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ABSTRACT

The Structural Dynamics of US Output and Inflation: What Explains the Changes?*

We examine the dynamics of US output and inflation using a structural time varying coefficient VAR. We show that there are changes in the volatility of both variables and in the persistence of inflation. Technology shocks explain changes in output volatility, while a combination of technology, demand and monetary shocks explain variations in the persistence and volatility of inflation. We detect changes over time in the transmission of technology shocks and in the variance of technology and of monetary policy shocks. Hours and labour productivity always increase in response to technology shocks.

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1 Introduction

There is considerable evidence suggesting that the US economy has fundamentally changed over the last couple of decades. For example, Blanchard and Simon (2000), McConnell and Perez Quiroz (2001), Sargent and Cogley (2001) and Stock and Watson (2003) have reported a marked decline in the volatility of real activity and inflation since the early 1980s and a reduction in the persistence of inflation over time. What causes these changes? One possibility is that there have been alterations in the mechanism through which exogenous disturbances spread across sectors and propagate over time. Since the transmission mechanism depends on the features of the economy, structural characteristics, such as the behavior of consumers and firms, or the preferences of policymakers, must have changed over time. The recent literature has paid particular attention to changes in policymakers' preferences. For example, Clarida, Gali and Gertler (2000), Cogley and Sargent (2001) and (2005), Boivin and Giannoni (2002), and Lubik and Schorfheide (2004) have argued that monetary policy was "loose" in fighting inflation in the 1970s but became more aggressive since the early 1980s. Leeper and Zha (2003), Sims and Zha (2004), Primiceri (2005), and Canova and Gambetti (2004) are critical of this view since they estimate a stable policy rule and find the transmission of policy shocks roughly unchanged over time.

There has been a resurgence of interest in the last few years in analyzing the dynamics induced by technology shocks, following the work of Gali (1999), Christiano, Eichenbaum and Vigfusson (2003), Uhlig (2004), Dedola and Neri (2004), Francis and Ramey (2005) and others. However, to the best of our knowledge, the link between structural changes and the way technology shocks are transmitted to the economy has not been made. This is a bit surprising given that the increase in productivity of the 1990s was to a large extent unexpected (see e.g. Gordon (2003)) and that it may have produced changes in the way firms and consumers responded to economic disturbances. Similarly, the way fiscal policy was conducted in the 1970s and the early 1980s differed considerably from the way it was conducted in the 1990s. For example, large deficits in the 1980s were turned into surpluses in the 1990s. Furthermore, benign neglect about the size of the public debt has been substituted by a keen awareness of the wealth effects and of the inflation consequences that large debts may have. Studying whether the dynamics induced by technology and fiscal shocks have changed over time may help to clarify which structural feature of the US economy has changed and whether variations in output and inflation dynamics reflect changes in the propagation mechanism or in the variance of the exogenous shocks.

This paper provides evidence on these issues investigating the contribution of technology,

government expenditure and monetary disturbances to the changes in the volatility and in the persistence of US output and inflation. We employ a time varying coefficients VAR model (TVC-VAR), where coefficients evolve according to a nonlinear transition equation, which puts zero probability on paths associated with explosive roots, and the variance of the forecast errors is allowed to vary over time. As in Cogley and Sargent (2001), (2005) we use Markov Chain Monte Carlo (MCMC) methods to estimate the posterior distributions of the quantities of interest. However, contrary to these authors, and as in Canova and Gambetti (2004), we analyze the time evolution of structural relationships. To do so, we identify structural disturbances which are allowed to have different features at different points in time. In particular, we permit time variations in the characteristics of the shocks, in their variance and in their transmission to the economy.

Our analysis is recursive. That is, we can construct posterior distributions for structural statistics, using the information available at that point in time. This complicates the computations significantly - a MCMC routine is needed at each t where the analysis is conducted - but provides a sharper picture of the time evolution of structural relationships. With this strategy our analysis becomes comparable with the one of Canova (2004), where a small scale DSGE model featuring three types of shocks with similar economic interpretations, is recursively estimated with MCMC methods.

We identify structural disturbances using robust sign restrictions obtained from a DSGE model featuring monopolistic competitive firms, distorting taxes, utility yielding government expenditure, and rules describing fiscal and monetary policy actions, which encompasses RBC style and New-Keynesian style models as special cases. We construct robust restrictions allowing the parameters to vary within a range which is consistent with statistical evidence and economic considerations. We focus on sign restrictions for several reasons. First, magnitude restrictions typically depend on the parameterization while the sign restrictions we employ are less prone to such problem. Second, our model fails to deliver the full set of zero restrictions one would need to identify the three shocks with more conventional approaches. Third, the link between the theory and the empirical analysis is more direct, making the analysis transparent and inference stand on more solid ground.

Because time variations in the coefficients induce important non-linearities, standard response analysis is inappropriate. For example, since at each t the coefficient vector is perturbed by a structural shock, assuming that between $t+1$ and $t+k$ no shocks other than the disturbance under consideration hit the system may give misleading conclusions. To trace out the evolution of the economy when perturbed by structural shocks, we define impulse responses as the difference between two conditional expectations, differing in the

arguments of their conditioning sets. Such a definition reduces to the standard one when coefficients are constant, allows us to condition on the history of the data and of the parameters, and permits the size and the sign of certain shocks to matter for the dynamics of the model (see e.g. Canova and Gambetti (2004)).

Our results are as follows. First, while there is evidence of structural variations in both the volatility of output and inflation and in the persistence of inflation, our posterior analysis fails to detect significant changes because of large posterior standard errors. Second, the three structural shocks we identify explain between 50 and 65 percent of the variability of output and inflation on average across frequencies for every date in the sample: technology shocks account for the largest portion of output variability at frequency zero and, on average, across frequencies, while real demand and monetary shocks account for the bulk of inflation variability at frequency zero and, on average, across frequencies. Variations in inflation persistence are due to a decline in the relative contribution of real demand and technology shocks while changes in output and inflation volatility are accounted for by all three shocks, with the contribution of technology shocks showing the largest time variations. Third, there are important variations in the transmission of technology shocks and significant changes in the variances of technology and monetary policy shocks. Finally, technology shocks always imply positive contemporaneous comovements of hours and productivity but the correlation turns negative after a few lags.

In sum, consistent with McConnell and Perez Quiroz (2001) and Gordon (2003), our analysis attributes to variations in the magnitude and the transmission of technology shocks an important role in explaining changes in output volatility. It also suggests that variations in the magnitude of both technology and monetary shocks and the transmission of technology shocks are important in explaining changes in the volatility and in the persistence of inflation. Therefore, it complements those of Sims and Zha (2004), Primiceri (2005) and Gambetti and Canova (2004), who only examined the role of monetary policy shocks.

The rest of the paper is organized as follows. The next section describes the empirical model. Section 3 presents a DSGE model which produces the restrictions used to identify structural shocks. Section 4 briefly deals with estimation - all technical details are confined to the appendix. Section 5 presents the results and section 6 concludes.

2 The empirical model

Let y_t be a 5×1 vector of time series including real output, hours, inflation and the federal funds rate and M1 with the representation

$$y_t = A_{0,t} + A_{1,t}t + A_{2,t}y_{t-1} + A_{3,t}y_{t-2} + ... + A_{p+1,t}y_{t-p} + \varepsilon_t \tag{1}$$

where $A_{0,t}, A_{1,t}$ are a 5×1 vectors; $A_{i,t}$, are 5×5 matrices, $i = 2, ..., p+1$, and ε_t is a 5×1 Gaussian white noise process with zero mean and covariance Σ_t. Letting $A_t = [A_{0,t}, A_{1,t}, A_{2,t}...A_{p+1,t}]$, $x_t' = [1_5, 1_5 * t, y_{t-1}'...y_{t-p}']$, where 1_5 is a row vector of ones of length 5, $vec(\cdot)$ denotes the stacking column operator and $\theta_t = vec(A_t')$, rewrite (1) as

$$y_t = X_t'\theta_t + \varepsilon_t \tag{2}$$

where $X_t' = (I_5 \bigotimes x_t')$ is a $5 \times (5p+2)5$ matrix, I_5 is a 5×5 identity matrix, and θ_t is a $(5p+2)5 \times 1$ vector. We assume that θ_t evolves according to

$$p(\theta_t|\theta_{t-1}, \Omega_t) \propto \mathcal{I}(\theta_t) f(\theta_t|\theta_{t-1}, \Omega_t) \tag{3}$$

where $\mathcal{I}(\theta_t)$ discards explosive paths of y_t and $f(\theta_t|\theta_{t-1}, \Omega_t)$ is represented as

$$\theta_t = \theta_{t-1} + u_t \tag{4}$$

where u_t is a $(5p+2)5 \times 1$ Gaussian white noise process with zero mean and covariance Ω_t. We select this specification because more general AR and/or mean reverting structures were always discarded in out-of-sample model selection exercises. We assume that $corr(u_t, \varepsilon_t) = 0$, and that Ω_t is diagonal. The first assumption implies conditional linear responses to changes in ε_t, while the second is made for computational ease - structural coefficients are allowed to change in a correlated fashion. Our model implies that forecast errors are non-normal and heteroschedastic even when $\Sigma_t = \Sigma$ and $\Omega_t = \Omega$. In fact, substituting (4) into (2) we have that $y_t = X_t'\theta_{t-1} + v_t$, where $v_t = \varepsilon_t + X_t'u_t$. Such a structure is appealing since whatever alters coefficients also imparts heteroschedastic movements to the variance of the forecasts errors. Since also Ω_t is allowed to vary over time, the model permits various forms of stochastic volatility in the forecast errors of the model (see Sims and Zha (2004) and Cogley and Sargent (2005) for alternative specifications).

Let S_t be a square root of Σ_t, i.e., $\Sigma_t = S_tS_t'$, let H_t be an orthonormal matrix, independent of ε_t, such that $H_tH_t' = I$ and set $J_t^{-1} = H_t'S_t^{-1}$. J_t is a particular decomposition of Σ_t which transforms (2) in two ways: it produces uncorrelated innovations (via the matrix

S_t) and it gives a structural interpretation to the equations of the system (via the matrix H_t). Premultiplying y_t by J_t^{-1} we obtain

$$J_t^{-1}y_t = J_t^{-1}A_{0,t} + J_t^{-1}A_{1,t}t + \sum_j J_t^{-1}A_{j+1,t}y_{t-j} + e_t \tag{5}$$

where $e_t = J_t^{-1}\varepsilon_t$ satisfies: $E(e_t) = 0$, $E(e_te_t') = I_5$. Equation (5) represents the class of "structural" representations of interest: for example, a Choleski system is obtained choosing $S_t = S$ to be lower triangular matrix and $H_t = I_5$, and more general patterns, with non-recursive zero restrictions, result choosing $S_t = S$ to be non-triangular and $H_t = I_5$.

In this paper, since S_t is an arbitrary square root matrix, identifying structural shocks is equivalent to choosing H_t. We select it so that the sign of the responses at $t+k, k = 1, 2, \ldots, K_1$, K_1 fixed, matches the robust model-based sign restrictions presented in the next section. We choose sign restrictions to identify structural shocks for three reasons. First, magnitude restrictions typically depend on the parameterization of the model while the sign restrictions we employ are less prone to such problem. Second, our model fails to deliver the full set of zero restrictions one would need to identify the three shocks of interest with more conventional approaches. Third, as it would be clear from the next section, the link between the theory and the empirical analysis is more direct.

Letting $C_t = [J_t^{-1}A_{0t}, \ldots, J_t^{-1}A_{p+1t}]$, and $\gamma_t = vec(C_t')$, (5) can be written as

$$J_t^{-1}y_t = X_t'\gamma_t + e_t \tag{6}$$

As in fixed coefficient VARs there is a mapping between the structural coefficients γ_t and the reduced form coefficients θ_t since $\gamma_t = (J_t^{-1} \bigotimes I_{5p})\theta_t$. Whenever $\mathcal{I}(\theta_t) = 1$, we have

$$\gamma_t = \gamma_{t-1} + \eta_t \tag{7}$$

where $\eta_t = (J_t^{-1} \bigotimes I_{5p})u_t$ satisfies $E(\eta_t) = 0$, $E(\eta_t\eta_t') = E((J_t^{-1} \bigotimes I_{5p})u_tu_t'(J_t^{-1} \bigotimes I_{5p})')$. Hence, the vector of structural shocks $\xi_t' = [e_t', \eta_t']'$ is a white noise process with zero mean and covariance matrix $E\xi_t\xi_t' = \begin{bmatrix} I_5 & 0 \\ 0 & E((J_t^{-1} \bigotimes I_{5p})u_tu_t'(J_t^{-1} \bigotimes I_{5p})') \end{bmatrix}$. Since each element of γ_t depends on several u_{it} via the matrix J_t, shocks to structural parameters are no longer independent. Note that the (6)-(7) contain two types of structural shocks: VAR disturbances, e_t, and structural parameters disturbances, η_t. This latter type of shocks will not be dealt with here and is analyzed in details in Canova and Gambetti (2004).

To study the transmission of disturbances in a fixed coefficient model one typically employs impulse responses. Impulse responses are generally computed as the difference between two realizations of $y_{i,t+k}$ which are identical up to time t, but one assumes that

between t and $t+k$ a shock in the j-th component of e_{t+k} occurs only at time t, and the other that no shocks take place at all dates between t and $t+k, k = 1, 2, \ldots,$.

In a TVC model, responses computed this way disregard the fact that structural coefficients may also change. Hence, meaningful response functions ought to measure the effects of a shock in e_{jt} on y_{it+k}, allowing future shocks to the structural coefficients to be non-zero. The responses we present are obtained as the difference between two conditional expectations of y_{it+k}. In both cases we condition on the history of the data and of the coefficients, on the structural parameters of the transition equation (which are function of J_t) and all future shocks. However, in one case we condition on a draw for the current shock, while in the other the current shock is set to zero.

Formally, let y^t be a history for y_t; θ^t be a trajectory for the coefficients up to t, $y_{t+1}^{t+k} = [y'_{t+1}, ...y'_{t+k}]'$ a collection of future observations and $\theta_{t+1}^{t+k} = [\theta'_{t+1}, ...\theta'_{t+k}]'$ a collection of future trajectories for θ_t. Let $V_t = (\Sigma_t, \Omega_t)$; recall that $\xi'_t = [e'_t, \eta'_t]$. Let $\xi_{j,t+1}^{\delta}$ be a realization of $\xi_{j,t+1}$ of size δ and let $\mathcal{F}_t^1 = \{y^t, \theta^t, V_t, J_t, \xi_{j,t}^{\delta}, \xi_{-j,t}, \xi_{t+1}^{t+\tau}\}$ and $\mathcal{F}_t^2 = \{y^t, \theta^t, V_t, J_t, \xi_t, \xi_{t+1}^{t+\tau}\}$ be two conditioning sets, where $\xi_{-j,t}$ indicates all shocks, excluding the one in the j-th component. Then a response to $\xi_{j,t}^{\delta}$, $j = 1, \ldots, 5$ is defined as:[1]

$$IR_y^j(t,k) = E(y_{t+k}|\mathcal{F}_t^1) - E(y_{t+k}|\mathcal{F}_t^2) \qquad k = 1, 2, \ldots \tag{8}$$

While (8) resembles the impulse response function suggested by Gallant et al. (1996), Koop et al. (1996) and Koop (1996), three important differences need to be noted. First, our responses are history but not state dependent - histories are not random variables. Second, the size and the sign of η shocks matter for the dynamics of the system but not the size and the sign of e_t. Third, since θ_{t+1} is a random variable, $IR_y^j(t,k)$ is also random variable.

When $\xi_{j,t}^{\delta} = e_{j,t}^{\delta}$, the case considered in the paper, responses are given by:

$$\begin{aligned} IR_y^j(t,1) &= J_t^{-1,i} e_{j,t} \\ IR_y^j(t,k) &= \Psi_{t+k,k-1}^j e_{j,t} \qquad k = 2, 3, \ldots \end{aligned} \tag{9}$$

where $\Psi_{t+k,k-1} = \mathcal{S}_{n,n}[(\prod_{h=0}^{k-1} \mathbf{A}_{t+k-h}) \times J_{t+k-(k-1)}]$, $\mathbf{A}_t$ is the companion matrix of the VAR at time t; $\mathcal{S}_{n,n}$ is a selection matrix which extracts the first $n \times n$ block of $[(\prod_{h=0}^{k-1} \mathbf{A}_{t+k-h}) \times J_{t+k-(k-1)}]$ and $\Psi_{t+k,k-1}^j$ is the column of $\Psi_{t+k,k-1}$ corresponding to the $j-$th shock.

When the coefficients are constant, $\prod_h \mathbf{A}_{t+k-h} = \mathbf{A}^k$ and $\Psi_{t+k,k-1} = \mathcal{S}_{n,n}(\mathbf{A}^k \times J)$ for all k, so that (9) collapses to the traditional impulse response function to unitary structural

[1] One could alternatively average out future shocks. Our definition is preferrable for two reasons: it is easier to compute and produces numerically more stable distributions; it produces impulses responses which are similar to those generated by constant coefficient impulse responses when shocks to the measurement equations are considered. Note also that since future shocks are not averaged out, our impulse responses will display larger variability.

shocks. In general, $IR_y^j(t,k)$ depends on the identifying matrix J_t, the history of the data and the dynamics of the reduced form coefficients up to time t.

3 The identification restrictions

The restrictions we use to identify the shocks come from a general equilibrium model that encompasses flexible price RBC and New-Keynesian sticky price setups as special cases. The restrictions we consider are robust, in the sense that there are generated by a wide range of parametrizations and for alternative specifications of the policy rules. We use a subset of the large number of model's predictions and, as in Canova (2002), we focus only on qualitative (sign) restrictions, as opposed to quantitative (magnitude) restrictions, to identify shocks. While it is relatively easy to find robust sign restrictions, magnitude restrictions are typically fragile and depend on the exact parametrization of the model.

The economy is a simplified version of the one in Pappa (2004). It features a representative household, a continuum of firms, a monetary authority and a fiscal authority which consumes goods that may yield utility for the households.

3.1 Households

Households derive utility from private, C_t^p, and public consumption, C_t^g, leisure, $1-N_t$ and real balances $\frac{M_t}{p_t}$. They maximize $E_0 \sum_{t=0}^{\infty} \beta^t \frac{[(aC_t^{p\frac{\varsigma-1}{\varsigma}}+(1-a)C_t^{g\frac{\varsigma-1}{\varsigma}})^{\frac{\theta_n\varsigma}{\varsigma-1}}(1-N_t)^{1-\theta_n}]^{1-\sigma}-1}{1-\sigma} + \frac{1}{1-\theta_M}(\frac{M_t}{p_t})^{1-\theta_M}$ choosing sequences for private consumption, hours, capital to be used next period K_{t+1}, nominal state-contigent bonds, D_{t+1}, nominal balances and government bonds, B_{t+1}. Here $0<\beta<1$ is the subjective discount factor and $\sigma>0$ a risk aversion parameter. Public consumption is exogenous from the point of view of households. The degree of substitutability between private and public consumption is regulated by $0<\varsigma\leq\infty$; $0<a\leq 1$ controls the share of public and private goods in consumption: when $a=1$, public consumption is useless from private agents' point of view. $\vartheta_M>0$ regulates the elasticity of money demand. Household time is normalized to one at each t. We assume $C_t^p=\left[\int_0^1 C_{it}^p(i)^{\frac{\lambda-1}{\lambda}}di\right]^{\frac{\lambda}{\lambda-1}}$; $C_t^g=\left[\int_0^1 C_{it}^g(i)^{\frac{\lambda-1}{\lambda}}di\right]^{\frac{\lambda}{\lambda-1}}$ and $\lambda>0$ measures the elasticity of substitution between types of goods. The sequence of budget constraints is:

$$\begin{aligned} P_t(C_t^p+I_t)+E_t\{Q_{t,t+1}D_{t+1}\}+R_t^{-1}B_{t+1}+M_{t+1} &\leq \\ (1-\tau^l)P_tw_tN_t+[r_t-\tau^k(r_t-\delta)]P_tK_t+D_t+B_t-T_tP_t+M_t+\Xi_t & \end{aligned} \tag{10}$$

where $(1-\tau^l)P_tw_tN_t$, is the after tax nominal labor income, $[r_t-\tau^k(r_t-\delta)]P_tK_t$ is the after tax nominal capital income (allowing for depreciation), Ξ_t are nominal profits distributed by

firms (which are owned by consumers), and $T_t P_t$ are nominal lump-sum taxes. We assume complete private financial markets: D_{t+1} are holdings of state-contingent nominal bonds, paying one unit of currency in period $t+1$ if a specified state is realized, and $Q_{t,t+1}$ is their period-t price. Finally, R_t is the gross return on a one period government bond B_t. With the disposable income the household purchases consumption goods, C_t^p, capital goods, I_t, and assets. Capital accumulates according to:

$$K_{t+1} = I_t + (1-\delta)K_t - \nu\left(\frac{K_{t+1}}{K_t}\right)K_t \tag{11}$$

where $0 < \delta < 1$ is a constant depreciation rate, $\nu\left(\frac{K_{t+1}}{K_t}\right) = \frac{b}{2}\left[\frac{K_{t+1}-(1-\delta)K_t}{K_t} - \delta\right]^2$ and $b \geq 0$ determines the size of the adjustment costs. Since households own and supply capital to the firms, they bear the adjustment costs.

