Time varying fiscal policy in the U.S.*

Manuel Coutinho Pereira
Banco de Portugal &
CEMAPRE

Artur Silva Lopes †
CEMAPRE &
ISEG-TULisbon

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Abstract

To investigate the time heterogeneity effects of fiscal policy in the U.S., we use a non-recursive, Blanchard and Perotti-like structural VAR with time-varying parameters, estimated through Bayesian simulation over the 1965:2–2009:2 period. Our evidence suggests that fiscal policy has lost some capacity to stimulate output but that this trend is more pronounced for taxes net of transfers than for government expenditure, whose effectiveness declines only slightly. Fiscal multipliers keep conventional signs throughout. An investigation of changes in fiscal policy conduct indicates an increase in the countercyclical activism of net taxes over time, which appears to have reached a maximum during the 2008-09 recession.

Keywords: fiscal policy; Bayesian estimation; structural change; macroeconomic stabilization.

JEL codes: C11, E32, E62

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†Corresponding author. Address: ISEG-UTL, Rua do Quelhas 6, Gab. 315, 1200 Lisboa, Portugal. E-mail: asl@iseg.utl.pt. Fax: +351-21-3922781. Phone: +351-21-3922796.

1 Introduction

Effectiveness of fiscal policy to stimulate activity remains a highly controversial topic, as it resurfaced in the discussion of the stimulus packages implemented in the awake of the recent recession. This controversy stems in the first place from the differences between the predictions of neoclassical and Keynesian and some New Keynesian macromodels. Empirical investigation could be expected to shed light on this, but the measurement of the effects of fiscal policy is fraught with problems of endogeneity and anticipation. Different ways to overcome them lead to different estimated shock series and measured impacts.

Yet another problem in this context is that, even within the same approach, results may vary substantially when the sample period varies. Subsample instability has been mentioned, but not much explored in the original SVAR contribution in the field by Blanchard and Perotti (2002). Subsequent work in this vein (e.g. Perotti (2004) and Pereira (2009)) paid more attention to the issue. However, in these and in other studies, inference appears somewhat fragile because the number and timing of the breaks has been imposed from the outset. Usually, only one abrupt change is allowed and its dating is made to coincide with the emergence of the "Great Moderation" or with the change in the conduct of monetary policy.

In the event study approach, the main alternative approach for identification of fiscal (spending) shocks, time heterogeneity issues were also initially overlooked. However, recent work belonging to this strand of the literature, as represented by Ramey (2010), has introduced improved measures of military spending shocks and presented some results on (in)stability of the findings. Ramey reports subsample results for one of the new shock measures proposed and, for instance, she finds clearly different impacts of fiscal policy when the sample starts in 1955 *vis-à-vis* when it includes the WW II.

The issue of time variation must be given careful consideration if one is to determine precisely what the existing identification methodologies imply in terms of the impacts of fiscal policy. This paper takes up this issue in the framework of the Blanchard and Perotti identification approach, by embedding it into a VAR with time-varying parameters (TVP). As argued forcefully in Primiceri (2005) and Boivin (2006), these models have great flexibility in terms of capturing non-linearities and time heterogeneity, and are free from the shortcomings of less formal alternative approaches, such as split- or rolling-sample estimates. On the one hand, they allow one to adopt an agnostic position concerning the number, the timing and the shape of the breaks. On the other hand, they also permit associating the uncovered time variation with some measure of its precision.

TVP-VAR models have been already used in a relatively large number of papers focusing on monetary policy (e.g. Cogley and Sargent (2001), Cogley and Sargent (2005), Primiceri (2005)). Applications to fiscal policy are almost inexistent. To the best of our knowledge, Kirchner et al. (2010) is the only study where a model of this kind is implemented for the euro area, and a recursive identification scheme is adopted.

The methodology for estimating reduced-form VARs with time-varying coefficients and covariance matrices is well established by now. However, its application to the case of identified VARs, particularly with non-recursive identification schemes, as the one we use, poses some questions insufficiently covered in the literature. The contribution of our paper is thus twofold. At the methodological level we extend the TVP-SVAR field to more general identification schemes, such as a Blanchard and Perotti-like one. In this framework, at the empirical level, we document changes in the effects and the conduct of fiscal policy in the U.S. over time.

The structure and key results of the paper are as follows. Sections 2 and 3 deal with methodological issues. TVP-VARs are usually estimated with the aid of Bayesian tools. More precisely, we use the Gibbs sampler as applied to the analysis of state-space models. An overview of the simulation procedure is given in the text, but the full details are left to an appendix. These sections also describe the identification strategy and the way how it is embedded into the simulation procedure. In Section 4 we adduce some evidence about parameter instability when our model is estimated with a traditional fixed-parameter specification. The outcome of the stability tests provides support to the use of a model where both coefficients and the covariance matrix are allowed to vary through time, i.e. the so-called heteroskedastic TVP model. The remaining sections of the paper present and discuss the results.

We identify shocks to the two fiscal variables, taxes net of transfers and government spending, and our estimation period stretches from 1965:2 to 2009:2 (using quarterly data). We find a drop in the effects of net taxes on output around mid-seventies, and then a further gradual weakening until the end of the sample. The effects of expenditure shocks have faded over time as well, but much more smoothly. This is our most important finding. Although this evidence agrees with the common belief that fiscal policy has lost power to stimulate activity in the last decades, it illuminates the recent debate with a different light because the discussion has been confined to the effects of government spending.

A particular hypothesis we also investigate is whether there has been an increase in policy effectiveness in the course of recessionary episodes, and find moderate support for it. The amount of time-variation we get is more modest than the one suggested by the estimation of the time-invariant parameter version of our model over a rolling sample, which we also present to have a bridge to previous studies.

We then go on to investigate the impacts of fiscal policy on consumption. Positive shocks to net taxes bring private consumption down, and the multiplier remains stable throughout. On the expenditure side, we find evidence of a negative and small multiplier within the quarter and, in recent decades, essentially zero multipliers for longer horizons. The evidence we get is not consistent with a sizeable Keynesian impact of expenditure shocks on consumption that SVARs are normally believed to corroborate, though it could square with some New Keynesian models.

The final issue we address are patterns of time-variation in the conduct of fiscal policy. As regards systematic policy, there has been an overall increase in the countercyclical responsiveness of net taxes to output over time. In particular, there was a jump in fiscal activism during the 1973-75 recession and this indicator appears to have reached a peak in the course of the 2008-09 recession. We get procyclical expenditure responses, featuring a decreasing trend throughout the simulation period.

2 Model specification and identification

In the time-varying parameter context it is convenient to write the VAR in such a way that the reduced-form coefficients are stacked into a single vector. Following this convention, the model we consider throughout the paper can be written as

$$\mathbf{x}_t = X_t \boldsymbol{\theta}_t + \mathbf{u}_t, \tag{1}$$

$$A_t \mathbf{u}_t = B_t \mathbf{e}_t, \tag{2}$$

$$\mathbf{e}_t = D_t \boldsymbol{\varepsilon}_t, \tag{3}$$

where $\mathbf{x}_t$ is a $n \times 1$ vector of endogenous variables and $X_t = I_n \otimes [1, \mathbf{x}'_{t-1}, ...\mathbf{x}'_{t-p}]$, $\otimes$ denoting the Kroenecker product; $\boldsymbol{\theta}_t$ is a $n(np+1) \times 1$ vector that stacks the reduced-form coefficients, equation by equation, i.e., $\boldsymbol{\theta}_t = vec[\boldsymbol{\mu}_t, \Theta_{1,t}, ..., \Theta_{p,t}]'$, with $\boldsymbol{\mu}_t$ a $n \times 1$ vector of (time varying) intercepts and $\Theta_{j,t}$ $(j = 1, ..., p)$ are $n \times n$ matrices containing the coefficients for the lag j of the endogenous variables); A_t and B_t are the $n \times n$ matrices of the contemporaneous coefficients, and D_t is a $n \times n$ diagonal matrix that contains the standard deviations of the orthogonalized shocks. System (1) is the reduced-form system, system (2) specifies the structural decomposition of the covariance matrix Σ_t, and system (3) specifies the volatility of the structural disturbances.

All parameters are allowed to vary stochastically over time, according to a specification whose presentation we postpone to the next section. It is assumed that $\boldsymbol{\varepsilon}_t$ is a $n \times 1$ Gaussian vector with $E[\boldsymbol{\varepsilon}_t] = \mathbf{0}$ and $E[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t] = I_n$, implying that $\mathbf{u}_t$ and $\mathbf{e}_t$ are vectors of Gaussian heteroskedastic disturbances such that

$$E[\mathbf{u}_t | A_t, B_t, D_t] = E[\mathbf{e}_t | D_t] = 0,$$

$$E[\mathbf{u}_t \mathbf{u}'_t | A_t, B_t, D_t] = A_t^{-1} B_t D_t D'_t B'_t (A_t^{-1})' = \Sigma_t,$$

and

$$E[\mathbf{e}_t \mathbf{e}'_t | D_t] = D_t D'_t.$$

Our baseline specification has four variables: net taxes (nt_t), government expenditure (g_t), inflation (p_t) and output (y_t) (see subsection 5.1 for more on the definition of the variables). Let $\mathbf{x}_t$ be equal to $[nt_t, g_t, p_t, y_t]'$, $\mathbf{u}_t$ to $[u_{nt,t}, u_{g,t}, u_{p,t}, u_{y,t}]'$ and $\mathbf{e}_t$ to $[e_{nt,t}, e_{g,t}, e_{p,t}, e_{y,t}]'$.

Previous studies estimating TVP-VARs have resorted to recursive identification schemes. This is the case, most notably, of Cogley and Sargent (2001), Primiceri (2005) and Kirchner et al. (2010). We depart from them in this regard and use a simplified version of the identification scheme in Perotti (2004) and Pereira (2009), in that there is no contemporaneous reaction of prices to net taxes. Furthermore, we do not include an interest rate variable in our VAR.

A first formulation of our identification scheme, useful to motivate it, is one such that matrices A_t and B_t in (2) are given, by (time subscripts omitted), respectively:

$$A_t = \begin{bmatrix} 1 & 0 & -a_{13} & -a_{14}^* \\ 0 & 1 & -a_{23}^* & 0 \\ 0 & -a_{32} & 1 & 0 \\ -a_{41} & -a_{42} & -a_{43} & 1 \end{bmatrix}, \quad B_t = \begin{bmatrix} 1 & b_{12} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{4}$$

We identify the shocks to net taxes and expenditure, and impose a convenient orthogonalization between price and output shocks ordering the latter variable in the second place. Net taxes respond contemporaneously to prices and output, but expenditure responds only to the first of these variables. This latter restriction is common in fiscal VARs identified by restrictions in the matrices of contemporaneous coefficients. Output is allowed to react within the quarter both to net taxes and expenditure, but prices can react to expenditure only. Further, government expenditure is ordered before net taxes.

The elasticities of net taxes to output and expenditure to prices, a_{14}^* and a_{23}^*, are calibrated according to the formulas given in Appendix A of Pereira, who elaborates on the procedure introduced by Blanchard and Perotti (2002). The calibrated figure for the first parameter varies over time while that for the second one is assumed constant. However, the price elasticity of taxes, a_{13}, is estimated.

Since the number of free parameters (six) is equal to the number of free elements of Σ_t less the four standard deviations in D_t, the order condition is met exactly in (4).

