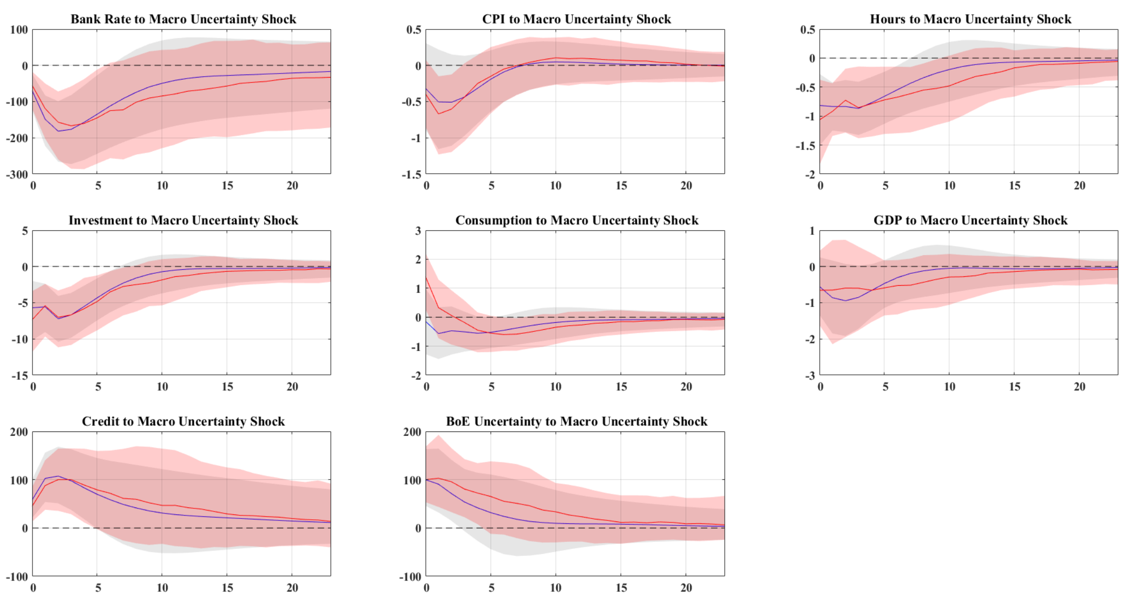
Economic Events

Figure 33: BoE uncertainty shocks with narrative sign restrictions on economic events, Baseline



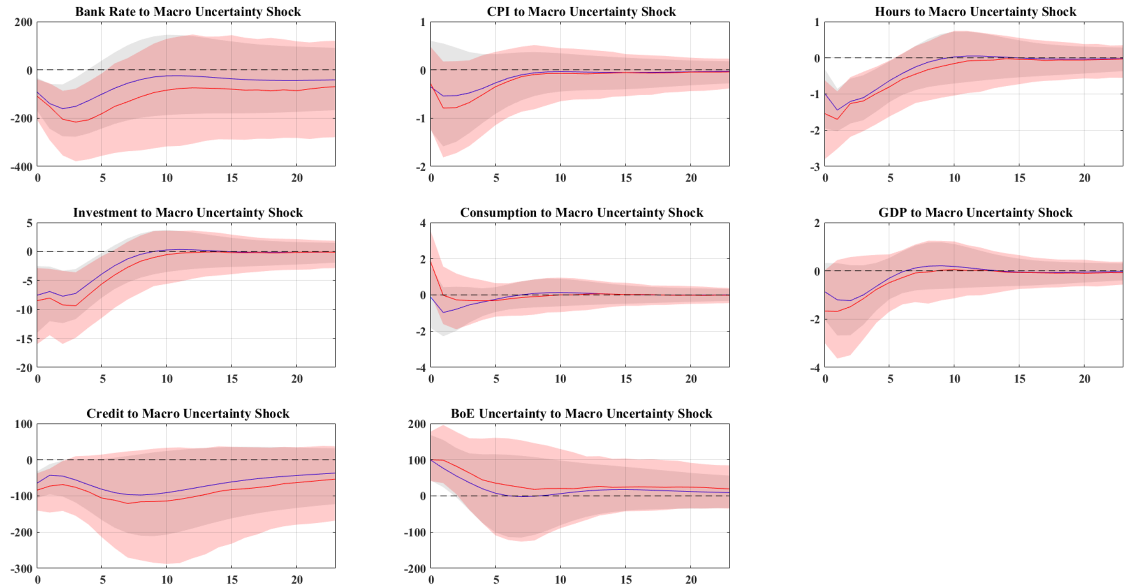
Response to one s.d. innovations with 68% credible intervals.

