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WHAT LIES BENEATH?

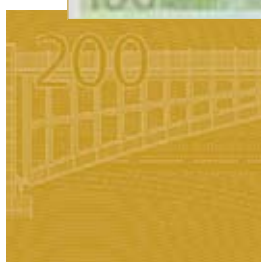
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MECHANISM**

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by Haroon Mumtaz², Pawel Zabczyk³
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Abstract

This paper uses a time-varying Factor Augmented VAR to investigate the evolving transmission of monetary policy and demand shocks in the UK. Simultaneous estimation of time-varying impulse responses of a large set of macroeconomic variables and disaggregated prices suggest that the response of inflation, money supply and asset prices to monetary policy and demand shocks has changed over the sample period. In particular, during the post-1992 inflation targeting period, monetary policy shocks started having a bigger impact on prices, a smaller impact on activity and began contributing more to overall volatility. In contrast, demand shocks had the largest impact on these variables before the 1990s. We also document changes in the response of disaggregated prices, with the median reaction to contractionary policy shocks becoming more negative and the distribution more dispersed post-1992.

Keywords: Transmission mechanism, monetary policy, Factor Augmented VAR, time-varying coefficients, sign restrictions.

JEL classification: C38, E44, E52

Non-technical Summary

How does an economy respond when shocks hit it, or when policymakers change interest rates? And can those responses change over time, if the underlying structure of the economy changes? These questions are of critical importance to macroeconomists and monetary policy makers around the world, as they go to the heart of how interest rates can be used to underpin growth and enshrine price stability. Unfortunately, standard empirical models that are used to examine how economies behave, and how they respond to shocks, are often too small to accommodate the rich underlying tapestry of the economy, or too inflexible to allow for the fact that the economy may today respond very differently to an unexpected change in interest rates, compared with twenty or thirty years ago.

In the past, economists have sometimes struggled to meet these challenges sufficiently well, for instance because they use small scale models – typically including three or four data series such as GDP, an inflation measure, and policy rates — that are easy to estimate but run the risk of misrepresenting the economy. In particular, these types of models often ignore asset prices or monetary aggregates, or only include them in a very limited fashion. This includes work that has tried to allow for the changing structure of the economy, as much of this literature only examines whether the dynamics of output or inflation have changed.

This paper seeks to address these challenges using a relatively new type of statistical model, which encompasses lots of different information and data, but remains relatively straightforward to use. In addition, our modelling approach allows for changes in the underlying structure of the economy, rather than imposing one configuration over the whole of our sample. This flexible approach is important, as we address these challenges from a UK perspective, examining the behavior and response of the economy from 1975 to 2005. During this period the UK economy changed in many significant ways, not least in the shift to inflation targeting in 1992 following sterling's exit from the European exchange rate mechanism (ERM), and the Bank of England's subsequent independence in 1997. In light of this, the flexibility of our approach is a key strength, as is our ability to capture the rich variety of UK macroeconomic data that are available, which reduces the chance that our model is misspecified.

Using quarterly UK data, we apply our modelling approach and uncover several important findings about the nature and structure of the UK economy. Using sign restrictions to identify two types of shocks – that is, constraining the initial response of variables to aggregate demand and monetary policy surprises – our results indicate that the structure of the UK economy has changed significantly, and suggest that models which do not allow for time-variation will be misleading. In addition, there is significant evidence that the shift to inflation targeting in 1992 had a material impact on the effectiveness of monetary policy: prior to that time, monetary policy appears to have had almost no impact on inflation, but after the change in regime inflation falls following an unexpected increase in interest rates. Furthermore, we observe that relative prices — the prices of individual goods and services,

relative to the aggregate — are also more dispersed than prior to 1992. At the same time, unexpected movements in demand now appear to have far less impact on UK inflation than they did before 1992, suggesting that the move to inflation targeting affected the way that households and businesses have responded to shocks. And, in aggregate, monetary policy appears to have been much more important since 1992 in driving movements in output, inflation, monetary aggregates and asset prices than it was before the introduction of inflation targeting.

Overall, our results suggest that the move to inflation targeting has had a clear and lasting impact on the structure of the UK economy, and possibly the behavior of firms and households. Unexpected movements in demand now have much less impact on the economy as a whole, consistent with the credibility of monetary policy. In addition, our model offers a new approach for policymakers who want to take time-variation seriously, while also allowing them to examine the impact of policy on a wide range of factors including equity prices, unemployment and money growth.

1 Introduction

Over the last three decades, the United Kingdom has undergone major structural changes. These changes could have occurred at the same time as shifts in the properties of structural shocks and, arguably, both would have affected the transmission mechanism of policy.¹ Quantifying the impact of such changes and identifying the key factors driving them are of first-order importance for economists and policy-makers alike. To this end, this paper proposes an empirical model which allows for the simultaneous estimation of time-varying impulse responses of a large set of variables to structural shocks.

The possibility of a changing transmission mechanism has been investigated for the UK largely via small scale vector autoregressions (VARs) that typically include three or four endogenous variables. For example, Benati (2008) uses a time-varying VAR in UK output, inflation, short-term interest rate and broad money and shows that there is little significant change (across time) in the response of these variables to a monetary policy shock. Similarly, Castelnuovo and Surico (2006) use a small scale VAR estimated on the pre and post-inflation targeting period to gauge the changing response of inflation to monetary policy shocks.

Note that while these papers provide results for the changing dynamics of variables such as output and inflation, there is little existing evidence on the changing transmission of shocks to asset prices, measures of real activity other than GDP, measures of inflation other than CPI and RPI, different monetary aggregates and sectoral prices and quantities. In addition, Benati and Surico (2009) suggest that small-scale VARs may suffer from model misspecification – with omitted variables potentially distorting estimates of reduced form VAR coefficients or hindering the correct identification of structural shocks.

The purpose of this paper is to re-examine the evolution of the UK monetary transmission mechanism using an empirical framework that incorporates substantially more information than the standard three or four variable-variable model used in most previous studies. In particular, we employ an extended version of the factor-augmented VAR (FAVAR) introduced in Bernanke *et al.* (2005). This model includes information from a large number of macroeconomic indicators representing various dimensions of the economy. Our extensions include allowing for time variation in the coefficients and stochastic volatility in the variances of the shocks. Our formulation has two clear advantages over previous studies: (i) we identify structural shocks using a model that incorporates around 350 macroeconomic and financial variables, hence making it less likely that our setup suffers from the shortcomings discussed above, (ii) our model allows us to estimate time-varying impulse responses for each of the variables contained in our panel. Therefore, we are able to derive results for the variation in responses of a wide variety of variables to the identified shocks. In particular, this paper

¹A number of papers including Benati (2004), Mumtaz and Surico (2008) and Benati (2008) have shown that the 1970s and the 1980s were characterized by volatile inflation and output growth. In addition, the persistence of inflation was estimated to be high during this period. In contrast the period after the introduction of inflation targeting in 1992 was associated with low inflation and output volatility and low inflation persistence.

not only provides evidence on the possible change in responses of the main macroeconomic variables, but also on the time-varying responses of components of the consumption deflator.

The proposed time-varying FAVAR model is estimated on quarterly UK data spanning the period 1975-2005. We use sign restrictions to identify a monetary policy shock and an aggregate demand shock. Our main results are as follows:

- Based on model selection criteria, a fixed coefficient FAVAR model is rejected in favor of the proposed model with time-varying parameters.
- The response of inflation measures to a monetary policy shock is estimated to have changed substantially over the sample period. The pre-1992 response to a contractionary policy shock is estimated to be close to zero while the response over the inflation targeting period is negative and statistically significant. The response of money supply and the long-term government bond yield to this shock displays a similar pattern, with the post-1992 response larger in magnitude.
- There is a substantial change in the response of inflation to an aggregate demand shock. While the response in the pre-1992 period to a positive demand shock was large and persistent, the inflation targeting regime is associated with a response which is smaller in magnitude.
- There is evidence that moments of cross-sectional distribution of the response of disaggregated prices to a monetary policy shock have shifted over time. The median of the price distribution is more negative now than in the late 1970s. Similarly, the distribution is more dispersed than in the past.
- Counterfactual experiments suggest that changes in the impulse response functions are linked to changes in the parameters of the FAVAR interest rate equation pointing to the role played by monetary policy.
- A forecast error variance decomposition exercise indicates that the monetary policy shock became important for measures of real activity, inflation, money and asset prices after 1992, while the demand shock made an important contribution in the pre-1992 period.

The paper is organized as follows: the next section presents the empirical model, section 3 discusses the estimated time-varying impulse responses to a monetary policy and demand shock, a time-varying forecast error variance decomposition is shown in section 4 and section 5 concludes.

2 The Empirical Model

Consider any model based on the standard, three-equation New Keynesian core. Bernanke *et al.* (2005) argue that assumptions made about the information structure are crucial when deciding whether the dynamics of such a model can be described by a vector autoregression. In particular, if it is assumed that the specific data series included in the VAR correspond exactly to the model variables and are observed by the central bank *and* the econometrician, then the VAR model provides an adequate description of the theoretical model. However, both these assumptions are difficult to justify. First, measurement error implies that measures of inflation and output are less than perfect proxies for model variables. Of course, this problem is much more acute for unobserved variables such as potential output. Furthermore, for broad concepts like economic activity and inflation there exists a multitude of observable indicators none of which will be able to match the theoretical construct precisely. Second, it is highly likely that the researcher only observes a subset of the variables examined by the monetary authority.

Note that measurement error and omitted variables can potentially affect small-scale VAR analyses of *changes* in the transmission of structural shocks quite acutely. When examining time variation in impulse responses, the assumptions about the measurement of model variables and the information set used by model agents apply at each point in time and are more likely to be violated. If important information is excluded from the VAR, this can affect inference on the temporal evolution of impulse responses and lead to misleading conclusions about changes in the transmission mechanism.

The obvious solution to this problem is to try and include more variables in the VAR. However, the degrees of freedom constraint becomes binding quite quickly in standard datasets.² Bernanke *et al.* (2005) suggest a more practical solution. They propose a ‘Factor-Augmented’ VAR (FAVAR) model, where factors from a large cross section of economic indicators are included as extra endogenous variables in a VAR.³ These factors proxy the information set of the central bank (part of) which may have been inadvertently excluded from the small scale VAR model. We extend the FAVAR model along two dimensions.

- First, we allow the dynamics of the system to be time-varying to capture changes in the propagation of structural shocks as a result of shifts in private sector behavior and/or monetary policy preferences.
- Second, our specification incorporates heteroscedastic shocks which account for variations in the volatility of the underlying series.

This extended FAVAR model provides a flexible framework to examine changes in the transmission of structural shocks. Moreover, our time-varying FAVAR model is less susceptible to

²This problem is even more acute in time-varying VARs as they usually impose a stability constraint (at each point in time) and this is less likely to be satisfied as the number of variables in the VAR increases.

³See also Forni and Gambetti (2010) for a recent application to US data based on sign-restrictions.

problems created by omitted variables and therefore provides a robust framework to examine changes in the transmission mechanism. As we discuss below, the results obtained from our model differ substantially from those obtained using a standard small-scale time-varying VAR.

More formally, our FAVAR model for the UK economy can be written in state space form. Consider first the observation equation

$$\begin{pmatrix} X_{1,t} \\ \cdot \\ \cdot \\ X_{N,t} \\ R_t \end{pmatrix} = \begin{pmatrix} \Lambda^{11} & \cdot & \Lambda^{K1} & \Psi^{11} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \Lambda^{1N} & \cdot & \Lambda^{KN} & \Psi^{1N} \\ 0 & \cdot & 0 & 1 \end{pmatrix} \begin{pmatrix} F_t^1 \\ F_t^2 \\ \cdot \\ F_t^K \\ R_t \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \\ \cdot \\ e_{Nt} \\ 0 \end{pmatrix} \quad (1)$$

where X_t is a panel of variables that contain information about real activity, inflation, money and asset prices in the UK (see data subsection below) while F_t^1 to F_t^K denote the K latent factors. We assume that these factors capture the dynamics of the UK economy and the Λ 's denote the factor loadings. Along similar lines as in Bernanke *et al.* (2005) the bank rate R_t is the 'observed factor'. We stress that the structure of the loading matrix implies that some of the variables are allowed to have a contemporaneous relationship with the short term interest rate – i.e. $\Psi \neq 0$ for data series that are expected to react promptly to monetary policy actions.

As we describe below, time variation is introduced into the model by allowing for drift in the coefficients and the error covariance matrix of the transition equation. Note that an alternative way of modelling time variation is to allow the factor loadings (Λ and Ψ) to drift over time.⁴ There are, however, several reasons why we do not adopt this alternative specification. First, such a setup implies that any time variation in the dynamics of each factor *and* the volatility of shocks to each factor is driven entirely by the drift in the associated factor loading. This assumption is quite restrictive, especially as it only allows changes in the mean and persistence of each factor to occur simultaneously with changes in the volatility of the shocks. Second, this model implies a much larger computational burden as the Kalman filter and a backward recursion have to be employed for each underlying series. Finally, apart from the computational costs, this specification implies that the dynamics of observed factors are time invariant and, in particular, that the central bank always reacts in the same way to the "state of the economy" (captured by the latent factors). Such an assumption is hard to justify given our sample period (1975Q1 to 2005Q1) and would be rather restrictive in a model designed to investigate the changing impact of monetary policy.

Equally, allowing for time variation in both, the factor loadings and the coefficients of the transition equation would entail serious identification problems since there would be three time-varying unobserved components, i.e. $\Gamma_t = [\Lambda_t, \Psi_t]$, ϕ_t and F_t . However, substituting

⁴See Del Negro and Otrok (2008) for this kind of approach in a different context.

the transition equation (2) into the observation equation (1) imparts a restricted form of time variation also in the factor loadings. This interaction between the loadings and the time-varying coefficients of the factors has the potential to generate rich dynamics for the impulse response functions of the underlying series.

As described below, time-variation is introduced into the model by allowing for drift in the coefficients and the error covariance matrix of the transition equation. More specifically, the transition equation of the system is a time-varying VAR model of the following form

$$Z_t = \sum_{l=1}^L \phi_{l,t} Z_{t-l} + v_t \quad (2)$$

where $Z_t = \{F_t^1, F_t^2, \dots, F_t^K, R_t\}$ and L is fixed at 2. We further postulate the following law of motion for the coefficients ϕ

$$\phi_t = \phi_{t-1} + \eta_t$$

and the innovation (v_t) covariance matrix is factored as

$$VAR(v_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})' \quad (3)$$

where the time-varying matrices H_t and A_t evolve as random walks.

The model described by equations 1 and 2 can incorporate a large amount of information about the UK economy. In particular, if the factors in equation 1 contain relevant information not captured by the three variables used in ‘standard’ VAR studies (eg Primiceri (2005)) then one might expect structural shocks identified within the current framework to be more robust. Our flexible specification for the transition equation also implies that the model accounts for the possibility of structural breaks in the dynamics that characterize the economy.