3.2 Firms

A firm j produces output according to the constant returns to scale production function:

$$Y_{tj} = (Z_t N_{tj})^{1-\alpha}(K_{tj})^{\alpha} \tag{12}$$

where K_{tj} and N_{tj} are capital and labor inputs and Z_t is an aggregate technology shock.

We assume perfect competition in the input markets [2]: firms minimize costs choosing private inputs and taking wages and the rental rate of capital as given. Since firms are identical, they all choose the same amount of inputs and cost minimization implies

$$\frac{K_{tj}}{N_{tj}} = \frac{\alpha}{(1-\alpha)}\frac{w_t}{r_t} \quad \forall j \tag{13}$$

Equation (13) and the production function imply that (nominal) marginal costs are:

$$MC_t = \frac{1}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}} Z_t^{\alpha-1} w_t^{1-\alpha} r_t^{\alpha} P_t \tag{14}$$

In the goods market firms are monopolistic competitors. The strategy used to set prices depends on whether they are sticky or flexible. In the former case, each domestic producer is allowed to reset her price with a constant probability, $(1-\gamma)$, independently of the time elapsed since the last adjustment. When a producer receives a signal, she chooses her new price, P_{tj}^*, to maximize $E_t \sum_{k=0}^{\infty} \gamma^k Q_{t+k+1,t+k}(P_{tj}^* - MC_{t+kj})Y_{t+kj}$ subject to the demand curve $Y_{t+kj} = (\frac{P_{tj}^*}{P_{t+k}})^{-\lambda} Y_{t+k}$. Optimization implies

$$\sum_{k=0}^{\infty} \gamma^k E_t\{Q_{t+k+1,t+k} Y_{t+kj}(P_{tj}^* - \frac{\lambda}{\lambda-1}\frac{1}{1-\tau^{\lambda}} MC_{t+k})\} = 0 \tag{15}$$

[2] The robust restrictions we emphasize below are independent of the presence of frictions in labor markets such as sticky wages or labor unions.

where $\tau^{\lambda} = -(\lambda - 1)^{-1}$ is a subsidy that, in equilibrium, eliminates the monopolistic competitive distortion . Given the pricing assumption, the aggregate price index is

$$P_t = [\gamma P_{t-1}^{1-\lambda} + (1-\gamma) P_t^{*1-\lambda}]^{\frac{1}{1-\lambda}} \tag{16}$$

When firms can reset the price at each t, prices become flexible and:

$$P_t = \frac{\lambda}{\lambda - 1} \frac{1}{1 - \tau^{\lambda}} MC_t, \qquad \forall t \tag{17}$$

3.3 Fiscal and Monetary Policy

Government's income consists of seigniorage, tax revenues minus subsidies to the firms and proceeds from new debt issue. The government budget constraint is:

$$P_t C_t^g + \tau^{\lambda} P_t Y_t - \tau^l w_t P_t N_t - \tau^k (r_t - \delta^p) P_t K_t - P_t T_t + B_t + M_t = R_t^{-1} B_{t+1} + M_{t+1} \tag{18}$$

We treat tax rates on labor and capital income parametrically; assume that the government takes market prices, hours and capital as given, and that B_t endogenously adjusts to ensure that the budget constraint is satisfied. In order to guarantee a non-explosive solution for debt (see e.g., Leeper (1991)), we assume a tax rule of the form:

$$\frac{T_t}{T^{ss}} = [(\frac{B_t}{Y_t})/(\frac{B^{ss}}{Y^{ss}})]^{\phi_b} \tag{19}$$

where the superscript ss indicates steady states. Finally, there is an independent monetary authority which sets the nominal interest rate according to the rule:

$$\frac{R_t}{R^{ss}} = (\frac{\pi_t}{\pi^{ss}})^{\phi_\pi} u_t \tag{20}$$

where π_t is current inflation, and u_t is a monetary policy shock. Given this rule, the authority stands ready to supply nominal balances that the private sector demands.

There are two types of aggregate constraints. First, labor supply must equate labor employed by the private firms. Second, aggregate production must equate the demand for goods from the private and public sector, that is $Y_t = C_t^p + I_t + C_t^g$.

We assume that the three exogenous processes $S_t = [Z_t, C_t^g, u_t]'$, evolve according to

$$\log(S_t) = (I_4 - \boldsymbol{\varrho}) \log(\overline{S}) + \boldsymbol{\varrho} \log(S_{t-1}) + V_t \tag{21}$$

where I_3 is a 3×3 identity matrix, $\boldsymbol{\varrho}$ is a 3×3 diagonal matrix with all the roots less than one in modulus, $\overline{S}$ is the mean of S and the 3×1 innovation vector V_t is a zero-mean, white noise process [3]. Let $\mathcal{A} = (\mathcal{A}^1, \mathcal{A}^2)$ represent the vector of parameters of the model.

[3] A previous version of the paper allowed also for goverment investment and goverment employment disturbances. Since the sign restrictions we emphasize are the same for shocks to goverment consumption, goverment investment and goverment employment, the last two type of shocks are curently omitted.

3.4 Deriving the identification restrictions

Table 1: Parameter values or ranges

β	discount factor	0.991
$(B/Y)^{ss}$	steady state debt to output ratio	1.2
σ	risk aversion coefficient	[0.5,6.0]
$1-a$	share of public goods in consumption	[0.0,0.15]
ς	elasticity of substitution public/private goods	[0.5,3.0]
θ_n	preference parameter	[0.1,0.9]
b	adjustment cost parameter	[0.1,10]
δ	capital depreciation rate	[0.013,0.05]
α	capital share	[0.2,0.4]
τ^l	average labor tax rate	[0,0.3]
τ^k	average capital tax rate	[0,0.2]
$(C^g/Y)^{ss}$	steady state C^g/Y ratio	[0.07,0.12]
γ	degree of price stickiness	[0.2,0.85]
ϕ_π	Taylor's coefficient	[1.1,2.0]
ϕ_b	coefficient on debt rule	[1.05, 4.05]
λ	elasticity of substitution between varieties	[7.0,8.0]
θ_M	elasticity of money demand	[1.0,10]
ρ_Z	persistence of Z_t shock	[0.8,0.95]
ρ_{C_g}	persistence of C_t^g shock	[0.6,0.9]
ρ_u	persistence of u_t^R shock	[0.7,0.9]

Figure 1 presents responses to impulses in the three shocks when the parameters are allowed to vary within the ranges listed in table 1. To be precise, each box reports 68% of the 10000 paths generated randomly drawing $\mathcal{A}_j,\ j = 1, 2, \ldots$ independently from a uniform distribution covering the range appearing in table 1. The first column of figure 1 represents responses to technology shocks, the second responses to government expenditure shocks, and the third responses to monetary shocks. Since our VAR includes output, hours, inflation, nominal rate and money, we only plot the responses of these variables.

A few words regarding the assumed ranges are in order. First, we decompose the parameter vector in two components: $\mathcal{A}^1$ includes the parameters held fixed to a particular value because of steady state considerations, while in $\mathcal{A}^2$ are the parameters which are allowed to vary. In $\mathcal{A}^1$ we have the discount factor, set so that the annual real interest rate equals 4%, and the debt ratio,$(\frac{B}{Y})^{SS}$, which is selected to match the average US debt to GDP ratio.

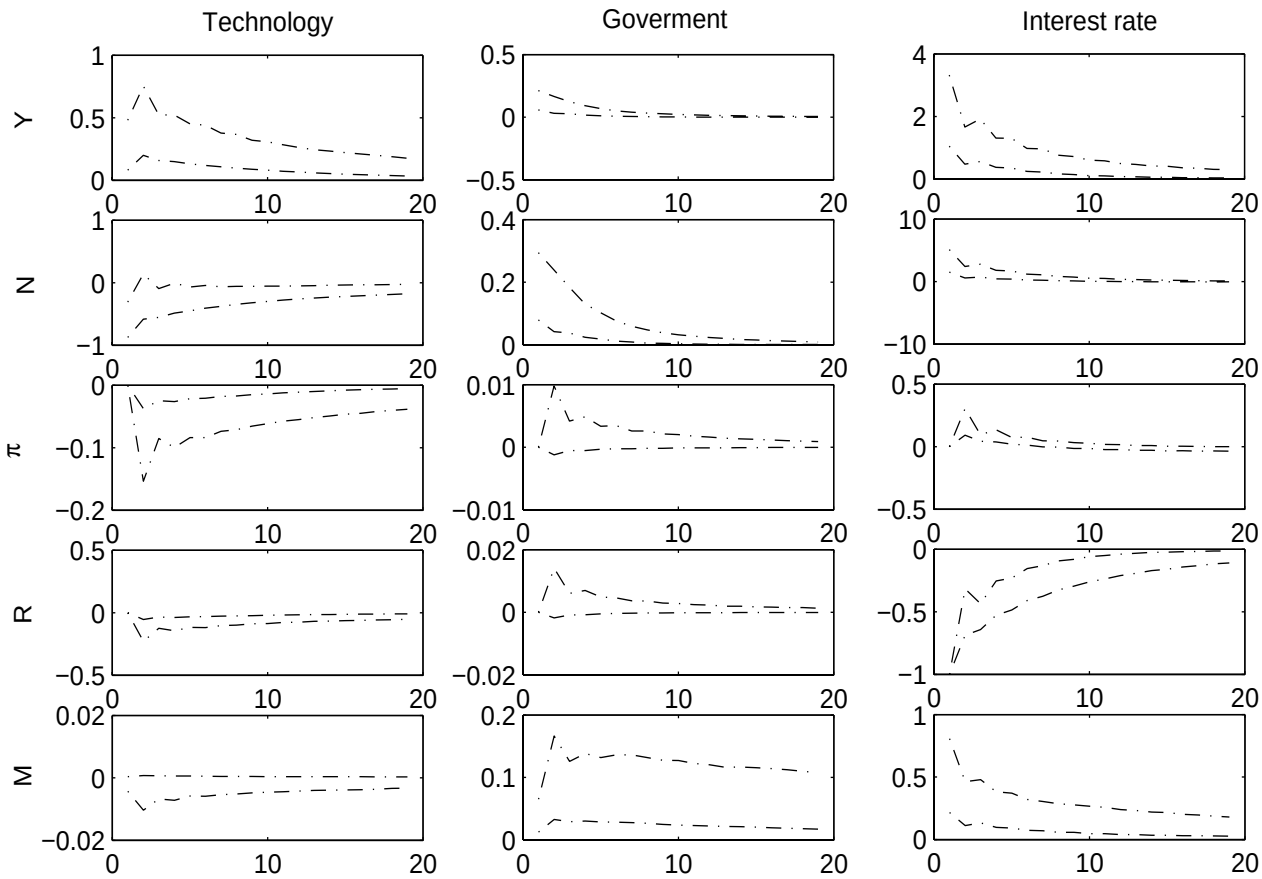


Figure 1: Responses to shocks in the model

The intervals for the other parameters are centered around standard values and the ranges are selected to contain existing estimates, values assumed in calibration exercises or chosen to satisfy theoretical considerations. For example, the range for the *risk aversion parameter* σ includes the values typically used in RBC (σ from 0.5 to 2), and New-Keynesian models (σ from 1 to 6). Theoretical considerations suggest that the share of public goods in total consumption, $1-a$, should be low (since the private wealth effects following fiscal shocks crucially depend on this parameter) and the chosen range reflect this concern. The range for ς allows for both complementarities and substitutabilities between private and public goods. The parameters θ_n, θ_M regulate the labor supply and money demand elasticity and the chosen ranges cover well the range of existing estimates. The ranges for the *capital share* in production, α, the *capital adjustment costs parameter*, b, and the *depreciation of capital*, δ include standard values. The ranges for labor and capital income tax parameters (τ^l, τ^k) cover the values of interest to policymakers and those for the expenditure ratio $(\frac{C^g}{Y})$ match the cross sectional range of values for US states. The range for the *degree of price stickiness* γ is wide and covers cases where prices are very sticky and almost flexible.

Finally, the *coefficient on inflation* ϕ_π, and the *coefficient on debt* ϕ_b in the policy rules control whether equilibria are determinate or not. The ranges we have selected imply that fiscal policy is passive and monetary policy is active, in the terminology of Leeper (1991); this insure determinacy of the equilibria and implies that our analysis neglects equilibria of the types considered in Lubik and Schorfheide (2004). Therefore, the interpretation of our monetary policy shocks is different from theirs. Considering active fiscal policy and passive monetary policy leave the qualitative features of the responses unchanged.

The model produces several robust sign implications in responses to the shocks. For example, a persistent technological disturbance increases output, decreases inflation, nominal rates and nominal balances and the sign of the response is independent of the horizon. Furthermore, when government consumption expenditure increase, output, hours, inflation, nominal interest rates and nominal balances all increase, while surprise decreases in the interest rate increase output, hours, inflation and nominal balances. Note, in particular, that these patterns obtain for a wide range of values of the elasticity of substitution between private and public goods, the strength of the reaction of interest rates and taxes to inflation and debt and the degree of price stickiness.

The identification restrictions used are summarized in table 2. Note that the dynamics of hours (and labor productivity) are unrestricted in all cases.

Table 2: Identification restrictions

	Output	Inflation	Interest rate	Money
Technology	≥ 0	≤ 0		
Government	≥ 0	≥ 0	≥ 0	≥ 0
Monetary	≥ 0	≥ 0	≤ 0	≥ 0

There are many ways of implementing sign restrictions. The results we present are obtained using an acceptance sampling scheme where draws that jointly satisfy the restrictions for all three shocks are kept and draws that do not are discarded. Tim Cogley pointed out to us that, since the bands in figure 1 do not insure that some parameter combinations may fail to satisfy the restrictions, an importance sampling scheme, which gives positive but different weights to different types of draws, could be more appropriate. In general, since identification restrictions make the prior for the reduced form parameters informative, one may want to analyze how sensitive are the conclusions we reach to these choices. We have tried few alternatives to implement an importance sampling scheme. First, we have weighted draws in proportion to the number of horizons at which restrictions are satisfied. Thus, if we impose restrictions at three horizons, we give weight $0.5/n_1$ to draws that satisfy restrictions at all horizons, weight $0.33/n_2$ to draws that satisfy restrictions at two hori-

zons, and weight $0.17/n_3$ to draws that satisfy restrictions at one horizon, $n_1+n_2+n_3=n$, where n is the total number of draws. Second, we have weighted the draws satisfying all the restrictions by $0.68/n_1$ and draws which do not satisfy all the restrictions by $0.32/n_2$, $n_1+n_2=n$. The results we present are qualitatively independent of the scheme used to weight draws even though, quantitatively, some conclusions become more or less significant. Appendix B contains the results obtained with these alternatives weighting schemes.

Since the sign restrictions we use are robust to the horizon, we are free to choose how many responses we wish to restrict. However, there is an important trade-off to be considered, since the smaller is the number of restrictions, the larger is the number of draws consistent with the restrictions but, potentially, the weaker is the link between the model and the empirical analysis. As the number of restricted responses increases, we tight up the empirical analysis to the model more firmly, but the number of draws satisfying the restrictions may drop dramatically, making estimates of standard errors inaccurate. Since the relationship between number of restrictions and number of accepted draws is highly nonlinear, there is no straightforward way to optimize this trade-off. We present results obtained imposing restrictions at two horizons (0 and 1) since this choice seems to account for both concerns.

4 Estimation

The model (6)-(7) is estimated using Bayesian methods. We specify prior distributions for $\theta_0, \Sigma_0, \Omega_0$, and H_0 and use data up to t to compute posterior estimates of the structural parameters. Since our sample goes from 1960:1 to 2003:2, we initially estimate the model for the period 1960:1-1970:2 and then reestimate it 33 times moving the terminal date by one year up to 2003:2

Our estimation approach proceeds in two steps. First, we characterize the (truncated) posterior distribution of the reduced form parameters. Second, given these posteriors and the identification restrictions, we construct posteriors for the structural parameters. Unfortunately, posterior distributions for the structural parameters are not available in a closed form. Therefore, MCMC methods are used to simulate posterior sequences consistent with the information available up to time t. Construction of the truncated posterior for reduced form parameters is relatively standard (see e.g. Cogley and Sargent (2005)): it requires treating the parameters which are time varying as a block in a Gibbs sampler algorithm. Hence, at each t and in each Gibbs sampler cycle, one runs the Kalman filter and the simulation smoother, conditional on the draw of the other time invariant parameters, and

discard paths for the coefficients generating explosive time series for the endogenous variables. These standard calculations are complicated in our setup by the fact that at each cycle, we need to obtain structural estimates of the time varying features of the model and that we need to run an MCMC routine for each t. This means that, in each cycle and each t, we also need to discard paths which do not satisfy the restrictions. Convergence was checked using a CUMSUM statistic. The results we present are based on 20,000 draws for each t - of these, after the non-explosive and the identification filters are used, about 200 are kept for inference. The methodology used to construct posterior distributions for the unknowns is contained, together with the prior specifications, in the appendix. The data comes from the FREDII data base of the Federal Reserve Bank of St. Louis and consists of GDP (GDPC1), GDP deflator inflation (ΔGDPDEF), the Federal funds rate (FEDFUNDS), hours of all persons in the non-farm business sector (HOANBS) and M1 (M1SL) - in parenthesis are the mnemonic used by FREDII. Four lags of each variable are used in the estimation.

5 The Results

5.1 The dynamics of structural volatility and persistence

Figure 2 presents posterior estimates of the structural spectrum for dates ranging from 1970:1 to 2003:2 (first panel); the median and the 68% central posterior bands for structural persistence (second panel) and for structural volatility (third panel) of output and inflation. Persistence is measured by the height of the spectrum at frequency zero; volatility by the value of the cumulative spectrum.

A few interesting features are worth commenting upon. First, the structural spectrum of inflation is relatively stable over time, except for the zero frequency. Therefore, changes in structural inflation volatility are closely associated with changes in its structural persistence. The spectrum of output is also relatively stable over time at almost all frequencies. However, variations in structural volatility are primarily linked to structural variations occurring in the frequencies corresponding to three to five years cycles ($\omega \in [0.314, 0.52]$).

