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**Conference Paper**

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2019: 30 Jahre Mauerfall - Demokratie und Marktwirtschaft - Session: Applied Macroeconometrics I, No. A13-V3

**Provided in Cooperation with:**

Verein für Socialpolitik / German Economic Association

*Suggested Citation:* Ettmeier, Stephanie; Kriwoluzky, Alexander (2019) : Active, or passive? Revisiting the role of fiscal policy in the Great Inflation, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2019: 30 Jahre Mauerfall - Demokratie und Marktwirtschaft - Session: Applied Macroeconometrics I, No. A13-V3, ZBW - Leibniz-Informationszentrum Wirtschaft, Kiel, Hamburg

This Version is available at:

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# Active, or passive? Revisiting the role of fiscal policy in the Great Inflation\*

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March 1, 2019

## Abstract

We revisit the question whether U.S. fiscal policy in the pre-Volcker period was active or passive. To determine the policy stance, we estimate a DSGE model with monetary and fiscal policy interactions employing a sequential Monte Carlo algorithm (SMC) for posterior evaluation. In contrast to previous studies, we do not have to treat the different policy regimes as distinct models, which have to be estimated separately. Instead, the SMC enables us to estimate the DSGE model over its entire parameter space to determine the prevailing policy mix. Our findings attribute the leading role to the fiscal authority, while the monetary authority accommodated its actions. For active monetary/passive fiscal policy, or passive monetary/passive fiscal policy we find no evidence in the data.

**JEL classification:** C11, C15, E63, E65

**Keywords:** Bayesian Analysis, DSGE Models, Monetary-Fiscal Policy Interactions, Monte Carlo Methods

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\*We would like to thank Sinem Hacıoglu Hoke, Chi Hyun Kim, Martin Kliem, Gernot Müller, Frank Schorfheide, and Moritz Schularick.

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# 1 Introduction

It is not since the recent economic crisis in the Eurozone that macroeconomists have put the interaction of monetary and fiscal policy on their research agenda. Questions like, “How does the transmission of monetary and fiscal policy work?”, or, “How can inflation be stabilized?”, are only some of the classical macroeconomic issues of importance for which the exact empirical characterization of the prevailing monetary-fiscal policy regimes is essential. Interestingly, for one historical episode, which is very instructive to all these questions, the debate about the monetary-fiscal policy mix is still unsettled. This episode is usually referred to as the Great Inflation of the 1960s and 1970s in the U.S.. In our study, we revisit this episode and determine the interaction of monetary and fiscal policy in the pre-Volcker period by estimating a DSGE model with three distinct monetary/fiscal policy regimes with a sequential Monte Carlo algorithm (SMC). Compared to previous studies, which estimated each possible policy regime as a distinct model, employing a SMC enables us to estimate the DSGE model over its entire parameter space. We find that during the pre-Volcker period the fiscal authority played the lead role and monetary policy acted passively.

The insight that monetary and fiscal policy are not independent from each other and have to be studied jointly has meanwhile a long tradition in modern macroeconomics and goes back to Leeper (1991), Sims (1994), Woodford (1996), and Cochrane (2001). While an active policy authority is able to realize its agenda, the passive authority is reduced to accommodate the counterparts’ actions. The literature largely agrees that monetary policy in the pre-Volcker period was passive. Clarida et al. (2000) and Mavroeidis (2010) estimate monetary policy reaction functions. Lubik and Schorfheide (2004) consider a monetary DSGE model that allows for indeterminacy, Boivin and Giannoni (2006) combine evidence from vector autoregressive and general equilibrium analysis and Coibion and Gorodnichenko (2011) include the trend level of inflation into their study to come to a similar conclusion. Concerning the stance of fiscal policy, however, the evidence is mixed. While Bhattarai et al. (2016) find that the fiscal authority was passive and strongly increased taxes to debt, Sims

(2011) and Bianchi and Ilut (2017) attribute fiscal policy the leading role.

To shed more light on this classical debate, we revisit the question whether U.S. fiscal policy was active or passive during the pre-Volcker period with a novel empirical toolkit. In particular, the SMC algorithm, established in the DSGE literature by Herbst and Schorfheide (2014, 2015) allows us to create new perspectives on an old question. Previous studies that relied on Bayesian-estimated DSGE models with distinct monetary/fiscal policy regimes, treated each regime as a different model. To determine the prevailing policy mix, typically each regime was successively imposed by estimating a restricted parameter space, draws from the corresponding posterior density were generated by a MCMC algorithm, usually the Random-Walk Metropolis-Hastings algorithm (RWMH), and finally the fit of each model was compared by a model selection criterion. We argue that employing a SMC algorithm for drawing conclusions on the stance of monetary and fiscal policy is beneficial in three dimensions. First, the SMC is able to deal with difficult posterior surfaces, an outcome that a priori cannot be excluded in the case of a DSGE model with monetary-fiscal policy interactions. Due to this feature the SMC enables us to estimate the DSGE model over its entire parameter space such that the most likely policy regime is directly determined by the data. Second, the SMC is amenable to parallelization and, thus, especially for larger DSGE models, computationally attractive. Third, the SMC can be easily initialized by taking independent draws from the prior density. A time-consuming search for a mode is not necessary.

The remainder of this paper is structured as follows. Section 2 describes the DSGE model with monetary-fiscal policy interactions. In Section 3, we outline the empirical analysis. We specify the SMC algorithm used for posterior sampling and discuss our estimation results. The final section concludes the study.

## 2 A DSGE model with monetary and fiscal policy interactions

In this section, we outline the DSGE model with monetary-fiscal policy interactions, characterize its distinct monetary-fiscal policy regimes, and present the solution method for the model.

### 2.1 Model description

We use the DSGE model set up in Bhattarai et al. (2016). It features a complete description of fiscal policy, a time-varying inflation and debt-to-output target, partial dynamic price indexation, and external habit formation in consumption. We here present only the first-order approximations of the model equations that determine equilibrium dynamics. For a detailed analysis of the model's characteristics, we refer the reader to the original study.

Consumption behavior of households is given by the consumption Euler equation:

$$\begin{aligned} \hat{C}_t = \frac{\bar{a}}{\bar{a} + \eta} E_t \hat{C}_{t+1} + \frac{\eta}{\bar{a} + \eta} \hat{C}_{t-1} - \left( \frac{\bar{a} - \eta}{\bar{a} + \eta} \right) \left( \hat{R}_t - E_t \hat{\pi}_{t+1} \right) + \frac{\bar{a}}{\bar{a} + \eta} E_t \hat{a}_{t+1} - \\ - \frac{\eta}{\bar{a} + \eta} \hat{a}_t + \left( \frac{\bar{a} - \eta}{\bar{a} + \eta} \right) \hat{d}_t, \end{aligned} \quad (1)$$

where  $\hat{C}_t$  is aggregate consumption,  $\hat{R}_t$  is the interest rate on government bonds,  $\hat{a}_t$  is the growth rate of technology,  $\hat{\pi}_t$  is the inflation rate, and  $\hat{d}_t$  stands for preferences.<sup>1</sup> The parameters  $\bar{a}$  and  $\eta$  denote the steady-state value of  $a_t$  and external habit formation, respectively.

The New Keynesian Phillips curve is denoted by

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<sup>1</sup>We define the log-linear deviation of a detrended variable from its corresponding steady state as  $\hat{X}_t = \ln X_t - \ln \bar{X}$ . Only the fiscal variables  $\hat{b}_t = b_t - \bar{b}$ ,  $\hat{g}_t = g_t - \bar{g}$ ,  $\hat{\tau}_t = \tau_t - \bar{\tau}$ , and  $\hat{s}_t = s_t - \bar{s}$  are normalized by output and linearized around their steady states.

$$\begin{aligned}\hat{\pi}_t = \frac{\beta}{1+\gamma\beta}E_t\hat{\pi}_{t+1} + \frac{\gamma}{1+\gamma\beta}\hat{\pi}_{t-1} + \kappa \left[ \left( \varphi + \frac{\bar{a}}{\bar{a}-\eta} \right) \hat{Y}_t - \frac{\eta}{\bar{a}-\eta} \hat{Y}_{t-1} + \frac{\eta}{\bar{a}-\eta} \hat{a}_t - \right. \\ \left. - \left( \frac{\bar{a}}{\bar{a}-\eta} \right) \left( \frac{1}{1-\bar{g}} \right) \hat{g}_t + \left( \frac{\eta}{\bar{a}-\eta} \right) \left( \frac{1}{1-\bar{g}} \right) \hat{g}_{t-1} \right] + \hat{u}_t,\end{aligned}\quad (2)$$

where  $\hat{Y}_t$  is aggregate output,  $\hat{g}_t$  represents the government spending-to-output ratio, and  $\hat{u}_t$  can be interpreted as cost-push shock. The parameters  $\beta, \gamma, \varphi$  and  $\bar{g}$  are, respectively, the discount factor, the degree of price indexation, the inverse of the Frisch elasticity of labour supply, and the steady-state value of government spending. Furthermore,  $\kappa := \frac{(1-\alpha\beta)(1-\alpha)}{\alpha(1+\varphi\bar{\theta})(1+\gamma\beta)}$ .  $\alpha$  stands for the degree of price rigidity in the economy and  $\bar{\theta}$  for the steady-state value of the elasticity of substitution between intermediate goods.

