Active or passive? Revisiting the role of fiscal policy in the Great Inflation

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Abstract

Which role did fiscal policy play during the Great Inflation? We estimate a DSGE model with three distinct monetary/fiscal policy regimes using a Sequential Monte Carlo (SMC) algorithm to evaluate the posterior distribution. In contrast to standard sampling algorithms, SMC enables us to determine the monetary/fiscal policy mix by sampling simultaneously from all regions of the parameter space, which makes comparing model fit across regimes unnecessary. A differentiated perspective results: pre-Volcker macroeconomic dynamics were similarly driven by passive monetary/passive fiscal policy and fiscal dominance. Fiscal policy actions, especially government spending, were critical in the pre-Volcker inflation build-up.

JEL classification: C11, C15, E63, E65

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1 Introduction

With the inevitable COVID-19 fiscal responses, the global sovereign debt level is set to rise to a record high. The need to prevent situations in which debt becomes unsustainable puts surprise inflation on the table as a policy option to reduce nominal debt. Not surprisingly, the almost entirely deficit financed $ 1.9 trillion of federal government spending, included in U.S. President Biden's American Rescue Plan Act, have sparked a controversial discussion among economists on the looming inflation risk (Blanchard, 2021; Summers, 2021). The fiscal theory of the price level (FTPL) puts the current mix of monetary and fiscal policies at center stage in this debate: in a situation in which the fiscal authority is not committed to stabilize debt by managing the primary surplus and the monetary authority acts accommodatively, increasing government spending could deanchor inflation expectations (Leeper et al., 2017).[1]

For one historical episode, which is very instructive for all these aspects, 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 the role of fiscal policy during the Great Inflation to obtain insights for potential policy options in the current economic crisis. We estimate a DSGE model with three distinct monetary/fiscal policy regimes using a Sequential Monte Carlo algorithm (SMC) - a posterior sampler established in the DSGE literature by Herbst and Schorfheide (2014, 2015). The SMC is able to deal with multimodal posterior surfaces and enables us to estimate a fixed-regime DSGE model with distinct monetary/fiscal policy regimes over its entire parameter space. We find that the macroeconomic dynamics during the pre-Volcker period were almost similarly driven by a passive monetary/passive fiscal policy regime and fiscal dominance. This new result calls for a more differentiated perspective on the causes of the Great Inflation. Not only did non-

[1] The insight that monetary and fiscal policy are not independent from each other and must be studied jointly has a long tradition in modern macroeconomics, going back to Sargent and Wallace (1981), Leeper (1991), Sims (1994), Woodford (1996), and Cochrane (2001). Cochrane (2011), Davig and Leeper (2011) and Bianchi and Melosi (2017) study the interaction of monetary and fiscal policy in a recession. Ascari et al. (2020) call for a new taxonomy for studying the interactions of monetary and fiscal policy. Bianchi et al. (2020) propose a concrete policy that involves coordination between the monetary and fiscal authorities in response to the COVID-19 pandemic.

policy shocks create inflationary pressure, but fiscal policy actions, in particular government spending, were also an equally important driver of U.S. inflation in the 1960s and 1970s.

Our findings contribute to the still open role of U.S. fiscal policy during the Great Inflation. The literature largely agrees that monetary policy in the pre-Volcker period was passive and, hence, was not able to stabilize prices.[2] However, concerning the stance of fiscal policy, the evidence is mixed. Bhattarai et al. (2016), who apply random walk Metropolis-Hastings sampling (RWMH) to estimate a fixed-regime DSGE model with monetary and fiscal policy interactions, find that the fiscal authority was passive and strongly increased taxes to debt.[3] On the contrary, studies relying on regime-switching DSGE models like Davig and Leeper (2006), Bianchi (2012), Bianchi and Ilut (2017), and Chen et al. (2019) mainly attribute the leading role in the pre-Volcker period to the fiscal authority.

By re-estimating the fixed-regime model of Bhattarai et al. (2016) with the more suitable SMC posterior sampler, we can finally dissolve the persisting dissonance between these two model classes. As shown by Herbst and Schorfheide (2014, 2015) and Cai et al. (2020), the SMC sampler outperforms the RWMH in the presence of multimodal posteriors. This result is particularly relevant for DSGE models with monetary-fiscal policy interactions that exhibit discontinuous likelihood functions around the policy regimes.[4] While Bhattarai et al. (2016) still estimated each regime separately by RWMH and determined the prevailing pol-

[2]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, while Coibion and Gorodnichenko (2011), including the trend level of inflation in their study, arrive at a similar conclusion. Bilbiie and Straub (2013) rationalize the Fed's passive policy response in the pre-Volcker period with limited asset market participation and find it was consistent with equilibrium determinacy. Ascari et al. (2019) also find evidence for passive monetary policy in the pre-Volcker period. However, their analysis explains the Great Inflation with temporary unstable inflation dynamics due to expectations, which were independent from monetary policy behavior.

[3]In an earlier study, Traum and Yang (2011) find no evidence for an active U.S. fiscal authority in the pre-Volcker period. Tan and Walker (2015) point out potential for observational equivalence across active and passive fiscal policy in a cashless version of the model of Leeper (1991).

[4]For instance, due to discontinuities in the posterior at the boundary of the policy regimes, transitions of the RWMH between areas of the parameter space with similar fit can be impeded. Ascari et al. (2019), Hirose et al. (2020), and Haque et al. (2021) are applications of the SMC algorithm for estimating a DSGE model with multiple regimes. However, all three studies examine exclusively the role of monetary policy and omit the fiscal side from the model.

icy mix by model comparison, we can execute the same estimation in one step using SMC.[5] Estimating the model over its continuous parameter space allows us to determine the posterior probability of each policy regime directly and to draw a more nuanced conclusion: in line with Bhattarai et al. (2016), we find that equilibrium indeterminacy indeed played an important role pre-Volcker. However, echoing the conclusion of regime-switching DSGE models, regime F, at 37 % posterior probability, mattered as well. Hence, putting all weight on indeterminacy is misleading for understanding the mechanism behind the Great Inflation.

The remainder of this paper is as follows. Section 2 describes the DSGE model with monetary-fiscal policy interactions. In Section 3, we outline our empirical approach and provide estimation results to determine the monetary-fiscal policy mix in the pre-Volcker period. In light of our findings, in Section 4, we examine what caused the build-up of U.S. inflation in the 1960s and 1970s. The final section concludes the study.

2 A DSGE model with monetary-fiscal policy interactions

In this section, we outline the fixed-regime DSGE model with monetary-fiscal policy interactions of Bhattarai et al. (2016), our reference model, characterize its distinct monetary-fiscal policy regimes, and present the solution method for the model.

2.1 Model description

We use the fixed-regime 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. Here, we only present

[5] Bianchi and Nicolò (2019) propose a novel solution method that is particularly relevant for models with an unknown degree of indeterminacy and/or unknown boundaries of the determinacy region. For inference, they suggest the SMC algorithm, as used in this study, or, as an alternative, a hybrid Metropolis-Hastings algorithm.

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:

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

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.[6] The parameters $\bar{a}$ and η denote the steady-state value of a_t and external habit formation, respectively.

The New Keynesian Phillips curve is denoted by

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

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 β, γ, φ, and $\bar{g}$ are, respectively, the discount factor, the degree of price indexation, the inverse of the Frisch elasticity of labor supply, and the steady-state value of government spending. Furthermore, $\kappa := \frac{(1-\alpha\beta)(1-\alpha)}{\alpha\left(1+\varphi\bar{\theta}\right)(1+\gamma\beta)}$. α 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:

[6] We define the log-linear deviation of a detrended variable from its corresponding steady state as $\hat{X}_t = lnX_t - ln\bar{X}$. 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.

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

$\hat{\pi}_t^*$ 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 ρ_R, ϕ_π, and ϕ_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:

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

$\hat{\tau}_t$ 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 (ρ_τ), systematic reactions of tax revenues to deviations of lagged debt from its target (ψ_b), and to deviations of output from natural output (ψ_Y).

The government spending rule is modeled as

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

$\hat{g}_t$ 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 $N(0, \sigma_g^2)$. ρ_g represents smoothing in government purchases and χ_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:

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

The government budget constraint is given by:

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

$\hat{s}_t$ 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:

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

The natural level of output is:

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

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

Preferences evolve as

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

Technology evolves as

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

Markup shocks are assumed to follow

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

Government transfers are given by

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

The inflation target evolves as

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

The debt-to-output ratio target follows

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

2.2 Model solution under different policy regimes

A unique equilibrium of the economy arises if either monetary policy is active while fiscal policy is passive (regime M or AMPF) or monetary policy is passive while fiscal policy is active (regime F or PMAF). If both monetary and fiscal policy are passive, multiple equilibria exist (PMPF). No stationary equilibrium exists if both authorities act actively (AMAF). The boundaries of the distinct policy regimes can be characterized analytically in Bhattarai et al. (2016)'s model. In particular, monetary policy is active if

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

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

$$\psi_b < \frac{1}{\beta} - 1. \tag{17}$$

We collect the parameters of the loglinearized model in the vector ϑ with domain Θ and solve the system of equations for its state-space representation.[7] 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

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

where z_t is a vector of state variables, ϵ_t is a vector of exogenous variables, while both Γ_1^* and Ψ^* are coefficient matrices that depend on the model parameters collected in the vector ϑ. Under indeterminacy, we apply the generalization of this procedure suggested by Lubik and Schorfheide (2003, 2004):

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

Under indeterminacy, the transmission of fundamental shocks ϵ_t is no longer uniquely determined as it depends not only on the coefficient matrix $\Gamma_{0,\epsilon}^*$, but also on the matrices $\tilde{M}$ and $\Gamma_{0,\zeta}^*$.[8] Second, an exogenous sunspot shock ζ_t, unrelated to the fundamental shocks ϵ_t, potentially affects the dynamics of the model variables z_t. This effect depends on the coefficient matrices $\Gamma_{0,\zeta}^*$ and M_ζ.

