Monetary Policy Neutrality? Sign Restrictions Go to MonteCarlo*

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Abstract

An estimated new-Keynesian DSGE model is estimated with U.S. data and used in a MonteCarlo exercise to generate artificial data with which VARs are estimated. Sign restrictions are imposed to identify the effects of a monetary policy shock with such VARs. Our exercise replicates Uhlig's (2005, *Journal of Monetary Economics*) result consistent with monetary policy shocks exerting very uncertain effects on output. We find this result to be driven by the very low participation of policy shocks to the variance of output. Sign restrictions are shown to correctly identify the negative effects on output in an alternative world in which the share of output variance explained by monetary policy shocks is counterfactually magnified. Under the imposition of a standard restriction on output, the outcome of our MonteCarlo exercise turns out to be very similar to that stemming from the use of actual U.S. great moderation data.

JEL classification: C22, E47, E52.

Keywords: Monetary policy shocks, VARs, sign restrictions, Dynamic Stochastic General Equilibrium models, monetary neutrality.

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1 Introduction

Conventional wisdom on the effects of monetary policy shocks is as follows. An unexpected policy rate hike increases the real interest rate, depresses demand on aggregate, therefore pushing inflation down in the short-run. An intriguing exercise by Uhlig (2005) cast doubts on this transmission mechanism. Working with a VAR estimated with post-WWII U.S. data, Uhlig (2005) shows that the response of output to a monetary policy shock is surrounded by a large amount of uncertainty, a result consistent with monetary policy neutrality.

This paper shows that such results may be obtained with data generated by a structural model in which monetary policy shocks *do* affect the macroeconomic environment as suggested by conventional wisdom. We set up a MonteCarlo exercise in which the Data Generating Process (DGP) is a new-Keynesian DSGE model predicting "textbook" effects as the reaction of output to monetary policy shocks. The DSGE model is estimated with U.S. quarterly data to condition our analysis on an empirically plausible DGP. Then, we feed our VARs with artificial data and identify a monetary policy shock by imposing a set of widely-accepted restrictions on the reactions of a set of macroeconomics variables (policy rate, inflation, output). Following Uhlig, we leave the reaction of output unconstrained at all horizons. In other words, we allow (but not require) output to react positively to a monetary policy shock. Jointly, we consider further restrictions to identify other structural shocks. We follow our strategy to augment the probability of correctly identify the shock of interest (Paustian (2007)). Such restrictions are consistent with a variety of models in the literature, our framework included.

Our results read as follows. The estimated DGSE model of the business cycle predicts a phase of economic bust and deflation after a policy tightening. However, our VARs return quite uncertain indications as for the reaction of output. In particular, about 2/3 of the responses conditional on a monetary policy unexpected tightening are positive, a result consistent with Uhlig's (2005) evidence based on U.S. data. Therefore, we are able to replicate Uhlig's (2005) evidence with VARs estimated with data generated by a DGP that clearly assigns monetary policy shocks a role. Our results suggest that Uhlig's (2005) evidence may also be interpreted as consistent with monetary policy *non*-neutrality. Further investigations show that our result is driven by the relatively little role played by policy shocks in determining the variance of output in our sample. When counterfactually augmenting policy shock's contribution to the simulated macroeconomic environment, sign restrictions are shown to correctly identify the negative effects on output. This result suggest that, *in principle*, nothing is wrong with the sign restrictions methodology. However, we confirm the result in Paustian (2007), i.e., sing restrictions are more likely to work well the more important (in relative terms) the shock of interest is. We then move to an exercise with actual U.S. data processed with a Sign Restrictions VAR (SRVAR). Intriguingly, we find reactions extremely close to those arising from a MonteCarlo exercise in which the same set of restrictions is imposed to both artificial and actual U.S. data. This result corroborates the employment of our DSGE model as DGP in our MonteCarlo exercise.

