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# Assessing the transmission of monetary policy shocks using dynamic factor models\*

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## Abstract

This paper extends the current literature which questions the stability of the monetary transmission mechanism, by proposing a factor-augmented vector autoregressive (VAR) model with time-varying coefficients and stochastic volatility. The VAR coefficients and error covariances may change gradually in every period or be subject to abrupt breaks. The model is applied to 143 post-World War II quarterly variables fully describing the US economy. I show that both endogenous and exogenous shocks to the US economy resulted in the high inflation volatility during the 1970s and early 1980s. The time-varying factor augmented VAR produces impulse responses of inflation which significantly reduce the price puzzle. Impulse responses of other indicators of the economy show that the most notable changes in the transmission of unanticipated monetary policy shocks occurred for GDP, investment, exchange rates and money.

## I Introduction

A challenge of great importance in modern macroeconomics is to identify the contribution of monetary policy shocks to the economy over time. Over the course of the last 40 years the US economy has been characterized by transitory exogenous shocks, and more pervasive events such as the liberalization of financial markets, and the decline in output volatility and inflation persistence since the early 1980s (see e.g. Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Stock and Watson, 2002). At the same time, the conduct of monetary policy has also changed, with maintaining price and output stability being the dominant strategy by the Fed. Since both monetary policy and the nature of exogenous shocks have evolved dramatically, there is an obvious

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empirical challenge in identifying the actual role of monetary policy actions in influencing observed changes in the economy. It is not surprising that currently there is a vast empirical literature measuring the monetary transmission mechanism with contradicting results. For instance, Boivin and Giannoni (2006b), Cogley and Sargent, (2001, 2005) and Clarida *et al.* (2000) argue in favor of a ‘good policy’ scenario, where monetary policy since the early 1980s became more aggressive in stabilizing shocks to prices and aggregate activity. Primiceri (2005), Sims and Zha (2006), Koop *et al.* (2009), and Canova and Gambetti (2009) follow the traditional VAR approach, formulated econometrically to allow for the parameters to drift over time, and end up with mixed results as to whether it is the shock or the propagation mechanism which has changed over time; Giannone, Lenza and Reichlin (2008) offer a detailed summary of this literature.

Common place in these studies is an attempt to measure the effects of monetary policy in the economy as a whole by using only a restricted set of variables, as implied by New-Keynesian DSGE models with three endogenous variables describing economic activity, aggregate prices and monetary policy. Stock and Watson (2005) and Bernanke *et al.* (2005) point out that when extracting the structural shocks from the innovations of a VAR it is important to make sure that there is no omitted variable bias. Since during the decision process there are hundreds of variables available to economic agents and policy makers, especially Central Banks (Bernanke and Boivin, 2003), it is expected that the innovations of a VAR with just three variables will not span the space of structural disturbances. This lack of information has also been identified as the source of the price puzzle - the fact that prices increase following a contractionary monetary policy. In light of this puzzle many authors, including Boivin and Giannoni (2006b), reformulate their 3-variable VAR by introducing a price index as an additional variable without success. In fact Castelnuovo and Surico (2010) show that including a measure of inflation expectations in the VAR is the way to correct the prize puzzle and they provide extensive simulations to support this finding. Nowadays it is recognized that adding more and more information to a VAR has the potential to resolve many anomalies observed empirically.

Dynamic factor analysis in the form described, for instance, in Stock and Watson (2005) can do exactly this without introducing a degrees of freedom problem. In essence, the Dynamic Factor Model is a means of summarizing information in a large data-set - in the order of some hundreds of variables - using just a few (usually less than 10) latent variables called factors. These factors can just be the first few principal components of the large data-set, but also different methods for estimating latent factors have been proposed over the course of the last years. Among the vast literature, notable recent studies include Boivin and Ng (2005), Giannone, Reichlin and Small (2008) and Boivin and Giannoni (2006a). The recent implementations of Stock and Watson (2005) and Bernanke *et al.* (2005) have the advantage of treating the dynamic factor model as a direct generalization of structural VAR’s.

This paper adopts a structural VAR framework combined with factors as the starting point. Then, for the purpose of modeling the evolution of monetary policy in the US, the parameters of the VAR are allowed to evolve over time. This assumption implies

that the transmission of monetary and non-monetary shocks can be measured over different points in time. Subsequently, this paper goes one step further from the standard dynamic factor literature to identify the merits of using the currently popular time-varying parameters VARs. That way, large datasets can be used in a model which allows both frequent and infrequent breaks and adapts immediately to changes in regimes. Specifically for the US, this modeling flexibility is of great importance. Historically, there were many episodes with short-run (financial shocks like the Black Monday of 1987) and long-run, structural (Great Inflation, Great Moderation) effects which imply smaller or larger abrupt changes in VAR parameters. Time-varying parameters of the form defined in this paper can capture all these changes efficiently.

The main purpose in this paper is to develop the econometric background for the proposed modeling strategy, and to tackle the complications which arise in practice when using this model for measuring monetary policy. For instance, Del Negro and Otrok (2008) is an ambitious study which uses a one-step estimator in a time-varying parameters dynamic factor model. Their approach has many advantages, including full treatment of uncertainty surrounding latent factors and model parameters. Nevertheless, their exact model can be computationally hard to estimate and lots of art is required from the researcher in order to apply normalization and identification restrictions.<sup>1</sup> Additionally, latent factors estimated in one-step lead to flat (unidentified) impulse responses; see for example Figure V of Bernanke *et al.* (2005) and the discussion therein.

In this paper I examine the performance of a simpler two-step estimator: the factors are replaced by the first principal components (PC) obtained from the singular value decomposition of the data matrix, and consequently are treated as observed. That way the time-varying parameters can be updated at a second step conditional on these observed factors. The principal components estimates have economic meaning and approximate asymptotically the true factors in the case of constant loadings. These factors are used in a time-varying VAR model (i.e. a factor-augmented VAR), where the drifting mean and variance parameters follow a random walk (Primiceri, 2005), an assumption which simplifies computations by using standard state-space methods. However, in this paper this random walk evolution of the VAR parameters is augmented using the flexible mixture innovation specification of Giordani and Kohn (2008). By specifying time-varying parameters with stochastic innovations that are mixtures of normals, it is possible to define endogenously whether these parameters vary in every time period or if they are constant in every period, plus all the possible combinations between those two (i.e. parameters which vary only in some periods).

Having established the advantage of accounting for omitted variable bias, this study adds to an expanding recent literature (Cogley and Sargent, 2005; Stock and Watson, 2002; Primiceri, 2005; Giannone, Lenza and Reichlin, 2008 to name but a few) which

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<sup>1</sup>Most importantly, their exact setting which was used to measure the synchronization of international business cycles is not attractive for measuring monetary policy shocks since - for identification issues - it assumes a diagonal covariance matrix of the shocks; see Del Negro and Otrok (2008).

tries to explain whether the Great Moderation in the U.S. has occurred due to a change in the Fed's reaction function ('good policy') or due to a decline in the volatility of exogenous shocks ('good luck').<sup>2</sup> I provide time-varying decompositions of the variance of inflation (as implied by the factor model) into the proportion explained by: i) all 143 observed series; ii) monetary policy (interest rate) and economic activity (GDP-unemployment); and iii) exogenous shocks. I show that both endogenous and exogenous shocks to the US economy played an important role in inflation volatility during the 1970s and early 1980s. I also examine the movements in non-systematic monetary policy as implied by the evolution of the factors and their time-varying covariances. This paper concludes with measuring monetary policy in three representative periods by means of impulse responses. I make comparisons of the impulse responses of inflation, unemployment and interest rate as estimated from the TVP-FAVAR and VARs with constant and time-varying parameters. The results show that the TVP-FAVAR significantly corrects the price puzzle in the 1970s. Finally, time-varying impulse responses of other indicators of the economy show that the most notable changes in the effects of monetary policy were for GDP, investment and exchange rate, while for money there was a different response only during the monetarist experiment of 1980-1984.

The remainder of the paper is as follows. In Section 2 I specify the dynamic factor model as a time-varying parameters VAR model on latent factors and the monetary policy variable. In Section 3 I describe the data and factors, the model fit and model selection issues. In Section 4 I provide the empirical results from this new model, and in Section 5 I conclude.

## II Methodology

### The model

The standard approach to examine the effects of monetary policy on the economy is to estimate a structural VAR on some key variables. Models of this form have the following reduced-form representation

$$y_t = b_1 y_{t-1} + \dots + b_p y_{t-p} + v_t \quad (1)$$

where  $y_t' = [z_t', r_t]$ ,  $z_t$  is a  $(l \times 1)$  vector of variables provide a representation of the economy (like output, prices, interest rates, monetary aggregates and so on), and  $r_t$  is a single series proxying the monetary policy instrument, i.e. the control variable of the

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<sup>2</sup>'Good policy' or 'good luck' are not the only explanations of the Great Moderation. McConnell and Perez-Quiros (2000) identify a change in the behavior of inventories which might be attributed in advances in information technology (Kahn, McConnell, and Perez-Quiros, 2002). Similarly Dynan, Elmen-dorf, and Sichel (2006) and Campbell and Hercowitz (2006) document easier access to external financing by households since the beginning of the 1980s. These are two alternative interpretations, however in this paper I will focus only on the role of monetary policy.

Central Bank. The coefficients  $b_i$ ,  $i = 1, \dots, p$  on each lagged value of  $y_t$  are of dimensions  $(l + 1) \times (l + 1)$ , and  $v_t \sim N(0, \Omega)$  with  $\Omega$  a  $(l + 1) \times (l + 1)$  covariance matrix. The number  $(l + 1)$  of variables in  $y_t$  in a typical VAR usually does not exceed 20. In many cases, as mentioned in the introduction, it is as low as three variables. If one has hundreds of observations in a  $n \times 1$  vector  $x_t$  that one would like to incorporate in the VAR, as is the case with researchers in Central Banks, it is obvious that a curse of dimensionality problem occurs immediately. A popular solution to this problem is to decompose the  $n$ -dimensional vector of observables  $x_t$  into a lower dimensional vector of  $k$  (which is much smaller than  $n$ , i.e.  $k \ll n$ ) factors,  $f_t$ . Additionally, by allowing the parameters of the VAR augmented with factors to vary over time, more complex dynamics can be modelled and the effects of monetary policy actions can also be assessed over time. The time-varying parameters factor-augmented VAR (TVP-FAVAR) takes the form

$$y_t = b_{1t}y_{t-1} + \dots + b_{pt}y_{t-p} + v_t \quad (2)$$

where now  $y_t' = [f_t', z_t', r_t']$ , with  $f_t$  a  $(k \times 1)$  vector of latent factors,  $[z_t', r_t']$  is still a vector containing observed variables plus the monetary policy tool and is of dimension  $((l + 1) \times 1)$ ,  $b_{jt}$  are  $m \times m$  coefficient matrices for  $j = 1, \dots, p$  and  $t = 1, \dots, T$ , and  $v_t \sim N(0, \Omega_t)$  with  $\Omega_t$  a  $m \times m$  full covariance matrix for each  $t = 1, \dots, T$ , with  $m = k + l + 1$ .