The equations from system (2), with matrices A_t and B_t as given in (4), contain endogenous regressors: u_t^g is endogenous in the price equation, u_t^p is endogenous in the net tax equation, and u_t^{nt} is endogenous in the output equation. Hence, in a time-invariant parameter setting, the structural decomposition in (4) would have to be estimated by 2SLS[1] (or a more general method, such as maximum likelihood).

When one moves to a time-varying context, it is convenient that matrices A_t and B_t are such that the equations from (2) include predetermined variables only. As explained in the next section, in this case the identification scheme can be easily embedded into the algorithms for normal linear state space models used to draw the matrix Σ_t. This condition holds in the alternative specification of matrices A_t and B_t as

$$A_t = \begin{bmatrix} 1 & 0 & 0 & -a_{14}^* \\ 0 & 1 & -a_{23}^* & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad B_t = \begin{bmatrix} 1 & \beta_{12} & \beta_{13} & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \beta_{32} & 1 & 0 \\ \beta_{41} & \beta_{42} & \beta_{43} & 1 \end{bmatrix}, \qquad (4')$$

which form an identification scheme equivalent to (4), in the sense that it yields the same impulse-responses in a time-invariant setting.[2] As shown in Appendix C, there is a one-to-one correspondence between the parameters of both schemes; in particular, the calibrated parameters coincide. Hence, Bayesian estimation take as a reference the definition of matrices A_t and B_t as given in (4').

When studying the effects of fiscal policy on private consumption, we consider a generalization of the baseline system including the latter variable. It is ordered last

[1] It would be estimated sequentially, using the residuals of previous steps as instruments for the endogenous regressors. Specifically, $\hat{e}_t^g$ as an instrument for $\hat{u}_t^g$ in the price equation, $\hat{e}_t^p$ as an instrument for $\hat{u}_t^p$ in the net tax equation, and $\hat{e}_t^{nt}$ as an instrument for $\hat{u}_t^{nt}$ in output equation.

[2] In Appendix C be we show that the estimated structural shocks ($\hat{\mathbf{e}}_t$) resulting from (4) and (4') fully coincide for net taxes and expenditure, and coincide except for a scale factor for output and prices.

in the system, and a convenient orthogonalization in relation to output and prices is imposed. This should be innocuous for the object of interest, the effects of the fiscal policy shocks. It is straightforward to modify the identification methodology for the baseline specification to accommodate such an extension.

3 Formalizing time variation and Bayesian simulations

Three blocks of time-varying parameters or states are considered. The first includes the coefficient states, i.e., the reduced form coefficients of vector $\boldsymbol{\theta}_t$. The second block contains the covariance states, the non-zero and non-unity elements of B_t in (4') (recall that matrix A_t has no unknown elements). Let $\mathbf{b}_{i,t}$ denote the vectors collecting the states corresponding to row i; there are three such vectors: $\mathbf{b}_{1,t}$ $\mathbf{b}_{3,t}$, and $\mathbf{b}_{4,t}$. The third block contains the volatility states, which are the elements in the main diagonal of D_t. These are taken in logarithms and collected in the vector $\log \mathbf{d}_t$.

As is common in empirical applications of this sort of models, the coefficient and the covariance states are assumed to follow driftless random walks, and the volatility states are assumed to evolve as geometric random walks:

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\epsilon}_t^{\theta}, \tag{5}$$

$$\mathbf{b}_{i,t} = \mathbf{b}_{i,t-1} + \boldsymbol{\epsilon}_t^{bi},\ i = 1, 3, 4, \tag{6}$$

$$\log \mathbf{d}_t = \log \mathbf{d}_{t-1} + \boldsymbol{\epsilon}_t^{d}, \tag{7}$$

where it is assumed that $\boldsymbol{\epsilon}_t^{\theta} \sim i.i.d.N(0, Q^{\theta})$, $\boldsymbol{\epsilon}_t^{bi} \sim i.i.d.N(0, Q^{b_i})$, and $\boldsymbol{\epsilon}_t^{d} \sim i.i.d.N(0, Q^{d})$, and that the disturbances $\boldsymbol{\epsilon}_t^{\theta}$, $\boldsymbol{\epsilon}_{i,t}^{b}$, and $\boldsymbol{\epsilon}_t^{d}$ are orthogonal to each other and also to $\boldsymbol{\varepsilon}_t$. The elements of matrices Q^{θ}, Q^{b_i} and Q^{d} are usually called the hyperparameters. Apart from the block-diagonality of the covariance of the innovations relating to covariance states, we impose no other restrictions on the matrices of the hyperparameters.

The simulation of the heteroskedastic TVP-VAR using Bayesian methods is by now fairly standard, so we outline here the main steps and give the full details in Appendix B. The algorithm iterates on a number of blocks using the conditioning feature of the Gibbs sampler. The time-varying parameters are treated as unobserved state variables whose dynamics are governed by the transition equations (5), (6) or (7). These, together with the measurement equations relating the state variables to the data, form a normal linear state-space model in each block. A Bayesian algorithm for this model, as proposed in Carter and Kohn (1994) (see also Kim and Nelson (1999b) for a description), is run sequentially, sampling the state vectors from the posterior Gaussian distributions with mean and covariance matrix obtained from running the ordinary Kalman filter followed by a backward recursion.

More precisely, the Gibbs simulation algorithm consists of going through the following steps at each iteration.

Step 1 The measurement equation in this block is given by (1) and the state equation by (5). A history of $\boldsymbol{\theta}_t$'s is generated conditional on the data, histories of covariance and volatility states (which yield a history of Σ_t's) and the covariance of innovations in the state equation (Q^{θ}).

Step 2 The normal linear state space algorithm is applied sequentially, equation by equation, conditional on the data, histories of coefficient and volatility states, and the covariance of innovations in state equations (Q^{b_i}). The measurement equations come from (4') and the state equations from (6). A history of $\mathbf{b}_3$'s is generated firstly; then, conditional on it, a history of $\mathbf{b}_1$'s and, finally, conditional on both, a history of $\mathbf{b}_4$'s.

Step 3 The measurement equation is based on a transformed version of (3) and the state equation is (7). A history of $\log \mathbf{d}$'s is generated conditional on the data, histories of coefficient and covariance states, and the covariance of innovations in state equation (Q^d).

Step 4 The model's hyperparameters, Q^{θ}, Q^{b_i} and Q^{d}, are generated conditional on histories of the corresponding state vectors ($\boldsymbol{\theta}_t$, $\mathbf{b}_{i,t}$ and $\log \mathbf{d}_t$).

There is one further aspect that merits discussion in our application of Bayesian methods, in this context of the multivariate stochastic volatility model. The methods that have been used in empirical macroeconomics to estimate a time-varying matrix Σ_t, notably in Cogley and Sargent (2005) and Primiceri (2005), require a decomposition of this matrix of the form

$$\Sigma_t = L_t H_t L_t',$$

with L_t lower triangular and H_t diagonal. Using this factorization, it is possible to draw blockwise from the distribution of the covariance states (L_t), and from the distribution of the volatility states (H_t). In this case, the measurement equations are given by $L_t \mathbf{u}_t = \mathbf{e}_t$ and $\mathbf{e}_t = H_t \boldsymbol{\varepsilon}_t$, which correspond to (2) and (3) above. Note also that the variables in the i-th measurement equation following from $L_t \mathbf{u}_t = \mathbf{e}_t$, that is u_{jt} with $j < i$, are predetermined. Hence, once independence between the states belonging to different equations is assumed, the normal linear state space algorithm can be applied equation by equation. This assumption is equivalent to a block-diagonal covariance matrix of the respective innovations, each block relating to a given equation.

However, the estimate of Σ_t obtained as described depends on the ordering of the variables underlying the triangular structure of L_t. This is, in general, a undesirable feature of the impulse responses coming from TVP-SVARs with stochastic volatility: not only they depend of an identification scheme applied to the draws of Σ_t, but the draws themselves also depend on a previous orthogonalization scheme. When the identification restrictions assume the form of a triangular factorization, as it is often the case in monetary policy VARs, a straightforward solution (also from the computational viewpoint) is to draw for Σ_t already using that factorization.[3] That is, the identification scheme is also embbebed into the simulation

[3] Primiceri (2005) suggests a more general procedure in case several factorizations i.e. orderings of the variables appear plausible. This is to impose a prior on each of them, and then average

procedure [4]. In our case, when formulation (4') is used, it is possible to proceed the same way because it gives raise to a system where all regressors are predetermined (in contrast to formulation (4)). The normal linear state space algorithm can also be applied equantionwise, as long as there is independence between the parameters belonging to the different rows of B_t.

3.1 Priors and practical issues

In order to make the whole procedure operational, prior distributions need to be specified, both for the initial states and the hyperparameters. We follow the previous TVP-VAR literature in this regard. The priors for the initial states are Gaussian, with means given by the point estimates $\hat{\boldsymbol{\theta}}_t$, $\hat{\mathbf{b}}_{i,t}$ and $\log \hat{\mathbf{d}}_t$ from estimating a time-invariant VAR over the training subsample 1947:1-1959:4, and covariance matrices equal to multiples of the corresponding asymptotic covariances[5] (see Appendix B). We note that the calibration of the priors for the initial states has typically almost no influence on *a posteriori* inference.

The hyperparameters have conjugate inverse-Wishart priors, with scale matrices equal to a constant fraction of the aforementioned asymptotic variances of the parameters estimated over the training subsample (multiplied by the respective degrees of freedom). This constant fraction summarizes the prior beliefs about the amount of time variation. In the prior for the covariance matrix of the innovations relating to coefficient states, Q^{θ}, this was set to the benchmark value of $(0.01)^2$, used by Cogley and Sargent (2001) and in virtually all subsequent TVP studies.[6] This is a conservative figure, as it can be interpreted as time variation accounting for 1 percent of the standard deviation of each coefficient. As discussed below, however, using larger values for this constant — implying more prior volatility of the states — changes little in the pattern of posteriori time variation in the effects

the results obtained on the basis of posterior probabilities.

[4] Except for the initial state of $\log \mathbf{d_t}$, whose covariance matrix is set to a multiple of the identity.

[5] Except for the initial state of $\log \mathbf{d}_t$ whose covariance matrix is set to a multiple of the identity.

[6] The corresponding value for Q^d was set to $(0.01)^2$ and the ones for Q^{b_i} to $(0.1)^2$, following Primiceri (2005).

of fiscal policy.

One issue arising in the simulation of TVP-VARs is whether to impose a stability condition that discards the draws of $\boldsymbol{\theta}_t$ that imply non-stable systems.[7] As one might expect, this condition makes more of a difference for the impulse responses at longer horizons (according to our experience in the - application, say, longer that 4 steps ahead), since the stability properties of the system become apparent as one projects them into the future. In Cogley and Sargent (2001) the variable of concern was inflation, and they imposed the stability condition on the grounds that Fed's behavior rules out explosive paths of this variable. In the context of fiscal policy, as noted in Kirchner et al. (2010), there might not be such a compelling theoretical reason for imposing this condition because fiscal policy may have not been on sustainable paths at some points in time. Hence, we chose to report results without the stability condition and, for the benchmark specification, we signal in the text how they change when it is imposed. A practical aspect about the stability condition is that it makes the simulation procedure more time consuming, since that part of the draws are thrown out. In the application at hand, we found that approximately two out of three draws were unstable.