Monetary policy is characterized by the following rule:

$$\hat{R}_t = \rho_R \hat{R}_{t-1} + (1 - \rho_R) \left[ \phi_\pi (\hat{\pi}_t - \hat{\pi}_t^*) + \phi_Y (\hat{Y}_t - \hat{Y}_t^*) \right] + \epsilon_{R,t}. \quad (3)$$

$\hat{\pi}_t^*$  is the inflation target, and  $\hat{Y}_t^*$  is potential output. The idiosyncratic monetary policy shock  $\epsilon_{R,t}$  is assumed to evolve as i.i.d.  $N(0, \sigma_R^2)$ . The parameters  $\rho_R, \phi_\pi$  and  $\phi_Y$  represent, respectively, interest rate smoothing, responses to deviations of inflation from its target, and responses to deviations of output from its natural level.

The fiscal authority sets lump-sum taxation by a rule:

$$\hat{\tau}_t = \rho_\tau \hat{\tau}_{t-1} + (1 - \rho_\tau) \left[ \psi_b (\hat{b}_t - \hat{b}_{t-1}^*) + \psi_Y (\hat{Y}_t - \hat{Y}_t^*) \right] + \epsilon_{\tau,t}. \quad (4)$$

$\hat{\tau}_t$  stands for the tax-revenue-to-output ratio,  $\hat{b}_t$  is the debt-to-output ratio, and  $\hat{b}_t^*$  is the debt-to-output ratio target. The non-systematic tax policy shock  $\epsilon_{\tau,t}$  is assumed to evolve as i.i.d.  $N(0, \sigma_\tau^2)$ . The tax policy rule features tax smoothing ( $\rho_\tau$ ), and systematic reactions of tax revenues to deviations of lagged debt from its target ( $\psi_b$ ) and to deviations of output from natural output ( $\psi_Y$ ).

The government spending rule is modeled as

$$\hat{g}_t = \rho_g \hat{g}_{t-1} - (1 - \rho_g) \chi_Y \left( \hat{Y}_{t-1} - \hat{Y}_{t-1}^* \right) + \epsilon_{g,t}. \quad (5)$$

$\hat{g}_t$  stands for the government spending-to-output ratio. The exogenous shock to government spending  $\epsilon_{g,t}$  is assumed to follow an i.i.d.-process with  $N(0, \sigma_g^2)$ .  $\rho_g$  represents smoothing in government purchases, and  $\chi_Y$  is the response of government spending to the lagged output gap. Under the assumption of flexible prices, the natural level of government spending is:

$$\hat{g}_t^* = \rho_g \hat{g}_{t-1}^* + \epsilon_{g,t}. \quad (6)$$

The government budget constraint is given by:

$$\hat{b}_t = \frac{1}{\beta} \hat{b}_{t-1} + \frac{\bar{b}}{\beta} \left( \hat{R}_{t-1} - \hat{\pi}_t - \hat{Y}_t + \hat{Y}_{t-1} - \hat{a}_t \right) + \hat{g}_t - \hat{\tau}_t + \hat{s}_t. \quad (7)$$

$\hat{s}_t$  is the ratio of government transfers to output and the parameter  $\bar{b}$  is the steady-state value of the debt-to-output ratio.

The aggregate resource constraint is given by:

$$\hat{Y}_t = \hat{C}_t + \frac{1}{1 - \bar{g}} \hat{g}_t. \quad (8)$$

The natural level of output is:

$$\hat{Y}_t^* = \frac{\eta}{\varphi(\bar{a} - \eta) + \bar{a}} \hat{Y}_{t-1}^* + \frac{\bar{a}}{[\varphi(\bar{a} - \eta) + \bar{a}](1 - \bar{g})} \hat{g}_t^* - \frac{\eta}{[\varphi(\bar{a} - \eta) + \bar{a}](1 - \bar{g})} \hat{g}_{t-1}^* - \frac{\eta}{\varphi(\bar{a} - \eta) + \bar{a}} \hat{a}_t. \quad (9)$$

Finally, six additional exogenous shocks drive economic fluctuations. They are all assumed to evolve according to univariate AR(1) processes.

Preferences evolve as

$$\hat{d}_t = \rho_d \hat{d}_{t-1} + \epsilon_{d,t} \quad \text{with } \epsilon_{d,t} \sim i.i.d. N(0, \sigma_d^2). \quad (10)$$

Technology evolves as

$$\hat{a}_t = \rho_a \hat{a}_{t-1} + \epsilon_{a,t} \quad \text{with } \epsilon_{a,t} \sim i.i.d. N(0, \sigma_a^2). \quad (11)$$

Mark-up shocks are assumed to follow

$$\hat{u}_t = \rho_u \hat{u}_{t-1} + \epsilon_{u,t} \quad \text{with } \epsilon_{u,t} \sim i.i.d. N(0, \sigma_u^2). \quad (12)$$

Governement transfers are given by

$$\hat{s}_t = \rho_s \hat{s}_{t-1} + \epsilon_{s,t} \quad \text{with } \epsilon_{s,t} \sim i.i.d. N(0, \sigma_s^2). \quad (13)$$

The inflation target evolves as

$$\hat{\pi}_t^* = \rho_\pi \hat{\pi}_{t-1}^* + \epsilon_{\pi,t} \quad \text{with } \epsilon_{\pi,t} \sim i.i.d. N(0, \sigma_\pi^2). \quad (14)$$

The debt-to-output ratio target follows

$$\hat{b}_t^* = \rho_b \hat{b}_{t-1}^* + \epsilon_{b,t} \quad \text{with } \epsilon_{b,t} \sim i.i.d. N(0, \sigma_b^2). \quad (15)$$

## 2.2 Policy regimes

A unique equilibrium of the economy arises if either monetary policy is active while fiscal policy is passive (regime M) or monetary policy is passive while fiscal policy is active (regime F). If both monetary and fiscal policy are passive multiple equilibria exist (indeterminacy). No stationary equilibrium exists if both authorities act actively (explosiveness). The boundaries of the four distinct policy regimes can be characterized analytically in Bhattarai et al.



(2016)'s model. In particular, monetary policy is active if

$$\phi_\pi > 1 - \phi_Y \left( \frac{1 - \tilde{\beta}}{\tilde{\kappa}} \right), \quad (16)$$

where  $\tilde{\beta} = \frac{\gamma + \beta}{1 + \gamma\beta}$  and  $\tilde{\kappa} = \frac{(1 - \alpha\beta)(1 - \alpha)}{\alpha(1 + \varphi\theta)(1 + \gamma\beta)} \left( 1 + \varphi + \frac{\chi_Y}{1 - \bar{g}} \right)$ , while fiscal policy is active if

$$\psi_b < \frac{1}{\beta} - 1. \quad (17)$$

### 2.3 Model solution under determinacy and indeterminacy

We collect the parameters of the loglinearized model in the vector  $\vartheta$  with domain  $\Theta$  and solve the system of equations for its state-space representation.<sup>2</sup> Under determinacy (regime F, regime M), we employ the solution algorithm for linear rational expectations models of Sims (2002) which expresses the model solution as

$$z_t = \Gamma_1^*(\vartheta)z_{t-1} + \Psi^*(\vartheta)\epsilon_t. \quad (18)$$

Under indeterminacy, we apply the generalization of this procedure suggested by Lubik and Schorfheide (2003, 2004):

$$z_t = \Gamma_1^*(\vartheta)z_{t-1} + \left[ \Gamma_{0,\epsilon}^*(\vartheta) + \Gamma_{0,\zeta}^*(\vartheta)\tilde{M} \right] \epsilon_t + \Gamma_{0,\zeta}^*(\vartheta)M_\zeta\zeta_t. \quad (19)$$

Equation 19 illustrates that indeterminacy changes the nature of the solution in two dimensions. First, the transmission of fundamental shocks  $\epsilon_t$  is no longer uniquely determined as it additionally depends on the matrix  $\tilde{M}$ . Second, an exogenous sunspot shock  $\zeta_t$ , unrelated to the fundamental shocks  $\epsilon_t$ , potentially affects the dynamics of the model variables  $z_t$ . Thus, indeterminacy introduces additional parameters.