Each of the  $i = 1, \dots, n$  original observed series  $x_{it}$  is linked to the factors, the other observed variables  $z_t'$ , and the monetary policy tool  $r_t$  through a factor analysis regression with autocorrelated errors and stochastic volatility of the form

$$x_{it} = \tilde{\lambda}_i^f f_t + \tilde{\lambda}_i^z z_t + \tilde{\lambda}_i^r r_t + u_{it} \quad (3a)$$

$$u_{it} = \rho_{i1} u_{it-1} + \dots + \rho_{iq} u_{it-q} + \varepsilon_{it} \quad (3b)$$

where  $\tilde{\lambda}^f$  is  $(n \times k)$ ,  $\tilde{\lambda}^z$  is  $(n \times l)$ , and  $\tilde{\lambda}^r$  is  $(n \times 1)$ , and  $\varepsilon_{it} \sim N(0, \exp(h_{it}))$ . The errors  $\varepsilon_{it}$  are assumed to be uncorrelated with the factors at all leads and lags and mutually uncorrelated at all leads and lags, namely  $E(\varepsilon_{it} f_t) = 0$  and  $E(\varepsilon_{it} \varepsilon_{jt}) = 0$  for all  $i, j = 1, \dots, n$  and  $t, s = 1, \dots, T$ ,  $i \neq j$  and  $t \neq s$ . In order to work with a model with uncorrelated errors, we need to transform eq. (3) into

$$x_t = \lambda^f f_t + \lambda^z z_t + \lambda^r r_t + \Gamma(L) x_t + \varepsilon_t \quad (4)$$

where  $\gamma(L) = \text{diag}(\rho^1(L), \dots, \rho^n(L))$ ,  $\rho^i(L) = \rho_{i1}L + \dots + \rho_{iq}L^q$ ,  $\lambda^j = (I_n - \gamma(L)) \tilde{\lambda}^j$  for  $j = f, z, r$ , and finally  $\varepsilon_t \sim N(0, H_t)$  with  $H = \text{diag}(\exp(h_{1t}), \dots, \exp(h_{nt}))$  where the individual log-volatilities evolve as a driftless random walk of the form

$$h_{it} = h_{it-1} + \eta_t^h$$

with  $\eta_t^h \sim N(0, \sigma_h)$ . The main TVP-FAVAR model consists of eqs (2) and (4) and for simplicity I will refer to them as the 'FAVAR' and 'factor model' equations, respectively.

In order to complete the model specification, it is necessary to characterize all model parameters and their dynamics.

Eq. (2) is a VAR system on the factors and the observable variables  $z_t'$  and  $r_t$  with drifting coefficients and stochastic volatility. Based on the recent literature on efficiently parametrizing large covariance matrices, Primiceri (2005), Cogley and Sargent (2005) and Canova and Gambetti (2009) use a decomposition of the (FA)VAR error covariance matrix of the form

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t' \quad (5)$$

or equivalently

$$\Omega_t = A_t^{-1} \Sigma_t \Sigma_t' (A_t^{-1})' \quad (6)$$

where  $\Sigma_t = \text{diag}(\sigma_{1,t}, \dots, \sigma_{k+1,t})$  and  $A_t$  is a unit lower triangular matrix with ones on the main diagonal

$$A_t = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{m1,t} & \dots & a_{m(m-1),t} & 1 \end{bmatrix} \quad (7)$$

Stacking all the parameters of eq. (2) in the vectors  $B_t = (\text{vec}(b_{1t})', \dots, \text{vec}(b_{pt})')'$ ,  $\log \sigma_t = (\log \sigma'_{1t}, \dots, \log \sigma'_{mt})'$  and  $\alpha_t = (a'_{j1,t}, \dots, a'_{j(j-1),t})'$  for  $j = 1, \dots, m$ , I follow the standard convention and assume that the set of drifting parameters  $B_t$ ,  $\alpha_t$  and  $\log \sigma_t$  follow random walks augmented with the flexible mixture innovation specification of Giordani and Kohn (2008). For each time period, the innovations of the random walk evolution of the parameters are defined as a mixture of two normal components (see Koop *et al.*, 2009), and take the following form

$$\begin{aligned} B_t &= B_{t-1} + J_t^B \eta_t^B \\ \alpha_t &= \alpha_{t-1} + J_t^\alpha \eta_t^\alpha \\ \log \sigma_t &= \log \sigma_{t-1} + J_t^\sigma \eta_t^\sigma \end{aligned} \quad (8)$$

where  $\eta_t^\theta \sim N(0, Q_\theta)$  are innovation vectors independent with each other, as well as  $u_t$  and  $v_t$ , while  $Q_\theta$  are innovation covariance matrices associated with each of the parameter vectors  $B_t, \alpha_t, \log \sigma_t$ , where for brevity define  $\theta_t \in \{B_t, \alpha_t, \log \sigma_t\}$ . Some correlation can be allowed between the disturbance terms appearing in (8), which could permit modeling more complex dynamics. However, this flexibility comes at the cost of the proliferation of the parameters that need to be estimated, and the assumption made here is that all error components appearing in eqs (2) and (4) are uncorrelated with each other.

The random variables  $J_t^\theta$  can only take two values, one and zero, at each time period  $t$  making the state errors a mixture of a Normal component with covariance  $Q_\theta$  and a second component which places all probability point mass at zero. As it is explained in section 3, the variables  $J_t^\theta$  are assigned with a prior distribution and are subsequently updated from the data likelihood. That way the mixture innovation specification is

flexible as it allows the information in the data to determine either one of the two extreme specifications of constant parameters (iff  $J_t^\theta = 0 \forall t = 1, \dots, T$ ) and of time-varying parameters (iff  $J_t^\theta = 1 \forall t = 1, \dots, T$ ). In between those two extremes, i.e. when  $J_t^\theta = 1$  for only some  $t$ , lie several specifications which can be interpreted as if only a few breaks occur over the sample. This flexible mixture innovation specification might be necessary when no prior opinion about the amount of variation in the parameters is available, and when marginal likelihoods are hard to obtain (as it is the case with time-varying parameters models). For instance, Sims and Zha (2006) using a Markov-switching VAR find evidence for time variation only on the covariance matrix of their VAR and not on the mean equation coefficients  $B_t$ . Finally, notice that the TVP-FAVAR model nests also the TVP-VAR model of Primiceri (2005), by simply setting the number of factors,  $k$ , equal to zero. Therefore, a large class of models - ranging from small (V)ARs with constant parameters to their time-varying parameters counterparts using hundreds of variables - can be examined using the single specification in this paper.

## Estimation

The latent factors can be treated as unobserved parameters and estimated along the other model parameters in one step, using Markov Chain Monte Carlo (MCMC). This approach is plausible since we can write the model in state-space form with the factors being the unknown state vector, so that standard filtering algorithms can be used (Carter and Kohn, 1994). However, this approach is computationally demanding, since already in this model expensive MCMC simulation methods have to be used to estimate the time-varying parameters in eq. (8). Furthermore, there are additional identification issues arising with likelihood-based estimation. For example, in the constant parameters dynamic factor model setting, Bernanke *et al.* (2005) use a triangular identification restriction in the upper  $k \times k$  block of the loadings matrix<sup>3</sup>, and argue that the Bayesian (and likelihood-based in general) estimation produces factors that do not capture information about real-activity and prices. In the time-varying setting, the identification problem is even more accented and will inevitably lead to impulse responses which are hardly in accordance with economic theory. Following Stock and Watson (2005) I apply a conceptually and computationally simple two-step estimation method. The factors are approximated using standard principal components, and then the model parameters are estimated conditional on these estimates of the factors. In this case we have to estimate independently  $n$  univariate regressions in (4) and a time-varying parameters VAR in the

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<sup>3</sup>This identification restriction is similar to the one that is met in cointegration analysis, i.e. the upper block is the identity matrix. This has the implication that the first series in the dataset loads exclusively on the first factor with coefficient 1, the second series loads exclusively on the second factor with coefficient 1 and so on. Hence the ordering of the variables in  $x_t$  plays a significant role as it alters the likelihood function, a serious problem that has been noted in the cointegration literature (Strachan, 2003). Unfortunately, when using factor models, Bayesian statisticians and econometricians rely heavily on such identification restrictions and, to my knowledge, there is no formal examination of their implications (other than a quick reference to this problem in the review paper of Lopes and West, 2004).



factors and observables in (2).

Posteriors of the time-varying parameters are not analytically available, however the conditional posteriors are readily available and the Gibbs sampler can be used for that purpose. The parameters in the factor equation are sampled using standard arguments for linear regression models (Koop, 2003), with the modification that the log-volatilities  $h_{it}$  are sampled using the algorithm of Kim *et al.* (1998). Conditional on the value of  $J_t^\theta$  the state eqs (8) have conditionally normal errors and the Kalman filter can be used to estimate the time-varying parameters  $\theta_t$ . The only modification needed to the Kalman filter algorithm is that when  $J_t^\theta = 0$  then the covariance matrix of the state innovations is  $J_t^\theta Q_\theta = 0$ , while when  $J_t^\theta = 1$  the covariance matrix becomes  $J_t^\theta Q_\theta = Q_\theta$ . Furthermore, conditional on each draw of the parameters  $\theta_t$ , the covariances of the states,  $Q_\theta$ , can be sampled using again standard formulas. In fact, these formulas are the same as in the previous TVP-VAR works of Cogley and Sargent (2005), Primiceri (2005) and Koop *et al.* (2009). The indicators  $J_t^\theta$  are sampled using the algorithm of Gerlach *et al.* (2000). This is an efficient approach to modelling dynamic mixtures given that  $J_t^\theta$  can be generated without conditioning on the states  $\theta_t$ . More computational details are provided in the working paper version of this paper; see also the review paper by Koop and Korobilis (2010) and the associated MATLAB page to estimate the models reported in this paper.

## Priors

The dimension of the model and the presence of time-varying parameters calls for some shrinkage in the model. For instance, given that the VAR autoregressive parameters  $B_t$  follow a random walk which can easily lead to explosive draws, Cogley and Sargent (2001, 2005) use ‘reflective barriers’ in those parameters. More specifically, they provide a simple accept/reject algorithm, where MCMC draws of  $B_t$  are retained only when the roots of the associated VAR polynomial lie outside the unit circle. However, as Koop and Potter (2011) prove, this generalization of the simple algorithm to retain stationary draws in VAR models is inefficient in TVP-VAR models with more than three variables (as well as mathematically wrong, see their Appendix A). In my simulations with the 6 variable TVP-FAVARs, almost 100% of the draws were rejected. Thus, a valid alternative way to provide shrinkage is to use the prior. Primiceri (2005) uses an informative prior based on a training sample which is quite tightly parametrized. The mixture innovation specification, specified in eqs (8), has the potential to provide some shrinkage by reducing the parameter space towards a model with constant parameters, but this might not be enough to guarantee a parsimonious specification. I use an Empirical Bayes prior which is very popular in the standard VAR setting, i.e. the Minnesota prior. This prior has the property that own lags of each variable take a larger weight, while higher order lags and lags on other variables are discounted more becoming a-priori less important. The reader is referred to Doan, Litterman and Sims (1986) for more information.