2.1 Identification of Structural Shocks

We identify two shocks: a monetary policy shock, and an aggregate demand shock. Following Canova and Nicolo (2002) and Uhlig (2005), the shocks are identified by placing contemporaneous sign restrictions on the response of some of the variables in X_t to an innovation to R_t . Our procedure works as follows: let $\Omega_t = P_t P_t'$ be the Cholesky decomposition of the VAR covariance matrix Ω_t , and let $\tilde{A}_{0,t} \equiv P_t$. We draw an $N \times N$ matrix, J , from the $N(0, 1)$ distribution. We take the QR decomposition of J , which gives us a candidate structural impact matrix as $A_{0,t} = \tilde{A}_{0,t} Q$. Next we compute the contemporaneous impulse response of



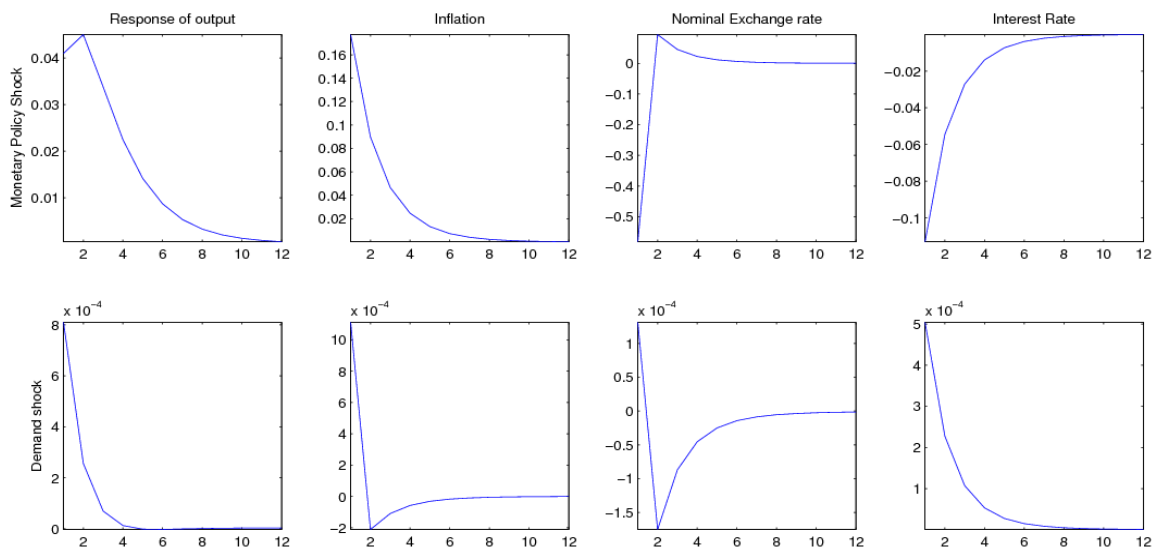


Figure 1: Impulse response to a monetary policy shock (top panel) and demand shock (bottom panel) using the model in Lubik and Schorfheide (2006).

$X_{1,t}, \dots, X_{N,t}$ as

$$\begin{pmatrix} \Delta X_{1,t} \\ \cdot \\ \cdot \\ \Delta X_{N,t} \\ \Delta R_t \end{pmatrix} = \begin{pmatrix} \Lambda^{11} & \cdot & \Lambda^{K1} & \Psi^{11} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \Lambda^{1N} & \cdot & \Lambda^{KN} & \Psi^{1N} \\ 0 & \cdot & 0 & 1 \end{pmatrix} \times A_{0,t}$$

where $\Delta X_{i,t}$ denotes the response of the i -th variable. We check if these satisfy our sign restrictions. If this is the case we store $A_{0,t}$ and repeat the procedure until we have 100 $A_{0,t}$ matrices that satisfy the sign restrictions. Out of these 100 stored $A_{0,t}$ matrices we retain the matrix with elements closest to the median across these 100 estimates. If the contemporaneous sign restrictions are not satisfied, we draw another J and repeat the above.

We motivate our sign restrictions using a structural, two-country model described in Lubik and Schorfheide (2006) – an estimated, open-economy extension of the standard, three-equation New Keynesian workhorse. The model-implied impulse responses to monetary policy and demand shocks are given in figures 1. In light of these impulse responses we impose the following: (1) contractionary monetary policy shocks are assumed to increase R , reduce GDP growth, reduce inflation and lead to a nominal effective exchange rate appreciation on impact; (2) positive demand shocks have a positive contemporaneous impact on GDP growth, inflation and the nominal rate. With this minimal set of restrictions, we are able to disentangle the two structural shocks.

Our identification method has a number of advantages over Bernanke et al.'s (2005) recursive scheme. First, contemporaneous sign restrictions allow us to be relatively ‘agnostic’ about the impact of structural shocks (beyond the contemporaneous effects) while simultaneously

imposing more structure than a Cholesky decomposition. Second, by using our identification scheme we are able to easily identify structural shocks other than those to monetary policy.

2.2 Estimation

We estimate the model using Bayesian methods. A detailed description of the prior and posterior distributions is provided in the appendix. Here we summarize the estimation algorithm. The Gibbs sampler cycles through the following steps:

1. Given initial values for the factors, simulate the VAR parameters and hyperparameters
 - The VAR coefficients ϕ_t and the off-diagonal elements of the covariance matrix α_t are simulated by using the methods described in Carter and Kohn (1994)
 - The volatilities of the reduced form shocks H_t are drawn using the date by date blocking scheme introduced in Jacquier *et al.* (2002).
 - The hyperparameters are drawn from their respective distributions.
2. Given initial values for the factors draw the factor loadings (Λ and Ψ) and the variance of the idiosyncratic components.
 - Given data on R_t and $X_{i,t}$ standard results for regression models can be used and the coefficients and the variances are simulated from a normal and inverse gamma distribution.
3. Simulate the factors conditional on all the other parameters
 - This is done in a straightforward way by employing the methods described in Bernanke *et al.* (2005) and Kim and Nelson (1999).
4. Go to step 1.

We use 55,000 iterations in this MCMC algorithm discarding the first 45,000 as burn-in. The cumulated means of the retained draws (see appendix) show little variation which provides some evidence of algorithm convergence.

2.2.1 Computation of Impulse Response Functions

We calculate the impulse responses Δ_t of $F_t^1, F_t^2, \dots, F_t^K$ and R_t to the monetary policy shock and the demand shock for each quarter. With these in hand, the time-varying impulse

responses of each underlying variable can be easily obtained using the observation equation (1) of the model. That is, the impulse responses of $X_{1,t}, \dots, X_{N,t}$ are computed as:

$$\begin{pmatrix} \Lambda^{11} & \cdot & \Lambda^{K1} & \Psi^{11} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \Lambda^{1N} & \cdot & \Lambda^{KN} & \Psi^{1N} \\ 0 & \cdot & 0 & 1 \end{pmatrix} \times \begin{pmatrix} \Delta_t^{F^1} \\ \cdot \\ \cdot \\ \Delta_t^{F^K} \\ \Delta_t^{R_t} \end{pmatrix} \quad (4)$$

Given the presence of time-varying parameters in the transition equation, computation of impulse response functions has to take into account the possibility of parameter drift over the impulse response horizon. Therefore, following Koop *et al.* (1996), we define the impulse response functions at each date as Δ_t

$$\Delta_{t+k} = E(Z_{t+k} | \Xi_{t+k}, \mu_{MP}) - E(Z_{t+k} | \Xi_{t+k}) \quad (5)$$

where Ξ denotes all the parameters and hyperparameters of the VAR and k is the horizon under consideration. Equation (5) states that the impulse response functions are calculated as the difference between two conditional expectations. The first term in equation (5) denotes a forecast of the endogenous variables conditioned on a monetary policy shock μ_{MP} . The second term is the baseline forecast, i.e. conditioned on the scenario where the monetary policy shock equals zero. Therefore, in effect, equation (5) integrates out future uncertainty in the VAR parameters. The conditional expectations in (5) are computed via Monte Carlo integration for 1000 replications of the Gibbs sampler. Details on the Monte Carlo integration procedure can be found in Koop *et al.* (1996).

2.3 Data

Our dataset is quarterly running from 1964 Q1 to 2005 Q1. As described in the appendix, we use the first 40 observations as a training sample with the estimation carried out starting 1975Q1. The dataset comprises around 60 macroeconomic UK data series. It includes activity measures such as GDP, consumption and industrial production, various price measures including RPI, CPI and the GDP deflator, as well as money and asset price data. In addition to these macro variables, we included a large number of disaggregated deflator and volume series for consumers' expenditure. The Office for National Statistics (ONS) publishes around 140 subcategories of consumer expenditure data both in volume *and* deflator terms, going back to the 1960s. This gives us a ready-made collection of consistent disaggregated price (and volume) data over a long time period. Further details on the dataset are provided in the appendix to the paper.

	<i>DIC</i>	\bar{D}	p_D
Time-varying parameter FAVAR with 1 factor	20199	19481	718
Fixed coefficients FAVAR with 1 factor	42107	41757	350
Time-varying parameter FAVAR with 2 factors	15715	14654	1061
Fixed coefficients FAVAR with 2 factors	35905	35225	680
Time-varying parameter FAVAR with 3 factors	22956	18330	4626
Fixed coefficients FAVAR with 3 factors	33214	32271	943

Table 1: Model Comparison via DIC. Best fit indicated by lowest DIC.

3 Results

3.1 Model Comparison

In order to select the number of latent factors and to assess the importance of time-variation that we introduce in the parameters of the FAVAR model, we compare our benchmark model (see equation 1) with a version of the model that assumes fixed parameters via the deviance information criterion (*DIC*). The *DIC* is a generalization of the Akaike information criterion – it penalizes model complexity while rewarding fit to the data. The *DIC* is defined as

$$DIC = \bar{D} + p_D.$$

The first term $\bar{D} = E(-2 \ln L(\Xi_i)) = \frac{1}{M} \sum_i (-2 \ln L(\Xi_i))$ where $L(\Xi_i)$ is the likelihood evaluated at the draws of all of the parameters Ξ_i in the MCMC chain. This term measures goodness of fit. The second term p_D is defined as a measure of the number of effective parameters in the model (or model complexity). This is defined as $p_D = E(-2 \ln L(\Xi_i)) - (-2 \ln L(E(\Xi_i)))$ and can be approximated as $p_D = \frac{1}{M} \sum_i (-2 \ln L(\Xi_i)) - \left(-2 \ln L\left(\frac{1}{M} \sum_i \Xi_i\right)\right)$.⁵

Note that the model with the lowest estimated *DIC* is preferred.

Estimation of the *DIC* requires evaluating the likelihood function for each MCMC iteration.⁶ Calculation of the likelihood function for the time-varying FAVAR with stochastic volatility is complicated due to the non-linear interaction of the volatility with levels in equation 2. We use a particle filter to evaluate the likelihood for each Gibbs draw. The Appendix presents a brief description of the particle filtering procedure.

Table 1 presents the estimated DIC for the time-varying parameter and fixed coefficient FAVAR.⁷ In general model complexity (p_D) is lower for the fixed coefficient FAVAR models.

⁵The first term in this expression is an average of -2 times the likelihood function evaluated at each MCMC iteration. The second term is $(-2$ times) the likelihood function evaluated at the posterior mean.

⁶The main advantage of *DIC* over Bayes factors is the difficulty in the accurate computation of the marginal likelihood in complex models. Although Monte Carlo-based methods such as the harmonic mean estimator can be used, the estimates tend to be influenced by outlying values of MCMC draws and can be inaccurate. The method described in Chib (1995) requires an additional Gibbs simulation for each parameter making its implementation difficult for the time-varying parameter model.

⁷Note that we limit the maximum number of factors to 3 for computational reasons. As common in the

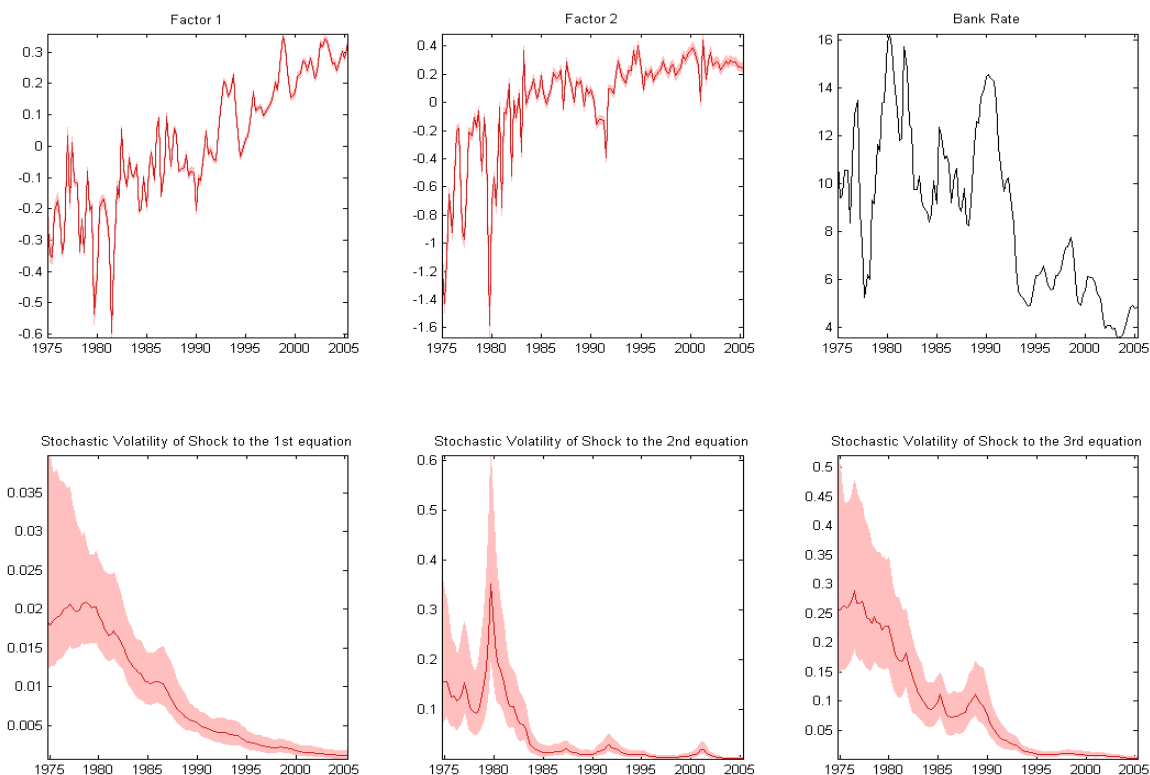


Figure 2: The estimated factors, the bank rate and the stochastic volatility of shocks to each transition equation.

However, this comes at the cost of model fit with \bar{D} estimated to be substantially larger for the fixed coefficient models. The *DIC* is minimized for the time-varying FAVAR with two factors and this model is used in the analysis below.

3.2 The Estimated Factors and Stochastic Volatility

The top left panels of figure 2 plot the estimated factors and the associated 68% error bands. Factor 2 is highly correlated with inflation measures in our dataset with a correlation of over -0.9 with CPI inflation and other inflation measures such as the change in the consumption deflator and the GDP deflator. Factor 2 also displays a reasonable correlation with GDP growth of around 0.4. This suggests that this factor captures the evolution of inflation and real activity in our dataset. On the other hand Factor 1 is highly correlated with financial variables included in our dataset, with the highest correlation (of 0.97) with the five year government bond yield.

The factors are quite precisely estimated with the volatility of the shocks to their transition equations estimated to be high during the 1970s and the 1980s. However this volatility

literature we require the time-varying transition equation of the FAVAR to be stable at each point in time. This constraint becomes very difficult to impose when the number of endogenous variables in equation 2 exceeds 4. Note that this computational constraint also prevents us from considering lag lengths longer than 2.