We denote the standard deviation of the sunspot shock as  $\sigma_\zeta$  and normalize as Lubik

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<sup>2</sup>More details on the implementation of the model solution are given in Appendix A.

and Schorfheide (2004)  $M_\zeta$  to unity. Also in accordance with Lubik and Schorfheide (2004), we replace  $\tilde{M}$  with  $\tilde{M} = M^*(\vartheta) + M$  to prevent that the transmission of fundamental shocks changes drastically when the boundary between the determinacy regimes and the indeterminacy regime is crossed. Around this boundary, small changes in  $\vartheta$  should rather leave the propagation mechanism of structural shocks unaffected. That is why we choose  $M^*(\vartheta)$  such that the impulse responses  $\partial z_t / \partial \epsilon'_t$  become continuous on the boundary. The vector  $M$ , in contrast, which determines the relationship between fundamental shocks and forecast errors, is estimated. It can be interpreted to capture agents' self-fulfilling beliefs and consists of the following entries:  $M = [M_{g_\zeta}, M_{d_\zeta}, M_{a_\zeta}, M_{u_\zeta}, M_{s_\zeta}, M_{R_\zeta}, M_{\tau_\zeta}, M_{\pi_\zeta}, M_{b_\zeta}]$ . For the parameters in  $M$  we choose priors centered around zero and thus let strictly the data decide how indeterminacy changes the transmission mechanism of structural shocks.

To compute the matrix  $M^*(\vartheta)$  which guarantees continuous model dynamics on the boundary, we proceed in several steps. First, we construct for every parameter vector  $\vartheta \in \Theta^I$  (indeterminacy) a reparametrized vector  $\vartheta^* = g^*(\vartheta)$  that lies on the boundary between the indeterminacy and the determinacy regimes. Then,  $M^*(\vartheta)$  is chosen by a least-squares criterion such that the impulse responses  $\frac{\partial z_t}{\partial \epsilon'_t}(\vartheta, M)$  conditional on  $\vartheta$  resemble the impulse responses conditional on the vector on the boundary  $\frac{\partial z_t}{\partial \epsilon'_t}(g^*(\vartheta))$ . The DSGE model with monetary-fiscal policy interactions presented in subsection 2, however, gives rise to two different determinate solutions (regime F and regime M) which are generally characterized by different transmission mechanisms. To deal with this ambiguity, we proceed as follows:

1. For every  $\vartheta \in \Theta^I$  we construct a vector  $\vartheta^M = g^M(\vartheta)$  that demarks the boundary between regime M and the indeterminacy regime and a vector  $\vartheta^F = g^F(\vartheta)$  that lies on the boundary to regime F. The function  $g^M(\vartheta)$  is obtained by replacing  $\phi_\pi$  in the vector  $\vartheta$  with

$$\tilde{\phi}_\pi = 1 - \phi_Y \left( \frac{1 - \tilde{\beta}}{\tilde{\kappa}} \right). \quad (20)$$

The function  $g^F(\vartheta)$  is obtained by replacing  $\psi_b$  in the vector  $\vartheta$  with

$$\tilde{\psi}_b = \frac{1}{\beta} - 1. \quad (21)$$

2. We solve the model successively with the reparametrized vectors  $\vartheta^M$  and  $\vartheta^F$  and compute

$$M^M(\vartheta) = [\Gamma_{0,\zeta}^M(\vartheta)' \Gamma_{0,\zeta}^M(\vartheta)]^{-1} \Gamma_{0,\zeta}^M(\vartheta)' [\Gamma_{0,\epsilon}^M g^M(\vartheta) - \Gamma_{0,\epsilon}^M(\vartheta)], \text{ and} \quad (22)$$

$$M^F(\vartheta) = [\Gamma_{0,\zeta}^F(\vartheta)' \Gamma_{0,\zeta}^F(\vartheta)]^{-1} \Gamma_{0,\zeta}^F(\vartheta)' [\Gamma_{0,\epsilon}^F g^F(\vartheta) - \Gamma_{0,\epsilon}^F(\vartheta)]. \quad (23)$$

3. To choose the  $M^*(\vartheta)$  that minimizes the discrepancy between  $\frac{\partial z_t}{\partial \epsilon_t'}(\vartheta, M)$  and  $\frac{\partial z_t}{\partial \epsilon_t'}(g^*(\vartheta))$ , we compute the distances to the respective boundaries as

$$D^M = [\Gamma_{0,\epsilon}^M g^M(\vartheta) - \Gamma_{0,\epsilon}^M(\vartheta)] - \Gamma_{0,\zeta}^M(\vartheta) M^M(\vartheta), \text{ and} \quad (24)$$

$$D^F = [\Gamma_{0,\epsilon}^F g^F(\vartheta) - \Gamma_{0,\epsilon}^F(\vartheta)] - \Gamma_{0,\zeta}^F(\vartheta) M^F(\vartheta). \quad (25)$$

4. As in our model all fundamental shocks are assumed to be independent from each other, we compute the Euclidean norm of each column in  $D^*$ , sum them up, and finally choose the  $M^*(\vartheta)$  that corresponds with<sup>3</sup>

$$\min \left[ \sum_{j=1}^9 \|d_j^M\|_2, \sum_{j=1}^9 \|d_j^F\|_2 \right].$$

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<sup>3</sup>For matrix  $D^* = (d_{ij}^*)$ , its  $i$ -th row and  $j$ -th column are denoted by  $d_i^*$  and  $d_j^*$ , respectively.

### 3 Empirical analysis

In this section, we present the empirical model analysis. First, we outline how we estimate the model. We describe the prior distributions and the dataset, and illustrate the procedure for posterior sampling. Finally, we present the parameter estimates and discuss the posterior probabilities of the distinct policy regimes.

#### 3.1 Estimation strategy

We use Bayesian methods and combine our priors with the likelihood of the model solution, calculated by the Kalman filter to construct the posterior distribution of the model parameters.

##### Prior distributions and calibrated parameters

In line with Bhattarai et al. (2016), we fix a few model parameters. We calibrate the inverse of the Frisch elasticity of labour supply to  $\varphi = 1$  and the steady-state value of the elasticity of substitution between goods to  $\tilde{\theta} = 8$ , since they cannot be separately identified from the Calvo parameter  $\alpha$ . We also fix the parameters measuring the persistence of the time-varying policy targets to  $\rho_\pi = \rho_b = 0.995$ .

Table 1: Prior distributions

Parameter	Prior				
	Range	Distribution	Mean	SD	90 percent int.
<i>Monetary policy</i>					
$\phi_\pi$ , interest rate response to inflation	$\mathbb{R}^+$	N	0.8	0.6	[0.14, 1.84]
$\phi_Y$ , interest rate response to output	$\mathbb{R}^+$	G	0.3	0.1	[0.16, 0.5]
$\rho_R$ , response to lagged interest rate	[0, 1)	B	0.6	0.2	[0.24, 0.9]
<i>Fiscal policy</i>					
$\psi_b$ , tax response to lagged debt	$\mathbb{R}$	N	0	0.1	[-0.16, 0.16]
$\psi_Y$ , tax response to output	$\mathbb{R}$	N	0.4	0.3	[-0.1, 0.9]
$\chi_Y$ , govt spending response to lagged output	$\mathbb{R}$	N	0.4	0.3	[-0.1, 0.9]