In this paper, a "filtered" variant of the simulation algorithm is used (as in Cogley and Sargent (2001) and Gambetti et al. (2008)). Full sets of iterations of the Gibbs sampler are sequentially implemented, with the simulation period extended by one year at a time. The starting date is always 1960:1; the first ending date is 1965:2, and the last one 2009:2. The full set iterations is thus repeated 45 times. For each ending date, 30,000 iterations of the Gibbs sampler are run, after a burn-in period of 5,000, and every 5th iteration is kept. The implied impulse-responses for each of the kept draws (6,000) are computed, and we report statistics of the distribution of those responses.

At the end of Appendix B we also report results concerning the autocorrelation functions of the draws, which give an indication about the convergence properties of the algorithm. These autocorrelations are generally low, indicating that the

[7] This is implemented in such a way that the whole history of $\boldsymbol{\theta}_t$'s generated at step 1 is discarded, in case the condition is not met at least for one t.

chain mixes well.

4 Some preliminary evidence about parameter instability

To motivate our application, providing support to the time-varying approach, in this section we apply parameter instability tests to the fixed-parameter version of our fiscal VAR. This sort of tests has been employed, for instance, in the recent literature investigating regime changes in macroeconomic relationships, as in Stock and Watson (2002) and Ahmed et al. (2004), focusing on the moderation in GDP growth volatility in recent decades. We perform two such tests. The first one is the Nyblom-Hansen (NH) test, as presented in Hansen (1992), which has precisely the random-walk TVP model as the alternative hypothesis. Both tests were implemented by estimating directly the structural form of the system, that is, in the notation of Section 2:

$$A\mathbf{x}_t = A\boldsymbol{\mu} + A\Theta_1\mathbf{x}_{t-1} + ... + A\Theta_p\mathbf{x}_{t-p} + B\mathbf{e}_t.$$

Given that 2SLS estimation (equation by equation) is used, the test statistic was computed according to the particular formulation for this estimator in Hansen (1990).

The second test is based on the Quandt likelihood-ratio statistic in Wald form (QLR), that is, the maximum of the Chow statistics calculated for a sequence of breakdates over a portion of the sample. Although it has also power against the randomly TVP alternative, this is a test for parameter constancy against the alternative of a single break of unknown timing. The sequential break dates were defined considering a symmetric trimming of 25%: noting that the usable sample is from 1948:2 to 2009:2, they start at 1963:2 and end at 1994:3. At each break date all coefficients in each equation were allowed to change by means of interacting dummies. The Wald statistic for the joint exclusion of these dummies was then computed taking the White heteroskedasticity-consistent covariance matrix and the p-values were obtained as described in Hansen (1997)). The display of the values of the test statistic over time is interesting, as it gives an indication about the occasion(s) where a structural break is more likely to have taken place.

After testing for a change in the coefficients, we have also tested for a break in the variances using a simple procedure from Stock and Watson (2002). We took the residuals from estimating each equation imposing a break in the coefficients at the date selected by the QLR test. We then repeated this test in regressions of each series of residuals in absolute value on a constant and a dummy defined again for each break date. Thus, the results of the variance stability test are made robust to the break in the coefficients.

It is well known that the distributions of the Nyblom-Hansen and Quandt likelihood ratio statistics are derived under the assumption of stationary regressors. Non-stationarity biases the results of the tests toward showing instability. This should not interfere with our results because, prior to estimation, we have detrended all variables. GDP, net taxes and expenditure were detrended assuming a quadratic trend and the price (inflation) variable is measured as the first differences of the log GDP deflator (see subsection 5.1 for further details).

Table 1: Results of parameter stability tests (p-values)

Equation	NH joint	NH variance	QLR coeffs.	QLR variance
Net taxes	0.16	0.07	0.00	0.73
Expenditure	0.01	0.00	0.00	0.00
GDP deflator	0.00	0.00	0.00	0.00
GDP	0.01	0.00	0.00	0.00

Note: p-values of the the Nyblom-Hansen (NH) test for driftless random-walk coefficients and variance (1st column) and variance only (2nd), and p-values of the QLR test for a single break of unknown timing in the coefficients (3rd) and variance (4th). The usable sample is 1948:2 to 2009:2 and the break search dates for the QLR test are located between 1963:2 and 1994:3.

Table 1 shows the p-values for the Hansen-Nyblom and QLR tests, and Figure

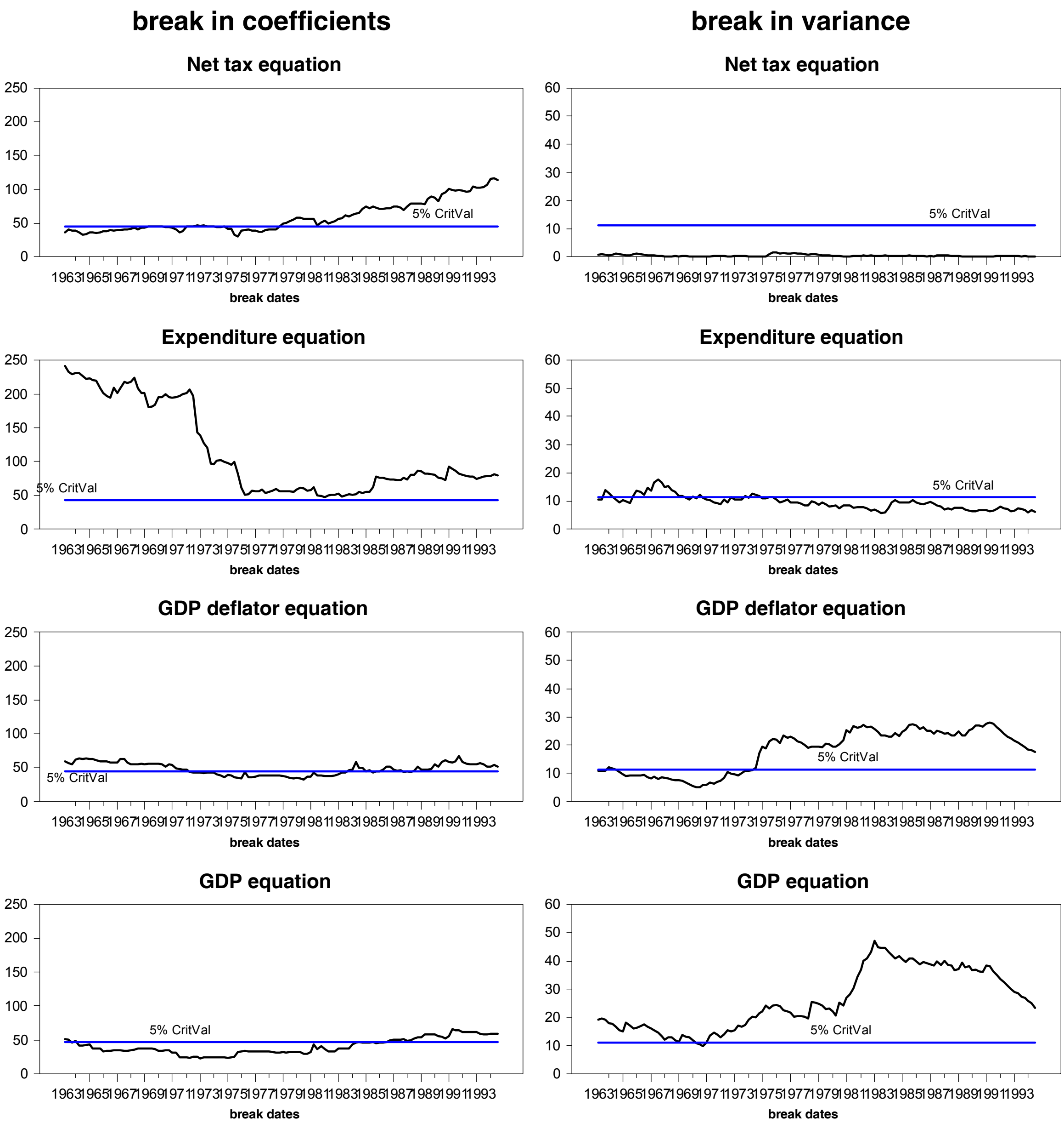

Figure 1: Sequencies of QLR statistics

1 plots the full sequences of QLR statistics. The p-values point to widespread parameter instability in the system. As regards the expenditure equation, the sequence of QLR statistics suggests a large break in the coefficients — much more strongly than the one in the variance — occurring toward the beginning of the sample. This might be accounted for by the Korea War, that made the stochastic process followed by expenditure in the early fifties very different from subsequently. As far as the output equation is concerned, in contrast, there is much stronger evidence of a break in the variance than in the coefficients (and a similar picture is observed for the price equation). This is consistent with the findings of the literature on the great moderation, that regime changes affected first and foremost the volatility of the shocks (see Stock and Watson (2002)). Furthermore, our estimate of the break date in (conditional) volatility is also consistent with most previous estimates (see, for instance, Kim and Nelson (1999a), McConnell and Perez-Quiros (2000) and Stock and Watson (2002)).

At the usual 5% level, the Nyblom-Hansen test does not reject the parameter constancy hypothesis for the net tax equation. The results from the QLR test are partly contradictory with this, since they do reject the null of constant coefficients, with the evidence cumulating in the second half of the sample. It might be that instability in the coefficients of this equation is more of the single break type, and thus best captured by the QLR statistic. As regards the variance, the evidence is reversed since only the Nyblom-Hansen test signals some instability (although not significant at the 5% level).

As a whole, the results of the tests clearly support the use of a specification with time-varying parameters against a fixed-parameter one. Moreover, they call for a model that accommodates stochastic volatility. Further still, the results of the QLR statistic indicate different break timings, depending on specific equations and parameters, and not a generalized regime change affecting all equations at the same point in time. Therefore, a model with time-varying parameters also appears superior to the traditional split- or rolling-sample estimates of a fixed parameter model.

5 Results

5.1 Data

Recall that our baseline specification includes four variables: taxes net of transfers, government expenditure (consumption plus investment)[8], GDP and inflation. We also estimate a specification including private consumption. Taxes net of transfers, government expenditure, output, and private consumption are in loglevels, in real and *per capita* terms. We detrend all these variables prior to estimation by regressing them on a second order polynomial in time. Inflation is calculated as the change in the log GDP deflator at annual rates. The data are on a quarterly basis, seasonally adjusted, and the lag length of the system is set to 2, the same value as in previous studies with TVP-VARs. A short lag length prevents the simulation procedure from becoming too heavy, as it reduces considerably the size of the vector of coefficient states (for instance, in the benchmark system, from 68 elements with 4 lags to 36 elements with 2 lags). Usually, in time-invariant settings, SVARs estimated with quarterly data contain 4 lags. Therefore, for the sake of comparison with previous studies, we also estimate such a version of our model over a rolling-sample, and adopt a lag length of 4 in that instance.

5.2 Time-varying responses of output to fiscal shocks

Figure 2 presents the percentage responses of output to fiscal shocks in the model with driftless random-walk parameters. The shocks have the size of 1 percent of GDP and so the figures have the interpretation of multipliers. The charts show for date t the simulated impulse-responses with the parameters indexed to that date[9] for four horizons: within the quarter and 1,2 and 3 years ahead. We present both the median response (darker line) and the average response (lighter line), as they

[8] For the sources of the data and for the precise way how fiscal variables are computed see the Appendix A.