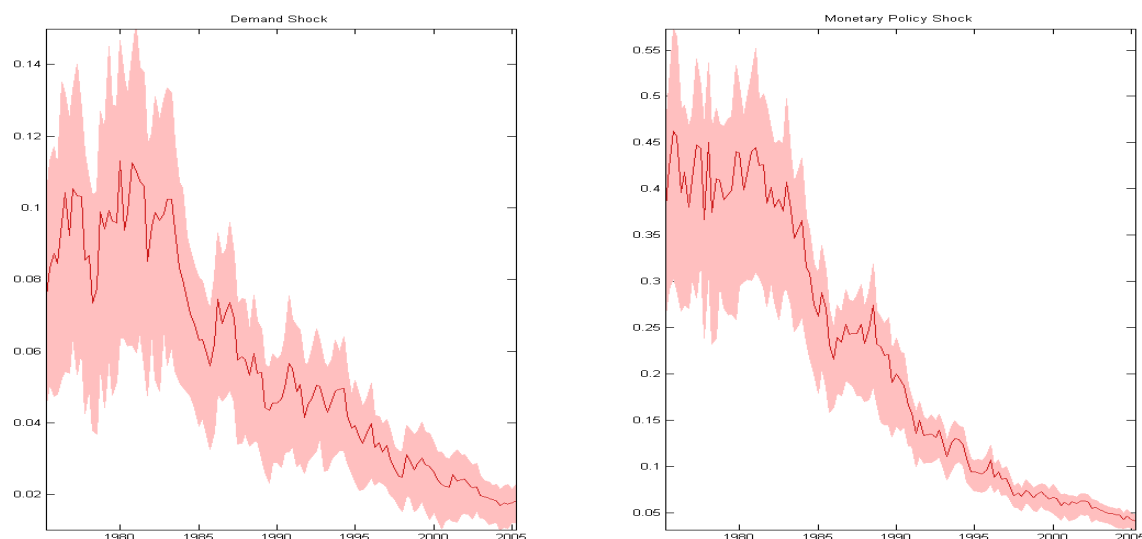


Figure 3: Volatility of the identified structural shocks.

declines substantially in the post-1985 period confirming the phenomenon referred to as the great moderation. The shock to the Bank rate equation was at its most volatile during the late 1970s. This volatility declined during the Thatcher dis-inflation of the early 1980s. The independence of the Bank of England saw a further decline in this volatility, with the variance close to zero over the period 1992-2005.

Figure 3 plots the estimated standard deviation of the structural shocks. This is calculated at each point in time as $\left(\bar{A}_{0,t}^{-1'}\Omega_t\bar{A}_{0,t}^{-1}\right)^{1/2}$ where $\bar{A}_{0,t}$ is the $A_{0,t}$ matrix with the elements divided by the diagonal of this matrix. The estimates of the shock volatilities show a similar pattern – the volatility is high before the early 1990s with the inflation targeting period associated with the lowest variance.

3.3 Impulse Response to a Monetary Policy Shock

3.3.1 Aggregate Series

Figure 4 plots the *cumulated* response of (the quarterly growth rate of) real activity indicators to a monetary policy shock normalized to increase the Bank rate by 100 basis points in the contemporaneous period (the time-varying response of the Bank rate to this shock is shown in figure 5). The left panel of the figure plots the median response in each quarter. The middle two panels display the median response and the 68% confidence interval over the pre and post-1992 period. Note that the post-1992 period coincides with the adoption of inflation targeting in the United Kingdom and this is generally regarded as the most significant change (since the 1970s) to the monetary framework. Therefore, we present the average impulse response in these two periods as a way to assess if this change in the monetary framework was associated with a change in the transmission of structural shocks. To gauge the significance

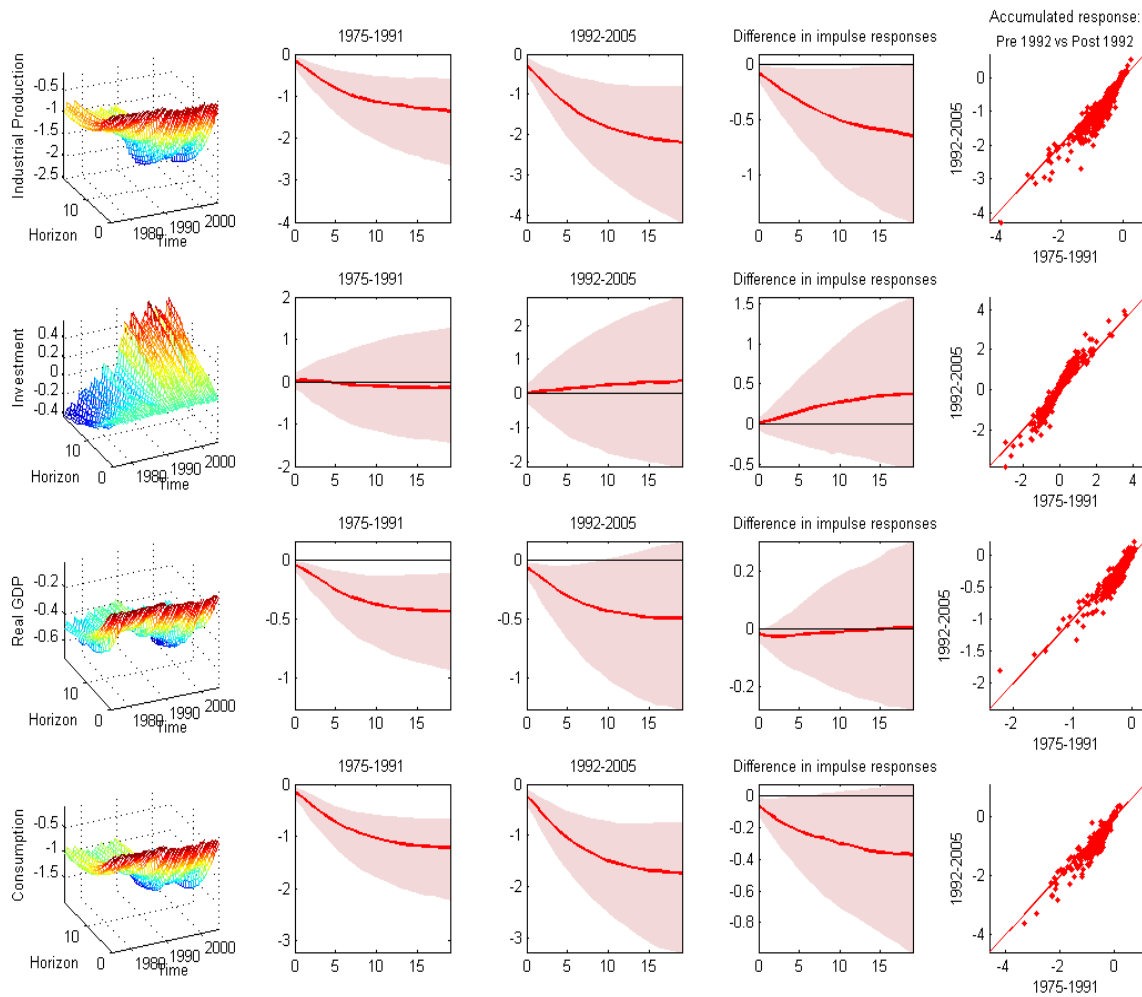


Figure 4: Impulse response of real activity to a monetary policy shock. The left panels present the time-varying median cumulated impulse response. The middle three panels show the average impulse response functions in the pre and post-1992 period and their difference, while the last panel shows the joint distribution of the cumulated response at the one year horizon in the pre and post-1992 period.

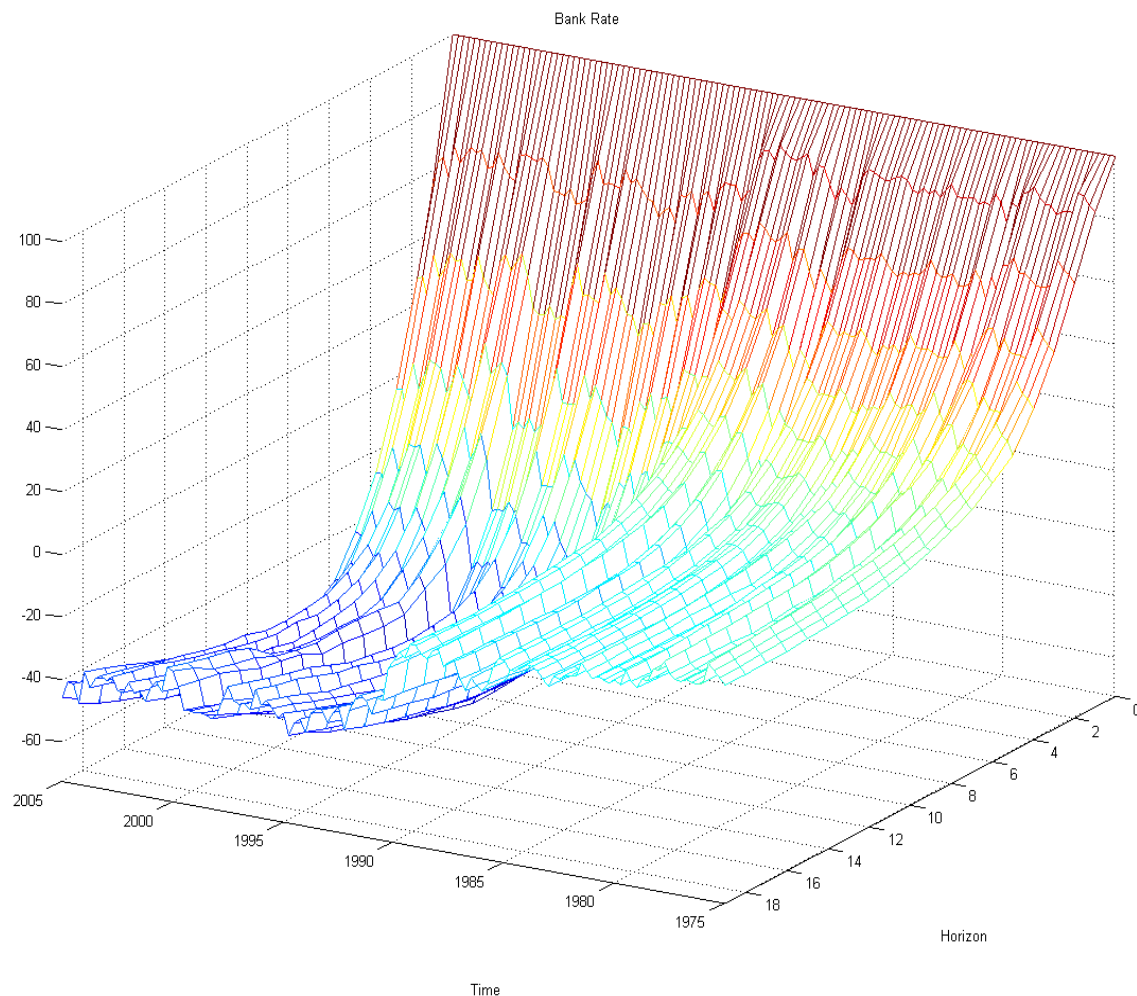


Figure 5: Time-Varying impulse response of the bank rate to the monetary policy shock.

of any difference across these sub-periods, we present two additional pieces of information. The fourth panel of the figure plots the difference in the impulse response across the two sub-periods. The final panel plots the estimated joint distribution of the cumulated impulse response (at the 4 quarter horizon) pre and post-1992. Note that systematic differences result in the points not being distributed symmetrically around the 45 degree line.⁸

The contractionary policy shock reduces GDP by around 0.2% after one year in the pre-1992 period. The post-1992 response is very similar with the joint distribution concentrated on the 45-degree line. The median response of industrial production and consumption is around 0.5% at the one year horizon in the pre-1992 period with some evidence that the magnitude of the response is somewhat larger in the post-1992 period. The response of consumption shows a similar pattern, although the change in the magnitude of the response in the post-1992 period is not statistically significant. The response of investment is imprecisely estimated.

The cumulated response of aggregate quarterly inflation measures to the monetary contrac-

⁸ A similar method has been used, for example, in Cogley *et al.* (2010).

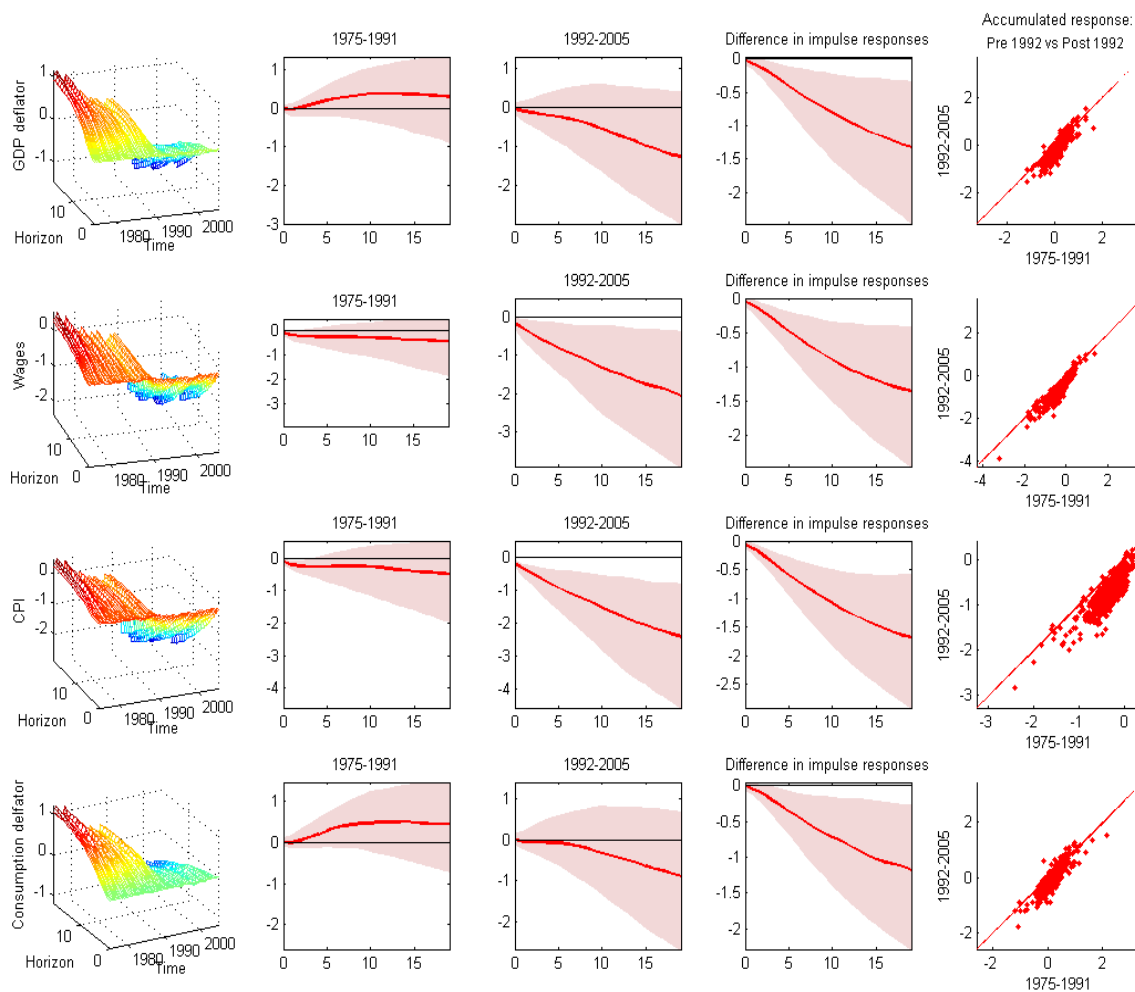


Figure 6: Impulse response of inflation to a monetary policy shock. The left panels present the time-varying median cumulated impulse response. The middle three panels show the average impulse response functions in the pre and post-1992 period and their difference, while the last panel shows the joint distribution of the cumulated response at the one year horizon in the pre and post-1992 period.

tion is presented in figure 6. In contrast to the response of real activity, the impulse response of inflation measures shows significant time-variation. The response of inflation measures is small and statistically insignificant in the pre-1992 period and large, negative and persistent during the inflation targeting period. The shift appears to be systematic, with the difference in the pre and post-1992 response significantly different from zero (and the joint distribution largely concentrated to the right of the 45 degree line).