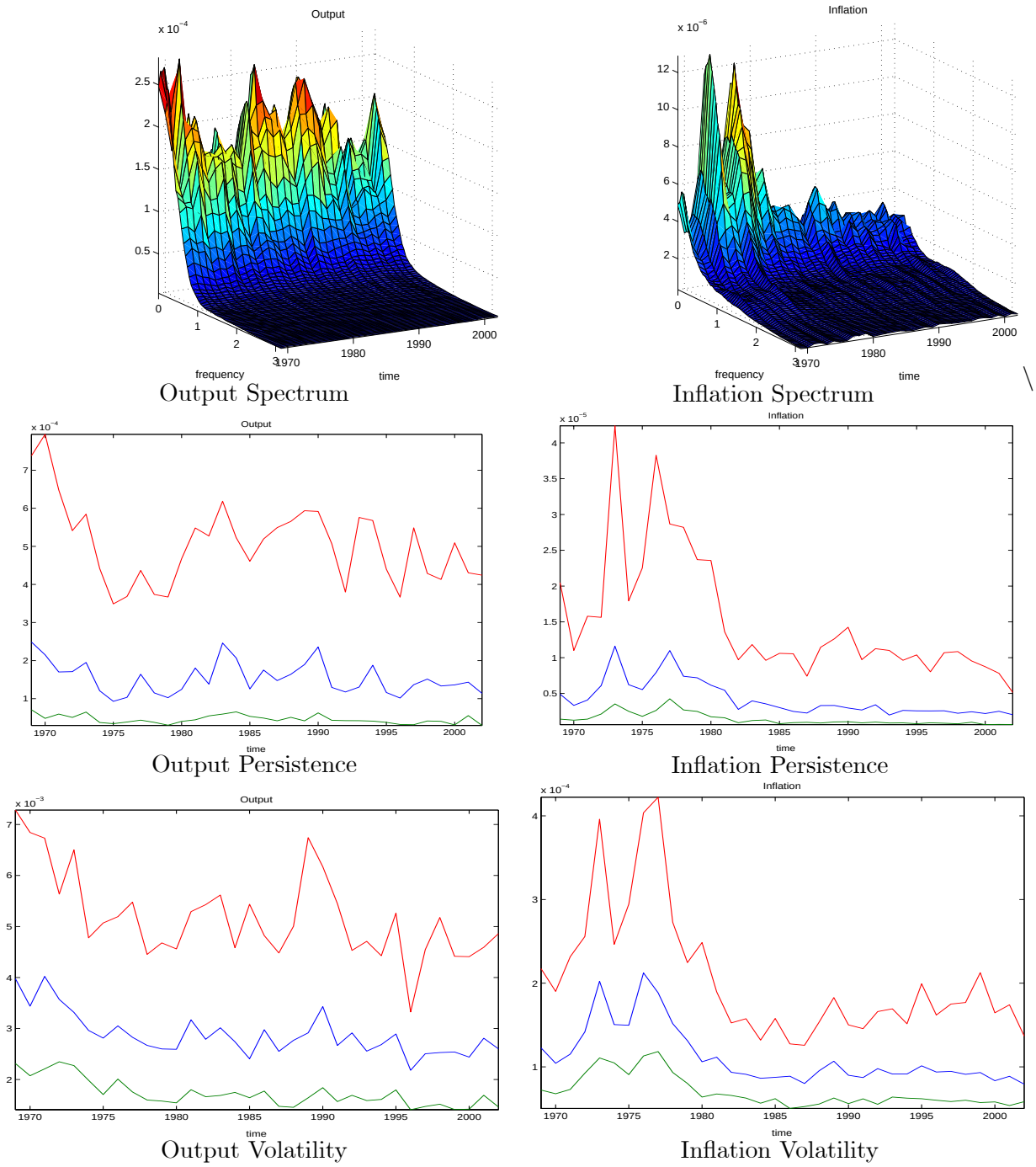


Figure 2: Structural Output and Inflation Dynamics, median and 68 % posterior bands

Second, inflation persistence shows a marked hump-shaped pattern: it displays a five fold increase in 1973-1974 and then again in 1977-1978, it drops dramatically after that date, and since 1982 the posterior distribution of inflation persistence displays marginal variations. The size of the drop is economically large: from its peak value, the median persistence in the 1990s is about 66 percent smaller. On the contrary, variations over time in the posterior distribution of output persistence are relatively small. Third, as expected from previous discussion, the dynamics of the posterior structural inflation volatility reflect those of the posterior of structural inflation persistence. On the other hand, the median of the posterior distribution of output volatility declines by roughly 25 percent from the beginning to the end of the sample.

Since posterior standard errors are large, even remarkable changes, like those displayed by the posterior median of inflation persistence, or of output volatility, turn out to be statistically insignificant. This outcome is consistent with the univariate, reduced form evidence presented by Pivetta and Reis (2004) and their classical statistical analysis and casts some doubts on inference derived analyzing the evolution of the mean (or the median) of these statistics. What features of our approach could be responsible for these large posterior standard errors? We singled out three possibilities. First, it could be that some parameter draws are more consistent than others with the sign restrictions. If these draws imply larger volatility in the coefficients, it could be that the estimated variance of the error in the law of motion of the coefficients is larger for accepted than rejected draws. This turns out not to be the case: the two variances are statistically indistinguishable. As a further check, we have computed posterior standard errors using a non-structural Choleski decomposition and results are unchanged. Second, figure 2 is constructed using recursive analysis. Therefore, our estimates contains less information than those produced using estimates of the parameters obtained from the full sample. Although standard errors are reduced when full sample estimates are considered, the pattern of changes is qualitative unaltered. Third, since our spectral estimates are constructed allowing future coefficients to be random, it could be that this uncertainty is responsible for the large standard errors we report. We have therefore repeated the computations averaging out future shocks to the coefficients and found that posterior standard errors are smaller by about 25 percent. Hence, even changing a few features in our estimation approach, we would not be able to confidently claim that the observed changes in output and inflation persistence and volatility are statistically large.

In summary, three points can be made. First, while there is visual evidence of a decline in the median estimates of output and inflation volatility, the case for evolving volatility is

considerably reduced once posterior standard errors are taken into account. This evidence should be contrasted with the one obtained with univariate, in-sample, reduced form methods, for example McConnell and Perez Quiroz (2001) or Stock and Watson (2003), which overwhelmingly suggest the presence of a significant structural break in the variability of the two series. Second, when structural, recursive, multivariate analysis is used, the case for evolving posterior distributions of persistence measures is also far weaker. Consistent with the evidence contained in Cogley and Sargent (2001) and (2005), the posterior median of inflation persistence shows a declining trend but posterior uncertainty is sufficiently large to make time differences irrelevant. The posterior distribution of output persistence, on the other hand, displays neither breaks nor evolving dynamics. Third, leaving aside issues of statistical significance, the timing of the changes in persistences and volatilities does not appear to be synchronized. Hence, contrary to what it is commonly perceived, it is unlikely that a single explanation accounts for the observed variations in output and inflation dynamics.

5.2 What drives variations in structural volatility and in persistence?

Recall that our structural model has implications for three types of disturbances, roughly speaking, supply, real demand and monetary shocks. Therefore, we can identify at most three of the five structural shocks driving the VAR. This means that there will be a residual capturing unexplained variations in output and inflation volatility and persistence.

Before discussing in details sources of structural volatility and persistence, we would like to note that our identification exercise was quite successful. Our three structural shocks explain between 50 and 65 percent of the variability of output and inflation on average across frequencies for every date we consider. We believe this magnitude is remarkable, given our analysis has completely disregarded e.g. labor supply or investment specific shocks, which Chang and Schorfheide (2004) and Fisher (2003) have shown to be important in explaining output (and potentially inflation) fluctuations. On average over time, technology shocks explain 25% of inflation variability and about 15% of output variability, demand shocks about 17% of inflation variability and 25% of output variability, and monetary shocks about 14% of inflation variability and 12% of output variability. When we look at specific frequencies, we find that technology shocks exercise their largest impact on inflation variability at business cycle and high frequencies (mean contribution is about 28%) while their largest impact on output variability is at low frequencies (mean contribution is about 17%). On the other hand, the two demand shocks explain the largest portion of inflation variability at low frequencies (roughly, 20% for real demand shock and 17% for monetary

shocks) and have their largest explanatory power for output fluctuations at business cycle frequencies (roughly, 25% for demand shocks and 17% for monetary shocks).

Given that the spectrum at frequency ω is uncorrrelated with the spectrum at frequency ω', when ω and ω' are Fourier frequencies, it is easy to compute the relative contribution of each of the three structural shocks to changes in the volatility and in the persistence of output and inflation. In fact, disregarding the constant and the trend, the (time varying) structural MA representation is $y_{it} = \sum_{j=1}^{5} \mathcal{B}_{jt}(\ell) e_{jt}$ where e_{it} is orthogonal to $e_{i't}$, $i' \neq i, i = 1, \ldots, 5$. Since structural shocks are independent, the (local) spectrum of y_{it} at frequency ω can be written as $S_{y_i}(\omega)(t) = \sum_{j=1}^{5} |\mathcal{B}_{jt}(\omega)|^2 S_{e_j}(\omega)(t)$. Therefore, the fraction of the persistence in y_{it} due to structural shock j is $S_{y_i}^{j}(\omega = 0)(t) = \frac{|\mathcal{B}_{jt}(\omega=0)|^2 S_{e_j}(\omega=0)(t)}{S_{y_i}(\omega=0)(t)}$ and the fraction of the volatility in y_{it} due to structural shock j is $\sum_{\omega} S_{y_i}^{j}(\omega)(t)$. Intuitively, these measures are comparable to variance decomposition shares. Variance decomposition shares inform us on the relative contribution of different shocks at various forecasting horizons. The measures we propose evaluate the contribution of structural shock j to the variability of y_{it} at either one frequency or at all frequencies.

We divide the discussion of the results into two parts. First, we examine the contribution of monetary policy shocks to the variations presented in figure 2. The large number of papers studying this issue and the consequent discussion that followed the original contribution of Clarida, Gali and Gertler (2000) justify our focus. Second, we assess the role of the two other shocks in accounting for the observed changes.

It is useful to recall that if the conventional wisdom is correct, the decline observed in the median of output and inflation volatility and inflation persistence should be largely explained by a decline in the contribution of monetary shocks to these statistics. Figure 3, which reports the median and the 68% posterior bands for the percentage of the persistence of output and inflation explained by the three shocks, and figure 4, which reports the same statistics for the volatility of output and inflation, tell a different story. For example, the share of inflation and output persistence attributable to monetary shocks displays an increasing trend and the median contribution at the end of the sample is about 30 percent larger than in the 1970s. Also, the contribution of monetary policy shocks to output and inflation volatility is roughly constant over time.

Several authors have attempted to relate changes in inflation persistence with changes in the stance of monetary policy (see e.g. Cogley and Sargent (2001), or Benati (2005)), or to the way monetary shocks are transmitted to the economy (see e.g. Leeper and Zha (2003) or Sims and Zha (2004)). Contrary to the views of many policymakers, our results suggest that monetary policy could not have been a major factor behind the observed declines in

inflation persistence, and that other shocks may have played a larger role. Similarly, the claim that the increased stability observed in the US economy since the mid 1980s, is a result of a more conservative monetary policy actions appears to be in contrast with the empirical evidence we present: the decline in output and inflation volatility is only partially explained by monetary policy and other sources of disturbances appear to have contributed to the decline.

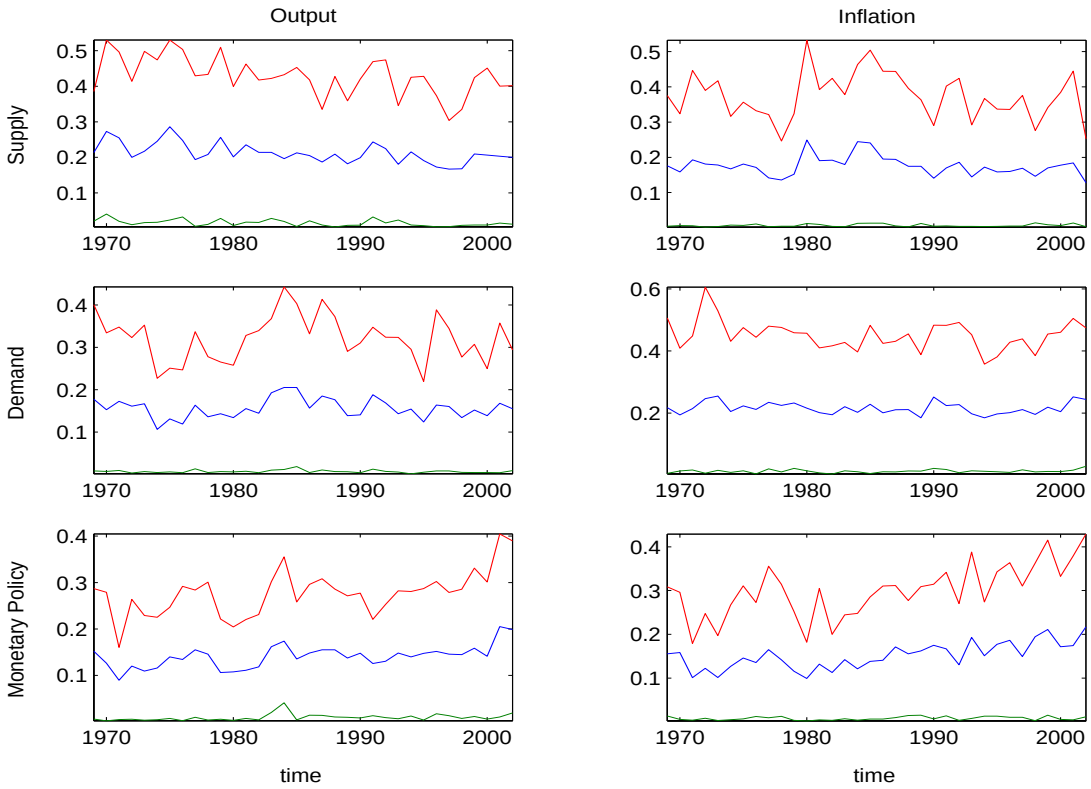


Figure 3: Persistence Shares, median and posterior 68% bands

The percentage of the persistence of output and inflation explained by real demand and supply shocks fluctuates around a constant mean value. Hence, these two shocks are equally responsible for the decline in inflation persistence we have observed since 1980s. Interestingly, the peak in inflation persistence in the early 1970s is attributed by our identification scheme to technology shocks while the one in the mid-late 1970s is attributed to demand disturbances. Furthermore, it appears that the sluggishness in the changes in inflation persistence is due to a very slow change in the contribution of technology shocks.

The relative contribution of real demand shocks to output and inflation volatility is relatively stable over time suggesting that the decline in inflation volatility since the beginning of the 1980s is due to a proportional decline in the contribution of these shocks. Finally, the mean contribution of technology shocks to output volatility declines over time and the mean contribution to inflation volatility shows first a downward jump in the mid of the 1970s and then upward jump in the end of the 1970s.

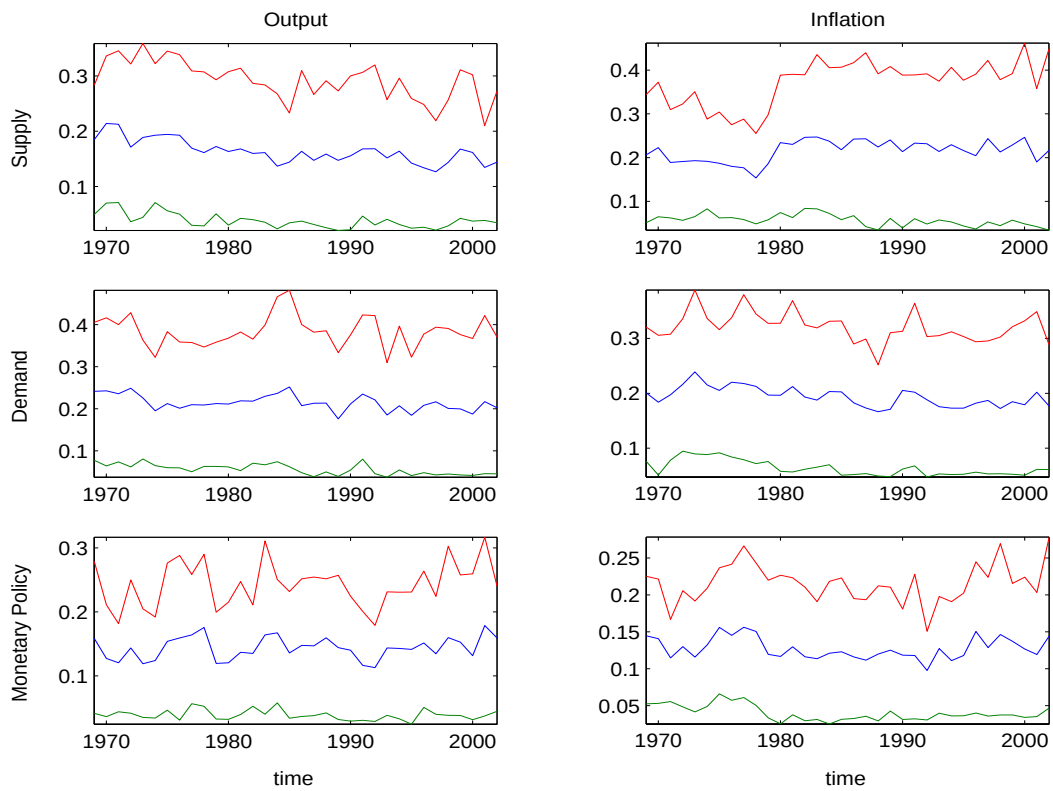


Figure 4: Volatility Shares, median and posterior 68% bands

In sum, while the decline in inflation persistence seems to be largely due to a decline in the contribution of real demand and technology shocks, the fall in output and inflation volatility is attributed by our identification scheme to all three structural shocks, with the contribution of technology shocks showing the largest variations over time.

5.3 Time Varying Transmission?

Since the relative contribution of a shock varies because its relative variance at frequency ω (i.e. $\frac{S_{e_j}(\omega)(t)}{S_{y_i}(\omega)(t)}$) changes, or because its transmission mechanism (i.e. $|\mathcal{B}_{jt}(\omega)|^2$) changes, we

need to disentangle the two sources of variations to explain the somewhat surprising set of results we obtain. In Figure 5 we plot the median responses of output and inflation to the three structural shocks. Since we normalize the impulse to be the same in every period, the evolution of these responses over time gives us an idea of the changes in the transmission of shocks in isolation from the changes in the distribution of the shocks (i.e. we trace out time variations in $\mathcal{B}_{jt}$.

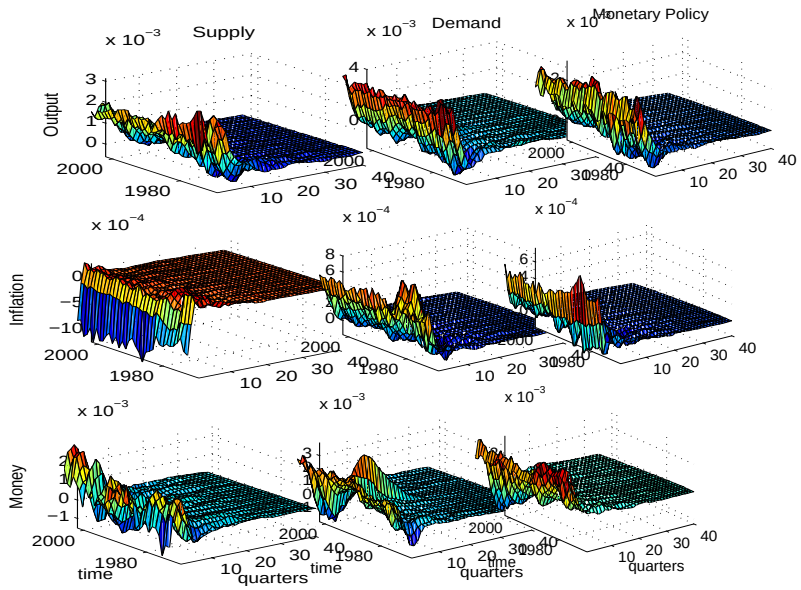


Figure 5: Output and Inflation responses, median estimates.

A few striking features of the figure are worth discussing. First, the pattern of responses to the three structural shocks is qualitatively similar over time. Second, there are quantitative changes in the magnitude of some responses. For example, the peak response of output to technology shocks changes location and size and the through response of inflation to demand shocks changes location over time. The most stable responses appear to be those to monetary shocks: the shape, the size and the location of output and inflation peak and through responses are very similar over time. Third, real demand shocks appear to produce the largest displacements of the two variables followed by technology and monetary shocks. Fourth, the largest relative changes in the transmission appear to be associated with output responses to technology shocks. For example, the magnitude of contemporaneous responses is 50% larger in the 1990s than in was in the 1970s.

Hence, while the qualitative features of the transmission of structural shocks are similar over time, changes in the quantitative features, involving the magnitude of the responses

and, at times, the location of the peak/through are present. Interestingly, while responses to monetary disturbances appear to be similar over time, the transmission of technology disturbances shows important changes.

5.4 Time Varying volatility of the structural shocks?

To examine whether there have been significant changes in the relative distribution of the structural shocks hitting the economy, we plot the time profile of the estimated posterior median of their volatility in figure 6. Real demand shocks are those associated with the first structural equation (normalized on output), supply shocks are those associated with the second structural equation (normalized on inflation) and the monetary policy shocks are those associated with the third structural equation (normalized on the nominal rate).

Overall, the volatility of supply and of the monetary policy disturbances has declined over time. However, while the decline is smoother for the former, it is much more abrupt for the latter, where a drop of 15% in the late 1970s is evident. The volatility of demand shocks is higher on average than for the other two shocks and, except for late 1980s and the late 1990s, it is relatively similar across time. Interestingly, the decline in the volatility of technology and monetary policy shocks terminates by the early 1980s and since then no changes are detected.

The decline in the volatility of monetary policy shocks of the late 1970s appears to precede the one found by Sims and Zha (2004). However, differences can be reconciled if one takes into account different estimation techniques and the different ways in which these volatilities are computed (recursive vs. smoothed estimates). Several authors have argued that there is very little evidence that the monetary policy rule and the transmission of monetary policy shocks have changed over time. Instead, they have suggested that drops in the volatility of monetary policy shocks could be responsible for the fall in the variability of output and inflation. Our results are consistent with these view but also suggest that the contribution of technology shocks to the changes observed in the US economy is non-negligible. The sharp increase and rapid decline in the variability of reduced form output and inflation forecast errors observed at the end of the 1970s is due, in part, to variations in the distribution from which technology shocks are drawn.

