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A NEW LOOK USING THE LIVINGSTON SURVEY**

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The changing role of expectations in US monetary policy: A new look using the Livingston Survey

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Abstract

Using a Bayesian structural vector autoregression (TVP-SVAR) with time-varying parameters and volatility we investigate monetary policy in the United States, in particular its interaction with the formation of inflation expectations and the linkages between monetary policy, inflation expectations and the behaviour of CPI inflation. We use Livingston Survey data for expected inflation, measured at a bi-annual frequency, actual inflation, unemployment and a nominal interest rate to estimate the VAR and show the significant changes that have occurred in the responses of these variables to monetary policy shocks or to shocks to expected and actual inflation. In so doing, we generalize the analysis undertaken by Leduc, Sill and Stark (2007) to allow for a more nuanced and detailed look at questions such as the impact of different chairmanship regimes at the Federal Reserve Board, the role of good policy versus good luck, and second round inflation effects. While some of the questions asked have a relatively long history, the methods used to undertake our investigations are very new, and the time-varying structure allows us to offer a more detailed picture. In using these methods we also undertake a substantial technical discussion to unearth the appropriateness of the TVP-SVAR models hitherto estimated in the literature, in particular the role of the choice of priors in determining the outcome of the estimations. As we discuss in the paper, this is an important issue which has remained rather hidden in the discussions surrounding the estimation of TVP-SVARs, yet may have a substantially important role to play in determining the results obtained.

JEL classification: E52;E31;C32

Keywords: monetary policy, expectations, inflation, time variation, VARs, impulse responses

Résumé

A l'aide d'un modèle VAR structurel bayésien (TVP-SVAR) avec paramètres et volatilité dynamiques, nous étudions la politique monétaire aux États-Unis, en particulier ses interactions avec la formation des anticipations d'inflation et les liens entre politique monétaire, anticipations d'inflation et la dynamique de l'inflation (CPI). Pour cela, nous utilisons les sources de l'enquêtes Livingston pour les anticipations d'inflation mesurées à une fréquence semestrielle, l'indice d'inflation, le chômage et un taux d'intérêt nominal pour estimer le modèle VAR. Nous montrons les changements significatifs qui se sont produits dans les réponses de ces variables aux chocs de politique monétaire ou encore aux chocs sur l'inflation ou ses anticipations. De cette façon, nous généralisons l'analyse réalisée par Leduc, Sill et Stark (2007) afin d'avoir une vision plus nuancée et détaillée sur des questions comme l'impact des différents régimes de gouvernance de président la FED, le rôle d'une politique active ou aléatoire (good policy vs good luck) et les effets inflationnistes de second tour. Bien que certaines des questions étudiées ici soient relativement classiques, les méthodes utilisées sont nouvelles et la structure dynamique nous permet d'y répondre plus précisément. En utilisant ces méthodes, nous soulevons une question technique pour mettre au jour la pertinence des modèles TVP-SVAR estimés jusqu'à présent dans la littérature, et en particulier le rôle des choix des priors dans la détermination des résultats de ces estimations. Comme il est indiqué dans le papier, il s'agit d'une question cruciale qui a été relativement peu discutée dans les débats portant sur l'estimation des ces modèles TVP-SVAR et qui pourrait influencer des résultats.

JEL classification: E52;E31;C32

Mot-clefs: politique monétaire, anticipations, inflation, variation temporelle, VARs, réponse impulsion

1 Introduction

In recent years, a very large literature has developed on the causes of the ‘Great Inflation’, and the ‘Great Moderation’ which followed, in the United States and possibly in other advanced OECD economies. Within this literature, attention has focused on (i) the impact of monetary policy, and of its change, on economic outcomes such as the behaviour of actual inflation, expectations of inflation, and unemployment; (ii) the role of supply shocks in affecting actual and expected inflation; and (iii) the possibility of second-round inflation effects.

In this connection the literature on the United States includes Leduc, Sill and Stark (2007), Mankiw (2001) and Romer and Romer (2004b), who have looked specifically at linking the behaviour of inflation, to the conduct of monetary policy under different chairmanship regimes of the Federal Reserve Board. For example, the pre-Volcker/post-Volcker dichotomy has been the subject of some scrutiny (see Federal Reserve Board of St Louis publication to celebrate 25th anniversary of October 1979 meeting held by Paul Volcker) with the pre-Volcker period, especially in the 1970’s, being associated by many as having been characterized by accommodative and inflationary monetary policy while the post-Volcker years are associated with responsible monetary policy and low volatility in inflation and output.

The paper by Leduc et al. (2007) is the one most closely related to our paper. Their objective is to use semi-annual data on expectations (as taken directly from the Livingston Survey) to examine if monetary policy reactions to movements in expected inflation contributed to the high inflation in the 1970’s and to the moderation following Volcker. Their methodology is to estimate time-invariant structural vector autoregressions (SVARs) on two sub-samples (1952:1-1979:1 and 1979:2-2001:1) of the data to show (using impulse-responses) that pre-1979, shocks to expected inflation had permanent effects on actual inflation. These did not seem to appear post-1979.

They also find that oil and fiscal shocks do not appear to trigger increases in expected inflation that eventually result in higher actual inflation. Significantly, they also argue that the contribution of monetary policy shocks to the variability of inflation is dwarfed by the importance of inflation expectations. In fact in a variance decomposition analysis their results show remarkably little role for monetary policy shocks (as measured by shocks to the interest rate variable) either pre- or post-1979. Instead, expectations of inflations and responses to these are by far the primary drivers.

Their system consists of $(\pi^e, \pi, pcom, u, r)$ where r , the 3-month nominal T-bill rate (r) is initially ordered last in the SVAR to reflect the idea that the Federal Reserve Board can freely adjust the interest rate in response to contemporaneous movements of all the other variables in the system.

Expected inflation π^e by contrast, in this ordering, is first to reflect the idea that this is pre-determined in the data since agents when formulating expectations do not have accurate knowledge of the forward behaviour of inflation or the likely responses of the policy makers. π is actual inflation, while $pcom$ is an index of commodity prices and u is unemployment.

The series are biannual to match the frequency at which expectations data are available from the Livingston survey. Later in their paper, Leduc et al. (2007) also consider an alternative ordering $(\pi, pcom, \pi^e, u, r)$ to allow for endogeneity in the formation of π^e .

The estimation is conditioned on dummies to account for either oil shocks or fiscal shocks, although neither of these variables is found to be important.

An important question to ask at the beginning of our paper concerns how we differ from Leduc et al. (2007) and, more importantly, how our more flexible approach allows us to consider questions not permitted by the discrete division of the sample into two discrete and essentially ad hoc sub-periods. Our approach is to estimate Bayesian time-varying SVARs (TVP-SVAR), building on techniques due to Primiceri (2005) and Nakajima (2011) (see also Cogley and Sargent,

2005 and Koop and Korobilis, 2010). The flexibility reveals itself in allowing for time variation in the estimation of the parameters throughout the sample and by incorporating time-varying volatility (as modelled by stochastic volatility in the structural shocks) in the estimation. After all, a key feature of the Great Moderation, as opposed to what preceded it (and what may have followed it), was a dramatic reduction in volatility of the behaviour of the key variables of the macroeconomy.

Our decision to use a time-varying framework is also motivated by a much more ambiguous reading of the economic record of the conduct of monetary policy in the United States. In particular, we feel that to take 1979:2 as a cut-off and to estimate two time-invariant SVARs is too restrictive an approach for several reasons.

First, the ostensible reason for the choice of this break date is to mark the change in monetary policy making that occurred with the appointment of Volcker in 1979. But the likely impact of chairmanship appointments may be anticipated significantly before the selected candidate takes up the position and agents in the economy may adjust their behaviour pre-appointment, especially if the change is believed to be a credible one. Note for example that Romer and Romer (2004b) argue that the likely behaviour of Federal Reserve Board chairmen can be anticipated from their pronouncements and writings, and a reading of their past record should form an essential part of the screening process for the appointment of chairmen.

Second, practice may vary even within the regime of a particular Federal Reserve Board chairman (for example see the discussion in Romer and Romer, 2004b, Mankiw, 2001 or Friedman, 2006, of the different chair regimes, in particular Volcker and Greenspan and their adherence (or otherwise) to money targeting or interest rate targeting). Thus how different the monetary policy regimes actually were, not only in pronouncements but also in effect, becomes much less clear once allowance is made for all the changes within regimes.

Third, not much attention is paid, at least in the estimation to the role of good luck versus good policy, although this is a recurring argument and one that Leduc et al. (2007) are careful to try to address. A properly time-varying framework is able to control continuously for changing economic circumstance.

Fourth, we are able ask if the finding of relative ineffectiveness of monetary policy (which is a somewhat surprising finding), as identified by Leduc et al. (2007), is a robust finding, once we allow for time variation and look at the evidence more closely. We also consider changing the ordering to make interest changes ‘exogenous’ in an alternative ordering instead of being completely endogenous as in the Leduc et al. (2007) setting.

We begin in Section 2 by describing the data and our estimation methodology, setting out briefly the Bayesian approach to estimation via Markov Chain Monte Carlo (MCMC).

Section 3 describes the preliminary estimation output, in particular the convergence diagnostics.

Section 4 is devoted to looking in detail at the results of our impulse response analysis focusing on shocks to r and interpreting the time variant responses in light of issues relating to monetary policy credibility and its link to chairmanship regimes of the Federal Reserve Board.

Section 5 contains an analysis of the crucially important issue of the choice of prior distributions of the parameters to be estimated and the influence of the choice on the results. Our need to capture time variation requires us to use methods developed by Primiceri (2005), Koop and Korobilis (2009, 2010) and Nakajima (2011) inter alia and we discuss and motivate here our choices for the prior distributions which differ in many cases from those used by Primiceri (2005).

We close Section 5 with a brief reconsideration of the impulse response analysis when r is ordered first in the VAR (instead of last as in the first ordering). This second ordering is meant to capture the idea that interest-rate setting may be active and used to determine inflation expectations and real economic activity instead of responding to these variables. It is useful to

consider the alternative ordering, not only to determine the robustness of our empirical results but also to address an essential difficulty in studying monetary policy making by the Federal Reserve Board - namely the absence of any explicit declared targets or goals. We show how there are periods of time where the ordering does not seem to matter. When it does, it can be seen to be closely linked up with an explicitly declared policy regime of the Federal Reserve Board.

In Section 6 we address some further issues of relevance to our discussion, including the influence of shocks to expected and actual inflation, in order to consider in some more detail the issue of persistence of the impact of shocks to inflationary expectations on actual inflation and vice versa. We also investigate if there is any evidence for price puzzles.

Section 7 concludes with a discussion of the results and some final remarks.

2 Data and methodology

We use semi-annual data, graphed in Figure 1, on expected inflation (π^e), actual inflation (π), the unemployment rate (u) and the 3-month T-bill rate (r). π^e , π and r are annualized rates. Data for π^e , and π are taken directly from the Livingston Survey provided by the Federal Reserve bank of Philadelphia. The series for u and r were derived from the Federal Reserve Economic Database (FRED) made available by the Federal Reserve Bank of St. Louis.²The span of the data is 1951:1 to 2010:2 which also enables us to look at the crisis and post-crisis periods to discover the impact of monetary policy in environments characterized by close-to-zero nominal interest rates.

A key variable here is expected inflation (π^e) data for which are taken directly from the long-running Livingston survey. This is a big advantage since we do not have to estimate these separately, or use proxies, as we would need to do for countries for which such data are unavailable.

Thus:

$$\begin{aligned}\pi_t^e &= \log \frac{CPI^e(December)}{CPI(April)}; \pi_{t+1}^e = \log \frac{CPI^e(June)}{CPI(October)} \text{ etc.} \\ \pi_t &= \log \frac{CPI^e(October)}{CPI(April)}; \pi_{t+1} = \log \frac{CPI^e(April)}{CPI(October)} \text{ etc.}\end{aligned}$$

The $CPI^e(December)$ is the expected price level in December of a given year, assumed to be formed after release of CPI April figure but before the release of CPI for May. π_t^e is an eight-month forecast (relatively long-term). We note of course the disjunction in timing with actual inflation π_t (in terms of the time period over which the variables are constructed). π_t^e is ordered ahead of π_t in this ordering to reflect when forecasts made at time t , agents do not know the time t realization of inflation.

2.1 Time-varying parameter VAR with stochastic volatility (TVP-SVAR)

Let us begin by defining the basic (time-invariant) structural VAR model as,

$$A\mathbf{y}_t = Q_1\mathbf{y}_{t-1} + \dots + Q_p\mathbf{y}_{t-p} + \boldsymbol{\xi}_t, \quad t = p + 1, \dots, T. \quad (1)$$

Here \mathbf{y}_t denotes an $m \times 1$ vector of observed variables; A and Q_1, \dots, Q_p are $m \times m$ matrices of coefficients. The disturbance term, $\boldsymbol{\xi}_t \sim N(0, \Sigma\Sigma')$ is an $m \times 1$ vector or structural shocks

²Livingston Survey and related documentation available at: <http://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey/>

FRED: <http://research.stlouisfed.org/fred2/>

where,

$$\Sigma = \begin{pmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_m^2 \end{pmatrix}.$$

Postulating a recursive identification scheme for the structural shocks would imply a lower-triangular structure for matrix A such that,

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{2,1} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{m,1} & \cdots & a_{m,m-1} & 1 \end{pmatrix}.$$

Re-writing system (1) as a reduced-form VAR yields,

$$\mathbf{y}_t = B_1 \mathbf{y}_{t-1} + \cdots + B_p \mathbf{y}_{t-p} + A^{-1} \Sigma \boldsymbol{\varepsilon}_t, \quad (2)$$

where $B_i = A^{-1} Q_i$ ($i = 1, \dots, p$) and $\boldsymbol{\varepsilon}_t \sim N(0, I_m)$. If we stack the elements in the rows of the coefficient matrices B_i to form a vector $\boldsymbol{\beta}$ of dimension $m^2 p \times 1$, and define $Y_t = I_m \otimes (\mathbf{y}'_{t-1}, \dots, \mathbf{y}'_{t-p})$, where \otimes denotes a Kronecker product, (2) can be further given by,

$$\mathbf{y}_t = Y_t \boldsymbol{\beta} + A^{-1} \Sigma \boldsymbol{\varepsilon}_t. \quad (3)$$

Finally, the expression (3) can be re-specified into the following time-varying parameter form,

$$\mathbf{y}_t = Y_t \boldsymbol{\beta}_t + A_t^{-1} \Sigma_t \boldsymbol{\varepsilon}_t, \quad t = p+1, \dots, T \quad (4)$$

for which we will now be required to model the process of evolution for the time-varying parameters contained in $\boldsymbol{\beta}_t$, A_t and Σ_t . To this end, we follow the methodology based on the seminal paper by Primiceri (2005) with further modifications as described in Nakajima (2011); see also Cogley and Sargent (2005) as well as Koop and Korobilis (2010) for a survey.