Before moving to the next Section, we note connections with some related literature. Fernández-Villaverde and Rubio-Ramírez (2006) and Fernández-Villaverde, Rubio-Ramírez, Sargent, and Watson (2007) derive a necessary condition to ensure the existence of the VAR representation of a DSGE model (i.e. to check if the DSGE model is 'invertible').[1] Ravenna (2007) discusses under which conditions a finite VAR representation exists, and shows that truncated VARs may provide misleading indications when the true DGP is an infinite order VAR. Further investigations on the distortions

[1] A VAR is invertible if its innovations do map into the shocks of the economic model even in population and under the correct identification scheme. Non-invertibilities typically arise when some relevant state variables of the model are not included in the VAR (for instance, because they are not observable). The relevance of non-invertibility is, of course, an empirical issue - see e.g. Sims (2009).

coming from the truncation bias, mainly focused on the identification of the effects of a technology shock on hours worked, are offered by Christiano, Eichenbaum, and Vigfusson (2006) and Chari, Kehoe, and McGrattan (2008). With respect to these contributions, we consider an invertible DSGE model that enjoys a finite order VAR(2) representation, i.e. no truncation bias is at work (in population). Carlstrom, Fuerst, and Paustian (2009) propose a theoretical investigation on the consequences of the timing discrepancy between DSGE and CVARs as for the macroeconomic reactions to a monetary policy shock. They show that, a-priori, 'anything goes', i.e. conditional on given calibrations of the DSGE model, CVARs may return a variety of predictions, including price and output puzzles, responses in line with the true DSGE reactions, muted responses, and so on. Our analysis provide empirical support to the simulations proposed by Canova and Pina (2005) and Carlstrom, Fuerst, and Paustian (2009), in that we deal with i) an *estimated* DSGE and ii) sign restrictions, as opposed to the Cholesky-identification scheme.

The paper develops as follows. Section 2 presents and estimates a standard new-Keynesian DSGE model with U.S. data. Such model is employed as DGP in Section 3, which sets up our Monte Carlo experiment. In this Section we contrast the impulse responses generated with our estimated DSGE with those coming from the SVARs in a controlled environment. Moreover, we propose an analysis based on actual U.S. data, and contrasts our results with those obtained with our simulations. Section 4 concludes.

2 A DSGE model as DGP

2.1 Model presentation

We work with a standard DSGE model. The log-linearized version of the model is the following:

$$\pi_t = (1+\alpha\beta)^{-1}[\beta E_t \pi_{t+1} + \alpha \pi_{t-1} + \kappa y_t + \varepsilon_t^{\pi}], \quad (1)$$

$$y_t = \gamma E_t y_{t+1} + (1-\gamma) y_{t-1} - \sigma^{-1}(R_t - E_t \pi_{t+1}) + Q(\rho_a - 1) a_t, \quad (2)$$

$$R_t = (1-\tau_R)(\tau_\pi \pi_t + \tau_y y_t) + \tau_R R_{t-1} + \varepsilon_t^R, \quad (3)$$

Eq. (1) is an expectational new-Keynesian Phillips curve (NKPC) in which π_t stands for the inflation rate, β represents the discount factor, y_t identifies the output gap, whose impact on current inflation is influenced by the slope-parameter κ, α identifies indexation to past inflation, and ε_t^{π} represents the 'cost-push' shock; γ is the weight of the forward-looking component in the intertemporal IS curve (2); σ^{-1} is the households' intertemporal elasticity of substitution; the convolution $Q \equiv (1+\nu)(\sigma+\nu)^{-1}$ involves the inverse of the Frisch labor elasticity ν, and a_t identifies the technological shock; τ_π, τ_y, and τ_R are policy parameters in the Taylor rule (3); the monetary policy shock ε_t^R allows for a stochastic evolution of the policy rate.

The model is closed with the following stochastic processes:

$$\begin{bmatrix} \varepsilon_t^{\pi} \\ a_t \\ \varepsilon_t^R \end{bmatrix} = \boldsymbol{F} \begin{bmatrix} \varepsilon_{t-1}^{\pi} \\ a_{t-1} \\ \varepsilon_{t-1}^R \end{bmatrix} + \begin{bmatrix} u_t^{\pi} \\ u_t^a \\ u_t^R \end{bmatrix}, \boldsymbol{F} \equiv \begin{bmatrix} \rho_\pi & 0 & 0 \\ 0 & \rho_a & 0 \\ 0 & 0 & \rho_R \end{bmatrix}, \quad (4)$$

where the martingale differences, mutually independent processes $\boldsymbol{u}_t$ are distributed as

$$\begin{bmatrix} u_t^{\pi} \\ u_t^a \\ u_t^R \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\pi^2 & 0 & 0 \\ 0 & \sigma_\pi^2 & 0 \\ 0 & 0 & \sigma_R^2 \end{bmatrix} \right). \quad (5)$$

This or similar small-scale models have successfully been employed to conduct empirical analysis concerning the U.S. economy. Clarida, Galí, and Gertler (2000) and Lubik and Schorfheide (2004) have investigated the influence of systematic monetary policy over the U.S. macroeconomic dynamics; Boivin and Giannoni (2006), Benati and