Figure 34: BoE uncertainty shocks with narrative sign restrictions on economic events, S1



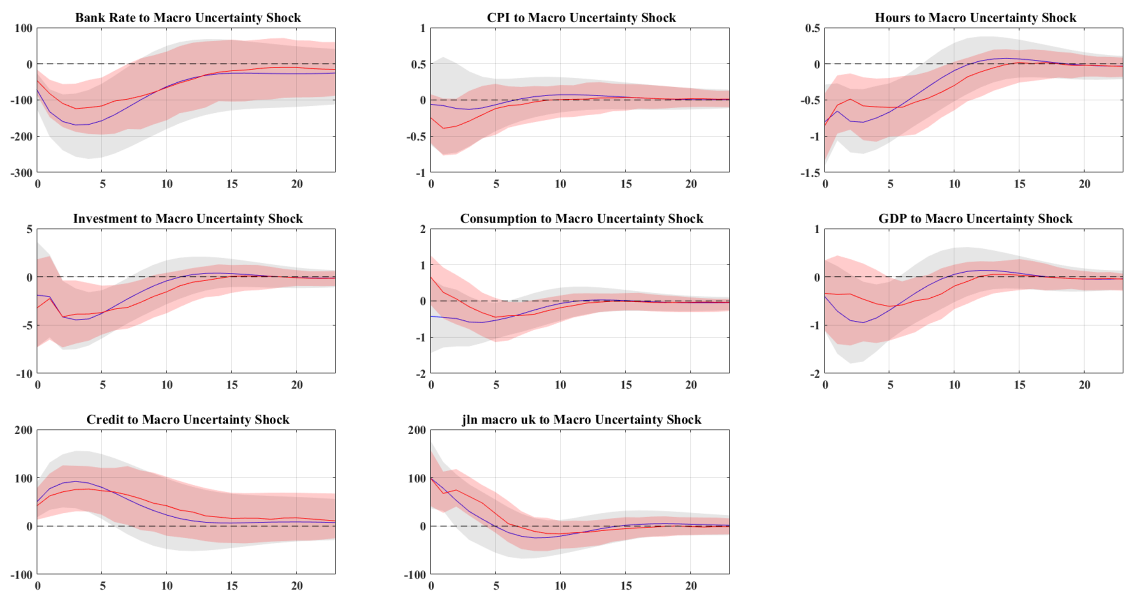
Response to one s.d. innovations with 68% credible intervals.

Figure 35: BoE uncertainty shocks with narrative sign restrictions on economic events, S2