3 Empirical Results

In this section, we present the empirical model results. In a first step, we describe the prior distributions and the dataset and illustrate the procedure for posterior sampling we choose that makes our study distinct. In a second step, we summarize the estimation results and

[7]More details on the implementation of the model solution are given in Appendix A.1.

[8]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. We choose $M^*(\vartheta)$ such that the impulse responses $\partial z_t / \partial \epsilon_t'(\vartheta, M)$ become continuous on the boundary and estimate the vector M. Appendix A.2 describes the approach in more detail.

Table 1: Prior distributions of monetary and fiscal policy parameters

Parameter	Range	Distribution	Mean	SD	90 percent int.
ϕ_π, active / passive monetary policy	$\mathbb{R}^+$	N	0.8	0.6	$[0.14, 1.84]$
ψ_b, active / passive fiscal policy	$\mathbb{R}$	N	0	0.1	$[-0.16, 0.16]$

determine the monetary-fiscal policy mix in the pre-Volcker period.

3.1 Estimation strategy

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 labor supply to $\varphi = 1$ and the steady-state value of the elasticity of substitution between goods to $\bar{\theta} = 8$, since these cannot be separately identified from the Calvo parameter α. We also fix the parameters measuring the persistence of the time-varying policy targets to $\rho_\pi = \rho_b = 0.995$. Our prior distributions extend over a broad range of parameter values.[9] As we initialize the SMC algorithm from the prior, we used prior predictive analysis to carefully tailor a prior that results in realistic model implications, but nevertheless remains agnostic about the prevailing policy regime.[10] In the following, we discuss only the key parameters of our analysis.

Specifically, the policy parameters in the monetary and fiscal policy rule, ϕ_π and ψ_b play a central role in our analysis as they determine the policy regime. Table 1 summarizes the details. For ϕ_π, we choose a Normal distribution restricted to the positive domain with an implied 90 % probability interval from 0.14 to 1.84, while the interval extends from -0.16 to 0.16 for ψ_b. Our choice is motivated by the consideration to construct prior distributions that yield more or less equal probabilities for regime F and the PMPF regime. In particular, as we

[9]Table 4 in Appendix B.1 specifies the prior distributions of all model parameters.

[10]In Appendix B.2 we show results from the 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.

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 PMPF regime receive almost identical support.

Table 2: Prior probability of pre-Volcker policy regimes

	AMPF	PMAF	PMPF
Probability	25.64	37.88	36.48

Note: The prior probabilities of the policy regimes are obtained from a prior predictive analysis. We drew ϑ 20,000 times from the priors specified in Table 4, solved the model with each draw and computed the shares of each policy regime.

A second group of parameters we want to highlight are those necessary to characterize the indeterminacy model solution. For the parameters in the vector M, representing agents' self-fulfilling beliefs, we choose, as Bhattarai et al. (2016), priors centered around zero in order to let the data decide if and how indeterminacy changes the propagation mechanism of the fundamental shocks.

Data

We use the dataset of Bhattarai et al. (2016).[11] 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. The list of observables includes output, inflation, nominal interest rates, the tax-revenue-to-output ratio, the market value of the government debt-to-output ratio, and the government spending-to-output ratio.

[11] The dataset is downloadable 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.

Sequential Monte Carlo posterior sampling

Posterior inference in DSGE models relies on sampling techniques as the moments of the posterior cannot be characterized in closed forms. For our application, we choose the SMC algorithm introduced to the DSGE literature by Creal (2007) then further enhanced and theoretically justified by Herbst and Schorfheide (2014, 2015).[12] As shown by Herbst and Schorfheide (2014, 2015) and Cai et al. (2020), the SMC algorithm outperforms the workhorse RWMH sampler in cases of multimodal posteriors, an outcome of extreme relevance in the case of the DSGE model with monetary-fiscal policy interactions with a discontinuous likelihood function. Due to this feature, neither are we obliged to estimate the model separately, nor must we compare model fit across regimes. Rather, we let the SMC algorithm explore the entire parameter space such that the probability of each policy regime is directly determined by the data.[13]

[12] Chopin (2002), Del Moral et al. (2006), and Creal (2012), among others, provide further details on SMC algorithms. Cai et al. (2020) advance the tuning of the algorithm in the context of DSGE model estimation.

[13] Appendix D includes a more detailed description of the SMC algorithm and our choice of tuning parameters.

3.2 The monetary-fiscal policy mix in the pre-Volcker period

Posterior estimates

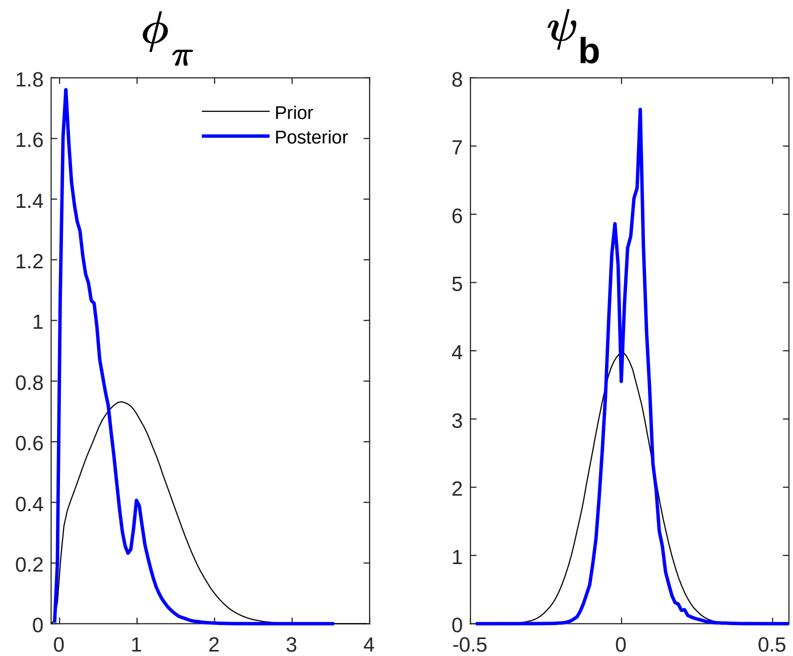

Figure 1: Prior and posterior densities of the policy parameters. The blue bold line depicts the posterior density, the black line the prior density.

Figure 1 shows prior and posterior density plots of the estimated policy parameters.[14] The posterior densities of ϕ_π and ψ_b display pronounced bimodalities around the policy regimes. For ϕ_π, the mode to the left of one corresponds to a passive monetary authority, while the mode on the right corresponds to an active central bank. The boundary of fiscal policy (ψ_b) lies around zero. The mode to the left of the boundary corresponds to an active fiscal authority, the mode to the right to a passive fiscal authority. It is also noticeable that the probability mass below each mode is unequally distributed.

[14] Appendix E.1 shows posterior estimates from an estimation in which we restrict the parameter space and apply SMC sampling to estimate each policy regime sequentially. The purpose of this exercise is to show (i) that the SMC sampler is able to replicate the RWMH estimation results of Bhattarai et al. (2016), our reference study, that the PMPF regime was the dominant regime pre-Volcker, and (ii) that our prior specification does not affect the probability of policy regimes in the posterior. Appendix E.2 contains the density plots of the remaining parameters from the unrestricted estimation as well as tables with estimated means, standard deviations, and credible bands for all parameters. Appendix E.3 contains posterior density plots of the unrestricted estimation conditional on regime F and the PMPF regime.

To shed more light on the estimated monetary-fiscal policy mix, we present the posterior probabilities of the policy regimes in the pre-Volcker period (Table 3). In line with Bhattarai et al. (2016), we find that the regime with the highest posterior probability in the pre-Volcker period is, at 43.54 %, the PMPF regime. However, in contrast to their analysis, we find that with 36.81 % probability, regime F scores only slightly worse. In line with the literature, regime M receives the least support from the data, at 19.65 %.[15]

Table 3: Posterior probability of pre-Volcker policy regimes

	AMPF	PMAF	PMPF
Probability	19.65	36.81	43.54

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 over 50 independent runs of the SMC algorithm.

Discussion

Although our estimation attributes indeterminacy a role in the pre-Volcker period, differently to Bhattarai et al. (2016), we draw a more differentiated conclusion and argue in the following that regime F also matters for the macroeconomic dynamics in the pre-Volcker period. First, in our analysis, regime F receives, at 36.81 %, considerable probability that is only seven percentage points less than the, on average, dominant PMPF regime. Due to this significant empirical support, regime F should not simply be neglected. Second, our results complement a range of studies that already convincingly discuss quantitative or narrative evidence for a leading fiscal authority during particular periods in the pre-Volcker era. Sims (2011), for instance, refers to the emerging primary deficits in the U.S. related to President Ford's tax

[15] The finding that monetary policy in the pre-Volcker period was mainly passive, is also widely established in the literature. Therefore, in the following, we focus our discussion entirely on the still open role of fiscal policy and look exclusively on regime F and the PMPF regime.

cuts and rebates in 1975. Bianchi and Ilut (2017), in a regime-switching DSGE model, even provide empirical evidence for fiscal dominance in the U.S. during the 1960s and 1970s, outlining the fiscal expansion due to the Vietnam War and Lyndon B. Johnson's Great Society reforms.[16] Our findings support their view that an active U.S. fiscal policy played a substantial role in the build-up of pre-Volcker inflation.

Our chosen SMC approach's merit is that it can create new perspectives in a fixed-regime model environment. As we can estimate the model over its entire parameter space, we remain agnostic and strictly let the data determine each policy regime's probability. In contrast, in our application, RWMH sampling works only for a subset of the parameter space and, hence, would force us to take a zero-one decision. As the model comparison results from the restricted estimation in Table 5 in Appendix E.1 show, we would conclude, like Bhattarai et al. (2016), that only the PMPF regime was in place pre-Volcker. The other policy regimes would not be considered. Instead, our analysis allows us to draw a more nuanced conclusion: although the PMPF regime receives slightly more posterior probability throughout the 1960:Q1 to 1979:Q2 sample, regime F also mattered.