Surico (2009), Canova (2009), and Lubik and Surico (2010) have replicated the U.S. great moderation; Benati (2008) and Benati and Surico (2008) have investigated the drivers of the U.S. inflation persistence; Ireland (2007) and Cogley, Primiceri, and Sargent (2010) have scrutinized the role of shocks to the low frequency component of the U.S. inflation.[2]

2.2 Model estimation

We estimate the model (1)-(5) with Bayesian methods. We work with quarterly U.S. data, sample: 1984:I-2008:II. This sample roughly coincides with the great moderation, a period beginning in the mid-1980s (McConnell and Perez-Quiros (2000)). The choice of this sample allows us to control for policy parameters' instability (Clarida, Galí, and Gertler (2000) and subsequent contributions), heteroskedasticity of the structural shocks (Justiniano and Primiceri (2008)), and omitted variables as, e.g., real money balances, which may have played an important role in determining output in the 1970s (Castelnuovo (2011)). Moreover, instabilities concerning VARs estimated over post-WWII and regarding the appointment of Paul Volcker as Federal Reserve Chairman have been detected by Bagliano and Favero (1998) and Castelnuovo and Surico (2010). Our sample ends in 2008:II to exclude the acceleration of the financial crises began with the bankruptcy of Lehman Brothers in September 2008, which triggered non-standard policy moves by the Federal Reserve. We employ three observables, which we demean prior to estimation. The output gap is computed as log-deviation of the real GDP with respect to the potential output estimated by the Congressional Budget Office. The inflation rate is the quarterly growth rate of the GDP deflator. For the short-term

[2] A richer description of the U.S. macroeconomic dynamics is provided by models à la Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Justiniano and Primiceri (2008), which feature a larger variety of shocks and frictions. The small-scale model presented in this Section allows us to maintain a firm control of the mapping between our DSGE model's impulse responses and the CVARs' responses in our MonteCarlo exercise presented in the next Section. We leave exercises on the CVAR's ability to recover the true effects of a monetary policy shock generated with larger scale-frameworks to future research.

nominal interest rate we consider the effective federal funds rate expressed in quarterly terms (averages of monthly values) . The source of the data is the Federal Reserve Bank of St. Louis' website.

The vector $\boldsymbol{\xi} = [\beta, \upsilon, \kappa, \alpha, \gamma, \sigma, \tau_{\pi}, \tau_{y}, \tau_{R}, \rho_{a}, \rho_{\pi}, \rho_{R}, \sigma_{a}, \sigma_{\pi}, \sigma_{R}]^{T}$ collects the parameters characterizing the model. We set $\beta = 0.99$ and $\nu = 1$, a very standard calibration in the literature.[3] The remaining priors are collected in Table 1. Details on the Bayesian algorithm are relegated in an Appendix available upon request.

Our posterior estimates are reported in Table 1. All the estimated parameters take conventional values. The parameters of the policy rule suggest an aggressive conduct to dampen inflation fluctuations, and a high degree of policy gradualism; the estimated degree of price indexation (posterior mean) is 0.09 (90% credible set: $[0.01, 0.17]$); the estimated weight of the forward looking component in the IS curve is 0.78 (90% credible set: $[0.70, 0.86]$). Figure 2 compares the actual series we aim at tracking with the DSGE's one step ahead predictions. This figure suggests that our estimated model enjoys a very good short-term predictive power over the three observables we employ in our empirical exercise.

3 Impulse responses: DSGE vs. SRVARs

3.1 MonteCarlo exercise

We now turn to the assessment of the ability of a CVAR to recover the effects of the true structural monetary policy shock u_t^R. Basically, we aim at comparing the true (DSGE-consistent) impulse responses with those produced with a VAR whose monetary policy shock is identified with sign restrictions. Our algorithm works as follows.

For $k = 1$ to K,

1. we sample a realization of the vector $\boldsymbol{\xi}^k$ from the estimated posterior density

[3] Perturbations of this baseline calibration confirmed the robustness of our results.