[9] We follow the usual practice of presenting a simplified version of the impulse-responses, in which the response for shocks at t is a function of the parameters estimated for that date all steps ahead.

differ somewhat for longer horizons, plus confidence bands corresponding to the 16 and 84 percentiles. The shaded areas in the charts are the NBER recessions.

We comment on the median response, which is less sensitive to the extreme responses brought about by unstable draws. There is a weakening of the effects of net tax shocks throughout the simulation period. The impact multiplier slowly evolves from around -0.8 in the mid-sixties to -0.4 toward 2009. This weakening is, however, more visible for longer horizons. For instance, 1 year ahead, the multiplier fluctuates around -2.0 until mid-seventies, then there is a peak of effectiveness in 1975 (-2.5). This is followed by a drop (in absolute terms) to about -1.5, and a further decrease to -1.0 by the end of the simulation period.

On the expenditure side, the amount of time variation provided by the TVP specification is more limited. In the responses one year ahead and longer, a slight weakening of the impacts occurs initially, until around 1977, from 1.25 to 0.75-0.5. Subsequently, the response essentially stabilizes around this latter figure. The profile of contemporaneous impacts is the opposite in the initial years, featuring a slightly increase from 0.25 to 0.50. There is as well a stabilization thereafter.

Results in Figure 2 indicate a fading of the effects of fiscal policy over time, this being much more evident for net taxes than for expenditure. Such a pattern corroborates the common belief that the effectiveness of fiscal policy in the U.S. has lost strenght in recent decades but puts almost all the burden for this on net taxes, not on government expenditure. Further, although for net taxes there is evidence of a sizeable one-off break in the mid-seventies, in general the responses evolve in a way that is well described by the gradual change hypothesis. Further still, in spite of the observed time variation, the multipliers keep conventional signs and reasonable sizes throughout. Hall (2009) summarizes the evidence on spending multipliers coming from regressions and VARs (SVAR and event study approaches) as lying in the interval from 0.5 to 1.0. The figures we get broadly conform to this interval. They are only marginally above it in the initial years and slightly below toward the end of the period. Evidence on net tax multipliers is much scarcer, but values from -2.0 to -1.0 are in the usual range as well.

An important caveat to note about our evidence is that it contains a consider-

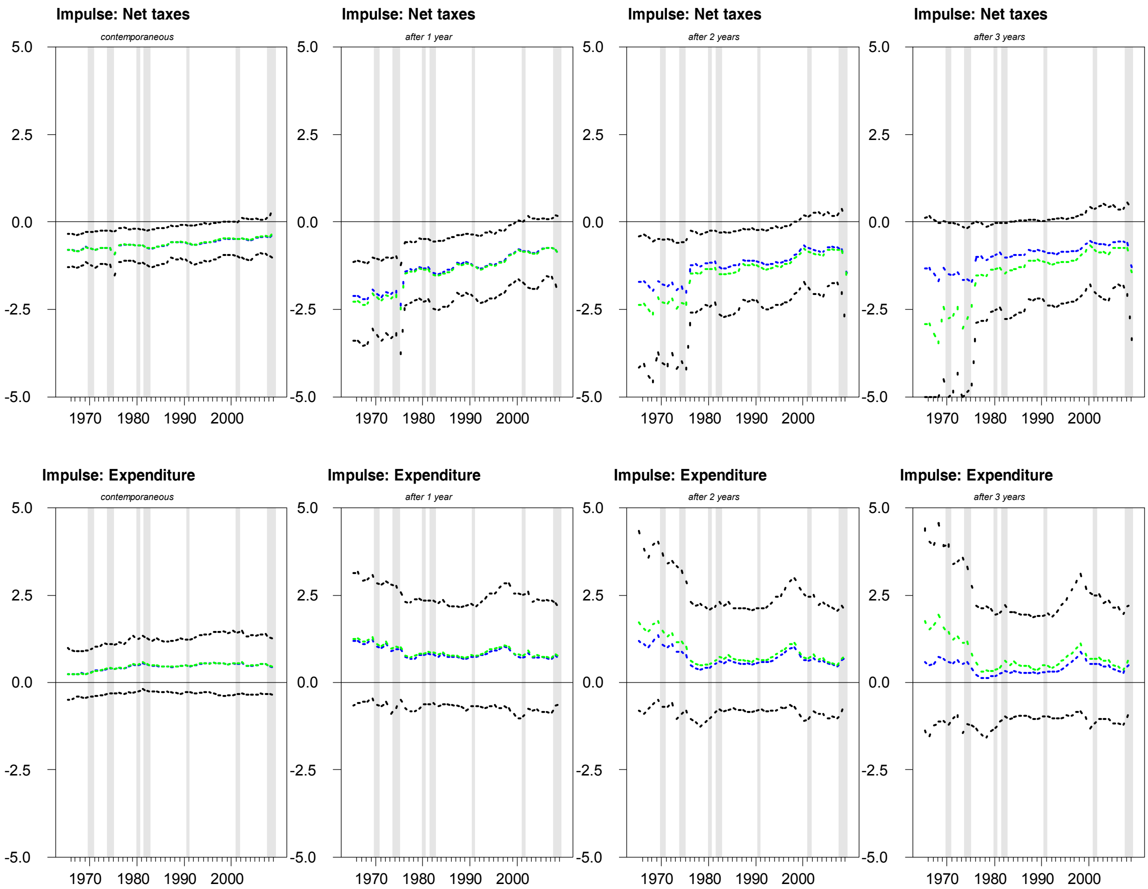

Figure 2: Time-profile of output responses – Bayesian simulation of a model with time-varying parameters

able amount of uncertainty. The confidence bands in Figure 2 are rather wide, and particularly so in the case of expenditure shocks, for which they comprise the x-axis at all horizons considered. Even for net tax shocks, since a horizontal line always fits within the area delimited by the two bands, one cannot reject the hypothesis of constant effects throughout the period.

When the stability condition is imposed, the pattern of the responses over time[10] is qualitatively similar, but those for 2 years after the shock and longer become noticeably more compressed. The median net tax multiplier 2 years ahead is in the range -1.4 to -0.5 with the stability condition, and -2.0 to -0.7 without it; similarly, the expenditure multiplier falls in the interval 0.25 to 0.9 instead of 0.4 to 1.3. When the average response instead of the median response is taken and/or responses for longer horizons are considered these discrepancies widen.

We present the NBER recessions in the charts with the impulse-responses, so as to provide informal evidence whether there has been a peak in policy effectiveness around such episodes. This hypothesis is sometimes mentioned in the literature (recently, for instance in Hall (2009)). As far as net tax shocks are concerned, there is some support for it in our results. We noted that the maximum impact of these shocks occurs in 1975, when the slack in the economy was very large.[11] Moreover, toward the end of longer recessions, such as the ones of 1969-70 and 1981-82, there is as well a hint of increase in effectiveness, and this occurs even more strongly in the recent contraction. Actually, notice that the multiplier changes from -0.8 in 2008 to -1.1 in 2009. On the side of expenditure shocks, the responses remain more or less flat during recessionary episodes.

We now compare our findings with those presented in Kirchner et al. (2010), where a similar type of model is used for the euro area. They identify shocks to spending only, ordering them before all the other variables (an identification assumption we also make), and report responses from 1980 on. Concerning the amount of time variation captured, their results are equally compressed as ours,

[10] Not shown but available from the authors on request.

[11] Note that the effects depicted in Figure 2 refer to the second quarter of each year, and the trough of the 1973-75 recession was in the first quarter.

or even somewhat more.[12] Otherwise, both the level and profile of their responses differ from the ones in this paper. They get a decrease in the size of the spending multiplier starting from late eighties, a period in which we get stability of the response. Furthermore, their one-year-ahead multiplier is below ours: marginally positive (always lower than 0.5) until 2000 and slightly negative thereafter.

5.3 Comparison with rolling samples estimates

We now take up a comparison between the responses in Figure 2 and those resulting from the estimation of a time-invariant specification over rolling samples of 25 years. The impact of fiscal shocks on GDP in t, depicted in Figure 3, refers to the estimates for the sample ending at that date. Note that the first year for which these estimates can be calculated is 1973, and therefore the time-span covered differs from the one in Figure 2 which starts in 1965. Median responses and 16- and 84-percentile confidence bands are shown.[13] The profiles of net tax responses are broadly consistent in the two methodologies, in that the response fades progressively.

However, rolling the model with time-invariant parameters yields a much sharper weakening toward the end of the simulation period, in such a way that perverse positive multipliers (up to about 0.5) arise from 2003 on. Turning to expenditure shocks, the results in Figure 3 are much more volatile than under the TVP specification. The multiplier one year ahead assumes values ranging from a maximum of around 1.5 to small negative (between the mid-eighties and the mid-nineties, although a zero multiplier is also inside the confidence bands during this period). Hence, when subsample sensivity is considered, the results of the SVAR model with

[12] The reason may be that, although Kirchner et al. (2010) do not impose the stability condition, they use a smoothed variant of the simulation procedure. Instead, we use a filtered variant.

[13] These are computed as follows. A time-invariant reduced form VAR is estimated for each of the rolling-samples. On the basis of the point estimate for the covariance matrix, one draws firstly for this matrix, assuming a inverse-Wishart distribution. The structural decomposition is applied to each draw. At the same time, one draws for the vector of coefficients, assuming a Gaussian distribution, conditional on the covariance matrix previously drawn. The implied impulse-responses are obtained on the basis of 1000 draws and the relevant statistics computed.

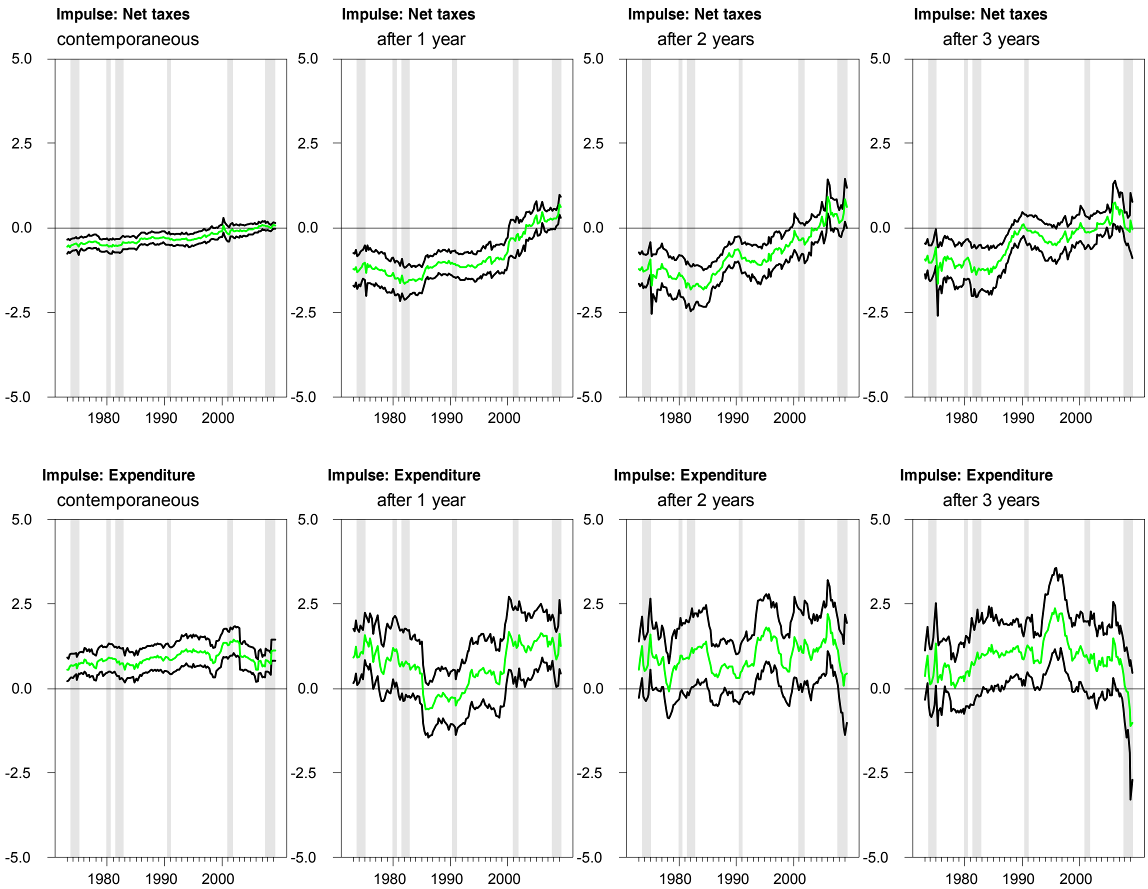

Figure 3: Time-profile of output responses – rolling-sample estimates of a model with fixed parameters

fixed parameters challenge the sizes and even the conventional signs of the output multipliers, as presented in Blanchard and Perotti (2002). Notice, however, that studies such as Perotti (2004) and Pereira (2009) already pointed in this direction[14].