Table 1: Prior distributions - continued

Parameter	Prior				
	Range	Distribution	Mean	SD	90 percent int.
$\rho_g$ , response to lagged govt spending	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
$\rho_\tau$ , response to lagged taxes	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
<i>Preference and HHs</i>					
$\eta$ , habit formation	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
$\mu := 100(\beta^{-1} - 1)$ , discount factor	$\mathbb{R}^+$	G	0.25	0.1	$[0.11, 0.44]$
<i>Frictions</i>					
$\alpha$ , price stickiness	$[0, 1)$	B	0.5	0.1	$[0.33, 0.67]$
$\gamma$ , price indexation	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
<i>Shocks</i>					
$\rho_d$ , preference	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
$\rho_a$ , technology	$[0, 1)$	B	0.4	0.2	$[0.1, 0.76]$
$\rho_u$ , cost-push	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
$\rho_s$ , transfers	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
$\sigma_g$ , govt spending	$\mathbb{R}^+$	Inv. Gamma	0.1	4	$[0.65, 0.24]$
$\sigma_d$ , preference	$\mathbb{R}^+$	Inv. Gamma	0.3	4	$[0.19, 0.72]$
$\sigma_a$ , technology	$\mathbb{R}^+$	Inv. Gamma	0.5	4	$[0.32, 1.17]$
$\sigma_u$ , cost-push	$\mathbb{R}^+$	Inv. Gamma	0.04	4	$[0.026, 0.094]$
$\sigma_s$ , transfers	$\mathbb{R}^+$	Inv. Gamma	0.08	4	$[0.052, 0.188]$
$\sigma_R$ , monetary policy	$\mathbb{R}^+$	Inv. Gamma	0.15	4	$[0.098, 0.353]$
$\sigma_\tau$ , tax	$\mathbb{R}^+$	Inv. Gamma	0.2	4	$[0.13, 0.48]$
$\sigma_\pi$ , inflation target	$\mathbb{R}^+$	Inv. Gamma	0.003	4	$[0.002, 0.007]$
$\sigma_b$ , debt/output target	$\mathbb{R}^+$	Inv. Gamma	0.05	4	$[0.033, 0.118]$
<i>Steady state</i>					
$a := 100(\bar{a} - 1)$ , technology	$\mathbb{R}$	N	0.55	0.1	$[0.38, 0.71]$
$\pi := 100(\bar{\pi} - 1)$ , inflation	$\mathbb{R}$	N	0.8	0.1	$[0.63, 0.96]$
$b := 100\bar{b}$ , debt/output	$\mathbb{R}$	N	35	2	$[31.71, 38.3]$
$\tau := 100\bar{\tau}$ , tax/output	$\mathbb{R}$	N	25	2	$[21.73, 28.27]$
$g := 100\bar{g}$ , govt spending/output	$\mathbb{R}$	N	22	2	$[18.81, 25.31]$
<i>Indeterminacy</i>					
$\sigma_\zeta$ , sunspot shock	$\mathbb{R}^+$	Inv. Gamma	0.2	4	$[0.13, 0.48]$
$M_{g\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$
$M_{d\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$
$M_{a\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$
$M_{u\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$
$M_{s\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$
$M_{R\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$

Table 1: Prior distributions - continued

Parameter	Prior				
	Range	Distribution	Mean	SD	90 percent int.
$M_{\tau\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$
$M_{\pi\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$
$M_{b\zeta}$	$\mathbb{R}$	N	0	1	$[-1.64, 1.64]$

*Note:* The Inverse Gamma prior distributions have the form  $p(x|\nu, s) \propto x^{-\nu-1}e^{-\nu s^2/2x^2}$ , where  $\nu = 4$  and  $s$  is given by the value in the column denoted as “Mean”.

Table 1 specifies the prior distributions. They extend over a broad range of parameter values. As we initialize the SMC algorithm from the prior, we carefully tailored a prior that results in realistic model implications, but nevertheless remains agnostic about the prevailing policy regime.<sup>4</sup> In the following, we discuss only the key parameters of our analysis. Particularly, the policy parameters in the monetary and fiscal policy rule  $\phi_\pi$  and  $\psi_b$  play a central role in our analysis as they determine the policy regime. For  $\phi_\pi$  we choose a Normal distribution restricted to the positive domain with an implied 90% probability interval from 0.14 to 1.84, while for  $\psi_b$  the interval extends from -0.16 to 0.16. Our choice is motivated by the consideration to construct prior distributions that yield more or less equal probabilities for regime F and indeterminacy. Especially, as we initialize the SMC algorithm from the prior we do not want to impose artificially a certain policy regime before confronting the model with the data. The implied prior probabilities of the policy regimes presented in Table 2 support our choice. Regime F and the indeterminacy regime receive almost identical support.

A second group of parameters we want to discuss are those necessary to characterize the indeterminacy model solution. For the parameters in the matrix  $M$ , representing agents’ self-fulfilling beliefs, we choose priors centered around zero in order to let the data decide if and how indeterminacy changes the propagation mechanism of the fundamental shocks. The prior of the sunspot shock’s standard deviation  $\sigma_\zeta$  is also identical to Lubik and Schorfheide

<sup>4</sup>In Appendix B we show results from a prior predictive analysis. In particular, we take 20,000 draws from the prior, simulate the model’s observables and plot these simulated time series against the actual data from 1960:Q1 to 1979:Q2 that we use for estimating the model.

Table 2: Prior probability of pre-Volcker policy regimes

	Regime M	Regime F	Indeterminacy	Explosiveness
Probability	19.67	30.5	29.14	20.69

*Note:* The prior probabilities of the policy regimes were obtained from a prior predictive analysis. We drew  $\vartheta$  20,000 times from the priors specified in Table 1, solved the model with each draw and computed the shares of each policy regime.

(2004).

## Data

We fit the loglinearized DSGE model to six quarterly U.S. time series and estimate the model for the pre-Volcker sample 1960:Q1 to 1979:Q2.<sup>5</sup> The list of observables includes output, inflation, nominal interests rates, the tax-revenue-to-output ratio, the market value of the government debt-to-output ratio, and the government spending-to-output ratio.

## Sequential Monte Carlo posterior sampling

We calculate the likelihood function of the model solution over the determinacy and indeterminacy region of the parameter space as

$$p(Y|\vartheta, M) = \{\vartheta \in \Theta^D\}p^D(Y|\vartheta) + \{\vartheta \in \Theta^I\}p^I(Y|\vartheta, M),$$

where  $Y$  is the relevant data and  $h(x) = \{x \in \mathfrak{X}\}$  is the indicator function that is one if  $x \in \mathfrak{X}$  and zero otherwise. We are interested in the posterior density  $p(\vartheta, M|Y)$ , which is

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<sup>5</sup>For the estimation we use the dataset of Bhattarai et al. (2016) downloaded from the supplemental material of their study <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/OHUWKM>. More details on the data and the corresponding measurement equations are given in Appendix C.

given by

$$p(\vartheta, M|Y) = \frac{p(Y|\vartheta, M)p(\vartheta, M)}{p(Y)}, \text{ where } p(Y) = \int p(Y|\vartheta, M)p(\vartheta, M)d\vartheta dM. \quad (26)$$

$p(\vartheta, M)$  stands for the prior density, and  $p(Y)$  represents the marginal data density.

Posterior inference in DSGE models relies on sampling techniques as the moments of  $p(\vartheta, m|Y)$  cannot be characterized in closed forms. For our application, we choose the sequential Monte Carlo algorithm introduced to the DSGE literature by Creal (2007) and further enhanced and theoretically justified by Herbst and Schorfheide (2014, 2015).<sup>6</sup> Three considerations make the SMC algorithm our preferred choice. First, the SMC is able to deal with difficult posterior surfaces, an outcome that a priori cannot be excluded in the case of the DSGE model with monetary-fiscal policy interactions. Due to this feature, we do not have to adopt the common estimation approach, which implies solving and estimating the model separately for each policy regime, and finally comparing the model fit across regimes. Rather, we let the SMC algorithm explore the entire parameter space such that the most likely policy regime is directly determined by the data. Second, the SMC is amenable to parallelization and, thus, especially for larger DSGE models, computationally attractive. Third, the SMC can be easily initialized by taking independent draws from the prior density. A time-consuming search for a mode is not necessary.