Note that one aspect of these results is in contrast to those presented in Castelnovo and Surico (2006) and Benati (2008) – i.e. our estimates are not characterized by a (statistically significant) price-puzzle during the 1970s as reported in these papers. This possibly reflects the fact that the identification of the monetary policy shock is more robust in our FAVAR model on account of it containing more information than the small scale models used in

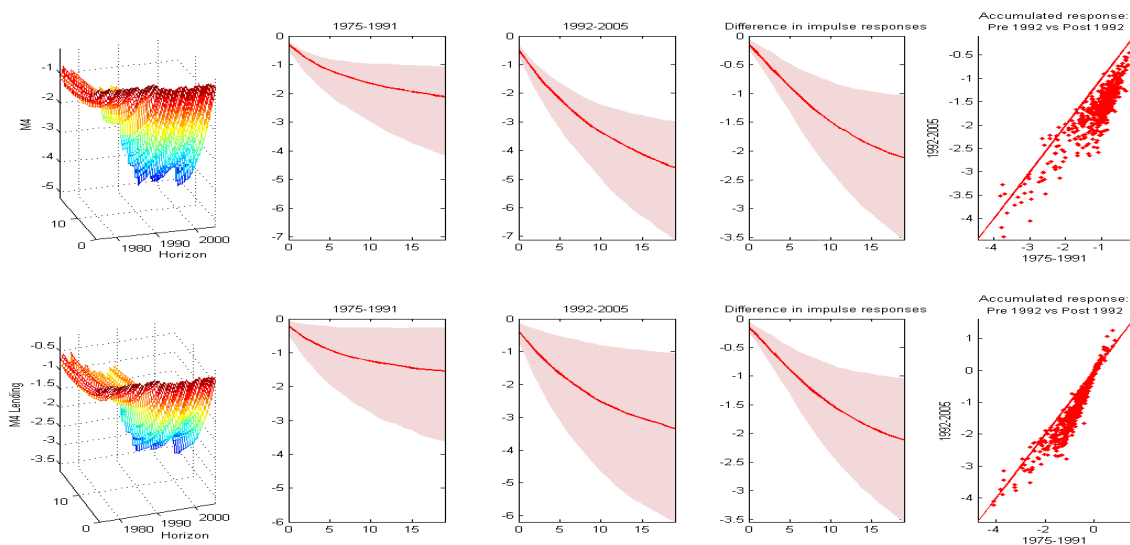


Figure 7: Impulse response of money to a monetary policy shock. The left panels present the time-varying median cumulated impulse response. The middle three panels show the average impulse response functions in the pre and post-1992 period and their difference, while the last panel shows the joint distribution of the cumulated response at the one year horizon in the pre and post-1992 period.

Castelnuovo and Surico (2006). However, as in Castelnuovo and Surico (2006) and Benati (2008) the price response is more negative over a policy regime associated with a higher degree of activism in response to inflation. Castelnuovo and Surico (2006) argue that this change in the response of inflation, reflects an underlying change in the monetary authorities' response to inflation, with higher activism consistent with a stronger negative response and an absence of the price puzzle. The increase in the magnitude of the response during the inflation targeting period is consistent with those arguments.

Figure 7 presents the response of broad money (M4 aggregate) and credit (M4 lending) growth to a monetary contraction. The estimates display a very similar pattern to those presented for inflation above. Generally, the (negative) response of M4 and M4 lending growth is stronger and more persistent in the post-1992 period, which is in line with the results reported in Benati (2008). A potential rationale for the 'liquidity puzzle' of the 70s and apparent instability of short-run money demand documented in figure 7 is developed in the theoretical paper of Alvarez and Lippi (2009).

The cumulated response of some key asset prices is shown in figure 8. The response of house prices shows little change over time with a decline of around 2% over the sample period. The FTSE reaction is somewhat stronger in the post-1992 period. Similarly, the NEER responds more to the policy shock in the post-1992 period. The response of the 10 year government bond yield shows the largest variation. In the pre-1992 period the cumulated fall in the yield is less than 1000 basis points in response to the policy shock (this corresponds to a 10 percentage point change). In the post-1992 period the magnitude almost doubles at the two year horizon with the joint distribution in the final column of the figure concentrated

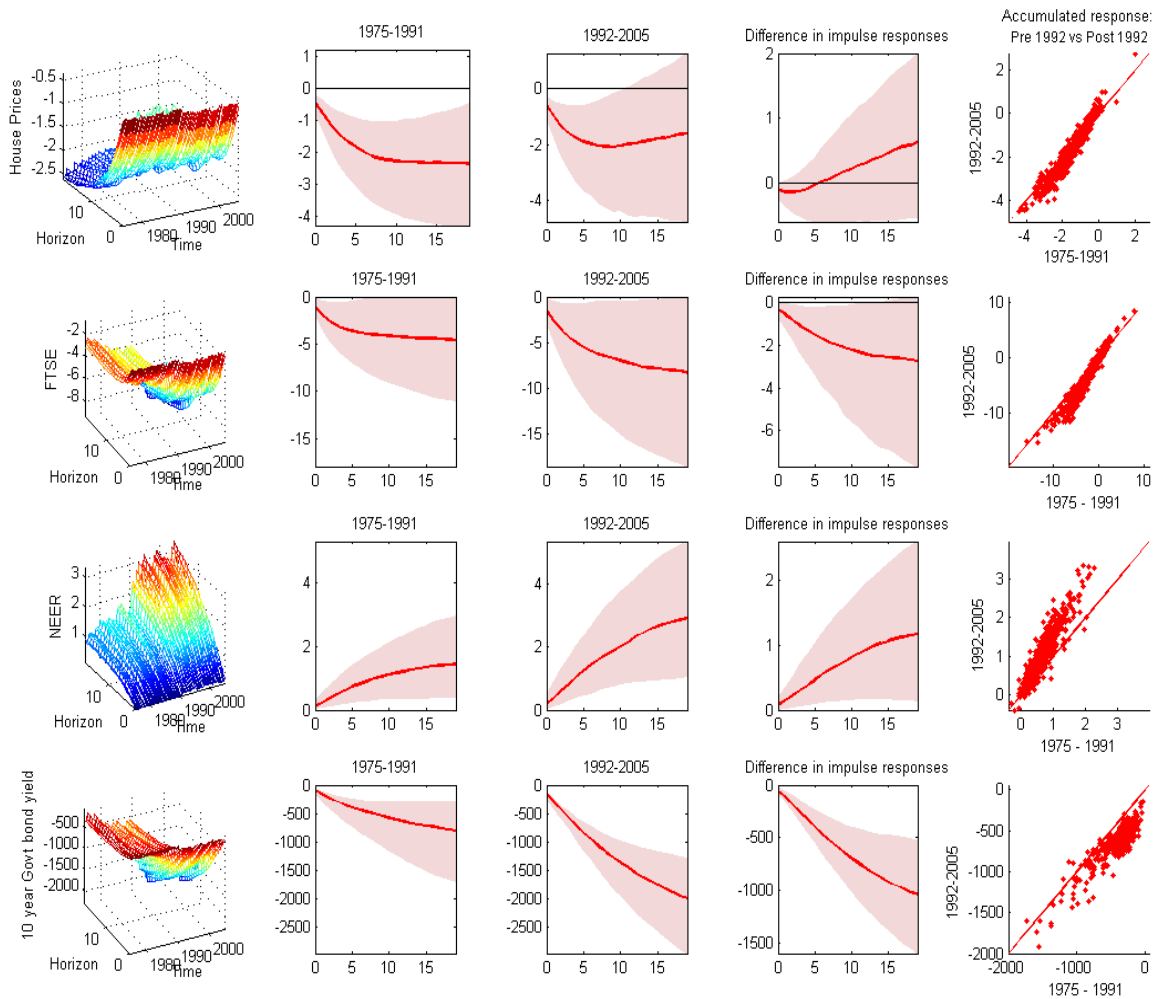


Figure 8: Impulse response of asset prices to a monetary policy shock. The left panels present the time-varying median cumulated impulse response. The middle three panels show the average impulse response functions in the pre and post-1992 period and the difference, while the last panel shows the joint distribution of the cumulated response at the one year horizon in the pre and post-1992 period.

to the right of the 45-degree line. This may reflect the fact that monetary policy was more credible during the inflation targeting period resulting in a larger response of inflation expectations implicitly reflected in the long term government bond yield. Note that a similar result is reported by Bianchi *et al.* (2009) who use a VAR model with yield curve factors to characterize yield curve dynamics.

3.3.2 Response of the Components of the Consumption Deflator

Our panel dataset comprises around 140 components of the consumption deflator. As in Boivin *et al.* (2009) our methodology allows us to derive the response of each of these series to a monetary policy shock. Moreover, we are also able to examine how the distribution of consumption deflator responses (across expenditure categories) has evolved over time.

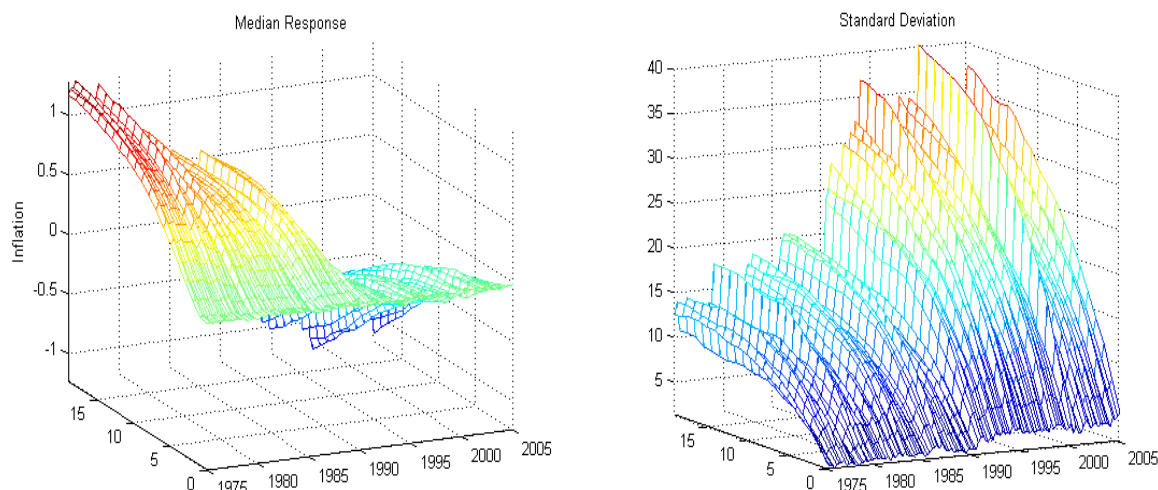


Figure 9: Changes in the distribution of the consumption deflator across time.

Figure 9 tracks the evolution of cross-sectional characteristics of the price level. The top left panel shows the evolution of the median response of the consumption deflator, which has clearly undergone a marked change. More specifically, in the pre-1992 period, although the price level initially falls in reaction to the monetary contraction, the fall is short-lived with the response becoming positive at longer horizons. This is in contrast to the post-1992 estimates where the median price level declines significantly. These results again point to the possible role of the changing monetary regime (see Castelnuovo and Surico (2006)).

Notably, the change in the median of the distribution is also associated with an increase in dispersion with the standard deviation (at longer horizons) higher during the 1990s. This means that although the median response is strongly negative in the current period, prices are more dispersed 20 quarters after the shock than during the 1980s. There is little systematic change in the skewness of the estimated distribution (not reported).

3.3.3 Impulse Response to Demand Shocks

Figure 10 shows the cumulated response of selected variables to the identified demand shock. The shock is normalized to increase GDP growth by 1% (in the initial period) at all dates in the sample. The cumulated response of industrial production shows little change across the sample period. On the other hand, the cumulated response of CPI inflation to the demand shock does change significantly. In particular, the median response of inflation in the post 1992 period is about half the magnitude of the pre-1992 response. Again, this could be related to changes in the monetary regime with inflation expectations possibly more firmly anchored under inflation targeting. Note that similar results for the US are reported in Leduc *et al.* (2007).

The pattern of the median response for money growth is similar to the results obtained for inflation. Finally, the post-1992 response of the long term government bond yield is smaller

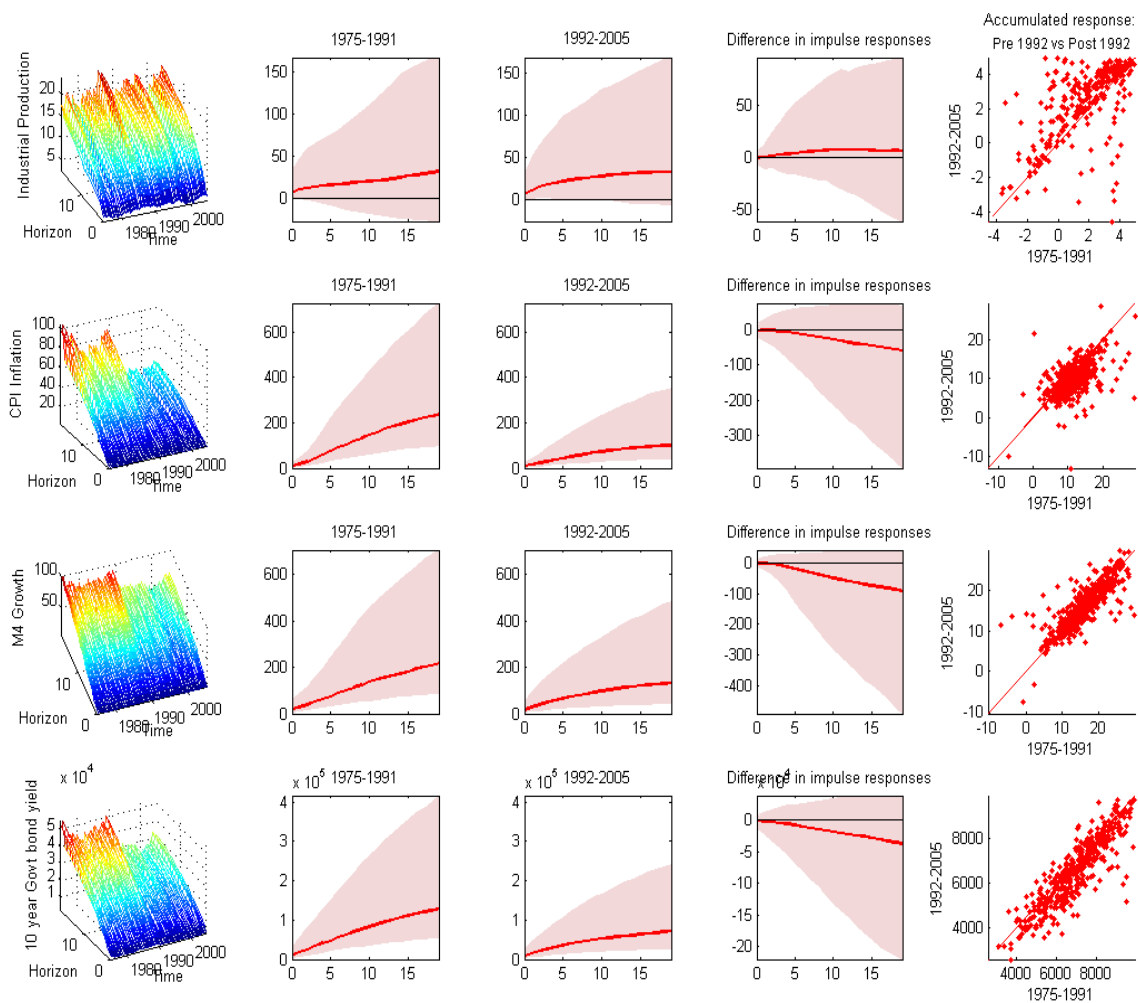


Figure 10: Impulse response to a demand shock. The left panels present the time-varying median cumulated impulse response. The middle three panels show the average impulse response functions in the pre and post-1992 period and their difference, while the last panel shows the joint distribution of the cumulated response at the one year horizon in the pre and post-1992 period.