The fact that the TVP specification shows comparatively much less instability raises the issue of whether the prior for the hyperparameters in the latter specification, in particular that for the covariance of the innovations relating to coefficient states, is compressing posterior time variation. To investigate this possibility, in calibrating the inverse-Wisharts for all the hyperparameters [15] we fed more prior volatility into the system by setting the constant fraction of the parameters' asymptotic variances to $(0.1)^2$. However, the results remained very similar to those in Figure 2. This finding suggests that the rolling samples estimates may be overestimating the actual drift, particularly for the responses to expenditure shocks. It appears to lack the flexibility of the TVP model to smoothly accommodate new observations, which brings about large changes in the estimated coefficients.

5.4 Time-varying responses of private consumption

A key disagreement between the predictions of some New Keynesian models and Neoclassical models concerns the impact of government expenditure on private consumption. The former predict a positive effect on this variable of a rise in government purchases, while the latter posit a negative effect. We now investigate this question on the basis of the simulation of a identified TVP-VAR including private consumption, in addition to output, prices, net taxes and government expenditure. The responses of private consumption to fiscal shocks are presented in Figure 4. Again, they can be interpreted as multipliers since fiscal shocks are now normalized to have the size of 1 percent of that variable.

[14] It is hard to blame the size of the rolling window (25 years) for this instability. For instance, although in a simpler context, Stock and Watson (2007) use rolling samples with only 10 years. The uncertainty surrounding the point estimates in Figure 3 is not unusually large for VAR standards.

[15] The benchmark value of this constant is $(0.1)^2$ for calibrating Q^θ and Q^d; see Section 3.1 and Appendix B.

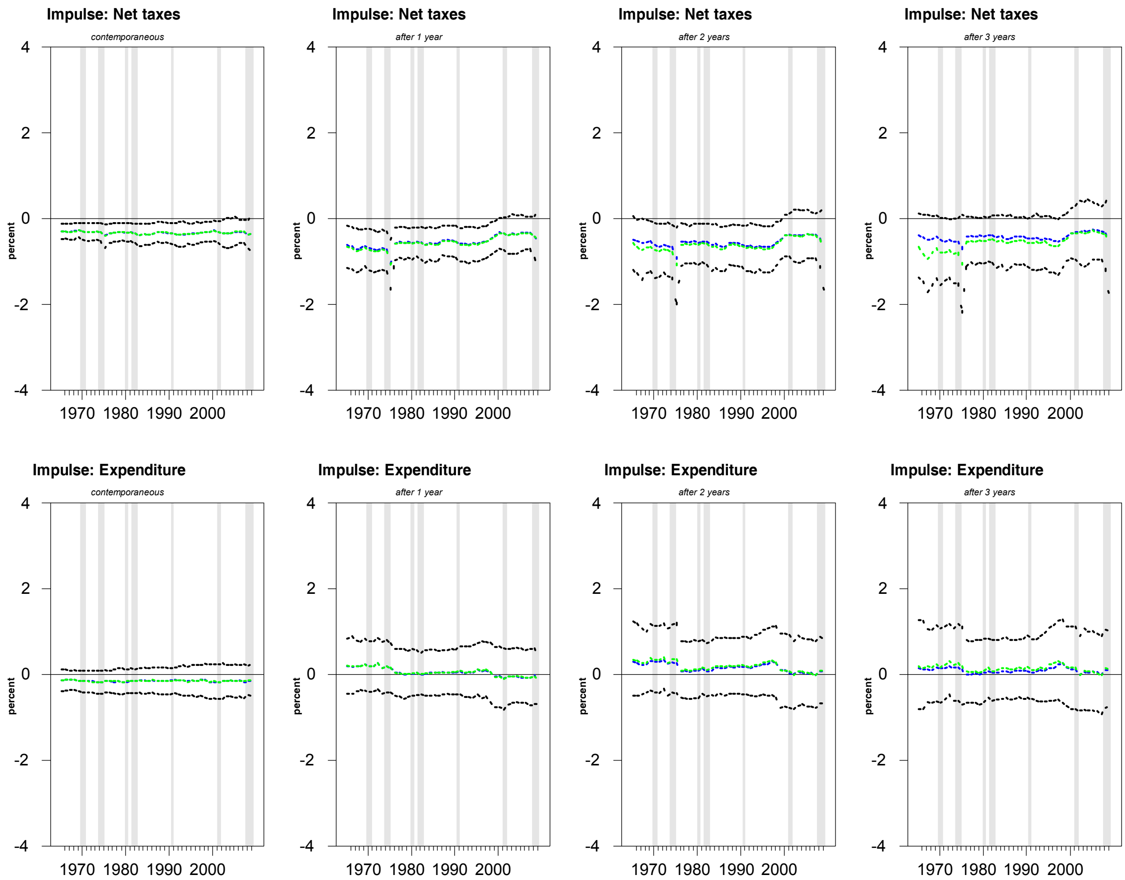

Figure 4: Time-profile of private consumption responses – Bayesian simulation of a model with time varying parameters.

We find that positive shocks to net taxes consistently reduce private consumption. The effects are smaller (in absolute terms) than for output: the multipliers one year ahead and longer remain not far from -0.5 throughout the whole period. The results for expenditure shocks have the interesting feature that the contemporaneous consumption multiplier is slightly negative, thus having the opposite sign of the output multiplier. For longer horizons, the indicator generally assumes small positive values (maximum of about 0.3) in the initial years, until mid-seventies, and then essentially decays to zero. This evidence is clearly not compatible with a large Keynesian impact of expenditure shocks on consumption, particularly in the more recent decades, and plays down this sort of reading of the SVAR evidence (as in Ramey (2010)), as opposed to the event study approach deemed to back up the neoclassical prior. It could fit with in New Keynesian models that may yield slightly positive or zero consumption multipliers, depending on the degree of deviation from the neoclassical benchmark assumptions.[16] It is worth noting that the consumption multipliers on the basis of the time-invariant rolling sample (not shown) parallel those for output in Figure 3. In the case of expenditure shocks, they fluctuate a lot, being generally positive, but assuming negative values between mid-eighties and mid-nineties.

5.5 Some evidence on time variation in the conduct of fiscal policy

We finalize this paper by using our framework to address questions such as time variation in exogenous fiscal policy and the responsiveness of endogenous policy to output. In contrast to monetary policy, relatively little attention has been devoted to them. For instance, there has been much debate over the existence of a drift in the coefficients of the reaction function of the Federal Reserve versus in the variance of the exogenous disturbances (see, e.g., Cogley and Sargent (2005), Boivin (2006)

[16]The size of the multipliers in these models depends, for instance, on the intensity of the (negative) relationship between the markup ratio and output and the (positive) elasticity of labour supply (Hall (2009)), or the proportion of non-Ricardian consumers (Galí et al. (2007)).

and Sims and Zha (2006) and references therein).

In a SVAR framework it is natural to distinguish between non-systematic and systematic policy. Given that our model incorporates stochastic volatility, we have direct evidence on the former coming from the time-varying figure for the standard errors of the structural fiscal shocks, which is a by-product of the simulation exercise. Things are more difficult concerning systematic policy. First, as usual in SVAR models, it is not possible to differentiate between discretionary and automatic components. Therefore, if one is to analyze how fiscal policy activism has changed over time, the two components must be considered together. An additional issue is that such an analysis is carried out by looking at the response of fiscal variables to output shocks.[17] However, as explained in Section 2, the identification of output shocks *vis-à-vis* price shocks is based on an arbitrary ordering (incidentally, a limitation that also applies to similar analyses for monetary policy, as in Primiceri (2005)). Notwithstanding these issues, we believe this is a worthwhile exercise to pursue.

We consider systematic policy first. Figure 5 shows the one-year-ahead responses of fiscal variables to output shocks. Note that in our system the contemporaneous responses are determined by the identification assumptions, i.e., a zero response in the case of expenditure and the calibrated elasticity in the case of net taxes. These assumptions also influence the responses for longer horizons, but the latter are increasingly determined by the remaining dynamics of the system, as one projects into the future. It is worth noting that the calibrated elasticity of net taxes to output fluctuates in the interval from 2.0 to 2.5, without a clearly defined trend for almost the whole period, but rise sharply to 3.5 in the two quarters of 2009.[18]

[17] It is worth noting that the the size of output (and price) shocks in identification scheme (4'), which we use in the simulations, does not coincide with the one in (4); see the Appendix B on this. However, since this difference is small — the standard deviation of the shocks is about 4 percent bigger in the first scheme in a fixed-parameter setting — we ignore this issue.

[18] This recent behavior is explained as follows. In the course of recessions there is a large decrease in net taxes, which results from the simultaneous fall in taxes and rise in social benefits. Therefore, the weight of taxes in total goes up and that of transfers, which is negative, becomes more negative. Since the elasticity of taxes to ouput is positive and the elasticity of transfers is

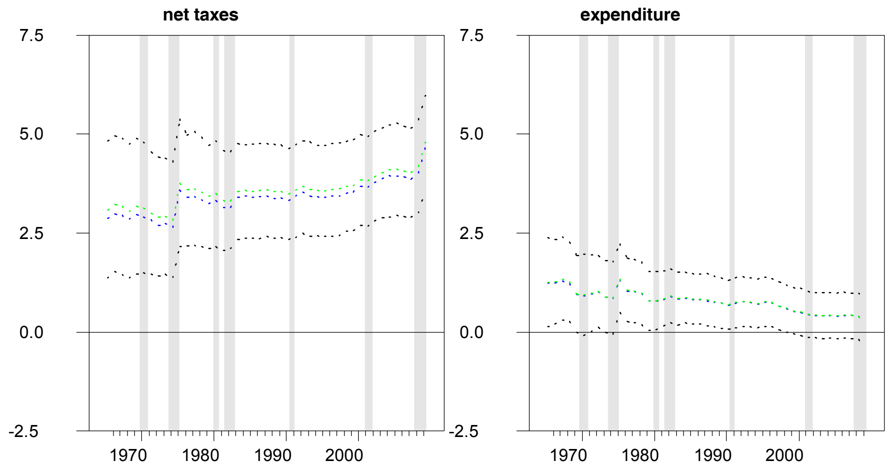

Figure 5: Time-profile of the one-year-ahead responses of fiscal variables to output shocks

As expected, net taxes respond positively to shocks to GDP, in line with the operation of the automatic stabilizers and the conduct of stabilization actions. A one percent shock to GDP triggers initially a rise close to 3 percent in net taxes, then there is a shift to responses around 3.5 percent from mid-seventies on, and further to around 4 percent toward the end of the simulation period. In the last time period considered, the second quarter of 2009, there is a jump in the response to a figure of 4.5. On the expenditure side, the responses are procyclical: they start with figures slightly over 1 percent and essentially show a decreasing trend throughout the period considered, to a value around 0.4. In order to put these figures into context, we first calculate the implied semi-elasticity of the deficit (as a percentage of output) to the output gap, a common indicator of fiscal policy responsiveness.[19] This semi-elasticity fluctuates in the range from 0.3 to 0.5 until the eighties and from 0.5 to 0.6 in the last two decades. The overall increase

negative, by itself this leads to an increase in the overall elasticity.