In particular, I specify the prior densities on the unrestricted (non-zero) parameters

in the factor model equation to be  $[\lambda_i^f, \lambda_i^z, \lambda_i^r] \sim N(0_{1 \times m}, 10I_m)$ ,  $\gamma_i(L) \sim N(0_{1 \times q}, 10I_q)$  and  $h_{i0} \sim N(0, 4)$ ,  $\sigma_h^{-1} \sim \text{Gamma}(0.01, 0.01)$  for each variable  $i = 1, \dots, n$ . For the parameters of the FAVAR equation I set  $B_0 \sim N(\underline{B}, \underline{V})$ ,  $\alpha_0 \sim N(0, 4I)$ ,  $\log \sigma_0 \sim N(0, 4I)$ ,  $Q_B^{-1} \sim W(0.005 \times (\dim(B) + 1) \times \underline{V}, (\dim(B) + 1))$ ,  $Q_\alpha^{-1} \sim W(0.01 \times (\dim(\alpha) + 1) \times I, (\dim(\alpha) + 1))$ , and  $Q_\sigma^{-1} \sim W(0.0001 \times (\dim(\sigma) + 1) \times I, (\dim(\sigma) + 1))$ , where  $\dim(B) = m \times m \times p$ ,  $\dim(\alpha) = m(m-1)/2$  and  $\dim(\sigma) = m$ . Here  $\underline{B}$  is set to 0.9 on the coefficient of the first own lag of each dependent variable and 0 elsewhere, and  $\underline{V}$  is a diagonal prior covariance matrix with diagonal elements defined from a Minnesota-type specification of the form

$$\underline{V}_{ij} = \begin{cases} \frac{1}{c^2} & \text{for parameters on own lags} \\ \frac{0.001s_i^2}{c^2s_j^2} & \text{for parameters on variable } j \neq i, \text{ for lag } c = 1, \dots, p \end{cases} \quad (9)$$

where  $s_i^2$  is the residual variance from the  $p$ -lag univariate autoregression for dependent variable  $i$ , and  $i = 1, \dots, m$ ,  $j = 1, \dots, mp$ .

The 'nonstandard' parameters in this model are the ones related to the mixture innovation extension. The 0/1 variables  $J_t^\theta$  are assumed to come from a Bernoulli distribution,  $p(J_t^\theta = 1) = \pi_\theta = 1 - p(J_t^\theta = 0)$ , for  $\theta \in \{B_t, \alpha_t, \log \sigma_t\}$ . The probabilities  $\pi_\theta$  control the transition of the index  $J_t^\theta$  between the two possible states (1:break - 0:no break), and an additional hierarchical prior is introduced in order to update them from the information in the data. A Beta prior of the form  $\pi_\theta \sim \text{Beta}(\tau_0, \tau_1)$  is placed on this hyper-parameter, which controls the prior belief about the number of breaks through the choice of  $\tau_0$  and  $\tau_1$ . I set these hyperparameters to be  $(\tau_0, \tau_1) = (1, 1)$ , which is an uninformative and uniform choice, with  $E(\pi_\theta) = 0.5$  and  $\text{std}(\pi_\theta) \cong 0.29$ . Note that for simplicity, and in the absence of prior information,  $\tau_0$  and  $\tau_1$  are the same for all three drifting parameters defined in Eq. (8).

## VAR representation and impulse response functions

It is easy to show that the time-varying FAVAR model admits a standard VAR representation with drifting parameters. First note that Equations (2) and (4) can be rewritten as

$$g_t = \Lambda y_t + \Gamma(L) g_t + W_t \epsilon_t^g \quad (10)$$

$$y_t = B_t(L) y_t + A_t^{-1} \Sigma_t \epsilon_t^y \quad (11)$$

where  $g_t' = [x_t', z_t', r_t']$ ,  $y_t' = [f_t', z_t', r_t']$ ,  $W_t = \text{diag}(\exp(h_{1t})/2, \dots, \exp(h_{nt})/2, 0_{1 \times l+1})$  such that  $W_t W_t' = [H_t, 0_{1 \times l+1}]'$ ,  $B_t(L) = b_{1t}L + \dots + b_{pt}L^p$ ,  $(\epsilon_t^g, \epsilon_t^y)$  are iid structural disturbances coming from a Normal distribution with zero mean and unit variance,  $\Lambda = \begin{bmatrix} \lambda^f & \lambda^{z,r} \\ 0_{(l+1) \times k} & I_{l+1} \end{bmatrix}$  with  $\lambda^{z,r} = [\lambda^z, \lambda^r]$ , and  $\Gamma(L) = [\gamma(L)', 0_{(l+1) \times n}]'$ . Replacing (11) into (10) we solve for the vector moving average (VMA) form of the model which is

$$g_t = \tilde{\Gamma}(L)^{-1} \Lambda \tilde{B}_t(L)^{-1} A_t^{-1} \Sigma_t \epsilon_t^y + \tilde{\Gamma}(L)^{-1} W_t \epsilon_t^g = \Delta_t(L) \zeta_t \quad (12a)$$

where  $\tilde{B}_t(L) = I - B_t(L)$ ,  $\tilde{\Gamma}(L) = I - \Gamma(L)$ , and  $\zeta_t$  is a  $N(0, 1)$  innovation vector.

**Identification of monetary policy shocks** I follow Bernanke and Blinder (1992) in setting the Federal funds rate as a means to proxy short-run monetary policy decisions by the Fed. The Federal funds rate is sorted last in the FAVAR eq. (11), and monetary policy is identified in a recursive manner. First, the reduced form model (11) is estimated and then a lower-triangular identification restriction has to be imposed. This procedure is equivalent to estimating a recursive model (see Lütkepohl, 2005), and implies that the other variables in the VAR respond to monetary policy with one lag (i.e. at least after one quarter).

However, as Bernanke *et al.* (2005) note, there is no need to impose the same assumption to the idiosyncratic components of the information variables. In particular, identification of the monetary policy shocks is implemented using two distinct methods that impose block lower-triangular restrictions, that is the lower-triangular restriction described above but in ‘blocks’ of variables.

The first identification scheme is that of Bernanke *et al.* (2005) (henceforth BBE). The first block includes all the slow-moving variables (like real activity measures), the second block consists of the monetary policy tool (the Federal funds rate) and, finally, in the third block fast-moving variables (like asset prices) are included. The assumption made is that the slow-moving variables are not allowed to respond contemporaneously to monetary policy shocks. However, there is also the last block, of fast-moving financial variables, which responds instantly to monetary policy shocks since financial markets are more sensitive to ‘news’ than the rest of the economy. The interested reader should consult Bernanke *et al.* (2005) for exact econometric details underlying this approach. I will call these factors, ‘BBE factors’ for short.

Following Belviso and Milani (2006), the second identification scheme is based on extracting the latent factors on blocks of statistical releases of the observed data. I define 5 factors to correspond to 5 major economic fundamentals, which are i) real activity factor; ii) money factor; iii) interest rate factor; iv) price factor; and v) expectations factor. Each factor is extracted only from a specific data release. For example series included in the Fed data releases ‘GDP and components’ and the ‘Employment situation’ are used to extract the activity factor. Short and long-term interest rates are used to extract the interest rate factor. PPI, CPI and their components, as well as PCE and GDP deflator series are used in the price factor, and so on. Appendix A provides more details on the grouping of variables. The reader should bear in mind that this form of extracting factors immediately provides restrictions on the loadings matrix. For example, GDP deflator is only allowed to load on the 4th (the ‘price’) factor, but not on the other ones. This is equivalent to setting all elements - but the fourth - of the row parameter vector  $\lambda_{GDPDEF}^f$  to zero. I will call the factors produced from this method, ‘block factors’ for brevity.

In this nonlinear setting impulse responses can be estimated using simulation methods (see Koop *et al.*, 1996), which is a computationally demanding task. Instead of this

approach, I follow the standard convention in the literature (see for instance Primiceri, 2005) and I apply a sequential estimation procedure, where first the parameters are estimated from the reduced-form model and then the structural shocks are recovered conditional on each time period  $t$ .

### III Empirical Results

In this section I focus on describing briefly the large dataset and then characterizing the two estimates of the principal components. I then present evidence on the evolution of the parameters in the FAVAR equation, and conclude with the task of assessing the price puzzle, and measuring monetary policy in general, through time-varying impulse response functions coming from 4 different specifications.

#### Data and Principal Component estimates

The data-set consists of quarterly observations on 143 U.S. macroeconomic time series spanning the period from 1959:Q1 to 2007:Q3. The series were downloaded from the St. Louis Fed FRED database and a complete description is given in the data appendix. The whole dataset is quite standard for this type of application, and includes among others data releases such as personal income and outlays; GDP and components; assets and liabilities of commercial banks in the United States; productivity and costs measures; exchange rates, and selected interest rates. All series are seasonally adjusted, where this is applicable, and transformed to be approximately stationary. All data series which are used to extract factors are demeaned and standardized. Exact details are provided in the appendix.

The two methods for identifying the factors described in the previous Section (BBE and block factors) are based on extracting principal components. Nevertheless, they produce estimates of the factors which have some economic interpretation compared to unrestricted principal components. In order to understand the differences between extracting factors as either fast/slow moving, or according to blocks of data releases, it is interesting to understand which economic concepts are captured by them. Figures 1 and 2 plot the first 3 BBE factors and the 5 block factors, respectively. The series used are described in the next section, and the data appendix. Each of the factors produced from both identification methods is plotted along with only one of the 143 observable series; this is the series that it approximates (graphically) most closely. For instance, in the first graph of Figure 1 the first BBE factor captures most of the movements in GDP, even though all 143 series load on this factor. This is a known characteristic of principal components: the first principal component of a ‘Stock-and-Watson type’ dataset (i.e. using hundreds of macro variables) captures real activity; see the discussion in Stock and Watson (2002, Section 3.3.2) and references therein. The second BBE factor is also an activity factor since it follows very close the movements in employment in manufacturing. Similarly the third BBE factor captures a large fraction of the movement in M1.

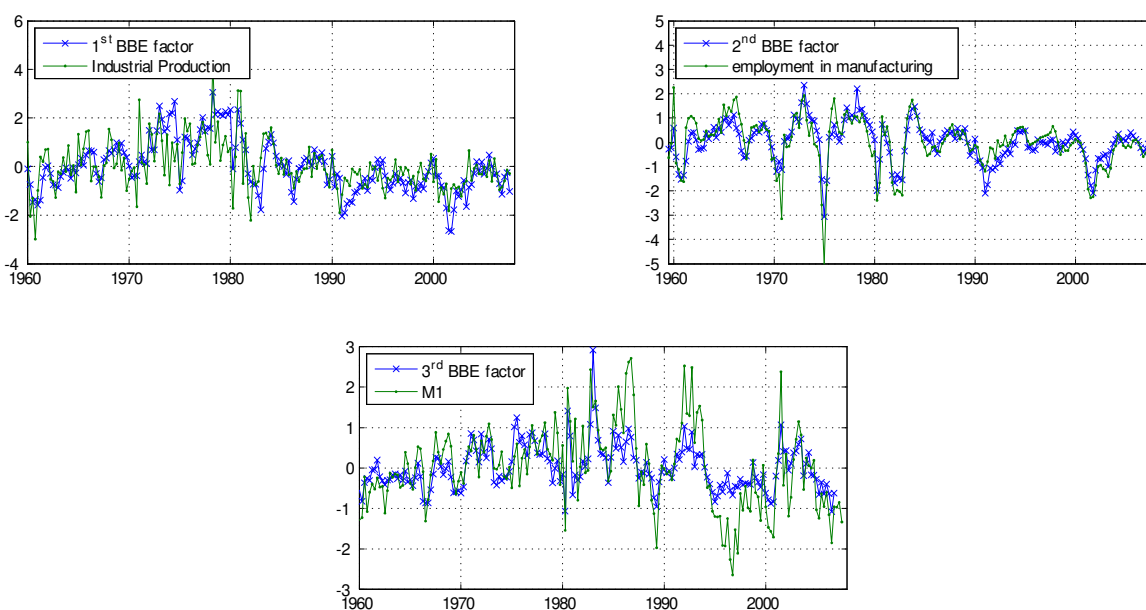


Figure 1: Graphs of BBE factors compared to some key macroeconomic series.