4 Revisiting the Great Inflation

The estimation in the previous section shows that the macroeconomic dynamics in the pre-Volcker period are similarly driven by a passive monetary/passive fiscal policy regime and fiscal dominance. In light of these results, we revisit one of the most pressing macroeconomic questions of this episode, namely, what caused the Great Inflation. In a first step, we use our findings to carry out a historical shock decomposition of pre-Volcker inflation. In a second step, we conduct a counterfactual analysis to quantify the importance of fiscal policy actions in the run up of inflation.

[16] Further references that provide evidence for fiscal dominance in the U.S. in the pre-Volcker period include, among others, Davig and Leeper (2006), Bianchi (2012), and Chen et al. (2019). All these studies employ regime-switching model frameworks.

4.1 Shock decomposition

We partition the draws from the posterior according to the corresponding policy regimes and conduct the historical decomposition for the PMPF regime and regime F separately.

Figure 2 shows the results for the PMPF regime. In line with the findings in Bhattarai et al. (2016), we find that, in the PMPF regime, pre-Volcker inflation was mainly driven by non-policy shocks, in particular, preference, markup, and technology shocks. Importantly, sunspot shocks played only a minor role in the pre-Volcker inflation build-up.[17]

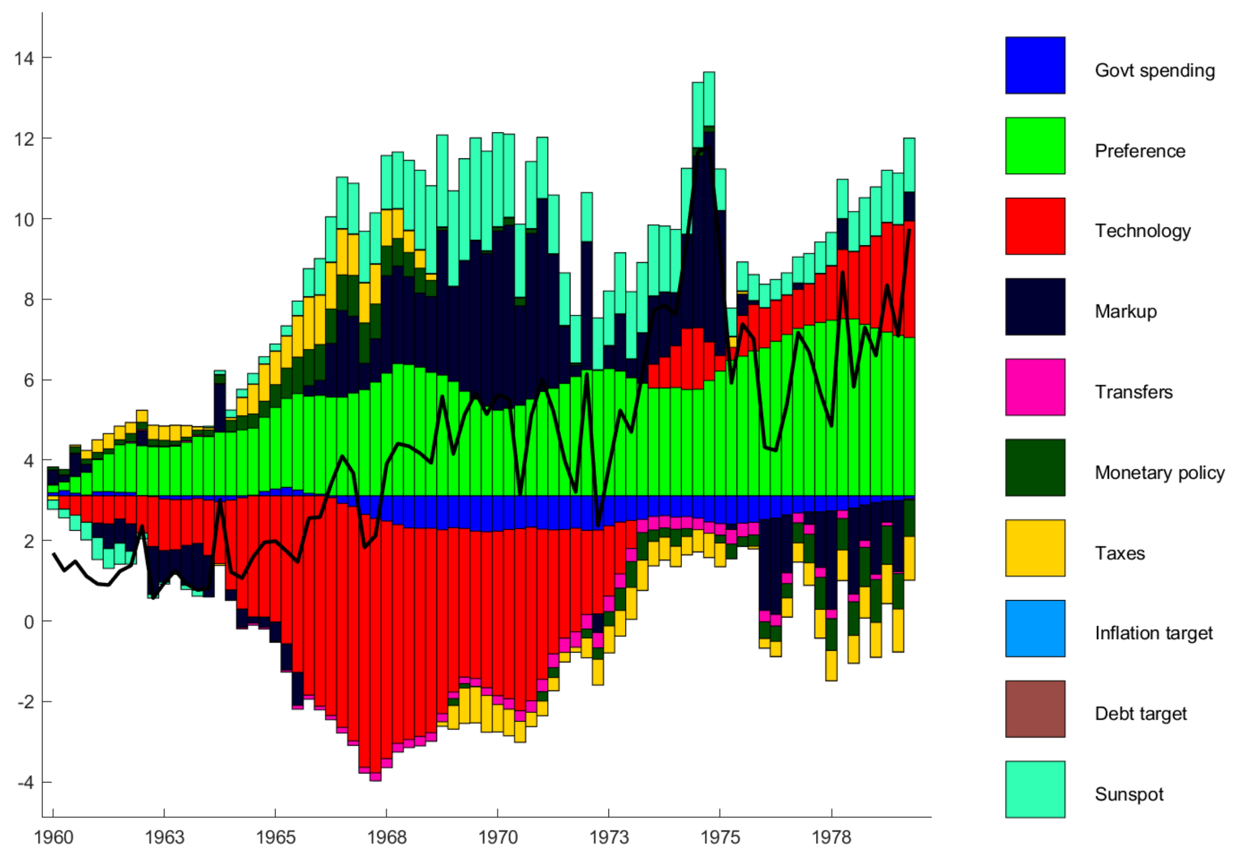

Figure 2: Contribution of each shock to inflation in the PMPF regime. The bold black line shows observed inflation. The historical decomposition is conducted at the posterior mean of the PMPF regime.

In regime F, the picture looks different. Figure 3 summarizes the findings. Technology and demand shocks played only a minor role in regime F. Instead, the mechanism of the

[17] The fact that sunspot shocks played no substantial role in the pre-Volcker inflation build-up is, for instance, also confirmed in Nicolò (2018).

FTPL is clearly present: fiscal actions, government spending in particular, lead to the build-up of inflation.

Summarizing our analysis, we find empirical evidence for the two most widely acknowledged explanations in the literature for the rising U.S. inflation in the pre-Volcker period. First, fundamental non-policy shocks generated persistent inflationary pressure. Sunspot disturbances played no substantial role. Second, fiscal actions, in particular government spending, were an important driver of inflation.

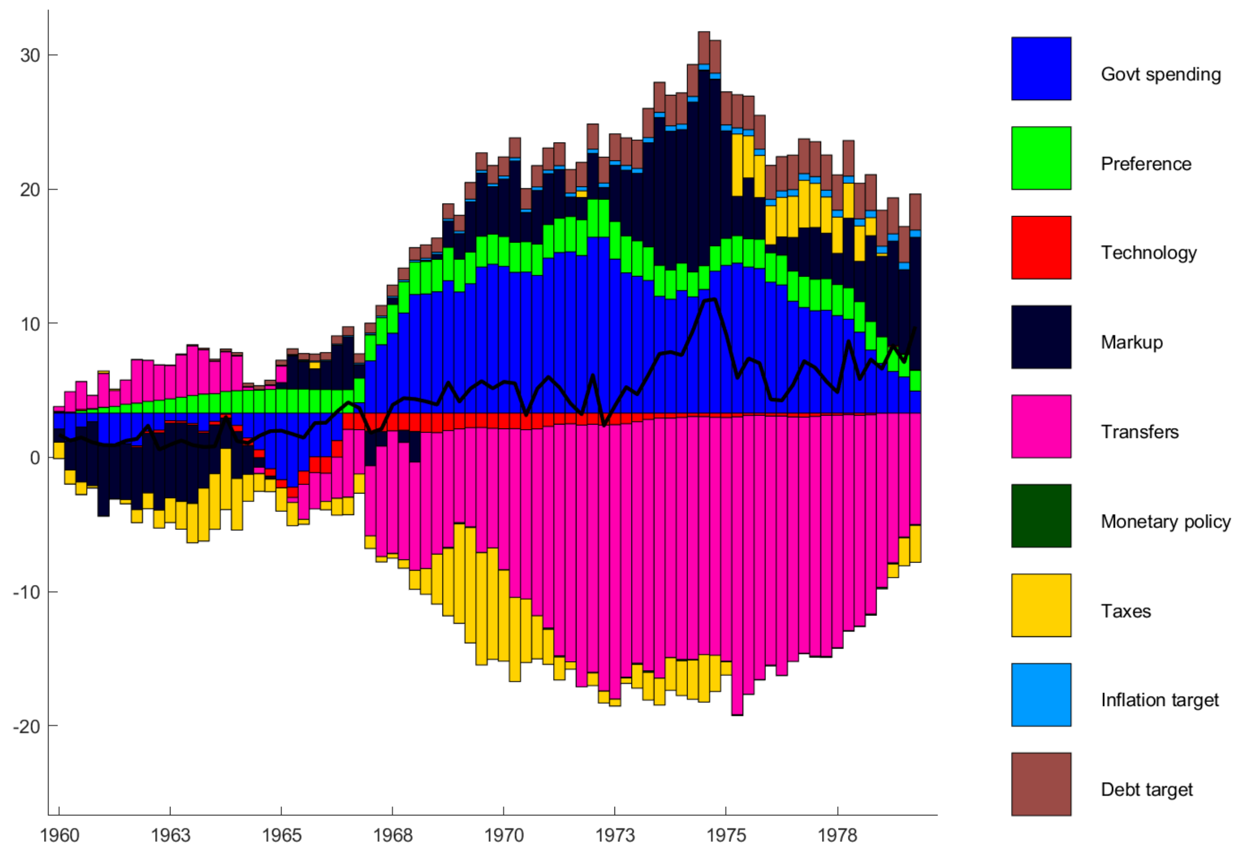

Figure 3: Contribution of each shock to inflation in regime F. The bold black line shows observed inflation. The historical decomposition is conducted at the posterior mean of regime F.

4.2 Counterfactual analysis

To further elaborate the role of government spending for pre-Volcker inflation, we carry out a counterfactual analysis. We set the contribution of government spending shocks in each regime to zero and simulate inflation with the remaining shocks. Figure 4 shows the result. In regime F, counterfactual inflation lies considerably below the observed time series. In the PMPF regime, on the other hand, the difference between actual and counterfactual inflation is almost negligible.

