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Alina Barnett,[(1)] Jan J J Groen[(2)] and Haroon Mumtaz[(3)]

Abstract

This paper examines how the interaction between inflation expectations and nominal and real macroeconomic variables has evolved for the United Kingdom over the post-WWII period until 2007. We model time-variation through a Markov-switching structural vector autoregressive framework with variants of the sign restriction identification scheme to back out the time-varying effect of different structural shocks. We investigate the following questions: (i) How has the impact of the mix of real and nominal shocks on the UK economy evolved over time and did this have a specific impact on UK inflation expectations? and (ii) Has there been an autonomous impact of inflation expectations on the UK economy and has it changed over time? Our results suggest that shocks to inflation expectations had important effects on actual inflation in the 1970s, but this impact had significantly declined towards the end of our sample. This seems to be mainly due to a relatively slower response of monetary policy to these shocks in the 1970s compared to later years. Similarly, oil price shocks and real demand shocks led to important changes in macroeconomic variables in the 1970s. Beyond that period and up to the end of our sample oil price shocks became less significant for the dynamics of actual inflation and output growth. However real demand shocks became a relatively more important determinant for fluctuations in those series during the 1990s and the beginning of the 2000s. The changing response of monetary policy to this type of shock appears to be crucial for this result.

Key words: Inflation expectations, Markov-switching structural VAR.

JEL classification: E5, C1.

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Summary

Since World War II, the United Kingdom has experienced a broad range of economic dynamics. The economy was faced with relatively low inflation and economic growth volatility in the period preceding the 1970s, an unprecedented period of high inflation and depressed economic growth during the 1970s, and with more stable inflation and growth prospects from the 1980s up to the end of our sample in 2007, in particular after the introduction of inflation targeting in 1992. Subsequently, the United Kingdom, in common with most of the world, has suffered a severe recession following the onset of the financial crisis in 2008, but our analysis is not intended to shed light on these very recent events.

These economic changes were associated with shifts in the behaviour of monetary authorities. For example, Bank of England work in 2004 suggested that the response of the Bank to expected inflation was stronger after the introduction of inflation targeting in 1992. Similar results are thought to hold for the United States, with the decrease in inflation and output volatility in the post-1979 period coinciding with an increase in the weight placed by the Federal Reserve on stabilising inflation.

Other commentators argue that the credibility of monetary policy might have had an impact on inflation dynamics by changing the manner in which inflation expectations are formed. According to this literature when the economy is hit by large, inflationary shocks (an ‘Inflation Scare’) and the central bank hesitates to respond promptly, this may result in a persistent increase in longer-term inflation expectations. This in turn presents the central bank with a choice; either substantially contracting policy to deflate this rise in expectations (and hence cause an economic slowdown); or to accommodate it and let these higher inflation expectations become entrenched in the economy (resulting in persistently higher actual inflation).

There have not been many studies that have looked at the observed time-varying economic dynamics of the UK economy by explicitly using measures of inflation expectations. The work which has been done on this topic is generally focused on the US economy. Some used surveys on inflation expectations from the Survey of Professional Forecasters while others used surveys such as the Livingston Survey. They typically find that monetary policy accommodated

temporary shocks to inflation expectations in the pre-1979 sample, a period with high inflation persistence, but not in the post-1979 Volcker-Greenspan period (a period with low inflation persistence).

Our study contributes to this debate by employing a complementary approach to analyse UK macroeconomic dynamics by using explicit measures of inflation expectations. We use a system of equations (a vector autoregression) where we use theory to identify the underlying structure. We then apply a time-varying structural methodology to generalise the analysis done for the US economy, allowing for shifts in the coefficients of our system that are caused by changing behaviour (are 'endogenous'). We also explicitly consider the role of demand and supply shocks.

Using this structure, we investigate two main questions relating to the UK economy between 1965 and 2007 (and therefore excluding the effects of the financial crisis and its aftermath). First, how has the impact of the mix of real and nominal shocks on the UK economy evolved over time and did this have a specific impact on UK inflation expectations? Second, has there been an autonomous impact of inflation expectations on the UK economy and has this changed over time?

Our results suggest that shocks to inflation expectations had important effects on actual inflation in the United Kingdom in the 1970s, but that this impact declined significantly towards the end of our sample in 2007. This seems to be mainly due to a relatively stronger response of monetary policy to these shocks during the inflation-targeting years. Similarly, oil price shocks and real demand shocks led to important changes in macroeconomic variables in the 1970s. Beyond that period oil price shocks become less significant for the dynamics of actual inflation and output growth, but real demand shocks, on the other hand, have in the latter part of our sample become a more important determinant for fluctuations in those series. The changing response of monetary policy to the real demand shock appears to be crucial for this result.

1 Introduction

As has been the case with other OECD economies, the United Kingdom has during the post-WWII period had a diverse experience with respect to its economic dynamics. There were relatively low inflation and GDP growth volatility in the period preceding the 1970s, an unprecedented period of high inflation and depressed economic growth during the 1970s (often called the 'Great Inflation'), and more stable inflation and growth prospects between the 1980s and the end of our sample in 2007, in particular after the introduction of inflation targeting in 1992. In fact, Benati (2004) has shown that in his sample the stability of the post-1992 period was unmatched in any other period since the gold standard. Subsequently, the United Kingdom, in common with most of the world, has suffered a severe recession following the onset of the financial crisis in 2008, but our analysis is not intended to shed light on these very recent events.

Shifts in the behaviour of monetary authorities have been associated with the changes in the dynamics of the UK economy. For example, Nelson (2001) reports a significant change in the degree of 'activism' of UK monetary policy after the introduction of inflation targeting in 1992. By estimating forward-looking Taylor rules on different subsamples, Nelson (2001) shows that the response of the Bank of England to expected inflation was at its highest over the post-1992 period. In a similar study for the United States, Clarida, Gali and Gertler (2000) show that a similar result holds for the United States, with the low and stable inflation and GDP growth of the post-1980 period and up to mid-2000s coinciding with an increase in the weight placed by the Federal Reserve on stabilising inflation.[1]

A related literature examines how changes in the credibility of the monetary policy regime may have more subtle effects on the economy by changing the manner in which inflation expectations are formed. For example Goodfriend (1993) considers what he denotes as the 'Inflation Scare' problem: when the economy is hit by large, inflationary shocks and the central bank hesitates to respond promptly to them, these might result in a persistent increase in longer-term inflation expectations. Erceg and Levin (2003) and Orphanides and Williams (2005) formalise

[1]However these results have been challenged in several recent studies. For the United Kingdom, Benati (2007) shows that a fall in the volatility of demand and supply shocks (estimated using a time-varying structural VAR) can explain most of the recent stability in the United Kingdom's output and inflation. For the United States, the authoritative study by Sims and Zha (2006) shows that a model that allows for variation in the volatility of shocks fits US data better than a model that allows for a change in the monetary policy rule. There are several related papers that arrive at similar conclusions for the United States. These include Cogley and Sargent (2005) and Primiceri (2005).

Goodfriend's notion of an inflation scare within a learning model where agents have imperfect knowledge about the economy: in Erceg and Levin (2003) agents are solely uncertain about the central bank's inflation target, whereas in Orphanides and Williams (2005) this uncertainty relates to the inflation process and the policymaker's reaction function. Under these circumstances economic shocks can result in persistent deviations of inflation expectations from their model-consistent level.

This paper adopts an empirical approach to investigate the relevance of these ideas for the United Kingdom. In particular, the paper investigates the relationship between measures of inflation expectations and key macroeconomic variables and examines how this relationship has changed over time. Our aim is to uncover (indirectly) evidence on how the credibility of UK monetary policy has changed over the last three decades.

Our work is closely related to Leduc, Sill and Stark (2007) who use inflation surveys for the United States to empirically proxy inflation expectations within a structural vector autoregressive (VAR) model of the US economy. The authors find that shocks to survey-based inflation expectations had large and persistent effects on the US economy in the pre-1979 period whereas this effect disappeared with the onset of Paul Volcker's chairmanship of the Fed.[2]

In our application to the UK economy we use a structural VAR model that is similar to that employed by Leduc *et al* (2007). However, we generalise the analysis in Leduc *et al* (2007) in three ways. Firstly, we do not conduct sample-split analysis but allow endogenous shifts in the VAR coefficients. Secondly, we explicitly consider the role of demand and supply shocks. Finally, we employ real-time macroeconomic data to partially capture the information set available to the forecaster. For example, for each quarterly inflation forecast we use the most recent GDP growth observation available at that time. While future data revisions are excluded for computational reasons, we believe our approach provides significant advantages over the traditional use of data (using final vintages for example). With this adapted framework, we investigate the following questions: *(i)* How has the impact of the mix of real and nominal shocks

[2]Erceg and Levin (2003) used surveys on US inflation expectations from the Survey of Professional Forecasters to show that inflation expectations indeed settled down at a lower average after the Volcker disinflation, confirming that agents changed their expectations in response to monetary policy shifts. The forecast errors for inflation based on these surveys, however, remain persistent throughout the sample period, which Erceg and Levin (2003) interpret as a consequence of the fact that the Federal Reserve has been unclear about an explicit target rate for inflation. Also, Piger and Rasche (2006) show for the United States that the contribution of long-horizon inflation forecasts, either from surveys or term structure data, to inflation dynamics by far dominates the contribution of the output gap (measured in several ways) and supply shock variables.

on the UK economy evolved over time and did this have a specific impact on UK inflation expectation formation? and *(ii)* Has there been an autonomous impact of inflation expectations on the UK economy and has it changed over time? Our results suggest that shocks to inflation expectations had important effects on actual inflation in the United Kingdom in the 1970s, but this impact declined significantly in the inflation-targeting period. This seems to be mainly due to a relatively slower response of monetary policy to these shocks in the 1970s compared to later years. Thus recent monetary policy has tended to act to anchor inflation expectations more than in the 1970s. Further to this, oil price shocks and real demand shocks led to important changes in macroeconomic variables in the 1970s. Beyond that period and up to the end of our sample oil price shocks become less significant for the dynamics of actual inflation and output growth, but real demand shocks, on the other hand, have in the recent period become a more important determinant for fluctuations in those series, and the changing response of monetary policy to this shock appears to be crucial for this result.

The remainder of this paper is organised as follows. Section 2 provides a sketch of the data used in the analysis, in particular with respect to our measure of UK inflation expectations. Our Markov-switching approach is outlined in Section 3 and stylised facts for our data set based on this approach are presented in Section 4.1. The structural analysis for the demand and supply shocks on the one hand and the inflation expectations shocks on the other are presented in Sections 5 and 5.2.1 respectively. Concluding remarks can be found in Section 6.

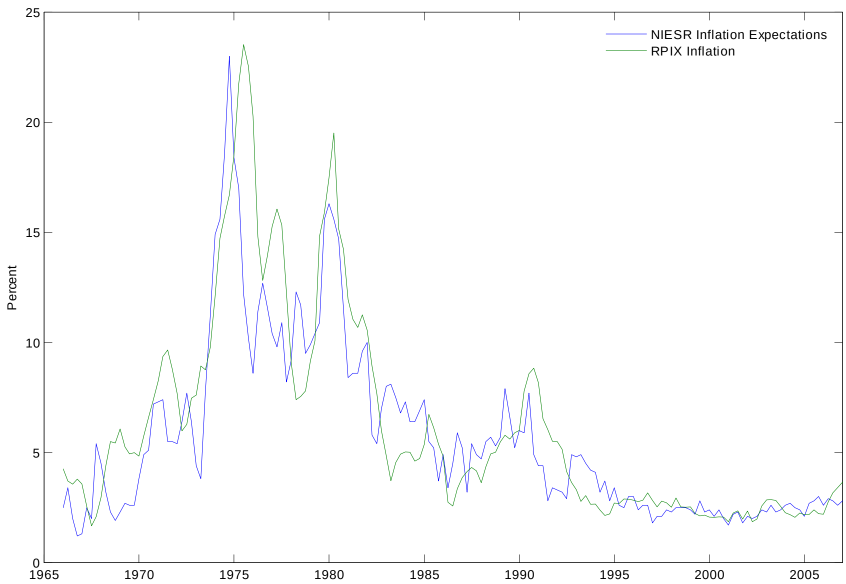
2 The data

Chart 1 plots UK RPIX inflation[3] and one-year ahead projections of RPIX inflation produced by the National Institute of Economic and Social Research (NIESR). We use these forecasts as our measure of inflation expectations. These data are published each quarter in the *National Institute Economic Review* and were originally collated by Young (1995). We extend the Young (1995) data back to 1965 and update it to 2007. It is interesting to note that the NIESR forecasts move very closely with actual inflation, with the peaks in the NIESR measure leading actual inflation.

Figure 1 presents an extract from the February 1970 issue of the *National Institute Economic Review*. The table presented in Figure 1 shows some of the forecasts made by NIESR in 1970 Q1

[3]RPIX refers to the retail prices index excluding mortgage interest payments.

Chart 1: UK data on RPIX inflation and inflation expectations from the National Institute of Economic and Social Research (NIESR)



and the timing of data available to them. For example, the third column of the table shows that the forecast for the consumer price index in 1970 and 1971 was based on data up to Q4 of 1969. We therefore align the remaining data used in our analysis to match this feature of the forecasting process and thus assume that the timing of the forecasts is at beginning of the current quarter. This means that the 1970 Q1 forecasts are timed to have been made in 1969 Q4, and thus the remaining series will be running up to 1969 Q4 for this particular forecast.