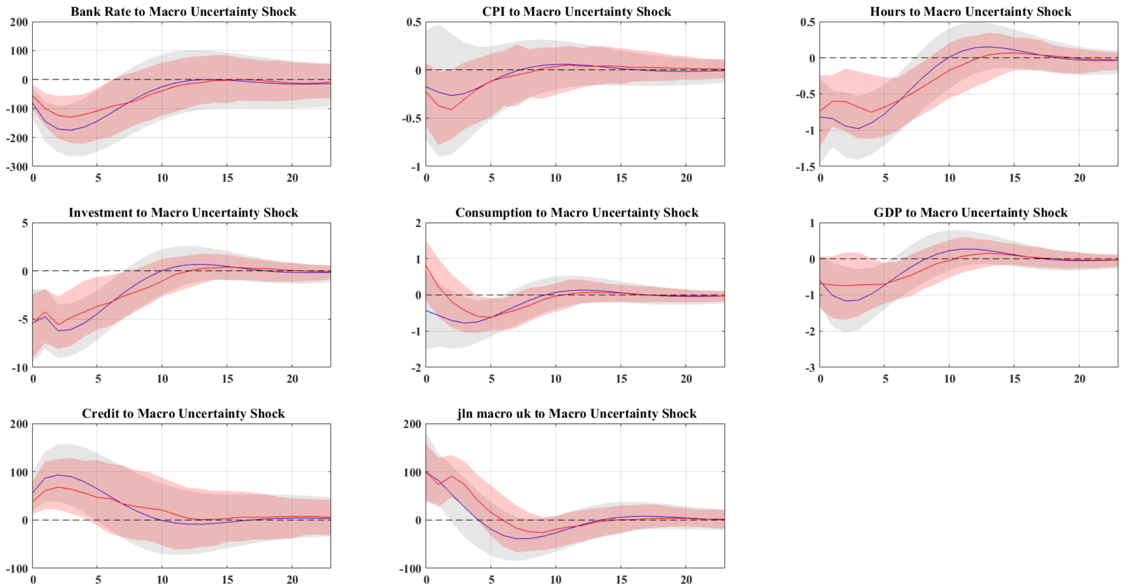
Response to one s.d. innovations with 68% credible intervals.

Figure 36: UK macro uncertainty shocks with narrative sign restrictions on economic events, baseline



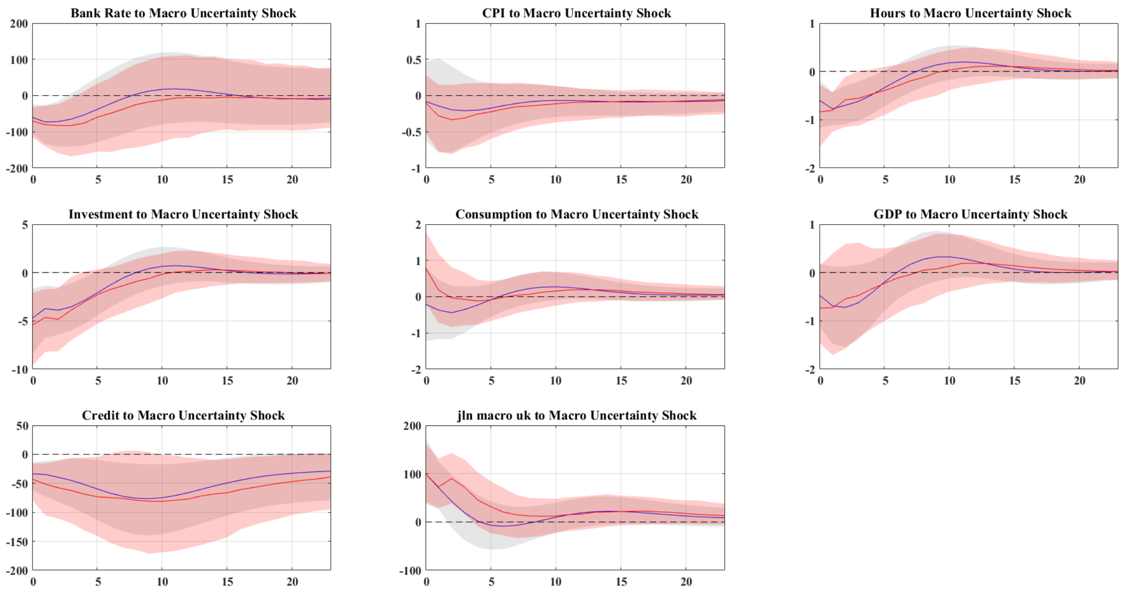
Response to one s.d. innovations with 68% credible intervals.