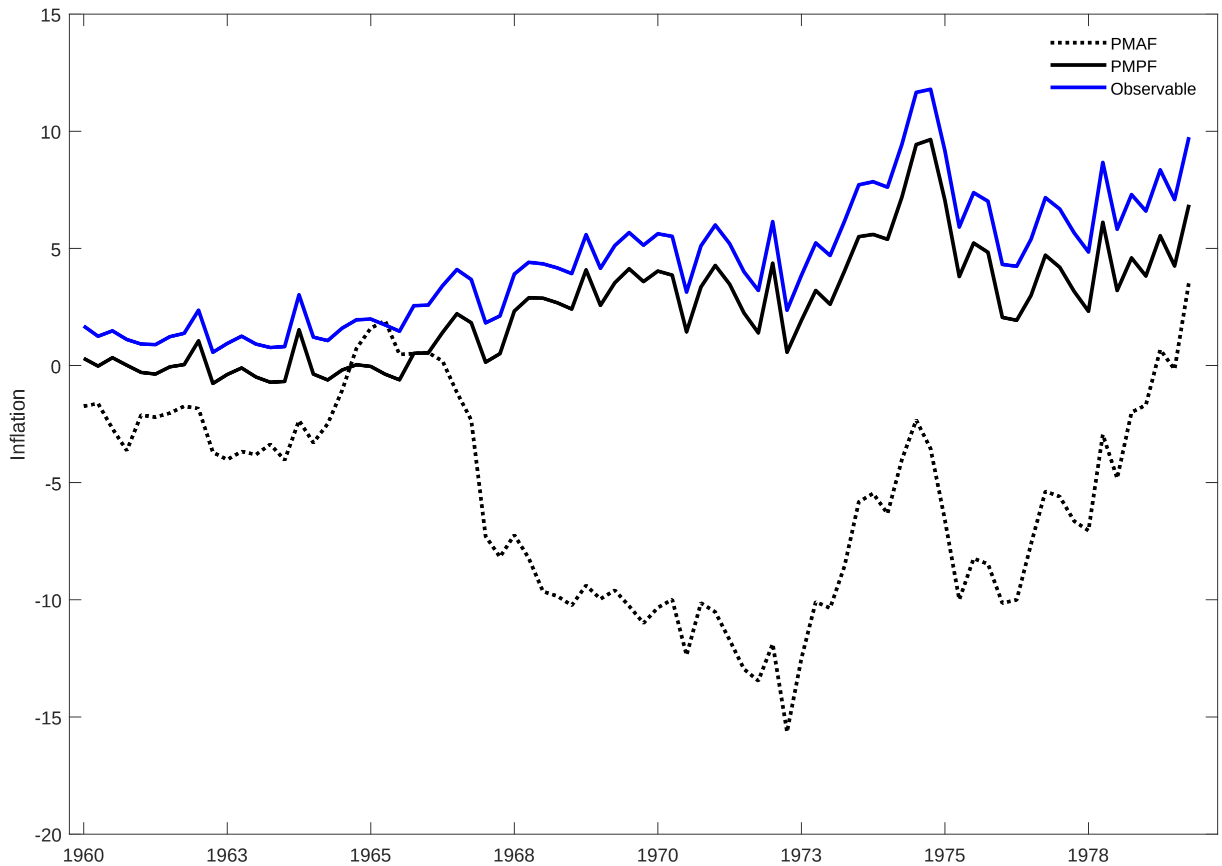

Figure 4: Evolution of inflation (in percentage points) without government spending shock in the PMPF regime and regime F. The counterfactual analysis is conducted at the posterior mean of each policy regime.

We can exclude that the trend of pre-Volcker inflation in regime F and the PMPF regime is due to the sheer size of the government spending shocks. Figure 5 shows that, pre-Volcker, the smoothed government spending shocks of regime F and the PMPF regime are nearly congruent.[18] Hence, the differing evolution of inflation is induced by the regimes themselves.

[18]Appendix F shows plots of the remaining smoothed shocks for regime F and the PMPF regime, respectively.

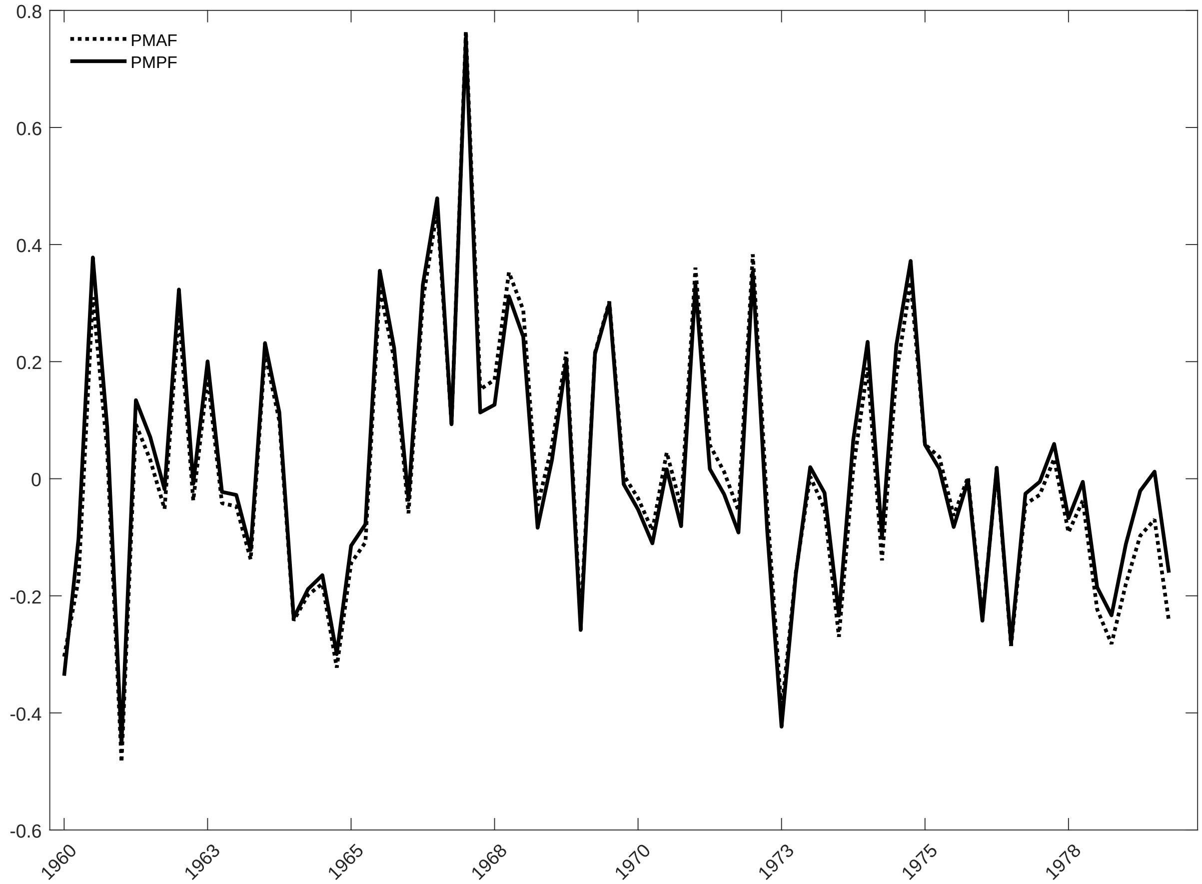

Figure 5: Smoothed government spending shock for 1960:Q1 to 1979:Q2 for regime F and the PMPF regime. The dotted line shows the shock computed at the posterior mean of regime F. The solid line shows the shock computed at the posterior mean of the PMPF regime.

The results of the counterfactual analysis are instructive to evaluate policy measures that effectively brought down pre-Volcker inflation. The Volcker action surely was one possible way to go. By increasing interest rates drastically, the central bank credibly signaled that it will take the lead role. Reagan complied and backed the monetary policy actions. As a result, the monetary-fiscal policy mix switched to regime M. However, conditional on the results in Figure 4, an alternative policy response crystallizes. Less consumption on the part of the fiscal authority during the 1970s would have also reduced the government spending-to-output ratio and, hence, countered the rising inflation.

Translating the experience of the Great Inflation to the ongoing economic disruption caused by the coronavirus, we learn that monetary and fiscal policy must be determined and analyzed jointly when assessing the evolution of inflation.

5 Conclusion

Was fiscal policy a driver of U.S. inflation in the pre-Volcker period? Using an SMC algorithm, we estimate a DSGE model with monetary-fiscal policy interactions over its entire parameter space. Our empirical findings are able to reconcile two opposing strands in the literature. Similar to studies that rely on fixed-regime DSGE models, we find that the PMPF regime receives highest posterior probability throughout the 1960:Q1 to 1979:Q2 sample. However, in line with the regime-switching literature, we also find strong evidence that regime F mattered in the pre-Volcker period. Our analysis attributes fiscal policy, especially government spending, an essential role in the build-up of U.S. inflation. This new result calls for a more differentiated perspective on the causes of the Great Inflation. Not only did non-policy shocks create inflationary pressure, but fiscal policy actions were also an equally important driver of U.S. inflation in the 1960s and 1970s.

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Appendix A Model solution

Appendix A.1 Implementation of the model solution

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

$$\Gamma_0(\vartheta)z_t = \Gamma_1(\vartheta)z_{t-1} + \Psi(\vartheta)\epsilon_t + \Pi(\vartheta)\eta_t. \tag{20}$$

z is the vector of state variables, the vector ϵ includes the exogenous variables, and η 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 A.2 Transmission mechanism around the regime boundaries

Equation 19 illustrates that indeterminacy changes the nature of the solution in two dimensions. First, the transmission of fundamental shocks ϵ_t is no longer uniquely determined as it additionally depends on the matrix $\tilde{M}$. Second, an exogenous sunspot shock ζ_t, unrelated to the fundamental shocks ϵ_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 σ_ζ and normalize as Lubik and Schorfheide (2004) M_ζ 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 ϑ 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. 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: $M = \left[M_{g_\zeta}, M_{d_\zeta}, M_{a_\zeta}, M_{u_\zeta}, M_{s_\zeta}, M_{R_\zeta}, M_{\tau_\zeta}, M_{\pi_\zeta}, M_{b_\zeta}\right]$. For the parameters in M, we choose priors centered around zero and, thus, strictly let the data decide how indeterminacy changes the transmission mechanism of structural shocks.