We use annual RPIX inflation rates, the three-month Treasury bill interest rate, annual oil price inflation based on the Sterling Brent oil price index (which denotes the oil price in pound sterling) and, finally, annual GDP growth. In the latter case, one needs to be cognisant that national accounts data are frequently revised, and hence care needs to be taken in their usage. The main problem that data revisions introduce is that the information set available to agents at the moment of the forecast consists of information which has been updated since the publication of the original data (final vintage) but also consists of information which is still to be revised.[4] To

[4]For a further discussion on the implications of taking into account real-time data when using direct measures of inflation expectations see Lee and Shields (2007).

Figure 1: An extract from National Institute Economic Review, 1970 Q1 (Vol. 51)

Table 5. Personal income and expenditure

The forecast figures are based on present policies and are not intended to be more precise than the general statements in the text

Seasonally adjusted

		Personal disposable income	Credit effect(a)	Consumers' price index(b)	Real disposable personal income	Consumers' expenditure	Savings(c)	Savings ratio(d)
		£ million current		1963 = 100	£ million, 1963 prices			Per cent
1968	I	7,227	24	117.1	6,171	5,758	413	6.7
	II	7,236	−23	119.5	6,055	5,505	550	9.1
	III	7,318	14	120.9	6,052	5,622	430	7.1
	IV	7,484	13	122.3	6,119	5,677	442	7.2
1969	I	7,633	−23	123.9	6,160	5,590	570	9.3
	II	7,562	−31	125.3	6,035	5,652	383	6.3
	III	7,683	−13	126.7	6,063	5,678	385	6.3
1969	IV (Estimate) ..	7,839	−15	128.1	6,119	5,706	413	6.8
Forecast								
1970	*I*	*7,955*	*0*	*129.5*	*6,144*	*5,715*	*428*	*7.0*
	II	*8,073*	*5*	*130.8*	*6,170*	*5,740*	*430*	*7.0*
	III	*8,179*	*10*	*132.1*	*6,194*	*5,765*	*428*	*6.9*
	IV	*8,272*	*15*	*133.2*	*6,208*	*5,788*	*420*	*6.8*
1971	*I*	*8,351*	*20*	*134.4*	*6,214*	*5,803*	*411*	*6.6*
	II	*8,428*	*25*	*135.5*	*6,222*	*5,815*	*407*	*6.5*

Percentage rates of change :	*1969/68*	*1970/69*	*1969 IV/68 IV*	*1970 IV/69 IV*
Consumers' price index	5.0	4.3	4.7	4.0
Real disposable income ..	−0.1	1.4	0.0	1.5
Consumers' expenditure	0.3	1.7	0.5	1.4

Source : *Economic Trends* and NIESR estimates.

(a) Weighted change in hire purchase debt and ' other ' personal bank advances outstanding.
(b) The implicit price deflator of the constant price consumers' expenditure series.
(c) The difference between real personal disposable income and consumers' expenditure.
(d) Ratio of savings to real personal disposable income.

address the latter problem, we use real-time data on UK GDP taken from Groen, Kapetanios and Price (2009).[5] The data used in the VAR model therefore incorporates for each quarterly inflation forecast, the most recent GDP growth observation available at that time. Whilst future data revisions are excluded for computational reasons, we believe our approach provides significant advantages over the traditional use of data (using final vintages for example).

It is clear from Chart 1 that the 1970s and the early 1980s were characterised by high and volatile inflation and inflation expectations. The level of both variables declined substantially in the early 1980s, but volatility remained elevated until the introduction of inflation targeting in 1992. As discussed in several recent studies the post-1992 period was characterised by low and stable inflation. Similarly, inflation expectations have remained low and stable over this period.

Note that the NIESR inflation forecasts are the only available series of UK inflation expectations

[5] Note that RPIX data is never revised.

that is available over a long back-run at a quarterly frequency. This introduces a potential caveat into our analysis. That is, our investigation relies on the ability of NIESR forecasts to accurately capture the evolution in UK inflation expectations. In contrast, survey-based measures on inflation expectations used in US studies (for eg the Livingstone Survey used in Leduc *et al* (2007)) are probably more robust proxies as they encompass expectations of a large number of forecasters. In order to test the reliability of our results we repeat the analysis documented in the next sections for a semi-annual series of OECD UK inflation forecasts starting 1975 and the resulting cross-checks are summarised in one of the appendices; we will refer to these results when discussing the analyses based on the NIESR data.

3 Modelling time-varying macroeconomic dynamics

We assume that the dynamics of the UK economy can be described by the following VAR model:

$$Y_t = \mu_s + \sum_{j=1}^{4} A_{j,s} Y_{t-i} + \Omega_S^{\frac{1}{2}} \nu_t \tag{1}$$

where Y_t is a 5×1 data vector, μ is the 5×1 vector of intercepts, A_j is the 5×5 matrix of coefficients for the j^{th} lags of the endogenous variables collected in Y_{t-j}, Ω is the 5×5 covariance matrix of the VAR disturbances, and the 5×1 vector ν_t with $\nu_t \sim N(\mathbf{0},\ I_5)$. The subscripts s and S denote unobserved state variables that we define below. The data vector Y_t contains a measure of inflation expectations that we describe in detail below $\left(\pi_t^e\right)$, annual RPIX inflation (π_t), annual GDP growth (Δy_t), the three-month Treasury bill rate (R_t) and annual sterling Brent oil price inflation (oil_t) . Our estimation sample runs from 1966 Q1 to 2007 Q1.

There are several ways of introducing time-variation in the parameters of **(1)**. For example, following Cogley and Sargent (2002) and Cogley and Sargent (2005) the dynamics of $B = \{\mu, A_j\}$ and $\ln diag\,(\Omega)$ can be modelled as random walks. However as discussed in DelNegro (2003), a model with this type of time-variation becomes increasingly hard to estimate as the number of endogenous variables in Y_t and the number of lags increase. This is mainly because the estimation algorithm for these models imposes the condition that the roots of A_j should be within the unit circle *at each point in time* and this restriction is hard to satisfy in a model with five variables and four lags without dampening the degree of time-variation. In order to avoid placing such restrictions we use a more structured form of time-variation. In particular we use a Markov-Switching specification and model the state variables s and S as stationary, time homogeneous, first-order Markov chains, where the two state variables are assumed to be independent. This formulation implies that the state variables take on discrete values, ie $s = 1...M$ and $S = 1...K$. Each distinct value of these state variables implies a different coefficient matrix B_s and covariance matrix $\Omega_{S.}$ The law of motion for these state variables is given by the following equations

$$s_t = \tilde{P} s_{t-1}$$

$$S_t = \tilde{Q} S_{t-1}$$

where $\tilde{P}$ and $\tilde{Q}$ are transition probability matrices of the following form

$$\tilde{P} = \begin{pmatrix} p_{11} & p_{21} & \cdots & p_{M1} \\ p_{12} & p_{22} & \cdots & p_{M2} \\ \vdots & \vdots & \cdots & \vdots \\ p_{1M} & p_{2M} & \cdots & p_{MM} \end{pmatrix}$$

$$\tilde{Q} = \begin{pmatrix} q_{11} & q_{21} & \cdots & q_{K1} \\ q_{12} & q_{22} & \cdots & q_{K2} \\ \vdots & \vdots & \cdots & \vdots \\ q_{1K} & q_{2K} & \cdots & q_{KK} \end{pmatrix}$$

where $p_{ij} = Pr\,(s_{t+1} = j|s_t = i)$ for $i, j = 1, \ldots, M$ and $q_{ij} = Pr\,(S_{t+1} = j|S_t = i)$ for $i, j = 1, \ldots, K$. We choose the maximum value of M to be 4 while the maximum value of K is set at 3. In addition, following Kim and Nelson (1999a) we place restrictions on elements of $\tilde{Q}$ to ensure a particular sequence of state transitions. In particular (for K = 3) we assume that $q_{21} = q_{31} = q_{13} = 0$ and $q_{33} = 1$. These restrictions effectively imply two possible (unknown) break points in the evolution of $\Omega_{S.}$ This simple formulation captures time-variation in volatility highlighted by Kim and Nelson (1999a) and Sims and Zha (2006) while still maintaining model parsimony.

Note that our model allows for rich time-variation in statistics of interest without inflating the number of estimated coefficients. This is best seen by rewriting the model in **(1)** in structural form. Let $A_{0,S}$ denote a structural decomposition of the covariance matrix Ω_s that identifies economic shocks of interest. Then the structural model is given by

$$A_{0,S}^{-1}Y_t = \sum_{j=1}^{4} A_{0,S}^{-1}A_{j,s}Y_{t-i} + \varepsilon_t \quad \textbf{(2)}$$

where $\varepsilon_t = A_{0,S}^{-1}\nu_t$ with $var(\varepsilon_t) = I_5$. The impulse response functions are given by

$$IRF_k = \Delta_s^k A_{0,S} \quad \textbf{(3)}$$

where k is the impulse response horizon, Δ_s denotes the coefficients of the moving average representation of **(1)** and are derived as functions of $A_{j,s}$. The evolution of IRF_k over time depends on the law of motion for both state variables s and S and this interaction generates rich dynamics for the impulse response function.

3.1 Estimation

Following Albert and Chib (1993) and Kim and Nelson (1999b, Chapter 9) we use Bayesian simulation methods to estimate the Markov-switching VAR (MS-VAR) models.[6] In particular, we use Gibbs sampling to simulate draws from the posterior distribution. Details of the prior and the posterior distributions are confined to Appendix A. Here, we briefly describe the main steps in the algorithm.

1. **Sampling s_t and S_t:**
   Following Kim and Nelson (1999b, Chapter 9) we use Multi-Move Gibbs sampling to draw s_t from the joint conditional density $f\left(s_t|Y_t, \mu_s, A_{1,s}, \ldots, A_{p,s}, P, S_t\right)$ and S_t from the joint conditional density $f\left(S_t|Y_t, \mu_s, A_{1,s}, \ldots, A_{p,s}, P, s_t\right)$.
2. **Sampling $\mu_s, A_{1,s}, \ldots, A_{p,s}, \Omega_S$:**
   Conditional on a draw for s_t and S_t the model is simply a sequence of Bayesian VAR models. The regime specific VAR coefficients are sampled from a normal distribution and the covariances are drawn from an inverted Wishart distribution.
3. **Sampling $\tilde{P}$ and $\tilde{Q}$:**
   Given the state variables s_t and S_t, the transition probabilities are independent of Y_t and the other parameters of the model and have a Dirichlet posterior.

[6] The likelihood function for the model can be calculated using the non-linear filter described in Hamilton (1994, Chapter 22) and Kim and Nelson (1999b). Although standard numerical techniques are readily available for maximising the likelihood function, the large number of free parameters make this a challenging task especially with independent regime switching in the VAR coefficients and the covariance matrix. In addition, model selection is greatly simplified in the Bayesian framework.

This sampling algorithm is complicated due to the possibility of 'label switching'. That is, the likelihood function of the model is exactly the same if $\mu_m, A_{j,m}, \tilde{P}_m$ are replaced with $\mu_n, A_{j,n}, \tilde{P}_n$ for $m \neq n$. This may imply that the resulting posterior distribution is multi-modal. We identify the regimes by imposing inequality restrictions on the level of mean inflation implied by the model across regimes. For example, when $M = 2$ we require that $\bar{\pi}_1 > \bar{\pi}_2$.

The choice of the number of states, M and K, is a crucial specification issue. Following Sims and Zha (2006) we select M and N by comparing marginal likelihoods across models with $M = 1, \ldots, 4$ and $N = 1, ..., 3$. For the model selection exercise we estimate each MS-VAR using 30,000 replications of the Gibbs sampler discarding the first 27,000 as burn-in. Finally, the selected model is re-estimated using 100,000 replications with first 95,000 discarded as burn-in.

4 Results

The sections below present our estimation results. Section 4.1 reports the model selection exercise and presents key reduced-form statistics from the chosen MS-VAR model. Section 5 reports the estimated time-varying impact of various fundamental on the UK economy. Finally Section 5.2.1 analyses the estimated impact of shocks to the inflation expectations series in our VAR.

4.1 Model selection and reduced-form results

A first step in the estimation of these MS-VAR models is to determine the optimal number of states M and N. Our model selection procedure involves the estimation of models with $M = 1, \ldots, 4$ and $N = 1, \ldots, 3$ and then selecting the MS-VAR with the highest marginal likelihood. Table A reports the estimated log marginal likelihoods. These marginal likelihoods are approximated using the modified harmonic mean method proposed by Gelfand and Dey (1994).[7] Table A shows that the time-invariant BVAR is rejected by the data. In fact, the marginal likelihood is maximised for an MS-VAR model with $M = 2$ and $N = 2$ suggesting changes both in VAR coefficients and the covariance of the shocks. This latter result does not seem to depend on our choice of the inflation expectations measure, as we also find evidence for

[7]See Sims and Zha (2006) for description of how this method is applied to Markov-switching models.

Table A: Log marginal likelihoods for MS-VAR model (1) estimated for the United Kingdom

M	N	Log marginal likelihood
1	1	3094.611
2	1	3541.162
3	1	3600.016
4	1	3733.73
1	2	3311.155
2	2	3748.549
3	2	3358.048
4	2	3205.963
1	3	3351.896
2	3	3303.609
3	3	3274.609
4	3	3146.336

Notes: The entries are log marginal likelihoods computed for MS-VAR model **(1)** estimated for lag orders $p = 1,\ 2$ and number of states $M = 1, \ldots, 4$ and $N = 1, \ldots, 3$. The modified harmonic mean method of Gelfand and Dey (1994) is used for computing the marginal likelihoods.