$p(\boldsymbol{\xi}\,|\,\boldsymbol{Y})$, where $\boldsymbol{Y}$ is the set of observables employed to estimate our model;

2. we compute the DSGE model-consistent impulse responses conditional on $\boldsymbol{\xi}^k$ to an unexpected nominal interest rate hike, and store them in the $[3xHxK]$ $\boldsymbol{DSGE\_IRFs}$ matrix, which accounts for the $[3x1]$ vector of variables we focus on, the $h \in \{1, ..., H\}$ step-ahead of the impulse responses of interest, and the $k \in \{1, ..., K\}$ draw of the vector of structural parameters $\boldsymbol{\xi}$;

3. we feed our VARs with the artificial data $\boldsymbol{x}^k_{ps,[3:T]}$ (ordering: inflation, output gap, nominal rate) generated with the DSGE model conditional on $\boldsymbol{\xi}^k$, compute the impulse responses to a monetary policy shock with sign restrictions (see explanation below), and store them in the $[3xHxK]$ $\boldsymbol{SRVAR\_IRFs}$ matrix.[4]

We run this algorithm by setting the number of repetitions $K = 5,000$, the horizon of the impulse response functions $H = 15$, and the length of the pseudo-data sample $T = 98$. This sample numerosity coincides with that of the actual data sample (1984:I-2008:II) we employed to estimate our DSGE model. Monetary policy shocks are normalized to induce an on-impact equilibrium reaction of the nominal rate equivalent to 25 quarterly basis points.

3.2 Sign restrictions

Sign restrictions represent an alternative strategy to identify a structural shock in VAR analysis. A non-exhaustive list of recent applications include Faust (1998), Canova and de Nicoló (2002), Franchi (2004), Peersman (2005), Canova and Pina (2005), Uhlig (2005), Farrant and Peersman (2006), and Rubio-Ramírez, Waggoner, and Zha (2010).

[4] Given that the DSGE model we deal with features a finite VAR(2) representation, our VARs are estimated with two lags. Robustness checks dealing with the optimal choice of the VAR lag-length based on the Schwarz criterion supported the solidity of our results. We also verified the robustness of our results to the imposition of DSGE model-consistent matrices to the VAR structure, and to the employment of an upper triangular (as opposed to the lower triangular used here) impulse matrix. These robustness checks are available upon request.

Canova and Paustian (2010) propose an algorithm which exploits sign restrictions to validate business cycle models.

In a nutshell, the idea is that of imposing sign restrictions *ex post* on a set of impulse responses. The advantage of sign restrictions is that of being able to replicate the true timing of the impact of a monetary policy shock on inflation and output without imposing any false zero restrictions on the impulse vector $\boldsymbol{B}[:,3]$.

In our application, we estimate $\boldsymbol{A}(L)$ and $\boldsymbol{\Lambda}$ from the data by using OLS. Then, we orthogonalize the VAR residuals via an eigenvalue-eigenvector decomposition such that $\boldsymbol{\Lambda} = \boldsymbol{P}\boldsymbol{D}\boldsymbol{P}^T$, where $\boldsymbol{P}$ is the matrix of eigenvectors and $\boldsymbol{D}$ is the diagonal matrix of eigenvalues. The non-uniqueness of the MA representation of the VAR is exploited to provide a set of alternative proposals for the shock(s) of interest via the employment of three Givens rotation matrixes $\boldsymbol{Q}_{ij}(\omega)$, where $\omega \in (0, 2\pi)$, and $\boldsymbol{R} = \boldsymbol{Q}_{12}(\omega_1)\boldsymbol{Q}_{13}(\omega_2)\boldsymbol{Q}_{23}(\omega_3), \boldsymbol{R}\boldsymbol{R}^T = \boldsymbol{I}_3$. The 'impulse' matrix loading the VAR with candidate 'shocks' is therefore given by $\widetilde{\boldsymbol{B}}(\boldsymbol{\omega}) = \boldsymbol{P}\boldsymbol{D}^{1/2}\boldsymbol{R}(\boldsymbol{\omega})$. If the impulse responses to the 'candidate' shocks satisfy all the required restrictions, then the draw $\boldsymbol{\omega}$ and responses are retained; otherwise, they are discarded.[5]

3.3 Results

We identify the monetary policy shock by imposing "textbook" constraints on the impulse responses of inflation, output, and the policy rate, i.e. by requiring non-positive (non-negative) realizations of inflation and output (quarters 1 and 2) and non-negative (non-positive) realizations of the policy rate (quarters 1, 2, and 3) after a shock.

Figure 1 (top row) depicts the impulse responses to a monetary policy shock obtained with sign restrictions in our in lab-exercise. Sign restrictions deliver negative reactions of inflation and output. The patterns are clear. A monetary policy impulse triggers a persistent output bust and a deflation. These indications are qualitatively in line

[5] For a textbook exposition on sign restrictions see Canova (2007), Chapter 4.

with our DSGE framework's. Then, sign restrictions, which do not hinge upon any zero restrictions, deliver result supporting monetary policy's ability to influence the economic conditions and inflation.