Figure 37: UK macro uncertainty shocks with narrative sign restrictions on economic events, S1



Response to one s.d. innovations with 68% credible intervals.

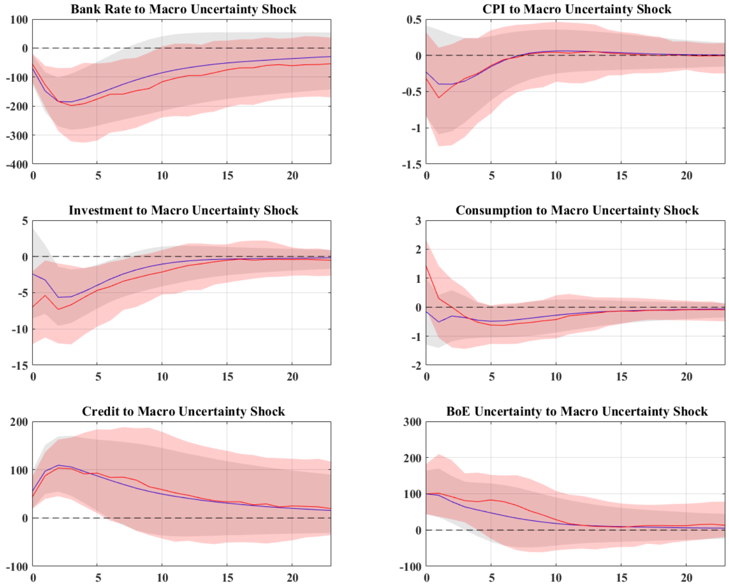
Figure 38: UK macro uncertainty shocks with narrative sign restrictions on economic events, S2



Response to one s.d. innovations with 68% credible intervals.

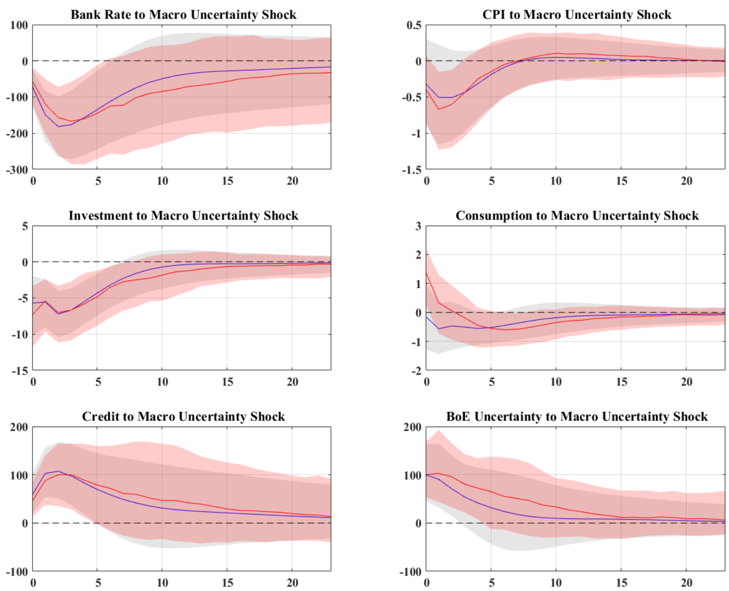
Tight General Elections

Figure 39: BoE uncertainty shocks with narrative sign restrictions on economic events, Baseline