Considering system (4) the lower-triangular elements of A_t can be stacked to form the vector $\mathbf{a}_t = (a_{2,1t}, a_{3,1t}, a_{3,2t}, \dots, a_{m,m-1t})'$. By defining elements $x_{j,t} = \log \sigma_{j,t}^2$ ($j = 1, \dots, m$) we can construct the stacked vector $\mathbf{x}_t = (x_{1,t}, \dots, x_{m,t})'$. Assuming that the parameters evolve according to a random walk process we have,

$$\begin{aligned} \boldsymbol{\beta}_{t+1} &= \boldsymbol{\beta}_t + \eta_{\boldsymbol{\beta}_t} \\ \mathbf{a}_{t+1} &= \mathbf{a}_t + \eta_{\mathbf{a}_t} \\ \mathbf{x}_{t+1} &= \mathbf{x}_t + \eta_{\mathbf{x}_t} \end{aligned} \quad (5)$$

where,

$$\begin{pmatrix} \boldsymbol{\varepsilon}_t \\ \eta_{\boldsymbol{\beta}_t} \\ \eta_{\mathbf{a}_t} \\ \eta_{\mathbf{x}_t} \end{pmatrix} \sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_{\boldsymbol{\beta}} & 0 & 0 \\ 0 & 0 & \Sigma_{\mathbf{a}} & 0 \\ 0 & 0 & 0 & \Sigma_{\mathbf{x}} \end{pmatrix} \right),$$

assuming uncorrelated shocks to the innovations amongst the time-varying parameters. Furthermore, the covariance matrices $\Sigma_{\mathbf{a}}$ and $\Sigma_{\mathbf{x}}$ are assumed to be diagonal. Here the initial states for the time-varying parameters are $\boldsymbol{\beta}_{p+1} \sim N(v_{\boldsymbol{\beta}_0}, \Sigma_{\boldsymbol{\beta}_0})$, $\mathbf{a}_{p+1} \sim N(v_{\mathbf{a}_0}, \Sigma_{\mathbf{a}_0})$ and $\mathbf{x}_{p+1} \sim N(v_{\mathbf{x}_0}, \Sigma_{\mathbf{x}_0})$. By treating the time-varying parameters as latent variables, the system constituted by (4) and (5) forms a state space specification. Following closely the exposition provided in Nakajima (2011), in the Appendix we detail the method of Bayesian inference for such a specification using a Markov Chain Monte Carlo (MCMC) scheme.³

³For more details on implementation we refer the reader to Nakajima (2011) and Primiceri (2005).

2.1.1 MCMC estimation procedure

The TVP-SVAR model just described is estimated by simulating the posterior distribution of the parameters of interest conditional upon the data. Letting $\mathbf{y} = \{\mathbf{y}_t\}_{t=1}^T$, the latent states $\boldsymbol{\beta} = \{\boldsymbol{\beta}_t\}_{t=p+1}^T$, $\mathbf{a} = \{\mathbf{a}_t\}_{t=p+1}^T$, $\mathbf{x} = \{\mathbf{x}_t\}_{t=p+1}^T$ and the set of hyperparameters $\psi = (\Sigma_{\boldsymbol{\beta}}, \Sigma_{\mathbf{a}}, \Sigma_{\mathbf{x}})$, the object of interest from which we need to sample is the joint posterior distribution, $q(\boldsymbol{\beta}, \mathbf{a}, \mathbf{x}, \psi | \mathbf{y})$ say, i.e. after setting appropriate prior probability densities $\Sigma_{\boldsymbol{\beta}}^0, \Sigma_{\mathbf{a}}^0$ and $\Sigma_{\mathbf{x}}^0$. We discuss the choice of priors and its effects on inference in our application in greater detail in Section 5.1.

There are several reasons for preferring Bayesian inference via MCMC on this class of model over a classical maximum likelihood estimation method. Although it is possible to write the likelihood function for such a model, from a practical stand point it is computationally infeasible to optimize over such a high-dimensional space. An estimation strategy based on MCMC circumvents the issue of dimensionality because it essentially deals with recursively sampling from lower dimensional objects, i.e. the conditional posterior densities of the model. This can be better understood from algorithm below.

MCMC algorithm for TVP-SVAR model:

1. Initialize $\boldsymbol{\beta}, \mathbf{a}, \mathbf{x}, \psi$
2. Sample $\boldsymbol{\beta} | \mathbf{a}, \mathbf{x}, \Sigma_{\boldsymbol{\beta}}, \mathbf{y}$
3. Sample $\Sigma_{\boldsymbol{\beta}} | \boldsymbol{\beta}$
4. Sample $\mathbf{a} | \boldsymbol{\beta}, \mathbf{x}, \Sigma_{\mathbf{a}}, \mathbf{y}$
5. Sample $\Sigma_{\mathbf{a}} | \mathbf{a}$
6. Sample $\mathbf{x} | \boldsymbol{\beta}, \mathbf{a}, \Sigma_{\mathbf{x}}, \mathbf{y}$
7. Sample $\Sigma_{\mathbf{x}} | \mathbf{x}$
8. Go to step 2. and repeat ⁴

As described by Shephard and Harvey (1990) (see also Stock and Watson, 1998 for a discussion), the maximum likelihood estimator may suffer from issues related to the so-called ‘pile-up problem’ if the variance of the time-varying coefficients is small, resulting in the maximum likelihood estimator of this variance having point mass at zero. Another drawback of classical maximum likelihood is again related to the high-dimensionality and nonlinearity of a TVP-SVAR. This may lead us to encounter a likelihood surface characterized by multiple peaks, some of which may be situated in implausible regions of the parameter space. The ability to incorporate prior information within this Bayesian apparatus by a careful choice of priors can provide various sorts of shrinkage to help mitigate problems associated with parameter proliferation. These are typically encountered in TVP-SVAR applications, given that the lengths of macroeconomic time series normally available far exceed the number of parameters to be estimated. Furthermore, by

⁴Continuing in this way for G iterations, the algorithm generates a sequence of random variates $\{\boldsymbol{\beta}^g, \mathbf{a}^g, \mathbf{x}^g, \psi^g\}_{g=1}^G$ which is not *i.i.d.* but instead forms a Markov Chain. This has the attractive property that under a number of metrics and mild regularity conditions, the distribution of the chain converges to target distribution $q(\boldsymbol{\beta}, \mathbf{a}, \mathbf{x}, \psi | \mathbf{y})$. The samples from the joint posterior can be used for parameter and state variable estimation using the Monte Carlo method; e.g. for a function $p(\boldsymbol{\beta}, \mathbf{a}, \mathbf{x}, \psi)$ the Monte Carlo estimate for the expectation $E(p(\boldsymbol{\beta}, \mathbf{a}, \mathbf{x}, \psi) | \mathbf{y})$ is estimated by $\frac{1}{G} \sum_{g=1}^G p(\boldsymbol{\beta}^g, \mathbf{a}^g, \mathbf{x}^g, \psi^g)$. As $G \rightarrow \infty$, two types of convergence operate simultaneously. In addition to the convergence of the Markov Chain to the target, there is a convergence of the partial sums $\frac{1}{G} \sum_{g=1}^G p(\boldsymbol{\beta}^g, \mathbf{a}^g, \mathbf{x}^g, \psi^g)$ to $E[p(\boldsymbol{\beta}, \mathbf{a}, \mathbf{x}, \psi) | \mathbf{y}]$. The Ergodic Theorem for Markov Chains (see Tierney (1994)) guarantees both types of convergence and conditions under which it holds can be generically verified for MCMC algorithms.

using MCMC, we are able to sample the latent state-variables and hyper-parameters simultaneously. This feature which allows us to make inference on these objects (and derive functions such as impulse responses) accounting for parameter uncertainty. From an empirical stand-point this is important and is an issue to which we shall return subsequently when discussing choice of priors. Details on the specific sampling of the latent states are provided in the Appendix.

3 Estimation results

We begin by ordering the variables as (π^e, π, u, r) to estimate a TVP-SVAR over the span 1951:1 to 2010:2, with lag length $p = 1$. 25,000 MCMC iterations were used for estimation discarding the initial 5,000 iterations as a burn-in period. Parameter inference was based on the remaining 20,000. The lag length was selected on the basis of Bayesian Information Criteria on a fixed parameter VAR over the same span, up to and including 4 lags.

In the impulse response analysis that follows subsequently, inference is conducted on the posterior median of last the 500 MCMC draws of the impulse responses, with the credible intervals chosen to be the 16th and 84th percentiles of their posterior distributions.

We provide estimation results; posterior mean, standard deviation, 95% *CI* (credible interval) and convergence diagnostic (*CD*) for some randomly selected parameters in Table 3 in the Appendix.⁵ The convergence diagnostic indicate the the hypothesis of convergence to the stationary distribution is not rejected a the 5% significance level. If we consider the results plotted in Figure 2 we can see that the autocorrelation functions (row 1) for these selected parameters decay in a stable manner which seems to suggest that our sampling scheme efficiently produces ‘near’ *i.i.d.* (low autocorrelation) draws. In addition, the trace plots (row 2) indicate that the chain is well-mixing and the posterior distributions (row 3) have well-behaved unimodal distributions, both of which reinforce the evidence of the algorithm having converged.

In Figure 3 we provide the estimates of stochastic volatility of structural shocks to expected and actual inflation. As expected, we witness dramatic peaks in the mid- to late-1970’s followed by the quieter periods in the 1990’s and the early years of the first decade of the 21st century. For both series there is a return to volatility in the later years of this decade caused by the renewed spikes in commodity prices and the uncertainty surrounding the financial crisis. What is also of particular interest (see Figure 1) is the high volatility of interest rates in the early 1980’s suggesting strong interest rate adjustment consequent upon the money targeting regime implemented by Volcker in this period. There is some evidence for this also in the middle part of the 1970’s as the authorities struggled presumably to cope with the effects of the oil shocks.

4 Shocks to r

The results for an interest rate shock on expected inflation are reported in Figures 4 and 5, where Figure 5 takes a more detailed look at the period around 1979:2 when Volcker first took up office and implemented the change in regime to focus on money targeting (presumably under the Friedmanian hypothesis that inflation was always and everywhere a monetary phenomenon.)

The left-hand vertical panel of Figure 4 shows for the entire sample the time varying median impulse responses of expected inflation to r at 0, 2, 3, 4, 6, 8 and 12 periods ahead. Using this evidence for time variation given in the left-hand panel, the right-hand vertical panel presents the impulse responses focused on particular points in time up to 12 periods ahead. Figure 5

⁵We use the diagnostic proposed by Geweke (1992) which suggests the comparison between the first g_0 and last g_1 draws, (post burn-in) dropping the middle draws. The statistic takes the form: $CD = (\bar{x}_0 - \bar{x}_1) \sqrt{\hat{\sigma}_0^2/g_0 + \hat{\sigma}_1^2/g_1}$ where $\bar{x}_d = \frac{1}{g_d} \sum_{i=h_d}^{h_d+g_d-1} x^{(i)}$; $x^{(i)}$ is the i -th draw and $\hat{\sigma}_d^2/g_d$ is the standard error of \bar{x}_d ; $d = 0, 1$. If the sequence of MCMC draws in stationary, the *CD* should converge in distributon to a standard Normal. We set $h_0 = 1$, $g_0 = 1,000$, $h_1 = 5,000$ and $g_1 = 5,000$.

repeats the exercise for the right-hand panel for seven extra points in time, around the beginning of the Volcker chairmanship.

The left-hand panel suggests that the response of expected inflation to an interest rate shock is largely positive in the years prior to 1970 but then become strongly negative in the years around 1980. The apparently positive responses may be misleading without taking confidence intervals into account, an issue to which we return later in the paper, since as may be seen in Figure 4 the response in 1974:2 of expected inflation to an interest rate shock, both immediate and in the longer term, is insignificant. This insignificance continues roughly until 1978:1 when perhaps in anticipation of Volcker shocks to r begin to have significant negative effects. What is surprising to note perhaps is that from 1983:2 onwards until the end of Volcker's chairmanship (and beyond) r ceases again to have significant impact until 1991:2. The period 1991:2 until roughly 1998:1, overlapping with the period in which interest rate setting is an explicit aim of the Federal Reserve Board, setting r appears again to be an effective policy until 1998:1 when the impulse responses slip again into insignificance.

In some sense, the response of expected inflation to interest rate appears to follow the broad narrative history associated with the different chairmen of the Federal Reserve Board. However, in contrast with Leduc et al. (2007), three special features are evident.

First there is ample evidence of the impact of Volcker happening in anticipation of Volcker.

Second, that while there is a temptation to believe (perhaps with justification) that Volcker marked a 'quantum' change compared to the behaviour of the FOMC pre-Volcker, this is somewhat countered by the responses evident even in the mid-1970's where it is not always clear that the monetary policy setters were being completely accommodating instead of being subject to shocks over which they had little control.

Third, even within regimes (as defined by chairmanship of the Board) there is a lot of variation in the responses. So credibility, or incredibility, is not consistently maintained, either because external circumstances change or the need to respond is no longer as imperative (which leads in turn to differential responses when in fact an intervention is made.)

Figure 6 gives the response of actual inflation to an interest rate shock with the left-hand panel presenting the summary of the responses for the entire sample and the right-hand panel providing the responses at particular dates. Here too there is large variation. The response of actual inflation to interest rate takes place with longer lags than the reaction of expected inflation although we do not observe significant persistent effects of an interest rate shock on actual inflation until late into the 1980's (therefore in the Greenspan era).