Some discrepancies occur from the quantitative standpoint. In particular, the magnitude of the output gap reaction is clearly overestimated. Paustian (2007) shows that sign restrictions work well the standard deviation of the shock one aims at identifying is large enough with respect to the remaining shocks' standard deviations. To investigate this issue, we re-run our in-lab exercise with the standard deviation of the monetary policy shock counterfactually increased by a factor of ten.

Figure 1 (bottom row) depicts the outcome of this exercise. Interestingly, all the responses are consistently and precisely estimated. Paustian (2007) stresses also the importance of imposing enough restrictions to the system of impulse responses. Our in lab exercise suggests that, once the policy shock's variance is large enough, our set of restrictions is sufficient to recover to true effects of a monetary policy shock.

These responses are robust to different perturbations of the restrictions imposed in our baseline case. We experimented with the following alternative scenarios:

i) identification based on a larger set of *on-impact restrictions involving other structural shocks*. On top of the restrictions imposed in our baseline case, we asked for non-negative (non-positive) realizations of inflation, output, and the policy rate as for the technology shock; and non-positive (non-negative) realizations of inflation and the policy rate, and non-negative (non-positive) realizations of the output gap as for the cost-push shock;

ii) identification based on *restrictions up to* $h = 4$ (fourth quarter) for all the variables of the vector.

3.4 The Uligh (2005) approach

Uhlig (2005) proposes an exercise in which the identification of the monetary policy shock does not rely upon any restrictions as for the reaction of ouput. Notice that, according to our DGP, the monetary policy shock is the only one, among the three structural shocks of our DSGE model, to cause a negative short-run correlation between inflation and the policy rate. Hence, we may very well drop the restrictions imposed on output in the former exercises without reducing our chances of identifying our policy shock.

The estimated impulse responses generated by this exercise are depicted in Figure 2 (top row). The responses of inflation and the policy rate are very similar to those found when imposing the reaction of output. In contrasts, the reaction of output looks dramatically different. In fact, most of the short run realizations suggest a positive reaction of output to an unexpected monetary policy tightening. This evidence mimics the intriguing result by Uhlig (2005), who finds no clear effect of monetary policy shocks on real GDP, a result consistent with monetary policy neutrality in the short run.

Interestingly, when boosting the magnitude of the structural monetary policy shock's standard deviation by a factor of ten, the set of restrictions 'à la Uhlig (2005)' recovers the true effects of a policy shock successfully (Figure 2, bottom row). Consequently, a possible reading of Uhlig's result is the following. Monetary policy shocks create recessions. However, a particular set of sign restrictions may generate a positive response of output in samples in which the variance of the policy shocks is not high enough (in relative terms with respect to the remaining shocks' variances).

What do actual U.S. data suggest as for the effects of a monetary policy shock identified via sign restrictions? Figure 3 (magenta lines) shows the impulse responses obtained when applying the restrictions imposed in our baseline scenario to the 1984:I-2008:II U.S. data. A number of interesting findings emerge. The reaction of output is larger than the one estimated with our structural DSGE model. The prediction of our SRVAR estimated with actual data, however, is very similar to the one obtained when feeding our SRVAR with pseudo-data (impulse responses plotted again in Figure 3 for ease of comparison). We conjecture that our SRVAR responses estimated with actual data may be importantly affected by the relatively low volatility of the monetary policy shock in the sample under scrutiny. Nevertheless, our estimated responses clearly predict a pattern for inflation and output qualitatively in line with the one produced by our estimated DSGE model, i.e. a persistent deflation and a recession.

4 Conclusions

An estimated new-Keynesian DSGE model is estimated with U.S. data and used in a MonteCarlo exercise to generate artificial data with which VARs are estimated. Sign restrictions are imposed to identify the effects of a monetary policy shock with such VARs. Our exercise replicates Uhlig's (2005) result consistent with monetary policy shocks exerting very uncertain effects on output. This result is due to the very low participation of policy shocks to the variance of output. Sign restrictions are shown to correctly identify the negative effects on output in an alternative world in which the share of output variance explained by monetary policy shocks is counterfactually magnified. Under the imposition of a standard restriction on output, the outcome of our MonteCarlo exercise turns out to be very similar to that stemming from the use of actual U.S. great moderation data.