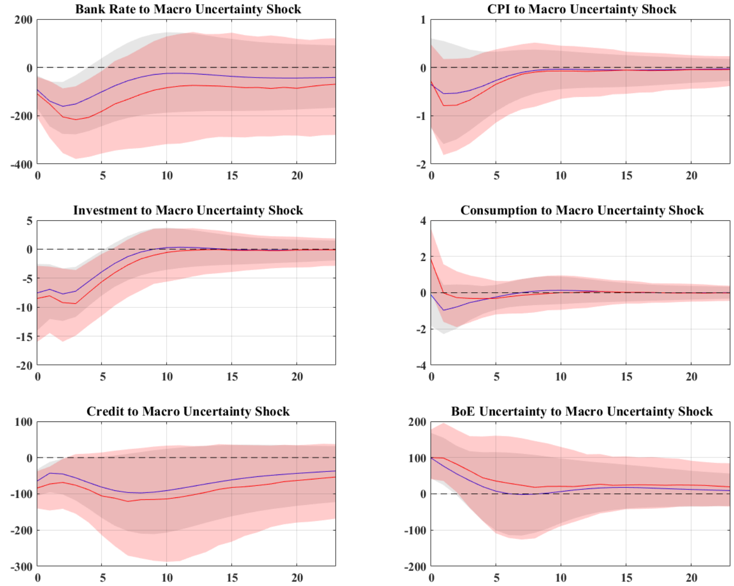
Response to one s.d. innovations with 68% credible intervals.

Figure 40: BoE uncertainty shocks with narrative sign restrictions on economic events, S1



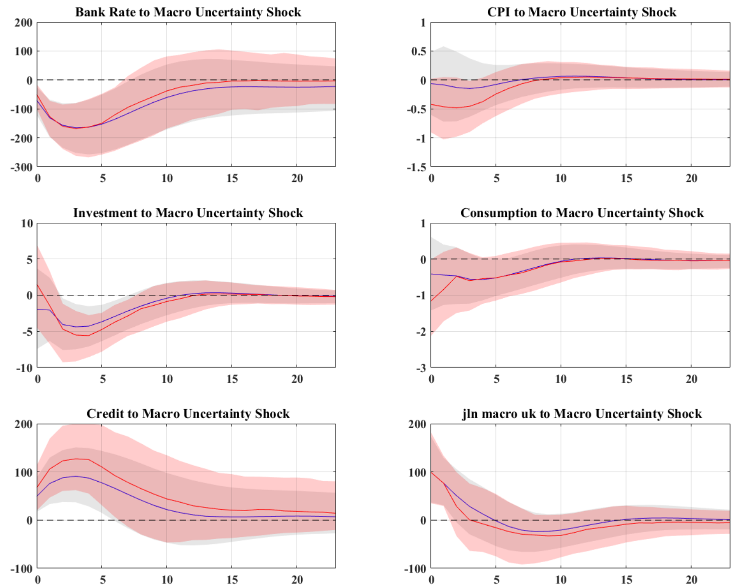
Response to one s.d. innovations with 68% credible intervals.

Figure 41: BoE uncertainty shocks with narrative sign restrictions on economic events, S2



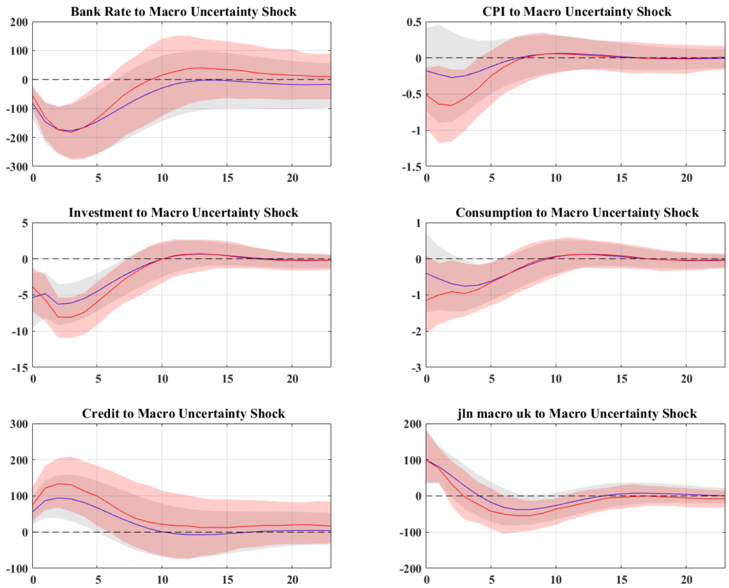
Response to one s.d. innovations with 68% credible intervals.