Time variation therefore is again the key to analyzing the impact of r , since taking account of such variation leads not only to a more interesting and nuanced analysis but also avoids the largely insignificant responses of expected inflation to r both pre-1979 and post-1979 in Leduc et al (2007) (see again Figure 5 in their paper).

4.1 Credibility of monetary policy

Within a framework of the narrative history of monetary policy during these years, taking the results reported above into account, we have considered several alternative sources of interpretation, with a view to assessing the Federal Reserve Board's monetary stance and its credibility.

This section therefore provides another way of looking at whether it was much more 'good luck' than 'good policy' that paved the way for the Great Moderation. This would be the case if we are able to show (largely corroborating the evidence from the previous section) either that policy actions in the inflationary (pre-Volcker) and contractionary/disinflationary (post-Volcker) regimes were not dramatically different, or that despite a relatively more aggressive stance, the latter regime remained prone to episodes of low credibility. Romer and Romer (2004a) shows a way into the first route while what have come to be known as 'inflation scares' throw some light on the latter. We consider both these issues below.

We may assume that a diluted, insignificant response of π^e to a shock in r is evidence of weak credibility of the Federal Reserve Board in pursuing a low inflation objective. In light of this we now attempt to understand more deeply the changing significance of these responses by considering how credibility may have been affected by certain developments in the long term bond markets. Goodfriend (1993, 2003) describes how the Federal Reserve Board’s credibility problem post-Volcker shows up as so-called ‘inflation scares’. If one takes the view that movements in long bond rates can reliably signal changes in expected inflation, inflation scares may be defined as steep rises in the long term bond rates reflecting rising long-term inflation expectations (see also Ireland, 1996). Inflation scares pose a costly dilemma for monetary authorities since ignoring them would cast doubt over the Federal Reserve Board’s commitment to maintain low inflation; but raising short term rates (r) in an attempt to restore credibility would increase the risk of falling into a recession. It is implicitly conjectured that these inflation scares, and developments in the bond market in general, may have informed on the forecasts put forth in the Livingston Survey during this period. This does not preclude the possibility that survey respondents were themselves market participants influencing the long bond rates. In what follows, there is evidence to suggest that to a large extent Federal Reserve Board policy over the period 1978-2000 was tailored in order to react to or preempt signals emanating from the bond markets which were reflective of a lack of credibility.

In the popular perception at least, pre-1978 the Federal Reserve Board had generally followed a largely expansionary policy aimed at bringing down unemployment. This in turn may have resulted in higher inflation and expectations of inflation witnessed in that era with agents demanding higher premia in bond rates. This, in the absence of nominal anchor for inflation, caused inflation expectations and hence bond rates to fluctuate widely. Goodfriend (2003) argues that this was an indication that the policy makers and the public could not discern each other’s objectives and hence the effects a policy action would have on expectations and the economy was difficult to predict. The insignificant impulse response e.g. 1974:2, Figure 4 can be taken as indicative of such an environment of low credibility. The subsequent disinflationary policies can be seen as an effort to rectify this situation.

But as will be described in detail below, there were episodes of low credibility, specifically three inflation scares documented during the period of 1979 to 1984. If we take the view that the perceived credibility of monetary policy is intimately related to the public’s understanding of policy markers’ objectives, then we also need to bear in mind that the volatility of the policy instrument was also the highest over this very period; i.e. relative to historical levels. This indicates that whilst there may have been an initial effort to curb inflation expectations by raising (sharply) short term rates, these moves were not consistently sustained for prolonged periods of time and were inter-twined with periods of more accommodative policy. Given the high inflation environment pre-1978, the uncertainty in r , as can be seen from the plot of stochastic volatility (Figure 3), may have contributed to perceptions of credibility becoming increasingly sensitive to policy changes. The result being that the Federal Reserve Board’s desire to build credibility was made even more difficult a task, especially in the early part of the Volcker era. Figure 7 illustrates the timing of the inflation scares over the span 1977:Q1 to 2010:Q3 in which we also plot the series *lbr*, 3-month T-bill rate, the spread, and actual inflation (all at monthly frequency) over the period spanning all the episodes of recorded inflation scares.

Before discussing the various inflation scares and policy actions taken in response we attempt to better understand the policy actions taken during this part of his chairmanship.

We can make use of the ‘new measure’ of monetary shocks made available by Romer and Romer (2004a). This measure is constructed using quantitative and narrative records to infer the Federal Reserve Board’s ‘intentions for the federal funds rate around FOMC meetings’⁶ In other words, to construct a measure purged of the endogeneity (with respect to economic

⁶Romer and Romer (2004a), abstract, line 3-4, page 1055.

conditions) which exists in the federal funds rate as a conventional measure of monetary policy.⁷

In order to draw a stark contrast, two separate periods are considered: the period of the ‘Great Inflation’ between 1973 and 1974 and the period of three years (1979 - 1982) following the appointment of Volcker. For both these periods, using Table 2 in Romer and Romer (2004a) we have computed the following summary statistics for the monetary shocks (computed by them for the time around each month of the FOMC meetings). The data are monthly and measured in percentage points:

1973m1 – 1974m12

Negative shock (expansionary) - occurrence in 10 periods

Max shock: -0.848 (October 1973)

Minimum shock: -0.022 (August 1974)

Average magnitude of negative shock: -0.28

Positive shock (contractionary) - occurrence in 14 periods

Max shock: 0.733 (March 1974)

Minimum shock: 0.064 (March 1973)

Average magnitude of positive shock: 0.31

1979m1 – 1982m12

Negative shock (expansionary) - occurrence in 18 periods

Max shock: -3.221 (April 1980)

Minimum shock: -0.011 (January 1980)

Average magnitude of negative shock: -0.49

Positive shock (contractionary) - occurrence in 17 periods

Max shock: 1.871 (November 1980)

Minimum shock: 0.045 (March 1979)

Average magnitude of positive shock: 0.56

In this period there was no activity (i.e. no action taken) on 13 occasions. Thus, looked at baldly, the second period contained expansionary shocks in 18 out of 48 months with an average shock magnitude of approximately 0.5 percentage points. The corresponding figures for the first period are 10 out of 24 periods with an average shock magnitude of 0.3 percentage points. The average percentage figure for the second period drops to 0.3 if the value for the maximum expansionary shock is omitted from the calculation of the average. As far as the contractionary shocks are concerned, the corresponding figures are respectively 17 out of 48 periods with an average magnitude of 0.6 percentage points and 14 out of 24 periods with an average shock size of 0.3 percentage points.

Thus while there was a tendency to be somewhat more contractionary/disinflationary in the second period, the expansionary impulses were lower in magnitude in 1973-74 compared to 1979-1982 and occurred approximately the same percentage of times in 1973-74 as in 1979-82. This cannot be regarded a ringing endorsement of the view that surrounds the profligacy or irresponsibility of the policy makers in the mid-1970s, and due regard must be given to the realization that the external circumstances facing the economy were rather different and continued to evolve differently. This is also the message from our time-varying impulse response functions.

⁷“..We then use the Federal Reserve’s internal forecasts of inflation and real activity to purge the intended funds rate of monetary policy actions taken in response to information about future economic developments...The resulting series for monetary shocks should be relatively free of both endogenous and anticipated actions.” from Romer and Romer (2004a), page 1056, paragraph 3.

4.1.1 Inflation scares of 1980 and 1981:

The initial policy actions Volcker took in an effort to curb inflation and tame expectations after becoming Federal Reserve Board chairman led to r (the nominal 3-month T-bill rate) rising from around 10 % in September 1979 to 15 % by April 1980. Nearly half of this 5 percentage point increase occurred in Autumn of 1979 after which the Federal Reserve Board held rates relatively steady until March 1980. January 1980 turned out to be an NBER business cycle peak so further monetary tightening was paused.⁸ But during this period, specifically December to February, the 30 year (long) bond rate (lbr) increased by approximately 2 percentage points even in the presence of recessionary pressures.

The evidence of a rise in inflation expectations due to a sharp increase in the lbr could perhaps be attributed to the ongoing increase in oil price, the unprecedented rise in the price of gold and the Soviet invasion of Afghanistan. In addition to these events, perhaps the lack of further tightening may have created doubts over the Federal Reserve Board's willingness to bear the costs of reduced output growth in favour of pursuing a low inflation objective. Thus, in spite of recessionary pressures, the Federal Reserve Board was compelled to react with a sharp tightening which increased r by approximately 2.5 percentage points. But from April to August there was indeed a steady decline of the rate by nearly 5 percentage points. This seemed to mark an end to the recession fairly quickly and led to an increase in real GDP growth to around 8 % in 1980:Q4; but inflation continued to remain stubbornly high. In response the Federal Reserve Board started raising interest rates again; by early 1981 r returned to the 15 % range where it was held steady until October. The NBER business cycle peak was reached in July and actual and expected inflation started declining gradually.⁹ Rates were kept high up till the summer of 1982 when they were reduced to around 8 %. The reason for maintaining such high rates even as the recession was deepening and unemployment rising was the observation that lbr was also rising, for most part, in parallel. This inflation scare was precipitated by an increase by 3 percentage points in the lbr from early 1981 to around 14 % in October. It held steady at the 13-14% range thereafter and only began to decline more persistently only in the summer of 1982.

4.1.2 Inflation scare of 1983-1984:

By early 1983, inflation was stable around 4 %. Nonetheless, an inflation scare in the bond markets raised the lbr from 10 % in summer 1983 to its peak in the following summer to around 13 % range. This was only 1 percentage point short of its 1981 peak even though inflation was over 6 percentage points lower in 1983 than in early 1981. Once again the Federal Reserve Board responded by tightening its monetary stance gradually which moved r up from the 8 to 11 % range from October 1983 to August 1984. Following this the lbr declined and the inflation scare started subsiding. Unlike the previous inflation scare, 1980 and 1981, the Federal Reserve Board's response to this one did not induce recessionary pressures. This may be attributed to the well paced-out gradual tightening of rates or because inflation rate was already quite low and relatively smaller increases in r were sufficient to yield effective real rates.

Figure 5 reveals that there was considerable evidence of the Federal Reserve Board's credibility in pursuing a low inflation objective in the early years of Volcker and just before he took over, i.e. 1978:2 to 1981:2 (as indicated by significant negative responses). The significance of these appears to decrease gradually from 1981:2 to 1983:2.¹⁰ These increasingly diluted responses may indicate that the survey respondents also began to reflect the perception of lack of policy credibility made evident by the three inflation scares over this period.

⁸Recessions start at the peak of a business cycle and end at the trough. (Source: NBER)

⁹Unemployment peaked at nearly 10% in the trough of the recession, around October 1982.

¹⁰By 1983:2 the response has become insignificant at all horizons.

4.1.3 Inflation scare of 1987:

The long bond rate rose by 2 percentage points from March to October 1987 but unlike previous scares the Federal Reserve Board reacted little to this one. The scare may have occurred because Volcker was at the end of his term and there was uncertainty about whether the next chairman was going to place a high enough weight on controlling inflation. In any event, the 1987 scare can be seen as particularly striking evidence of sensitivity of the Federal Reserve Board's commitment to low inflation- possibly connected to the transition for one chairman to another. The 1987 stock market crash forced the Federal Reserve Board to ease monetary policy and delayed raising policy rates until August 1988 when r increased from near 7% to the 9% range by March 1989. The effect of this was that long term bond rates did not return to their early 1987 levels until 1992. As suggested by Goodfriend (2003), it essentially took Greenspan's Federal Reserve Board five years to overcome the 1987 scare. This seems like a costly repercussion of what appeared to be a minor loss of credibility.

As shown in Figure 4 the impulse responses remain insignificant post 1983:2. It appears that the effects of the inflation scares may perhaps have persisted in the expectation formation of the Livingston survey respondents from 1984 to 1987. Given that our evidence suggests that impulse responses started becoming negative and significant almost a year before Volcker took over, i.e. in anticipation of Volcker's chairmanship, it may also be the case that anticipation of the eventual end of his term may also be reflected in the responses. Indeed, the 1987 inflation scare brought about by the uncertainty surrounding the chairmanship transition seems to be evidence of the view that the public's (forecasters') perception of credibility was still very fragile.

4.1.4 Preemptive policy in 1994:

Greenspan tentatively reduced the policy rate from late 1990 (when r around 7%) to the Autumn of 1992 (r around 3%). During this time, unemployment also came down to near 6.6%, inflation was close to 3% and the lbr fell close to 6%. The inflation rate also fell slightly during this time and it seems to suggest that the Federal Reserve Board had gained an increased degree of credibility. But from late 1993 to November 1994 the lbr crept up slightly by 2 percentage points. Thus in order to reinforce this newly gained credibility, Greenspan initiated a series of policy actions in order to raise interest rates as a preemptive measure from February 1994 to February 1995. r increased by 2 percentage points to near 5%, the result of which was that the lbr declined back to near 6% by 1996.

From Figure 4 it appears that the significance of impulse responses re-emerges by late 1991:2 in line with the policy actions taken in 1988/1989. The magnitude and significance of the responses increases till around 1996:2 after which they begin to dilute and start becoming insignificant. By 1999 the responses are insignificant again at all horizons. It is conjectured that by 2000 the Federal Reserve Board had shifted attention to bringing aggregate demand back in line with potential; i.e. so as to not risk increased inflation expectations/scares. In fact the Federal Reserve Board was able to reduce real rates to near zero without a hint of an inflation scare; proof of Greenspan's apparent prescience in realizing the huge productivity gains that would occur in the latter half of the decade of the 1990s. The observation of insignificant responses 1999 onwards may indicate that the survey forecasters perhaps understood this change of stance by the Federal Reserve Board. Once credibility had been achieved the Federal Reserve Board's actions to control inflation expectation were not really the issue anymore.

In summary, the overall evidence seems to suggest that it is not only the stance of the monetary policy authorities that matters (accommodative or otherwise) but also the magnitudes and speeds of adjustment that matter in determining credibility. It is possible to argue in terms of thinking of a particular chairman (and consequently the FOMC under his direction) to be more aggressive towards inflation than another. But the facts are somewhat different in terms

of what is actually observed in the data where problems of credibility may occur and lead to inflation scares, even in a world with tough chairmen. The point is that preemptive action when taken should perhaps be take immediately and in one go. Progressive, but small, increases in interest rates have a destabilizing impact on expectations leading to inflation scares.