Appendix - Bayesian estimation

To perform our Bayesian estimations we employed `DYNARE`, a set of algorithms developed by Michel Juillard and collaborators (Adjemian, Bastani, Juillard, Mihoubi, Perendia, Ratto, and Villemot (2011)). `DYNARE` is freely available at the following URL:

http://www.dynare.org/.

The simulation of the target distribution is basically based on two steps.

- First, we initialized the variance-covariance matrix of the proposal distribution and employed a standard random-walk Metropolis-Hastings for the first $t \leq t_0 = 20,000$ draws. To do so, we computed the posterior mode by the "csminwel" algorithm developed by Chris Sims. The inverse of the Hessian of the target distribution evaluated at the posterior mode was used to define the variance-covariance matrix C_0 of the proposal distribution. The initial VCV matrix of the forecast errors in the Kalman filter was set to be equal to the unconditional variance of the state variables. We used the steady-state of the model to initialize the state vector in the Kalman filter.

- Second, we implemented the "Adaptive Metropolis" (AM) algorithm developed by Haario, Saksman, and Tamminen (2001) to simulate the target distribution. Haario, Saksman, and Tamminen (2001) show that their AM algorithm is more efficient than the standard Metropolis-Hastings algorithm. In a nutshell, such algorithm employs the history of the states (draws) so to 'tune' the proposal distribution suitably. In particular, the previous draws are employed to regulate the VCV of the proposal density. We then exploited the history of the states sampled up to $t > t_0$ to continuously update the VCV matrix C_t of the proposal distribution. While not being a Markovian process, the AM algorithm is shown to possess the correct ergodic properties. For technicalities, see Haario, Saksman, and Tamminen (2001).

We simulated two chains of 200,000 draws each, and discarded the first 90% as burn-in. To scale the variance-covariance matrix of the chain, we used a factor so to achieve an acceptance rate belonging to the [23%,40%] range. The stationarity of the chains was assessed via the convergence checks proposed by Brooks and Gelman (1998). The region of acceptable parameter realizations was truncated so to obtain equilibrium uniqueness under rational expectations.

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Param.	*Interpretation*	*Priors*	*Posterior Means* [5h,95th]
β	Discount factor	*Calibrated*	0.99 [–]
v^{-1}	Frisch elasticity	*Calibrated*	1 [–]
κ	NKPC, slope	$Normal(0.1, 0.015)$	0.12 [0.10,0.14]
α	Price indexation	$Beta(0.5, 0.2)$	0.09 [0.01,0.17]
γ	IS, forw. look. degree	$Beta(0.5, 0.2)$	0.78 [0.70,0.86]
σ	Inverse of the IES	$Normal(3, 1)$	5.19 [3.95,6.45]
τ_π	T. Rule, inflation	$Normal(1.5, 0.3)$	2.21 [1.85,2.56]
τ_y	T. Rule, output gap	$Gamma(0.3, 0.2)$	0.16 [0.05,0.25]
τ_R	T. Rule, inertia	$Beta(0.5, 0.285)$	0.81 [0.77,0.86]
ρ_a	AR tech. shock	$Beta(0.5, 0.285)$	0.89 [0.84,0.94]
ρ_π	AR cost-push shock	$Beta(0.5, 0.285)$	0.98 [0.97,0.99]
ρ_R	AR mon. pol. shock	$Beta(0.5, 0.285)$	0.43 [0.30,0.56]
σ_a	Std. tech. shock	$InvGamma(1.5, 0.2)$	1.50 [1.10,1.91]
σ_π	Std. cost-push. shock	$InvGamma(0.35, 0.2)$	0.09 [0.07,0.11]
σ_R	Std. mon. pol. shock	$InvGamma(0.35, 0.2)$	0.14 [0.12,0.15]

Table 1: **Bayesian estimates of the DSGE model.** 1984:I-2008:II U.S. data. Prior densities: Figures indicate the (mean,st.dev.) of each prior distribution. Posterior densities: Figures reported indicate the posterior mean and the [5th,95th] percentile of the estimated densities. Details on the estimation procedure provided in the text.