There is no need to actually test how close is each factor to a specific series. Since the loadings matrix is unrestricted, all series load in each and every factor.

Figure 2 repeats the same exercise for the factors extracted from blocks of statistical releases. This time, instead of doing a “guess” of what the nature of each factor might be (i.e. finding one out of the 143 series which graphically looks closer to that factor), this figure plots each of the five factors in comparison to a representative series of each statistical block. Subsequently, the real activity factor is plotted against real GDP, the money factor against M1, the interest rate factor against the 3-month Treasury bill rate, the price factor against CPI, and finally the expectations factor against the University of Michigan index of consumer expectations measure. All these factors fit quite well to the representative series chosen. However the advantage of using the principal components, instead of these five original observed series as factors, is that the former are more robust to measurement errors than the latter. For example GDP is subject to large data revisions. Additionally, GDP is only an incomplete proxy for what economists define as real activity. The real activity factor instead is constructed using a diverse set of series including GDP, employment and housing construction among others. Thus, it is not surprising that the interest rate factor is extremely close to the 3-month Treasury bill rate, since interest rates are measured without error.

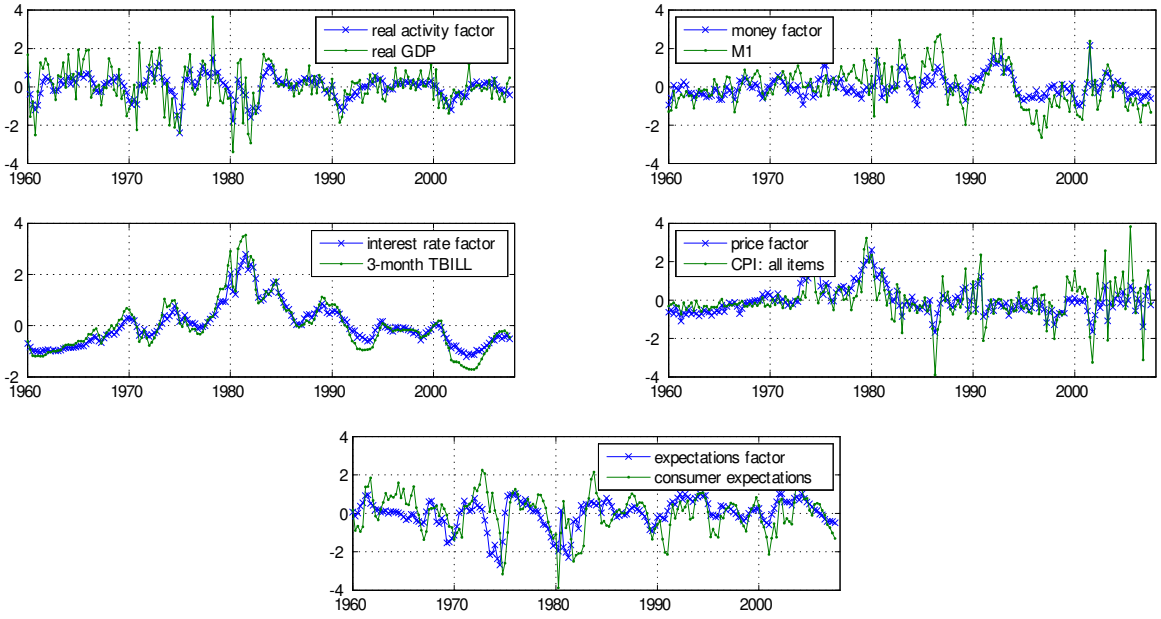


Figure 2: Graphs of block factors compared to representative series in each block.

The number of block factors is given and fixed to five. For the BBE factors comparing the impulse responses from models using three and five factors gives the same qualitative results. Thus, given that the number of parameters proliferates in a time-varying setting, I only present results with three BBE factors in order to preserve parsimony. In the following discussion results are reported from the two models, the TVP-FAVAR with BBE identification and the TVP-FAVAR with block identification. In the former model, the vector  $y'_t = [f'_t, z'_t, r_t]$  consists of three BBE factors ( $f'_t$ ), inflation and unemployment ( $z'_t$ ), and the Fed funds rate ( $r_t$ ), while in the latter model the vector  $y'_t = [f'_t, z'_t, r_t]$  consists of the five block factors ( $f'_t$ ) and the Fed funds rate ( $r_t$ ) and (for the shake of parsimony) no observables are included in  $z'_t$ . See also the impulse response section below.

## Testing parameter evolution

Different restricted versions of the TVP-FAVAR can be considered where we can begin from the FAVAR with constant parameters and allow several (combinations of) parameters to drift. Estimating and testing all possible model combinations with marginal likelihoods is a necessary task, albeit computationally demanding; see Koop and Korobilis (2010) for a discussion. The mixture innovation extension makes this process much easier by providing posterior probabilities on the time varying nature of each parameter. That way, the mixture innovation specification can be regarded as a special form of Bayesian model selection based on the Gibbs sampler (see for example George and McCulloch, 1997). Roughly speaking, in this latter literature an indicator variable

$\gamma$  is used to select which regression parameter is zero or not, while here the indicator variable  $J_t^\theta$  determines which parameter  $\theta$  is time-varying or constant.

Note that we can obtain probabilities of a break at each point in time, defined as the average of the posterior draws of  $J_t^\theta$ . That is, if we have a sequence of  $S$  draws from the posterior density  $p(J_t^\theta|Data)$ , then we can easily get the quantity

$$E(J_t^\theta|Data) = \frac{1}{S} \sum_{s=1}^S (J_t^\theta)_s \quad (13)$$

which is a time-varying proportion of models visited that had  $J_t^\theta = 1$ , where  $J_t^{\theta(l)}$  is the  $s$ -th MCMC draw of  $J_t^\theta$ . Presenting all posterior probabilities of jumps analytically for each parameter and each time period is not possible. However we can examine what type of time variation is supported in the FAVAR equation by the data and the factors by looking at the average probabilities of a break over the whole sample period  $t = 1, \dots, T$ . These are simply the posteriors of the probability parameters  $\pi_\theta$ , denoted  $p(\pi_\theta|Data)$ . Table 1 presents the posterior probabilities of a break for each parameter of interest  $\theta \in \{B_t, \alpha_t, \log \sigma_t\}$  in eqs (2) and (8). From this table it can be seen that there is evident time variation in all of the parameters in the FAVAR equation using the uninformative Beta prior, but the same is true if an informative Beta prior is used which favours only a few breaks a-priori (results available upon request). Koop *et al.* (2009) report similar evidence on their mixture innovation TVP-VAR using inflation, unemployment and interest rate. This contradicts for instance the results of Sims and Zha (2006) who find that there is evidence of time variation (in the form of regime switching) in the volatility but not in the mean of their VAR.

TABLE 1

*Evidence on time variation*

Model	$p(\pi_B data)$	$p(\pi_\alpha data)$	$p(\pi_{\log \sigma} data)$
TVP-FAVAR BBE factors	0.982	0.912	0.993
TVP-FAVAR block factors	0.886	0.977	0.948

Notes: Entries in this table are the posterior “probability of drift” quantity  $p(\pi_\theta|data)$  for each time-varying parameter  $\theta \in \{B_t, \alpha_t, \log \sigma_t\}$ .

## Monetary policy and the Great Moderation

In principle, it is wise to first examine the non-systematic policy, i.e movements in the Fed’s funds rate which are attributed to exogenous shocks and not to changes in the structure of the economy. In order to achieve that, Figures 3 and 4 present the median posterior estimates of the standard errors coming from the TVP-FAVAR models with BBE and block factors respectively. These are the square roots of the main-diagonal elements of the matrices  $\Omega_t$ , for all  $t$ . High variance of monetary policy shocks is connected with

higher policy mistakes. It is obvious from the last panel (e) of Figures 3 and 4 that during 1979-1984 the volatility of the shocks in the Federal funds rate is quite high relative to the rest of the sample. In this period there was a shift of focus from interest rates (prices) to reserves available to banks (quantities) leading the interest rate to rise at the most rapid rate in the history of the U.S.

The time-varying standard deviations of the BBE factors and the observables (inflation and unemployment) in Figure 3, and the block factors in Figure 4, reveal patterns like the Great Inflation and the Monetarist Experiment (peaks of volatility circa 1975 and 1980, respectively) due to the oil shocks and the increase of interest rates, respectively. Additionally, activity factors like the first BBE factor and the first block factor, the variation in these time-varying standard deviations is much lower after approximately 1984 compared to the pre-1984 era, indicating the Great Moderation for the US economy. From these graphs it is visible that there are many similarities, but also many differences, between the BBE factors and the block factors TVP-FAVARs. For instance, the third BBE factor in Figure 3, which was identified as capturing closely the movements in M1, has similar shock pattern with the second block (“money”) factor in Figure 4. However, the fourth block factor (prices) in Figure 4 peaks at completely different dates than the observed GDP deflator inflation in Figure 3. That in turn suggests that this price block factor captures movements in price volatility which are not contained in GDP deflator alone.

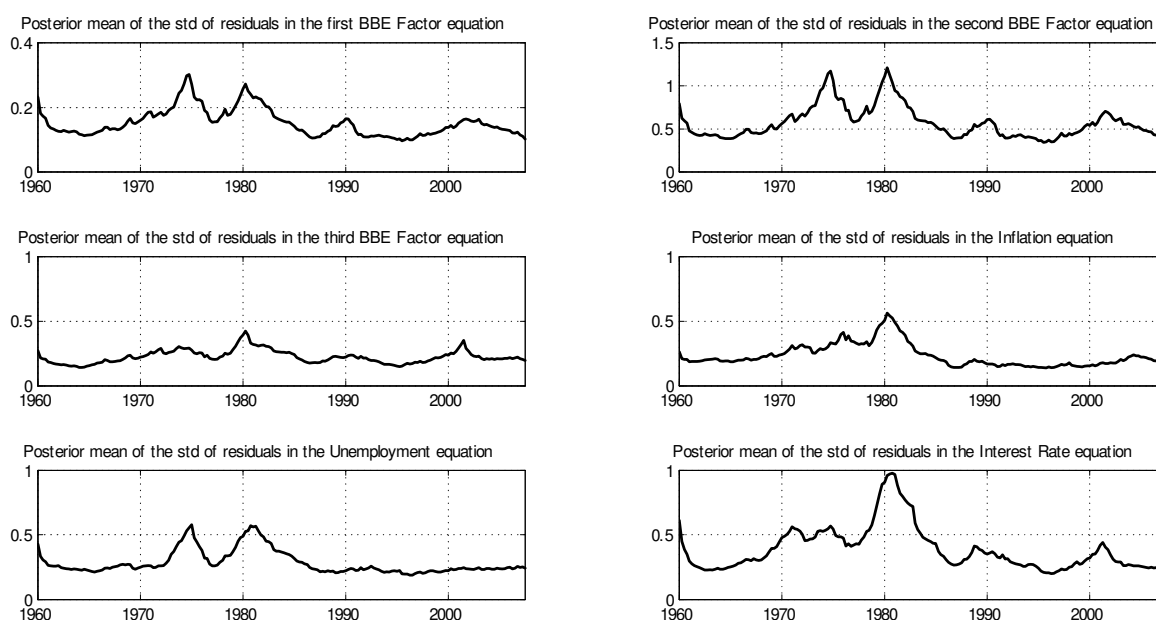


Figure 3: Time-varying standard deviations (std) of errors in the TVP-FAVAR with BBE identification of the factors.