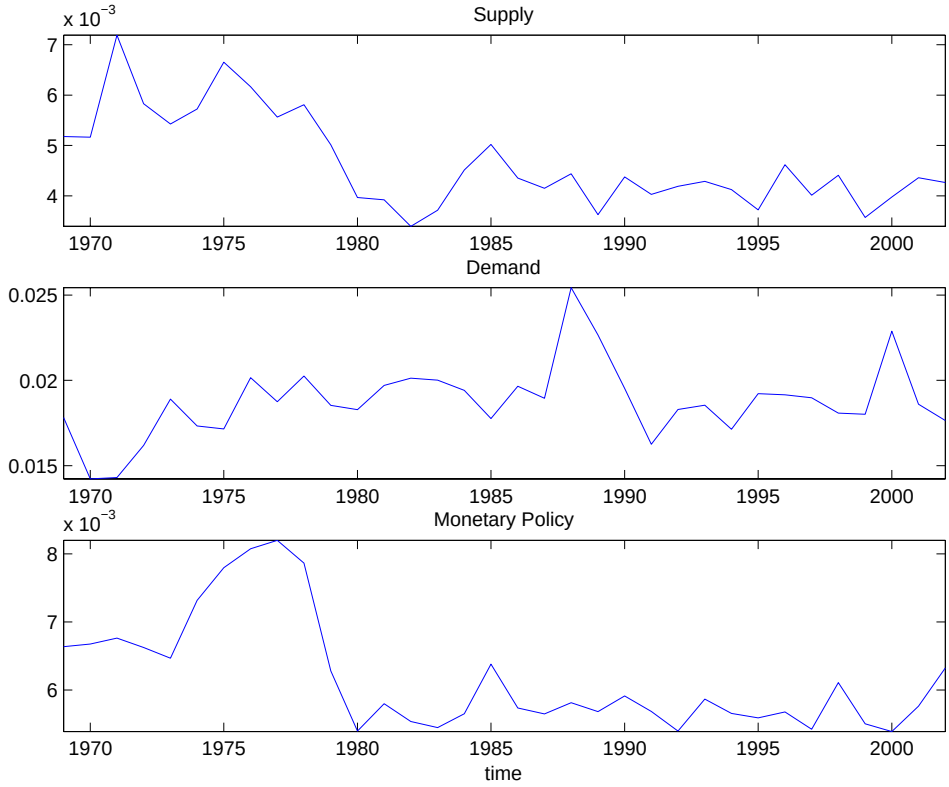


Figure 6: Structural shock variances

5.5 The dynamics of hours and labor productivity

Although somewhat unrelated to the main scope of the paper, our estimated structural system allows us to also discuss a controversial issue which has been at the center of attention in the macroeconomic literature since work by Gali (1999), Christiano, et. al. (2003), Uhlig (2003), Dedola and Neri (2004) and others: the dynamics of hours and productivity in response to technology shocks. The empirical evidence on this issue is at best mixed, it appears that under some identification and some data transformations (in particular, identification via long run restrictions and variables in the VAR in growth rates) technology disturbances increase labor productivity and decrease hours while with other identifications and other data transformations (in particular, hours in log level and identification based on short or medium run restrictions) both labor productivity and hours increase.

The dynamics of hours and labor productivity are thought to provide important information about sources of business cycle dynamics. In fact, a negative response of hours to technology disturbances is considered by some to be inconsistent with RBC-flexible price

based explanations of business cycles (a point disputed e.g. by Francis and Ramey (2005)). In a basic RBC model, in fact, technology shocks act as a supply shifter and therefore have positive effects on hours, output and productivity, unless they induce considerable wealth effects. On the other hand, in a basic sticky price model without capital, technology shocks act as labor demand shifters. Therefore, regardless of the nature of the technological disturbance, firms experience a decline in their marginal costs but, because price are sticky, aggregate demand increases less than proportionally than the increase in output making hours decline. These qualitative patterns are present in the model we have presented in section 3: when prices are flexible and the policy rules appropriately chosen, technology disturbances imply robust positive contemporaneous hours responses; when prices are sticky, the contemporaneous response of hours is mostly negative.

Our estimated structural model allows us to investigate two interesting questions related to this the issue. First, what are the dynamics of hours and labor productivity when sign restrictions derived from a general model are used to identify technology shocks? It is well known, at least since Faust and Leeper (1997), that long run restrictions are only weakly identifying the objects of interest and that they are vacuous in near-integrated systems, despite the fact that the time series pattern of integrated and near-integrated systems can hardly be distinguished with finite stretches of data. Since model based robust sign restrictions offer a viable alternative, void to a large extent of these problems, they can be used to sharpen our understanding of the effects of technology shocks in near-integrated systems. Second, is there any evidence that the responses of hours to technology shocks displays a time varying pattern? In other words, could it be that the contemporaneous response of hours changes sign as the sample changes?

Figure 7 indicates that the contemporaneous response of hours and productivity to technology shocks is positive at all dates. Interestingly, the response of hours is humped shaped, with the peak occurring after 2 or 3 quarters and this, combined with a smoothly declining output responses, implies that labor productivity becomes negative after some periods. While the results are consistent with a RBC-flexible price explanation of the propagation of technology shocks, one should also stress that the technology shocks we recover are not necessarily permanent and that permanent shocks in the model may deliver sign restrictions different from those we use. Hence, although are conclusions are fully comparable with the evidence in Ulhig (2004), Dedola and Neri (2004), or Peersman and Straub (2005), they do not necessarily disproof the idea that permanent technological improvements may induce a decline in hours worked.

There are quantitative variations in the responses of hours and productivity over time,

but the sign of the responses is the same at every date in the sample. Therefore, the mixed results found in the literature can not be due to time variations in the response of hours. Note also that, consistent with both RBC and sticky price models, hours positively comove with output in response to both demand shocks. However, the magnitude of the changes is such that in response to demand shocks labor productivity responds positively instantaneously but turns negative afterwards, while in response to monetary policy shocks labor productivity responses are instantaneously negative and the sign of the responses changes with the horizon of the analysis.

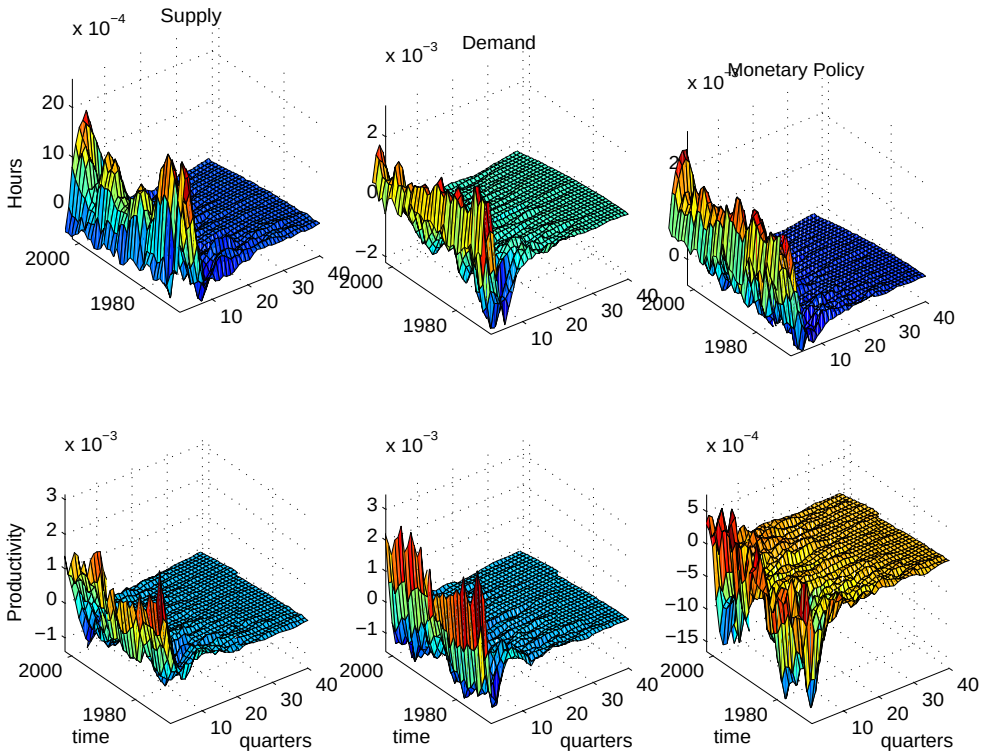


Figure 7: Hours and Productivity Responses

6 Conclusions

In this paper we examined structural sources of output and inflation volatility and persistence and attempted to draw some conclusions about the causes of the variations experienced in the US economy over the last 30 years. There has been a healthy discussion in the literature on this issue, thanks to the work of Clarida, Gali and Gertler (2000), Cog-

ley and Sargent (2001) (2003), Boivin and Giannoni, (2002), Leeper and Zha (2003), Sims and Zha (2004), Lubik and Schorfheide (2004), Primiceri (2005) and Canova and Gambetti (2004) among others, and although opinions differ, remarkable methodological improvements occurred trying to study questions having to do with time variations in structure of the economy and in the distributions of the shocks.

In this paper, we contribute to advance the technical frontiers estimating a structural time varying coefficient VAR model; identifying a number of structural shocks using sign restrictions derived from a general DSGE model; providing recursive analysis, consistent with information available at each point in time; and using frequency domain tools to address questions concerning time variations in persistence and volatility. In our opinion, the paper also contributes to advance our understanding of the cause of the observed variations in output and inflation. In particular, we show that while there are time variations in both the volatility of output and inflation and in the persistence of inflation, differences are statistically insignificant. Standard errors are larger than in other studies for two reasons: our recursive analysis makes them depend on the information available at each t; shocks to future parameters are not averaged out.

We show that output has become less volatile because the contribution of technology shocks has declined over time and that changes in the persistence and the volatility of inflation are jointly explained by changes in the contribution of technology, real demand and monetary policy shocks. Furthermore, we find that there are changes in the transmission of technology shocks and that the variance of both technology and monetary policy shocks has declined over time. We also provide novel evidence on the effects of technology shocks on labor market variables. In our estimated system, technology shocks robustly imply positive contemporaneous comovements of hours and labor productivity, even though the correlation between the two variables turns negative after a few lags.

All in all, our results question the conventional wisdom which attributes changes in the dynamic properties of output and inflation to monetary policy, and instead indicates that variations in both the magnitude and the transmission of technology shocks are an important vehicle to explain observed variations. Therefore, our conclusions are consistent with those of McConnell and Perez Quiroz (2001) and Gordon (2003) and those of Sims and Zha (2004), Canova and Gambetti (2004) and Primiceri (2005).

A Few words of caution are important to put our results in the correct perspective. First, by construction, our analysis excludes the possibility that in one period of history the monetary policy rule produced indeterminate equilibria. Therefore, our analysis differ from the one of Lubik and Schorfheide (2004), even though it points out that we can

account for a large portion of the observed variations without the need to resort to sunspot explanations. Second, while the decline in the volatility of the shocks is consistent with exogenous explanations of the changes in output and inflation dynamics, such a pattern is also consistent with explanations which give policy actions some role. For example, if monetary policy had a better control of inflation expectations over the last 20 years and no measure of inflation expectations is included in the VAR, such an effect may show up as a reduction of the variance of the shocks.

Clearly, much work still needs to be done. We think it would be particularly useful to try to identify other structural shocks, for example, labor supply or investment specific shocks, and examine their relative contribution to changes in output and inflation volatility and persistence. It would also be interesting to study in details what are the technology shocks we have extracted, how do they correlate with what economists think are technological sources of disturbances and whether they proxy for missing variables or shocks. The model has implications for a number of variables which are excluded from the empirical analysis. Enlarging the size of our VAR could provide additional evidence on the reasonableness of the structural disturbances we have extracted. Finally, while much of the evidence is available for the US, very few exercises have looked at other countries or compared sources of output and inflation volatility and persistence across countries.

Appendix A

Priors

We choose prior densities which give us analytic expressions for the conditional posteriors of subvectors of the unknowns. Let T be the end of the estimation sample and let K_1 be the number of periods for which the identifying restrictions must be satisfied. Let $H_T = \rho(\varphi_T)$ be a rotation matrix whose columns represents orthogonal points in the hypershere and let φ_T be a vector in R^6 whose elements are $U[0,1]$ random variables. Let $\mathcal{M}_T$ be the set of impulse response functions at time T satisfying the restrictions and let $F(\mathcal{M}_T)$ be an indicator function which is one if the identifying restrictions are satisfied, that is, if $(\Psi^i_{T+1,1}, ..., \Psi^i_{T+K_1,K_1}) \in \mathcal{M}_T$, and zero otherwise. Let the joint prior for θ^{T+K_1}, Σ_T, Ω_T and H_T be

$$p(\theta^{T+K_1}, \Sigma_T, \Omega_T, \omega_T) = p(\theta^{T+K}|\Sigma_T, \Omega_T)p(\Sigma_T, \Omega_T)F(\mathcal{M}_T)p(H_T) \tag{22}$$

Assume that $p(\theta^{T+K}|\Sigma_T, \Omega_T) \propto I(\theta^{T+K})f(\theta^{T+K}|\Sigma_T, \Omega_T)$ where $f(\theta^{T+K}|\Sigma_T, \Omega_T) = f(\theta_0)$ $\prod_{t=1}^{T+K} f(\theta_t|\theta_{t-1}, \Sigma_t, \Omega_t)$ and $I(\theta^{T+K}) = \prod_{t=0}^{T+K} I(\theta_t)$. Since $f(\theta^{T+K}|\Sigma_T, \Omega_T)$, is normal $p(\theta^{T+K}|\Sigma, \Omega_T)$ is truncated normal.

We assume that Σ_0 and Ω_0 have independent inverse Wishart distributions with scale matrices Σ_0^{-1}, Ω_0^{-1} and degrees of freedom ν_{01} and ν_{02}, and assume that $\Sigma_t = \alpha_1\Sigma_{t-1} + \alpha_2\Sigma_0$ and $\Omega_t = \alpha_3\Omega_{t-1} + \alpha_4\Omega_0$, $\forall t$, where $\alpha_i, i = 1,2,3,4$ are fixed. We also assume that the prior for θ_0 is truncated Gaussian independent of Σ_T and Ω_T, i.e. $f(\theta_0) \propto I(\theta_0)N(\bar{\theta}, \bar{P})$. Finally we assume a uniform prior $p(H_T)$, since all rotation matrices are a-priori equally likely. Collecting pieces, the joint prior is:

$$p(\theta^{T+K_1}, \Sigma_T, \Omega_T, \omega_T) \propto I(\theta^{T+K})F(\mathcal{M}_T)[f(\theta_0)\prod_{t=1}^{T+K} f(\theta_t|\theta_{t-1}, \Sigma_t, \Omega_t)]p(\Sigma_t)p(\Omega_t) \tag{23}$$

We "calibrate" prior parameters by estimating a fixed coefficients VAR using data from 1960:1 up to 1969:1. We set $\bar{\theta}$ equal to the point estimates of the coefficients and $\bar{P}$ to the estimated covariance matrix. Σ_0 is equal to the estimated covariance matrix of VAR innovations, $\Omega_0 = \varrho\bar{P}$ and $\nu_{10} = \nu_{20} = 4$ (so as to make the prior close to non-informative). After some experimentation we select $\alpha_2 = \alpha_2 = 0, \alpha_2 = \alpha_4 = 1$. The parameter ϱ measures how much time variation is allowed in coefficients. Although as T grows the likelihood dominates, the choice of ϱ matters in finite samples. We choose ϱ as a function of T i.e. for the sample 1969:1-1981:2, $\varrho = 0.0025$; for 1969:1-1983:2, $\varrho = 0.003$; for 1969:1-1987:2, $\varrho = 0.0035$; for 1969:1-1989:2, $\varrho = 0.004$; for 1969:1-1995:4, $\varrho = 0.007$; for 1969:1-1999:1, $\varrho = 0.008$, and for 1969:1-2003:2, $\varrho = 0.01$. This range of values implies a quite conservative

prior coefficient variations: in fact, time variation accounts between 0.35 and a 1 percent of the total coefficients standard deviation.

Since impulse response functions depend on $\Phi_{T+k,k}$, S and H_T, we first characterize the posterior of $\theta^{T+K}, \Sigma_T, \Omega_T$, which are used to construct $\Phi_{T+k,k}$ and S, and then describe an approach to sample from them.

Posteriors

To draw posterior sequences we need $p(H_T, \theta_{T+1}^{T+K}, \theta^T, \Sigma_T, \Omega_T | y^T)$, which is analytically intractable. However, note that

$$\begin{aligned} p(H_T, \theta_{T+1}^{T+K}, \theta^T, \Sigma_T, \Omega_T | y^T) &\equiv p(H_T, \theta^{T+K}, \Sigma_T, \Omega_T | y^T) \\ &\propto p(y^T | H_T, \theta^{T+K}, \Sigma_T, \Omega_T) p(H_T, \theta^{T+K}, \Sigma, \Omega_T) \end{aligned} \quad (24)$$

Second, since the likelihood is invariant to any orthogonal rotation $p(y^T | H_T, \theta^{T+K}, \Sigma_T, \Omega_T) = p(y^T | \theta^{T+K}, \Sigma_T, \Omega_T)$. Third, $p(H_T, \theta^{T+K}, \Sigma_T, \Omega_T) = p(\theta^{T+K}, \Sigma_T, \Omega_T) F(\mathcal{M}_T) p(H_T)$. Thus

$$p(H_T, \theta^{T+K}, \Sigma_T, \Omega_T | y^T) \propto p(\theta^{T+K}, \Sigma_T, \Omega_T | y^T) F(\mathcal{M}_T) p(H_T) \quad (25)$$

where $p(\theta^{T+K}, \Sigma_T, \Omega_T | y^T)$ is the posterior distribution for the reduced form parameters, which, in turn can be factored as

$$p(\theta^{T+K}, \Sigma_T, \Omega_T | y^T) = p(\theta_{T+1}^{T+K} | y^T, \theta^T, \Sigma_T, \Omega_T) p(\theta^T, \Sigma_T, \Omega_T | y^T) \quad (26)$$

The first term on the right hand side of (26) represents beliefs about the future and the second term the posterior density for states and hyperparameters. Note that $p(\theta_{T+1}^{T+K} | y^T, \theta^T, \Sigma_T, \Omega_T) = p(\theta_{T+1}^{T+K} | \theta^T, \Sigma_T, \Omega_T) = \prod_{k=1}^{K} p(\theta_{T+k} | \theta_{T+k-1}, \Sigma_T, \Omega_T)$ because the states are Markov. Finally, since θ_{T+k} is conditionally truncated normal with mean $\theta_{T+k-1}$and variance Ω_T,

$$\begin{aligned} p(\theta_{T+1}^{T+K} | \theta^T, \Sigma_T, \Omega_T) &= I(\theta_{T+1}^{T+K}) \prod_{k=1}^{K} f(\theta_{T+k} | \theta_{T+k-1}, \Sigma_T, \Omega_T) \\ &= I(\theta_{T+1}^{T+K}) f(\theta_{T+1}^{T+K} | \theta_T, \Sigma_T, \Omega_T) \end{aligned} \quad (27)$$

The second term in (26) can be factored as

$$p(\theta^T, \Sigma_T, \Omega_T | y^T) \propto p(y^T | \theta^T, \Sigma_T, \Omega_T) p(\theta^T, \Sigma_T, \Omega_T) \quad (28)$$

The first term in (28) is the likelihood function which, given the states, has a Gaussian shape so that $p(y^T | \theta^T, \Sigma_T, \Omega_T) = f(y^T | \theta^T, \Sigma_T, \Omega_T)$. The second term is the joint posterior for states and hyperparameters. Hence:

$$p(\theta^T, \Sigma_T, \Omega_T | y^T) \propto f(y^T | \theta^T, \Sigma_T, \Omega_T) p(\theta^T | \Sigma_T, \Omega_T) p(\Sigma_T, \Omega_T) \quad (29)$$

Furthermore, since $p(\theta^T|\Sigma_T,\Omega_T) \propto I(\theta^T)f(\theta^T|\Sigma_T,\Omega_T)$ where $f(\theta^T|\Sigma_T,\Omega_T) = f(\theta_0|\Sigma_T,\Omega_0)$ $\prod_{t=1}^T f(\theta_t|\theta_{t-1},\Sigma_t,\Omega_t)$and $I(\theta^T) = \prod_{t=0}^T I(\theta_t)$, we have

$$p(\theta^T,\Sigma,\Omega_T|y^T) \propto I(\theta^T)f(y^T|\theta^T,\Sigma_T,\Omega_T)f(\theta^T|\Sigma_T,\Omega_T)p(\Sigma_T,\Omega_T) = I(\theta^T)p_u(\theta^T,\Sigma_T,\Omega_T|y^T) \tag{30}$$

where $p_u(\theta_T,\Sigma_T,\Omega_T|y^T) \equiv f(y^T|\theta^T,\Sigma_T,\Omega_T)f(\theta^T|\Sigma_T,\Omega_T)p(\Sigma_T,\Omega_T)$ is the posterior density obtained if no restrictions are imposed. Collecting pieces, we finally have

$$\begin{aligned} p(H_T,\theta_{T+1}^{T+K},\theta^T,\Sigma_T,\Omega_T|y^T) \quad \propto \quad & \left[\prod_{t=0}^T I(\theta_t)f(\theta_{T+1}^{T+K}|\theta^T,\Sigma_T,\Omega_T)I(\theta^T)p_u(\theta^T,\Sigma_T,\Omega_T|y^T)\right] \\ & F(\mathcal{M}_T)p(H_T) \end{aligned} \tag{31}$$

Drawing structural parameters

Given (31) draws for the structural parameters can be obtained as follows

1. Draw $(\theta^T,\Sigma_T,\Omega_T)$ from the unrestricted posterior $p_u(\theta^T,\sigma_T,\Omega_T|y^T)$ via the Gibbs sampler (see below). Apply the filter $I(\theta^T)$.
2. Given $(\theta^T,\Sigma_T,\Omega_T)$, draw future states θ_{T+1}^{T+K}, i.e. obtain draws of u_{T+k} from $N(0,\Omega_T)$ and iterate in $\theta_{T+k} = \theta_{T+k-1} + u_{T+k}$, K times. Apply the filter $I(\theta^{T+K})$.
3. Draw $\varphi_{i,T}$ for $i = 1,...,6$ from a $U[0,1]$. Draw $H_T = \rho(\varphi_T)$.
4. Given Σ, find the matrix S_T, such that $\Sigma_T = S_T S_T'$. Construct J_T^{-1}.
5. Compute $(\Psi_{T+1,1}^{i,\ell},...,\Psi_{T+K,K}^{i,\ell})$ for each replication ℓ. Apply the filter $F(\mathcal{M}_T)^\ell$ and keep the draw if the identification restrictions are satisfied.