To compute the matrix $M^*(\vartheta)$ that 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 ϑ resemble the impulse responses conditional on the vector on the boundary $\frac{\partial z_t}{\partial \epsilon_t'}(g^*(\vartheta))$. However, the DSGE model, with monetary-fiscal policy interactions presented in subsection 2, gives rise to two different determinate solutions (regime F and regime M) that 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 ϕ_π in the vector ϑ with

$$\tilde{\phi_\pi} = 1 - \phi_Y \left(\frac{1 - \tilde{\beta}}{\tilde{\kappa}} \right). \tag{21}$$

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

$$\tilde{\psi}_b = \frac{1}{\beta} - 1. \tag{22}$$

2. We solve the model successively with the reparametrized vectors ϑ^M and ϑ^F and compute

$$M^M(\vartheta) = \left[\Gamma^M_{0,\zeta}(\vartheta)'\Gamma^M_{0,\zeta}(\vartheta)\right]^{-1} \Gamma^M_{0,\zeta}(\vartheta)' \left[\Gamma^M_{0,\epsilon}(g^M(\vartheta)) - \Gamma^M_{0,\epsilon}(\vartheta)\right], \text{ and} \tag{23}$$

$$M^F(\vartheta) = \left[\Gamma^F_{0,\zeta}(\vartheta)'\Gamma^F_{0,\zeta}(\vartheta)\right]^{-1} \Gamma^F_{0,\zeta}(\vartheta)' \left[\Gamma^F_{0,\epsilon}(g^F(\vartheta)) - \Gamma^F_{0,\epsilon}(\vartheta)\right]. \tag{24}$$

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

$$D^M = \left[\Gamma^M_{0,\epsilon}(g^M(\vartheta)) - \Gamma^M_{0,\epsilon}(\vartheta)\right] - \Gamma^M_{0,\zeta}(\vartheta)M^M(\vartheta), \text{ and} \tag{25}$$

$$D^F = \left[\Gamma^F_{0,\epsilon}(g^F(\vartheta)) - \Gamma^F_{0,\epsilon}(\vartheta)\right] - \Gamma^F_{0,\zeta}(\vartheta)M^F(\vartheta). \tag{26}$$

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[19]

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

Here, we show plots to demonstrate that our approach delivers effectively continuous impulse response functions on the boundary between policy regimes. We draw 20,000 times from the prior distribution outlined in Section 3.1 and solve with each draw the model. If a

[19]For matrix $D^* = (d^*_{ij})$, its i-th row and j-th column are denoted by d^*_i and d^*_j, respectively.

draw lies in the indeterminacy region, we first determine with the least-square criterion if it is closer to the monetary (regime M) or the fiscal boundary (regime F) of the determinacy region. Then we conduct the following steps:

If the draw's position in the parameter space is closer to the monetary boundary, we reparametrize the parameter vector to lie on the monetary boundary.

1. We solve the model on the boundary and compute impulse responses.
2. We step numerically from the boundary into the indeterminacy region, solve the model and compute impulse responses.
3. To check if the transmission mechanism changes when crossing the boundary, we compute the difference between the impulse responses on the boundary, and the impulse responses from the indeterminacy region.

We repeat the three steps for the draws that are located closer to the fiscal boundary. Figures 6 and 7 show that the impulse responses (IRFs) are nearly congruent.

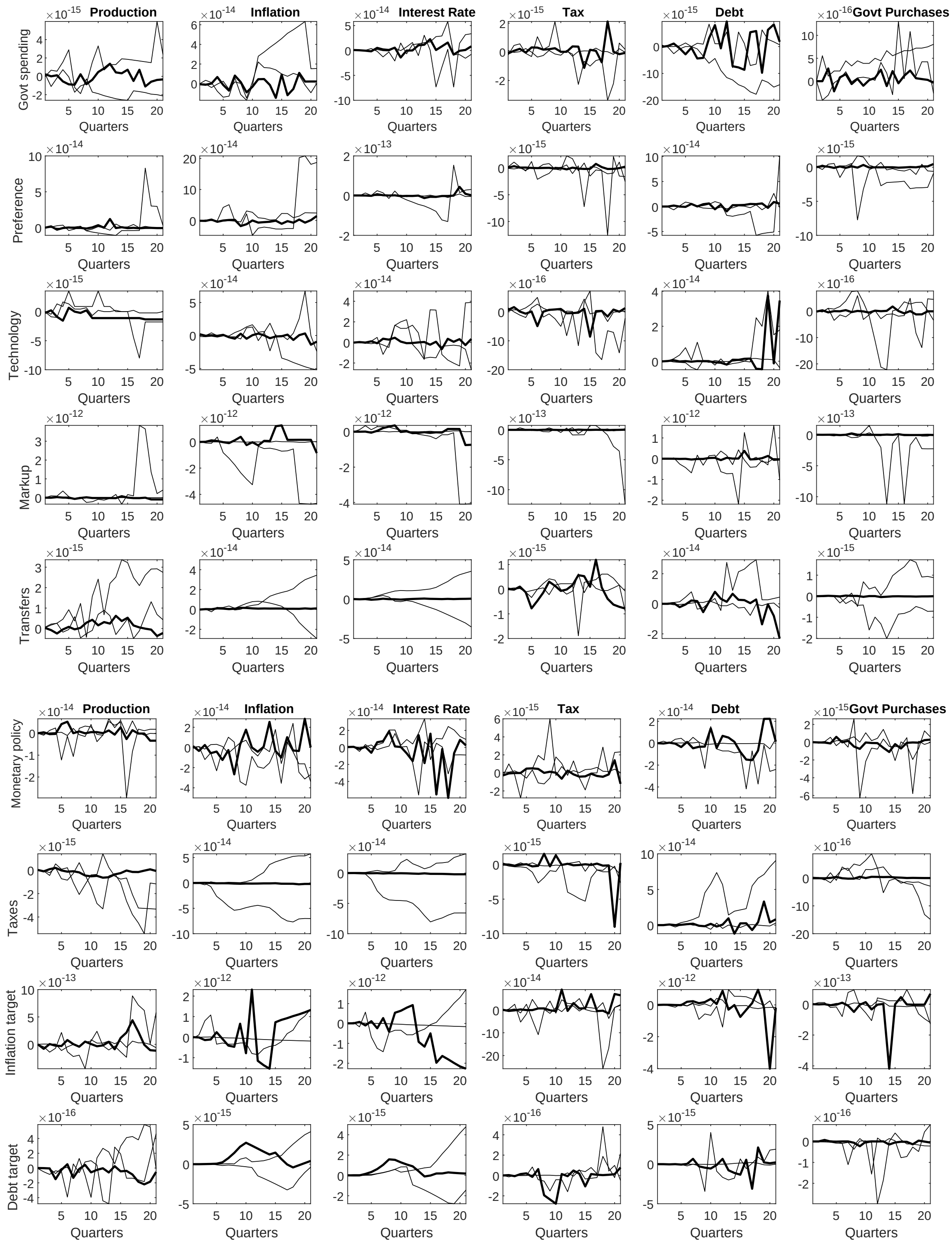


Figure 6: Difference of IRFs computed in the determinacy and the indeterminacy region around the monetary boundary. The bold line shows posterior means and the solid line 90% credible sets.

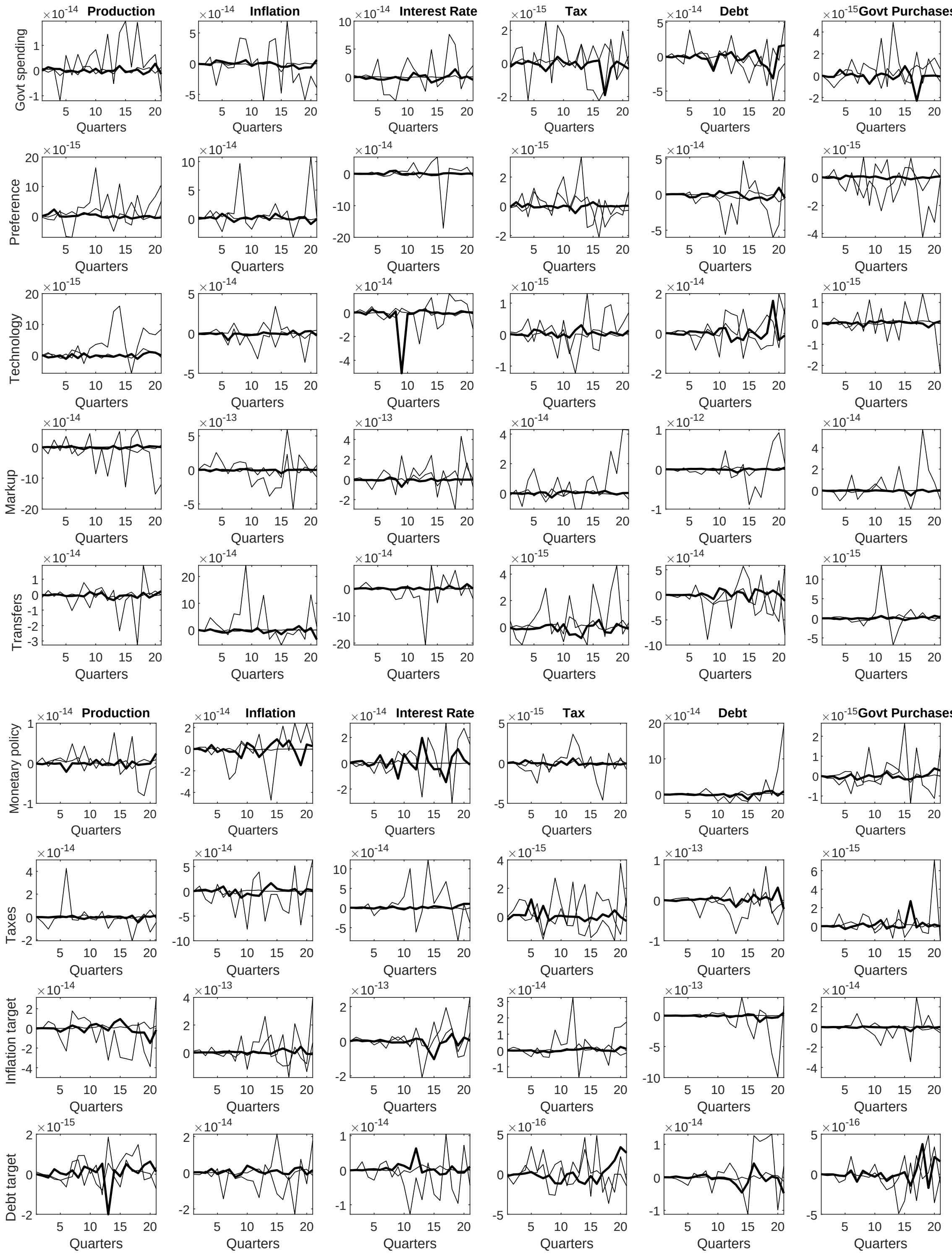


Figure 7: Difference of IRFs computed in the determinacy and the indeterminacy region around the fiscal boundary. The bold line shows posterior means and the solid line 90% credible sets.