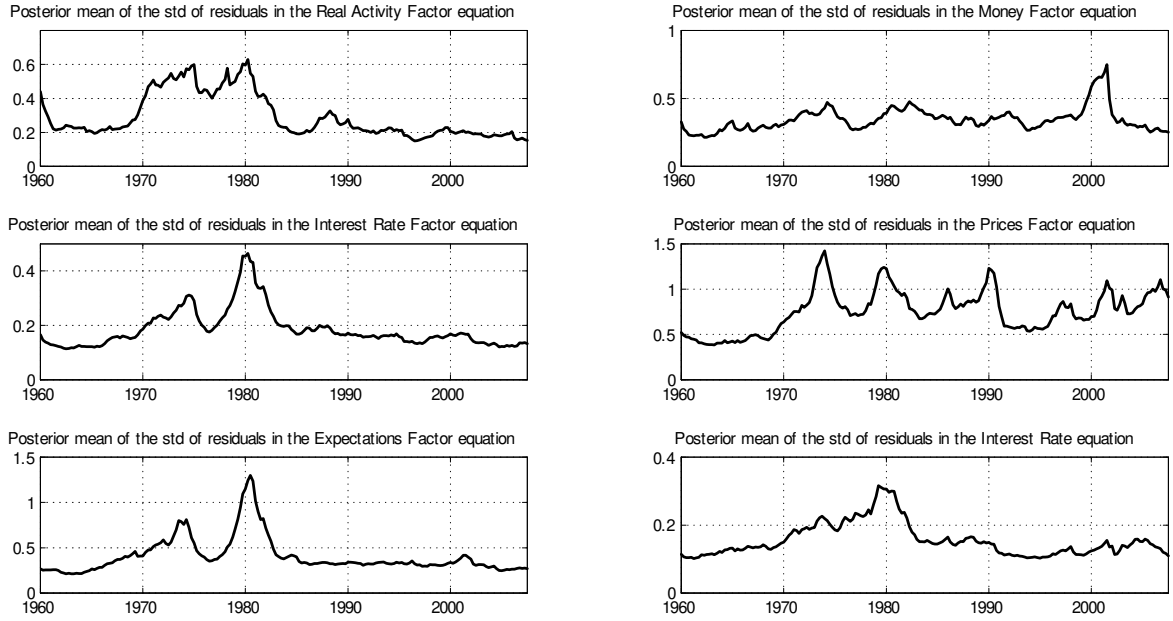


Figure 4: Time-varying standard deviations (std) of errors in the TVP-FAVAR with block factors.

The information contained in the factors has the implication that the standard errors in the Fed's funds rate equation are quite low compared to the typical trivariate TVP-VARs used in the past. The reader is advised to make comparisons with, for example, the time-varying standard deviations estimated in Koop, Leon-Gonzales and Strachan (2009) and Primiceri (2005). Lastly, while detecting the Great Moderation can be accomplished when using factors, this is not true when a small scale tri-variate vector autoregression is used. The observation that two out of the three BBE factors as well as three out the five block factors have a big drop in their standard errors around 1984 is consistent with the fact that the decline in volatility has occurred broadly across the economy, affecting employment, prices and wages, and consumption.

For that reason, we can use the factor model to examine the estimated time-varying volatilities not only in the factors, but also in the original observed variables. Using eq. (3a) we can recover the implied decomposition of the time varying model covariances of the data matrix  $x_t$ .<sup>4</sup> These are defined as

$$var(x_t|\lambda_t, H_t, \Omega_t) = \Lambda\Omega_t\Lambda' + H_t = \Sigma_t^{com} + \Sigma_t^{ind} \quad (14)$$

where  $\Sigma_t^{com}$  is the covariance due to the common fluctuations among the series, and  $\Sigma_t^{ind}$  is the matrix of individual variations in each series. This identity implies that the variance of variable  $i$  takes the form  $var(x_{it}|\lambda_i, H_{ii,t}, \Omega_t) = \lambda_i\Omega_t\lambda_i' + \exp(h_{it})$  for  $i = 1, \dots, n$ . The TVP-FAVAR model allows for other statistics to be calculated, like the ratio

<sup>4</sup>Basically, the formula applies to  $\tilde{x}_t = x_t(I_n - \gamma(L))$  and not  $x_t$  itself. However to maintain interpretability, the assumption of autocorrelated errors is dropped in this analysis (and hence  $\gamma(L) = 0_{n \times n}$ ).

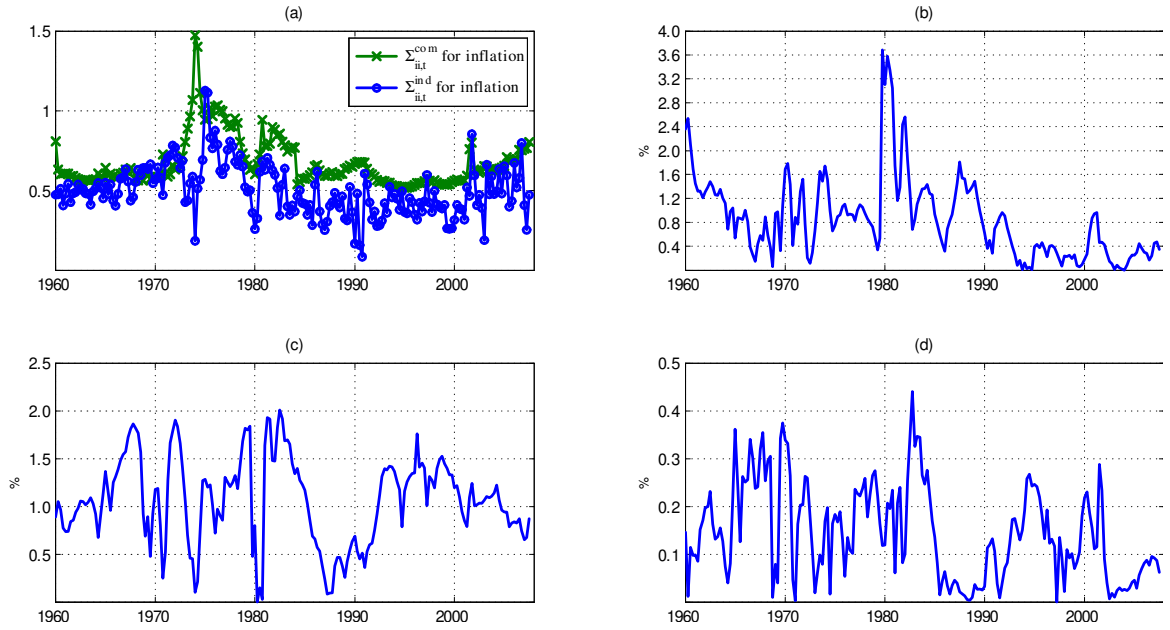


Figure 5: Time-varying parameters factor model decomposition of the variance of inflation. Panel (a) shows the variance of the common component  $\Sigma_{it}^{com}$ , and the idiosyncratic/individual component  $\Sigma_{it}^{ind}$ , for  $i$ =GDP deflator inflation. Panels (b), (c) and (d) show the percentage of the variance in inflation explained by the Federal funds rate, unemployment rate and GDP, respectively.

of the variance explained by the factor model to the total variance  $\Sigma_{it}^{com} / (\Sigma_{it}^{com} + \Sigma_{it}^{id})$ , or the percentage of the variability in series  $i$  explained by series  $j$ , i.e. the quantity

$$\tilde{w}_{ij} = \frac{\lambda_i \Omega_t \lambda_j'}{\sum_{k=1}^n \lambda_i \Omega_t \lambda_k'}$$

These factor model decompositions of the variance allow us to examine which part of the Great Moderation is explained by the large set of observed (endogenous) explanatory variables and which part is attributed to random (exogenous) shocks. For price inflation (GDP deflator series: GDPDEFL) in particular, graphs are plotted in panel (a) of Figure 5 for the part of the conditional variance which is due to exogenous shocks pertaining to inflation,  $\Sigma_{ii,t}^{id} = \exp(h_{it})$ , and the part which is explained by the whole economy, i.e. the whole set of factors,  $\Sigma_{ii,t}^{com} = \lambda_i \Omega_t \lambda_i'$ . Observe that this decomposition comes from the TVP-FAVAR with block factors. In the TVP-FAVAR with BBE factors I treat GDP deflator inflation in the vector of observables  $z_t$  (and then inflation enters the factor equation as a simple regressor).

In panel (a) of Figure 5 the reader can see some very interesting features. The peak in inflation variance during the late 1970s is attributed to a peak in the exogenous

shock  $\exp(h_{it})$  and the factors (i.e. the comovements between endogenous variables in the economy). This result gives an intuition of why previous studies based on small tri-variate VARs do not agree on the nature of inflation volatility. The factor model decomposition indicates that the causes of high volatility in that period are a mixture of both endogenous and exogenous shocks, with the former preceding the latter by one year. In a similar manner we can observe that during the early 1980s the peak in inflation volatility is mostly attributed to the variation of the factors and less to the idiosyncratic volatility. If this event is to be attributed to the variation in other variables in the economy, then theory postulates that these variables should be monetary policy (interest rate), or the output gap and unemployment (as implied by the Philips curve). In order to test this assumption, I plot in panels (b)-(d) of Figure 5 the proportion of volatility in inflation as explained by the Federal funds rate, unemployment and GDP respectively. This is the quantity  $\tilde{w}_{ij}$  described above where  $i = GDPDEFL$  and  $j = FEDFUNDS, GDPC, UNRATE$  respectively. It is the Fed funds rate which explains a much larger proportion of inflation, especially during the early 1980s. The contribution of GDP to inflation volatility also increases, but this increase is much smaller as a percentage and also comes with a lag (i.e. after 1982) due to the effect of high interest rates on GDP in the early 1980s and the double-dip recession of 1980 and 1981-82.

Finally, the standard *forecast error variance decompositions* - typical in VAR models (Lütkepohl, 2005) - can also be implemented in the case of the TVP-FAVAR model for all 143 series. In particular, in this model these decompositions are also time-varying. Estimates are not presented here, since these are, on average, similar to the ones reported in previous studies (see for example the non-time-varying estimates in Table I of Bernanke *et al.*, 2005).