Figure 42: UK macro uncertainty shocks with narrative sign restrictions on tight general elections, baseline



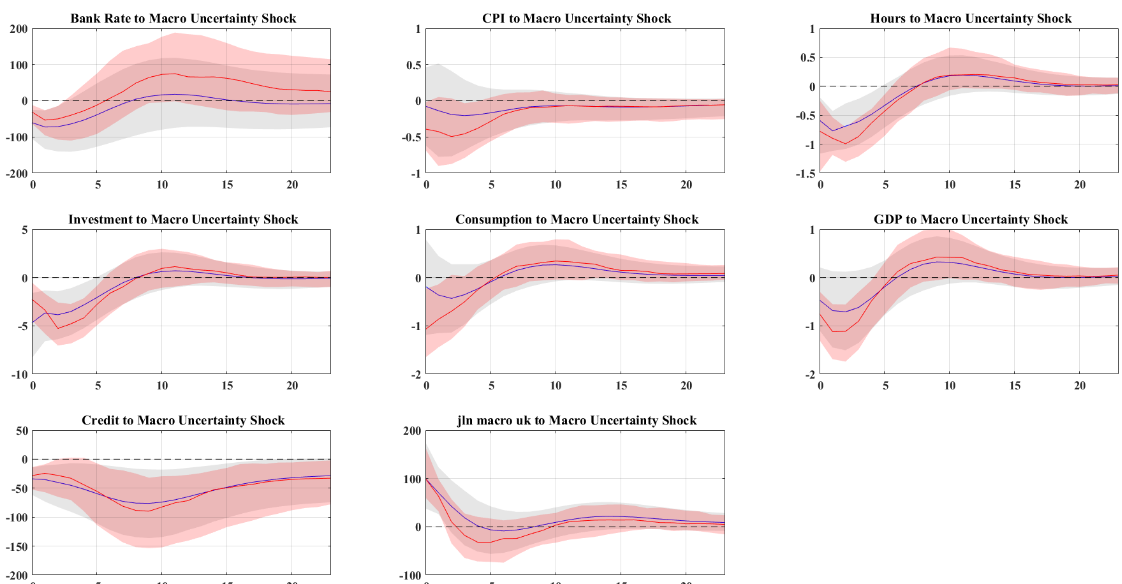
Response to one s.d. innovations with 68% credible intervals.

Figure 43: UK macro uncertainty shocks with narrative sign restrictions on tight general elections, S1



Response to one s.d. innovations with 68% credible intervals.