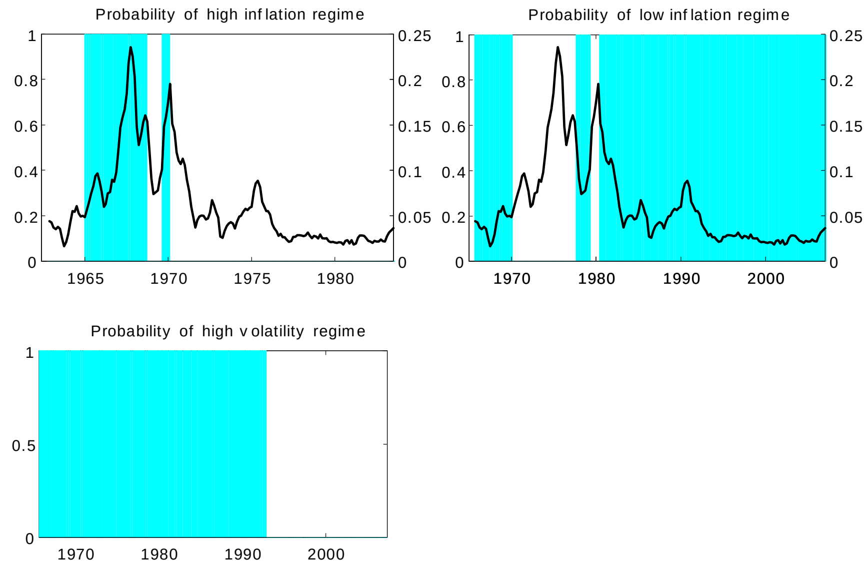
the optimality of this MS-VAR specification when we use OECD inflation expectations in Appendix A with similar timing of the different states.

Chart 2 plots the probabilities of being in each state. The top row of the chart plots the probabilities associated with the VAR coefficient states $s = 1,2$. Note that our state identifying assumption implies that $s = 1$ is associated with a higher trend inflation rate. This is clear from Chart 2 which shows that this state prevailed until the early 1980s. The bottom row of the chart shows that the break in the covariance matrix coincided very closely with the start of the inflation-targeting regime in 1992.

Chart 3 plots the implied estimates of trend inflation expectations, trend inflation and trend GDP growth. These are calculated as the unconditional mean of the endogenous variables implied by the VAR coefficients in each regime. The 1970s were characterised by annual mean realised and expected inflation of around 10% while mean GDP growth was less than 1% over this period.

The top panel of Chart 4 presents evidence on inflation persistence and plots the normalised

Chart 2: Median probabilities for the United Kingdom



Note: The blue shaded areas in the top two charts are the median probabilities for the United Kingdom that $p\left(s_t = 1\right)$ estimated from the draws of s_t in the Gibbs sampling estimation of MS-VAR model **(1)** with $p = 4$, $M = 2$ and $N = 2$. The blue shaded areas in the bottom chart indicates when the disturbance covariance matrix of the MS-VAR models is in variance state 1 (ie the era before the structural break in this covariance matrix).

spectral densities of RPIX inflation and inflation expectations. These are calculated for each regime as

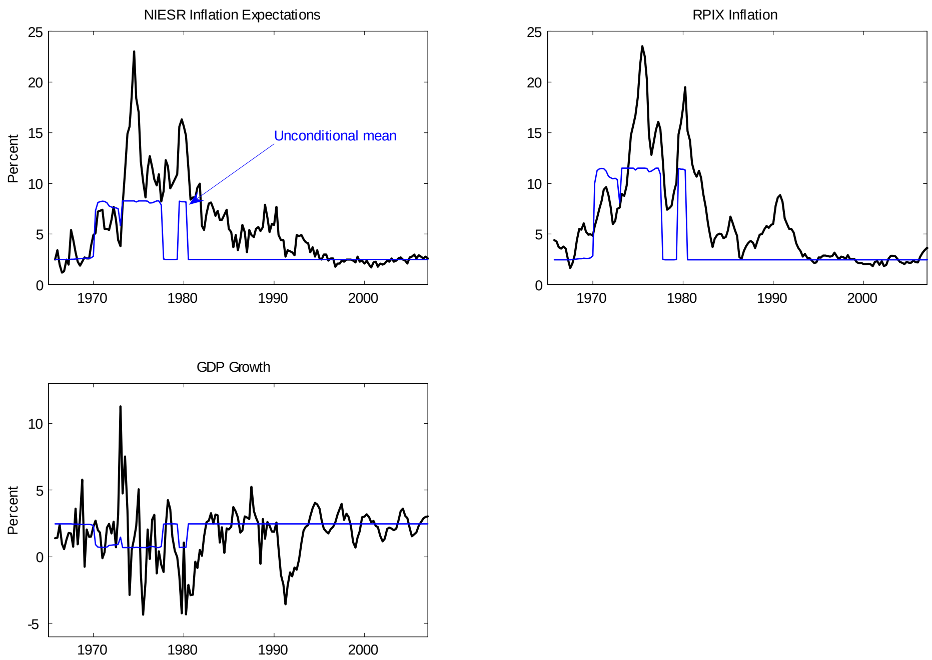
$$\frac{S_\pi\left(\varpi, s\right)}{\int_\varpi S_\pi\left(\varpi, s\right)} \tag{4}$$

where

$$S_\pi\left(\varpi, s\right) = \frac{1}{2\pi}\left(I - \tilde{A}_s e^{-i\varpi}\right)^{-1} \hat{\Omega}_S \left(I - \tilde{A}_s' e^{i\varpi}\right)^{-1} \tag{5}$$

and ϖ denotes the frequency, I is a conformable identity matrix, $\tilde{A}_s$ denotes the companion matrix formed at the posterior mean and $\hat{\Omega}_S$ is the posterior mean estimate of the covariance matrix. Chart 4 reports the weighted average of the normalised spectrum across the regimes. The normalised spectrum for the RPIX inflation confirms recent evidence presented in Benati (2004) with the spectral density high during the 1970s. In addition the spectral density for inflation expectations shows a very similar pattern. Persistence in the inflation expectations measure was

Chart 3: MS-VAR (1) implied trend levels



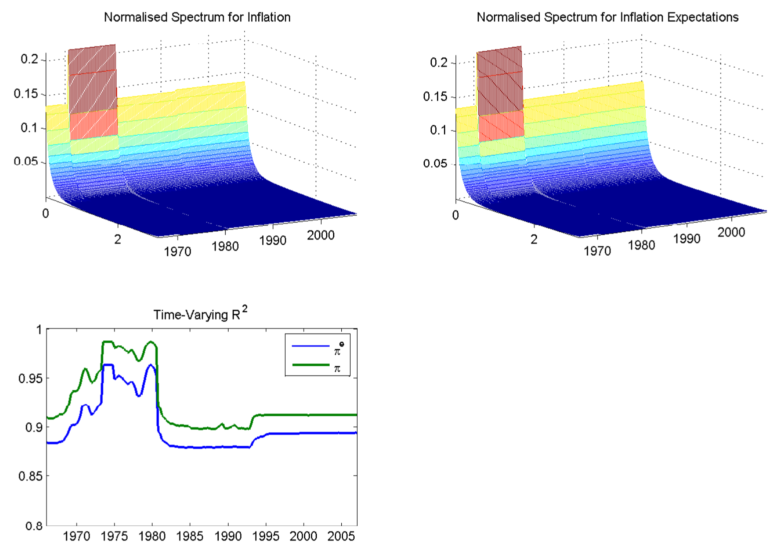
high in the 1970s but has remained low since the early 1980s.[8] The bottom panel of this chart presents the (one quarter ahead) time-varying R^2 for RPIX inflation and inflation expectations. As discussed in Diebold and Kilian (2001) this measure provides information about the contribution of past shocks to current and future variation in the variable of interest.[9] The chart shows that the 1970s were characterised by a high R^2 for actual and expected inflation, again indicating that persistence of these variables was high over this period.

The discussion above presents clear evidence for changes in the mean and persistence of inflation and output growth. Chart 5 shows that this is also the case for the volatility of these variables. The chart presents the volatility of the reduced-form shocks of the MS-VAR equations (ie the square root of the diagonal element of Ω_s) and the unconditional volatility of inflation, inflation

[8]Note that for OECD inflation expectations this time-variation in persistence is less marked; see Appendix A.

[9]Cogley, Primiceri and Sargent (2008) also apply this measure when characterising developments in the persistence of several US inflation measures.

Chart 4: Normalised spectral density and time-varying R^2



expectations and GDP growth. The unconditional volatility is calculated as

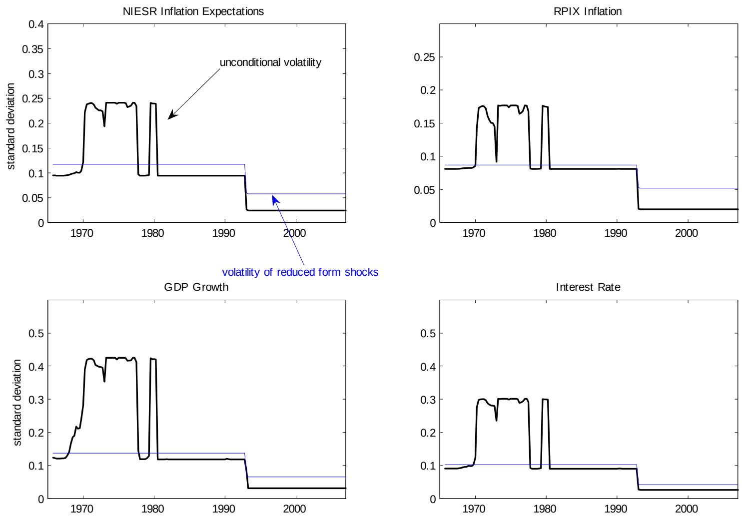
$$\int_{\varpi} S_{\pi}\left(\varpi, s\right) \tag{6}$$

where $S_{\pi}(.)$ is defined in equation **(5)**. The main decline in volatilities coincides with the introduction of inflation targeting at the end of 1992. Note, however, that the sharp increase in volatility and subsequent decrease of the 1970s and early 1980s was not related to a change in the volatility of shocks. That is, while the unconditional volatility increased in the mid-1970s the volatility of shocks remained constant. This suggests that shifts in the long-run means of the series are more likely to have caused the increase in the unconditional volatility in the mid-1970s.

5 The time-varying impact of structural shocks

A number of alternative explanations have been put forward for the high inflation rates seen in the 1970s and the early 1980s. The first strand of explanations focus on the role of oil price and supply shocks and/or monetary policy and aggregate demand shocks in bringing about high and volatile inflation in the 1970s. An alternative channel focuses on the role of inflation expectations. For example, Chari, Christiano and Eichenbaum (1998) build on Kydland and Prescott (1977) and develop models that allow for the possibility of self-fulfilling inflation

Chart 5: Standard deviations of shocks and endogenous variables



expectations shocks.[10] Clarida *et al* (2000) develop a related framework for examining self-fulfilling inflation expectations shocks. They show that inflation can become self-fulfilling if the coefficient on inflation in the monetary authorities' reaction function become less than one.[11]

In this section we attempt to shed light on the relevance of these explanations for the United Kingdom's inflation experience. In particular, we explore how the impact of real and nominal structural shocks on the UK economy has evolved over time. In addition, we investigate how important exogenous changes in inflation expectations have been in determining the dynamics of actual inflation.

The first subsection, 5.1, explains how we identify these real and nominal shocks from the estimated MS-VAR **(1)** model. The second subsection 5.2 discusses the results. Subsection 5.2.1 analyses the impulse responses to the real and nominal shocks and presents the identification of

[10]Their expectations trap hypothesis involves a situation where a monetary authority is forced to accommodate private sector inflation expectations in order to avoid loss of output and employment. Self-fulfilling inflation expecations shocks can come about due to dynamic inconsistency and absence of commitment.

[11]The intuition behind this result is straightforward – an inflation coefficient less than one implies that the real interest rate falls in response to an increase in expected inflation. This decline in the real rate boosts aggregate demand and puts upward pressure on inflation and therefore confirms elevated inflation expectations. One of the aims of our analysis is to try and gauge the relative importance of these different channels in determining UK inflation outcomes in the 1970s

Table B: A summary of the sign restrictions

	π^e	π	Δy	R	oil	$oil - \pi$
Oil	$\times$	+	-	$\times$	$\times$	+
Non-oil supply-side	$\times$	+	-	$\times$	$\times$	-
Monetary policy	$\times$	-	-	+	$\times$	$\times$
Real demand	$\times$	+	+	+	$\times$	$\times$

Notes: In this table a '$\times$' indicates that the contemporaneous response of a variable to the shock is unrestricted, whereas a '+' ('-') indicates that this contemporaneous response is restricted to be positive (negative).

exogenous inflation expectations shocks. Subsection 5.2.2 presents the time varying contribution of shocks to the unconditional variance of the endogenous variables.

5.1 Identifying real and nominal structural shocks

We use sign restrictions, see Uhlig (2005), to identify four structural shocks: a nominal oil price shock, a non-oil supply-side shock, a real demand shock (an *IS* curve shock) and a monetary policy shock. The sign restrictions are imposed on the contemporaneous impact matrix. We assume that a real oil price shock decreases GDP growth, increases inflation and increases real oil price inflation. A (negative) supply-side shock is identified by assuming that it increases inflation and decreases output growth but leads to a fall in real oil price inflation. This last effect occurs as the supply shock is assumed to push up the general price inflation more than the increase in the nominal oil price inflation, simply because the negative supply shock leads to a decrease in production capacity which in turn decreases the demand for energy. A real demand shock is assumed to increase inflation, GDP growth and the short-term interest rate. Finally, a contractionary monetary policy shock leads to a contemporaneous increase in the short-term interest rate, a fall in RPIX inflation and GDP growth.