Drawing reduced form parameters

The Gibbs sampler we use to compute the posterior for the reduced form parameters iterates on two steps. The implementation is identical to Cogley and Sargent (2001).

• Step 1: States given hyperparameters
Conditional on (y^T,Σ_T,Ω_T), the unrestricted posterior of the states is normal and $p_u(\theta^T|y^T,\Sigma_T,\Omega_T) = f(\theta_T|y^T,\Sigma_T,\Omega_T)\prod_{t=1}^{T-1} f(\theta_t|\theta_{t+1},y^t,\Sigma_t,\Omega_t)$. All densities on the right hand side are Gaussian and their conditional means and variances can be computed using a simulation smoother. Let $\theta_{t|t} \equiv E(\theta_t|y^t,\Sigma_t,\Omega_t); P_{t|t-1} \equiv Var(\theta_t|y^{t-1},\Sigma_t,\Omega_t); P_{t|t} \equiv Var(\theta_t|y^t,\Sigma_t,\Omega_t)$. Given

$P_{0|0}$, $\theta_{0|0}$, Ω_0 and Σ_0, we compute Kalman filter recursions

$$\begin{aligned} P_{t|t-1} &= P_{t-1|t-1} + \Sigma_t \\ \mathcal{K}_t &= (P_{t|t-1}X_t)(X_t'P_{t|t-1}X_t + \Omega_t)^{-1} \\ \theta_{t|t} &= \theta_{t-1|t-1} + \mathcal{K}_t(y_t - X_t'\theta_{t-1|t-1}) \\ P_{t|t} &= P_{t|t-1} - \mathcal{K}_t(X_t'P_{t|t-1}) \end{aligned} \tag{32}$$

The last iteration gives $\theta_{T|T}$ and $P_{T|T}$ which are the conditional means and variance of $f(\theta_t|y^T, \Sigma, \Omega_T)$. Hence $f(\theta_T|y^T, \Sigma, \Omega_T) = N(\theta_{T|T}, P_{T|T})$.

• Step 2: Hyperparameters given states

Conditional on the states and the data ε_t and u_t are observable and Gaussian. Combining a Gaussian likelihood with an inverse-Wishart prior results in an inverse-Wishart posterior, so that $p(\Sigma_t|\theta^T, y^T) = IW(\Sigma_{1t}^{-1}, \nu_{11}); p(\Omega_t|\theta^T, y^T) = IW(\Omega_{1t}^{-1}, \nu_{12})$ where $\Sigma_{1t} = \Sigma_0 + \Sigma_T$, $\Omega_{1t} = \Omega_0 + \Omega_T$, $\nu_{11} = \nu_{01} + T$, $\nu_{12} = \nu_{02} + T$ and Σ_T and Ω_T are proportional to the covariance estimator $\frac{1}{T}\Sigma_T = \frac{1}{T}\sum_{t=1}^T \varepsilon_t\varepsilon_t'$; $\frac{1}{T}\Omega_T = \frac{1}{T}\sum_{t=1}^T u_t u_t'$. Under regularity conditions and after a burn-in period, iterations on these two steps produce draw from $p_u(\theta^T, \Sigma, \Omega|y^T)$.

In our exercises T varies from 1970:2 to 2003:2. For each of these T, 20000 iterations of the Gibbs sampler are made. CUMSUM graphs are used to check for convergence and we found that the chain had converged roughly after 2000 draws for each date in the sample. The densities for the parameters obtained with the remaining draws are well behaved and none is multimodal. We keep one every four of the remaining 8000 draws and discard all the draws generating explosive paths. The autocorrelation function of the 2000 draws which are left is somewhat persistent but this is not a problem since only about 10% of these draws satisfy the identification restrictions in each sample.

Computing structural impulse responses and spectra

Given a draw from the posterior of the structural parameters, calculation of impulse responses to VAR shocks is straightforward. In fact, given a draw for $(\theta^{T+K}, \Sigma, \Omega_T, H_{T+1})$ we calculate $\Psi_{T+k,k}$, compute the posterior median and the 68% central credible set at each horizon k across draws. Then, spectra are computed as described in section 5.2.

Appendix B

This appendix reports results obtained with:

• A reduced form model.

• A model with Choleski identified shocks.

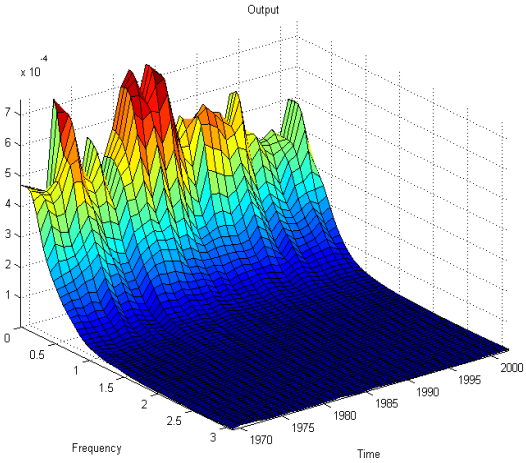
• Structural analysis where draws which satisfy the restrictions at all horizons are given weight $0.5/n_1$, draws which satisfy the restrictions at two horizons are given weight $0.33/n_2$ draws which satisfy the restrictions at one horizons are given the weight $0.17/n_3$ $n_1 + n_2 + n_3 + n_4 = n$, where n is the total number of draws. (weighting 1)

• Structural analysis where draws satisfying all the restrictions are given weight $0.68/n_1$ and draws which do not satisfy all the restrictions are given weight $0.32/n_2$, $n_1 + n_2 = n$.(weighting 2)

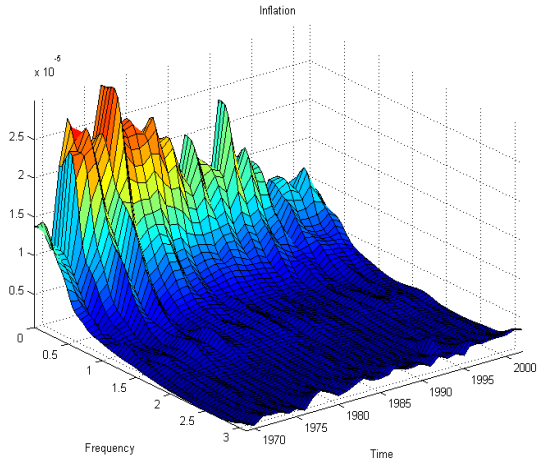
• Structural analysis where shocks to future coefficients are set to zero.

• Non-recursive estimation of the structural variances.

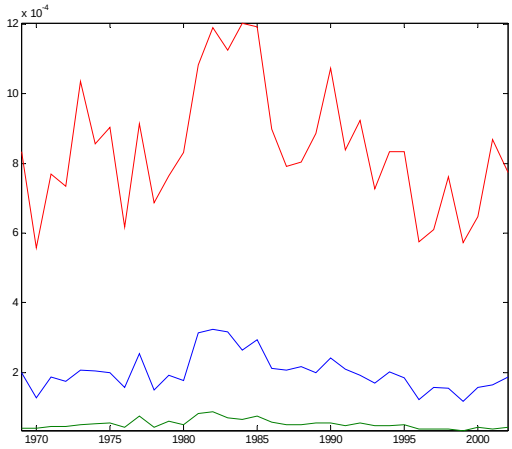
1) Reduced form model



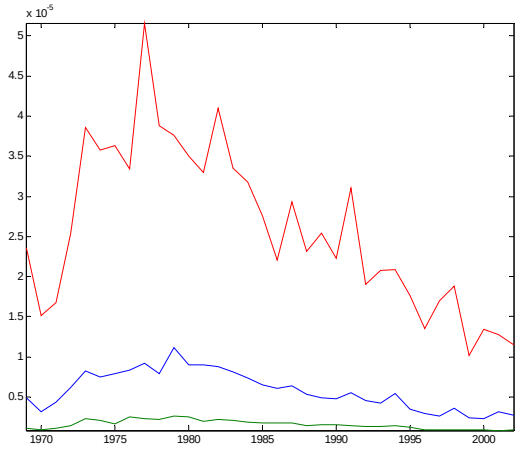
Output spectrum



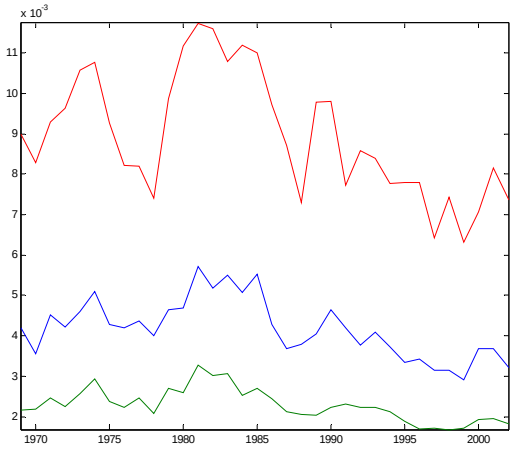
Inflation spectrum



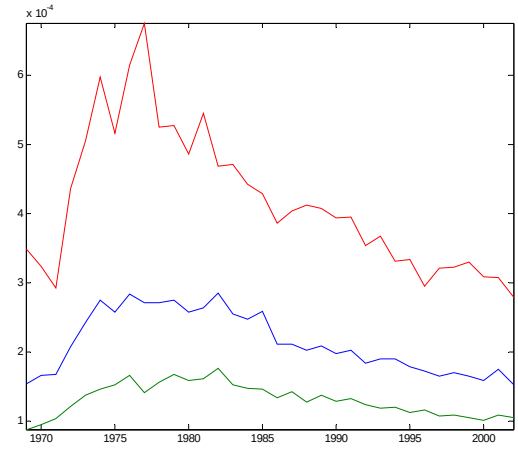
Output persistence



Inflation persistence

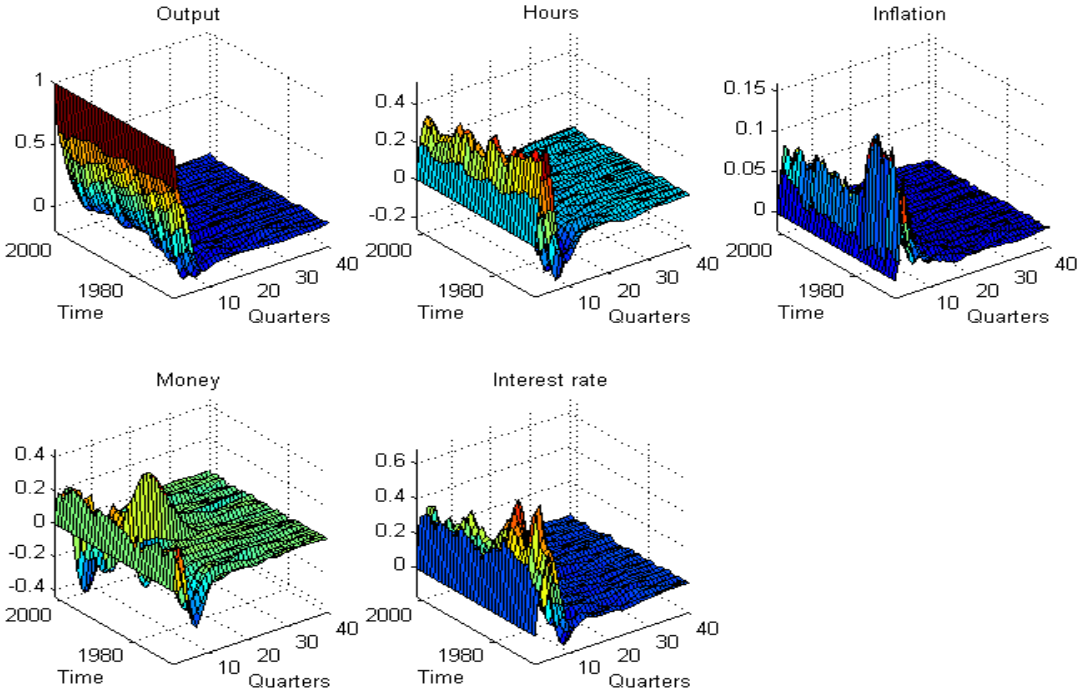


Output volatility

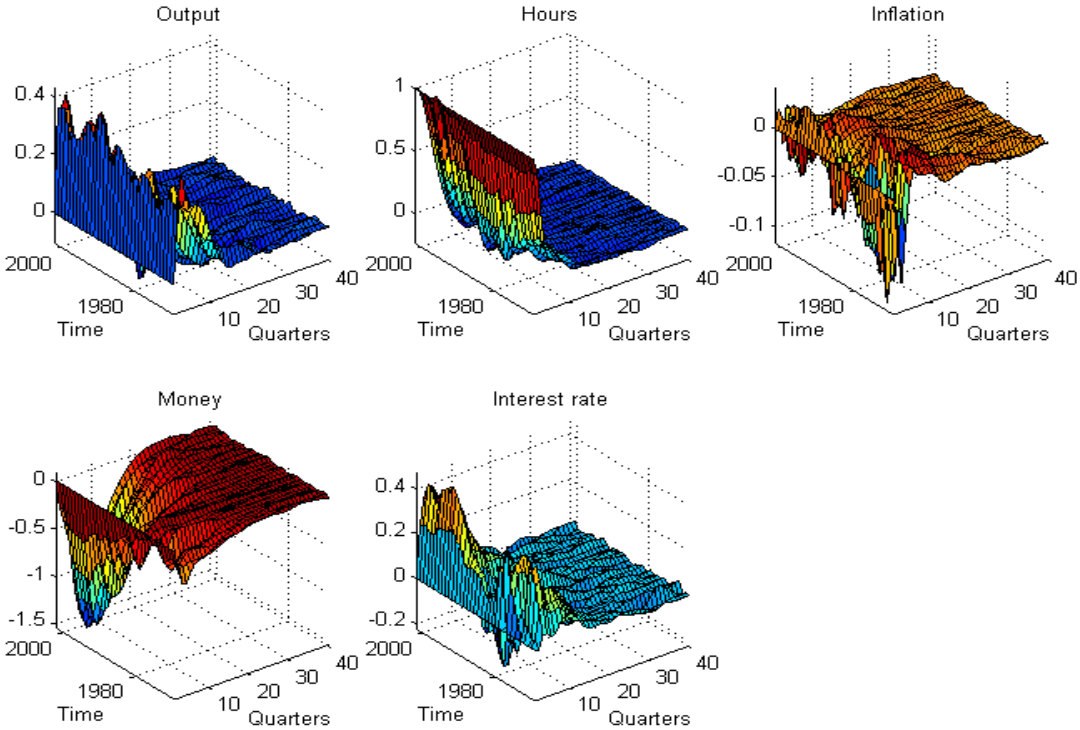


Inflation volatility

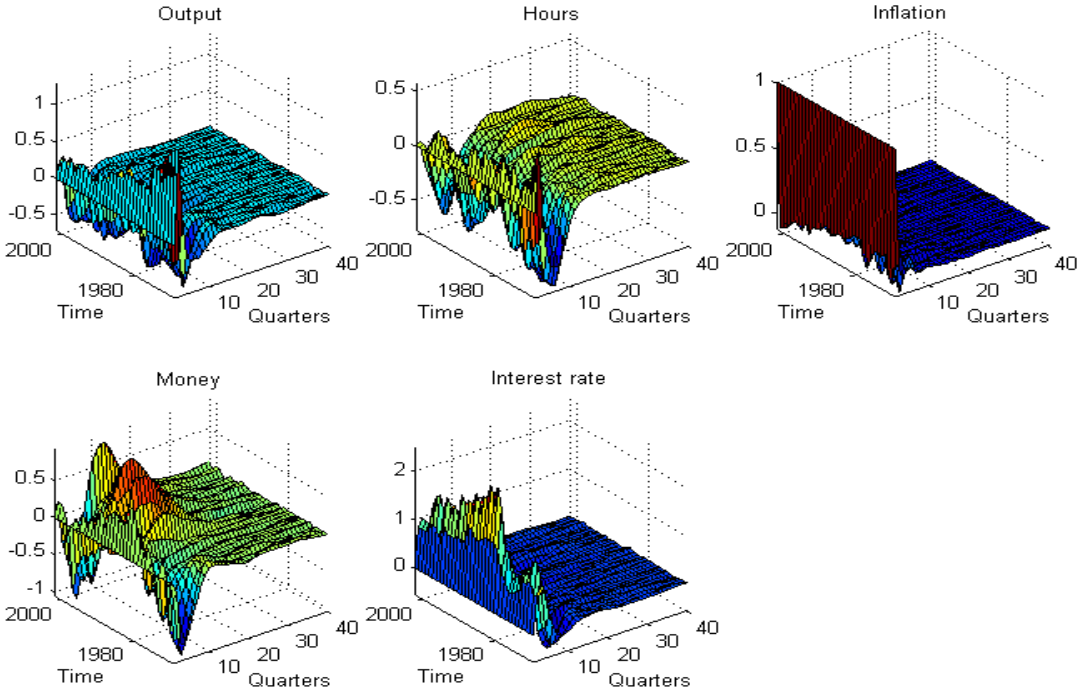
Figure A1: Structural Output and Inflation Dynamics