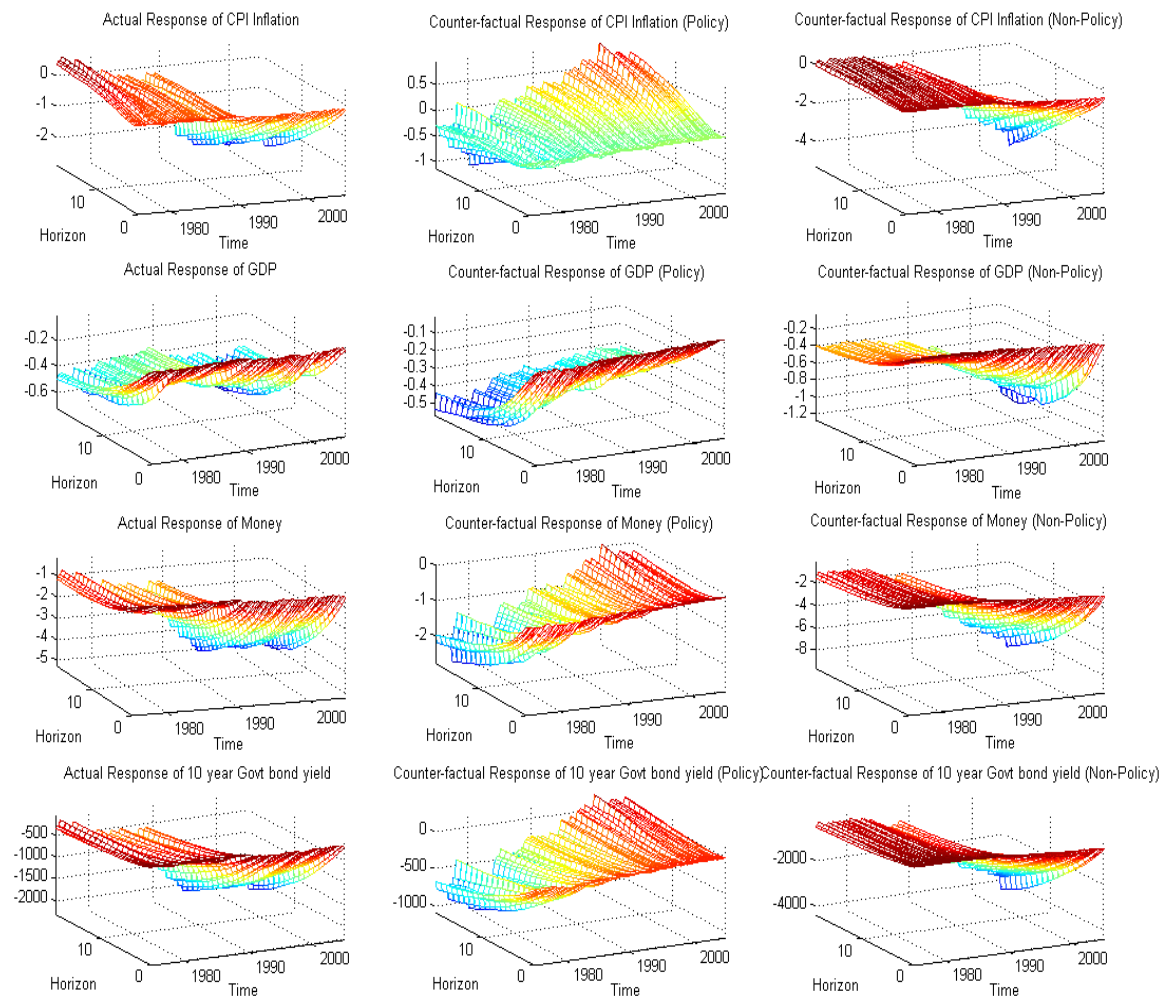


Figure 11: Impulse response to a monetary policy shock: actual and counterfactual.

than during the earlier period, again possibly reflecting the impact of the new monetary regime in anchoring inflation expectations.

3.3.4 A Counterfactual Experiment to Assess the Role of Monetary Policy

The estimated impulse response function reported above show significant time-variation in the responses of several key variables. The timing of these changes coincides with the onset of inflation targeting in the early 1990s and provides some prima facie evidence for the role played by policy. However, in order to explore this issue further, we use the estimated TVP-FAVAR to carry out a simple counterfactual experiment which aims to highlight the role of changes in the policy equation in driving the observed IRF shifts. The experiment involves the following steps: (a) denote the pre-1992 period sample1 and the post-1992 period sample2. For each Gibbs sampling replication we draw randomly from the lagged and contemporaneous coefficients and volatility associated with the transition equation of the model (equation 2) in sample 1. (b) we then consider two counterfactual paths for the

parameters of equation 2. In the first case the elements of the interest rate equation are fixed at all time periods at the value of the corresponding parameters drawn in step (a). In the second case, the elements of the non-interest rate equations are fixed at those drawn from sample 1. (c) using these counterfactual parameters we estimate the impulse response of key variables at each point in time. The aim is to compare these counterfactual impulse response functions with the actual estimates. If changes in the parameters of the FAVAR policy rule are important then the impulse response functions estimated under case 1 in step b should not be characterized by the shifts across time evident in the actual estimated responses. Similarly, if the change in the parameters of the non-policy block of the FAVAR is important, then the counterfactual impulse responses under case 2 should have a different time-path than the actual estimates.⁹

Figure 11 shows the main results. The left column of the figure shows the actual estimated (cumulated) response of inflation, GDP growth, M4 and the 10 year government bond yield. The middle panel shows the estimated response under the assumption that the parameters of the FAVAR policy rule are fixed at values prevailing in the pre-1992 period. The final column shows the estimated response under the scenario that the parameters of the non-policy equations are fixed at values prevailing in the pre-1992 period. It is immediately clear from the second column of the figure that once the policy rule is constrained at pre-1992 values, the changes seen in the magnitude of actual impulse responses post-1992 disappear. In particular, the counterfactual response of inflation, money and the bond yield *does not* increase in magnitude over the inflation targeting period which is in sharp contrast to the actual estimates. Note from the third column that this is not the case when the non-policy block of the FAVAR is constrained with the estimated responses showing a pattern very similar to the actual estimates. These results support the conclusion that the reported changes in impulse response functions are largely driven by changes in the parameters of the FAVAR policy rule.

Figure 12 provides further evidence along these lines. The figure shows the moments of the distribution of the impulse response of the consumption deflator (to a monetary policy shock) estimated under the counterfactual scenario that the parameters of the FAVAR policy rule are fixed at values prevailing in the pre-1992 period. In contrast to the estimates shown in figure 9, there is no shift in the median or the standard deviation of the distribution in the post-1992 period.

4 Forecast Error Variance Decomposition

In order to assess the relative importance of identified structural shocks, we calculate the time-varying forecast error variance decomposition. Figure 13 shows the median decompo-

⁹Notably, this experiment is not immune to the Lucas critique as we are unable to take into account the expectation effects of the assumed parameter changes.

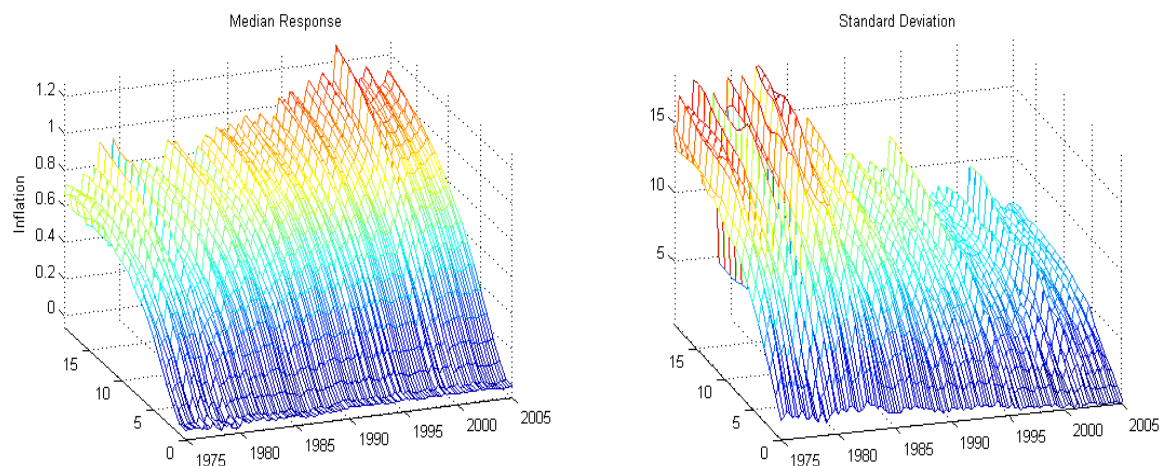


Figure 12: Changes in the distribution of the consumption deflator across time (counterfactual estimates).

sition for real activity indicators. Note that the X-axis of each panel represents the time-periods, the Y-axis is the horizon in quarters while the Z-axis is the contribution to the forecast error variance. The monetary policy shock makes an important contribution to real activity indicators during the 1980s and the 1990s. The demand shock is less important on average but contributes around 20% during the mid 1980s and the end of the sample period.

For inflation indicators (see figure 14) the demand shock contributes the most in the pre-inflation targeting period, (especially the 1980s) explaining about 30% to 40% of the forecast error variance of inflation indicators. Over the inflation targeting period, the contribution of this shock is less than 10%. In contrast, the monetary policy shock appears to contribute more to inflation measures during the mid-1980s and the early 1990s.

Figure 15 plots the time-varying variance decomposition for money and credit growth. It is interesting to note that the contribution of monetary policy shocks increases substantially after 1990 rising to around 60%. In contrast, demand shocks are more important during the 1970s and 1980s.

The monetary policy shock appears to be more important in terms of explaining the forecast error variance of the nominal exchange rate and the 10 year government bond yield after the 1990s (see figure 16). This shock explains about 60% of the forecast error variance of house prices and the FTSE during the 1980s and the 1990s. In contrast, the contribution of the demand shock to these asset prices is higher in the pre-1992 period, especially for house prices and the government bond yield.

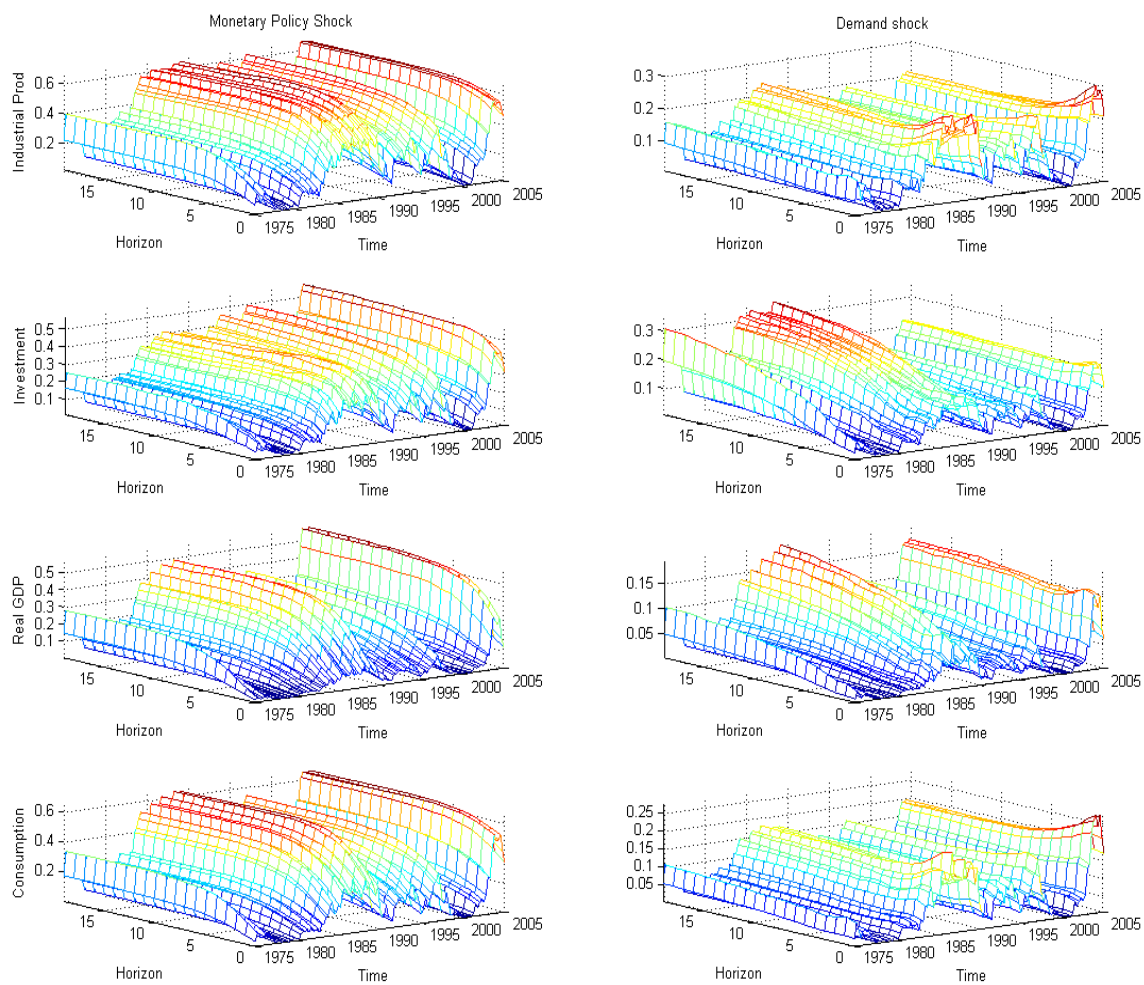


Figure 13: Forecast error variance decomposition of real activity indicators.