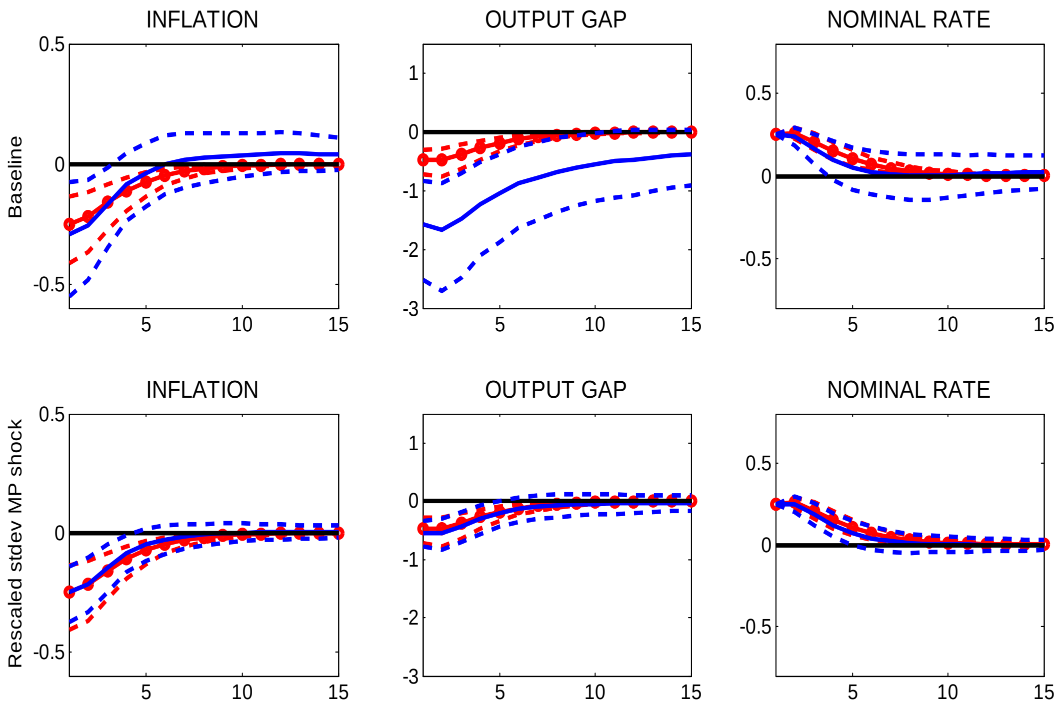

Figure 1: **DSGE and Sign Restrictions VAR impulse response functions to a monetary policy shock.** Circled red lines: DSGE Bayesian mean impulse responses; Dashed red lines: 90% credible sets. Solid blue line: SRVAR mean impulse responses; Dashed blue lines: [5h,95th] percentiles. Top panels: estimated DSGE shocks's variances. Bottom panels: Monetary policy shock's variances increased tenfold. Moments computed the impulse response function distributions simulated by drawing 5,000 realizations of the vector of parameters of the DSGE model, which is also used to generate the pseudo-data to feed the VARs. Identification of the monetary policy shock achieved via the imposition of sign-restrictions on the impulse responses of the VAR (see text for details). VAR estimated with two lags.