Appendix B Prior

In this appendix, we summarize the details of our prior distribution and show results of a prior predictive analysis.

Appendix B.1 Prior distribution

Table 4: Prior distributions

Parameter	Prior				
	Range	Distribution	Mean	SD	90 percent int.
Monetary policy					
ϕ_π, interest rate response to inflation	$\mathbb{R}^+$	N	0.8	0.6	$[0.14, 1.84]$
ϕ_Y, interest rate response to output	$\mathbb{R}^+$	G	0.3	0.1	$[0.16, 0.5]$
ρ_R, response to lagged interest rate	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
Fiscal policy					
ψ_b, tax response to lagged debt	$\mathbb{R}$	N	0	0.1	$[-0.16, 0.16]$
ψ_Y, tax response to output	$\mathbb{R}$	N	0.4	0.3	$[-0.1, 0.9]$
χ_Y, govt spending response to lagged output	$\mathbb{R}$	N	0.4	0.3	$[-0.1, 0.9]$
ρ_g, response to lagged govt spending	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
ρ_τ, response to lagged taxes	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
Preference and HHs					
η, habit formation	$[0, 1)$	B	0.5	0.2	$[0.17, 0.83]$
$\mu := 100(\beta^{-1} - 1)$, discount factor	$\mathbb{R}^+$	G	0.25	0.1	$[0.11, 0.44]$
Frictions					
α, price stickiness	$[0, 1)$	B	0.5	0.2	$[0.17, 0.83]$
γ, price indexation	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
Shocks					
ρ_d, preference	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
ρ_a, technology	$[0, 1)$	B	0.4	0.2	$[0.1, 0.76]$
ρ_u, cost-push	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
ρ_s, transfers	$[0, 1)$	B	0.6	0.2	$[0.24, 0.9]$
σ_g, govt spending	$\mathbb{R}^+$	Inv. Gamma	0.1	4	$[0.07, 0.24]$
σ_d, preference	$\mathbb{R}^+$	Inv. Gamma	0.3	4	$[0.19, 0.72]$
σ_a, technology	$\mathbb{R}^+$	Inv. Gamma	0.5	4	$[0.32, 1.17]$
σ_u, cost-push	$\mathbb{R}^+$	Inv. Gamma	0.04	4	$[0.026, 0.094]$
σ_s, transfers	$\mathbb{R}^+$	Inv. Gamma	0.08	4	$[0.052, 0.188]$

Table 4: Prior distributions - continued

Parameter	Range	Distribution	Mean	SD	90 percent int.
	Prior				
σ_R, monetary policy	$\mathbb{R}^+$	Inv. Gamma	0.15	4	$[0.098, 0.353]$
σ_τ, tax	$\mathbb{R}^+$	Inv. Gamma	0.2	4	$[0.13, 0.48]$
σ_π, inflation target	$\mathbb{R}^+$	Inv. Gamma	0.003	4	$[0.002, 0.007]]$
σ_b, debt/output target	$\mathbb{R}^+$	Inv. Gamma	0.05	4	$[0.033, 0.118]$
Steady state					
$a := 100(\bar{a} - 1)$, 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	$[18.81, 25.31]$
Indeterminacy					
σ_ζ, 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	$[-1.64, 1.64]$
$M_{\tau\zeta}$	$\mathbb{R}$	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".

Appendix B.2 Prior implications

Here, we show results of a prior predictive analysis for the prior specification outlined in Section 3.1. In particular, we take 20,000 draws from the prior and simulate with these draws 20,000 times the model's observables.

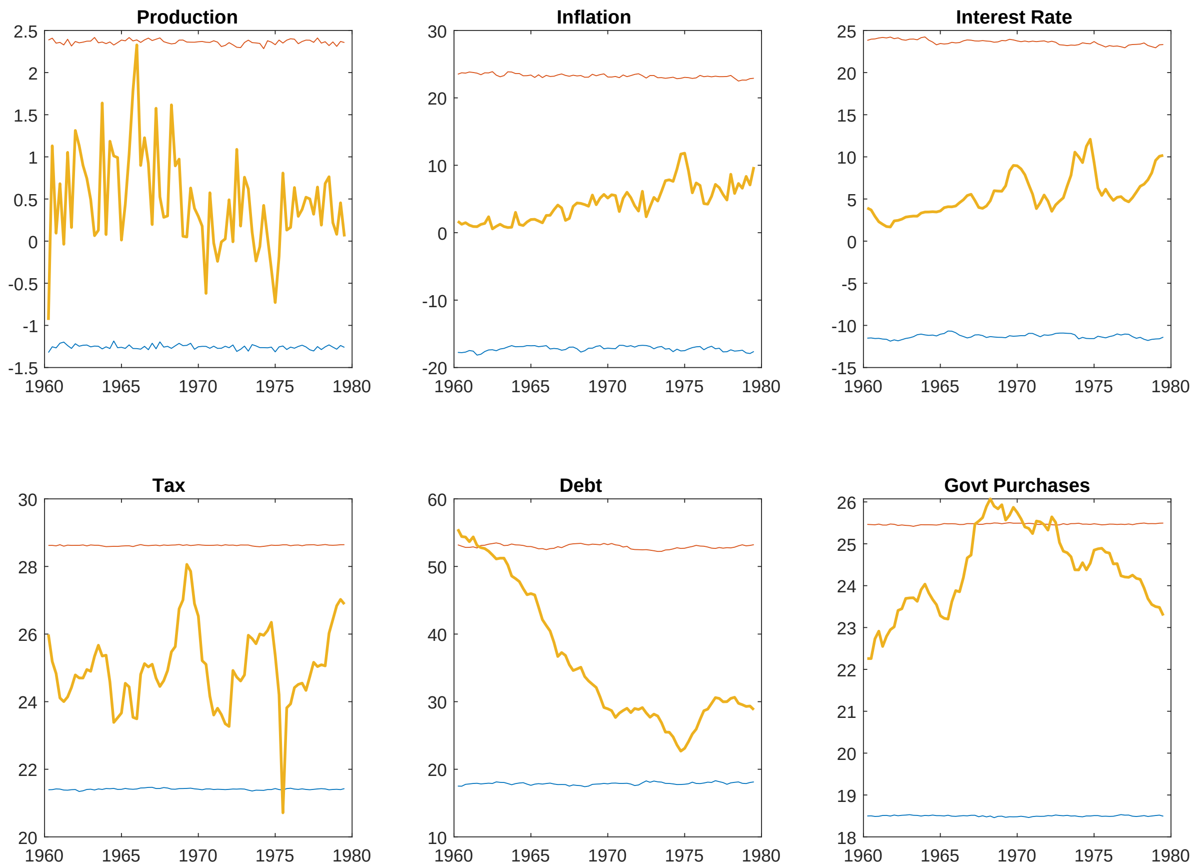


Figure 8: Simulated model observables vs. real data for 1960:Q1 to 1979:Q2. The bold yellow line shows the actual time series we use for estimating the model. The blue and the red line show the 90 % intervall of the simulated time series.

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 poulation 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

$$\begin{bmatrix} 100 \times \Delta \ln \text{Production}_t \\ \text{Inflation}_t \ (\%) \\ \text{Interest}_t \ (\%) \\ \text{TaxRev}_t \ (\%) \\ \text{GovtDebt}_t \ (\%) \\ \text{GovtPurch}_t \ (\%) \end{bmatrix} = \begin{bmatrix} a \\ 4\pi \\ 4(a+\pi+\mu) \\ \tau \\ b \\ g \end{bmatrix} + \begin{bmatrix} \hat{Y}_t - \hat{Y}_{t-1} + \hat{a}_t \\ 4\hat{\pi}_t \\ 4\hat{R}_t \\ \hat{\tau}_t \\ \hat{b}_t \\ \hat{g}_t \end{bmatrix}. \tag{27}$$

Appendix D SMC algorithm

This appendix gives a 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 - intuition

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 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

$$p_n(\vartheta, M|Y) = \frac{[p(Y|\vartheta, M)]^{\delta_n} p(\vartheta, M)}{\int [p(Y|\vartheta, M)]^{\delta_n} p(\vartheta, M) d\vartheta dM}, \quad n = 1, ..., N_\delta. \tag{28}$$

We follow Herbst and Schorfheide (2014) and choose the tuning parameter δ_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 λ determines how much information from the likelihood is incorporated in each proposal density.

In a nutshell, the SMC draws in N_δ stages sequentially N parameter vectors $\vartheta^i, i = 1, ..., N$ 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 a 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 $\{(\vartheta^i_{n-1}, \tilde{W}^i_{n-1})\}_{i=1}^N$ 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 $p_n(\vartheta, M|Y)$.

To estimate the model, we choose the following tuning parameters for the SMC. We use $N = 20,000$ particles, $N_\delta = 600$ stages, $\lambda = 2.4$, $N_{blocks} = 10$, $M_{MH} = 2$. As suggested by Herbst and Schorfheide (2014), λ is 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 λ until 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 $M_{MH} = 2$ ensured a stable acceptance rate of 25% without down-scaling the proposal variance too much.

Appendix D.2 SMC with likelihood tempering - the algorithm

1. The SMC is **initialized** by drawing the particles of the first stage ($n = 1$; $\delta_1 = 0$) from the prior density.[20]

$$\vartheta^i_1 \overset{i.i.d.}{\sim} p(\vartheta) \quad i = 1, ..., N.$$

   In the first stage, each particle receives equal weight such that $W^i_1 = 1$.