5 Robustness analysis

5.1 Choice of priors

It is necessary to justify our choice of priors in order to help with the interpretation of our results. We have essentially considered three different specifications for priors (i.e. Σ_β^0 , $\Sigma_{\mathbf{a}}^0$ and $\Sigma_{\mathbf{x}}^0$) for the hyperparameters to employed in our MCMC estimation strategy. These are given below in Table 1 as Priors (a), (b) and (c). Here $IW(\gamma, \Delta)$ and $IG(\alpha, \Lambda)$ refer to inverse-Wishart and

Prior (a)	Prior (b)	Prior (c)
$\Sigma_\beta^0 \sim IW(1 + n_\beta, \kappa_\beta^2 \cdot (1 + n_\beta) \cdot I_{n_\beta})$	$\Sigma_\beta^0 \sim IW(1 + n_\beta, \kappa_\beta^2 \cdot I_{n_\beta})$	$\Sigma_\beta^0 \sim IW(1 + n_\beta, 0.02 \cdot I_{n_\beta})$
$\Sigma_{a_j}^0 \sim IG(\frac{1+n_a}{2}, \frac{\kappa_a^2 \cdot (1+n_a)}{2})$	$\Sigma_{a_j}^0 \sim IG(\frac{1+n_a}{2}, \frac{\kappa_a^2}{2})$	$\Sigma_{a_j}^0 \sim IG(\frac{1+n_a}{2}, \frac{0.04}{2})$
$\Sigma_{x_j}^0 \sim IG(\frac{1+n_x}{2}, \frac{\kappa_x^2 \cdot (1+n_x)}{2})$	$\Sigma_{x_j}^0 \sim IG(\frac{1+n_x}{2}, \frac{\kappa_x^2}{2})$	$\Sigma_{x_j}^0 \sim IG(\frac{1+n_x}{2}, \frac{0.04}{2})$
Initial states: $\beta_{p+1} \sim N(0, 4 \cdot I_{n_\beta}), a_{p+1} \sim N(0, 4 \cdot I_{n_a}), x_{p+1} \sim N(0, 4 \cdot I_{n_x})$		

Table 1: *Different choices of priors for the hyperparameters and initial states of TVP-SVAR model considered for estimation.*

inverse-Gamma distributions, governed by γ , the prior degrees of freedom parameter, the scale parameter Δ , prior shape parameter α and scale parameter Λ , respectively. Given the diagonality assumption, j indicates the j -th diagonal element of $\Sigma_{\mathbf{a}}^0$ and $\Sigma_{\mathbf{x}}^0$ (and correspondingly $\Sigma_{\mathbf{a}}$ and $\Sigma_{\mathbf{x}}$).¹¹ $n_\beta = 20$, $n_{\mathbf{a}} = 6$ and $n_{\mathbf{x}} = 4$, are the dimensions of each matrix. The usual recommendation is to use a scale parameter which is an identity matrix with values of the diagonal entries reflecting the expected magnitude of the variance components. The weights entering the scale parameters in the prior distributions, $\kappa_\beta = 0.01$ (as initially used by Cogley and Sargent, 2001), $\kappa_{\mathbf{a}} = 0.1$ and $\kappa_{\mathbf{x}} = 0.01$ are identical to those used in Primiceri (2005).¹² These weights have been used elsewhere in the TVP-SVAR literature and primarily contribute to parameterizing prior beliefs concerning the magnitude of time variation (as opposed to time variation itself). Setting the priors as in Prior (a) are in line with those proposed in Koop and Korobilis (2009). In Prior (b) we reduce the magnitude of the scale parameters whilst leaving the degrees of freedom and shape parameters the same as in (a). Prior (c) is similar in spirit to Nakajima (2011) in which the same value of the scale parameter is endowed to all three distributions. Initial state parameters $\beta_{p+1}, a_{p+1}, x_{p+1}$ are set in accordance with Koop and Korobilis (2009).

¹¹If the $m \times m$ matrix $X \sim IW(\gamma, \Delta)$; then a univariate specialization of the IW , i.e. when $m = 1$ is distributed as $IG(\alpha, \Lambda)$, where $\alpha = \frac{\gamma}{2}$ and $\Lambda = \frac{\Delta}{2}$.

¹²See Primiceri (2005) for a detailed discussion concerning the choice of $\kappa_\beta = 0.01$.

We decided to employ Prior (b) in our estimation strategy for a number of reasons which we discuss below.

Our selection criteria were based on certain general considerations such as (i) assessing objects related to convergence diagnostics of the algorithm; (similar to those considered in Table 3 (Appendix) and Figure 2) and (ii) examining the plausibility of the shapes of generated impulse responses, while trying to maintain as diffuse and uninformative a prior specification as is feasible. By diffuse and uninformative we do not of course imply flat, improper priors. ‘Plausible’ shapes preclude impulse responses displaying explosive behaviour with statistically significant counter-intuitive signs. Given that the analysis in this paper focuses on investigating the changes in responses of subjective inflation expectations, maintaining fairly diffuse priors is also intuitively desirable in order to ensure that the influence of prior information on the responses remains minimal.

In the case of all three priors we found that the convergence diagnostics for the MCMC algorithm (25,000 iterations) for randomly selected parameters seemed to behave fairly well. The autocorrelation functions exhibited stable decay indicating efficient sampling. In addition, the posterior distributions displayed well-behaved unimodal shapes.

Turning our attention to impulse response analysis we found that the signs and magnitudes of the responses did not change very substantially across the three prior specifications considered. Lower values of scale parameter, as in Prior (b), tend to make the shape of the responses slightly smoother, relatively more persistent, but are in general qualitatively similar to those generated when using Priors (a) and (c).

In order to illustrate this further, in Figure 8 (left panel) we present impulse response functions of expectations to an interest rate shock at three different dates, 1980:1, 1985:1 and 1989:2 using the three Priors (a), (b) and (c). There does not seem to be any significant visual differences in the magnitude of the responses. This is also the case for Prior (c) but we found that in many instances the responses of actual and expected inflation to an interest rate shock were undesirably noisy with implausible oscillatory behaviour; especially during the 1990s and the period spanning the Great Moderation when volatility was known to be decreasing and/or was relatively lower than the earlier period of the estimation sample. Prior (b) therefore appeared to be the ideal candidate from the perspective of our impulse response analysis.

We argue that choice of Prior (b) is also justified by the fact that our analysis uses semi-annual data. From this point of view it seems to us reasonable that the data will be characterized by a lower expected magnitude of time variation in comparison to higher frequency data as has been typically employed in the TVP-SVAR literature. This would argue in favour of setting scale parameters for the priors to relatively lower magnitudes as compared to those constituting Priors (a) and (c) since the latter are more in line with the quarterly data applications of Primiceri (2005) and Nakajima (2011). We have also experimented with values, $\{\Delta, \Lambda_{\text{Prior (b)}}, \Lambda_{\text{Prior (c)}}\} = \{0.0001; 0.0001; 0.0001\}$ and $\{0.0001; 0.005; 0.005\}$ but did not find any substantial difference in the results except for very slight changes in the magnitude of the responses.

However, the feature found to be most important when assessing variants of the degrees of freedom and scale parameters was the magnitude of the degree of freedom parameter in Σ_{β}^0 specifically γ . Increasing this parameter appears to have the most extreme effect on the amount of time-variation of the generated impulse responses, irrespective of the value of scale parameters.

This feature can be understood by noting that the random variable $\Sigma_{\beta}|\beta$ (distributed as inverse-Wishart) has a conditional posterior mean which is essentially a weighted combination of prior and likelihood information. This can be defined as,

$$E(\Sigma_{\beta}|\beta) = \frac{\gamma}{\gamma + T} \frac{\Delta}{\gamma} + \frac{T}{\gamma + T} \Sigma_{\beta}^*$$

where Σ_{β}^* corresponds to the maximum likelihood estimate of $\Sigma_{\beta}|\beta$.¹³ Since the weights are given by the relative magnitudes of degrees of freedom and sample size, we see that the degree of influence the prior scale parameter has on $E(\Sigma_{\beta}|\beta)$ increases as $\gamma \rightarrow \infty$. An attractive feature from our perspective of the $IW(\gamma, \Delta)$ is that there is a natural lower bound for γ in order for it to be a proper distribution. The lowest permissible value for γ must equal the dimension of the matrix, in our case n_{β} . Any increase above this lower bound is equivalent to tightening the prior around the scale parameter which will tilt results increasingly towards the information contained in this parameter. Considering the specific case of Prior (b) this implies, in other words, that $\Delta = \kappa_{\beta}^2 \cdot I_{n_{\beta}}$ will parameterize time variation when the degrees of freedom tend to infinity. As can be noted we confine ourselves to (only) considering $\gamma = 1 + n_{\beta}$ which essentially yields as diffuse a prior as is possible whilst remaining proper; an approach also followed *inter alia* by Benati and Mumtaz (2007).¹⁴

It is well-known that in most cases parameter proliferation in TVP-SVAR models can be quite severe with the number of parameters to be estimated exceeding the typical lengths of macroeconomic time series. The difficulty in obtaining very precise coefficient estimates will be reflected in very dispersed posterior distributions for objects of interest such as impulse response functions. This can be countered by tightening the prior, Σ_{β}^0 . From an inferential perspective, a tighter prior should lead to less dispersed posterior distributions with tighter credible intervals for impulse response functions as compared to those generated when employing a relatively diffuse prior.¹⁵ But as $\gamma \rightarrow \infty$, the trade-off faced is that of generating responses (even reasonably well spaced in time) characterized by a rapid reduction in any statistically discernible time variation.

We demonstrate the latter assertion by means of revisiting our empirical exercise illustrated in Figure 8. In the right panel of Figure 8 we provide results of tightening Prior (b) by a factor of 2, i.e. to $2 \times (1 + n_{\beta})$. It is evident that the impact of using a tighter prior can be quite substantial in terms of diluting the flexibility of the TVP-SVAR apparatus in detecting and facilitating time-variation of impulse responses over the span.

A strategy often employed in the literature is to inform the priors (and initial values for state variables) using OLS estimates from a standard time-invariant VAR on a training sample (see Primiceri, 2005). We chose not to pursue this route since our aim here is to generate results which are not influenced to any meaningful degree by the behaviour of the system before the start of our estimation sample. Moreover, we prefer to maximize the information contained in the entire data span available to us and not be led into a situation where a tighter prior around an OLS-based scale estimate may be required in order to circumvent potential misbehaviour of the impulse responses.¹⁶ Indeed, the length and location of the training sample can be a fairly arbitrary choice and perhaps difficult to justify. Specifically with regard to location, if for example the pre-sample OLS estimate for scale parameter is computed over a span characterized by a low monetary policy credibility regime, then setting an excessively tight prior around this parameter could in essence be interpreted as increasing the probability with which responses are

¹³The scale parameter in the IW has the interpretation of the sum of squared residuals, rendering the object $\frac{\Delta}{\gamma}$ interpretable as a variance and hence comparable to Σ_{β}^*

¹⁴In our application, both the priors $\Sigma_{a_j}^0$ and $\Sigma_{x_j}^0$ are somewhat tighter than would be attainable by setting $\alpha = \frac{1}{2}$. This being latter being the lowest permissible value of α for which the inverse-Gamma remains proper. Results from impulse response analysis were found to be largely unaffected even when we set $\alpha = \frac{1}{2}$ in Prior (a), (b) and (c) but in most instances we obtained very counterintuitive results for estimated stochastic volatility paths of structural shocks. Most striking of which were moderate peaks in volatility of π and r , during latter half of the Great Moderation.

¹⁵We would like to re-iterate that inference in our analysis is based on the median of the posterior distributions of the impulse responses, with credible intervals being the 16th and 84th percentiles. The uncertainty in the parameter estimates brought about by setting a relatively diffuse prior will be reflected in the dispersion of the posterior distributions of the impulse responses.

¹⁶Of course, as $T \rightarrow \infty$ the posterior mean should converge towards the maximum likelihood estimator; thus mitigating the influence of the prior.

anchored in prior beliefs about the state of the economy during this regime. The result of this would be a lowering in the ability for responses to adjust freely to changing regimes and thus evolve over the course of the sample. This would run counter to the spirit of our analysis of allowing for both agnostic and time-varying responses.

In order to assess the sensitivity of our results to employing some external source of information we also considered a prior specification calibrated on OLS estimates for the full sample available to us. Such a strategy has been suggested by Canova (2007) and Canova and Ciccarelli (2009) for cases when employing a training sample may not be feasible; see also Kirchner, Cimadomo and Hauptmeier (2010). A VAR model (2) in Section 2.1 with ordering (π^e, π, u, r) is thus estimated by OLS over 1951:1 to 2010:2, assuming a lower-triangular structure for matrix A . In Table 2 below, $\hat{\beta}$ and $\hat{\Sigma}_\beta$ are the vector of OLS point estimates of the VAR and their covariance matrix respectively. \hat{a}_j and $\hat{\Sigma}_{a_j}$ denote the point estimates and variances of the lower-triangular elements of \hat{A} . Given that the covariance matrix of the estimated VAR, $\hat{\Xi}$ say,

OLS-based Prior

$$\Sigma_\beta^0 \sim IW(1 + n_\beta, \kappa_\beta^2 \hat{\Sigma}_\beta), \quad \Sigma_{a_j}^0 \sim IG(\frac{1}{2}, \frac{\kappa_a^2 \hat{\Sigma}_{a_j}}{2}), \quad \Sigma_{x_j}^0 \sim IG(\frac{1}{2}, \frac{\kappa_x^2}{2})$$

$$\text{Initial states: } \beta_{p+1} \sim N(\hat{\beta}, 4 \hat{\Sigma}_\beta), \quad a_{j,p+1} \sim N(\hat{a}_j, 4 \hat{\Sigma}_{a_j}), \quad x_{p+1} \sim N(\hat{\phi}, 4 I_{n_x})$$

Table 2: *OLS-based Prior specification.*

can be decomposed as $\hat{\Xi} = \hat{A}^{-1} \hat{\Sigma} \hat{\Sigma}' (\hat{A}^{-1})'$, we can denote $\hat{\Phi} = \hat{\Sigma} \hat{\Sigma}'$. From this the vector of diagonal elements $\hat{\phi}$ of matrix $\hat{\Phi}$ is recovered.