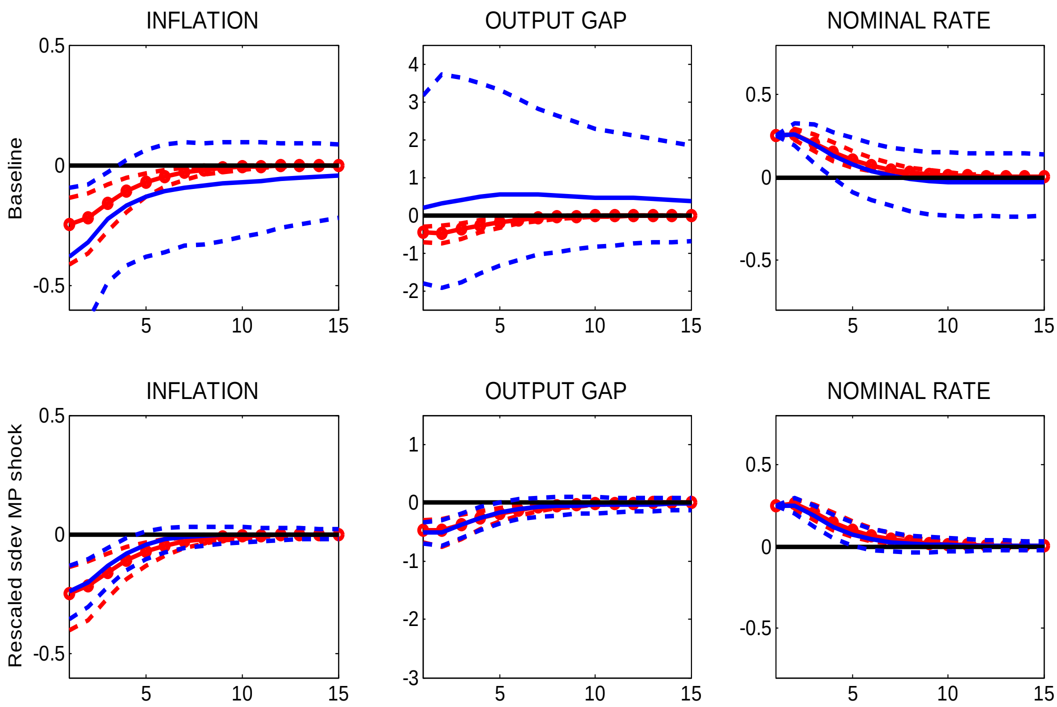

Figure 2: **DSGE and Sign Restrictions VAR impulse response functions to a monetary policy shock - Sign restriction on output not imposed.** Circled red lines: DSGE Bayesian mean impulse responses; Dashed red lines: 90% credible sets. Solid blue line: SRVAR mean impulse responses; Dashed blue lines: [5h,95th] percentiles. Top panels: estimated DSGE shocks's variances. Bottom panels: Monetary policy shock's variances increased tenfold. Moments computed the impulse response function distributions simulated by drawing 5,000 realizations of the vector of parameters of the DSGE model, which is also used to generate the pseudo-data to feed the VARs. Identification of the monetary policy shock achieved via the imposition of sign-restrictions on the impulse responses of the VAR (see text for details). VAR estimated with two lags.

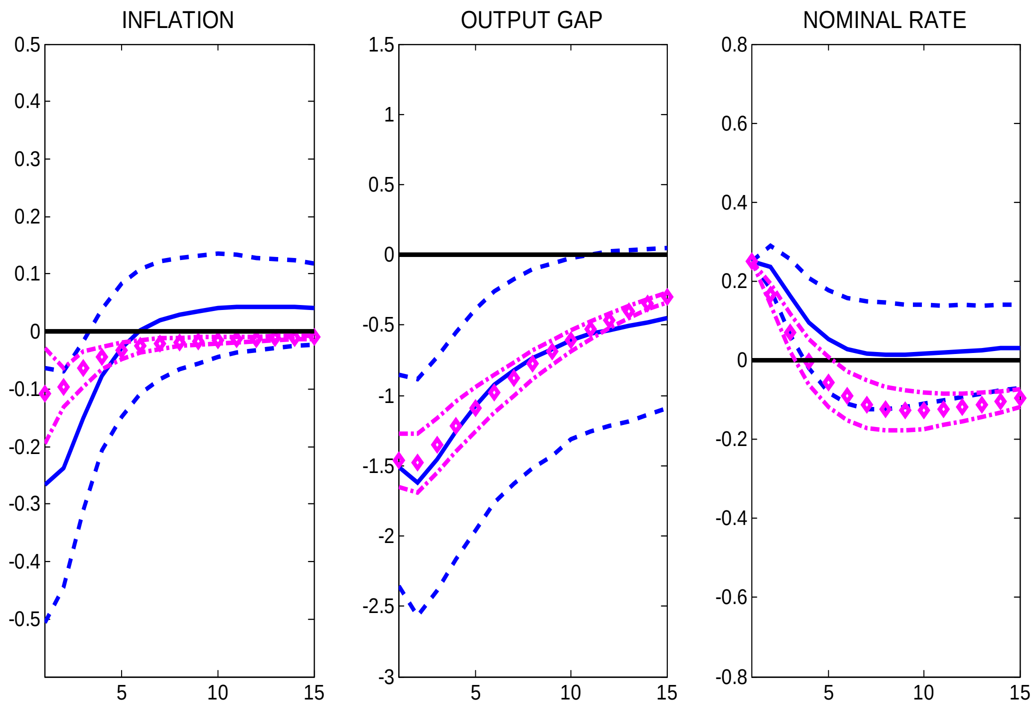

Figure 3: **Sign Restrictions VAR impulse response functions to a monetary policy shock: U.S. data, 1984:I.2008:II.** Green diamonded and dash-dotted lines lines: VAR estimated with actual U.S. data, mean (diamonds) and [5th,95th] percentiles (dash-dotted lines). Blue solid and dashed lines: VAR estimated with pseudo-data, mean (solid line) and [5th,95th] percentiles (dashed lines). Moments constructed with 5,000 set of responses meeting the sign restrictions. Lags of the VARs optimally selected according to the Schwarz criterion.