[19] This is obtained as the difference between the products of the response of each fiscal variable and the ratio of that variable to GDP. Note that our semi-elasticity actually refers to the primary deficit, since the definition of fiscal variables we adopt excludes interest outlays.

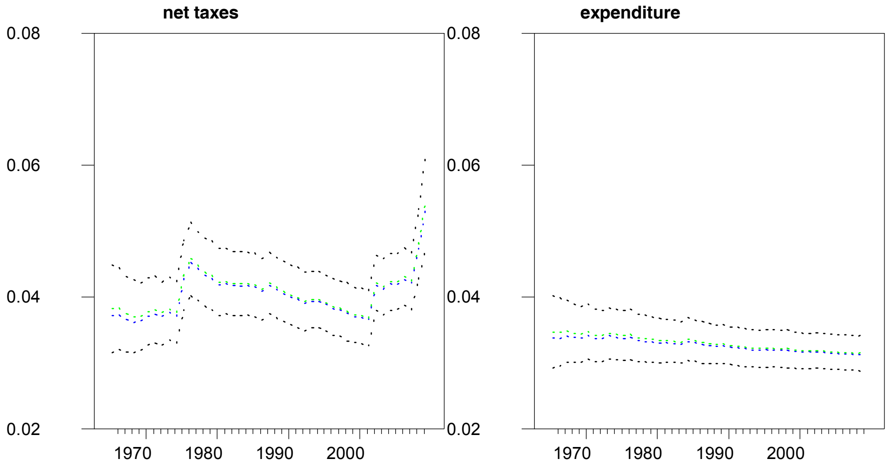

Figure 6: Time-profile of the standard deviation of structural fiscal shocks

in responsiveness we get is consistent with previous findings, as in Taylor (2000) and Auerbach (2002). In particular, our figures broadly match the response of the surplus to the output gap presented in the first of these studies (0.32 for the sample 1960-1982 and 0.68 for the sample 1983-1999).

Figure 5 shows in particular two jumps in the strength of net tax responses coinciding, respectively, with the 1973-75 and the 2008-09 recessions. The countercyclical action around these recessionary episodes is likely to contribute to the measured increase in responsiveness. Moreover, as previously observed, in the course of the recent recession there was a large increase in the calibrated elasticity.

The behavior of expenditure is procyclical. The responses are generally significant; the lower confidence band becomes slightly below the x-axis from 1999 on but only marginally. In a regression of discretionary Federal expenditure on output gap, Auerbach (2002) finds evidence of countercyclicality, albeit statistically insignificant. The difference to our results may be due to the inclusion of the spending of state and local government, which has been found to follow a procyclical pattern.

We now move on to non-systematic policy. Figure 6 presents the evolution of the volatility of structural fiscal shocks since mid-sixties. As far as net taxes are concerned, there was a rise in this volatility from early to mid-seventies, with a peak around 1975. Factors such as bracket creeping in the Personal Income Tax in a period of rising inflation[20], and large countercyclical one-off measures around the 1973-75 recession (notably the Nixon tax rebate), despite partly captured by the systematic part of the VAR, may "pass on" to the shocks to some extent. Volatility goes progressively down, to a minimum around 2000, and subsequently there is a large increase toward the end of the sample. This recent evolution should reflect firstly the tax cuts enacted by the Bush II administration and, more recently, the tax and benefit measures included in the stimulus packages of 2008-2009 albeit, similarly to above, these are also accommodated by the systematic reaction to the recession, reinforced by the measured enhanced responsiveness. As a matter of fact, the fall in net taxes in the course of the 2008-09 recession, about 50 percent, was the largest one throughout the simulation period. The corresponding figure for the 1973-75 recession (including the Nixon tax rebate) was around 30 percent, and the one for the 1982-83 recession (contemporary with Reagan's tax cuts) around 20 per cent. The standard deviation of spending shocks remained comparatively more stable, featuring a minor decrease throughout the period.

6 Conclusions

In this paper we presented the results of the simulation of a fiscal policy VAR with time-varying parameters, embedding a non-recursive, Blanchard and Perotti-like identification scheme into a Bayesian simulation procedure. Our evidence suggests that policy effectiveness has come down substantially over the period considered, 1965:2 to 2009:2, particularly as far as net taxes are concerned. On the expenditure side, a fading of the effects of policy shocks is detected as well, but of a much smaller magnitude. Private consumption responds negatively to net tax shocks and very little to expenditure shocks. In this case, the effects are found to remain stable over time. We have also addressed time-variation in the conduct of fiscal policy,

[20] The rates and brackets of the Personal Income Tax remained unchanged between the Tax Reform Act of 1969 and the Tax Reform Act of 1976 (Tax Foundation (2007)).

finding that endogenous net taxes have increasingly reacted to output, while the respective exogenous component has fluctuated much and been particularly volatile in the recent years.

With the exception of the stance of the business cycle, we do not perform any exercise relating the documented time-profile of the fiscal multipliers to possible underlying factors. Many other hypotheses have been put forward in this context, as it is well known, such as the degree of openness of the economy or the easing of liquidity constraints. In order to investigate them in a rigorous manner, one would have to set up a non-linear system whose specification and simulation pose questions that are left to further research.

References

Ahmed, S., A. Levin, and A. Wilson (2004). Recent US macroeconomic stability: good policies, good practices or good luck? *The Review of Economics and Statistics 86*(3), 824–832.

Auerbach, A. J. (2002). Is there a role for discretionary fiscal policy? Working Paper 9306, National Bureau of Economic Research.

Blanchard, O. J. and R. Perotti (2002). An empirical characterization of the dynamic effects of changes in government spending and taxes on output. *Quarterly Journal of Economics 117*(4), 1329–1368.

Boivin, J. (2006). Has monetary policy changed? Evidence from drifting coefficients and real time data. *Journal of Money Credit and Banking 38*(5), 1149–1173.

Carter, C. K. and R. Kohn (1994). On Gibbs sampling for state-space models. *Biometrika 81*(3), 541–553.

Cogley, T. and T. J. Sargent (2001). Evolving post-World War II inflation dynamics. *NBER Macroeconomic Annual 16*, 331–373.

Cogley, T. and T. J. Sargent (2005). Drifts and volatilities: monetary policies and outcomes in the post-WW II US. *Review of Economic dynamics 8*, 262–302.

Galí, J., J. D. Lopez-Salido, and J. Vallés (2007). Understanding the effects of government spending on consumption. *Journal of the European Economic Association 5*, 227–270.

Gambetti, L., E. Pappa, and F. Canova (2008). The structural dynamics of US output and inflation: What explains the changes? *The Journal of Money Credit and Banking 40*(2-3), 369–388.

Hall, R. E. (2009). By how much does GDP rise if government buys more output? *Brookings Papers on Economic Activity* (2), 183–249.

Hansen, B. E. (1990). Lagrange multiplier tests for parameter instability in non-linear models. Working paper, University of Rochester.

Hansen, B. E. (1992). Testing for parameter instability in linear models. *Journal of Policy Modeling 14*(4), 517–533.

Hansen, B. E. (1997). Approximate asymptotic p-values for structural change tests. *Journal of Business and Economic Statistics 15*(1), 60–67.

Kim, C.-J. and C. R. Nelson (1999a). Has the U.S. economy become more stable? A Bayesian approach based on a Markov-switching model of the business cycle. *The Review of Economics and Statistics 81*(4), 608–616.

Kim, C.-J. and C. R. Nelson (1999b). *State space models with regime switching.* Cambridge, Massachusetts: Massachusetts Institute of Technology.

Kim, S., N. Shephard, and S. Chib (1998). Stochastic volatility: likelihood inference and comparison with ARCH models. *Review of Economic Studies 65*, 361–393.

Kirchner, M., J. Cimadomo, and S. Hauptmeier (2010). Transmission of fiscal shocks in the euro area: time variation and driving forces. Research Paper 21/2, Tinbergen Institute.

McConnell, M. M. and G. Perez-Quiros (2000). Output fluctuactions in the United States: what has changed since the early 1980's? *American Economic Review 90*(5), 1464–1476.

Pereira, M. C. (2009). Empirical evidence on the stabilizing role of fiscal and monetary policy in the US. MPRA Paper 19675, University Library of Munich.

Perotti, R. (2004). Estimating the effects of fiscal policy in OECD countries. Working paper, Bocconi University.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies 72*(3), 821–852.

Ramey, V. (2010). Identifying government spending shocks: It's all in the timing. Working paper, University of California, San Diego, forthcoming in Quarterly Journal of Economics.

Sims, C. A. and T. Zha (2006). Where there regime switches in us monetary policy? *The American Economic Review 96*(1), 54–81.

Stock, J. H. and M. W. Watson (2002). Has the business cycle changed and why? Working Paper 9127, National Bureau of Economic Research.

Tax Foundation (2007). Federal individual income tax rates history. Tables, available at www.taxfoundation.org.

Taylor, J. B. (2000). Reassessing discretionary fiscal policy. *The Journal of Economic Perspectives 14*(3), 21–36.

7 Appendices

A Definition of variables and data sources

All the data we use are taken from the *National Income and Product Accounts*, NIPA, which are freely available in the website of the Bureau of Economic Analysis. Fiscal data are from NIPAs Table 3.1., *Government Current Receipts and*

Expenditures: data on the components of government consumption, including the breakdown defense/non-defense, are from NIPAs Table 3.10.5, *Government Consumption Expenditures and General Government Gross Output*; data on social benefits including unemployment and health-related benefits are from NIPAs Table 3.12., *Government social benefits* (annual data, the share for the year as a whole was assumed for the quarter). Gross domestic product is from NIPAs Table 1.1.5., *Gross Domestic Product.* Gross domestic product deflator is from NIPAs Table 1.1.4., *Price Indexes for Gross Domestic Product.* Population is from NIPAs Table 2.1., *Personal income and its Disposition.*

Taxes = Personal current taxes + Taxes on production and imports + Taxes on corporate income + Contributions for government social insurance + Capital transfer receipts (the latter item is composed mostly by gift and inheritance taxes).

Transfers = Subsidies + Government social benefits to persons + Capital transfers paid − Current transfer receipts (from business and persons).

Net taxes = Taxes − Transfers.

Purchases of goods and services = Government consumption − Consumption of fixed capital[21] + Government investment.