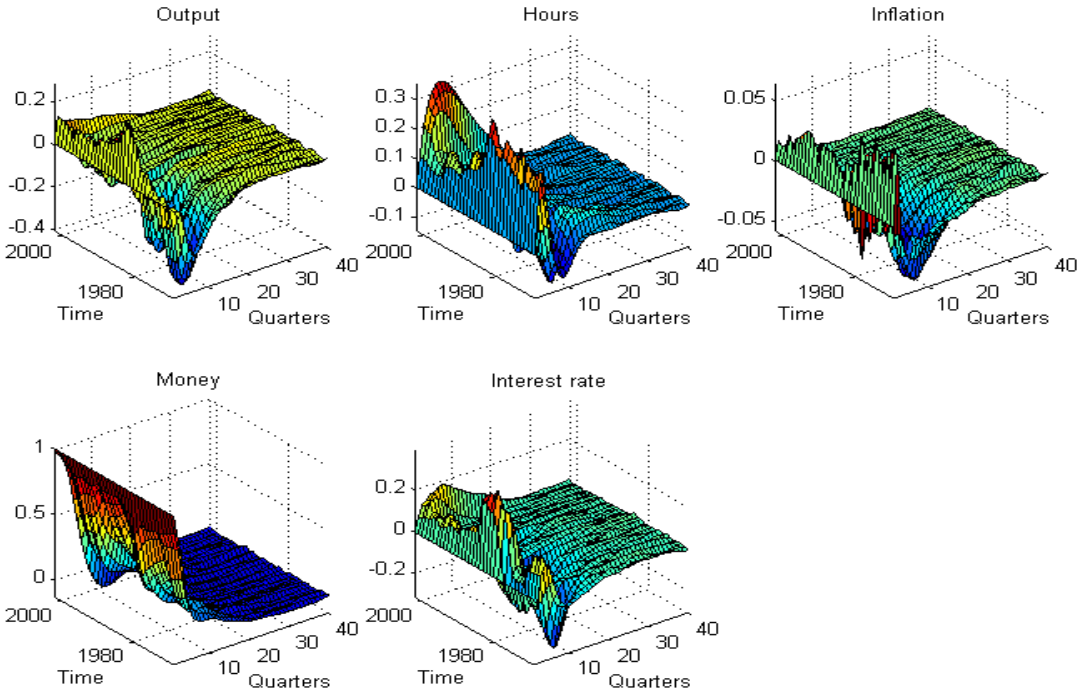
Response to Shock 1



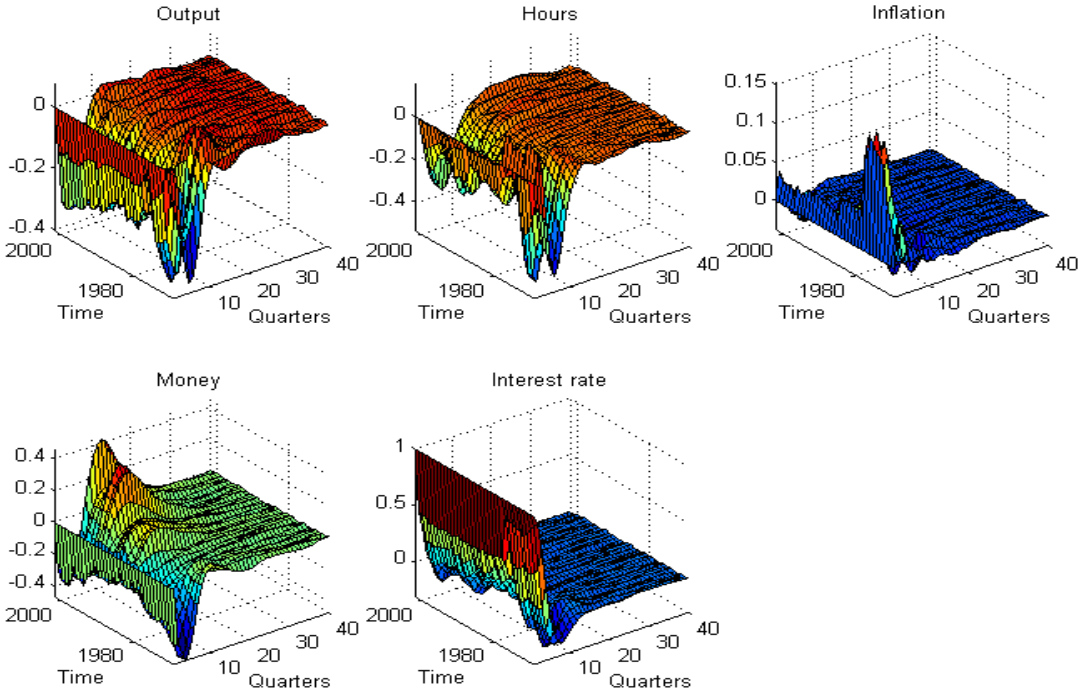
Response to Shock 2



Responses to shock 3



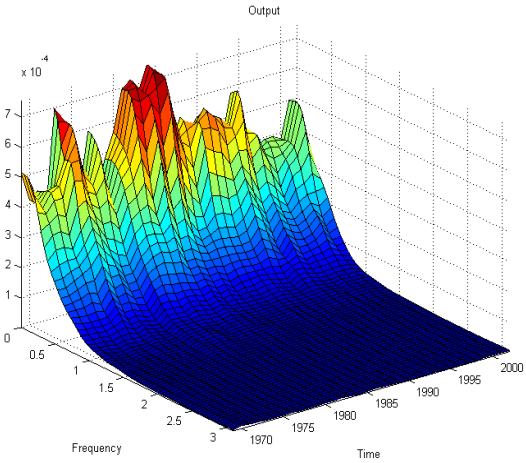
Responses to shock 4



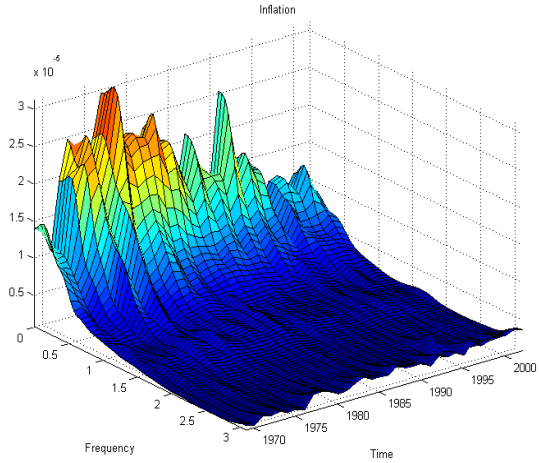
Responses to shock 5

Figure A2: Responses to Reduced form Shocks

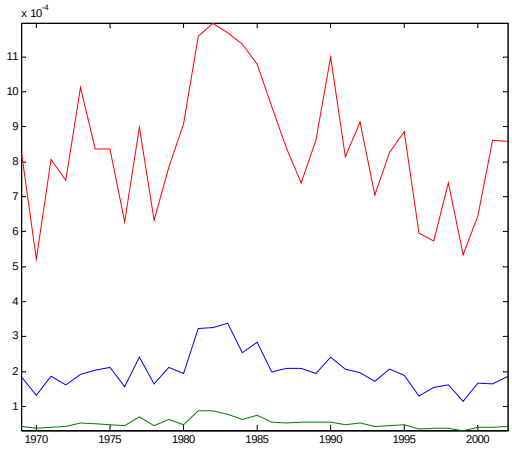
2) Choleski Identified shocks



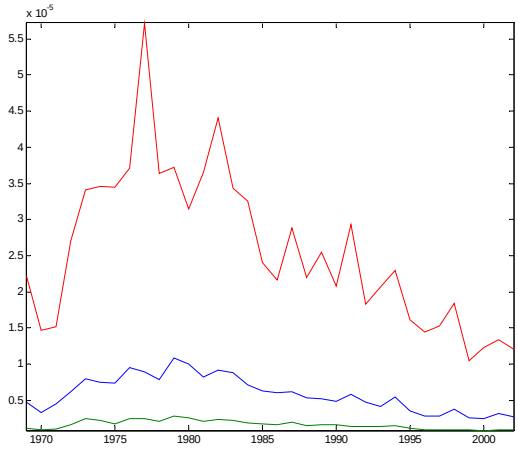
Output spectrum



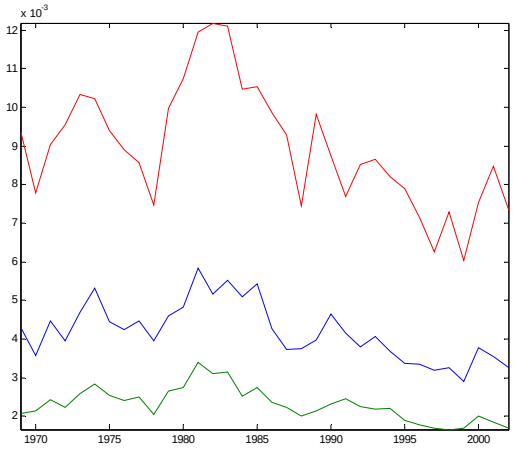
Inflation spectrum



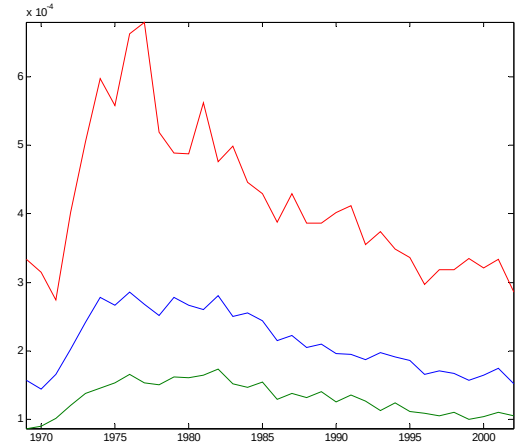
Output persistence



Inflation persistence



Output volatility



Inflation volatility

Figure A3: Structural Output and Inflation Dynamics

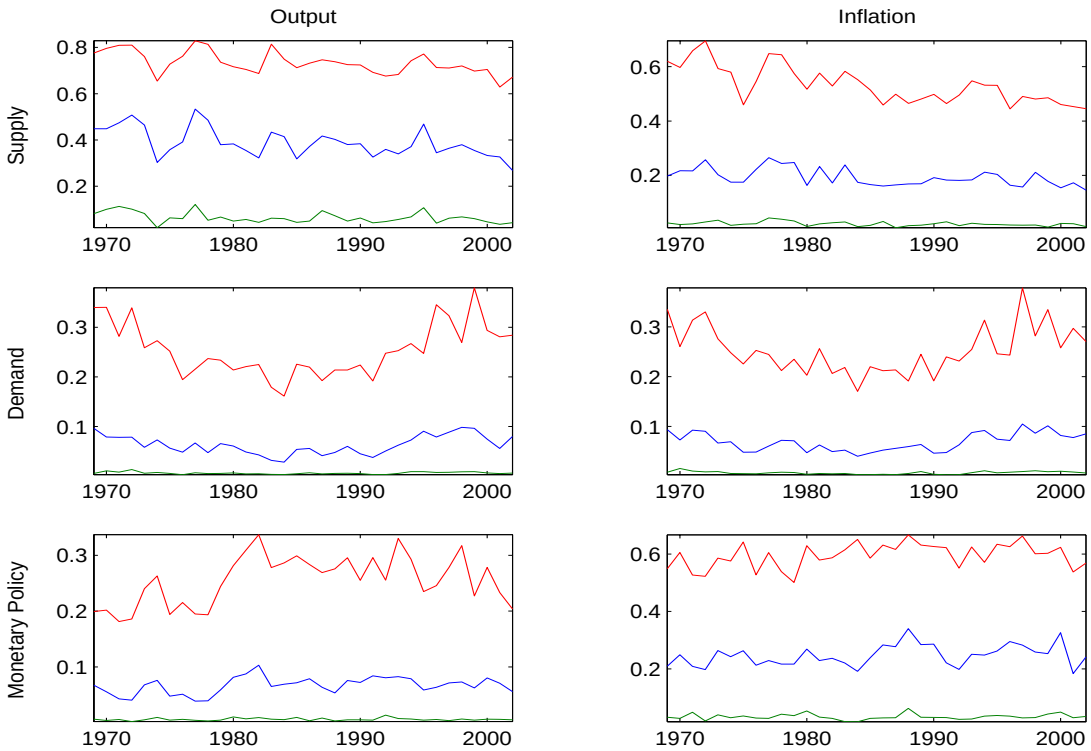


Figure A4: Persistence Shares

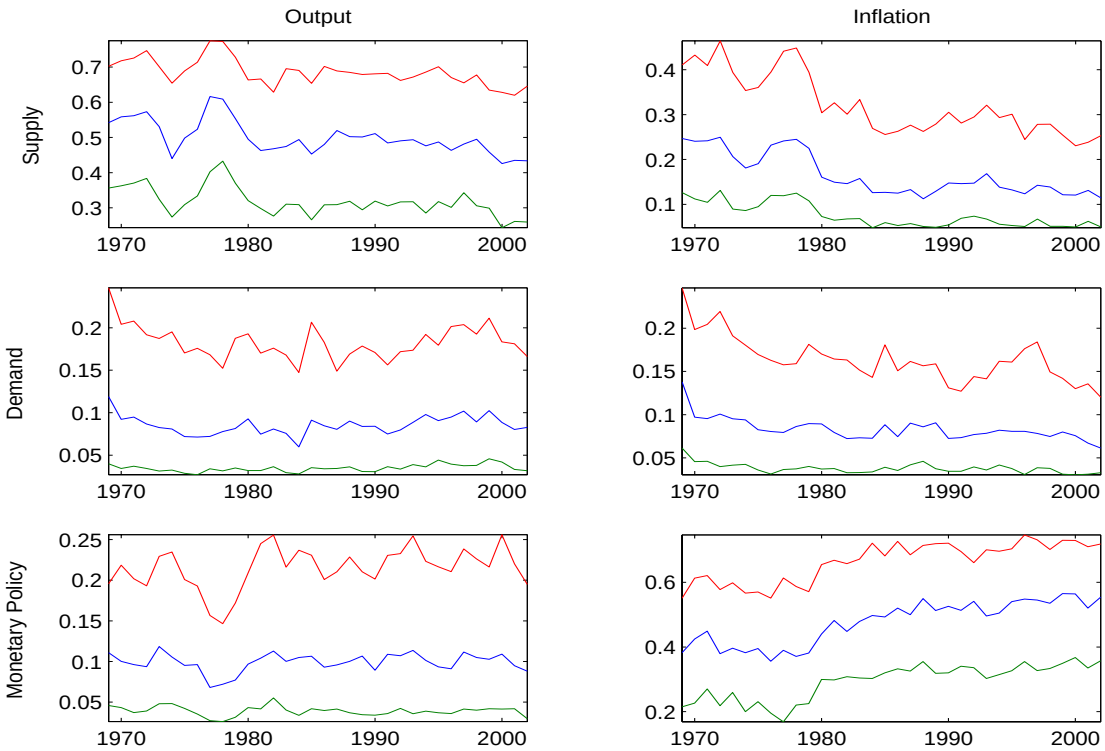
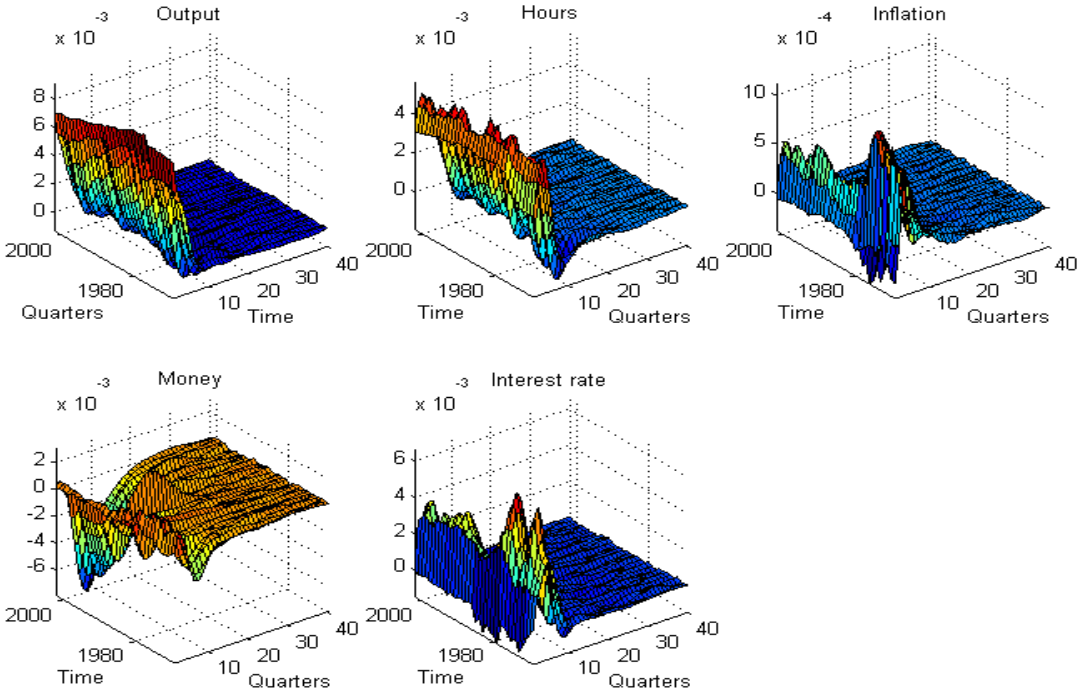
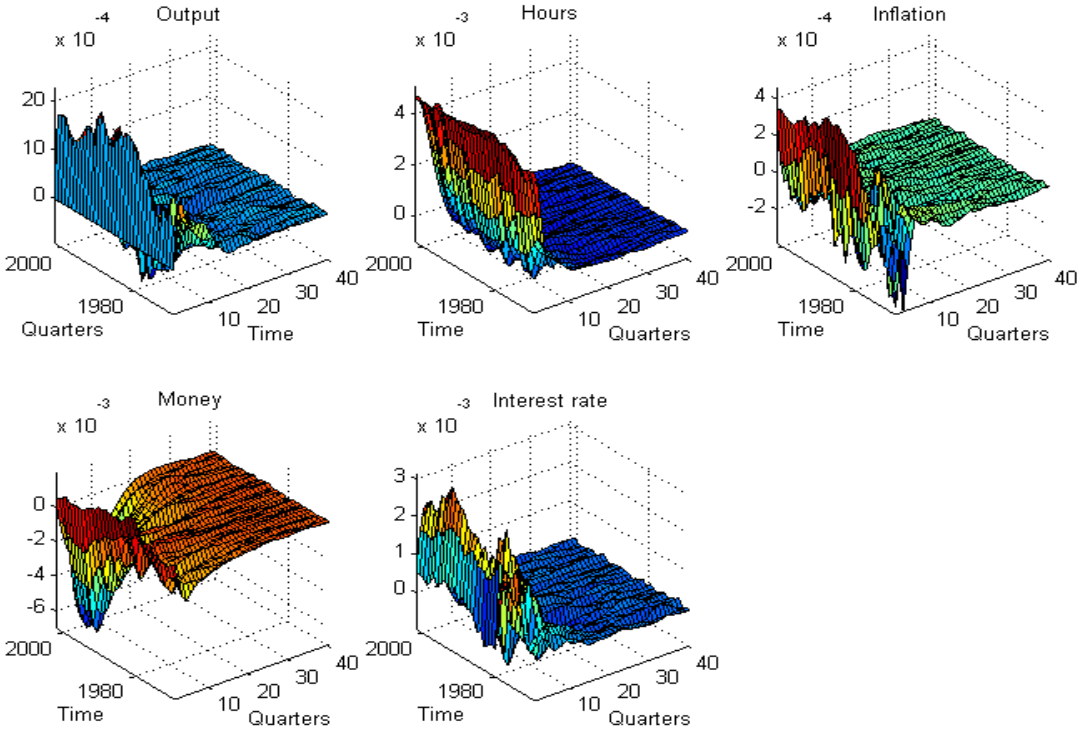