Table B summarises these restrictions in each row. Two features of the sign restrictions are worth noting. Firstly, when specifying these shocks we leave their contemporaneous impact on inflation expectations unconstrained. Secondly our baseline structural model does not restrict the contemporaneous response of the oil price to supply, demand and monetary policy shocks to be zero. As such a restriction may be appropriate for a small open economy such as the United Kingdom, we experiment with a version of the sign restrictions in Table B that incorporate these additional zero restrictions. Overall, this modified identification scheme produces very similar results to the baseline specification.

The identification scheme is implemented as follows. We compute the time-varying structural impact matrix, $A_{0,S}$, via the procedure recently introduced by Rubio, Waggoner and Zha (2005). Specifically, let $\mathbf{\Omega}_S = P_S D_S P_S'$ be the eigenvalue-eigenvector decomposition of the MS-VAR's covariance matrix $\mathbf{\Omega}_S$, and let $\tilde{A}_{0,S} \equiv P_S D_S^{\frac{1}{2}}$. We draw an $N \times N$ matrix $\bar{K}$ from the $N(0,1)$ distribution. We take the QR decomposition of $\bar{K}$. That is we compute Q and R such that $\bar{K} = QR$. We then compute a candidate structural impact matrix as $A_{0,S} = \tilde{A}_{0,S} \cdot Q'$. If $A_{0,S}$ satisfies the sign restrictions we keep it. Otherwise we move to the next iteration of the Gibbs sampler. The resulting $A_{0,S}$'s are then used in **(2)** and **(3)** to compute time-varying impulse response functions for each variable in the MS-VAR model when hit by one of the structural shocks; see also Appendix A. To save computation time we only compute these impulse response functions for the last quarter of every year.

In addition to time-varying impulse response functions for the structural shocks, we also report results from a time-varying decomposition of the unconditional volatility of the main variables in the MS-VAR (reported in Chart 5). Recall that the unconditional variance is given by

$$\int_{\varpi} S_{\pi}(\varpi, s) \qquad \textbf{(7)}$$

where the spectral density $S_{\pi}(\varpi, s)$ equals

$$S_{\pi}(\varpi, s) = \frac{1}{2\pi}\left(I - \tilde{A}_s e^{-i\varpi}\right)^{-1} \hat{\mathbf{\Omega}}_S \left(I - \tilde{A}_s' e^{i\varpi}\right)^{-1} \qquad \textbf{(8)}$$

The variance due to a particular structural shock *only* can be calculated using **(8)** but replacing $\tilde{\mathbf{\Omega}}_t$ with $\bar{\mathbf{\Omega}}_t$ where

$$\bar{\mathbf{\Omega}}_t = \bar{A}_{0,t}' \bar{H}_t \bar{A}_{0,t} \qquad \textbf{(9)}$$

where $\bar{A}_{0,t}'$ is a draw of $A_{0,t}$ that satisfies the structural decomposition (and is normalised by dividing each column by $diag\left(A_{0,t}\right)$) and $\bar{H}_t$ is a diagonal matrix of the variance of the shocks where the volatility of all shocks except the structural shock of interest is set equal to zero. The contribution of the i^{th} shock is then calculated as the ratio of this new measure of volatility and $\int_{\varpi} S_{\pi}(\varpi, s)$.

5.2 Results

5.2.1 Time-varying impulse response functions

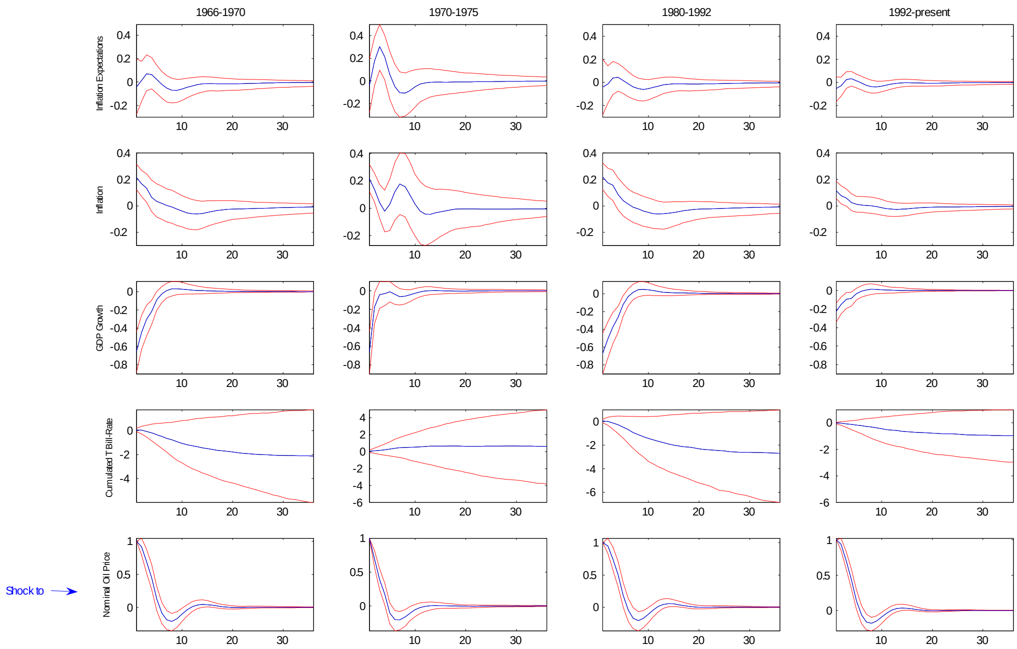
Oil price shocks

What role was played by oil price rises in instigating the Great Inflation of the 1970s? We analyse this question by examining the evolution of the response of economy to an increase in real oil price inflation.

In Chart 6 we plot the averages of the respective impulse response function and their error bands across a number of key subsamples: the pre-Great Inflation period, the Great Inflation period of the 1970s, the period since the election of Margaret Thatcher as Prime Minister of the United Kingdom up to the introduction of inflation targeting, and the inflation-targeting period. This figure shows that there were important changes in the time path of the impulse response functions. An increase in the oil price had a larger, positive, impact on expected inflation in the 1970s than in the other subsamples. Actual inflation and economic growth also seem to react more in the 1970s, and to a lesser extend in the subsample after that, than for other periods. It is interesting to note that the response of inflation to this shock in the 1970s is accompanied by a significant response of inflation expectations. This possibly suggests that inflation was not only reacting to the increase in the oil price but also to the resulting increase in inflation expectations. Such an effect appears to have been absent during the other time periods we consider.

Chart 7 considers the statistical significance of the reported changes in the impulse response functions. It plots the joint distribution of the cumulated response (at the one-year horizon) in the 1970s and in the inflation-targeting period. Shifts of the distribution away from the 45-degree line indicate a systematic change across these two subsamples. The top left panel of the chart shows strong evidence of a systematic decrease in the response of NIESR inflation expectations to the oil price shock, with 84% of the joint distribution lying below the 45-degree line. Similarly, most of the distribution of the GDP response (around 83%) lies above the 45-degree line indicating a significant decrease in the response across the sample period. Results for RPIX inflation are less clear-cut. About 60% of the points on the joint distribution are below the 45-degree line suggesting some, albeit weak, evidence for a fall in the impact of the oil price shock.

Chart 6: Response to an oil price shock in some key periods (per cent)



Non-oil supply side shocks

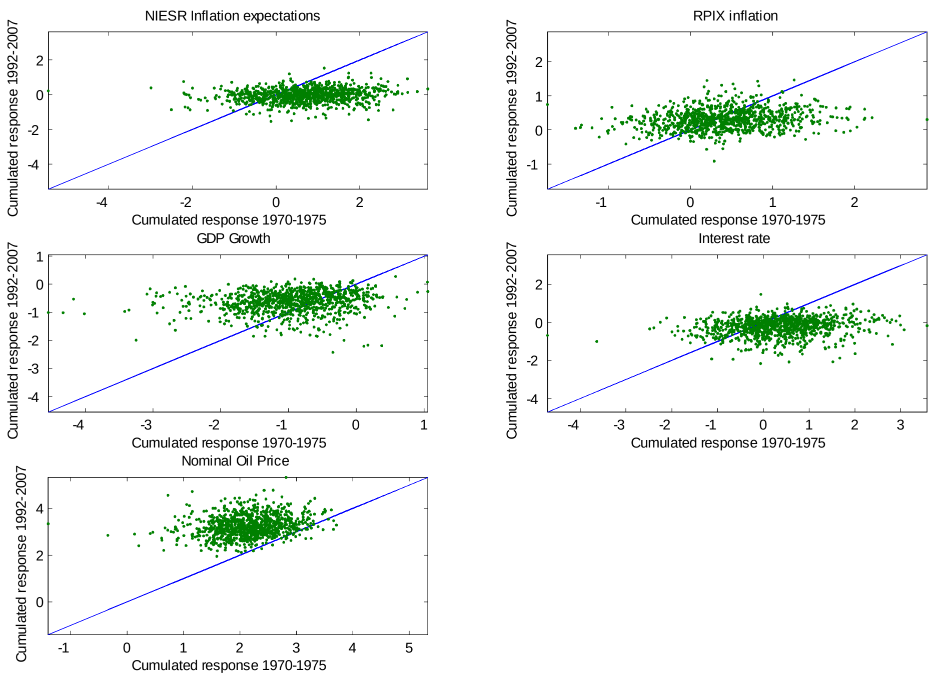
Chart 8 plots the response to a negative supply shock across key periods. Note that we normalise the shock so that it increases actual inflation by 1% over all years in the sample period. The response of inflation expectations to such a supply shock is largely insignificant.

Chart 9 plots the joint distribution of the cumulated responses in the mid-1970s and the current period. There is little evidence of systematic changes in the response of GDP growth and inflation expectations to this shock.

Monetary policy shocks

Chart 10 shows the response of the UK economy to a contraction in monetary policy across the different subsamples. The contemporaneous negative reaction of actual inflation is particularly significant in the inflation-target period. During the 1970s the RPIX inflation response beyond the current period suggests the presence of a slight delayed 'price puzzle', albeit that this does

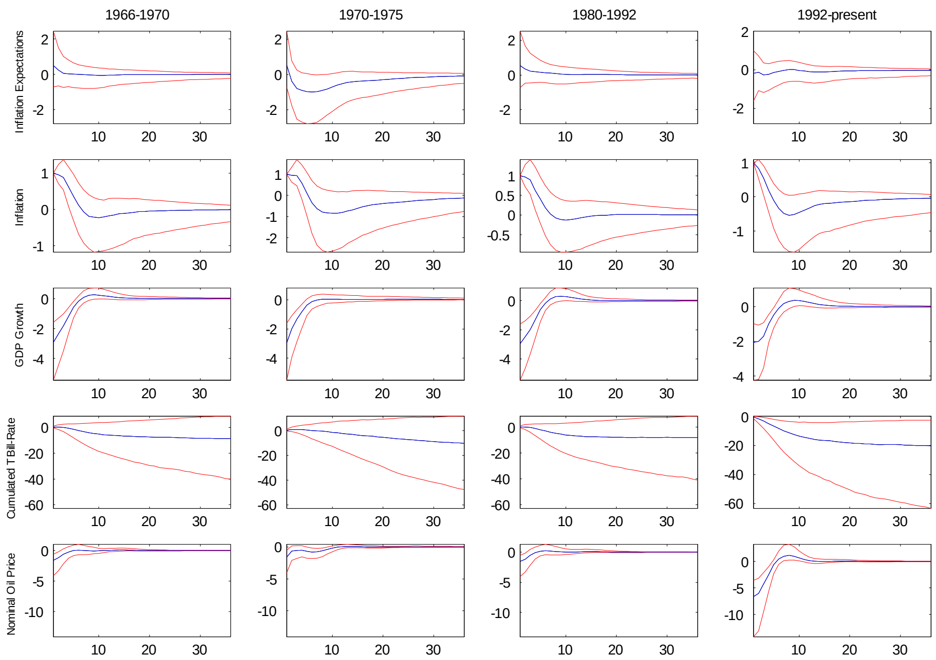
Chart 7: Joint distribution of the cumulated response (one-year horizon) to oil price shocks in 1970-75 and 1992-2007



not appear to be significant. This matches the predictions of the analysis in Castelnuovo and Surico (2006) and Lubik and Schorfheide (2004) who suggest that periods of indeterminancy (in a DSGE model) are characterised by this type of anomalous response. GDP growth always decreases in response to an exogenous monetary policy contraction, as expected. Finally, note that on average the inflation expectations appear not to be very sensitive to exogenous monetary policy shocks.

Chart 11 shows that there is some evidence to indicate that the response of inflation and GDP growth (to the monetary policy shock) is the largest in the current period, with most of the distribution (72% and 62% respectively) below the 45-degree line. There is little evidence of a systematic shift in the inflation expectations response to this shock.