The basic concept of the SMC relies on importance sampling, which means that the posterior  $p(\vartheta, M|Y)$  is approximated by an easy-to-sample proposal, or source density. However, in the high-dimensional parameter space of DSGE models good proposal densities are difficult to obtain. That is why the SMC constructs proposal densities sequentially. More precisely, the algorithm draws from a sequence of bridge densities that link a known starting distribution with the targeted posterior density. A meaningful starting distribution constitutes the prior  $p(\vartheta, M)$ . The bridge distributions, in contrast, differ in the amount of

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<sup>6</sup>Chopin (2002), Del Moral et al. (2006), and Creal (2012), among others, provide further details on SMC algorithms.



information from the likelihood they contain. At each stage of the algorithm an increment of the likelihood is added to the proposal density. At the moment the full information from the likelihood has been released, an approximation of the posterior is obtained. In particular, the sequence of  $n$  distributions is given by

$$p_n(\vartheta, M|Y) = \frac{[p(Y|\vartheta, M)]^{\delta_n} p(\vartheta, M)}{\int p(Y|\vartheta, M)^{\delta_n} p(\vartheta, M) d\vartheta dM}, \quad n = 1, \dots, N_\delta. \quad (27)$$

We follow Herbst and Schorfheide (2014) and choose the tuning parameter  $\delta_n$  as an increasing sequence of values such that  $\delta_1 = 0$  and  $\delta_{N_\delta} = 1$ . The length of this sequence coincides with the number of importance samplers. At the first stage of the algorithm,  $p_1(\vartheta, M|Y)$  is the prior density  $p(\vartheta, M)$ . At the last stage, the final proposal density  $p_{N_\delta}(\vartheta, M|Y)$  constitutes the posterior  $p(\vartheta, M|Y)$ . In particular, our tempering schedule  $\{\delta_n\}_{n=1}^{N_\delta}$  is given by  $\delta_n = ((n-1)/(N_\delta-1))^\lambda$ . The tuning parameter  $\lambda$  determines how much information from the likelihood is incorporated in each proposal density.

In a nutshell, the SMC draws in  $N_\delta$  stages sequentially  $N$  parameter vectors  $\vartheta^i, i = 1, \dots, N$  from the proposal densities and assigns them with importance weights  $\tilde{W}^i$ . Each of the  $i$  pairs  $(\vartheta^i, \tilde{W}^i)$  is known as particle, and the set of particles  $\{(\vartheta^i, \tilde{W}^i)\}_{i=1}^N$  approximates the density in iteration. Each stage of the SMC consists of three steps. First, in the *correction* step of stage  $n$ , the particles of the previous stage  $\{(\vartheta_{n-1}^i, \tilde{W}_{n-1}^i)\}_{i=1}^N$  are reweighted to correct for the difference between  $p_{n-1}(\vartheta, M|Y)$  and  $p_n(\vartheta, M|Y)$ . The second step, the *selection* step, controls the accuracy of the particle approximation. Whenever the distribution of weights becomes too uneven, systematic resampling restores a well-balanced set of particles. In the last step, the *mutation* step, the particle values are propagated around in the parameter space by  $M_{MH}$  iterations of a RWMH algorithm with  $N_{blocks}$  random blocks. The particles' new location determines the updated density  $p_n(\vartheta, M|Y)$ .<sup>7</sup>

To estimate the model, we choose the following tuning parameters for the SMC. We use  $N = 20,000$  particles,  $N_\delta = 600$  stages,  $\lambda = 2.4$ ,  $N_{blocks} = 10$ ,  $M_{MH} = 3$ . As suggested by

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<sup>7</sup>A more detailed description of the SMC algorithm is given in Appendix D.

Herbst and Schorfheide (2014),  $\lambda$  was determined by examining the particle degeneracy after the first piece of information of the likelihood was added to the prior density in  $n = 1$ . We increased  $\lambda$  till at least 80% of the total number of particles (16,000) was retained. To choose  $N_{blocks}$  and  $M_{MH}$ , we monitored the acceptance rate in the mutation step in preliminary runs.  $N_{blocks} = 10$  and  $M_{MH} = 3$  ensured a stable acceptance rate of 25% without down-scaling the proposal variance too much.

### 3.2 Results

We start our discussion with the posterior probabilities of the policy regimes in the pre-Volcker period. As Table 3 shows, we find with 99.8 % nearly perfect empirical support for regime F. The indeterminacy regime, as well as regime M, receive no support from the data.

Table 3: Posterior probability of pre-Volcker policy regimes

	Regime M	Regime F	Indeterminacy	Explosiveness
Probability	0.2	99.8	0	0

*Note:* To obtain the posterior probabilities, we solved the model with each of the 20,000 particles and computed the shares of each policy regime.

The posterior mean estimates presented in Table 4 provide further evidence for this finding. In line with the corresponding literature, we find with  $\phi_\pi = 0.37$  that monetary policy in the pre-Volcker period was passive. The fiscal authority, however, played the lead role during this period. With  $\psi_b = -0.045$  fiscal policy is characterized as active. Although we allow for indeterminacy in our estimation approach, the mix of passive monetary and passive fiscal policy is not supported by the data. Except  $\sigma_\zeta$ , all parameters related to the indeterminacy regime are insignificant.<sup>8</sup> Thus, our results are in line with the findings of Sims (2011) and Bianchi and Ilut (2017) who also provide evidence for a leading fiscal

<sup>8</sup>In Appendix E we present for all estimated parameters plots of their corresponding prior and posterior densities.

authority in the U.S. during the 1960s and 1970s.

Table 4: Posterior distributions for estimated parameters

Parameter	Posterior		
	Mean	SD	90 percent credible set
<i>Monetary policy</i>			
$\phi_\pi$ , interest rate response to inflation	0.37	0.14	[0.12, 0.6]
$\phi_Y$ , interest rate response to output	0.46	0.1	[0.29, 0.65]
$\rho_R$ , response to lagged interest rate	0.32	0.13	[0.12, 0.57]
<i>Fiscal policy</i>			
$\psi_b$ , tax response to lagged debt	-0.045	0.02	[-0.08, -0.012]
$\psi_Y$ , tax response to output	-0.49	0.26	[-0.95, -0.09]
$\chi_Y$ , govt spending response to lagged output	-0.45	0.15	[-0.7, -0.19]
$\rho_g$ , response to lagged govt spending	0.86	0.03	[0.8, 0.91]
$\rho_\tau$ , response to lagged taxes	0.71	0.05	[0.6, 0.79]
<i>Preference and HHs</i>			
$\eta$ , habit formation	0.6	0.1	[0.43, 0.77]
$\mu := 100(\beta^{-1} - 1)$ , discount factor	0.18	0.09	[0.05, 0.36]
<i>Frictions</i>			
$\alpha$ , price stickiness	0.7	0.07	[0.57, 0.82]
$\gamma$ , price indexation	0.15	0.1	[0.02, 0.34]
<i>Shocks</i>			
$\rho_d$ , preference	0.59	0.1	[0.42, 0.75]
$\rho_a$ , technology	0.29	0.18	[0.03, 0.62]
$\rho_u$ , cost-push	0.47	0.14	[0.18, 0.66]
$\rho_s$ , transfers	0.18	0.13	[0.02, 0.49]
$\sigma_g$ , govt spending	0.25	0.03	[0.2, 0.32]
$\sigma_d$ , preference	1.01	0.35	[0.5, 1.7]
$\sigma_a$ , technology	0.55	0.16	[0.31, 0.87]
$\sigma_u$ , cost-push	0.13	0.03	[0.08, 0.2]
$\sigma_s$ , transfers	1.15	0.21	[0.81, 1.53]
$\sigma_R$ , monetary policy	0.17	0.03	[0.12, 0.23]
$\sigma_\tau$ , tax	0.83	0.12	[0.64, 1.06]
$\sigma_\pi$ , inflation target	0.008	0.006	[0.001, 0.02]
$\sigma_b$ , debt/output target	0.2	0.13	[0.04, 0.44]
<i>Steady state</i>			
$a := 100(\bar{a} - 1)$ , technology	0.38	0.1	[0.2, 0.55]

Table 4: Posterior distributions for estimated parameters - continued

Parameter	Posterior		
	Mean	SD	90 percent credible set
$\pi := 100(\bar{\pi} - 1)$ , inflation	0.87	0.09	[0.59, 1.14]
$b := 100\bar{b}$ , debt/output	35.62	3.11	[30.41, 40.63]
$\tau := 100\bar{\tau}$ , tax/output	24.58	0.24	[24.53, 25.44]
$g := 100\bar{g}$ , govt spending/output	24.57	0.14	[24.17, 24.99]
<i>Indeterminacy</i>			
$\sigma_\zeta$ , sunspot shock	0.36	0.21	[0.11, 0.76]
$M_{g\zeta}$	0.17	2	[-3.12, 3.43]
$M_{d\zeta}$	0.07	2.04	[-3.22, 3.46]
$M_{a\zeta}$	0.15	2.1	[-3.28, 3.65]
$M_{u\zeta}$	0.16	2.04	[-3.13, 3.5]
$M_{s\zeta}$	0.29	1.91	[-2.79, 3.62]
$M_{R\zeta}$	-0.52	2.09	[-3.91, 3.01]
$M_{\tau\zeta}$	0.17	2.33	[-3.54, 4.01]
$M_{\pi\zeta}$	0.21	1.57	[-2.29, 2.92]
$M_{b\zeta}$	1.22	2.23	[-2.48, 4.67]
Log Marginal data density	-608.49		

*Note:* Means, standard deviations and estimates of the log marginal data density are for one run of the SMC algorithm with  $N = 20,000$ ,  $N_\delta = 600$ ,  $\lambda = 2.4$ ,  $N_{blocks} = 10$ , and  $M_{MH} = 3$ . The log marginal data density is obtained as a by-product during the correction step of the SMC algorithm, see Herbst and Schorfheide (2014) for further details.