## Measuring monetary policy: Comparing different models and different time periods

At this point, it is interesting to examine the impulse responses of different time periods in a data rich environment, and compare those to traditional VAR models (which, as explained earlier, are all restricted versions of the TVP-FAVAR model). Among the vast number of different specifications nested in the TVP-FAVAR, I will use or compare four benchmark specifications. These models are:

- i **VAR:** 4 variable VAR on subsamples of data. This model can be obtained if we set  $k = J_t^B = J_t^\alpha = J_t^\sigma = 0$  for all  $t$ . In this case equation (10) is eliminated and we are estimating only equation (11) on the subsamples 1960:Q1 - 1975:Q1, 1960:Q1 - 1981:Q3, and 1960:Q1 - 1996:Q1. In this case the dependent variable is  $y'_t = [z'_t, r_t]$  where  $z'_t$  includes inflation, unemployment and inflation expectations, and  $r_t$  is the fed funds rate.
- ii **TVP-VAR:** 3 variable TVP-VAR as in Primiceri (2005). The variables in  $y'_t = [z'_t, r_t]$  are inflation, unemployment and fed funds rate.

- iii **TVP-FAVAR-BBE:** TVP-FAVAR with BBE identification. In this model, the vector  $y'_t = [f'_t, z'_t, r_t]$  consists of three BBE factors ( $f'_t$ ), inflation and unemployment ( $z'_t$ ), and the fed funds rate ( $r_t$ ). In this case inflation and unemployment are not used in  $x_t$  to extract factors, while their impulse responses are immediately available only through equation (11).
- iv **TVP-FAVAR-Block:** TVP-FAVAR with block identification. In this model, the vector  $y'_t = [f'_t, z'_t, r_t]$  consists of the five block factors ( $f'_t$ ) and the fed funds rate ( $r_t$ ). For the sake of maintaining parsimony, no observables are included in  $z'_t$  (i.e., using the notation of Section 2,  $l = 0$ ). Thus inflation and unemployment measures are only included in the variable  $x_t$ , and their impulse responses are identified through the price and real-activity factors, respectively.

The dataset has several measures of inflation, unemployment, inflation expectations and interest rate. When these quantities are included as observables in the vector  $z'_t$  (models 1,2 and 3 above), I use the series GDPDEF (Gross Domestic Product: Implicit Price Deflator), UNRATE (Unemployment Rate: All Workers, 16 Years & Over), INFEXP (University of Michigan Inflation Expectations), and FEDFUNDS (Effective Federal Funds Rate), as proxies for “inflation”, “unemployment”, “inflation expectations” and “interest rate”, respectively. Since all 4 models can be obtained as special cases of the TVP-FAVAR model, the priors described in Section 2 are applied to all models in order to maintain comparability<sup>5</sup>. Lastly, following the TVP-VAR literature (Primiceri, 2005; Canova and Gambetti, 2009; Koop *et al.*, 2009) I set the number of VAR lags in all models to be  $p = 2$ , while the lag length of the idiosyncratic shocks in the TVP-FAVAR models (see eq. (3b)) is set to  $q = 2$ .

Figures 6 through 9 plot the impulse responses of the 3 common variables in all models, i.e. inflation unemployment and the interest rate. These variables are plotted for three representative periods, 1975:Q1, 1981:Q3 and 1996:Q1 which were chosen in Primiceri (2005) as representative of the chairmanships of Burns, Volcker and Greenspan. Responses for any quarter in 2006-7, which would correspond to the inclusion of a "Bernanke regime" in the analysis, are not included for two reasons. First, there does not seem to be differences between responses in 1996 and any of the quarters of 2006 and 2007 in the sample. Second, there are not enough observations for the Bernanke chairmanship, while these few representative observations are at the end of the sample and may be prone to the measurement error associated with using data which, most probably, are going to be revised again in the future.

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<sup>5</sup>In that case priors are defined only for parameters which are not restricted to be zero. For instance, we can obtain the TVP-VAR if we restrict the number of factors to be zero ( $k = 0$ ), which implies that the parameters  $[\lambda_i^f, \lambda_i^z, \lambda_i^r], h_i^2$  and  $\rho_i$  are all zero and no prior is set on them. In that case it is only the priors for  $B_t, \alpha_t, \log \sigma_t$  and  $J_t$  which are elicited on a similar way among the TVP-VAR and the TVP-FAVAR specifications.

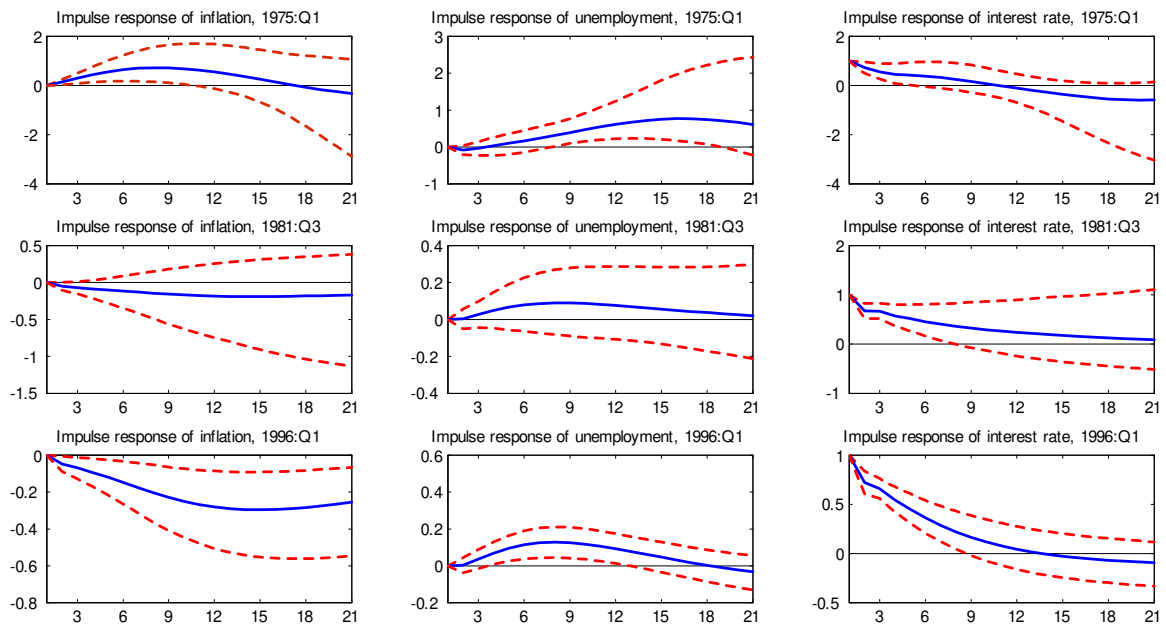


Figure 6: Impulse responses (10-th, 50-th and 90-th percentiles) of inflation, unemployment and interest rate from the VAR model with Inflation expectations, estimated on 3 subsamples ending in 1975:Q1, 1981:Q3 and 1996:Q1, respectively.

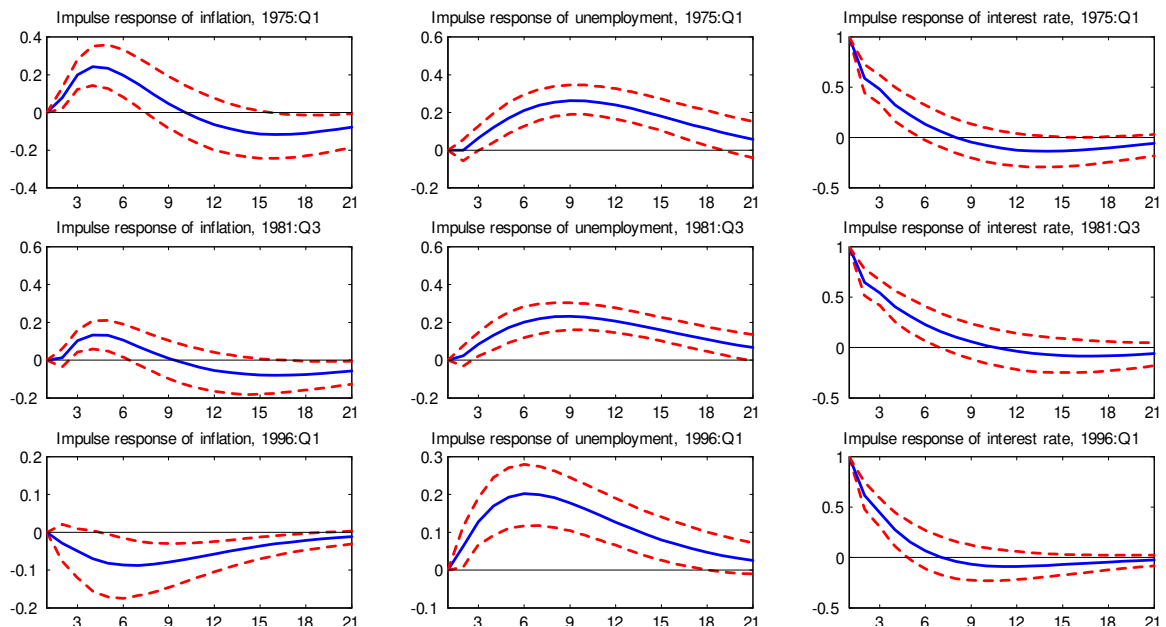


Figure 7: Impulse responses (10-th, 50-th and 90-th percentiles) of inflation, unemployment and interest rate from the TVP-VAR model.

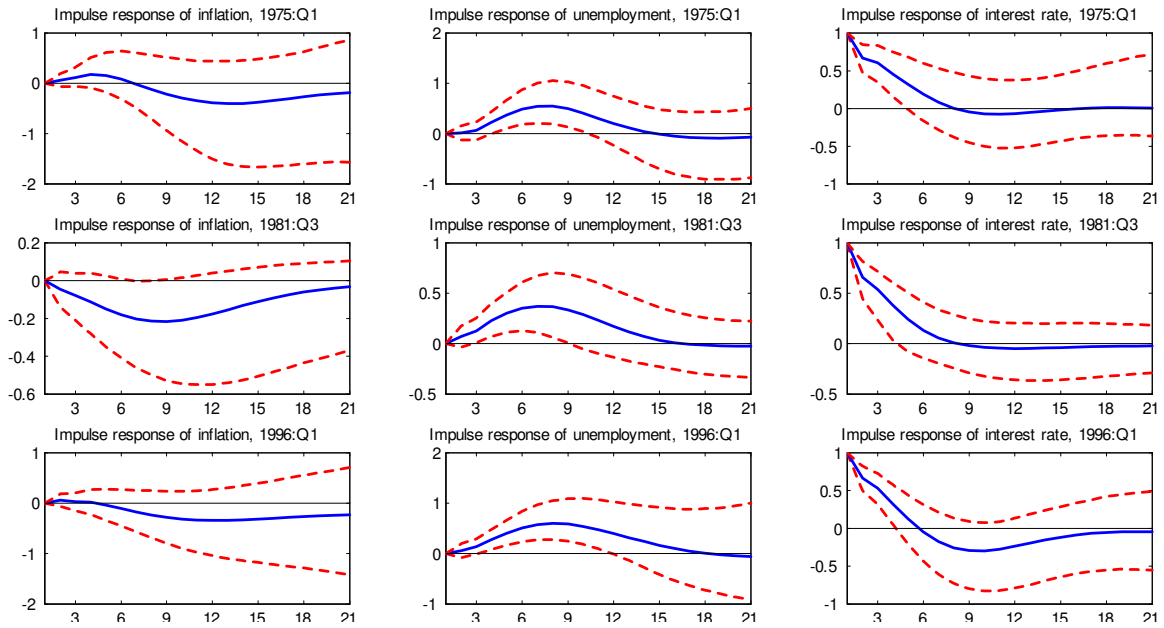


Figure 8: Impulse responses (10-th, 50-th and 90-th percentiles) of inflation, unemployment and interest rate from the TVP-FAVAR model with BBE factors.