[20] To ease notation in Appendix D, we assume that the parameters in M are part of ϑ.

2. **Recursions:**

   `for n=2:`N_δ

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

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

   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` $ESS_n < N/2$

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

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

      `else`

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

      `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.3 for further details.

   `end for`

3. Process **posterior draws**.

Appendix D.3 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 two features. First, we reduce the dimensionality of the parameter vector ϑ by spliting it into N_{blocks} blocks, thus making it easier to approximate the target density in each of the RWMH's M_{MH} steps.[21] 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 or decrease c_n 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 ϑ into N_{blocks}. b denotes the block of the parameter vector such that $\vartheta^i_{b,n}$ refers to the b elements of the ith particle, and $\vartheta^i_{<b,n}$ 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 bth block is given by

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

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

3. **MH steps:**

[21] Chib and Ramamurthy (2010) and Herbst (2012) provide evidence that parameter blocking is benefical for estimating DSGE models.

```
for m=1:M_MH
```

for m=1:M_{MH}

for b=1:N_{blocks}

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

$\vartheta^* = [\vartheta^i_{m,<b,n}, \vartheta^*_b, \vartheta^i_{m-1,>b,n}]$ and $\vartheta^i_{m,n} = [\vartheta^i_{m,<b,n}, \vartheta^i_{m-1,\geq b,n}]$.

2. With probability

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

set $\vartheta^i_{m,b,n} = \vartheta^*_b$. Otherwise, set $\vartheta^i_{m,b,n} = \vartheta^i_{m-1,b,n}$.

end for

end for

Appendix E Posterior estimates

Appendix E.1 Restricted estimation

In this appendix, we show results of estimations in which we restrict the parameter space and apply SMC sampling to estimate each policy regime sequentially. The purpose of this exercise is to show (i) that the SMC sampler is able to replicate the RWMH estimation results of Bhattarai et al. (2016), our reference study, and (ii) that our prior specification does not affect the probability of policy regimes in the posterior. Hence, potential differences in findings are driven neither by the prior specification nor the sampling technique, but rather induced by restricting or not restricting the parameter space.

Restricted estimation - prior as in Bhattarai et al. (2016)

To understand how changing the posterior sampler influences the estimation results, we apply the SMC algorithm and replicate, in a first step, the study of Bhattarai et al. (2016). For this exercise, we follow strictly the approach of Bhattarai et al. (2016). We use the same dataset, and the same prior distributions.[22] Only in terms of posterior sampling, we do not rely on RWMH sampling, but apply the SMC algorithm instead. We restrict the parameter space and estimate each policy regime 50 times with the SMC sampler.

Looking at the estimated marginal data densities of each regime, presented in Table 5, we come to the same conclusion as Bhattarai et al. (2016): the U.S.-economy in the pre-Volcker period was in the PMPF regime. In this estimation, regime F and regime M receive no support from the data.

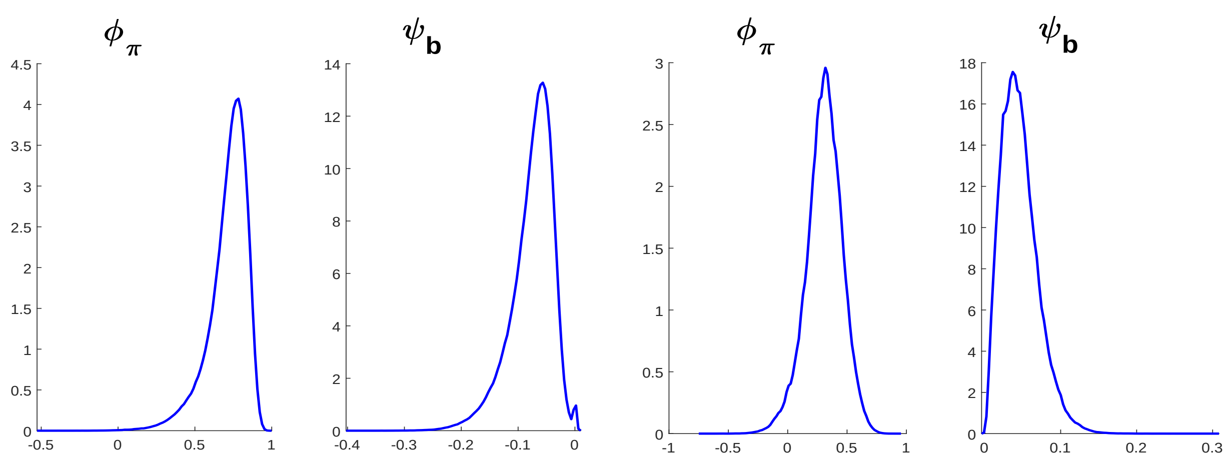
[22]For details on this prior specification, we refer the reader to the Online Appendix of the original study.

Table 5: Log marginal data densities for each policy regime from restricted estimation

	AMPF	PMAF	PMPF
Log MDD	-541.85	-537.54	-521.41

Note: 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. For each regime, its mean is computed over 50 independent runs of the SMC algorithm.

Figure 9 shows plots of the posterior densities of the policy parameters for regime F and the PMPF regime. The mean estimates for the Taylor-coefficient ϕ_π (regime F: 0.71; PMPF: 0.31) and ψ_b (regime F: -0.08; PMPF: 0.05) are in line with the findings of Bhattarai et al. (2016). Hence, using the SMC instead of the RWMH algorithm for posterior sampling does not influence the estimation results.

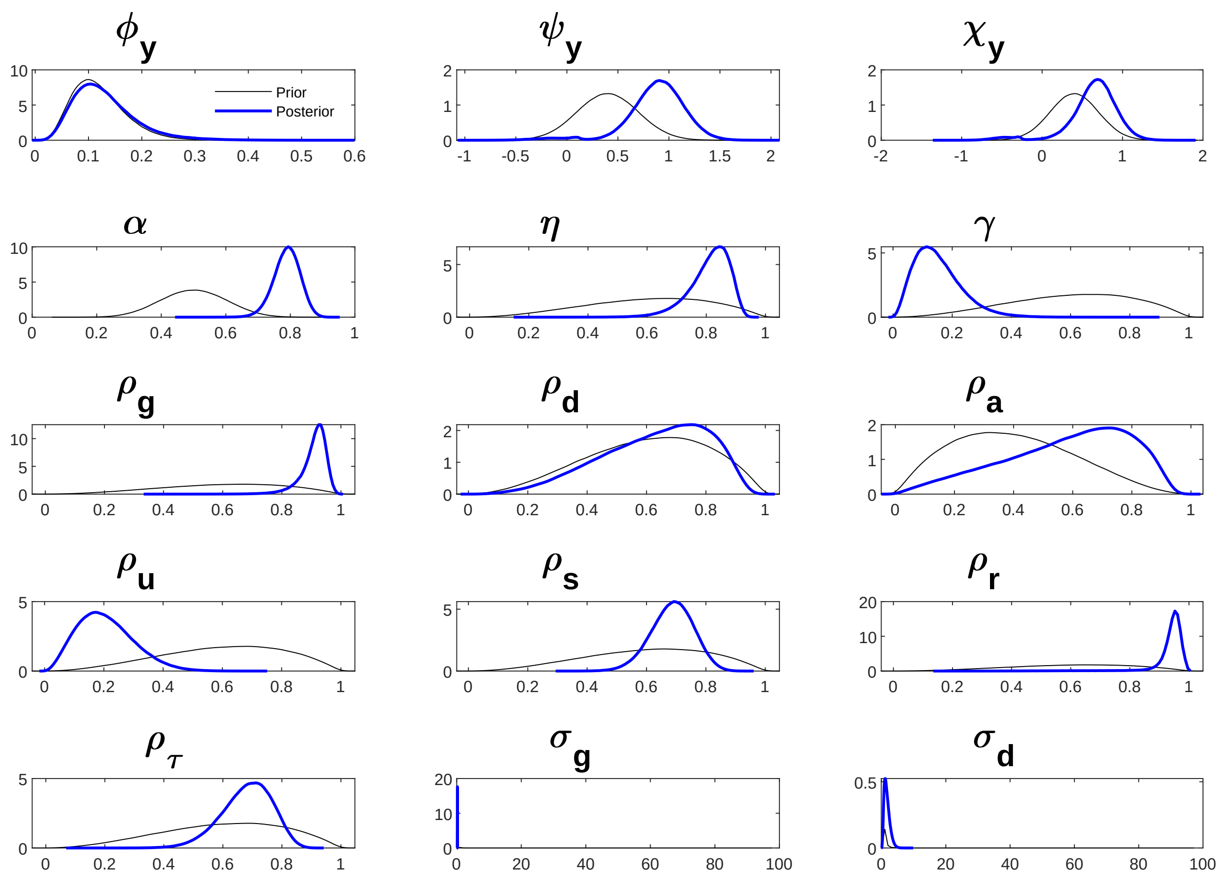


(a) Regime F (b) PMPF regime

Figure 9: Posterior densities of the policy parameters ϕ_π and ψ_b for regime F and the PMPF regime.

In the following, we show plots of the prior and posterior densities for the remaining parameters.