## 4 Conclusion

Was U.S. fiscal policy in the pre-Volcker period active or passive? We revisit this classical question of modern macroeconomics with a novel empirical toolkit. Using a SMC algorithm, we are able to estimate a DSGE model with monetary-fiscal policy interactions over its entire parameter space. Our empirical findings strongly support a setting in which the fiscal authority played the leading role in the period of the Great Inflation and the monetary authority acted passively.

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## Appendix A Implementation of the model solution

The linear rational expectation form of the DSGE model presented in Section 2 is given by

$$\Gamma_0(\vartheta)z_t = \Gamma_1(\vartheta)z_{t-1} + \Psi(\vartheta)\epsilon_t + \Pi(\vartheta)\eta_t. \quad (28)$$

$z$  is the vector of state variables, the vector  $\epsilon$  includes the exogenous variables, and  $\eta$  is a vector of expectation errors. To apply the solution algorithm of Sims (2002), we define for a generic variable  $\hat{x}_t$  the corresponding one-step-ahead rational expectations forecast error as  $\eta_{x,t} = \hat{x}_t - E_{t-1}[\hat{x}_t]$ . In our application, the vectors of the general model form are defined as:

$$z_t = [\hat{c}_t \ \hat{\pi}_t \ \hat{a}_t \ \hat{R}_t \ \hat{d}_t \ \hat{Y}_t \ \hat{g}_t \ \hat{u}_t \ \hat{\pi}_t^* \ \hat{Y}_t^* \ \hat{\tau}_t \ \hat{b}_t \ \hat{b}_t^* \ \hat{s}_t \ \hat{g}_t^* \ \hat{c}_{t-1} \ \hat{\pi}_{t-1} \ \hat{g}_{t-1} \ \hat{Y}_{t-1}]',$$

$$\epsilon_t = [\epsilon_{g,t} \ \epsilon_{d,t} \ \epsilon_{a,t} \ \epsilon_{u,t} \ \epsilon_{s,t} \ \epsilon_{R,t} \ \epsilon_{\tau,t} \ \epsilon_{\pi,t} \ \epsilon_{b,t}]', \text{ and}$$

$$\eta_t = [\eta_{c,t} \ \eta_{\pi,t}]'.$$



## Appendix B Prior implications

Here, we show results of a prior predictive analysis. In particular, we take 20,000 draws from the prior and simulate with these draws 20,000 times the model's observables.

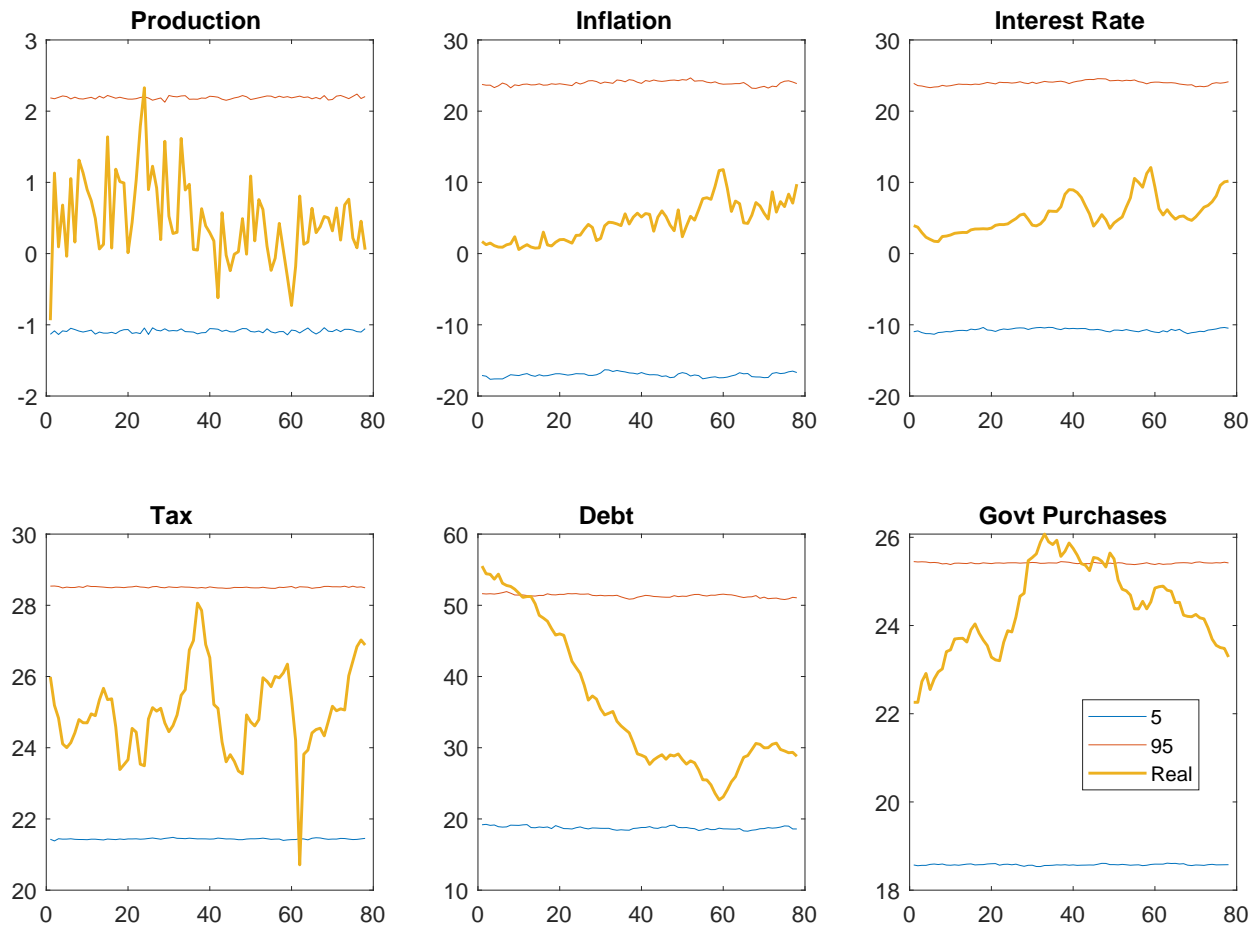


Figure 1: Simulated model observables vs. real data for the period 1960:Q1 to 1979:Q2. The bold yellow line shows the actual time series we use for estimating the model. The blue and the red line show the 90% interval of the simulated time series.

## Appendix C Data description

We use the dataset of Bhattarai et al. (2016). Unless otherwise noted, the data is retrieved from the National Income and Product Accounts Tables published by the Bureau of Economic Analysis. All time series in nominal values are converted to real values by dividing them by the GDP deflator.

**Per capita output:** Per capita output is the sum of personal consumption of nondurables and services, and government consumption divided by civilian noninstitutional population. Civilian noninstitutional population is taken from the FRED database of the Federal Reserve Bank of St. Louis.

**Inflation:** The gross inflation rate is the annualized GDP deflator.

**Interest rate:** The annualized nominal interest rate is the effective federal funds rate from the FRED database of the Federal Reserve Bank of St. Louis.

**Tax revenues:** The tax-revenues-to-output ratio is defined as the sum of current tax receipts and contributions for government social insurance divided by output.

**Government debt:** Government debt corresponds to the market value of privately held gross federal debt, retrieved from the Federal Reserve Bank of Dallas. The government debt-to-output ratio is obtained by dividing the series by output.