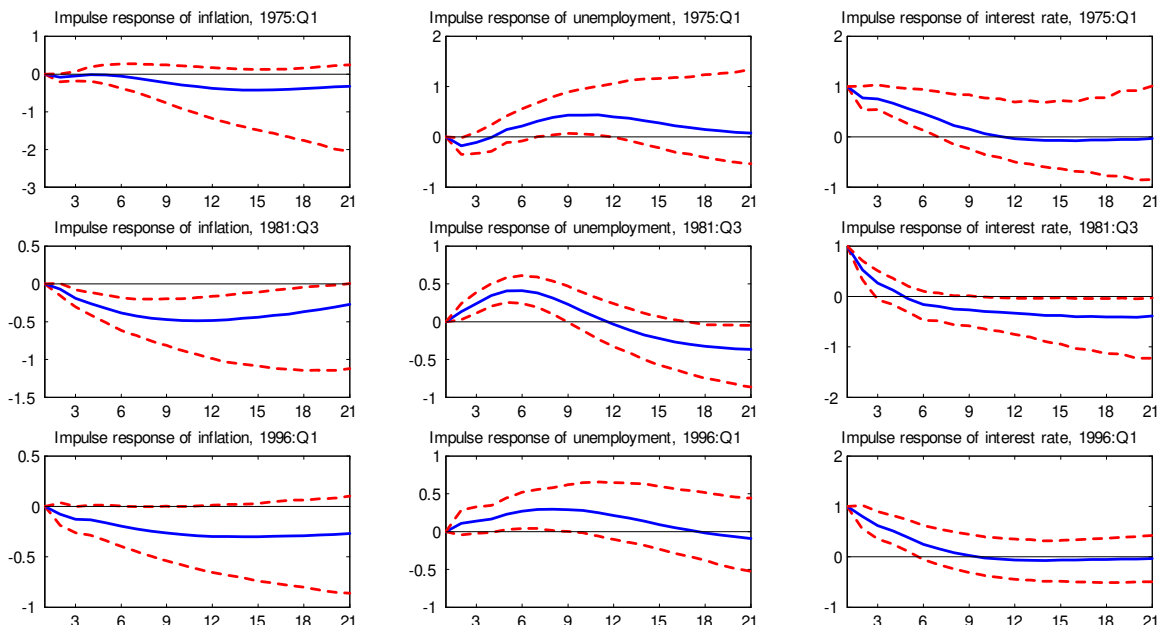


Figure 9: Impulse responses (10-th, 50-th and 90-th percentiles) of inflation, unemployment and interest rate from the TVP-FAVAR model with block factors.

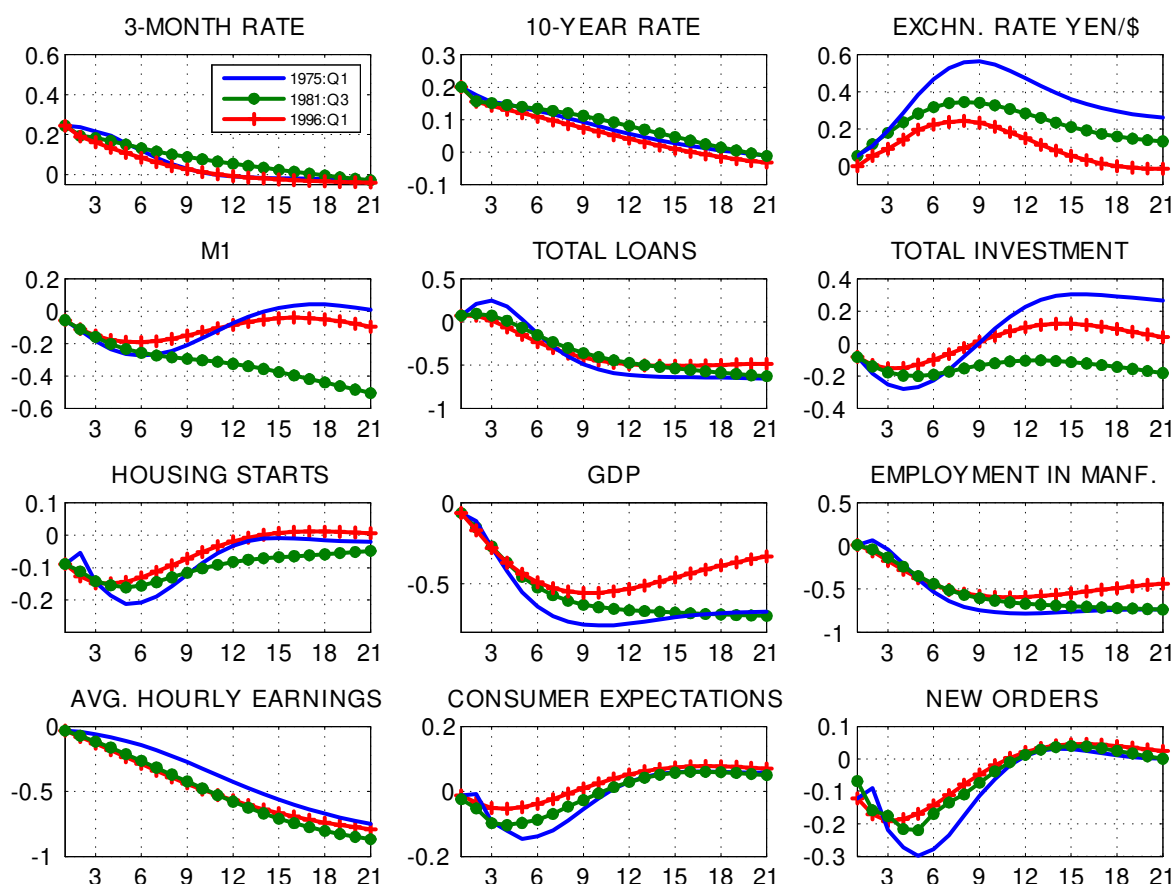


Figure 10: Posterior medians of impulse responses for selected indicators of the US economy for the periods 1975:Q1, 1981:Q3 and 1996:Q1.

As expected according to economic theory, inflation should decrease following a contractionary policy shock. However the criticism over VAR models is that they reproduce what is called the price puzzle: a positive hump-shaped response of inflation. The four-variable recursive VAR estimated in subsamples is motivated by the finding of Castelnuovo and Surico (2010) that if the price puzzle is an artefact of VAR models, then including measures of inflation and output gap expectations should correct this problem. We can see from Figures 6 to 9 that the FAVAR model with block factors performs the best in not introducing positive responses of inflation, especially in the 1970s. The tri-variate TVP-VAR model introduces the puzzle in the 70s and early 80s, while adding the inflation expectations variable in the VAR in subsamples vanishes the puzzle only in the 80s. This finding is consistent with the conjecture that a misspecified VAR will not cover the space of structural shocks (see Stock and Watson, 2005).

Castelnuovo and Surico (2010) find that zero restrictions are responsible for reproducing this puzzle, while sign restrictions (Uhlig, 2005) give impulse responses in ac-

cordance with theory and DSGE models. One can argue that the simple VAR responses could be ‘corrected’ using sign restrictions, something that can also be generalized to the TVP-VAR model case. For example, the Canova and Gambetti (2009) TVP-VAR with sign restrictions does reduce the price puzzle (while the TVP-VAR ‘a-la’ Primiceri (2005) used here does not). However, given that sign restrictions are hard to justify when using a VAR with unobserved factors, I use the recursive identification scheme in all models in order to focus only on the positive effects of adding more variables in a VAR. In that respect, the (TVP-) FAVAR models are - as expected - superior to the simple VARs.

Another argument in favor of the TVP-FAVAR is that we are able to examine what has happened at different points in time to all major indicators of the economy. For the sake of brevity I only plot in Figure 10 the results from the TVP-FAVAR with block factors (the results from the TVP-FAVAR with BBE factors are very similar and say exactly the same story). This Figure says for instance that GDP would have responded more moderately in 1996 in a contractionary shock, compared to 1975 and 1981. M1 in 1981 (the period of the ‘monetarist experiment’) would actually continue to be negative and decrease even after 21 quarters ahead, while in 1975 and 1996 it would begin to get back to zero after approximately 12 quarters. Exchange rates and total investments were affected by the varying conditions in 1975, 1981 and 1996, as these are measured by the differences in magnitudes of their responses during these periods. In contrast, short and long term interest rates (and subsequently loans), and employment and productivity measures were not altered during the Chairmanships of Burns, Volcker and Greenspan.

## IV Conclusions

There is a large literature that examines the evolution of post World War II U.S. monetary policy. During these decades lots of changes have occurred in the U.S. economy, such as the moderation of GDP and inflation volatility dated circa 1984. Many papers try to shed light on historical events as well as the operation of monetary policy over the last 40 years using small data-sets. One of the main contributions of this paper is the conjecture that by using large data-sets we are able to better understand the nature of correlations and comovements between macroeconomic variables. This paper shows that, unlike previous small VARs, there were important changes in the responses of output, investment and the quantity of money to monetary shocks, over three different representative periods.

The second contribution of this paper is empirical and it relates to the fact that all the merits of the constant parameters Dynamic Factor Model can be used successfully in a time-varying setting. Using Bayesian methods in order to preserve parsimony in estimating the time-varying parameters, and standard principal components in order to avoid identification issues arising when estimating latent factors, we can end up with a model that provides sensible time-varying impulse response functions for the whole economy. In that respect, the time-varying FAVAR produces impulse responses which do not replicate the prize puzzle at all periods.



In order to answer increasingly involved questions in the future, factor models can play a significant leading role since their advantages are numerous. At the same time, the fact that dynamic factor models are atheoretic time series models, can be tackled if they are combined with DSGE models. For instance, Boivin and Giannoni (2006a) show that factors can be used in a DSGE setting in order to reduce variable measurement uncertainty, combining that way the merits of large data-sets with those of structural economic models.