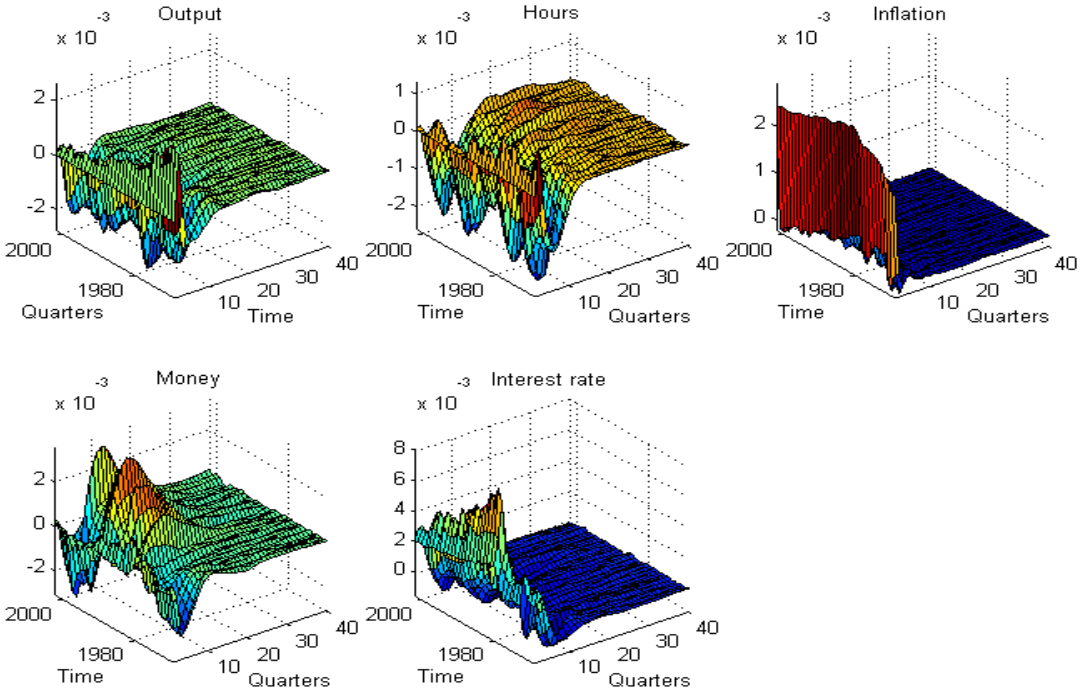
Figure A5: Volatility Shares



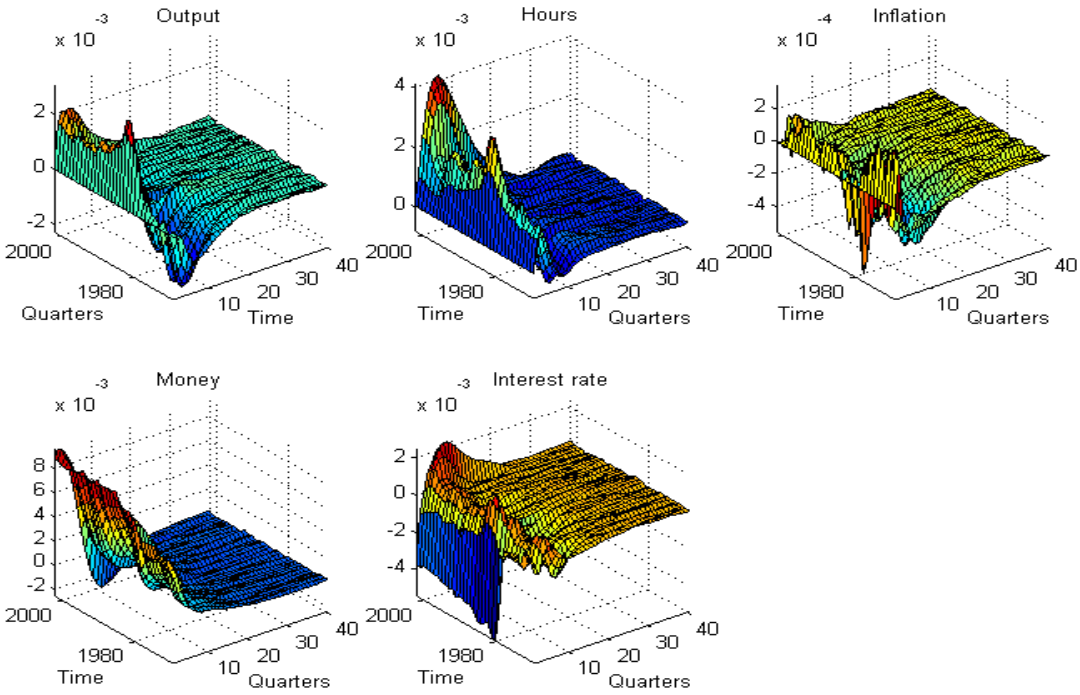
Response to Shock 1



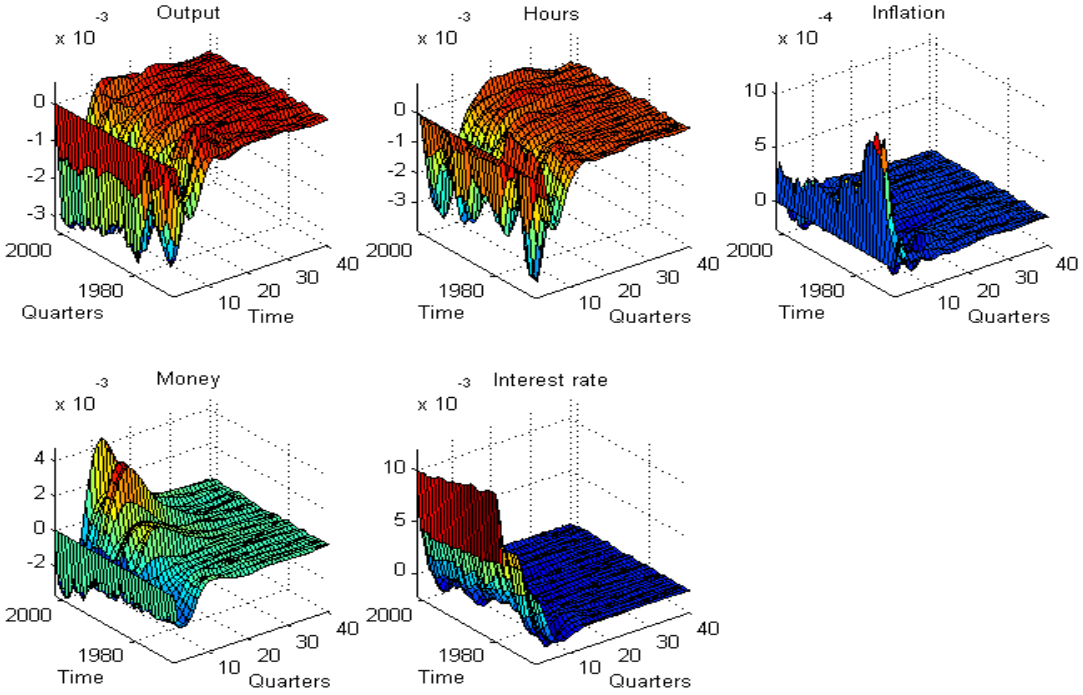
Response to Shock 2



Responses to shock 3



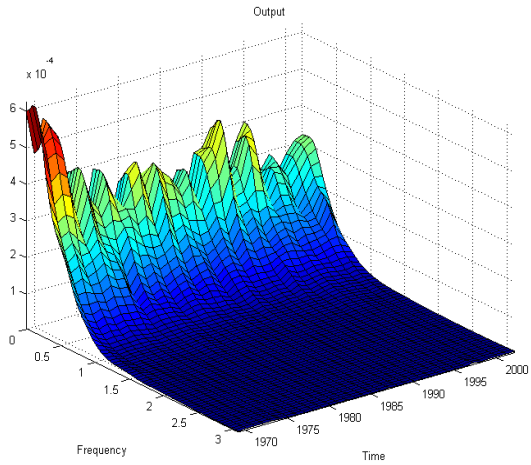
Responses to shock 4



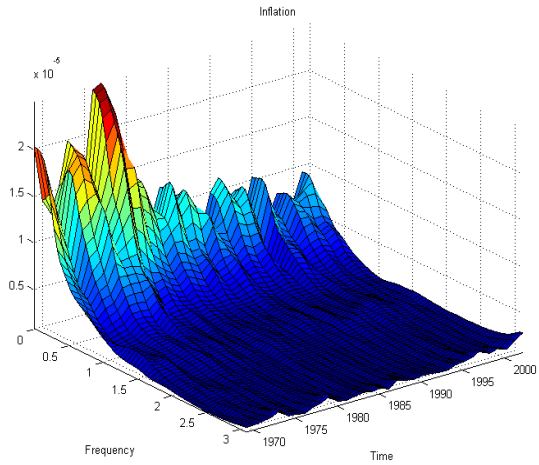
Responses to shock 5

Figure A6: Responses to Shocks

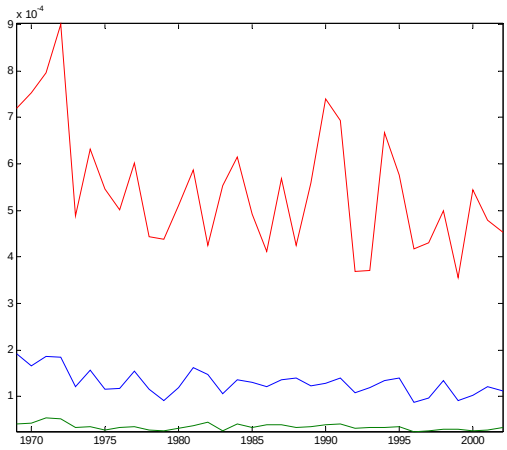
3) Weighting 1



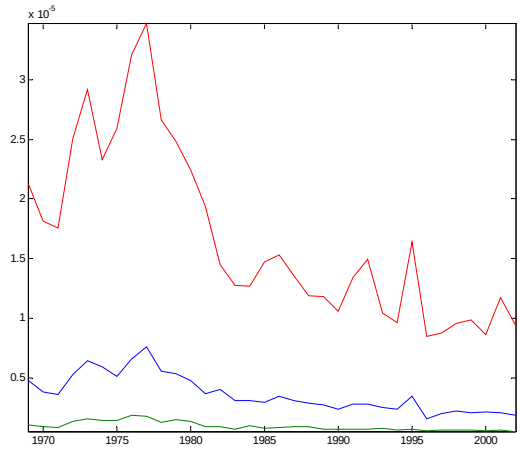
Output spectrum



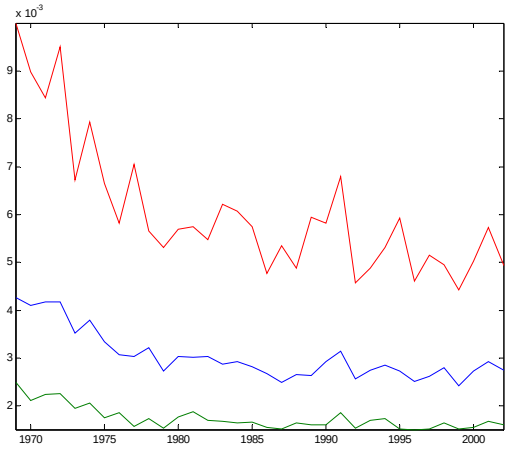
Inflation spectrum



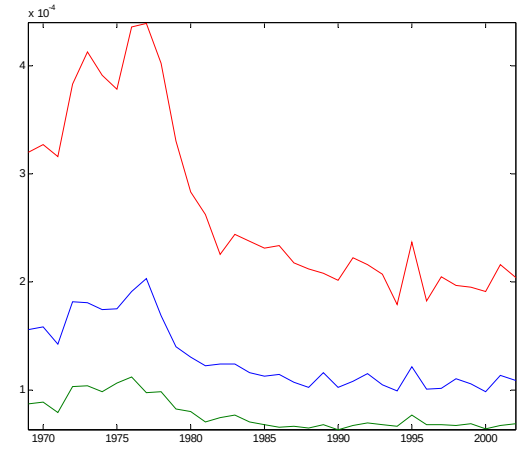
Output persistence



Inflation persistence



Output volatility



Inflation volatility

Figure A7: Structural Output and Inflation Dynamics

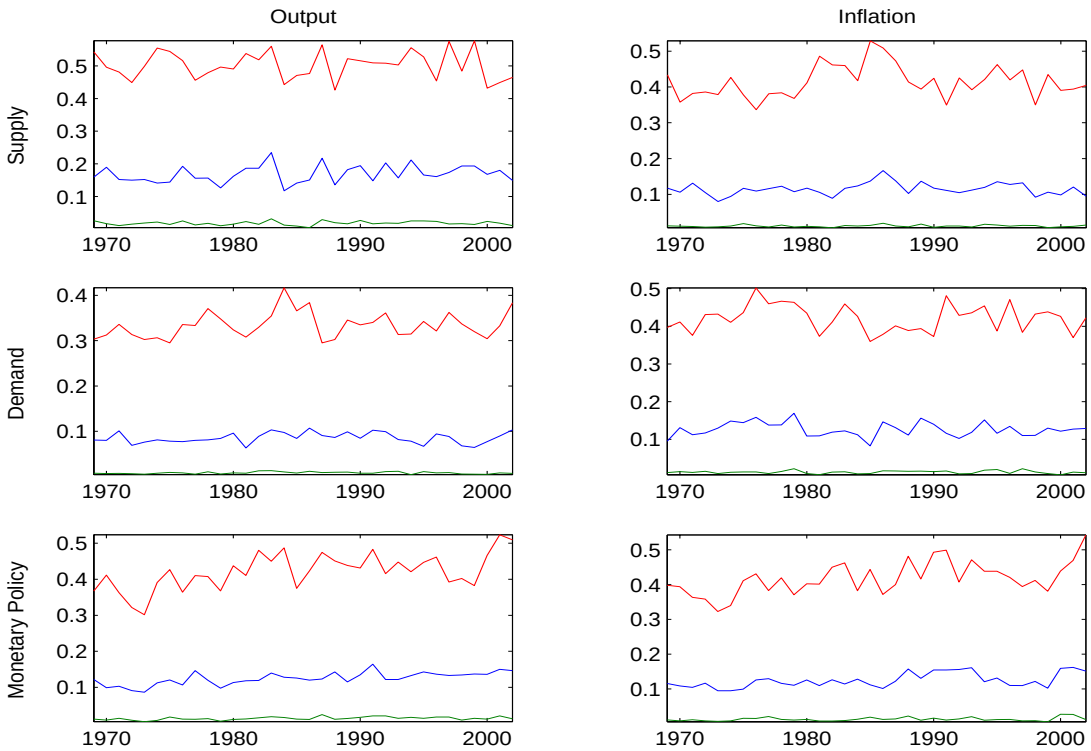


Figure A8: Persistence Shares

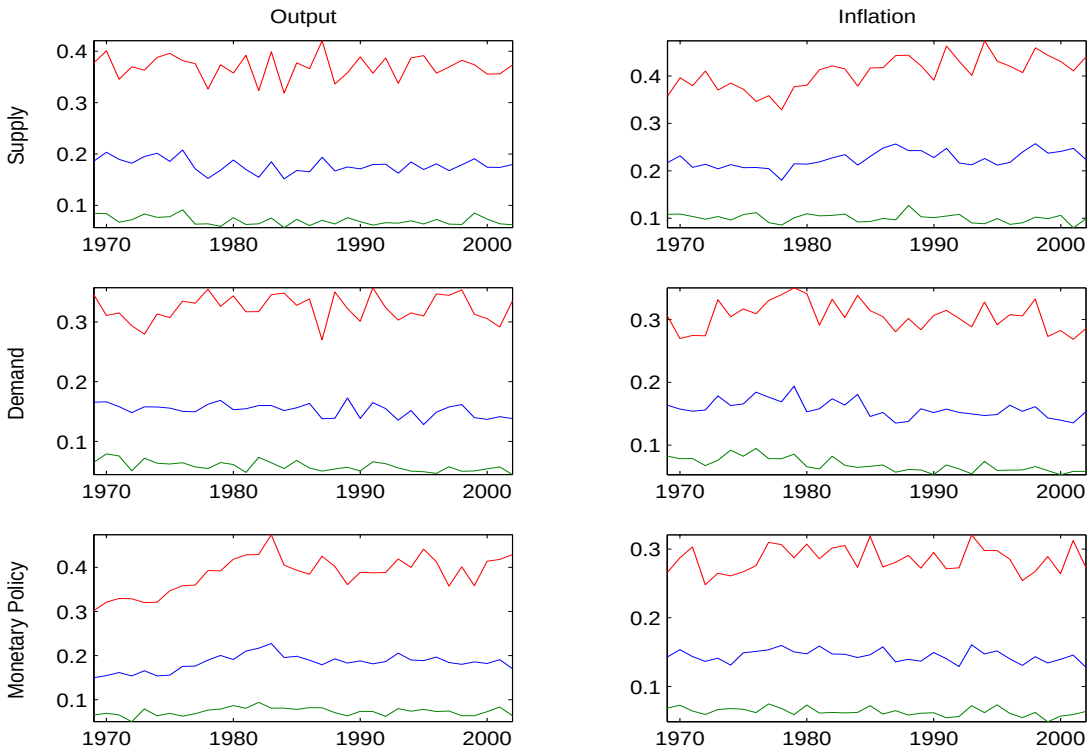
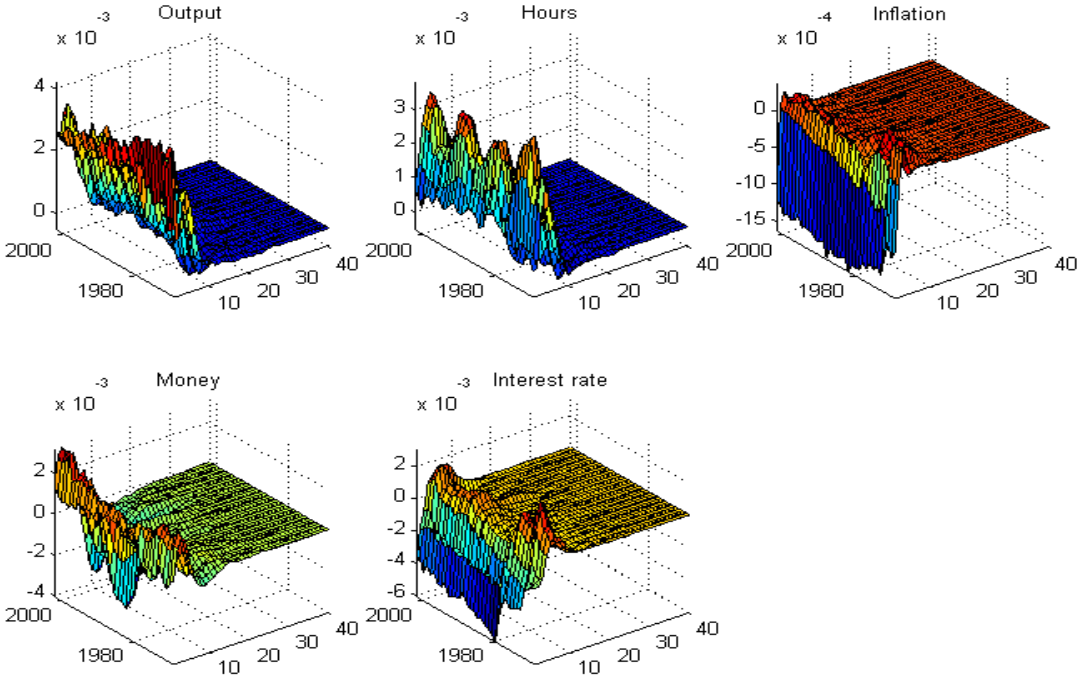
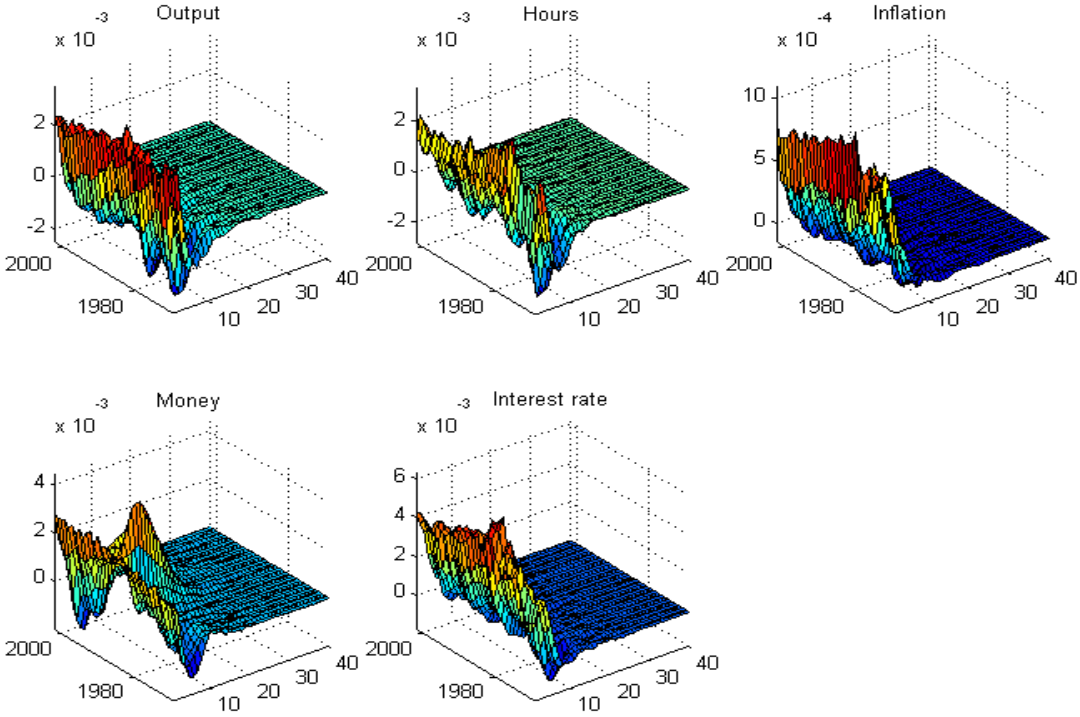