**Government spending:** The government spending-to-output ratio is defined as government consumption divided by output.

The relationship between observables and model variables is given by

$$\begin{bmatrix} 100 \times \Delta \ln \text{Output}_t \\ \text{Infl}_t (\%) \\ \text{Interst}_t (\%) \\ \text{TaxRev}_t (\%) \\ \text{GovDebt}_t (\%) \\ \text{GovSpend}_t (\%) \end{bmatrix} = \begin{bmatrix} a \\ 4\pi \\ 4(a + \pi + \mu) \\ \tau \\ b \\ g \end{bmatrix} + \begin{bmatrix} \hat{Y}_t - \hat{Y}_{t-1} + \hat{a}_t \\ 4\hat{\pi}_t \\ 4\hat{R}_t \\ \hat{\tau}_t \\ \hat{b}_t \\ \hat{g}_t \end{bmatrix}. \quad (29)$$

## Appendix D SMC algorithm

This appendix completes the technical description of the implemented SMC algorithm. In terms of exposition and notation it draws heavily on Herbst and Schorfheide (2014, 2015) and Bognanni and Herbst (2018).

### Appendix D.1 SMC with likelihood tempering

1. The SMC is **initialized** by drawing the particles of the first stage ( $n = 1$ ;  $\delta_1 = 0$ ) from the prior density.<sup>9</sup>

$$\vartheta_1^i \stackrel{i.i.d.}{\sim} p(\vartheta) \quad i = 1, \dots, N.$$

In the first stage, each particle receives equal weight such that  $W_1^i = 1$ .

#### 2. Recursions:

for  $n=2:N_\delta$

1. *Correction:* Reweight the particles from stage  $n - 1$  by defining the incremental and normalized weights as

$$\tilde{w}_n^i = [p(Y|\vartheta)]^{\delta_n - \delta_{n-1}}, \quad \tilde{W}_n^i = \frac{\tilde{w}_n^i W_{n-1}^i}{\frac{1}{N} \sum_{i=1}^N \tilde{w}_n^i W_{n-1}^i}, \quad i = 1, \dots, N.$$

2. *Selection:* Check particle degeneracy by computing the effective sample size

$$ESS_n = \frac{N}{\frac{1}{N} \sum_{i=1}^N (\tilde{W}_n^i)^2}.$$

The ESS monitors the variance of the particle weights. The larger this variance, the more inefficient runs the sampler. If the distribution of particle weights becomes too uneven, resampling the particles helps to improve accuracy.

if  $ESS_n < N/2$

---

<sup>9</sup>To ease notation in Appendix D, we assume that the parameters in  $M$  are part of  $\vartheta$ .

Resample the particles via systematic resampling and set the weights to uniform

$$W_n^i = 1, \quad \hat{\vartheta}_n^i \sim \{\vartheta_{n-1}^j, \tilde{W}_n^j\}_{j=1, \dots, N} \quad i = 1, \dots, N.$$

else

$$W_n^i = \tilde{W}_n^i, \quad \hat{\vartheta}_n^i = \vartheta_{n-1}^i, \quad i = 1, \dots, N$$

end if

3. *Mutation*: Propagate each particle  $\{\tilde{\vartheta}_N^i, W_n^i\}$  via  $M_{MH}$  steps of a RWMH with  $N_{blocks}$  random blocks. See Appendix D.2 for further details.

end for

### 3. Process **posterior estimates**.

## Appendix D.2 Mutation step

In this section, we specify the RWMH sampler we use for particle mutation. In accordance with Herbst and Schorfheide (2014) and Bognanni and Herbst (2018) the RWMH steps in our application are characterized by the following two features. First, we reduce the dimensionality of the parameter vector  $\vartheta$  by splitting it into  $N_{blocks}$  blocks, thus making it easier to approximate the target density in each of the RWMH's  $M_{MH}$  steps.<sup>10</sup> Second, we scale the variance of the proposal density adaptively. Let  $\hat{\Sigma}_n$  be the estimate of the covariance of  $p_n(\vartheta|Y)$  after the selection step, and  $c_n$  be a scaling factor. We set  $c_n$  as a function of the previous stage's scaling factor  $c_{n-1}$ , and the average empirical acceptance rate of the previous stage's mutation step  $\hat{A}_{n-1}$ . We target an acceptance rate of 25 % and hence increase  $c_n$  if the acceptance rate in stage  $n - 1$  was too high, and decrease  $c_n$

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<sup>10</sup>Chib and Ramamurthy (2010) and Herbst (2012) provide evidence that parameter blocking is beneficial for estimating DSGE models.

if it was too low. In particular, the functional form is given by  $\hat{c}_n = \hat{c}_{n-1}f(\hat{A}_{n-1})$ , where  $f(x) = 0.95 + 0.1 \frac{e^{16(x-0.25)}}{1+e^{16(x-0.25)}}$ .

1. In every  $n$  stage after the *selection* step, create a **random partitioning** of the parameter vector  $\vartheta$  into  $N_{blocks}$ .  $b$  denotes the block of the parameter vector such that  $\vartheta_{b,n}^i$  refers to the  $b$  elements of the  $i$ th particle, and  $\vartheta_{<b,n}^i$  denotes the remaining partitions.
2. **Compute** an estimate of the **covariance** of the parameters as

$$\hat{\Sigma}_n = \sum_{i=1}^N W_n^i (\hat{\vartheta}_n^i - \hat{\mu}_n)(\hat{\vartheta}_n^i - \hat{\mu}_n)' \quad \text{with} \quad \hat{\mu}_n = \sum_{i=1}^N W_n^i \hat{\vartheta}_n^i.$$

The covariance for the  $b$ th block is given by

$$\hat{\Sigma}_{b,n} = [\hat{\Sigma}_n]_{b,b} - [\hat{\Sigma}_n]_{b,-b} [\hat{\Sigma}_n]_{-b,-b}^{-1} [\hat{\Sigma}_n]_{-b,b},$$

where  $[\hat{\Sigma}_n]_{b,b}$  refers to the  $b$ th block of  $\hat{\Sigma}_n$ .

### 3. MH steps:

for  $m=1:M_{MH}$

for  $b=1:N_{blocks}$

1. Draw a proposal density  $\vartheta_b^* \sim N(\vartheta_{m-1,b,n}^i, c^2 \hat{\Sigma}_{b,n})$ .

$$\vartheta^* = [\vartheta_{m,<b,n}^i, \vartheta_b^*, \vartheta_{m-1,>b,n}^i] \quad \text{and} \quad \vartheta_{m,n}^i = [\vartheta_{m,<b,n}^i, \vartheta_{m-1,\geq b,n}^i].$$

2. With probability

$$\alpha = \min \left\{ \frac{[p(Y|\vartheta^*)]^{\delta_n} p(\vartheta^*)}{[p(Y|\vartheta_{m,n}^i)]^{\delta_n} p(\vartheta_{m,n}^i)}, 1 \right\},$$

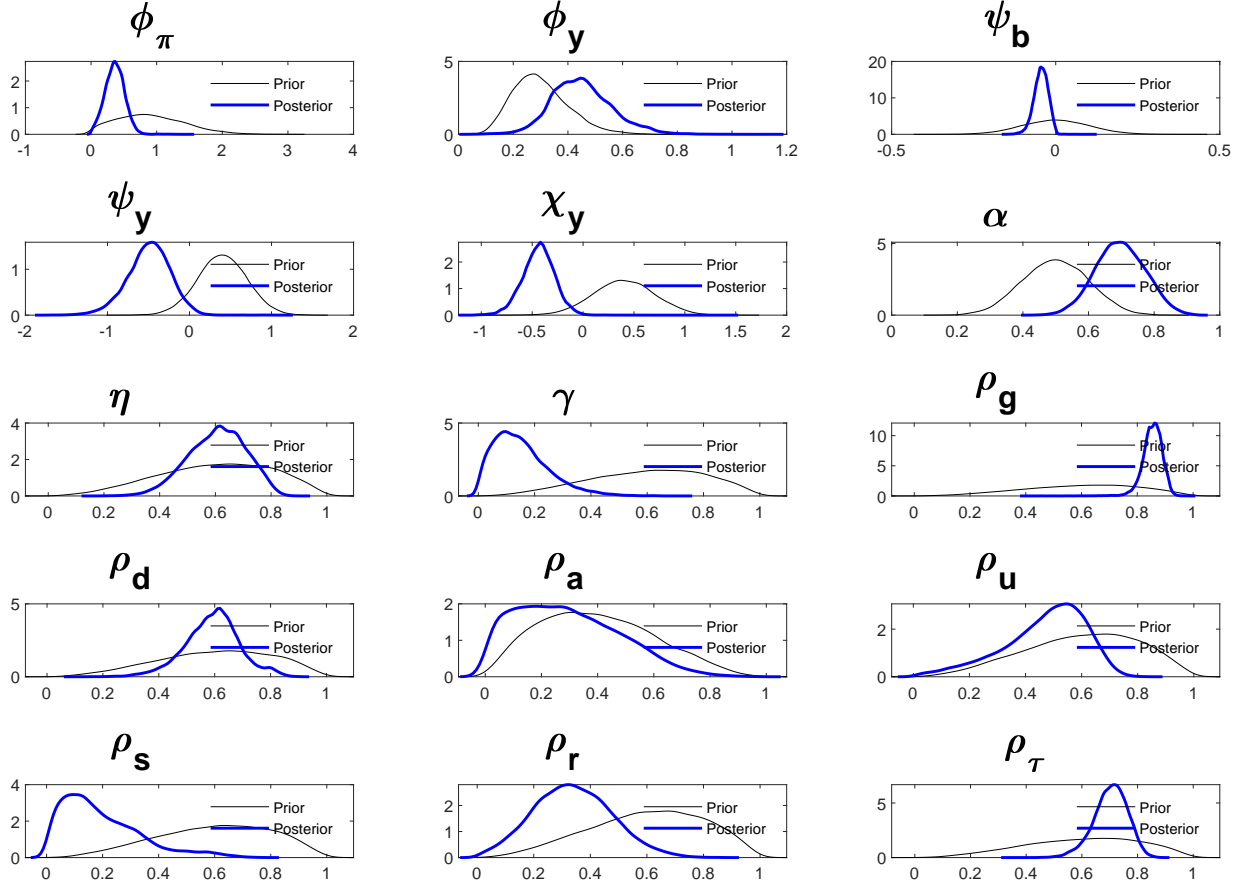
set  $\vartheta_{m,b,n}^i = \vartheta_b^*$ . Otherwise, set  $\vartheta_{m,b,n}^i = \vartheta_{m-1,b,n}^i$ .