B Detailed simulation procedure

The simulation procedure uses the Gibbs sampler, iterating on four steps. Histories of states are sequentially generated and, in the last step, the model's hyperparameters, conditional on the results for the other steps. Throughout this appendix we follow the usual convention of denoting the history of a vector $\mathbf{w}_t$ up to time s, $\{\mathbf{w}_t\}_{t=1}^{s}$, by $\mathbf{w}^s$. The description of the procedure is for the baseline system with four variables, i.e. n equal to 4 and $\mathbf{x}_t$ to $[nt_t, g_t, p_t, y_t]'$.

[21] Consumption of fixed capital is excluded on two grounds. Firstly, there are no shocks to this variable, which is fully determined by the existing capital stock and depreciation rules. Secondly, from the viewpoint of the impact on aggregate demand, it is the cost of capital goods at time of acquisition (already recorded in government investment) that matters and not at time of consumption.

B.1 Step 1 - drawing for the coefficient states (θ_t)

The measurement equation in this step is given by (1). The state-space model is thus

$$\mathbf{x}_t = \mathbf{X}_t \boldsymbol{\theta}_t + \mathbf{u}_t, \tag{A1}$$

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\epsilon}_t^{\theta}, \tag{A2}$$

where $\mathbf{u}_t \sim i.i.d.N(0, \Sigma_t)$, $\boldsymbol{\epsilon}_t^{\theta} \sim i.i.d.N(0, Q^{\theta})$, and $\mathbf{u}_t$ and $\boldsymbol{\epsilon}_t^{\theta}$ are independent. The full history of coefficient states $\boldsymbol{\theta}^T$ is drawn conditional on the data, $\mathbf{x}^T$, a history of covariance and volatility states summarized in Σ^T, and the hyperparameters in Q^{θ}. The posteriori distributions are (see Kim and Nelson (1999b), Ch.8):

$$\boldsymbol{\theta}_T \mid \mathbf{y}^T, \Sigma^T, Q^{\theta} \sim N(\boldsymbol{\theta}_{T|T}, P^{\theta}_{T|T}) \tag{A3}$$

and

$$\boldsymbol{\theta}_t \mid \mathbf{y}^T, \boldsymbol{\theta}_{t+1}, \Sigma^T, Q^{\theta} \sim N(\boldsymbol{\theta}_{t|t,\boldsymbol{\theta}_{t+1}}, P^{\boldsymbol{\theta}}_{t|t,\boldsymbol{\theta}_{t+1}}), t = 1, ..., T-1, \tag{A4}$$

where the conditional mean and variance in expression (A3), $\boldsymbol{\theta}_{T|T}$ and $P^{\boldsymbol{\theta}}_{T|T}$, can be obtained as the last iteration of the usual Kalman filter, going forward from

$$\boldsymbol{\theta}_{t|t} = \boldsymbol{\theta}_{t|t-1} + P^{\theta}_{t|t-1} X_t (X_t' P^{\theta}_{t|t-1} X_t + \Sigma_t)^{-1} (\mathbf{y}_t - X_t' \boldsymbol{\theta}_{t|t-1}),$$
$$P^{\theta}_{t|t} = P^{\theta}_{t|t-1} - P^{\theta}_{t|t-1} X_t (X_t' P^{\theta}_{t|t-1} X_t + \Sigma_t)^{-1} X_t' P^{\theta}_{t|t-1},$$
$$\boldsymbol{\theta}_{t|t-1} = \boldsymbol{\theta}_{t-1|t-1},$$
$$P^{\boldsymbol{\theta}}_{t|t-1} = P^{\boldsymbol{\theta}}_{t-1|t-1} + Q^{\theta},$$

starting from the initial values $\boldsymbol{\theta}_{0|0}$ and $P^{\theta}_{0|0}$. These initial values are given by the mean and covariance matrix of the prior, $\boldsymbol{\theta}_0 \sim N(\hat{\boldsymbol{\theta}}, 4V(\hat{\boldsymbol{\theta}}))$, obtained as coefficient vector and covariance matrix from the OLS estimation of the reduced-form system (1) for the training subsample 1947:1-1959:4. The elements in $\boldsymbol{\theta}^{T-1}$ are drawn from (A4) going backward. That is, $\boldsymbol{\theta}_{T-1}$ is drawn conditional on the realization of $\boldsymbol{\theta}_T$, $\boldsymbol{\theta}_{T-2}$ conditional on the realization of $\boldsymbol{\theta}_{T-1}$ and so on up to $\boldsymbol{\theta}_1$. The conditional mean and variance in (A4) are given by

$$\boldsymbol{\theta}_{t|t,\boldsymbol{\phi}_{t+1}} = \boldsymbol{\theta}_{t|t} + P^{\theta}_{t|t} (P^{\theta}_{t|t} + Q^{\theta})^{-1} (\boldsymbol{\theta}_{t+1} - \boldsymbol{\theta}_{t|t}),$$
$$P^{\theta}_{t|t,\boldsymbol{\theta}_{t+1}} = P^{\theta}_{t|t} - P^{\theta}_{t|t} (P^{\theta}_{t|t} + Q^{\theta})^{-1} P^{\theta}_{t|t}.$$

B.2 Step 2 - drawing for the covariance states ($\mathbf{b}_{i,t}$)

The system of measurement equations is now based on (2), i.e. $A_t\mathbf{u}_t = (B_t - I_n)\mathbf{e}_t + \mathbf{e}_t$, with matrices A_t and B_t as given in (4'). As explained in the text, it is assumed that there is independence between the states in B_t belonging to different equations, that is, the covariance matrix of the state innovations is block-diagonal, with the block for equation i given by Q^{bi}, $i = 1, 3, 4$.

The simulations in this step are conditional on $\mathbf{x}^T$ and $\boldsymbol{\theta}^T$, which makes $\mathbf{u}^T$ observable, a history of volatility states, D^T, and the the hyperparameters in Q^{bi}. Note also that the elements of A_t are known. Since there is independence among states in different equations and, at the same time, the covariance matrix of the error term in the measurement equation (D_tD_t') is diagonal, the state-space problem can be tackled equation by equation. Moreover, the structure of matrix B_t is such that the elements of $\mathbf{e}_t$ entering each equation as regressors are predetermined, so the assumptions of the linear state-space model are met.

The simulations proceed in the following sequence. Firstly, given $\mathbf{u}^T$ and A^T, e_g^T is observable. The first state-space problem is

$$u_{p,t} = e_{g,t}\mathbf{b}_{3,t} + e_{p,t}, \tag{A5}$$

$$\mathbf{b}_{3,t} = \mathbf{b}_{3,t-1} + \boldsymbol{\epsilon}_t^{b3}, \tag{A6}$$

where $\mathbf{b}_{3,t} = [\beta_{32,t}]$, $e_{p,t} \sim i.i.d.N(0, d_{33}^2)$, d_{33} denoting the third element in the main diagonal of $\mathbf{D}_t$, $\epsilon_t^{b3} \sim i.i.d.N(0, Q^{b3})$, and $e_{p,t}$ and $\boldsymbol{\epsilon}_{i,t}^{b3}$ are independent. This simulation yields a history b_3^T and, conditional on it, a history e_p^T.

The next state-space model is

$$u_{nt,t} - a_{14}^{*}u_{y,t} = [e_{g,t}e_{p,t}]\mathbf{b}_{1,t} + e_{nt,t}, \tag{A7}$$

$$\mathbf{b}_{1,t} = \mathbf{b}_{1,t-1} + \boldsymbol{\epsilon}_t^{b1}, \tag{A8}$$

where $\mathbf{b}_{1,t} = [\beta_{12,t}\beta_{13,t}]$, $e_{p,t} \sim i.i.d.N(0, d_{11}^2)$, d_{11} denoting the first element in the main diagonal of $\mathbf{D}_t$, $\boldsymbol{\epsilon}_t^{b1} \sim i.i.d.N(0, Q^{b1})$, and $e_{nt,t}$ and $\boldsymbol{\epsilon}_t^{b1}$ are independent. This simulation yields a history $\mathbf{b}_1^T$ and, conditional on it, a history e_{nt}^T.

The third state-space problem is

$$u_{y,t} = [e_{nt,t} e_{g,t} e_{p,t}]\mathbf{b}_{4,t} + e_{y,t}, \tag{A9}$$

$$\mathbf{b}_{4,t} = \mathbf{b}_{4,t-1} + \boldsymbol{\epsilon}_t^{b4}, \tag{A10}$$

where $\mathbf{b}_{4,t} = [\beta_{41,t}\beta_{42,t}\beta_{43,t}]$, $e_{y,t} \sim i.i.d.N(0, d_{44}^2)$, d_{44} denoting the fourth element in the main diagonal of D_t, $\boldsymbol{\epsilon}_t^{b4} \sim i.i.d.N(0, Q^{b4})$ and $e_{y,t}$ and $\boldsymbol{\epsilon}_t^{b4}$ are independent. This simulation yields $\mathbf{b}_4^T$ and, conditional on it, a history e_y^T.

The simulations for each of the three state-space models are conducted precisely in the same way as described for Step 1, on the basis of the distributions corresponding to (A3) and (A4) above. The initial values for the Kalman filter, $\mathbf{b}_{i,0|0}$ and $P_{0|0}^{b_i}$, are from the mean and covariance matrix of the priors: $\mathbf{b}_{i,0} \sim N(\hat{\mathbf{b}}_i, 4V(\hat{\mathbf{b}}_i))$. These parameters are obtained from estimating by OLS the structural decomposition (4') for the training subsample 1947:1-1959:4.

B.3 Step 3 - drawing for the volatility states ($\mathbf{D}_t$)

The system of measurement equations is now based in (3), i.e. $\mathbf{e}_t = \mathbf{D}_t\boldsymbol{\varepsilon}_t$. Squaring and taking logarithms on both sides of each measurement equation, the state-space model becomes:

$$\mathbf{e}_t^+ = 2\log\mathbf{d}_t + \log\boldsymbol{\varepsilon}_t^2, \tag{A11}$$

$$\log\mathbf{d}_t = \log\mathbf{d}_{t-1} + \boldsymbol{\epsilon}_t^d, \tag{A12}$$

where $\mathbf{e}_t^+ = \log(\mathbf{e}_t^2 + 0.001)$ denotes the logarithm of the square of each element of $\mathbf{e}_t$ plus a offsetting constant equal to 0.001, $\log\mathbf{d}_t$ denotes the elementwise logarithm of the vector $\mathbf{d}_t$ and $\log(\boldsymbol{\varepsilon}_t^2)$ the elementwise logarithm of the vector $\boldsymbol{\varepsilon}_t$. Furthermore, $\epsilon_t^d \sim i.i.d.N(0, Q^d)$ and, since $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\epsilon}_t^d$ are independent, the same applies to $\log\boldsymbol{\varepsilon}_t^2$ and $\boldsymbol{\epsilon}_t^d$.[22]

[22] This description of the simulation procedure assumes that the covariance matrix of the state innovations, Q^d, is unrestricted and thus the volatility states are drawn jointly. One could alternatively assume a diagonal Q^d matrix — i.e. independent state innovations —, in which case the

The algorithms for the Gaussian linear state space model cannot be directly applied in this case, because the disturbances $\log \boldsymbol{\varepsilon}^2_{i,t}, i = 1, ...4$, are not Gaussian. The distribution of these disturbances can, however, be approximated using a mixture of seven Gaussian densities (see Kim et al. (1998) for the details):

$$f(\log \boldsymbol{\varepsilon}^2_{i,t}) \approx \textstyle\sum_{j=1}^{7} q_j f_N(\log \boldsymbol{\varepsilon}^2_{i,t}; m_j - 1.2704, v_j^2), \tag{A13}$$

where q_j, m_j and v_j^2 are known constants which depend on j. Then, conditioning on the realization of an indicator random variable $s_{i,t}, i = 1, ...4$, taking on values in $\{1, 2, 3, 4, 5, 6, 7\}$, one element of the family of normals is selected:

$$\log \boldsymbol{\varepsilon}^2_{i,t} \mid s_{i,t} = j \sim N(m_j - 1.2704, v_j^2). \tag{A14}$$

Therefore, a history $\log \mathbf{d}^T$ can be drawn conditional on $\mathbf{s}^T$, in addition to $\mathbf{x}^T$, $\boldsymbol{\theta}^T$, $\mathbf{B}^T$(making $\mathbf{e}^T$ or $\mathbf{e}_t^{+T}$ observable) and the hyperparameters in Q^d. It is straightforward to adapt the formulae in Step 1 to this end. The initial values for the Kalman filter are, as previously, from the mean and covariance matrix of the prior which is given by $\log \mathbf{d}_0 \sim N(\log \hat{\mathbf{d}}, I_n)$. The figures in $\log \hat{\mathbf{d}}$ are the log standard deviations of the structural shocks from the abovementioned estimation of the system in the training subsample.