The prior hyperparameters Σ_β^0 and $\Sigma_{x_j}^0$ are set as in Benati and Mumtaz (2007), whereas the prior $\Sigma_{a_j}^0$ is what was employed in Kirchner et al (2010). Similar to our set-up, the latter also assumes an inverse-Gamma prior for Σ_a . The initial states are set in line with Primiceri (2005).

When considering the effects of using the OLS-based prior we found that the results from our impulse response analysis were qualitatively similar to those obtained using priors with no OLS information embedded. This can be seen in Figure 8 (bottom plot, left panel). Again, the impact of tightening the prior by a factor of 2 yields the same observation as before in terms of diluting time-variation save for a slight difference in the magnitude of the responses. See Figure 8, right panel. Most importantly, we found that in spite of informing the priors in this manner, the overall results/conclusions remained unchanged from an inferential perspective.

5.2 Alternative ordering

To return to our discussion of monetary credibility, Figure 9 undertakes a robustness analysis by altering the ordering in the TVP-SVAR to put r first. The ordering therefore becomes (r, π^e, π, u) in order to capture the notion that interest-rate-setting policy is pro-active and moves first (guided by historical information but NOT reactive to current economic circumstance in the nominal and real sectors of the economy.) In line with this ordering of the variables is the preemptive raising of rates in 1994 discussed above. The impulse responses depicted in the four vertical panels provide both the summary responses of expected and actual inflation to an interest rate shock over the whole sample and snap-shots of these responses at different points in time. For the second ordering there is not much significance evident, either for expected

inflation or actual inflation, apart from as expected for the period between 1991:2 and 1995:2, a period within which the Greenspan preemption would have taken hold. This is coherent with the responses under the alternative ordering and appears to be the period where the responses of actual and expected inflation to an interest rate shock coincide regardless of the ordering adopted and is also the period where interest-rate targeting was explicitly adopted.

6 Some further issues

6.1 Shocks to π^e and π

Figure 10 looks at the impact of a shock to expected inflation on actual inflation while Figure 11 considers the impact on a shock to actual inflation on expected. In Figure 10, the strongest responses occur within the period 1974:2 to 1979:2 although there is very wide variation in the responses at the longer horizons. The responses become insignificant at the longer horizon particularly from 1987:2 onwards while there is a dramatic rise in the response (at all horizons) from 1995:2. The responses remain quite persistent but decline in magnitude until 2004:2 and appear to become insignificant thereafter.

Figure 11 enables us to take a direct look at the issue of second-round effects whereby shocks to inflation feed into inflationary expectations, thereby into inflationary wage expectations (and hence into actual wage inflation, either via indexation or bargaining arrangements) and into inflation at the second round. Since we are working with headline or CPI inflation figures, we are assuming that these shocks to actual inflation occur via (unmodelled) supply shocks. We are agnostic however about the targeting policy of the US monetary authorities in their choice between a core or headline measure of inflation (assuming that an inflation targeting policy has existed or exists in the first place.)

It is easy to see from Figure 11 that the strongest responses, as expected, occur in the mid-1970s, with significance dying down in the 1980's (possibly as a reflection of Volcker induced credibility). But in common with our experience with time variation, there is a significant increase in response around 1998:1, almost equal in magnitude to those seen in the mid-1970's and a similar spike is evident in 2006. What is more, the responses are all significant at long horizons, with significance persisting 15 periods ahead. This is in contrast to the results of Leduc et al. (see Figure 6 in their paper) where a contrast in the persistence of responses is drawn between pre-1979 and post-1979. Therefore, a more detailed reading does not allow for such simple distinctions to be made. This returns to our earlier point of variation being evident in responses even within regimes, caused possibly by changing economic circumstance, and reinforcing the importance of good luck perhaps over (but certainly in addition to) good policy.

6.2 Price puzzles?

The issue of a price puzzle - an upward (immediate) reaction of the price level to a contractionary policy shock - continues to be debated in the literature and many 'remedies' have been suggested, including increasing the dimensionality in the SVAR by using factor-based approaches to estimate the models. The idea is that the unanticipated policy shock is thereby identified correctly, by conditioning on (or controlling for) all other variables that might be used to anticipate monetary policy. Since high-dimensional VAR's are difficult to estimate reliably, factors are extracted from the large-dimension data set and are incorporated into the SVAR.

Our SVAR is small-dimensional and an obvious extension of this work is to think of looking at the impact of policy shocks within the framework of a time varying factor augmented structural VAR. Nevertheless within our four-dimensional system there is some evidence apparent (at least in the initial and latter parts of the sample) of an increase in prices in response to a

contractionary shock (see Figures 4, 6 and 9). It therefore is worth spending a little time investigating this issue.

The second vertical panel of Figure 9 provides the median (time-varying) responses under the first ordering of actual inflation to a one standard deviation shock to r . It is clear from looking at the first graph in this panel that under the first ordering there is no evidence of a price puzzle. The fourth vertical panel provides the corresponding responses of actual inflation under the second ordering of the VAR. Here there is some evidence of a puzzle which bears further examination using confidence intervals. Figure 12 therefore provides the 0-period and 1-period responses of actual inflation to r under the second ordering. Apart from very brief episodes (the early 1970's and in the early 1980's) once confidence intervals are taken into account there is little to support a price puzzle based on a consideration of the short-run responses to the shock.

Figures 13 and 14 extend the analysis of a price-puzzle to looking at the behaviour of expected inflation. Although the theoretical considerations are perhaps less clear, and therefore the expected responses more of a puzzle by themselves, Figure 13 provides the median (time-varying) 1-period and 2-period responses with confidence intervals under the first ordering of expected inflation to a one standard shock to r . Here, because expected inflation is ordered first, immediate responses (i.e. 0-period responses) cannot be considered. Figure 14 provides the median (time-varying) 0-period and 1-period responses with confidence intervals under the second ordering of expected inflation to a one standard shock to r . Now because r is ordered first, immediate responses can be considered.

It may be seen from Figure 13 that under the first ordering, there is evidence of a positive response of prices until roughly the mid-1960's and then again after 2000 but in the central region of the curves, which is the primary focus of our interest in this paper, expected inflation too is well behaved in its responses to interest rate shocks. Figure 14 demonstrates price-puzzle-like behaviour in the decade following 2000, particularly after 2005, but interestingly there is also evidence of inflation expectations being revised upwards in the mid-seventies following a contractionary shock, although only the immediate response is affected. The 1-period ahead responses are very largely insignificant, so the expectations price puzzle, if named as such, dies away quickly.

7 Conclusions

Using a Bayesian structural vector autoregression (TVP-SVAR) with time-varying parameters and volatility we have undertaken a detailed investigation of monetary policy in the United States, in particular its interaction with the formation of inflation expectations and the linkages between these variables and the behaviour of CPI inflation.

We have used data measured at a semi-annual frequency for annualized 8 month growth rate in expected inflation, derived from the Livingston Survey, actual inflation, unemployment and a nominal interest rate to estimate a structural VAR and show the significant changes that have occurred in the responses of these variables to monetary policy shocks and to shocks to expected inflation over the lifetime of our long sample running from the early part of the 1950's until 2010. In so doing, we generalize the analysis undertaken by Leduc et al. (2007) to allow for a more nuanced and detailed look at questions such as the impact of different chairmanship regimes at the Federal Reserve Board, the role of good policy versus good luck, and second round inflation effects. While some of the questions asked have a relatively long history, the methods used to undertake our investigations are very new, and the time-varying structure allows us to offer a more detailed picture.

Our results seem to justify the use of time variation to address questions concerning the response of inflationary expectations to monetary policy shocks. Time variation is seen clearly in many of the response functions presented and is important from a policy perspective when

thinking for example of justifying the validity of constructs such as a Taylor rule or a new Keynesian Phillips curve. Wide variation of expectations therefore makes any of these constructs difficult to apply without allowing explicitly for such time variation. This seems to be one of the important lessons to learn from our paper.

At a technical level, we have analyzed in some detail issues relating to the choice of priors in Bayesian estimation in this framework. Depending upon the choices of degrees of freedom and scaling parameters we have discussed how it is possible to end up with low time variation in the final results and have argued against such tight specifications.

Our analysis has highlighted the anticipatory role played by agents within the economy. It may be difficult then to pin down the impact of a particular policy precisely, since, if the policy move were seen to be credible or, even more importantly, anticipated, the markets would take such moves into account, leading to the problem of associating particular episodes of the economic history with particular governors. We argue therefore that long before a change occurs its effects are already anticipated. The time variation mechanism simply brings this out very clearly, with considerable overlap across monetary policy regimes, stringent or lax.

Not only that, allowing for time variation enables us to provide a somewhat heterodox view concerning the general perception that the adverse inflationary outcomes of the mid-seventies was very largely due to accommodative monetary policy in the mid-seventies, and that it was only Volcker and post-Volcker which saw the return to credible monetary policy. This is borne out in part but not completely, and the role of good luck *versus* good policy bears renewed consideration.

References

- Benati, L., and Mumtaz, H., 2007. U.S. Evolving Macroeconomic Dynamics: A Structural Investigation. ECB Working Paper No. 746.
- Canova, F., 2007. *Methods for Applied Macroeconomic Research*. Princeton University Press, Princeton.
- Canova, F., and Ciccarelli, M., 2009. Estimating Multi-Country VAR Models. *International Economic Review* 50, 929–959.
- Carlin, B. P., Polson, N. G. and Stoffer, D. S., 1992. A Monte Carlo approach to nonnormal and nonlinear state space modeling. *Journal of the American Statistical Association* 87, 493-500.
- Carter, C. K. and Kohn, R., 1994. On Gibbs sampling for state-space models. *Biometrika* 81, 541-553.
- Cogley, T. and Sargent, T. J., 2005. Drift and volatilities: monetary policies and outcomes in the post WWII U.S. *Review of Economic Dynamics* 8, 262-302.
- Chib, S. and Greenberg, E., 1995. Understanding the Metropolis-Hastings algorithm. *The American Statistician* 49, 327-335.
- de Jong, P. and Shephard, N., 1995. The simulation smoother for time series models. *Biometrika* 82, 339-350.
- Durbin, J. and Koopman, S. J., 2002. Simple and efficient simulation smoother for state space time series analysis. *Biometrika* 89, 603-616.
- Friedman, B., 2006. The Greenspan era: discretion, rather than rules. *American Economic Review* 96, 174-177.
- Fruhwirth-Schnatter, S., 1994. Data augmentation and dynamic linear models. *Journal of Time Series Analysis* 15, 183-202.
- Geweke, J. 1992. Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. In: J. M. Bernardo, J. O. Berger, A. P. Dawid, and A. F. M. Smith, eds., *Bayesian Statistics 4*, 169–188. New York: Oxford University Press.
- Goodfriend, M., 1993. Interest rate policy and the inflation scare problem: 1979-1992. *Federal Reserve Bank of Richmond Economic Quarterly* 79, 1-24.
- Goodfriend, M., 2003. Inflation targeting in the United States? In: B. Bernanke and M. Woodford, eds., *The Inflation Targeting Debate*, Chicago: National Bureau of Economic Research, University of Chicago Press.
- Ireland, P., 1996. The role of countercyclical monetary policy. *Journal of Political Economy* 104, 704-724.
- Jacquier, E., Polson, N. G. and Rossi, P. E., 1994. Bayesian analysis of stochastic volatility models. *Journal of Business and Economic Statistics* 12, 371-389.
- Kim, S., Shephard, N. and Chib, S., 1998. Stochastic volatility: likelihood inference and comparison with ARCH models. *Review of Economic Studies* 65, 361-393.

Kirchner, M., Cimadomo, J. and Hauptmeier, S., 2010. Transmission of government spending shocks in the euro area: Time variation and driving forces. ECB Working Paper No. 1219.

Koop, G. and Korobilis, D., 2009. Manual to accompany MATLAB package for Bayesian VAR models. Available at: http://personal.strath.ac.uk/gary.koop/KoKo_Manual.pdf

Koop, G. and Korobilis, D., 2010. Bayesian multivariate time series methods for empirical macroeconomics. *Foundations and Trends in Econometrics* 3 (4), 267-358.

Leduc, S., Sill, K. and Stark, T., 2007. Self-fulfilling expectations and the inflation of the 1970s: Evidence from the Livingston survey. *Journal of Monetary Economics* 54, 433-459.

Mankiw, N. G., 2001. U.S. monetary policy during the 1990s. NBER Working Paper 8471.

Nakajima, J., Kasuya, M. and Watanabe, T., 2011. Bayesian analysis of time-varying parameter vector autoregressive model for the Japanese economy and monetary policy. *Journal of the Japanese and International Economies* 25, 225-245.

Nakajima, J., 2011. Time-varying parameter VAR model with stochastic volatility: An overview of methodology and empirical applications. *Monetary and Economic Studies* 29, 107-142.

Primiceri, G., 2005. Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies* 72, 821-852.

Romer, C.D. and Romer, D.H., 2004a. A new measure of monetary shocks: derivations and implications. *American Economic Review* 94, 1055-1084.

Romer, C.D. and Romer, D.H., 2004b. Choosing the Federal Reserve Chair: Lessons from history. *Journal of Economic Perspectives* 18, 129-162.

Shephard, N. and Harvey A. C., 1990. On the probability of estimating a deterministic component in the local level model. *Journal of Time Series Analysis* 11 (4), 339-347.

Shephard, N. and Pitt, M. K., 1997. Likelihood analysis of non-Gaussian measurement time series. *Biometrika* 84, 653-667.

Stock, J. and Watson, M. W., 1998. Asymptotically median unbiased estimation of coefficient variance in a time varying parameter model. *Journal of the American Statistical Association* 93, 349-358.

Tierney, L., 1994. Markov chains for exploring posterior distributions. *Annals of Statistics* 21, 1701-1762.

Watanabe, T., 2000. Bayesian analysis of dynamic bivariate mixture models: Can they explain the behavior of returns and trading volume? *Journal of Business & Economic Statistics* 18, 199-210.