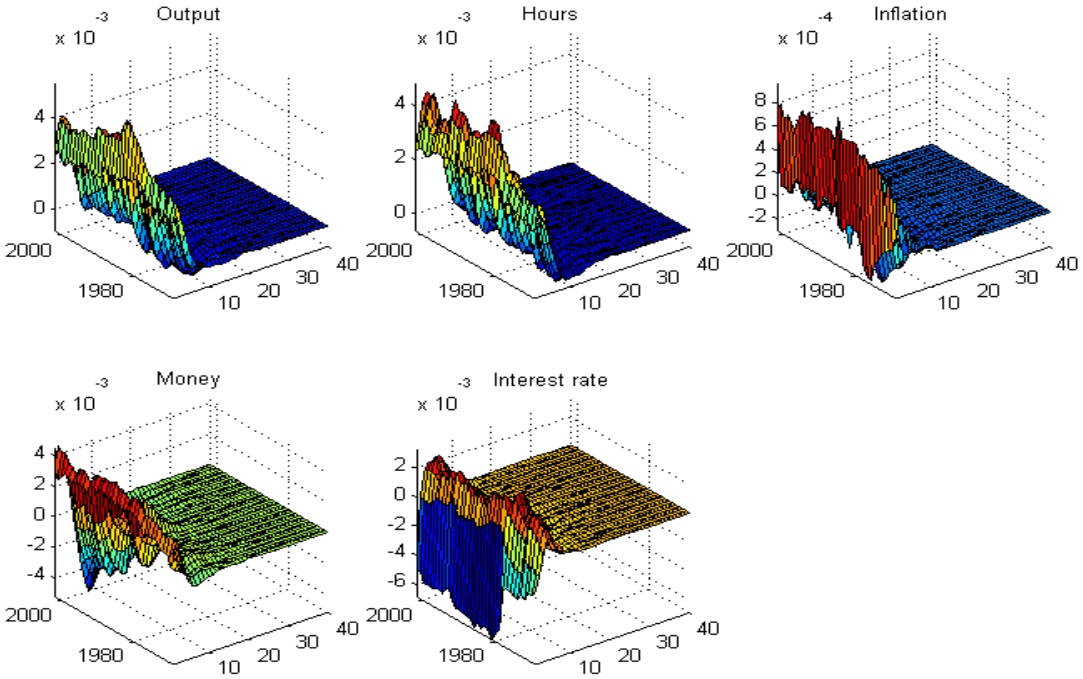
Figure A9: Volatility Shares



Response to Supply Shocks



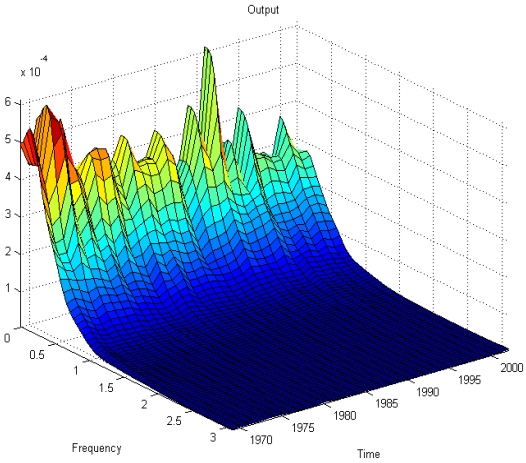
Response to Demand shocks



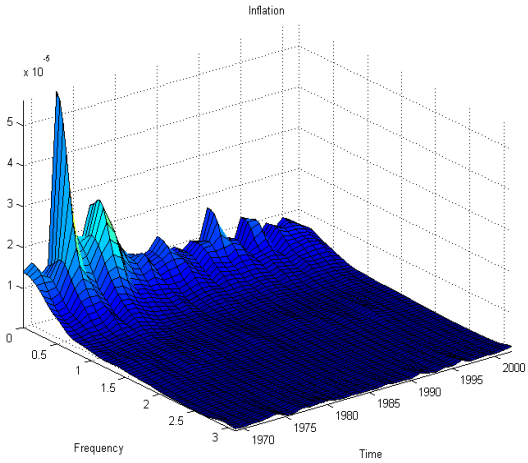
Responses to Monetary Policy shocks

Figure A10: Responses to Shocks

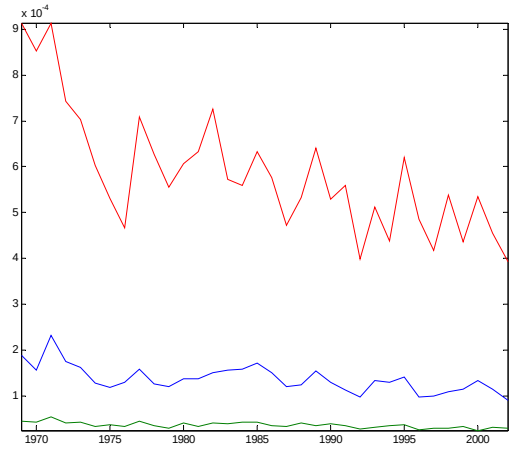
4) Weighting 2



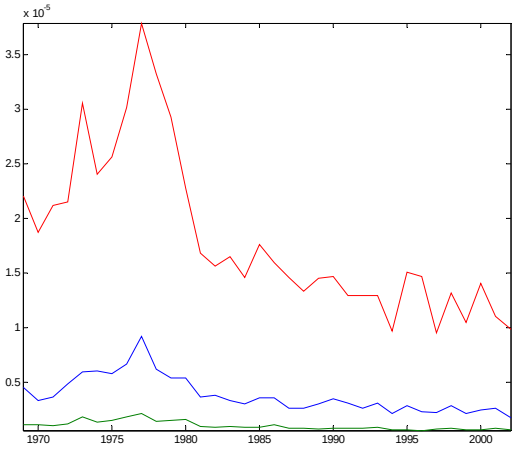
Output spectrum



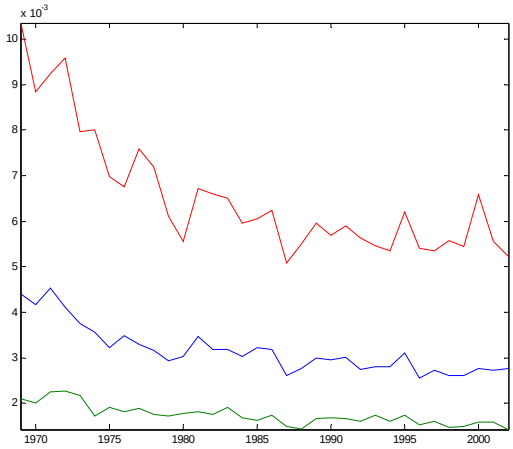
Inflation spectrum



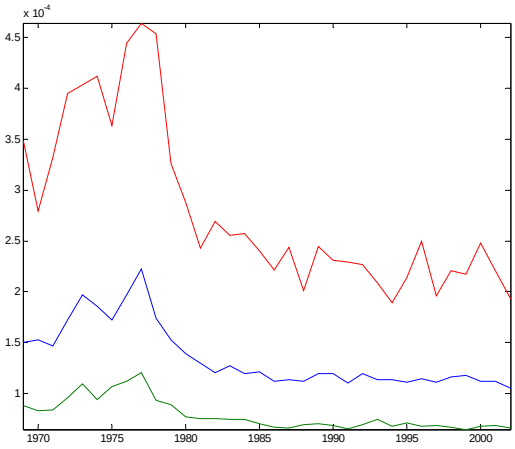
Output persistence



Inflation persistence

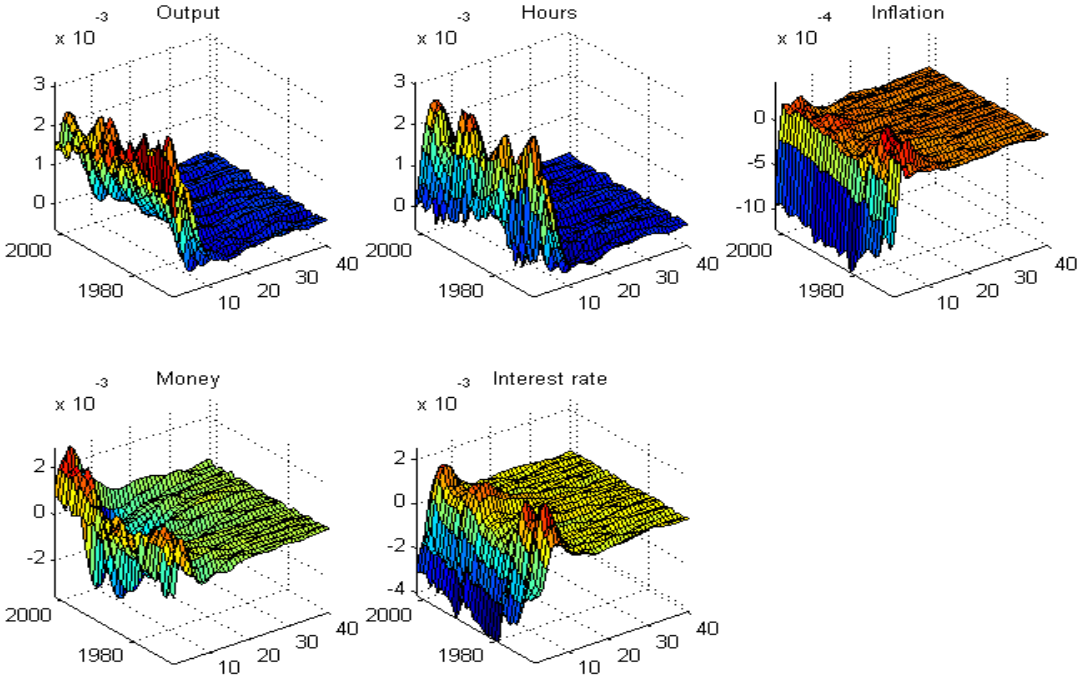


Output volatility

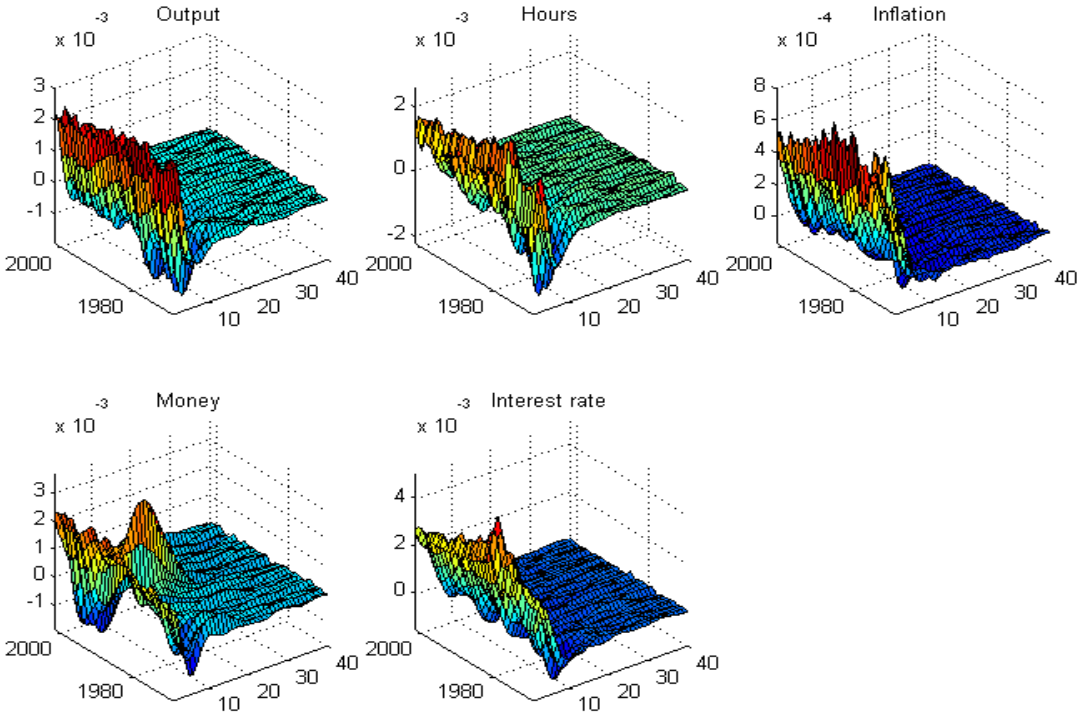


Inflation volatility

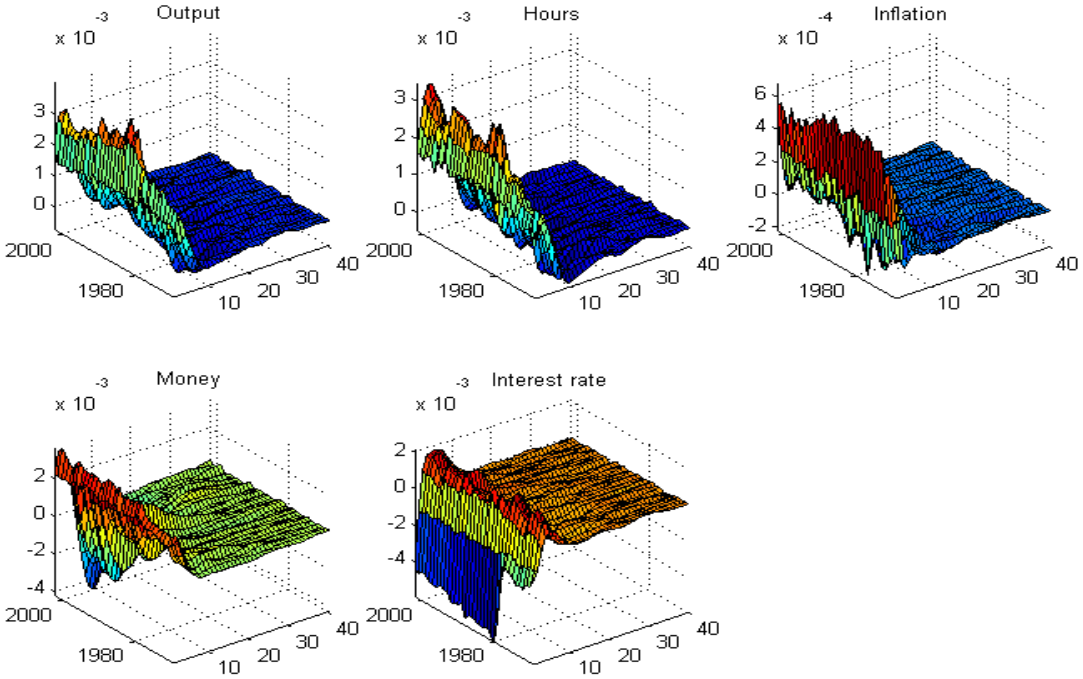
Figure A11: Structural Output and Inflation Dynamics



Response to Supply Shocks



Response to Demand shocks



Responses to Monetary Policy shocks

Figure A12: Responses to Shocks

5) Future coefficient shocks set to zero

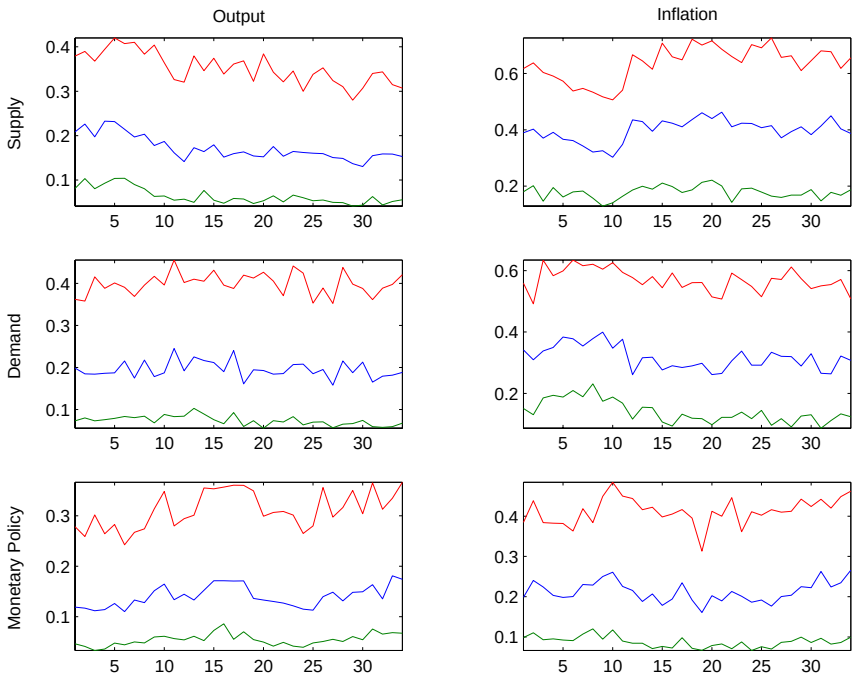


Figure A13: Persistence Shares

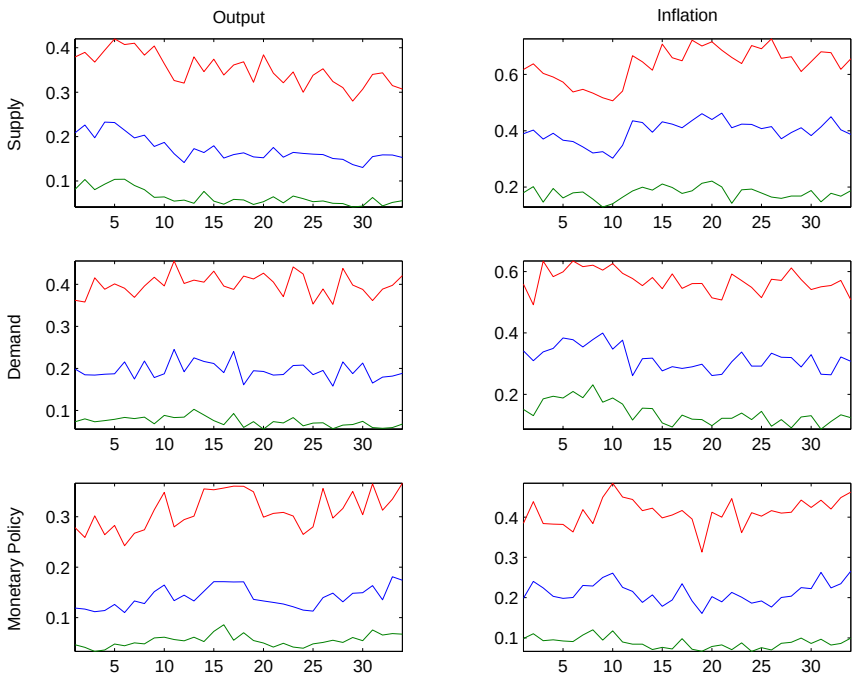


Figure A14: Variance Shares

6) Non recursive estimation

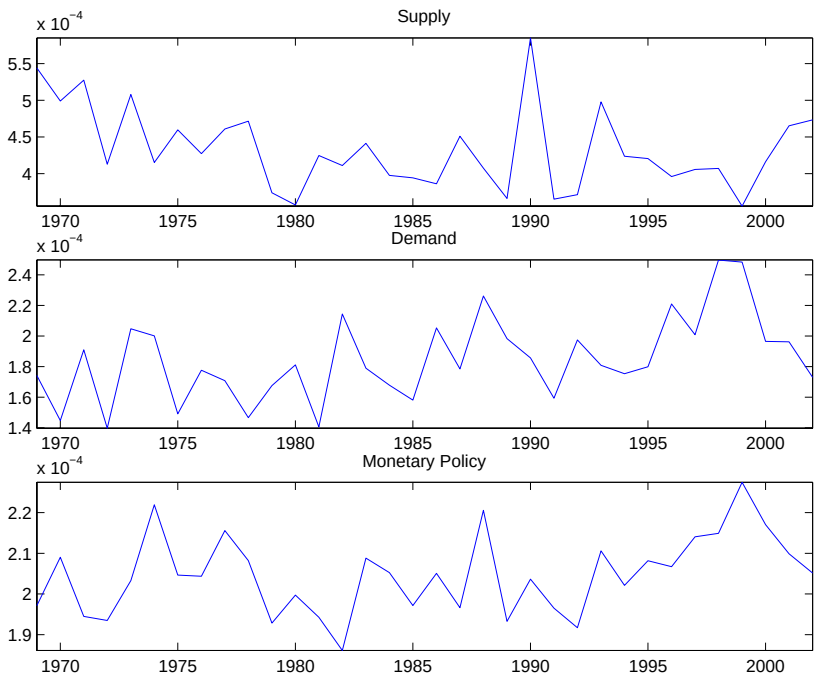


Figure A15: Structural Variances

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