B.3.1 Step 3A: drawing for s_t

A history $\mathbf{s}^T$ is sampled independently for $i = 1, ..., 4$ and $t = 1, ...T$, given $\mathbf{e}_t^{+T}$ and $\log \mathbf{d}^T$, using the following result

$$Pr(s_{i,t} = j \mid \mathbf{e}^+_{i,t}, \log d_{i,t}) \propto q_j f_N(\mathbf{e}^+_{i,t}; 2 \log d_{i,t} + m_j - 1.2704, v_j^2), \tag{A15}$$

with j defined in $\{1, 2, 3, 4, 5, 6, 7\}$ and q_j, m_j and v_j^2 known constants.

simulations would be carried out equation by equation. We experimented with both possibilities and the results were similar.

B.4 Step 4: Drawing for the hyperparameters

The prior and posterior distributions of the hyperparameters are conjugate inverse-Wishart. The hyperparameters are drawn conditioning on the data and histories of coefficient, covariance and volatility states, which makes the innovations in all state equations (i.e. $\boldsymbol{\epsilon}^{\theta T}$, $\boldsymbol{\epsilon}^{b1T}$, $\boldsymbol{\epsilon}^{b3T}$, $\boldsymbol{\epsilon}^{b4T}$ and $\boldsymbol{\epsilon}^{dT}$) observable.

The prior distribution of Q^{θ} is $IW(\bar{Q}^{\theta}, T_0)$, with $\bar{Q}^{\theta} = k_{\theta}^2 T_0 V(\hat{\boldsymbol{\theta}})$, where $V(\hat{\boldsymbol{\theta}})$ is the covariance matrix of the reduced-form coefficients, used to calibrate the prior for $\boldsymbol{\theta}_0$ above, T_0 is the number of observations in the training sample[23] and k_{θ}^2 is a chosen parameter. We set k_{θ} to 0.01. The posteriori distribution of Q^{θ} is $IW((\bar{Q}^{\theta} + \sum_{t=1}^{T} \boldsymbol{\epsilon}_t^{\theta} \boldsymbol{\epsilon}_t^{\theta\prime})^{-1}, T_0 + T)$.

The prior distribution for Q^{b3} is $IW(\bar{Q}^{b3}, 2)$, with $\bar{Q}^{b3} = 2k_b^2 V(\hat{\mathbf{b}}_3)$, where $V(\hat{\mathbf{b}}_3)$ is the covariance matrix of the coefficients of the structural decomposition, used to calibrate the prior for $\mathbf{b}_{3,0}$ above, and k_b^2 is a chosen parameter. This parameter is set to 0.1. The posterior for Q^{b3} is given by $IW((\bar{Q}^{b3} + \sum_{t=1}^{T} \boldsymbol{\epsilon}^{b3} \boldsymbol{\epsilon}^{b3\prime})^{-1}, 2 + T)$.

The prior distribution for Q^{b1} is $IW(\bar{Q}^{b1}, 3)$, with $\bar{Q}^{b1} = 3k_b^2 V(\hat{\mathbf{b}}_1)$, where $V(\hat{\mathbf{b}}_1)$ is the covariance matrix of the coefficients of the structural decomposition, used to calibrate the prior for $\mathbf{b}_{1,0}$ above, and k_b^2 equal to 0.1. The posterior for Q^{b1} is given by $IW((\bar{Q}^{b1} + \sum_{t=1}^{T} \boldsymbol{\epsilon}^{b1} \boldsymbol{\epsilon}^{b1\prime})^{-1}, 3 + T)$.

The prior distribution for Q^{b4} is $IW(\bar{Q}^{b4}, 4)$, with $\bar{Q}^{b4} = 4k_b^2 V(\hat{\mathbf{b}}_4)$, where $V(\hat{\mathbf{b}}_4)$ is the covariance matrix of the coefficients of the structural decomposition, used to calibrate the prior for $\mathbf{b}_{4,0}$ above, and k_b^2 is equal to to 0.1. The posterior for Q^{b4} is given by $IW((\bar{Q}^{b4} + \sum_{t=1}^{T} \boldsymbol{\epsilon}^{b4} \boldsymbol{\epsilon}^{b4\prime})^{-1}, 4 + T)$.

The prior distribution for Q^{d} is $IW(\bar{Q}^{d}, 5)$, with $\bar{Q}^{d} = 5k_d^2 I_4$, where k_d^2 is a chosen parameter. This is set to 0.01. The posterior for Q^{d} is given by $IW((\bar{Q}^{d} + \sum_{t=1}^{T} \boldsymbol{\epsilon}^{d} \boldsymbol{\epsilon}^{d\prime})^{-1}, 5 + T)$.

[23] In the 5-variable system including private consumption, T_0 is set to 56. This is equal to the size of the vector $\boldsymbol{\theta}_t$ plus 1, the minimum number of degrees of freedom for the prior to be proper (and exceeds the number of observations in the training sample).

B.5 Convergence diagnostics for the simulation procedure

We conclude this appendix by reporting a set of results concerning autocorrelations of the draws. The convergence of the Gibbs sampler is known to be faster when the draws are approximately independent. Following Primiceri (2005), we report the 20th sample autocorrelation of the kept draws for last iteration of the Gibbs sampler, corresponding to the simulation period 1960:1-2009:2. The number of parameters is very large and we thus present this statistic for a selection comprising the coefficient states in the first equation ($1782 = 9 \times 198$), the volatility states ($792 = 4 \times 98$) and the hyperparameters (686). Figure 7 shows that the autocorrelations are close to zero in most cases and, when they are higher, remain nevertheless below 0.2. The only exception is for the hyperparameters in Q^{bi}, featuring autocorrelations in the range from 0.2 to 0.3 (see the end of the third panel).

C Mapping between the identification schemes (4) and (4') in Section 2

The system of equations implied by scheme (4) in Section 2 is

$$u_t^{nt} = a_{13}u_t^p + a_{14}^* u_t^y + b_{12}e_t^g + e_t^{nt}, \tag{B1}$$

$$u_t^g = a_{23}^* u_t^p + e_t^g, \tag{B2}$$

$$u_t^p = a_{32}u_t^g + e_t^p, \tag{B3}$$

$$u_t^y = a_{41}u_t^{nt} + a_{42}u_t^g + a_{43}u_t^p + e_t^y. \tag{B4}$$

Note that equation (B2) has no unknown parameters. In order to reparameterize equation (B3), one has to replace u_t^g as given by (B2) in it, yielding

$$u_t^p = \beta_{32}e_t^g + e_t^{+p}, \tag{B3'}$$

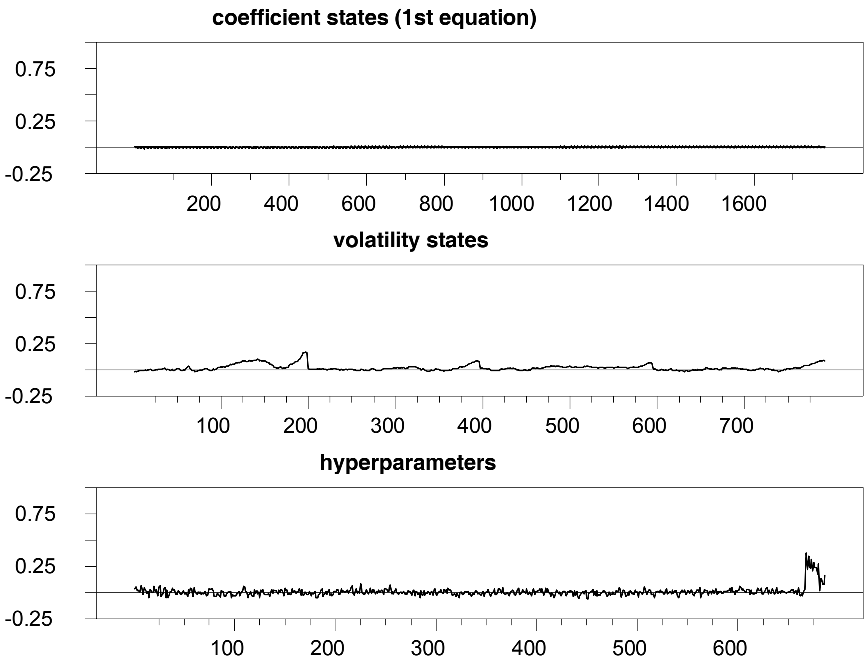

Figure 7: Autocorrelation of the draws for selected sets of parameters

where $\beta_{32} = a_{32}/(1 - a_{32}a_{23}^*)$ and $e_t^{+p} = e_t^p/(1 - a_{32}a_{23}^*)$.

Consider now equation (B1). Using the expression for u_t^p in (B3') and simplifying yields

$$u_t^{nt} - a_{14}^* u_t^y = \beta_{12} e_t^g + \beta_{13} \varepsilon_t^{+p} + e_t^{nt}, \tag{B1'}$$

where $\beta_{12} = b_{12} + \beta_{32} a_{13}$ and $\beta_{13} = a_{13}$.

Finally, equation (B4) can be rewritten as

$$u_t^y = \beta_{41} e_t^{nt} + \beta_{42} e_t^g + \beta_{43} \varepsilon_t^{+p} + e_t^{+y} \tag{B4'}$$

where $\beta_{41} = (1 - a_{41}a_{14}^*)^{-1} a_{41}$, $\beta_{42} = (1 - a_{41}a_{14}^*)^{-1}[(a_{41}a_{13} + a_{42}a_{23}^* + a_{43})\beta_{32} + a_{41}b_{12} + a_{42}]$, $\beta_{43} = (1 - a_{41}a_{14}^*)^{-1}(a_{41}a_{13} + a_{42}a_{23}^* + a_{43})$ and $e_t^{+y} = e_t^y/(1 - a_{41}a_{14}^*)$.

It is easy to check that the set of equations implied by scheme (4') in Section 2 consists of (B1'), (B2), (B3') and (B4').