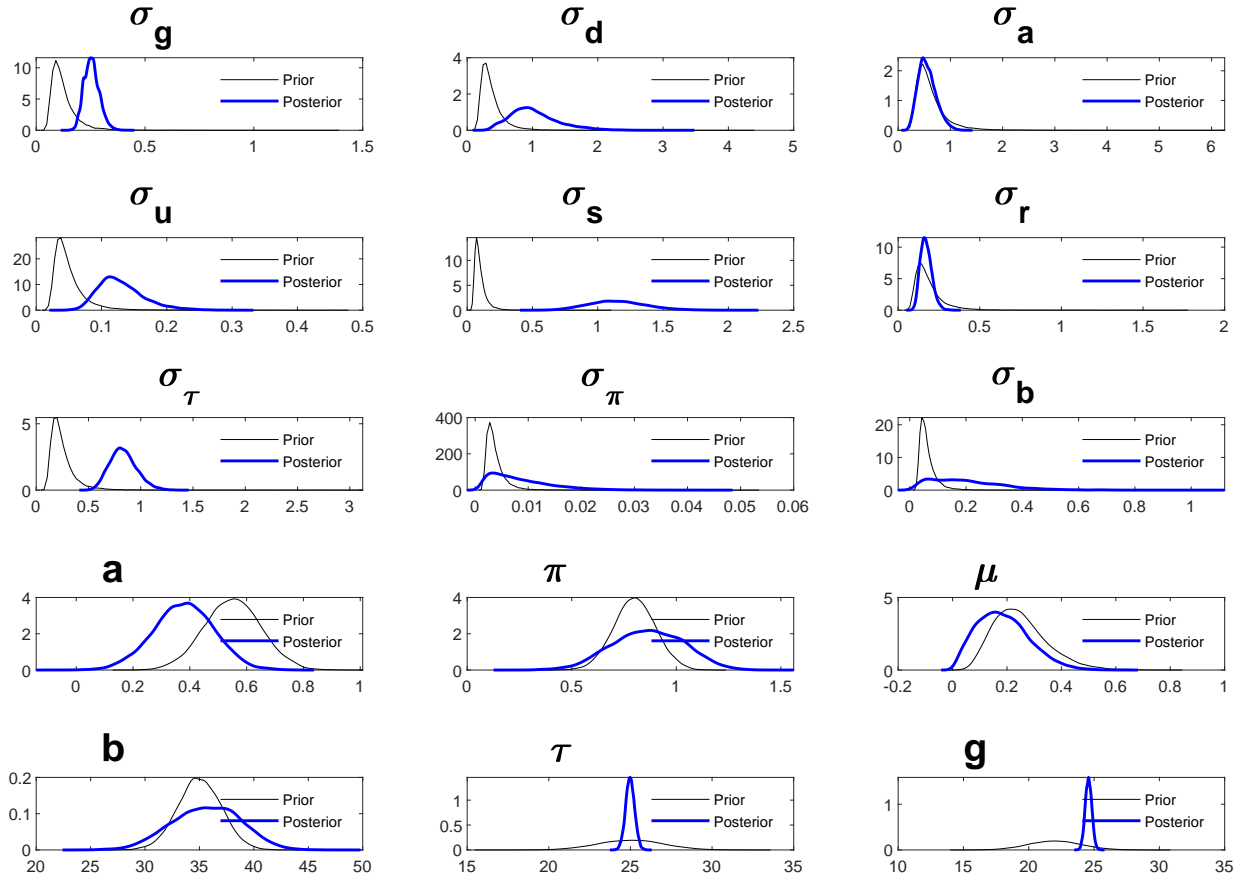
end for

end for

## Appendix E Prior and posterior densities

Here, we show the prior and posterior densities of the estimated model parameters.







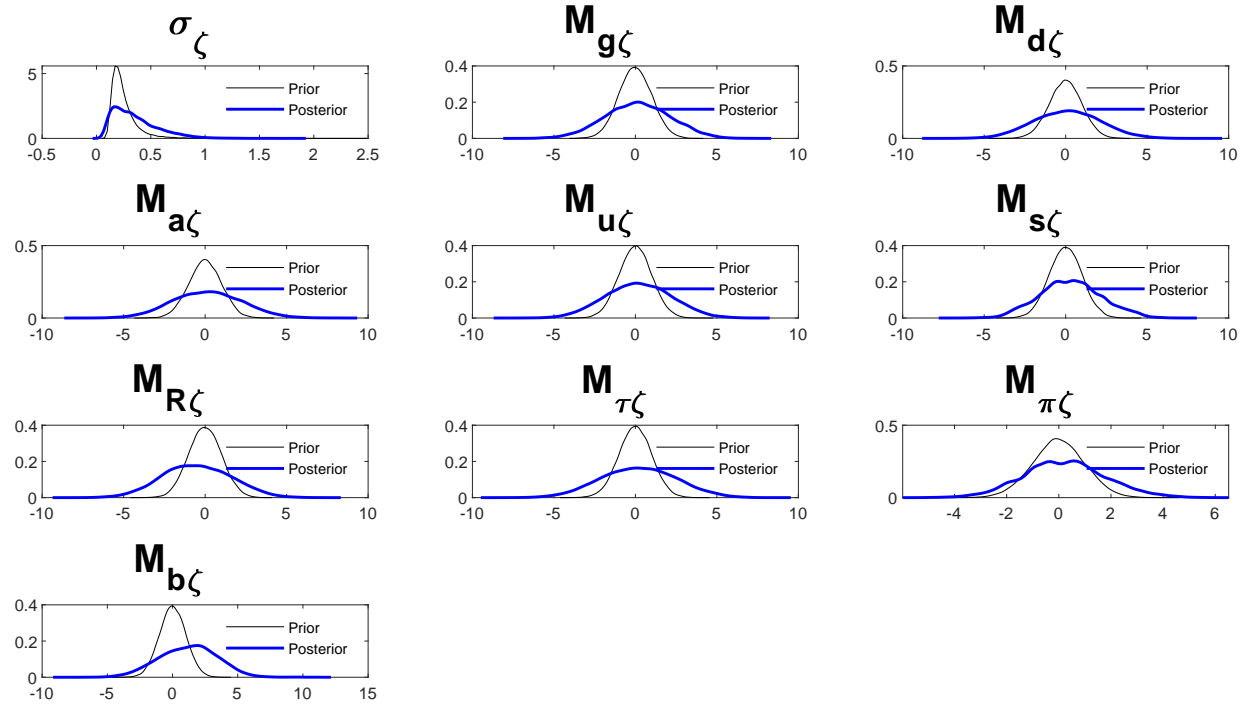


Figure 2: Prior and posterior densities of the estimated model parameters. The blue bold line depicts the posterior density, the black line the prior density.