Watanabe, T. and Omori, Y., 2004. Multi-move sampler for estimating non-Gaussian time series models: Comments on Shephard and Pitt (1997). *Biometrika* 91, 246-248.

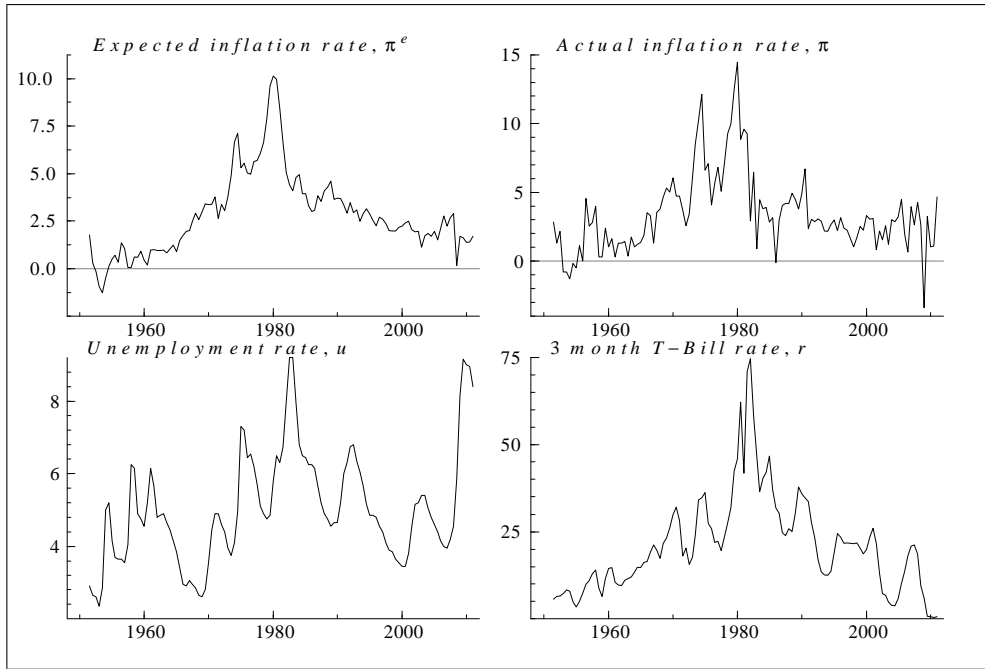


Figure 1: *Data plots. Semi-annual data over the span 1951:1 - 2010:2.*

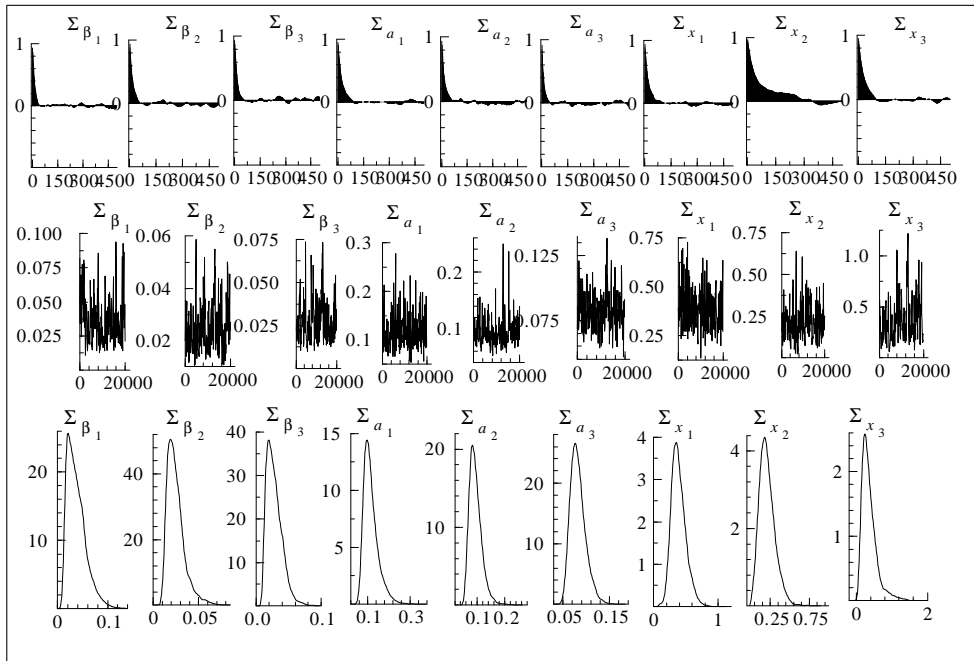


Figure 2: *Diagnostic analysis for randomly selected parameters of the TVP-SVAR, based on 20,000 MCMC iterations. First row: Sample autocorrelation functions of draws. Second row: Trace plots. Third row: Posterior densities.*

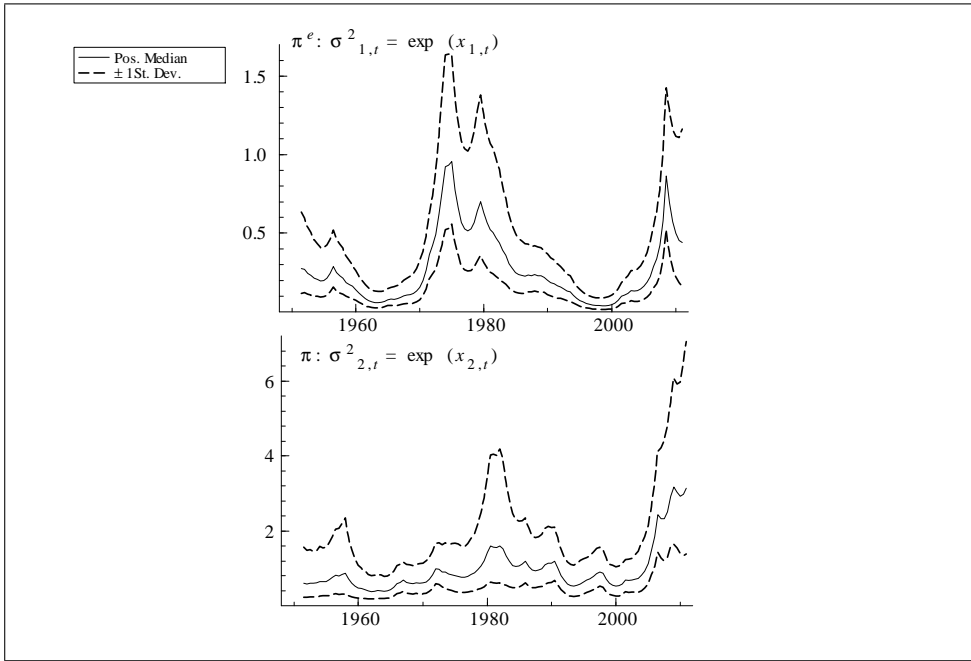


Figure 3: *Posterior estimates of stochastic volatility (SV) of structural shocks for π^e and π . Solid line: Posterior median. Dashed lines: 16th and 84th percentiles.*

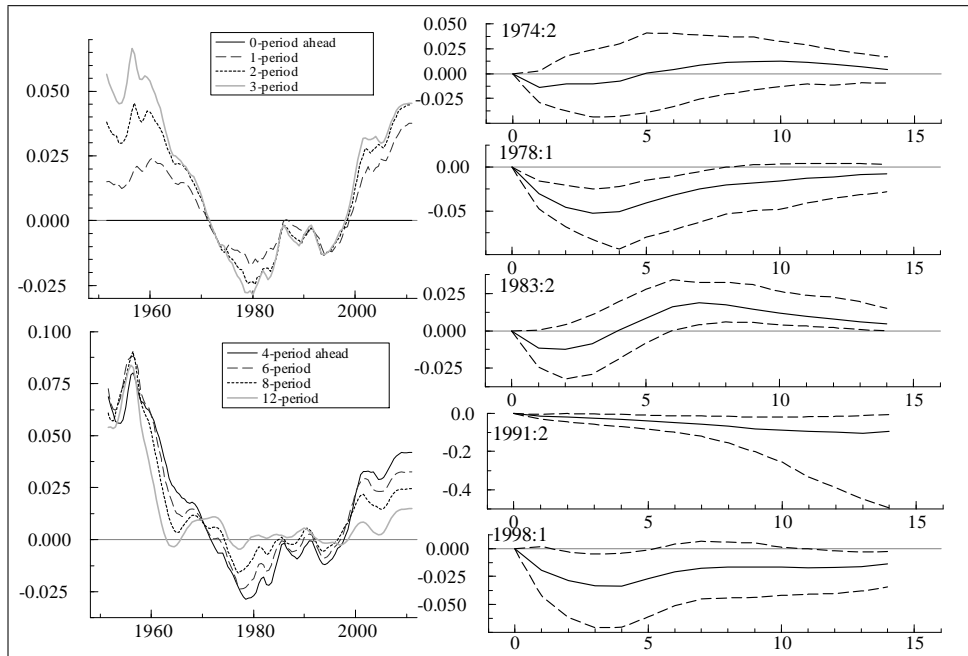


Figure 4: *Impulse responses of π^e to a one standard deviation shock in r . LEFT panel: time-varying impulse responses over the span 1951:1 - 2010:2 at different horizons. RIGHT panel: Impulse responses at selected dates. Solid line: posterior median: Dashed lines: 16th and 84th percentiles.*

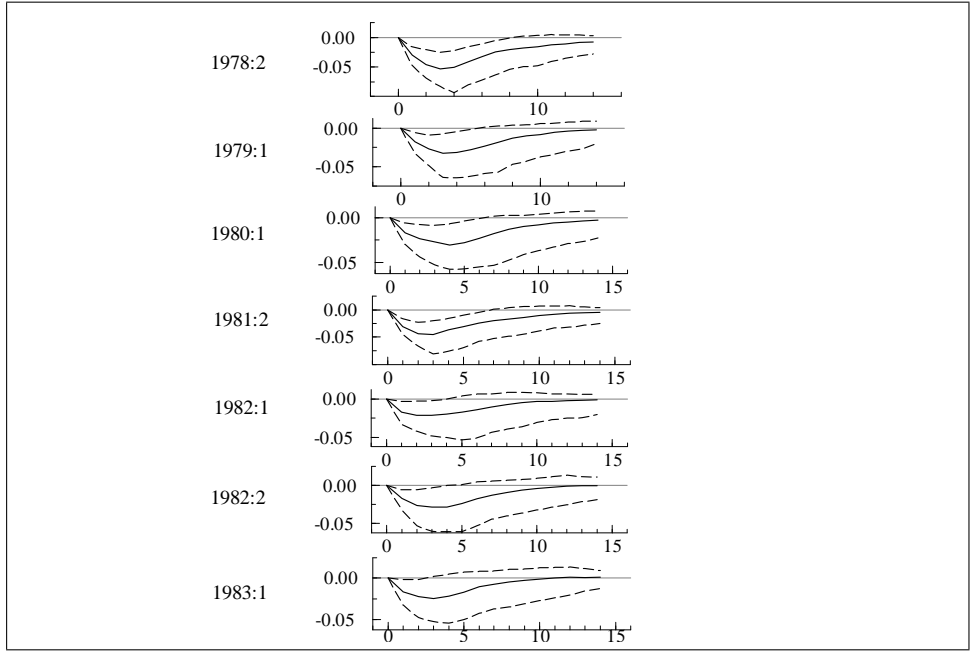


Figure 5: Impulse responses of π^e to a one standard deviation shock in r at selected dates focusing on the period around when Volcker took office. Solid line: posterior median: Dashed lines: 16th and 84th percentiles.

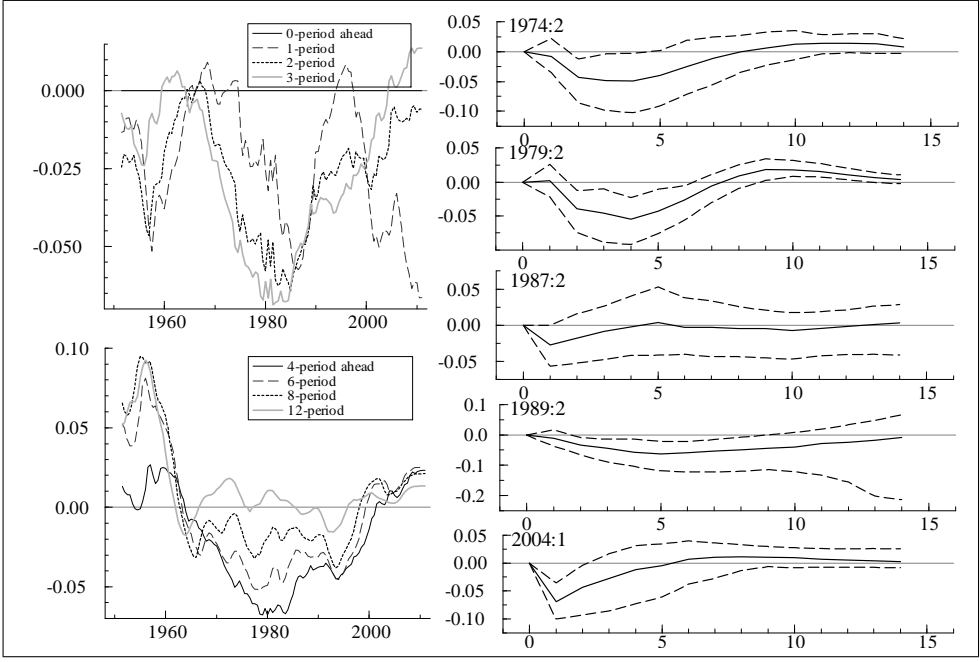


Figure 6: Impulse responses of π to a shock in one standard deviation shock in r . LEFT panel: time-varying impulse responses over the span 1951:1 - 2010:2 at different horizons. RIGHT panel: Impulse responses at selected dates. Solid line: posterior median: Dashed lines: 16th and 84th percentiles.