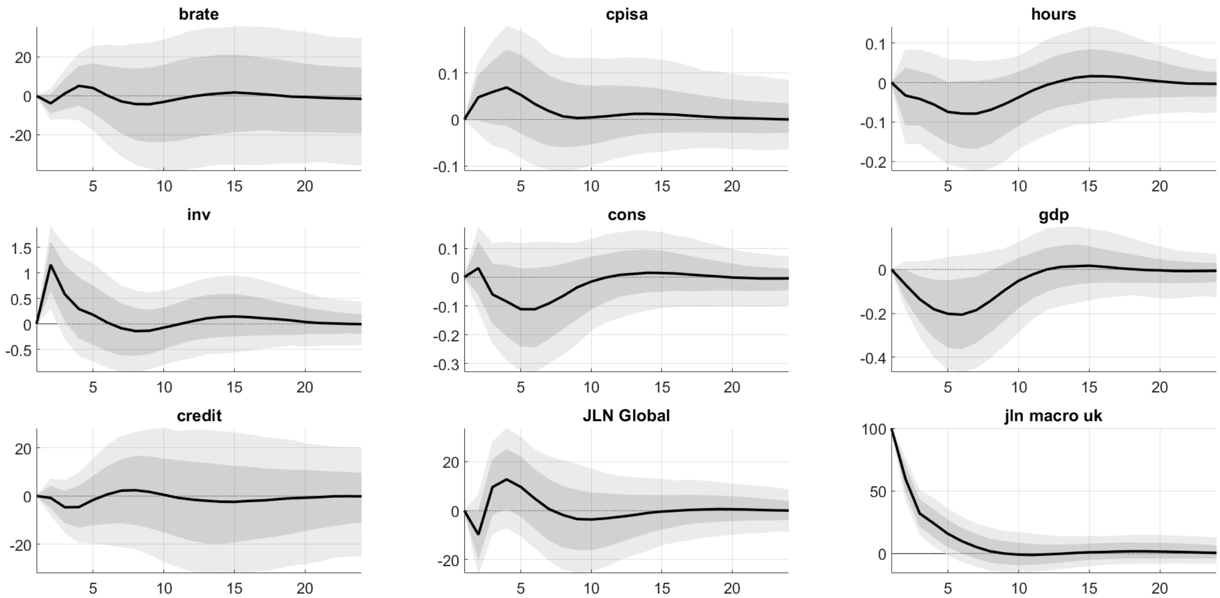
Figure 44: UK macro uncertainty shocks with narrative sign restrictions on tight general elections, S2



Response to one s.d. innovations with 68% credible intervals.

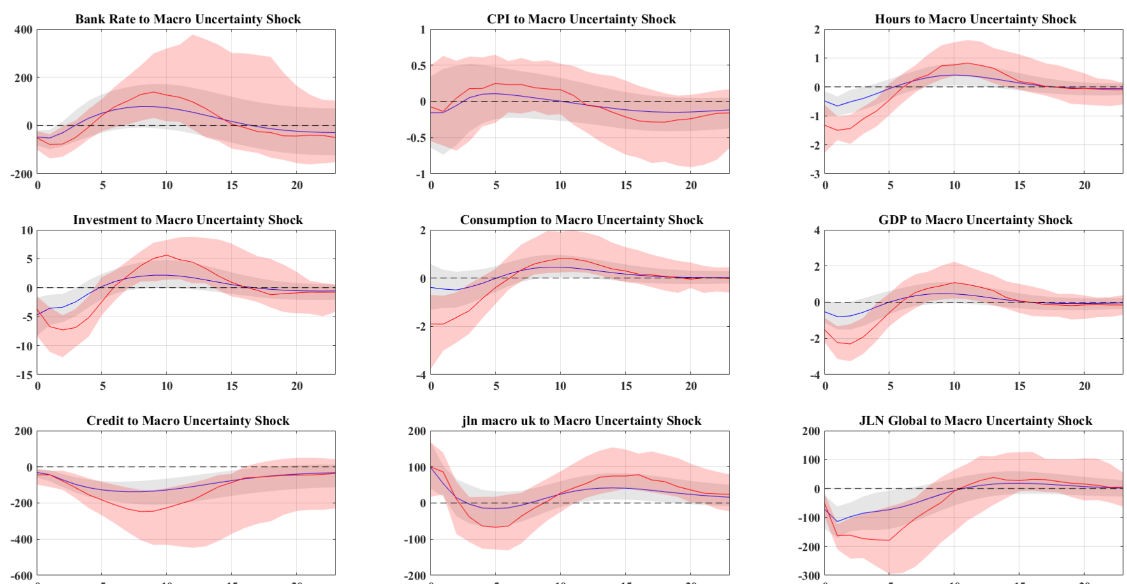
Global Uncertainty

Figure 45: UK Macro uncertainty shocks (conditional on no contempoaneous Global uncertainty shock) with recursive identification



Response to one s.d. innovations with 68% credible intervals.

Figure 46: UK Macro uncertainty shocks with narrative sign restrictions on tight general elections, S2 + no global uncertainty shock



Response to one s.d. innovations with 68% credible intervals.