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## Appendix A: Data and Transformations

All series were downloaded from St. Louis' FRED database and cover the quarters Q1:1959 to Q3:2007. The series HHSNTN, PMNO, PMDEL, PMNV, MOCMQ, MSONDQ come from the Global Insights Basic Economics Database, and were kindly provided by Mark Watson. The series INFEXP comes from the University of Michigan database (<http://www.sca.isr.umich.edu/>). All series were seasonally adjusted: either taken adjusted from FRED or by applying to the unadjusted series a quarterly X11 filter based on an AR(4) model (after testing for seasonality). Some series in the database were observed only on a monthly basis and quarterly values were computed by averaging the monthly values over the quarter. All variables are transformed to be approximately stationary. In particular, if  $z_{i,t}$  is the original untransformed series, the transformation codes are (column Tcode below): 1 - no transformation (levels),  $x_{i,t} = z_{i,t}$ ; 2 - first difference,  $x_{i,t} = z_{i,t} - z_{i,t-1}$ ; 4 - logarithm,  $x_{i,t} = \log z_{i,t}$ ; 5 - first difference of logarithm,  $x_{i,t} = \log z_{i,t} - \log z_{i,t-1}$ ; 10 - quarter-over-quarter growth rate,  $x_{i,t} = 400 * (z_{i,t}/z_{i,t-1} - 1)$  (only for the GDP deflator).

Following Bernanke et al. (2005), the fast moving variables are interest rates, stock returns, exchange rates and commodity prices. The rest of the variables in the dataset are the slow moving variables (output, employment/unemployment etc). The data table below has been separated into 5 blocks, referring to the respective block factor when using the alternative identification scheme (see also Belviso and Milani, 2006).

### 1. Real Activity Factor

#	Mnemonic	Tcode	Description
1	GDPC	5	Real Gross Domestic Product, 3 Decimal
2	CBI	1	Change in Private Inventories
3	FINSAL	5	Final Sales of Domestic Product
4	FSDP	5	Final Sales to Domestic Purchasers
5	FINSLC96	5	Real Final Sales of Domestic Product, 3 Decimal
6	GGSAVE	1	Gross Government Saving
7	TGDEF	1	Net Government Saving
8	GSAVE	5	Gross Saving
9	FPI	5	Fixed Private Investment
10	PRFI	5	Private Residential Fixed Investment
11	SLINV	5	State & Local Government Gross Investment
12	SLEXPND	5	State & Local Government Current Expenditures
13	EXPGSC96	5	Real Exports of Goods & Services, 3 Decimal
14	IMPGSC96	5	Real Imports of Goods & Services, 3 Decimal
15	CIVA	1	Corporate Inventory Valuation Adjustment
16	CP	5	Corporate Profits After Tax
17	CNCF	5	Corporate Net Cash Flow
18	DIVIDEND	5	Net Corporate Dividends
19	PCE	5	Personal Consumption Expenditures

20	PCES	5	Personal Consumption Exp.: Services
21	PCEDG	5	Personal Consumption Exp.: Durable Goods
22	PCEND	5	Personal Consumption Exp.: Nondurable Goods
23	INDPRO	5	Industrial Production Index
24	NAPM	1	ISM Manufacturing: PMI Composite Index
25	HOABS	5	Business Sector: Hours of All Persons
26	RCPHBS	5	Business Sector: Real Compensation Per Hour
27	ULCBS	5	Business Sector: Unit Labor Cost
28	COMPNFB	5	Nonfarm Business Sector: Compensation Per Hour
29	HOANBS	5	Nonfarm Business Sector: Hours of All Persons
30	COMPRNFB	5	Nonfarm Bus. Sector: Real Compensation Per Hour
31	ULCNFB	5	Nonfarm Business Sector: Unit Labor Cost
32	UNRATE	1	Unemployment Rate: All Workers, 16 Years & Over
33	UEMPLT5	5	Civilians Unemployed - Less Than 5 Weeks
34	UEMP5TO14	5	Civilian Unemployed for 5-14 Weeks
35	UEMP15OV	5	Civilians Unemployed - 15 Weeks & Over
36	UEMP15T26	5	Civilians Unemployed for 15-26 Weeks
37	UEMP27OV	5	Civilians Unemployed for 27 Weeks and Over
38	NDMANEMP	5	All Employees: Nondurable Goods Manufacturing
39	MANEMP	5	Employees on Nonfarm Payrolls: Manufacturing
40	SRVPRD	5	All Employees: Service-Providing Industries
41	USTPU	5	All Employees: Trade, Transportation & Utilities
42	USWTRADE	5	All Employees: Wholesale Trade
43	USTRADE	5	All Employees: Retail Trade
44	USFIRE	5	All Employees: Financial Activities
45	USEHS	5	All Employees: Education & Health Services
46	USPBS	5	All Employees: Professional & Business Services
47	USINFO	5	All Employees: Information Services
48	USSERV	5	All Employees: Other Services
49	USGOVT	5	All Employees: Government
50	AHECONS	5	Average Hourly Earnings: Construction
51	AHEMAN	5	Average Hourly Earnings: Manufacturing
52	AWOTMAN	1	Average Weekly Hours: Overtime: Manufacturing
53	AWHMAN	1	Average Weekly Hours: Manufacturing
54	HOUST	4	Housing Starts: Total: New Privately Owned Housing Units Started
55	HOUST1F	4	Privately Owned Housing Starts: 1-Unit Structures
56	PERMIT	4	New Private Housing Units Authorized by Building Permit

## 2. Money, Credit and Finance Factor

#	Mnemonic	Tcode	Description
57	NONREVSL	5	Total Non-revolving Credit Outstanding
58	USGSEC	5	U.S. Government Securities at All Commercial Banks

59	OTHSEC	5	Other Securities at All Commercial Banks
60	TOTALSL	5	Total Consumer Credit Outstanding
61	BUSLOANS	5	Commercial and Industrial Loans at All Commercial Banks
62	CONSUMER	5	Consumer (Individual) Loans at All Commercial Banks
63	LOANS	5	Total Loans and Leases at Commercial Banks
64	INVEST	5	Total Investments at All Commercial Banks
65	REALLN	5	Real Estate Loans at All Commercial Banks
66	BOGAMBSL	5	Board of Governors Monetary Base, Adjusted for Changes in Reserve Req.
67	TRARR	5	Board of Governors Total Reserves, Adjusted for Changes in Reserve Req.
68	BOGNONBR	5	Non-Borrowed Reserves of Depository Institutions
69	REQRESNS	5	Required Reserves, Not Adjusted for Changes in Reserve Requirements
70	RESBALNS	5	Reserve Balances with Fed. Res. Banks, Not Adj. for Changes in Res. Req.
71	BORROW	5	Total Borrowings of Depository Institutions from the Federal Reserve
72	M1SL	5	M1 Money Stock
73	CURRSL	5	Currency Component of M1
74	DEMDEPSL	5	Demand Deposits at Commercial Banks
75	TCDSL	5	Total Checkable Deposits
76	TVCKSSL	5	Travelers Checks Outstanding
77	M2SL	5	M2 Money Stock
78	M2OWN	5	M2 Own Rate
79	M2MSL	5	M2 Minus Small Time Deposits
80	M2MOWN	5	M2 Minus Own Rate
81	MZMSL	5	MZM Money Stock
82	EXCRESNS	5	Excess Reserves of Depository Institutions
83	NFORBRES	1	Net Free or Borrowed Reserves of Depository Institutions
84	SVSTCBSL	5	Savings and Small Time Deposits at Commercial Banks
85	SVSTSL	5	Savings and Small Time Deposits - Total
86	SVGCBSL	5	Savings Deposits at Commercial Banks
87	SVGTI	5	Savings Deposits at Thrift Institutions
88	SAVINGSL	5	Savings Deposits - Total
89	STDCBSL	5	Small Time Deposits at Commercial Banks
90	STDTI	5	Small Time Deposits at Thrift Institutions
91	STDSL	5	Small Time Deposits - Total
92	USGVDDNS	5	U.S. Government Demand Deposits and Note Balances - Total
93	USGDCB	5	U.S. Government Demand Deposits at Commercial Banks
94	CURRCIR	5	Currency in Circulation

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### 3. Interest Rate Factor

#	Mnemonic	Tcode	Description
95	TB3MS	1	3-Month Treasury Bill: Secondary Market Rate
96	TB6MS	1	6-Month Treasury Bill: Secondary Market Rate
97	GS1	1	1-Year Treasury Constant Maturity Rate
98	GS3	1	3-Year Treasury Constant Maturity Rate
99	GS5	1	5-Year Treasury Constant Maturity Rate
100	GS10	1	10-Year Treasury Constant Maturity Rate
101	MPRIME	1	Bank Prime Loan Rate
102	AAA	1	Moody's Seasoned AAA Corporate Bond Yield
103	BAA	1	Moody's Seasoned BAA Corporate Bond Yield
104	EXSZUS	5	Switzerland / U.S. Foreign Exchange Rate
105	EXJPUS	5	Japan / U.S. Foreign Exchange Rate
106	EXUSUK	5	U.S. / U.K Foreign Exchange Rate
107	EXCAUS	5	Canada / U.S. Foreign Exchange Rate

### 4. Price Factor

#	Mnemonic	Tcode	Description
108	GDPDEF	10	Gross Domestic Product: Implicit Price Deflator
109	GDPCTPI	5	Gross Domestic Product: Chain-type Price Index
110	PCECTPI	5	Personal Consumption Expenditures: Chain-type Price Index
111	PPIACO	5	Producer Price Index: All Commodities
112	PPICRM	5	Producer Price Index: Crude Materials for Further Proc.
113	PPIFCF	5	Producer Price Index: Finished Consumer Foods
114	PPIFCG	5	Producer Price Index: Finished Consumer Goods
115	PFCGEF	5	Producer Price Index: Finished Consumer Goods Excl. Foods
116	PPIFGS	5	Producer Price Index: Finished Goods
117	PPICPE	5	Producer Price Index Finished Goods: Capital Equipment
118	PPIENG	5	Producer Price Index: Fuels & Related Products & Power
119	PPIIDC	5	Producer Price Index: Industrial Commodities
120	PPIITM	5	Producer Price Index: Intermediate Materials
121	CPIAUCSL	5	Consumer Price Index For All Urban Consumers: All Items
122	CPIUFDSL	5	Consumer Price Index for All Urban Consumers: Food
123	CPIENGSL	5	Consumer Price Index for All Urban Consumers: Energy
124	CPILEGSL	5	Consumer Price Index for All Urban Consumers: All Items Less Energy
125	CPIULFSL	5	Consumer Price Index for All Urban Consumers: All Items Less Food
126	OILPRICE	5	Spot Oil Price: West Texas Intermediate

### 5. Expectations Factor

#	Mnemonic	Tcode	Description
127	INFEXP	1	U. Of Mich. Inflation Expectations
128	HHSNTN	1	U. Of Mich. Index Of Consumer Expectations
129	PMNO	1	NAPM New Orders Index
130	PMDEL	1	NAPM Vendor Deliveries Index
131	PMNV	1	NAPM Inventories Index
132	MOCMQ	5	New Orders (Net) - Consumer Goods & Materials
133	MSONDQ	5	New Orders, Nondefense Capital Goods
134	sTB3MS	1	TB3MS - FEDFUNDS
135	sTB6MS	1	TB6MS - FEDFUNDS
136	sGS1	1	GS1 - FEDFUNDS
137	sGS3	1	GS3 - FEDFUNDS
138	sGS5	1	GS5 - FEDFUNDS
139	sGS10	1	GS10 - FEDFUNDS
140	sMPRIME	1	MPRIME - FEDFUNDS
141	sAAA	1	AAA - FEDFUNDS
142	sBAA	1	BAA - FEDFUNDS

### Monetary policy

#	Mnemonic	Tcode	Description
143	FEDFUNDS	1	Effective Federal Funds Rate