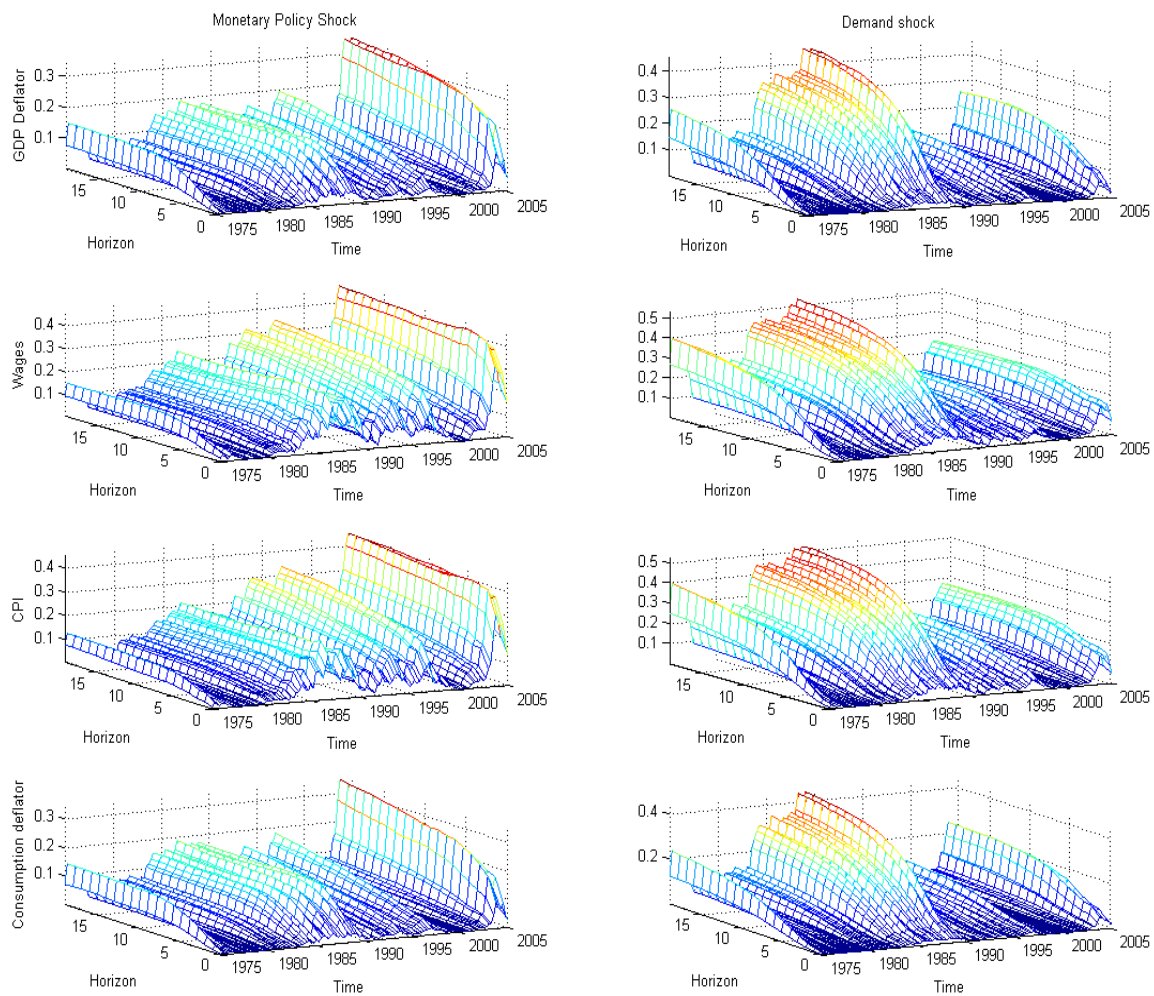


Figure 14: Forecast error variance decomposition of inflation measures.

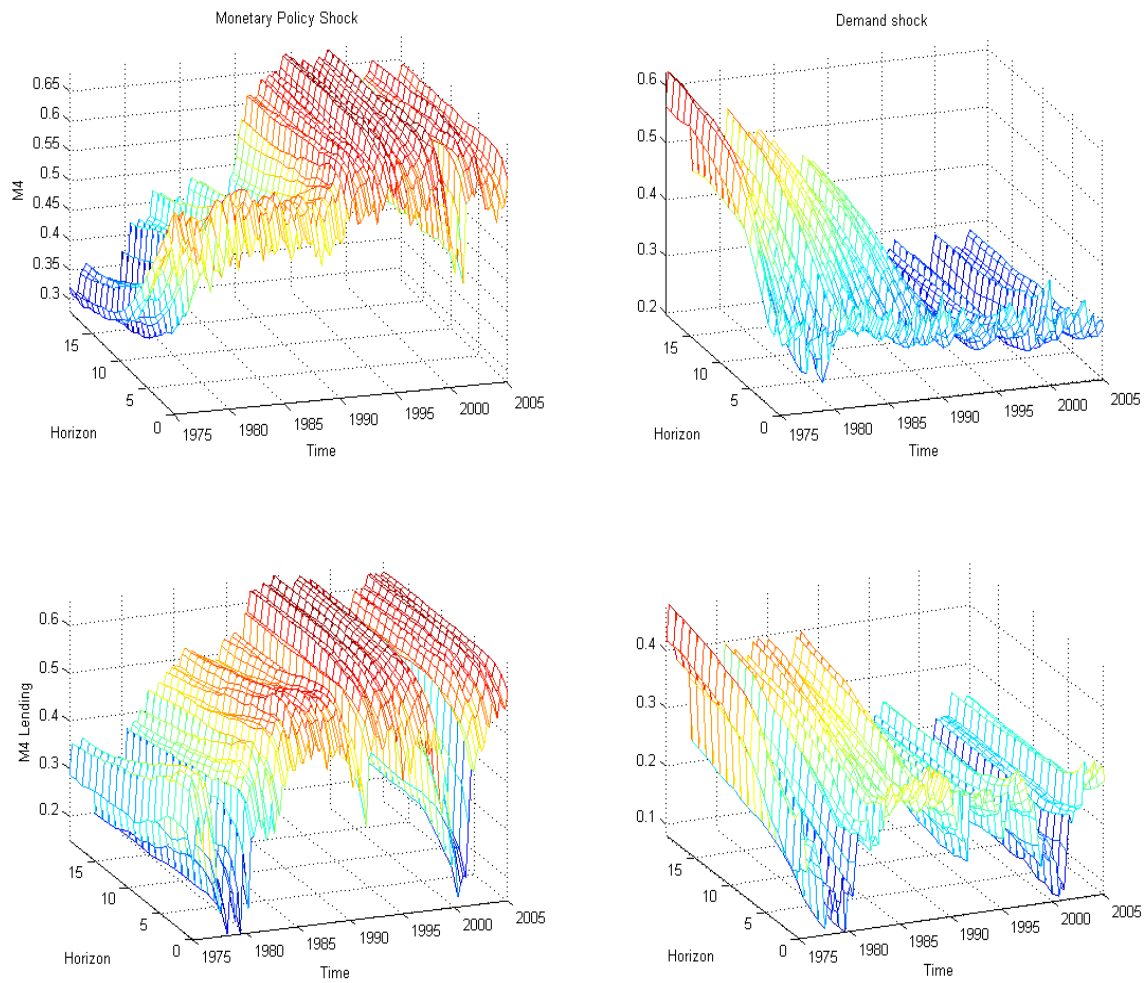


Figure 15: Forecast error variance decomposition of money supply measures.

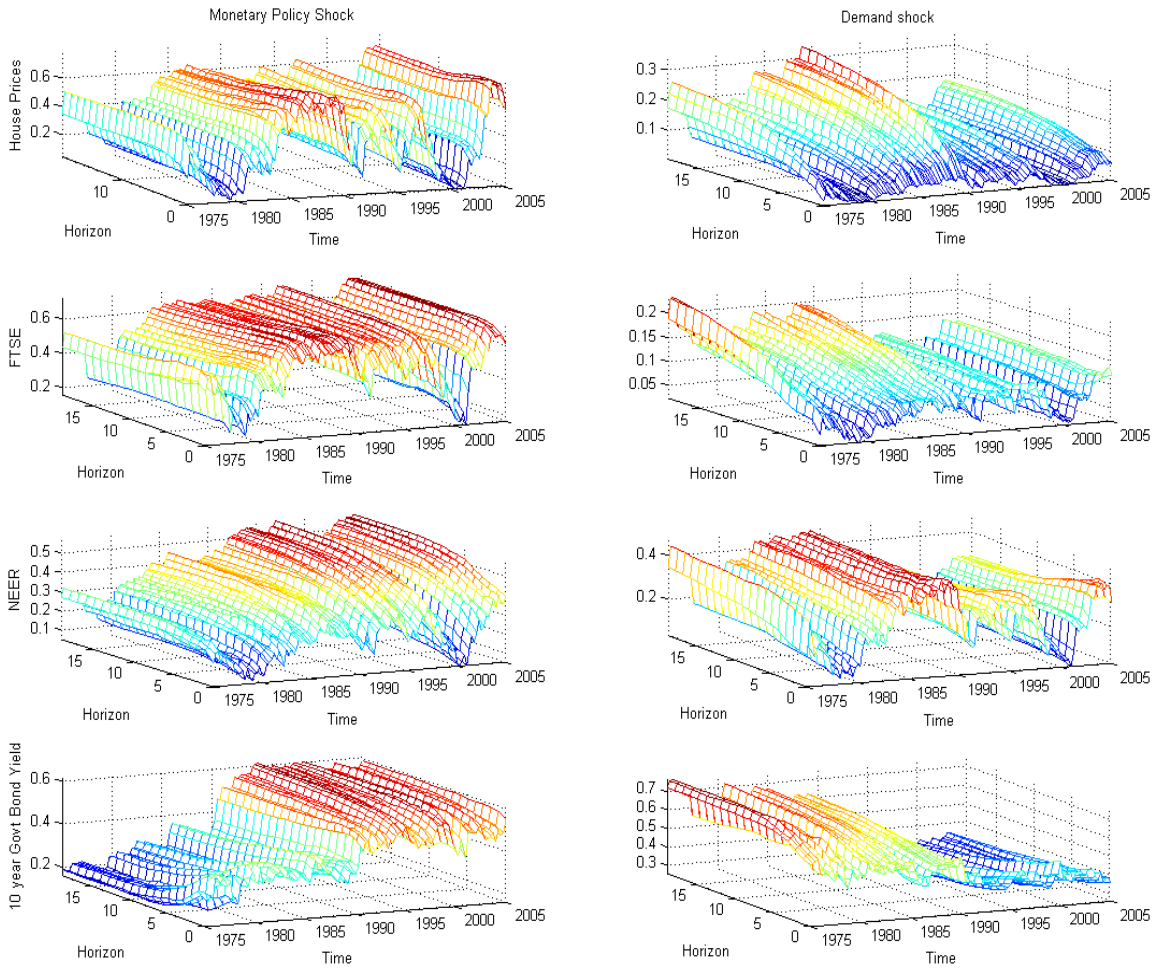


Figure 16: Forecast error variance decomposition of asset prices.

5 Conclusions

Our aim in this paper was to empirically study the evolving transmission of monetary policy and demand shocks in the UK. To this end, we estimated a novel, factor-augmented VAR with time-varying coefficients and shock volatility which made possible the simultaneous analysis of changing impulse responses of a large set of aggregate macroeconomic variables, disaggregated prices and quantities.

We documented that the impulse responses to UK monetary policy, and demand shocks have changed visibly over the last thirty years. Both the impulse responses and variance decompositions show that around the beginning of the nineties monetary policy shocks started having a bigger impact on prices and began contributing more to overall volatility. We also present evidence of changes in the response of asset prices and components of the consumption deflator – with the median reaction of the latter to contractionary policy shocks becoming more negative. Counterfactual experiments show that these changes are linked to changes in the parameters of the policy rule in our empirical model.

Our results suggest that time-variation should be taken seriously, which has clear implications for structural economic models. They also highlight a number of interesting links between the evolution of real and nominal variables and asset prices. While attempting to account for these links and for the way they change over time in a stochastic, dynamic, general-equilibrium framework is beyond the scope of this paper, we believe that it would be a worthwhile extension.

APPENDIX

A Priors and Estimation

Our time-varying FAVAR model consists of the following equations

$$\begin{pmatrix} X_{1,t} \\ \cdot \\ \cdot \\ X_{N,t} \\ R_t \end{pmatrix} = \begin{pmatrix} \Lambda^{11} & \Lambda^{21} & \Psi^{11} \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \Lambda^{1N} & \Lambda^{2N} & \Psi^{1N} \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} F_t^1 \\ F_t^2 \\ R_t \end{pmatrix} + \begin{pmatrix} e_{1t} \\ \cdot \\ \cdot \\ e_{Nt} \\ 0 \end{pmatrix} \quad (6)$$

$$Z_t = \sum_{l=1}^L \phi_{l,t} Z_{t-l} + v_t \quad (7)$$

with $Z_t = \{F_t^1, F_t^2, R_t\}$, L fixed at 2 and the coefficients ϕ assumed to evolve according to

$$\phi_t = \phi_{t-1} + \eta_t.$$

The covariance matrix of the innovations v_t is factored as

$$\text{VAR}(v_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})' \quad (8)$$

where the time-varying matrices H_t and A_t are given by

$$H_t \equiv \begin{bmatrix} h_{1,t} & 0 & 0 \\ 0 & h_{2,t} & 0 \\ 0 & 0 & h_{3,t} \end{bmatrix} \quad A_t \equiv \begin{bmatrix} 1 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 \end{bmatrix} \quad (9)$$

with the $h_{i,t}$ evolving as geometric random walks

$$\ln h_{i,t} = \ln h_{i,t-1} + \nu_t.$$

Following Primiceri (2005) we postulate that the non-zero and non-one elements of the matrix A_t evolve as driftless random walks

$$\alpha_t = \alpha_{t-1} + \tau_t \quad (10)$$

and we also assume that $[e_t', v_t', \eta_t', \tau_t', \nu_t']' \sim N(0, V)$ with

$$V = \begin{bmatrix} R & 0 & 0 & 0 & 0 \\ 0 & \Omega_t & 0 & 0 & 0 \\ 0 & 0 & Q & 0 & 0 \\ 0 & 0 & 0 & S & 0 \\ 0 & 0 & 0 & 0 & G \end{bmatrix} \quad \text{and} \quad G = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 \\ 0 & 0 & 0 & \sigma_4^2 \end{bmatrix}. \quad (11)$$

Bernanke *et al.* (2005) show that identification of the FAVAR model given by equations 6 and 7 requires putting some (in our case contemporaneous) restrictions on the matrix of factor loadings. Following their example we assume that the top $J \times J$ block of Λ is an identity matrix and the top $J \times M$ block of Ψ equals zero. The model is then estimated using a Gibbs sampling algorithm with the conditional prior and posterior distributions described below.

A.1 Prior Distributions and Starting Values

A.1.1 Factors and Factor Loadings

Following Bernanke *et al.* (2005) we center our prior on the factors (and obtain starting values) by using a principal components (PC) estimator applied to each $X_{i,t}$. In order to reflect the uncertainty surrounding the choice of starting values, a large prior covariance of the states ($P_{0/0}$) is assumed.

Starting values for the factor loadings are also obtained from the PC estimator after imposing the above restrictions. The priors on the diagonal elements of R are assumed to be inverse gamma

$$R_{ii} \sim IG(R_0, V_0).$$

where $R_0 = 0.01$ and $V_0 = 1$ denote the prior scale parameter and the prior degrees of freedom respectively.