Chart 8: Response to a negative supply shock in key years (per cent)

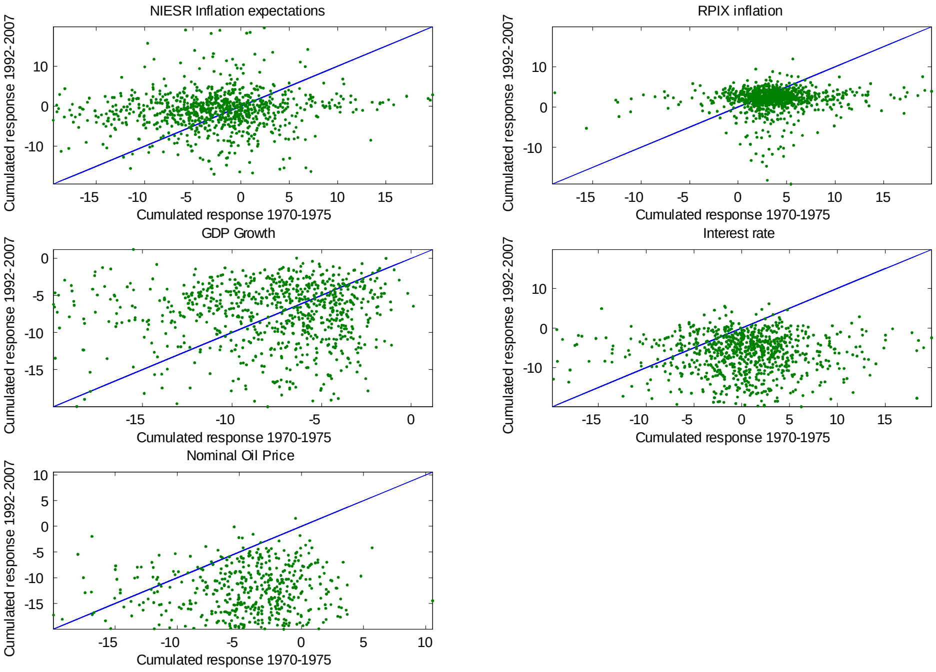


Real demand shocks

The response to an aggregate demand shock, shown in Chart 12 provides further evidence of important changes in the transmission mechanism and the role of monetary policy. An expansionary demand shock leads to large increases in inflation and expected inflation in the 1970s. Interestingly, when we focus on the response of inflation expectations we notice that in the 1970s inflation expectations significantly and persistently increase because of such a shock, with a delay of a couple of quarters, but that this response is insignificant in other subsamples. This could indicate the existence of a Goodfriend (1993) 'Inflation Scare' problem in the 1970s in the United Kingdom: ie when the economy is hit by a large inflationary shock, in this case a real demand shock, and the central bank hesitates in responding to it, the shock will lead to a persistent increase in inflation expectations.

Chart 13 provides further evidence to support this idea. Firstly, the top left panel of the chart provides evidence in favour of a systematic shift in the inflation expectations response to this

Chart 9: Joint distribution of the cumulated response (one-year horizon) to supply shocks in 1970-75 and 1992-2007

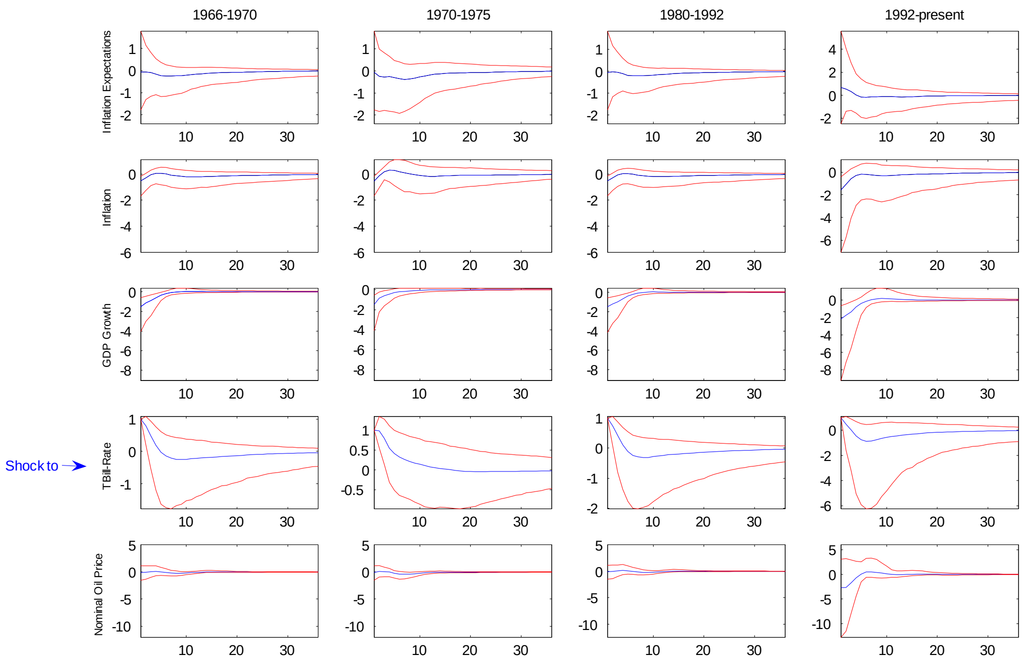


shock, with 80% of the distribution above the 45-degree line. Secondly, there is some, albeit weak, evidence of a shift in the response of the cumulated T-bill rate, with around 60% of the estimated distribution in the inflation-targeting period larger than the corresponding estimates in the mid-1970s.

The time-varying impact of exogenous inflation expectations shocks

Having explored the time-varying response of our real and nominal structural shocks in the previous section, this section will focus on the economy-wide effect, over time, of exogenous inflation expectations shocks. In order to be able to do that we have to adapt the shock identification scheme from Section 5.1, and we do that in Section 5.2.1. The resulting impulse response functions and variance decompositions can be found in Section 5.2.1.

Chart 10: Response to a monetary policy shock in key years (per cent)

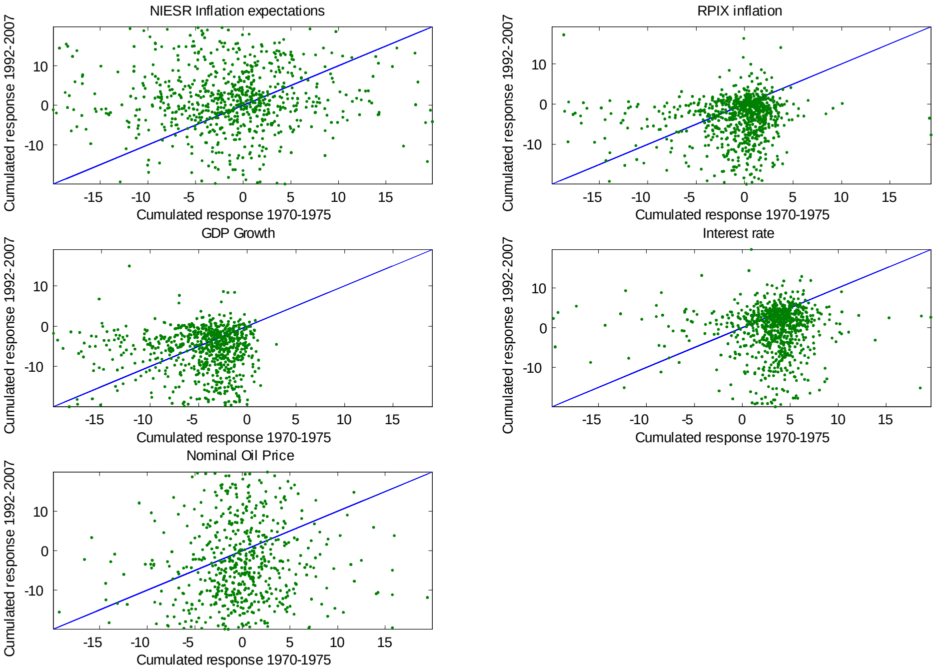


Identifying inflation expectations shocks

In this section we consider the time-varying response of the endogenous variables to shocks to the NIESR inflation expectations series. Following, Leduc *et al* (2007), we impose a timing restriction to identify this shock. In paricular, we order inflation expectations first in a recursive Choleski ordering. This is based on the rationale that the NIESR forecasters did not observe current realisations of the data while making their forecasts. This can clearly be seen in the extract from the *National Institute Economic Review* depicted in Figure 1. In addition, as described above, we also attempt to ensure that the variables that enter the VAR reflect information available to forecasters while making that forecast. In particular we employ a real-time measure of GDP growth. Table C presents the augmented identification scheme, with the zeros in the first column imposing our assumptions about the contemporaneous information available to the NIESR forecasters.

By using the Choleski decomposition approach to identify an ‘inflation expectations’ shock we

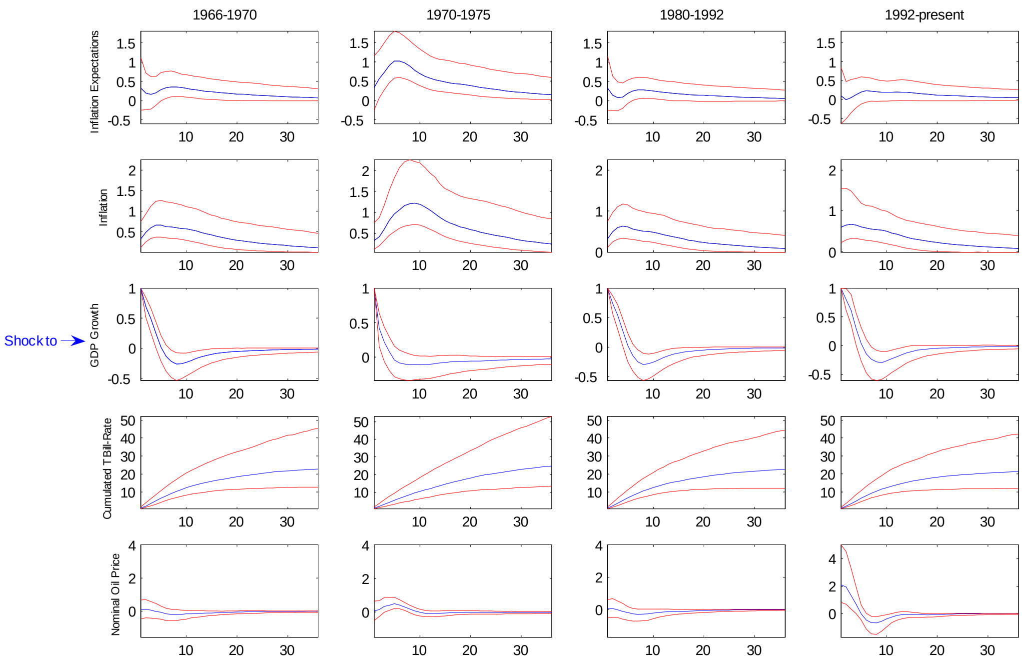
Chart 11: Joint distribution of the cumulated response (one-year horizon) to monetary policy shocks in 1970-75 and 1992-2007



mechanically identify this shock as being purely orthogonal to the rest of the system. Although we do not really take a stand on what this shock actually means, we do note that such an identification scheme can be compatible with different interpretations. One is that of a missing 'fundamental' shock: this can be a sunspot shock to expectations due to monetary accommodation to increases in inflation expectations (Clarida *et al* (2000)), or the effect of an 'Inflation Scare' where learning-based inflation expectations increase beyond the model-consistent level (ie the linear combination of state variables) due to a 'too' muted policy response to structural shocks (Orphanides and Williams (2005)), or, simply, it measures a shock to macroeconomic fundamentals that are not included in the MS-VAR model. The recursive identification scheme can also be interpreted as expectations in general being more consistent with adaptive learning, as in Erceg and Levin (2003) or Orphanides and Williams (2005), than with rational, model-consistent, expectations, because it implies that current inflation expectations are solely driven by its own lags as well as lags in the other variables.[12]

[12] A related literature uses information extracted from the yield curve to proxy the bond markets perception of inflation expectations. See for example Diebold and Li (2006).

Chart 12: Response to a real demand shock in key years (per cent)

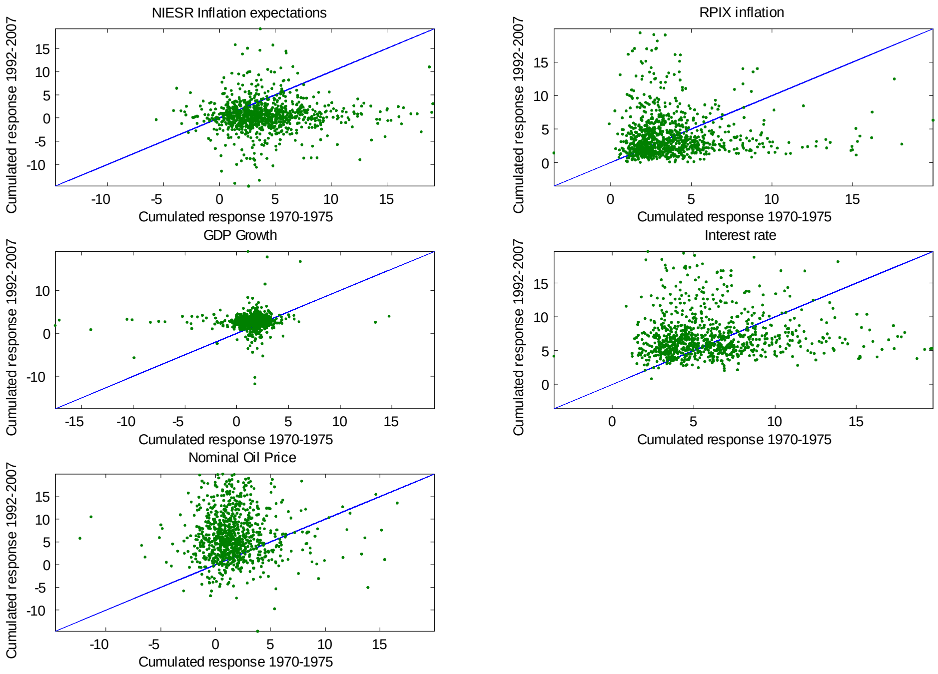


Results

We present the response of the endogenous variables to an inflation expectations shock that increases the NIESR forecast measure by 1%. In order to make the responses comparable over time, the impulse to inflation expectations is normalised to equal 1% in each year of the sample. Chart 14 presents the average response over key years.