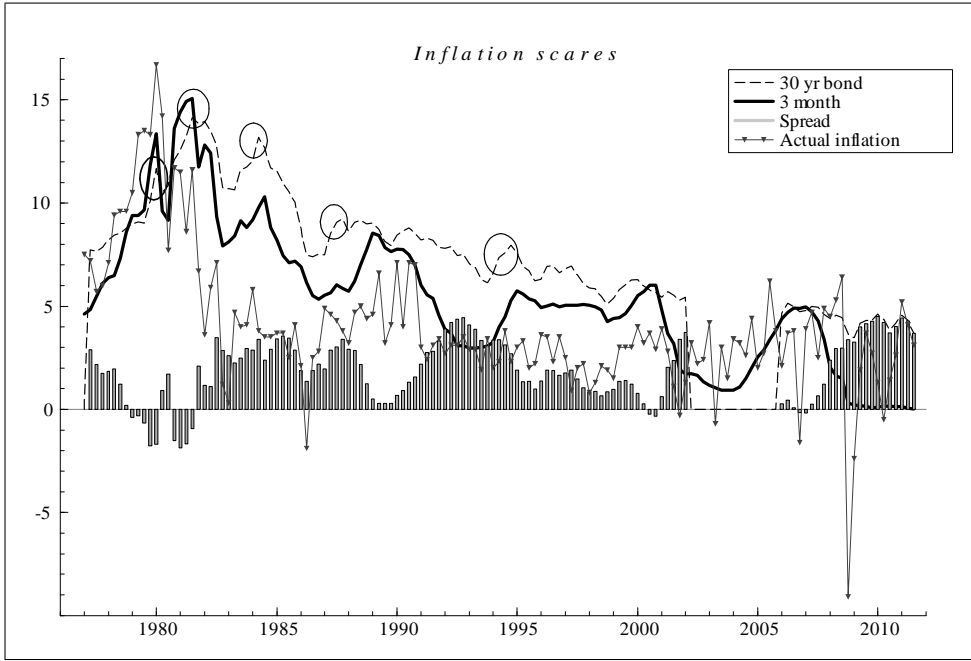


Figure 7: *Inflation scores chronology provided in Goodfriend (2003): Dates indicated by circles. All data at monthly frequency. *Note: The 30-year Treasury constant maturity series was discontinued on February 18, 2002, and reintroduced on February 9, 2006.*

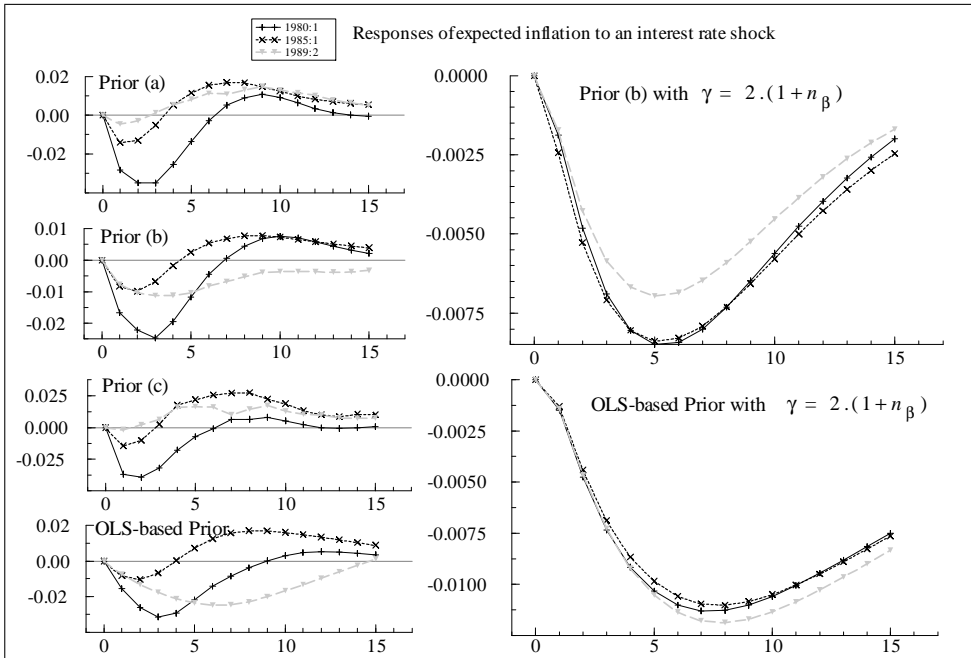


Figure 8: *LEFT panel: Investigating the influence of different choices of priors, i.e. Priors (a), (b), (c) and (d) by generating impulse responses of π^e to a shock in r at selected dates. RIGHT panel: Results using Priors (b) and (d) with higher degrees of freedom.*

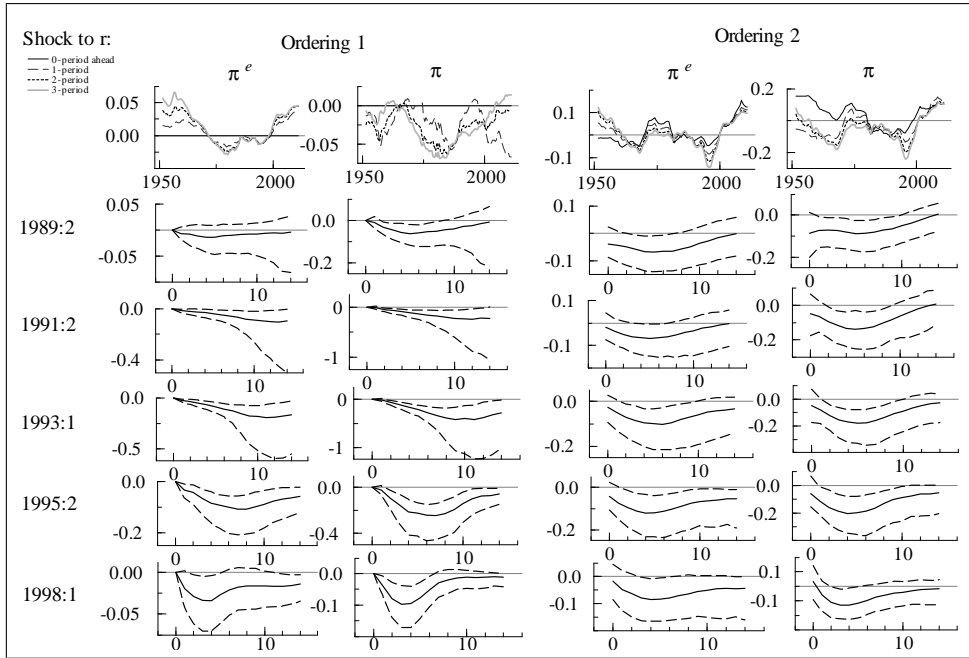


Figure 9: Comparison of the two orderings. Time varying impulse responses of π^e and π to a one standard deviation shock in r (first row). Responses at selected dates during the Greenspan era. Solid line: posterior median: Dashed lines: 16th and 84th percentiles.

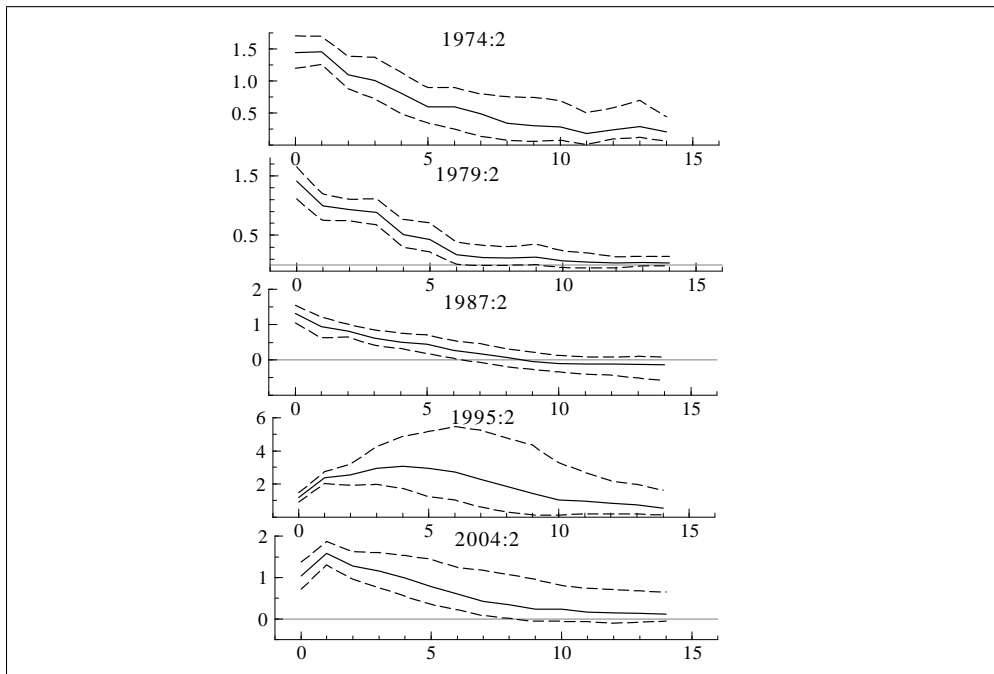


Figure 10: Impulse responses of π to a one standard deviation shock in π^e at selected dates. Solid line: posterior median: Dashed lines: 16th and 84th percentiles.

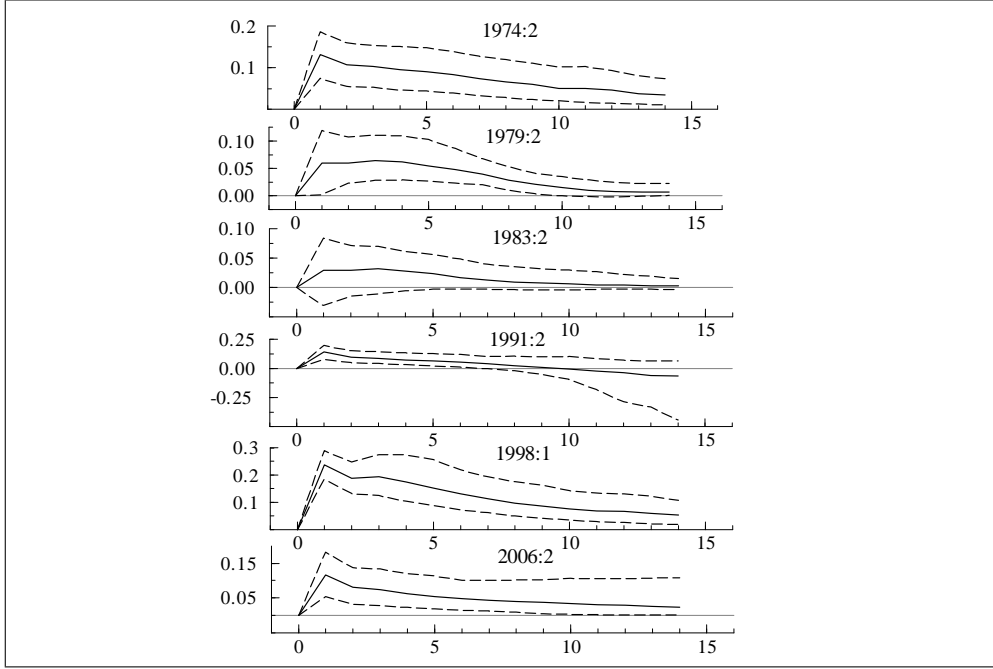


Figure 11: *Impulse responses of π^e to a one standard deviation shock in π at selected dates. Solid line: posterior median: Dashed lines: 16th and 84th percentiles.*

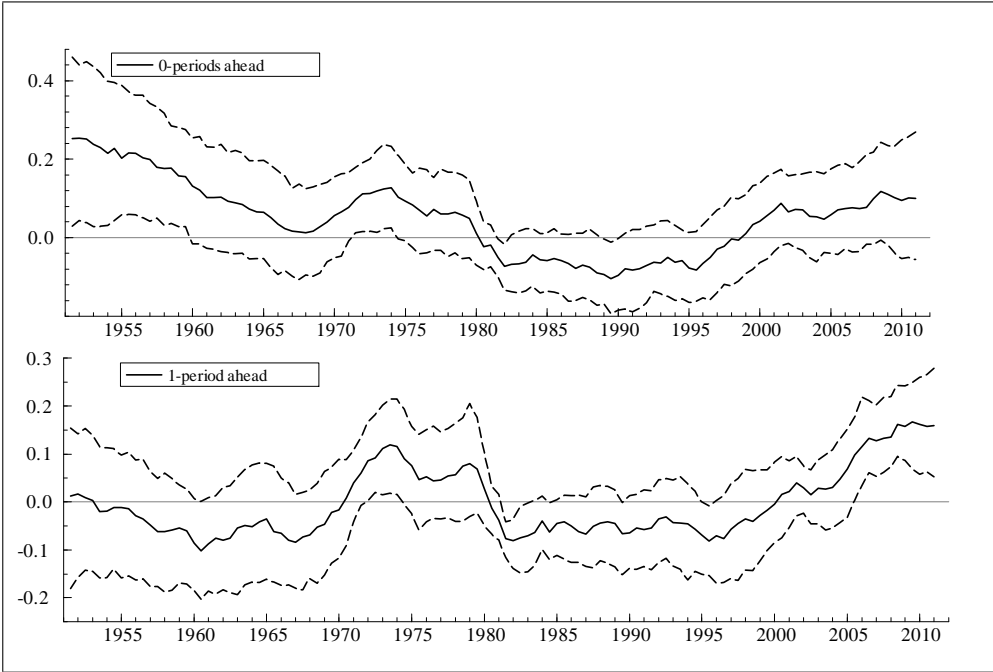


Figure 12: *Ordering 2: 0 and 1-period ahead time varying impulse responses of π to a one standard deviation permanent shock in r . Dashed lines: 16th and 84th percentiles.*