A.1.2 VAR Coefficients

The prior for the VAR coefficients is obtained via a fixed coefficients VAR model estimated over the first 10 years of the sample using the principal component estimates of the factors. Accordingly, ϕ_0 is equal to

$$\phi_0 \sim N(\hat{\phi}^{OLS}, V)$$

where V equals 0.0001 times OLS estimates of the main diagonal of $var(\hat{\phi}^{OLS})$.

A.1.3 Elements of H_t

Let \hat{v}^{ols} denote the OLS estimate of the VAR covariance matrix estimated on the pre-sample data described above. The prior for the diagonal elements of the VAR covariance matrix (see equation 9) is as follows

$$\ln h_0 \sim N(\ln \mu_0, I_N)$$

where μ_0 are the diagonal elements of the Cholesky decomposition of \hat{v}^{ols} .

A.1.4 Elements of A_t

The prior for the off-diagonal elements of A_t is

$$A_0 \sim N\left(\hat{a}^{ols}, V\left(\hat{a}^{ols}\right)\right)$$

where \hat{a}^{ols} are the off-diagonal elements of \hat{v}^{ols} , with each row scaled by the corresponding element on the diagonal. The matrix $V(\hat{a}^{ols})$ is assumed to be diagonal with the diagonal elements set equal to 10 times the absolute value of the corresponding element of \hat{a}^{ols} .

A.1.5 Hyperparameters

The prior on Q is assumed to be inverse Wishart

$$Q_0 \sim IW(\bar{Q}_0, T_0)$$

where \bar{Q}_0 is assumed to be $\text{var}(\hat{\phi}^{OLS}) \times 10^{-4} \times 3.5$ and T_0 is the length of the sample used for calibration. The prior distribution for the blocks of S is also inverse Wishart

$$S_{i,0} \sim IW(\bar{S}_i, K_i)$$

where i indexes the blocks of S and \bar{S}_i is calibrated using \hat{a}^{ols} . Specifically, \bar{S}_i is a diagonal matrix with the relevant elements of \hat{a}^{ols} multiplied by 10^{-3} . Finally, following Cogley and Sargent (2005), we postulate an inverse-gamma distribution for the elements of G

$$\sigma_i^2 \sim IG\left(\frac{10^{-4}}{2}, \frac{1}{2}\right).$$

A.2 Simulating the Posterior Distributions

A.2.1 Factors and Factor Loadings

This closely follows Bernanke *et al.* (2005). Details can also be found in Kim and Nelson (1999).

Factors The distribution of the factors F_t is linear and Gaussian

$$\begin{aligned} F_{T \setminus X_{i,t}, R_t, \Xi} &\sim N(F_{T \setminus T}, P_{T \setminus T}) \\ F_t \setminus F_{t+1}, X_{i,t}, R_t, \Xi &\sim N(F_{t \setminus t+1, F_{t+1}}, P_{t \setminus t+1, F_{t+1}}) \end{aligned}$$

where $t = T - 1, \dots, 1$, the vector Ξ holds all other FAVAR parameters and

$$\begin{aligned} F_{T \setminus T} &= E(F_T \setminus X_{i,t}, R_t, \Xi) \\ P_{T \setminus T} &= \text{Cov}(F_T \setminus X_{i,t}, R_t, \Xi) \\ F_{t \setminus t+1, F_{t+1}} &= E(F_t \setminus X_{i,t}, R_t, \Xi, F_{t+1}) \\ P_{t \setminus t+1, F_{t+1}} &= \text{Cov}(F_t \setminus X_{i,t}, R_t, \Xi, F_{t+1}). \end{aligned}$$

In line with Carter and Kohn (1994) the simulation consists of several steps. First we use the Kalman filter to draw $F_{T \setminus T}$ and $P_{T \setminus T}$ and then proceed backwards in time using

$$F_{t|t+1} = F_{t|t} + P_{t|t} P_{t+1|t}^{-1} (F_{t+1} - F_t)$$

$$P_{t|t+1} = P_{t|t} - P_{t|t} P_{t+1|t}^{-1} P_{t|t}.$$

If more than one lag of the factors appears in the VAR model, this procedure has to be modified to take account of the fact that the covariance matrix of the shocks to the transition equation (used in the filtering procedure described above) is singular. For details see Kim and Nelson (1999).

Elements of R Following Bernanke *et al.* (2005) R is a diagonal matrix. The diagonal elements R_{ii} are drawn from the following inverse gamma distribution

$$R_{ii} \sim IG(\bar{R}_{ii}, T + V_0)$$

where

$$\bar{R}_{ii} = \hat{e}'_i \hat{e}_i + R_0$$

with \hat{e}_i denoting the residual $X_{it} - \Gamma_i F_{jt}$ where $\Gamma_i = \Lambda_i$ or $\Gamma_i = [\Lambda_i, \Psi]$ for the appropriate equation.

Elements of Λ and Ψ Letting $\Gamma_i = \Lambda_i$ or $\Gamma_i = [\Lambda_i, \Psi]$ for the appropriate equation, the factor loadings are sampled from

$$\Gamma_i \sim N(\bar{\Gamma}_i, R_{ii} \bar{M}_i^{-1})$$

where $\bar{\Gamma}_i = \bar{M}_i^{-1} (F'_{i,t} F_{i,t}) \hat{\Gamma}_i$, $\bar{M}_i = \bar{M}_0 + (F'_{i,t} F_{i,t})$ and $\hat{\Gamma}_i$ represents an OLS estimate and $\bar{M}_0 = I$.

A.2.2 Time-Varying VAR

Given an estimate of the factors, the model becomes a VAR with drifting coefficients and covariances. This type of specification has become fairly standard in the literature and details on the posterior distributions can be found in a number of papers including Cogley and Sargent (2005), Cogley *et al.* (2005) and Primiceri (2005). Accordingly, we only provide a summary of the estimation algorithm – referring to the references above for further details.

The Gibbs sampler cycles through the following steps:

1. Given initial values for the factors, the VAR parameters and hyperparameters are simulated.
 - As in the case of the unobserved factors the VAR coefficients ϕ_t and the off-diagonal elements of the covariance matrix α_t are simulated using the methods described in Carter and Kohn (1994). In particular, given a draw for ϕ_t the VAR model can be written as

$$A'_t (\tilde{Z}_t) = u_t$$

where $\tilde{Z}_t = Z_t - \sum_{l=1}^L \phi_{l,t} Z_{t-l} = v_t$ and $VAR(u_t) = H_t$. This is a system of equations

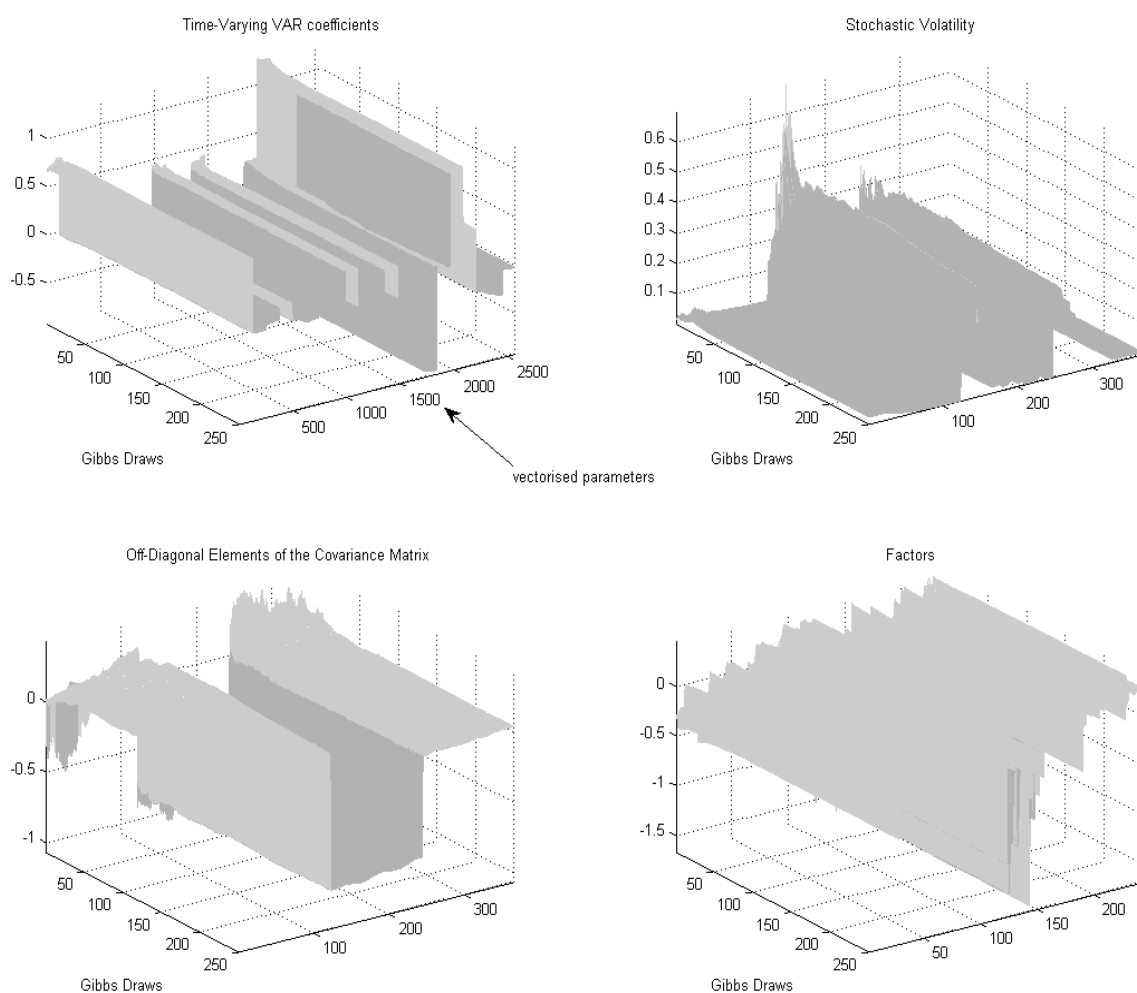
with time-varying coefficients and so, given a block diagonal form for $Var(\tau_t)$, the standard methods for state space models can be applied.

- Following Cogley and Sargent (2005), the volatilities of the reduced form shocks H_t are drawn using the date by date blocking scheme introduced in Jacquier *et al.* (2002).
 - The hyperparameters are drawn from their respective distributions. Conditional on Z_t , $\phi_{l,t}$, H_t , and A_t , the innovations to $\phi_{l,t}$, H_t , and A_t are observable, which allows us to draw the hyperparameters—the elements of Q , S , and the σ_i^2 —from their respective distributions.
2. Given initial values for the factors, the factor loadings Λ and Ψ and the variances of the idiosyncratic components are drawn.

- Given data on R_t and $X_{i,t}$ standard results for regression models can be used and the coefficients and the variances are simulated from a normal and inverse gamma distribution.
3. Finally, the factors are simulated given all the other parameters.
 - This is done in a straightforward way by employing the methods described in Bernanke *et al.* (2005) and Kim and Nelson (1999).
 4. Go to step 1.

A.3 Convergence

We use 55,000 iterations in this MCMC algorithm discarding the first 45,000 as burn-in. The figure below shows the recursive means of the retained draws. These show limited fluctuations providing some evidence of convergence.



A.4 Particle Filter to Evaluate the Likelihood for the TVP-FAVAR

An excellent detailed description of particle filtering and its application to macroeconomic models can be found in Fernandez-Villaverde and Rubio-Ramirez (2008) and the references

cited therein. Below we provide a brief description of the filter as applied to our FAVAR model.

Consider the distribution of the state variables (i.e. the time-varying coefficients, stochastic volatilities and the factors) in the Time-Varying FAVAR model denoted Φ_t conditional on information up to time t (denoted by z_t)

$$f(\Phi_t \setminus z_t) = \frac{f(X_t, \Phi_t \setminus z_{t-1})}{f(X_t \setminus z_{t-1})} = \frac{f(X_t \setminus \Phi_t, z_{t-1}) \times f(\Phi_t \setminus z_{t-1})}{f(X_t \setminus z_{t-1})}. \quad (12)$$

Equation 12 says that this density can be written as the ratio of the joint density of the data and the states $f(X_t, \Phi_t \setminus z_{t-1}) = f(X_t \setminus \Phi_t, z_{t-1}) \times f(\Phi_t \setminus z_{t-1})$ and the likelihood function $f(X_t \setminus z_{t-1})$ where the latter is defined as

$$f(X_t \setminus z_{t-1}) = \int f(X_t \setminus \Phi_t, z_{t-1}) \times f(\Phi_t \setminus z_{t-1}) d\Phi_t. \quad (13)$$

Note also that the conditional density $f(\Phi_t \setminus z_{t-1})$ can be written as

$$f(\Phi_t \setminus z_{t-1}) = \int f(\Phi_t \setminus \Phi_{t-1}) \times f(\Phi_{t-1} \setminus z_{t-1}) d\Phi_{t-1}. \quad (14)$$

These equations suggest the following filtering algorithm to compute the likelihood function:

1. Given a starting value $f(\Phi_0 \setminus z_0)$ calculate the predicted value of the state

$$f(\Phi_1 \setminus z_0) = \int f(\Phi_1 \setminus \Phi_0) \times f(\Phi_0 \setminus z_0) d\Phi_0$$

2. Update the value of the state variables based on information contained in the data

$$f(\Phi_1 \setminus z_1) = \frac{f(X_1 \setminus \Phi_1, z_0) \times f(\Phi_1 \setminus z_0)}{f(X_1 \setminus z_0)}$$

where $f(X_1 \setminus z_0) = \int f(X_1 \setminus \Phi_1, z_0) \times f(\Phi_1 \setminus z_0) d\Phi_1$ is the likelihood for observation 1. By repeating these two steps for observations $t = 1 \dots T$ the likelihood function of the model can be calculated as $\ln lik = \ln f(X_1 \setminus z_0) + \ln f(X_2 \setminus z_1) + \dots \ln f(X_T \setminus z_{T-1})$.

In general, this algorithm is inoperable because the integrals in the equations above are difficult to evaluate. The particle filter makes the algorithm feasible by using a Monte-Carlo method to evaluate these integrals. In particular, the particle filter approximates the conditional distribution $f(\Phi_1 \setminus z_0)$ via M draws or particles using the transition equation of the FAVAR model. For each draw of the state variables the conditional likelihood $W^m = f(X_1 \setminus z_0)$ is evaluated. Conditional on the draw for the state variables, the predicted value for the variables \hat{X}_{i1}^M can be computed using the observation equation and the prediction error decomposition is used to evaluate the likelihood W^m . The update step involves a draw from the density $f(\Phi_1 \setminus z_1)$. This is done by sampling with replacement from the sequence of particles with the re-sampling probability given by $\frac{W^m}{\sum_{m=1}^M W^m}$. This re-sampling step updates the draws for Φ based on information contained in the data for that time period. By the law of large numbers the likelihood function for the observation can be approximated as $\ln lik_t = \ln \frac{\sum_{m=1}^M W^m}{M}$.

B Dataset

The full list of the 350 data series, along with their FAME codes, is presented below. This appendix provides an overview of the dataset. The dataset contains data on real activity and inflation. We also include some indicators of money and key asset prices. As shown in the table below we take the first log difference of non-stationary series.

Real activity data includes real GDP, industrial production (with a broad sectoral breakdown), imports and exports, investment and real household consumption expenditure. The dataset includes a very detailed sectoral breakdown of consumption quantities. The data is obtained from the Office of National Statistics (ONS).

Inflation data includes the main price indices (GDP deflator, CPI, RPI and RPIX) and components of the consumption deflator. ONS and the Bank of England are the main sources for the data.