Chart 14 shows that actual inflation always reacts significantly to the inflation expectations shock, although the contemporaneous response is insignificant. From the second row of this chart it also is apparent that in the 1970s there was a larger increase in actual inflation following the shock than in the other periods, in particular from the 1980s onward. Note that the top right panel of Chart 15 suggests that this was a systematic shift with about 85% of the distribution below the 45-degree line. Notice also that this coincides with a less significant response in the cumulated short-term interest rate at shorter horizon for the 1970s relative to other periods. On the other hand, GDP growth is never significantly affected. Note that this pattern is less consistent with

Chart 13: Joint distribution of the cumulated response (one-year horizon) to real demand shocks in 1970-75 and 1992-2007



Clarida *et al* (2000) where the expectations trap is accompanied by an output boom due to a less than proportionate response in the policy rate. We therefore think that this phenomenon is more consistent with the existence of an 'Inflation Scare' in the 1970s, more so because inflation expectations seems to significantly increase due to real demand shocks in the 1970s; see previous subsection, 'Real demand shocks'. Note also that these conclusions are fairly robust across different inflation expectations measures, given the similarity of the structural analysis using OECD inflation expectations in Appendix A.

5.2.2 Time-varying variance decomposition

In this section we present results on the contribution of the identified shocks to the unconditional variance of the endogenous variables in the system. As explained in Section 5.1, we approximate the unconditional variance using the spectral density. The variance due to an identified shock is approximated using the estimate of the spectral density under the counterfactual scenario that only the shock of interest is active. Note that for this variance decomposition exercise we use the

Table C: Augmenting the sign restrictions with an inflation expectations shock restriction

π^e	π	Δy	R	oil	$oil - \pi$	
Expectations	**1**	×	×	×	×	×
Oil	**0**	+	−	×	×	+
Non-oil supply-side	**0**	+	−	×	×	−
Monetary policy	**0**	−	−	+	×	×
Real demand	**0**	+	+	+	×	×

Notes: See the notes for Table B. In addition '**0**' indicates that the contemporaneous response of a variable to the shock is restricted to be zero and, similarly, '**1**' restricts to contemporaneous response to be unity.

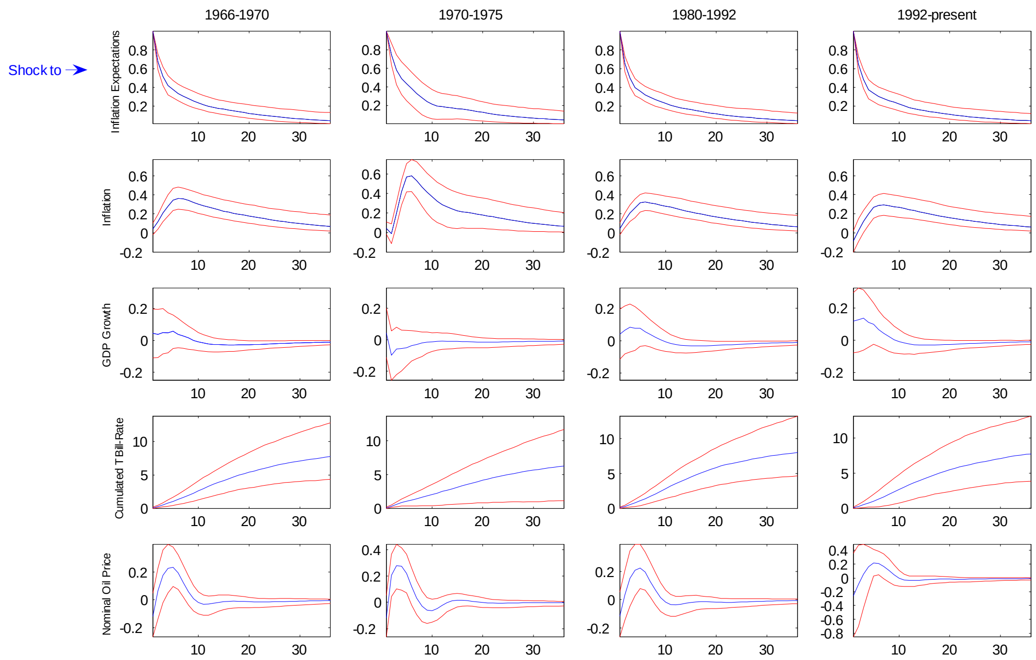
augmented identification scheme reported in Table C.

The results are reported in Chart 16 where each row presents estimates of the variance due to a particular shock. Note that the variance is decomposed at different frequencies (ϖ) . The frequency is reported on the y-axis in each individual panel in Chart 16. The x-axis reports the date while the z-axis reports the percentage of the variance explained.

The top panel of the chart reports the contribution made by the oil price shock to the unconditional variance of the variables in the VAR. These shocks made the highest contribution (around 30%) to inflation expectations in the early and mid-1970s (largely at the business cycle and low frequencies), with the contribution fluctuating around 5% in subsequent years. Similarly, the oil shock explains about 48% of the volatility of inflation in the mid-1970s with the subsequent contribution around 25%. The contribution of this shock to actual inflation and GDP growth has been largely constant over the sample period. Overall, our results indicate that while oil price shocks contributed to the economic uncertainty in the 1970s, these certainly cannot been seen as the sole trigger of the Great Inflation in the 1970s.

The pattern of the variance contribution of the identified supply shock (second row of Chart 16) suggests that the contribution of the supply shock to inflation expectations was at its highest in

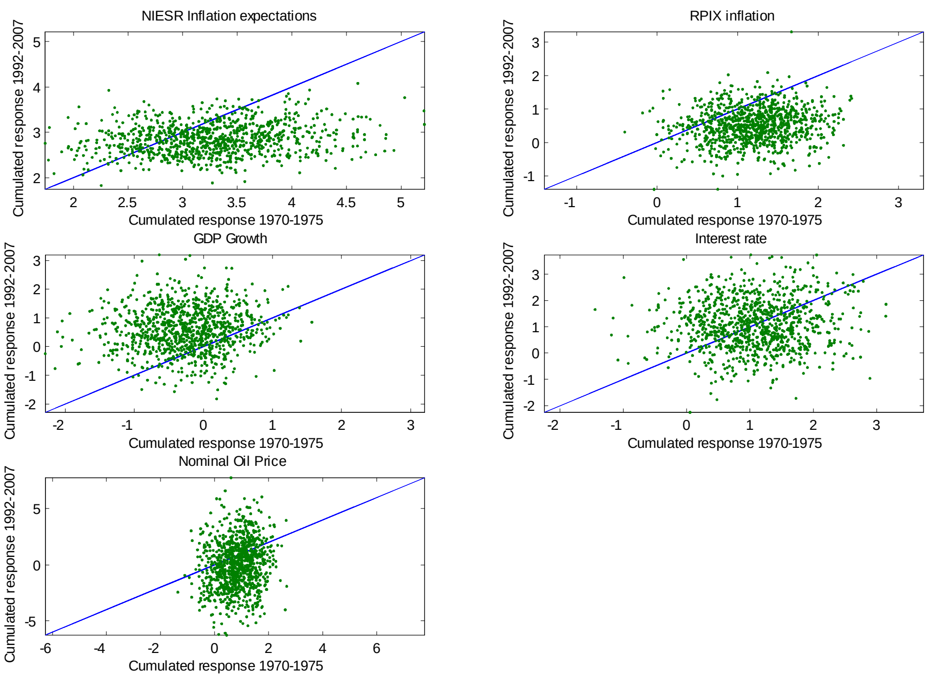
Chart 14: Response to an inflation expectation shocks in key years (per cent)



the first half of the 1970s at around 15% and it subsequently fluctuated between 3% and 5%, indicating that the large fluctuations in inflation expectations cannot be attributed to the non-oil supply-side shock. Similarly, the contribution of this shock to inflation volatility at the business cycle frequency has remained around 30% over the entire sample. This shock only seems to contribute just under 30% to the volatility of actual inflation and GDP growth, in particular at higher frequencies, and that this contribution has been relatively stable over time.

There are interesting fluctuations in the contribution of the monetary policy shock as displayed in the third row of Chart 16. In particular, there is a change in the contribution of policy shocks to inflation expectations. The contribution to inflation expectations was the highest in the early and mid-1970s, and this contribution more than halved with the onset of the Thatcher era. However, it is doubtful whether monetary policy shocks really significantly determined inflation expectations over time, as the contribution of this shock to the variability of inflation expectations is at the most around 10% in the long term. Note also that the contribution of this shock to the interest rate follows the pattern identified in Bianchi, Mumtaz and Surico (2009). In

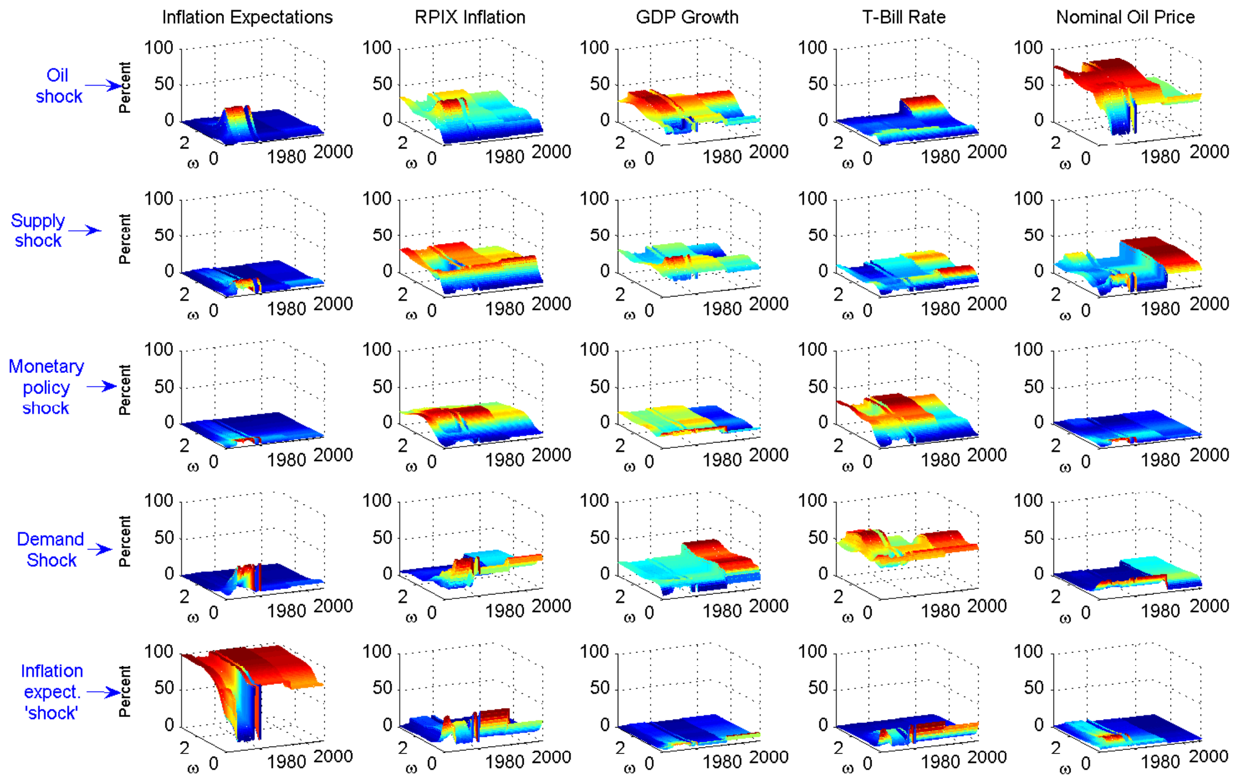
Chart 15: Joint distribution of the cumulated response (one-year horizon) to inflation expectations shocks in 1970-75 and 1992-2007



particular, the contribution is at its lowest over the inflation-targeting period. This suggests that current interest rate changes have largely been driven by concerns about the variables included in our model and that deviations from systematic policy are less important. There is a similar change in the contribution of this shock to actual inflation and GDP growth with the post-1992 period characterised by a fall in the importance of this shock for these variables.

The fourth column of Chart 16 indicates that real demand shocks appear to be quite important for fluctuations in output growth and actual inflation, with the magnitude of their contribution increasing in the early 1990s. The contribution of the real demand shocks to short-term rate variability increases a lot at the start of the 1990s, especially in the long run. Real demand shocks made a significant contribution to inflation expectation volatility in the early 1970s and explain about 30% of the movement in inflation expectations. This suggests that real demand shocks were a major determinant of expectations during the Great Inflation, possibly because of an 'Inflation Scare' due to a muted monetary policy response to these shocks. Given the results reported above, it is likely that the effect of this on the rest of the economy was magnified by the

Chart 16: Time-varying decomposition of unconditional variance at different frequencies (denoted by ϖ)



occurrence of oil price shocks during that period.

The final row of Chart 16 depicts the contribution of the inflation expectations shock to the volatility of the variables in the MS-VAR model. The inflation expectations shock hardly contributes to the variability of GDP growth, whereas it mainly determined the (long-run) behaviour of actual inflation in the 1980s. The contribution to actual inflation variability is at its minimum in the current inflation-targeting period (20% in the long run). One interesting feature of these variance decompositions is that actual inflation volatility in the 1970s is not affected to a large extent by the expectations shock, at the most 30% at medium-term horizons. Note also that the exogenous shock to inflation expectations appear in the 1970s only to matter for the shorter-term dynamics of inflation expectations and the contribution dies out in the long term. In the periods following the 1970s the inflation expectations shock remains the most important driver for inflation expectations across the whole spectrum of frequencies and this is accompanied with a structurally higher long-run contribution to the short-term interest rate dynamics for those subsamples.

6 Conclusions

In this paper, we attempt to answer two questions for the economic dynamics of the United Kingdom during the period 1965-2007 (and therefore excluding the effects of the financial crisis and its aftermath) by means of a Markov-switching VAR model: *(i)* How has the impact of the mix of real and nominal shocks on the UK economy evolved over time and did this have a specific impact on UK inflation expectations? and *(ii)* Has there been an autonomous impact of inflation expectations on the UK economy and has it changed over time?