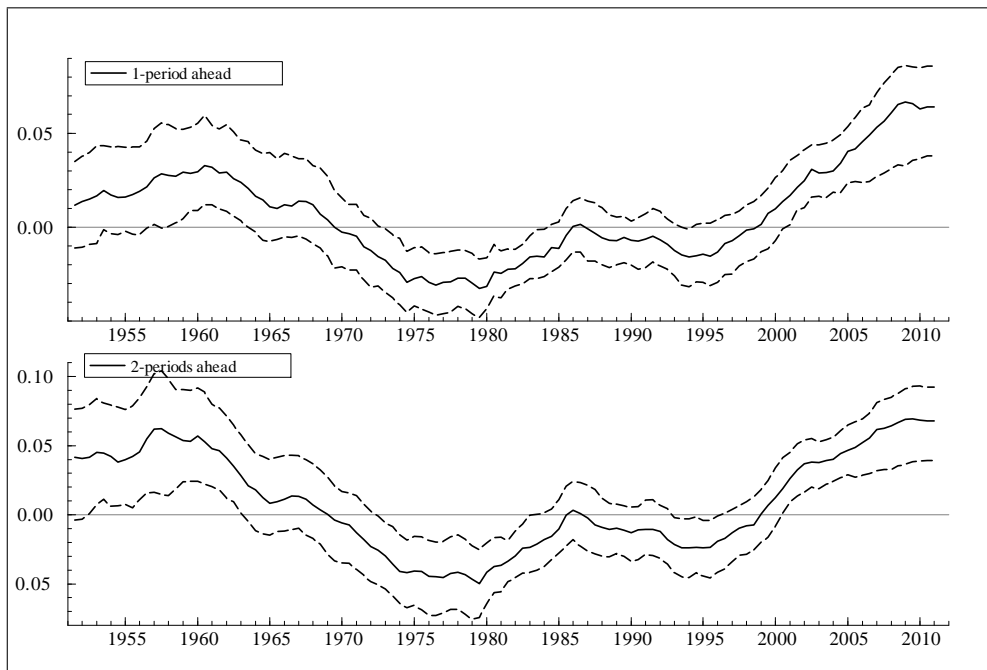


Figure 13: *Ordering 1: 1 and 2-period ahead time varying impulse responses of π^e to a one standard deviation permanent shock in r . Dashed lines: 16th and 84th percentiles.*

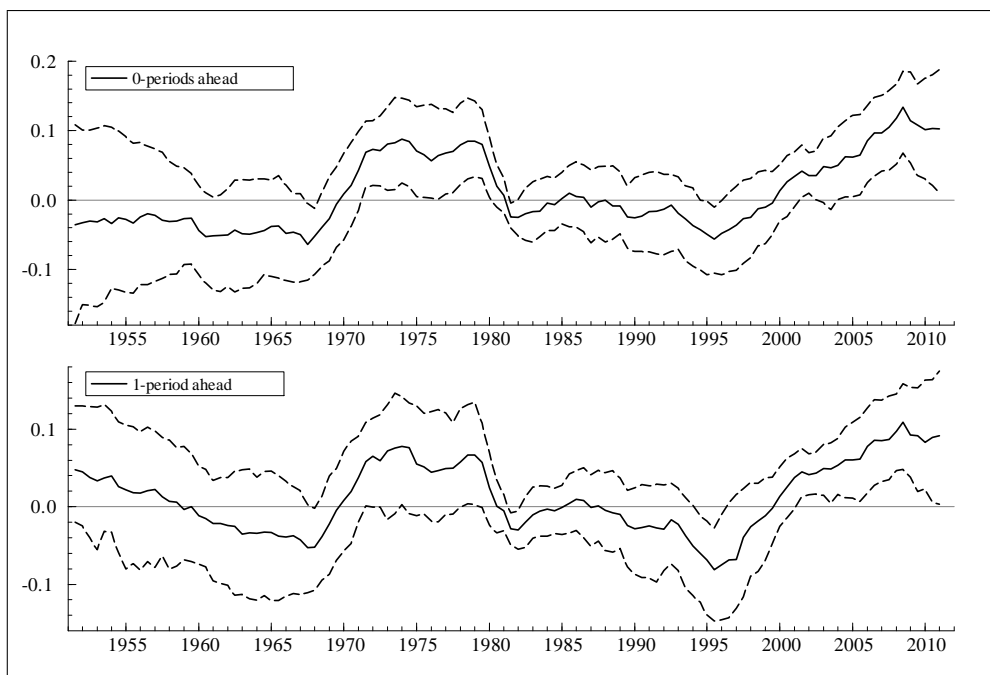


Figure 14: *Ordering 2: 0 and 1-period ahead time varying impulse responses of π^e to a one standard deviation permanent shock in r . Dashed lines: 16th and 84th percentiles.*

Appendix

<i>Parameter</i>	<i>Post. Mean</i>	<i>St.Dev.</i>	<i>95% CI</i>	<i>CD</i>
Σ_{β_1}	0.0376	0.0185	[0.0136, 0.0831]	0.176
Σ_{β_2}	0.0249	0.0096	[0.0124, 0.0499]	0.033
Σ_{β_3}	0.0280	0.0118	[0.0120, 0.0557]	0.674
Σ_{a_1}	0.1155	0.0352	[0.0678, 0.2032]	0.217
Σ_{a_2}	0.0942	0.0229	[0.0611, 0.1487]	0.426
Σ_{a_3}	0.0824	0.0164	[0.0565, 0.1198]	0.747
Σ_{x_1}	0.3880	0.1141	[0.2027, 0.6476]	0.068
Σ_{x_2}	0.2113	0.1013	[0.0519, 0.4407]	0.534
Σ_{x_3}	0.3607	0.2216	[0.0957, 0.9754]	0.021

Table 3: *Estimation results for randomly selected hyper-parameters of the TVP-SVAR model, based on 20,000 MCMC iterations, post burn-in.*

Sampling the latent states

In constructing an efficient MCMC sampling scheme for the latent states, β , \mathbf{a} , (and also \mathbf{x})¹⁷ (related to steps 2., 4. and 6. of the MCMC algorithm in Section 2.1.1), many strategies could be successfully employed, all of which have relative advantages in terms of computational cost, flexibility on implementation and efficiency. One strategy proposed in the literature is that of single-move sampling; the earliest references to which is Carlin, Polson and Stoffer (1992)¹⁸. This sampling strategy proved to be highly inefficient with the sampled state variables displaying undesirably high autocorrelation. High autocorrelation in MCMC samples will result in slow convergence of the Markov chain and will thus require considerably large numbers of samples in order to conduct inference. In response to this shortcoming, multi-move samplers have been independently suggested by Carter and Kohn (1994) and Fruhwirth-Schnatter (1994) and refined further by de Jong and Shephard (1995) (see also Durbin and Koopman, 2002). These relatively more efficient samplers involve sampling the entire vector of latent states, e.g. β simultaneously from the conditional posterior $\pi(\beta | \mathbf{a}, \mathbf{x}, \Sigma_\beta, \mathbf{y})$. This reduces the autocorrelation in the MCMC samples allowing for faster convergence. These samplers essentially entail employing (variants of) algorithms called simulation smoothers. The approach followed in this paper is that of de Jong and Shephard (1995). It is computationally simple, relatively more efficient and avoids problems of singularities and may be preferred in case of degenerate states.¹⁹

Sampling stochastic volatility

The implementation of the simulation smoother as employed for the state variables above is facilitated by the fact that the relevant state space form is linear and Gaussian. In contrast, the equations relating to stochastic volatility (SV) are of non-linear and non-Gaussian state space form rendering the task of sampling the volatility states from $\pi(\mathbf{x} | \beta, \mathbf{a}, \Sigma_x, \mathbf{y})$ (step 6. of the MCMC algorithm) comparatively more complicated. Moreover, if we were operating in a maximum likelihood estimation framework, this non-linearity and non-Gaussianity would render

¹⁷We discuss specific details of sampling with regard to \mathbf{x} in more detail in the next section.

¹⁸Their approach relies on sampling from the state vector β one element at a time; for example from $\pi(\beta_t | \beta^t, \mathbf{a}, \mathbf{x}, \Sigma_\beta, \mathbf{y})$ where β^t is β excluding β_t and cycling over t . Each draw serves to redefine a single state β_t . This utilizes the Markov properties of the state-space form and to condition on neighbouring states.

¹⁹We refer the reader to Nakajima (2009; Appendix) for implementation details of this simulation smoother for sampling β and \mathbf{a} .

the likelihood function intractable. Given this combination of linear and non-linear aspects of the state space form of the TVP-SVAR model, a Bayesian approach to estimation appears to be a natural one to take.

In order to illustrate, considering expression (4) in section 2.1, let us denote,

$$\hat{\mathbf{y}}_t = A_t(\mathbf{y}_t - Y_t\boldsymbol{\beta}_t) = \Sigma_t\boldsymbol{\varepsilon}_t. \quad (6)$$

Given the diagonality assumption on $\Sigma_{\mathbf{x}}$, inference for $\{\mathbf{x}_{j,t}\}_{t=p+1}^T$ ($j = 1, \dots, m$) is carried out separately. Hence the j -th element of $\hat{\mathbf{y}}_t$ is given by $\hat{\mathbf{y}}_{j,t}$ and the state space form of the SV model may be given by,

$$\begin{aligned} \hat{\mathbf{y}}_{j,t} &= \exp(\mathbf{x}_{j,t}/2)\boldsymbol{\varepsilon}_{j,t} \\ \mathbf{x}_{j,t+1} &= \mathbf{x}_{j,t} + \eta_{\mathbf{x}_{j,t}} \end{aligned} \quad (7)$$

$$\begin{pmatrix} \boldsymbol{\varepsilon}_{j,t} \\ \eta_{\mathbf{x}_{j,t}} \end{pmatrix} \sim N\left(0, \begin{pmatrix} 1 & 0 \\ 0 & v_j^2 \end{pmatrix}\right),$$

for $t = p, \dots, T - 1$ and v_j^2 being the j -th diagonal elements of $\Sigma_{\mathbf{x}}$.

There have been many sampling schemes put forth for this class of model. Single-move algorithms for this class of state space models can be employed, see for example Jacquier, Polson and Rossi (1994). Although feasible, these are subject to the same criticism i.e. being characterized by high autocorrelation amongst draws and decreased efficiency. One approach using a mixture sampler within a simulation smoothing framework was proposed Kim, Shephard and Chib (1998). As employed by Primiceri (2005), this multi-move approach essentially requires the recasting of (7) into an ‘approximate’ model which has a linear, albeit non-Gaussian state space form.²⁰

Alternatively, Shephard and Pitt (1997) (as modified by Watanabe and Omori (2004)) propose another method which is not based on approximations of the model and samples from the exact posterior distribution of the original non-linear, non-Gaussian specification (7). This approach, which is well described in Nakajima, Kasuya and Watanabe (2011) and Nakajima (2011) in the context of TVP-VAR (see also Watanabe, 2000) for another application), entails sampling state errors as opposed to state variables directly using a Metropolis-Hastings accept-reject (MHAR) algorithm. In order to reduce inefficiency the state variables are divided into several blocks and each block is sampled one at a time. Candidate points are drawn by first approximating the true posterior density for a block of states errors conditional on the other blocks and parameters by a linear Gaussian system and applying the simulation smoother of de Jong and Shephard (2005).

In order to be slightly more specific, the sampling method is based around sampling blocks of errors, $\eta_{\mathbf{x}_{j,t}}^k = (\eta_{\mathbf{x}_{j,t-1}}, \dots, \eta_{\mathbf{x}_{j,t-k-1}})'$, for example, conditional on initial and end conditions $\mathbf{x}_{j,t-1}$ and $\mathbf{x}_{j,t+1+k}$, the observations and hyperparameters. There is of course a deterministic relationship between $\eta_{\mathbf{x}_{j,t}}^k$ and $\mathbf{x}_{j,t}^k = (\mathbf{x}_{j,t}, \dots, \mathbf{x}_{j,t+k})'$. Hence we can equally imagine these (blocks of) states being sampled, given the initial and end conditions which are termed ‘stochastic knots’. k is a tuning parameter indicating the lengths of blocks to be selected. Typically it is chosen to be stochastic, thus varying the stochastic knots at each iteration of the sampler.²¹ Central to

²⁰As described in Kim et al. (1998), this is achieved by squaring and taking the logarithm of each element of (6). Hence the new measurement disturbance term is given by $\bar{\boldsymbol{\varepsilon}}_{jt} = \log(\boldsymbol{\varepsilon}_{jt}^2) \sim \log \chi^2(1)$. In order to convert the the system into a Gaussian form a mixture of normals ‘approximation’ of the $\log \chi^2$ distribution is employed. The approximation error is (typically) fairly small can be corrected by a re-weighting procedure discussed in Kim et al. (1998). This correction is not adopted in Primiceri (2005).

²¹A fixed number of L states which are widely spaced over the time domain are chosen to remain fixed for one iteration of the MCMC method. For example if we propose to work with a collection of stochastic knots at times

the method here will be the second-order Taylor expansion of the conditional posterior density,

$$\log f = \log f(\eta_{\mathbf{x}_{j,t}}^k | \theta_j^k), \quad (8)$$

where $\theta_j^k = (\mathbf{x}_{j,t-1}, \mathbf{x}_{j,t+1+k}; \widehat{\mathbf{y}}_{j,t}, \dots, \widehat{\mathbf{y}}_{j,t+k}; v_j^2)$ around some preliminary estimate, i.e. $\widehat{\mathbf{x}}_{j,t}^k$ in order to form a proposal density.²² Constructing the proposal density in this way enables the use of the simulation smoother (de Jong and Shephard (1995)) to sample candidate points/suggestions for $(\eta_{\mathbf{x}_{j,t-1}}, \dots, \eta_{\mathbf{x}_{j,t-k-1}})$ to be then be used in the MHAR algorithm; see Tierney (1994) and also Chib and Greenberg (1995). This will allow sampling from the true posterior density f .

$l = 1, \dots, L$; then we can determine

$$k_l = \text{int} \left[\frac{T(l + U_l)}{L + 2} \right],$$

where $U_l \sim \text{U}(0,1)$ and $\text{int}(\cdot)$ indicates rounded to the nearest integer. Here we set $k_0 = p$ and $k_{L+1} = T$.

²²The values for $\widehat{\mathbf{x}}_{j,t}^k$ around which the Taylor expansion takes place are selected at the mode of the conditional density of $\mathbf{x}_{j,t}^k$, i.e. $p(\mathbf{x}_{j,t}^k | \mathbf{x}_{j,t-1}, \mathbf{x}_{j,t+1+k}; \widehat{\mathbf{y}}_{j,t}, \dots, \widehat{\mathbf{y}}_{j,t+k}; v_j^2)$, which can be found using a moment smoother.

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