Money data for the U.K. includes M0 and M4, with a sectoral breakdown of the latter. This data is obtained from the Bank of England.

The asset price data includes house prices, stock prices, exchange rates (pounds in terms of US dollars, Euros, Yen, Canadian and Australian Dollars) and the term structure of interest rates. The data are obtained from the Global Financial Database and the Bank of England.

NR	FAME CODE	SERIES NAME
	log-diff. unless otherwise stated	
1	NMRY	General Government: Final consumption expenditure
2	GDQB	ESA95 Output Index: F: Construction:
3	IKBK	Balance of Payments: Trade in Goods & Services: Total exports
4	IKBL	Balance of Payments: Imports: Total Trade in Goods & Services
5	NPQT	Total Gross Fixed Capital Formation
6	ABMI	Gross Domestic Product: chained volume measures
7	CKYY	IOP: Industry D: Manufacturing: CVMSA NAYear
8	GDQH	SA95 Output Ind.: I : Transport storage & communication
9	GDQS	SA95 Output Ind.: G-Q: Total
10	GDQE	ESA95 Output Ind.: G & H: Distrib., hotels & catering; repairs
11	CKYW	IOP: Industry C,D,E: All production industries
12	CKYZ	IOP: Industry E: Electricity, gas and water supply:
13	CKZA	IOP: Industry DA: Manuf of food, drink & tobacco
14	CKZF	IOP: Industry DF: Manuf coke/petroleum prod/nuclear fuels
15	CKZG	IOP: Industry DG: Manuf of chemicals & man-made fibres
16	ABJR	Household final consumption expenditure
17	NPEL	Business investment
Household final consumption expenditure:durable goods (volumes)		
18	UTID	Total
19	LLKX	All furnishing & household
20	ATQX	Furniture and households
21	ATRD	Carpets and other floor coverings
22	XYJP	Major household appliances
23	XYJR	Major tools and equipment
24	LLKY	All Health
25	UWIC	Therapeutic appliances and equipment

26	LLKZ	All Transport
27	TMMI	All Purchase of vehicles
28	TMML	Motor Cars
29	TMMZ	Motor cycles
30	TMNO	Bicycles
31	LLLA	All Communication
32	ATRR	Telephone and telefax equipment
33	LLLB	All recreation and culture
34	ATRV	Audio visual equipment
35	ATRZ	Photo and cinema equip and optical instruments
36	ATSD	Information processing equipment
37	TMNB	Major durables for outdoor recreation
38	XYJT	Musical instruments and major durables for indoor recreation
39	LLLC	All miscellaneous
40	ZAYM	Jewelery, clocks and watches
Household final consumption expenditure: semi-durable goods (volumes)		
41	UTIT	Total
42	LLLZ	All clothing and footwear
43	XYJN	Clothing materials
44	ZAVK	Garments
45	XYJO	Other articles of clothing and clothing accessories
46	ATQV	Shoes and other footwear
47	LLMA	All furnishings and household goods
48	ATRF	Household textiles
49	XYJQ	Small electric household appliances
50	ATRJ	Glassware, tableware and household utensils
51	XYJS	Small tools and miscellaneous accessories
52	LLMB	All transport
53	AWUW	Motor vehicle spares
54	LLMC	All recreation and culture
55	ATSH	Recording media
56	ATSL	Games, toys and hobbies
57	XYJU	Equipment for sport, camping etc
58	CDZQ	Books
59	LLMD	All miscellaneous
60	XYJX	Electrical appliances for personal care
61	ATSX	Other personal effects
Household final consumption expenditure: non-durable goods (volumes)		
62	UTIL	Total
63	ZWUN	All food and non-alcoholic beverages
64	UWBK	All food
65	UWBL	Bread and cereals
66	CCTK	Meat
67	CCTL	Fish
68	CCTM	Milk, cheese and eggs
69	CCTN	Oils and fats
70	CCTO	Fruit
71	UWFD	Vegetables
72	UWFX	Sugar and sweet products

73	UWGH	Food products n.e.c.
74	UWGI	All non-alcoholic beverages
75	CCTT	Coffee, tea and cocoa
76	CCTU	Mineral, water and soft drinks
77	ZAKY	All alcoholic beverages and tobacco
78	UUIS	Spirits
79	UTHW	Wine, cider and sherry
80	UUVG	Beer
81	ZWUP	Tobacco
82	LLLL	All Housing, water, electricity, gas and other fuels
83	ATUA	Materials for the maintenance and repair of the dwelling
84	UTZN	Water supply
85	ZWUR	All electricity, gas and other fuels
86	CCUA	Electricity
87	LTZA	Gas
88	LTZC	Liquid fuels
89	TTAB	Solid fuels
90	LLLM	All furnishing and household goods
91	UWHO	Non-durable household goods
92	LLLN	All health
93	UTXP	Pharmaceutical products
94	UWIB	Other medical products
95	LLLO	All transport
96	CCTY	Vehicle fuels and lubricants
97	LLLP	All recreation and culture
98	AWUX	Gardens, plants and flowers
99	UWKQ	Pets and related products
100	CDZY	Newspapers and periodicals
101	XYJV	Miscellaneous printed matter
102	XYJW	Stationery and drawing materials
103	LLLQ	All miscellaneous
104	ATSP	Other products for personal care
Household final consumption expenditure: services (volumes)		
105	UTIP	Total
106	LLLR	All clothing and footwear
107	UWHI	Clothing, repair and hire of clothing
108	AWUY	Repair and hire of footwear
109	LLLS	All housing, water, electricity, gas and other fuels
110	ZAVQ	All actual rentals for housing
111	GBFG	Actual rentals paid by tenants
112	GBFK	All imputed rentals for housing
113	CCUO	Imputed rentals of owner-occupiers
114	GBFN	Other imputed rentals
115	AWUZ	Services for the maintenance and repair of the dwelling
116	UWHK	Refuse collection
117	UTZX	Sewerage collection
118	LLLT	All furnishings and household services
119	UWHM	Repair of furniture, furnishings and floor coverings
120	UWHN	Repair of household appliances

121	UWIA	Domestic and household services
122	LLLU	All health
123	ZAWG	All out-patient services
124	ZAWI	Medical services
125	ZAWK	Dental services
126	UTMH	Paramedical services
127	UTYF	Hospital services
128	LLLV	Total transport
129	AWVA	Vehicle maintenance and repair
130	ZAWQ	Other vehicle services
131	ZAWS	All transport services
132	AWVB	Railways
133	ZAWU	Road
134	AWVC	Air
135	AWVD	Sea and inland waterway
136	AWVE	Other
137	LLLW	All communication
138	CCVM	Postal services
139	ZAWY	Telephone and telefax services
140	LLLX	All recreation and culture
141	UWKO	Repair of audio-visual, photo and information processing equip.
142	UWKP	Maintenance of other major durables for recreation and culture
143	UWLD	Veterinary and other services for pets
144	ZAXI	All recreational and cultural services
145	ZAXK	Recreational and sporting services
146	ZAXM	Cultural services
147	CCVA	Games of chance
148	ZWUT	Education
149	ZAXS	All restaurants and hotels
150	ZAXU	All catering services
151	ZAXW	Restaurants, cafes etc.
152	ZAYC	Canteens
153	ZAYE	Accommodation services
154	LLLY	All miscellaneous
155	CCVZ	Hairdressing salons and personal grooming establishments
156	ZAYO	Social protection
157	ZAYQ	All insurance
158	UTYH	Life insurance
159	ZAYS	Insurance connected with the dwelling
160	ZAYU	Insurance connected with health
161	ZAYW	Insurance connected with transport
162	ZAZA	All financial services n.e.c.
163	ZAZC	All financial services other than FISIM
164	ZAZE	Other services n.e.c.
DEFLATORS		
165	FRAH	RPI Total Food
166	FRAI	RPI Total Non-Food
167	FRAK	RPI Total All items other than seasonal Food
168	ROYJ	Wages

169	YBGB	GDP deflator
170		CPI
171	ABJS	CONSUMPTION
172	IMF data	Import prices
173	IMF data	Export prices
Household final consumption expenditure: durable goods (deflators)		
174	UTKT	Total
175	LLOS	All furnishing & household
176	AWQK	Furniture and households
177	AWQL	Carpets and other floor coverings
178	AWQN	Major household appliances
179	AWQQ	Major tools and equipment
180	LLOT	All Health
181	AWQW	Therapeutic appliances and equipment
182	LLOU	All Transport
183	UTPP	All Purchase of vehicles
184	AWRA	Motor Cars
185	AWRB	Motor cycles
186	AWRC	Bicycles
187	LLOV	All Communication
188	UTPT	Telephone and telefax equipment
189	LLOW	All recreation and culture
190	AWRM	Audio visual equipment
191	AWRN	Photo and cinema equip and optical instruments
192	AWRO	Information processing equipment
193	AWRR	Major durables for outdoor recreation
194	AWRS	Musical instruments and major durables for indoor recreation
195	LLOX	All miscellaneous
196	AWSL	Jewelery, clocks and watches
Household final consumption expenditure: semi-durable goods (deflators)		
197	UTLB	Total
198	LLPU	All clothing and footwear
199	AWPP	Clothing materials
200	AWPQ	Garments
201	AWPR	Other articles of clothing and clothing accessories
202	AWPT	Shoes and other footwear
203	LLPV	All furnishings and household goods
204	UTPH	Household textiles
205	AWQO	Small electric household appliances
206	UTPJ	Glassware, tableware and household utensils
207	AWQR	Small tools and miscellaneous accessories
208	LLPW	All transport
209	AWRD	Motor vehicle spares
210	LLPX	All recreation and culture
211	AWRP	Recording media
212	AWRU	Games, toys and hobbies
213	AWRV	Equipment for sport, camping etc
214	AWSC	Books
215	LLPY	All miscellaneous

216	AWSJ	Electrical appliances for personal care
217	AWSM	Other personal effects
Household final consumption expenditure: non-durable goods (deflators)		
218	UTKX	Total
219	UTJO	All food and non-alcoholic beverages
220	UTOV	All food
221	AWPB	Bread and cereals
222	AWPC	Meat
223	AWPD	Fish
224	AWPE	Milk, cheese and eggs
225	AWPF	Oils and fats
226	AWPG	Fruit
227	AWPH	Vegetables
228	AWPI	Sugar and sweet products
229	AWPJ	Food products n.e.c.
230	UTOW	All non-alcoholic beverages
231	AWPK	Coffee, tea and cocoa
232	AWPL	Mineral, water and soft drinks
233	UTJP	All alcoholic beverages and tobacco
234	AWPM	Spirits
235	AWPN	Wine, cider and sherry
236	AWPO	Beer
237	UTOY	Tobacco
238	LLPG	All Housing, water, electricity, gas and other fuels
239	AWPZ	Materials for the maintenance and repair of the dwelling
240	AWQB	Water supply
241	UTPF	All electricity, gas and other fuels
242	AWQF	Electricity
243	AWQG	Gas
244	AWQH	Liquid fuels
245	AWQI	Solid fuels
246	LLPH	All furnishing and household goods
247	AWQS	Non-durable household goods
248	LLPI	All health
249	AWQU	Pharmaceutical products
250	AWQV	Other medical products
251	LLPJ	All transport
252	AWRE	Vehicle fuels and lubricants
253	LLPK	All recreation and culture
254	AWRW	Gardens, plants and flowers
255	AWRX	Pets and related products
256	AWSD	Newspapers and periodicals
257	AWSJ	Stationery and drawing materials
258	LLPL	All miscellaneous
259	AWSK	Other products for personal care
Household final consumption expenditure: services (deflators)		
260	UTKZ	Total
261	LLPM	All clothing and footwear
262	AWPS	Clothing, repair and hire of clothing

263	AWPU	Repair and hire of footwear
264	LLPN	All housing, water, electricity, gas and other fuels
265	AWPV	All actual rentals for housing
266	AWPV	Actual rentals paid by tenants
267	UTPC	All imputed rentals for housing
268	AWPX	Imputed rentals of owner-occupiers
269	AWPY	Other imputed rentals
270	AWQA	Services for the maintenance and repair of the dwelling
271	AWQD	Sewerage collection
272	LLPO	All furnishings and household services
273	AWQM	Repair of furniture, furnishings and floor coverings
274	AWQP	Repair of household appliances
275	AWQT	Domestic and household services
276	LLPP	All health
277	UTPN	All out-patient services
278	AWQX	Medical services
279	AWQY	Dental services
280	AWQZ	Paramedical services
281	UTPO	Hospital services
282	LLPQ	Total transport
283	AWRF	Vehicle maintenance and repair
284	AWRG	Other vehicle services
285	UTPR	All transport services
286	AWRH	Railways
287	AWRI	Road
288	AWRJ	Air
289	AWRK	Sea and inland waterway
290	AWRL	Other
291	LLPR	All communication
292	UTPS	Postal services
293	UTPU	Telephone and telefax services
294	LLPS	All recreation and culture
295	AWRQ	Repair of audio-visual, photo and information processing equip.
296	AWRY	Veterinary and other services for pets
297	UTPY	All recreational and cultural services
298	AWRZ	Recreational and sporting services
299	AWSA	Cultural services
300	AWSB	Games of chance
301	UTJX	Education
302	UTJY	All restaurants and hotels
303	UTQG	All catering services
304	AWSG	Restaurants, cafes etc.
305	AWSH	Canteens
306	UTQH	Accommodation services
307	LLPT	All miscellaneous
308	AWSI	Hairdressing salons and personal grooming establishments
309	UTQK	Social protection
310	UTQL	All insurance
311	AWSN	Life insurance

312	AWSO	Insurance connected with the dwelling
313	AWSP	Insurance connected with health
314	AWSQ	Insurance connected with transport
315	UTQM	All financial services n.e.c.
316	AWSS	All financial services other than FISIM
317	UTQN	Other services n.e.c.
MONEY SERIES		
318	M4SA	M4 deposits Total
319	M4ISA	M4 deposits PNFCs
320	M4OSA	M4 deposits OFCs
321	M4PSA	M4 deposits Households
322	M4LISA	M4 lending Total
323	M4LOSA	M4 lending PNFCs
324	M4LPSA	M4 lending Households
ASSET PRICES		
325		Real Nationwide house prices
326		UK FT-Actuaries Dividend Yield (w/GFD extension)
327		UK FT-Actuaries PE Ratio (w/GFD extension)
328	GFD data	FTSE ALL Share Index
329	IMF data	NEER
330	GFD data	pounds/dollar
331	GFD data	pounds/euro
332	GFD data	pounds/yen
333	Global fin. data	pounds/canadian dollar
334	Global fin. data	pounds/australian dollar
335	non-transformed	Bond Yield 6 Months
336	non-transformed	Bond Yield 9 Months
337	non-transformed	Bond Yield 12 Months
338	non-transformed	Bond Yield 15 Months
339	non-transformed	Bond Yield 18 Months
340	non-transformed	Bond Yield 21 Months
341	non-transformed	Bond Yield 24 Months
342	non-transformed	Bond Yield 30 Months
343	non-transformed	Bond Yield 36 Months
344	non-transformed	Bond Yield 48 Months
345	non-transformed	Bond Yield 60 Months
346	non-transformed	Bond Yield 72 Months
347	non-transformed	Bond Yield 84 Months
348	non-transformed	Bond Yield 96 Months
349	non-transformed	Bond Yield 108 Months
350	non-transformed	Bond Yield 120 Months

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