During the 1970s the UK economy was mainly hit by oil price and real demand shocks. Real demand shocks had significant and persistent effects on inflation expectations during the 1970s. Subsequently, the oil price shocks decrease in importance whereas the real demand shocks remain important for the dynamics of actual inflation and output growth. Non-oil supply-side shocks and monetary policy shocks were relatively less important between 1965 and 2007.

Further to this, our results suggest that shocks to inflation expectations had important effects on actual inflation in the United Kingdom in the 1970s, mainly in the short run. There were smaller effects in the 1980s, although inflation expectations had the least effect on inflation in the inflation-targeting period. This seems to be largely due to a relatively slower response of monetary policy to these shocks in the 1970s (when short-term interest rates tended to react less to inflation expectations shocks), compared to later years of our sample.

Appendices

A. Estimation algorithm

The Gibbs sampler cycles through the following steps.

1. **Sampling the covariance states** S_t:

Given starting values for the VAR parameters and covariances, the unobserved state variable for the two covariance regimes S_t is drawn using Multi-Move Gibbs sampling to draw from the joint conditional density $f\left(S_t|Y_t, \mu_s, A_{1,s}, \ldots, A_{p,s}, \tilde{P}, \tilde{Q}\right)$. Kim and Nelson (1999b, Chapter 9) show that the Markov property of S_t implies that

$$f(S_t|Y_t) = f(S_T|Y_T)\prod_{t=1}^{T-1} f(S_t|S_{t+1}, Y_t) \qquad \textbf{A-1}$$

where we have suppressed the conditioning arguments. This density can be simulated in two steps:

1. (i) Calculating $f(S_T|Y_T)$: The Hamilton (1989) filter provides $f(S_t|Y_t)$, $t = 1, ...T$. The last iteration of the filter provides $f(S_T|Y_T)$.
   (ii) Calculating $f(S_t|S_{t+1}, Y_t)$: Kim and Nelson (1999b, Chapter 9) show that

$$f(S_t|S_{t+1}, Y_t) \propto f(S_{t+1}|S_t)\, f(S_t|Y_t) \qquad \textbf{A-2}$$

   where $f(S_{t+1}|S_t)$ is the transition probability and $f(S_t|Y_t)$ is obtained via Hamilton (1989) filter in step a. Kim and Nelson (1999b) (page 214) show how to sample S_t from (A-2).
2. Sampling the covariance matrices Ω_S :

The covariance matrix in each regime $S = 1, 2$ is drawn from an inverse Wishart distribution. That is

$$\Omega_S^{-1} \sim W\left(\bar{S}_S^{-1}, \upsilon_S\right)$$

where the scale matrix $\bar{S}_1 = I(S_t = 1)\left(\bar{E}_t'\bar{E}_t\right)$ and $\bar{S}_2 = I(S_t = 2)\left(\bar{E}_t'\bar{E}_t\right)$ where $E_t = Y_t - \mu - \sum_{j=1}^{p} A_j Y_{t-j}$ and the 'bars' denote the average across $s_t = 1..M$ with the weights given by s_t. $I(.)$ is an indicator function that selects the observations for $S = 1, 2$. υ_S is set equal to the number of observations in each regime.[13]

3. **Sampling the coefficient states** s_t:

Given Ω_S, we rewrite the model as

$$Y_t^* = A_{j,s}X_t^* + \breve{V}_t \qquad \textbf{A-3}$$

where $Y_t^* = I(S_t = 1)\left[\left(\Omega_1^{-1} \otimes I_t\right)^{1/2} \times vec(Y_t)\right] + I(S_t = 2)\left[\left(\Omega_2^{-1} \otimes I_t\right)^{1/2} \times vec(Y_t)\right]$, $X_t^* = I(S_t = 1)\left[\left(\Omega_1^{-1} \otimes I\right)^{1/2} \times (X_t \otimes I_5)\right] + I(S_t = 2)\left[\left(\Omega_2^{-1} \otimes I\right)^{1/2} \times (X_t \otimes I_5)\right]$, where X_t denotes the lags and deterministic terms in the model. $E\left(\breve{V}_t'\breve{V}_t\right) = \tilde{I}_5$ where $\tilde{I}_5$ is a 5×5 identity matrix. This is an MSVAR model with a switching intercept and autoregressive parameters but a homoscedastic covariance matrix. We again use Multi-Move Gibbs sampling to draw $s_t, t = 1, 2, ...T$ from the joint conditional density $f\left(s_t | Y_t^*, \mu_s, A_{1,s}, \ldots, A_{p,s}, P\right)$ using the methods detailed in Kim and Nelson (1999b).

4. **Sampling** $\mu_s,\ A_{1,s}, \ldots, A_{p,s}$:

Conditional on a draw for s_t the model in equation A-3 is simply a sequence of Bayesian VAR models (with an identity covariance matrix). Collecting the VAR coefficients for regime $s = i$ into the $(N \times (N \times P + 1))$ vector Υ_s and the RHS (ie lags and the intercept terms) of equation **(1)** into the matrix X_t^* and letting $\hat{\Upsilon}_s$ denote the OLS estimates of the VAR coefficients the conditional posterior distributions are given by (see Uhlig (2005)):

$$\Upsilon_s \sim N\left(\bar{\Upsilon}_s, \tilde{I}_5 \otimes \hat{V}_s\right)$$

[13] Note that we require each (coefficient and variance) regime to have at least $N(N \times P + 1) + 5$ observations.

where

$$\bar{\Upsilon}_s = \left(N_0 + X_t^{*s\prime} X_t^{*s}\right)^{-1} \left(N_0 \Upsilon_0 + X_t^{*s\prime} X_t^{*s} \hat{\Upsilon}_s\right)$$

$$\hat{V}_s = \left(N_0 + X_t^{*s\prime} X_t^{*s}\right)^{-1}$$

and Υ_0 and N_0 denote the prior mean and variance. X_t^{*s} for $s = 1, ..M$ denotes observations for a particular regime. In specifying the prior mean, we loosely follow Sims and Zha (1998). We assume that Υ_0 implies an AR(1) structure (with the intercept equal to zero) for each endogenous variable. As our variables are already in growth rates we centre the prior at the OLS estimates of the AR(1) coefficient for each variable (rather than 1, ie a random walk). As in Sims and Zha (1998), the variance of the prior distribution is specified by a number of hyperparameters that control the variation around the prior. Our choice for these hyperparameters implies a fairly loose prior for the autoregressive coefficients in the VAR. The prior on the intercept terms is tighter and this choice ensures that trend values of the endogenous variables are more precisely estimated within each regime.[14] We do not consider 'unit root' or 'cointegration' priors.

5. **Sampling $\tilde{P}$ and $\tilde{Q}$:**

The prior for the elements of the transition probability matrix p_{ij} and q_{11}, q_{12} is of the following form

$$p_{ij}^0 = D\left(u_{ij}\right) \qquad \textbf{A-4}$$

$$q_{11}^0 = D\left(u_{11}\right), q_{12}^0 = D\left(u_{12}\right)$$

where $D(.)$ denotes the Dirichlet distribution and $u_{ij} = 20$ if $i = j$ and $u_{ij} = 1$ if $i \neq j$. This choice of u_{ij} implies that the regimes are fairly persistent. The posterior distribution is:

$$p_{ij} = D\left(u_{ij} + \eta_{ij}\right) \qquad \textbf{A-5}$$

$$q_{11} = D\left(u_{11} + \bar{\eta}_{11}\right), q_{12} = D\left(u_{11} + \bar{\eta}_{12}\right)$$

where η_{ij} denotes the number of times regime i is followed by regime j. $\bar{\eta}_{11}$ and $\bar{\eta}_{12}$ denote the same quantities for the variance regimes.

[14] Letting μ denote the hyperparameters, we set $\mu_0 = 1$, $\mu_1 = 0.5$, $\mu_2 = 1$, $\mu_3 = 1$ and $\mu_4 = 0.01$. The diagonal elements of the prior covariance matrix N_0 (relating to the autoregressive coefficients) are given as $\left(\frac{\mu_0\mu_1}{\sigma_j p^{\mu_3}}\right)^2$ where σ_j denotes the variance of the error from an AR regression for the j^{th} variable and $p = 1..P$ denotes the lags in the VAR. The intercept terms in the VAR are controlled by the term $\left(\mu_0\mu_4\right)^2$.

Two issues arise in the Gibbs sampling algorithm outlined above. First, as mentioned in the text, normalisation restrictions need to be placed on the draws of the VAR coefficients. We implement this in a straightforward manner by imposing the condition that $\bar{\pi}_{i+1} < \bar{\pi}_i$ where $i = 1, 2, ..M$. This normalisation is imposed via rejection sampling. The second issue concerns draws where one of the regimes is not visited. As noted by Sims and Zha (2006), this implies that in the next step of the sampler, the data are not informative for the redundant regime. We deal with such draws in the following way: if a redundant (coefficient or variance) state is encountered in step 1, we discard this draw and keep on redrawing s_t until all regimes are reached or the number of these intermediate draws exceeds 1,000. In the latter case we use the intial conditions to evaluate step 2 and step 3 but do not retain the draw.[15]

B. Generalised impulses responses for Markov-switching models

The MS-VAR model can be written as follows (in companion form)

$$Z_t = A_s Z_{t-1} + \Sigma_S^{-1/2} \upsilon_t$$

where there are two state variables s = 1...M and S = 1..N, with former representing the coefficient regimes and the latter representing the covariance regimes. The transition probability matrices for the two state variables are P and Q respectively

The law of motion for these two state variables is given by

$$E\left(\xi_{t+1}\right) = P\xi_t + \eta$$

$$E\left(\varkappa_{t+1}\right) = P\varkappa_t + \varsigma$$

where ξ represents the coefficient states (ie ξ is a $T \times 1$ vector that equals 1 for state 1, 2 for state 2 etc), $\varkappa$ represents the covariance states.

A generalised impulse response is given by

$$GIRF = E\left(Z_{t+k}/Z_t, A_s, \Sigma_S, \Delta\right) - E\left(Z_{t+k}/Z_t, A_s, \Sigma_S\right)$$

where the first term is a k period forecast of Z conditioned on a shock Δ while the second term is forecast of Z_{t+k} where no shock occurs. Computation of the impulse responses require computation of the forecasts.

[15]For the main MS-VAR models, this upper limit is reached rarely.

Albert and Chib (1993) show that the prediction density of Z ie $F(Z_{t+k}/Z_t)$ is given by

$$F(Z_{t+k}/Z_t) = \int F(Z_{t+k}/\xi, Z_t) \times F(\xi_{t+k}/\xi_t)$$

where the first term is the distribution of Z_{t+k} conditional on the state (we ignore the fact that we have two state variables here, but that is easy to incorporate) and the second term is the probability that of being in state J at time $t+k$. To calculate $F(Z_{t+k}/Z_t)$ we need to iterate on the following two steps:

(a) Sample ξ_{t+k} and $\varkappa_{t+k}$ from $F(\xi_{t+k}/\xi_t)$ and $F(\varkappa_{t+k}/\varkappa_t)$

(b) Using ξ_{t+k} and $\varkappa_{t+k}$ sample from $F(Z_{t+k}/Z_t)$

Algorithm for computing impulse responses

Practically, the impulse response exercise involves the following steps.

Step 1 Collect the MS-VAR coefficients, covariances, transition probabilities and states for time t and Gibbs iteration n. Set starting values for $Z_t, \xi_t, \varkappa_t$ using these estimates and form the transition probability matrices P and Q.

Step 2 Projecting the state variables into the future: calculate the probabilties $p(\xi_t = j)$ and $p(\varkappa_t = k)$ using the Hamilton filter. Then iterate these forward using the following equations

$$p(\xi_{t+k} = j) = P \times p(\xi_{t+k-1} = j)$$

$$p(\varkappa_{t+k} = k) = Q \times p(\varkappa_{t+k-1} = k)$$

These will give us the probabilties associated with each state at each point over the forecast horizon. We need to sample ξ_{t+k} and $\varkappa_{t+k}$ from these discrete probabiltity distributions.

Step 3 With samples for ξ_{t+k} and $\varkappa_{t+k}$ we can calculate $\hat{Z}_{t+k}$ and $\hat{Z}_{t+k}/\Delta$ from the following relations

$$Z_{t+k} = I(\xi_{t+k} = j) \times (A_j Z_{t+k-1}) + \left(I(\varkappa_{t+k} = k) \times \Sigma_S^{-1/2}\right) \upsilon_t$$

$$Z_{t+k}/\Delta = I(\xi_{t+k} = j) \times (A_j Z_{t+k-1}) + \left(I(\varkappa_{t+k} = k) \times \Sigma_S^{-1/2}\right) \upsilon_t \text{ if k>1}$$

$$Z_{t+k}/\Delta = I(\xi_{t+k} = j) \times (A_j Z_{t+k-1}) + (I(\varkappa_{t+k} = k) \times A0_s)\, shock \text{ if k=1}$$

where v is drawn from a normal distribution and $I(.)$ indicate indicator functions (equal to 1 when the condition inside brackets is true) and shock is vector of shocks that are non-zero for the variable that we are interested in shocking

Step 4 Repeat steps 2 and 3 M times and calculate $\frac{1}{M}\sum_M Z_{t+k}/\Delta$ and $\frac{1}{M}\sum_M Z_{t+k}$ which are approximations for the conditional expectations above. The generalised impulse response function at time t is $\frac{1}{M}\sum_M Z_{t+k}/\Delta - \frac{1}{M}\sum_M Z_{t+k}$

Step 5 Repeat these steps for time $t = 1...T$ for a time-varying impulse response function. Repeat for N Gibbs iterations.

C. Results using OECD inflation expectations

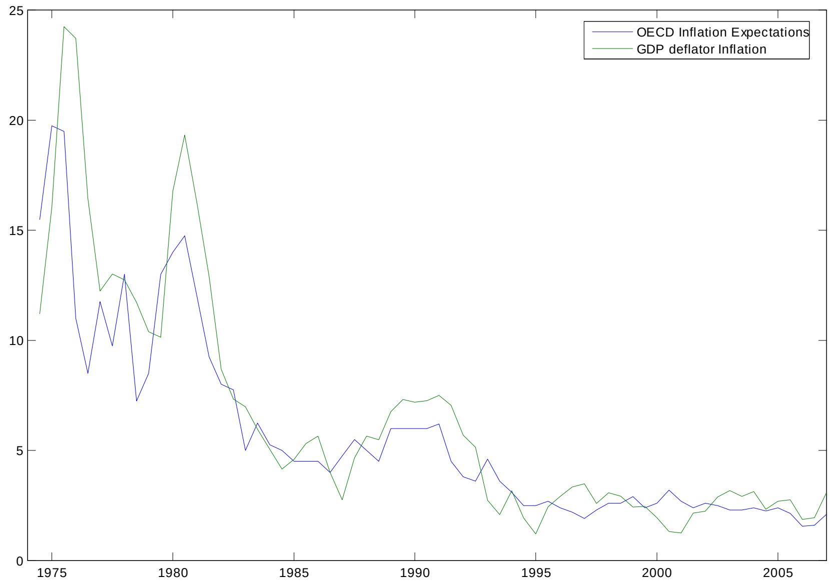
We conduct sensitivity analysis by using an alternative measure of inflation expectations in our MS-VAR model. For the UK long time series on inflation expectations (ie both from professional forecasters and the general public) are hard to come by. To our knowledege, a *quarterly* series that covers the 1970s is unavailable. However, forecasts for the GDP deflator were conducted by the OECD and reported in their biannual *Economic Outlook*. These forecasts are available consistently at a semi-annual frequency from 1973. We use these OECD forecasts as an alternative to our benchmark data set.

Chart C.1 plots the OECD forecasts for GDP deflator inflation. Note, that these forecasts refer to a year ahead projection. For example, the July 1973 issue of the OECD *Economic Outlook* reports the forecast for GDP deflator inflation in 1974 H1. We assume that when making these forecasts, the information set of the forecaster includes variables dated one period before the date of the forecast. For example, the July 1973 forecast is assumed to be based on information dated 1972 H2. We estimate the MS-VAR model using biannual data on OECD GDP deflator inflation forecasts, lagged GDP deflator inflation, GDP growth, lagged T-bill rate and lagged oil prices. The variables are at semi-annual frequency and the estimation sample is 1973 H1 to 2007 H1.

Reduced-form results

We conduct our model selection exercise, setting $\max(M) = 3$ and $\max(N) = 3$, where the former choice is driven by the need to preserve degrees of freedom. Table C.1 reports the

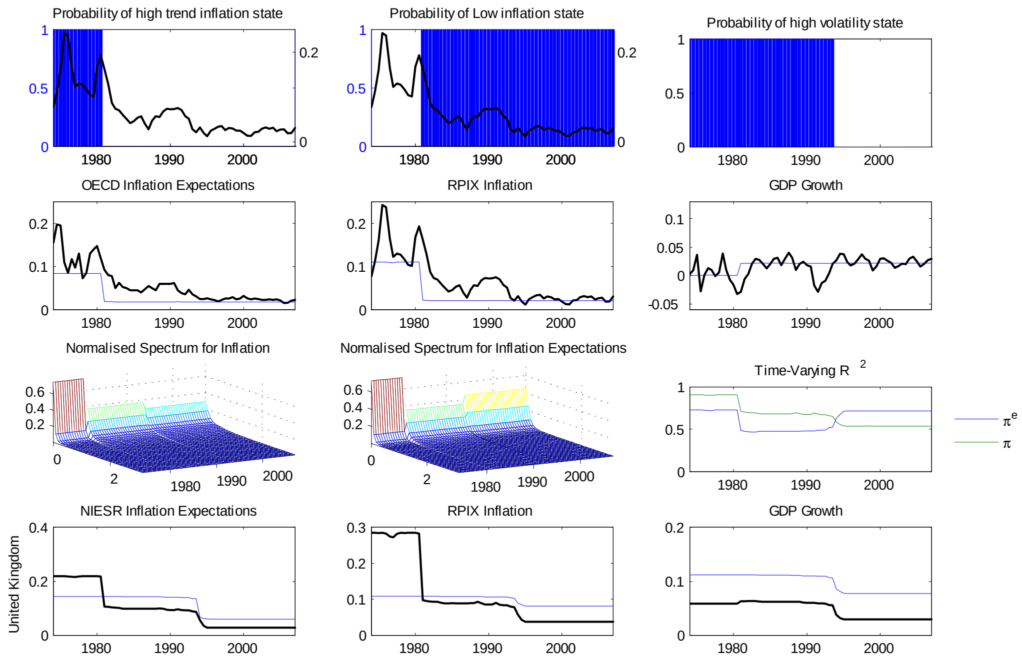
Chart C.1: Forecasts for GDP deflator inflation from the OECD



resulting log marginal likelihoods.

As in the benchmark case, the model with $M = 2$ and $N = 2$ is clearly preferred by the data (Table C.1). Chart C.2 reports some of the main reduced form using the preferred model. The top panel shows that the state probabilities are broadly similar to those obtained using the NIESR forecast data. Similarly, the estimated trends are very similar to those reported in the text with the 1970s characterised by high trend inflation, trend inflation expectations and low trend GDP growth. The normalised spectral densities in the third row again suggest a fall in the persistence of inflation and inflation expectations persistence in the post-1980s period. Although the time-varying R^2 for GDP deflator inflation suggests a similar conclusion, our estimates for the time-varying R^2 for the OECD forecasts is less clear-cut than the estimate for the NIESR measure. Finally, the last row shows a large drop in the unconditional standard deviations (black line) in the early 1980s with a further decline in the post-1992 period.

Chart C.2: Reduced-form results



Structural results

We present some of the key impulse responses from this alternative model as a comparison to our benchmark results. The shocks are identified using the augmented scheme depicted in Table C.

Chart C.3 shows the response to an exogenous increase in the inflation expectations measure, where the shock is identified via a recursive ordering with inflation expectations ordered first. As in the benchmark case, this shock increases inflation more in the 1970s than in the subsequent period. Therefore, these results are in line with the estimates reported in the main text.

The responses to an oil price shock (shown in Chart C.4) are estimated imprecisely. The wide error bands around the inflation expectations response makes it difficult to draw firm conclusions. Similarly, the time-variation in the response of GDP deflator inflation and GDP growth is less clear-cut than the benchmark model.

The reponse to real demand shocks is very similar to our benchmark model. Chart C.5 shows that

Table C.1: Log marginal likelihoods for MS-VAR model (1) estimated with OECD inflation expectations

M	N	Log Marginal Likelihood
1	1	1049.2
2	1	1269.49
3	1	1193.028
1	2	1179.384
2	2	1504.589
3	2	1021.583
1	3	1138.803
2	3	811.7276
3	3	814.9207

Notes: See the notes for Table A.

the demand shock had a larger impact on inflation and inflation expectations in the 1970s. The response of these variables is substantially smaller in the post-1992 period.

The estimated responses to the monetary policy and non-oil supply shocks are fairly similar to our benchmark estimates. These estimates are available on request.

Chart C.6 reports the variance of the main endogenous variables attributed to the identified shocks. Some of the key conclusions reached in the benchmark model are unaffected. The variance of inflation expectations in the 1970s is largely driven by the inflation expectations shocks, with the oil shock making a noteworthy contribution. In the 1980s, the inflation expectations shock is the main contributor to the variance of inflation expectations. The inflation expectations shock is important for actual inflation both in the 1970s and the 1980s and, as before, the oil shock makes an important contribution in the mid-1970s. Finally, the contribution of the monetary policy shock to movements in the T-bill rate are smaller in the post-1992 period

Chart C.3: Response to an inflation expectations shock

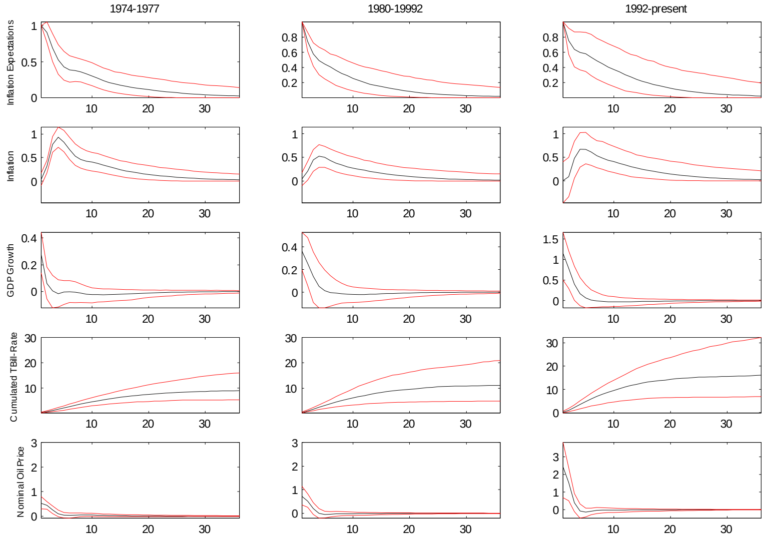


Chart C.4: Response to an oil price shock

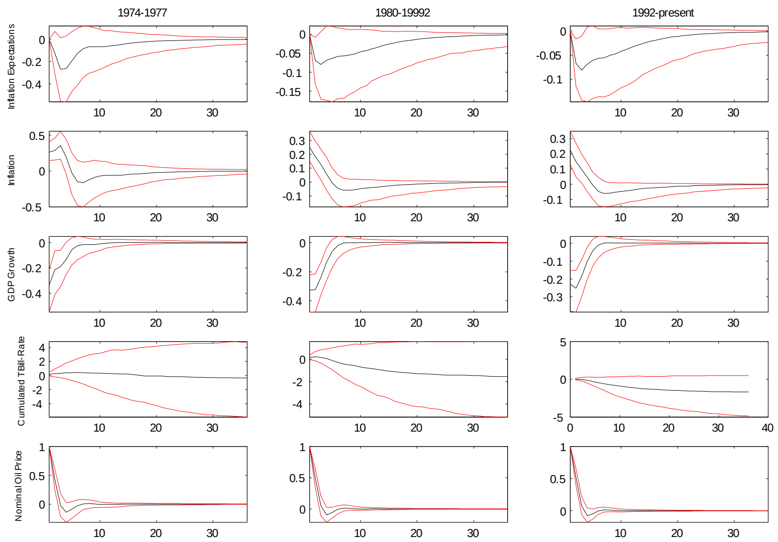


Chart C.5: Response to a real demand shock

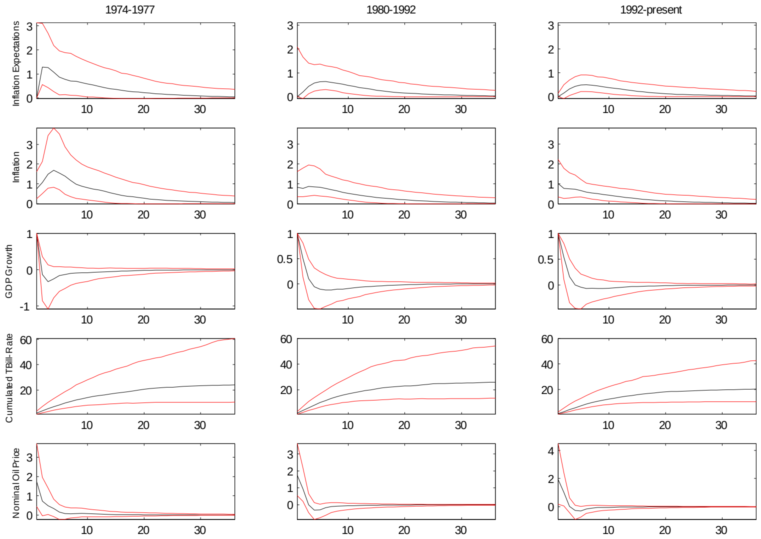
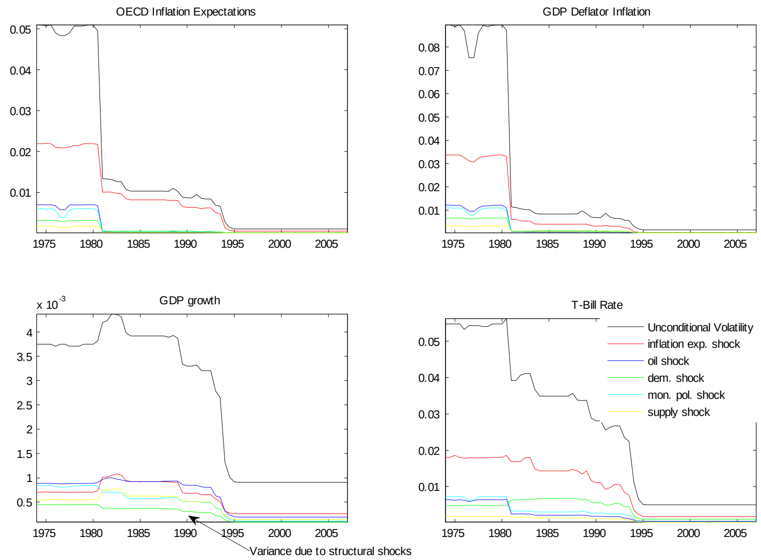


Chart C.6: Variance due to structural shocks



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