Regime F


ϕ_y
ψ_y
χ_y
Prior
Posterior
α
η
γ
ρ_g
ρ_d
ρ_a
ρ_u
ρ_s
ρ_r
ρ_τ
σ_g
σ_d

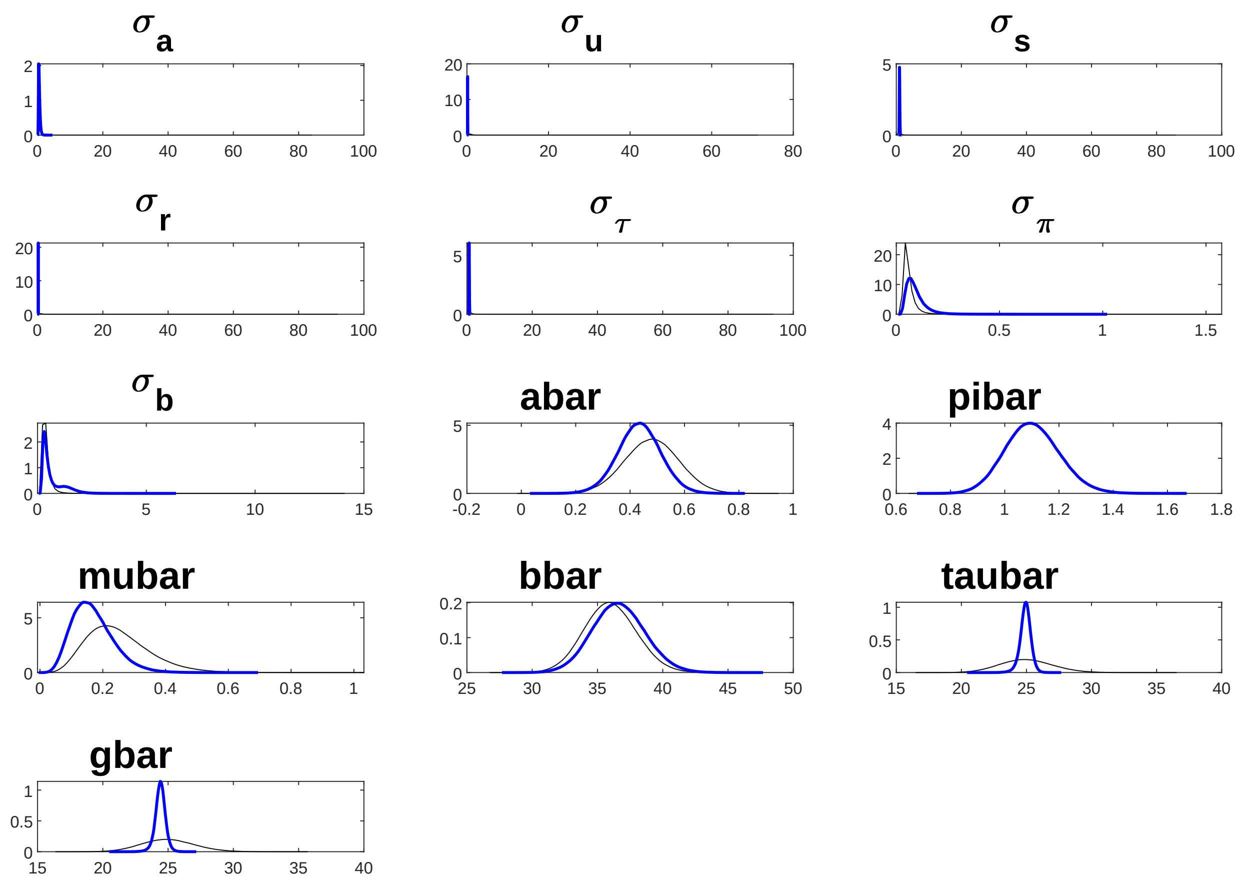


Figure 10: Prior and posterior densities of the estimated model parameters for regime F. The blue bold line depicts the posterior density, the black line the prior density. The prior densities are specified as in Bhattarai et al. (2016).

Table 6: Posterior distributions for estimated parameters (Regime F)

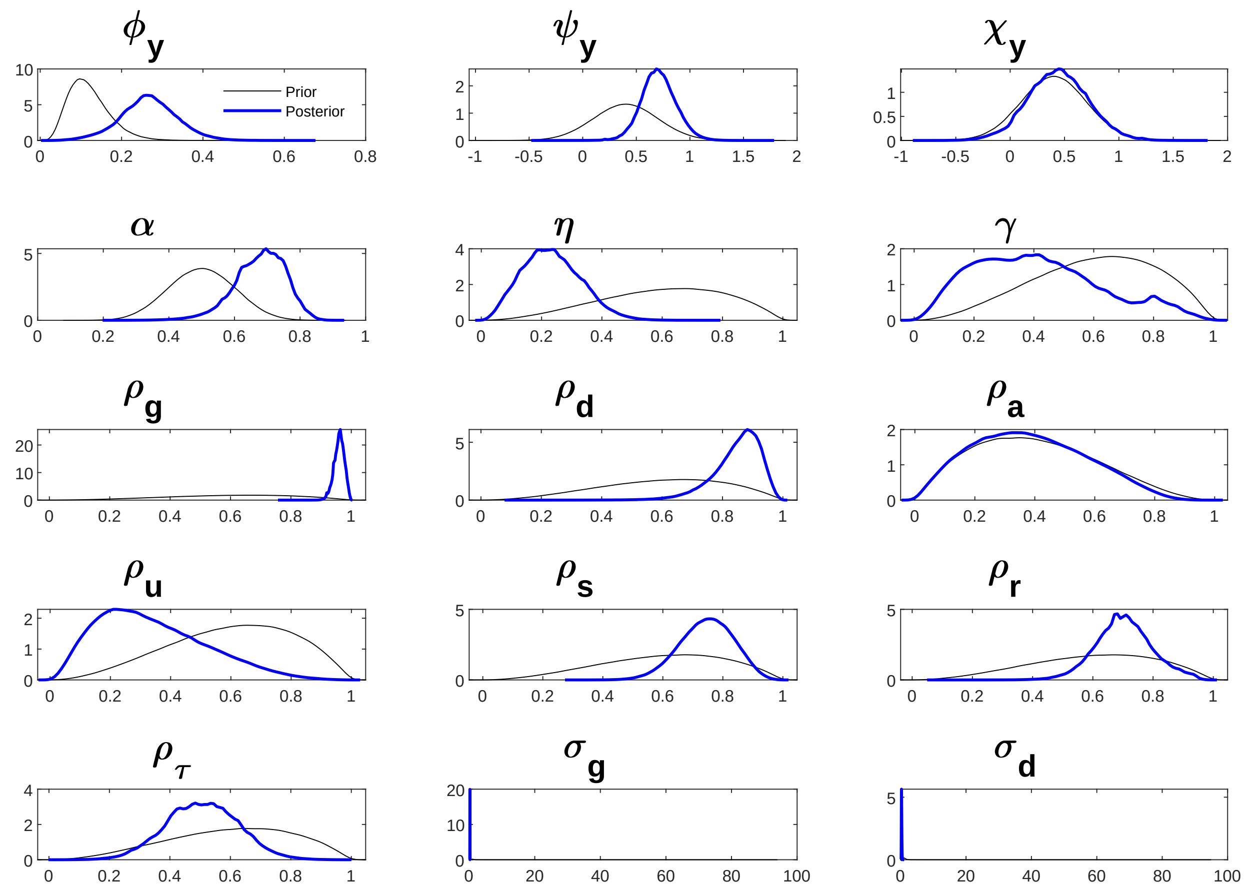
Parameter	Posterior Mean	SD	90 percent credible set
Monetary policy			
ϕ_π, interest rate response to inflation	0.71	0.13	[0.53, 0.9]
ϕ_π^*, distance to monetary boundary	0.27	0.13	[0.09, 0.46]
ϕ_Y, interest rate response to output	0.13	0.06	[0.04, 0.21]
ρ_R, response to lagged interest rate	0.93	0.07	[0.9, 0.99]
Fiscal policy			
ψ_b, tax response to lagged debt	-0.08	0.04	[-0.14, -0.02]
ψ_b^*, distance to fiscal boundary	0.08	0.04	[0.02, 0.14]
ψ_Y, tax response to output	0.87	0.3	[0.49, 1.33]
χ_Y, govt spending response to lagged output	0.63	0.31	[0.24, 1.11]
ρ_g, response to lagged govt spending	0.91	0.04	[0.85, 0.97]
ρ_τ, response to lagged taxes	0.68	0.08	[0.55, 0.82]
Preference and HHs			
η, habit formation	0.81	0.07	[0.71, 0.91]
$\mu := 100(\beta^{-1} - 1)$, discount factor	0.17	0.07	[0.06, 0.27]
Frictions			
α, price stickiness	0.79	0.04	[0.72, 0.86]
γ, price indexation	0.15	0.08	[0.03, 0.27]
Shocks			
ρ_d, preference	0.63	0.18	[0.35, 0.91]
ρ_a, technology	0.58	0.21	[0.24, 0.9]
ρ_u, cost-push	0.21	0.09	[0.05, 0.35]
ρ_s, transfers	0.69	0.07	[0.57, 0.8]
σ_g, govt spending	0.21	0.02	[0.18, 0.25]
σ_d, preference	1.71	0.89	[0.41, 3.03]
σ_a, technology	0.54	0.25	[0.19, 0.89]
σ_u, cost-push	0.18	0.02	[0.14, 0.22]
σ_s, transfers	1.01	0.09	[0.87, 1.15]
σ_R, monetary policy	0.22	0.02	[0.19, 0.25]
σ_τ, tax	0.7	0.07	[0.59, 0.81]
σ_π, inflation target	0.09	0.05	[0.3, 0.15]
σ_b, debt/output target	0.65	0.49	[0.17, 1.44]
Steady state			
$a := 100(\bar{a} - 1)$, technology	0.43	0.08	[0.31, 0.56]
$\pi := 100(\bar{\pi} - 1)$, inflation	1.1	0.1	[0.94, 1.26]

Table 6: Posterior distributions for estimated parameters (Regime F) - continued

Parameter	Posterior		
	Mean	SD	90 percent credible set
$b \coloneqq 100\bar{b}$, debt/output	36.63	2.01	[33.33, 39.93]
$\tau \coloneqq 100\bar{\tau}$, tax/output	24.92	0.42	[24.26, 25.6]
$g \coloneqq 100\bar{g}$, govt spending/output	24.4	0.4	[23.78, 25.05]

Note: Means, and standard deviations are over 50 independent runs of the SMC algorithm with $N = 14,000$, $N_\delta = 500$, $\lambda = 2.5$, $N_{blocks} = 6$, and $M_{MH} = 1$. We compute 90 % highest posterior density intervals.

PMPF regime



ϕ_y
ψ_y
χ_y
Prior
Posterior
α
η
γ
ρ_g
ρ_d
ρ_a
ρ_u
ρ_s
ρ_r
ρ_τ
σ_g
σ_d

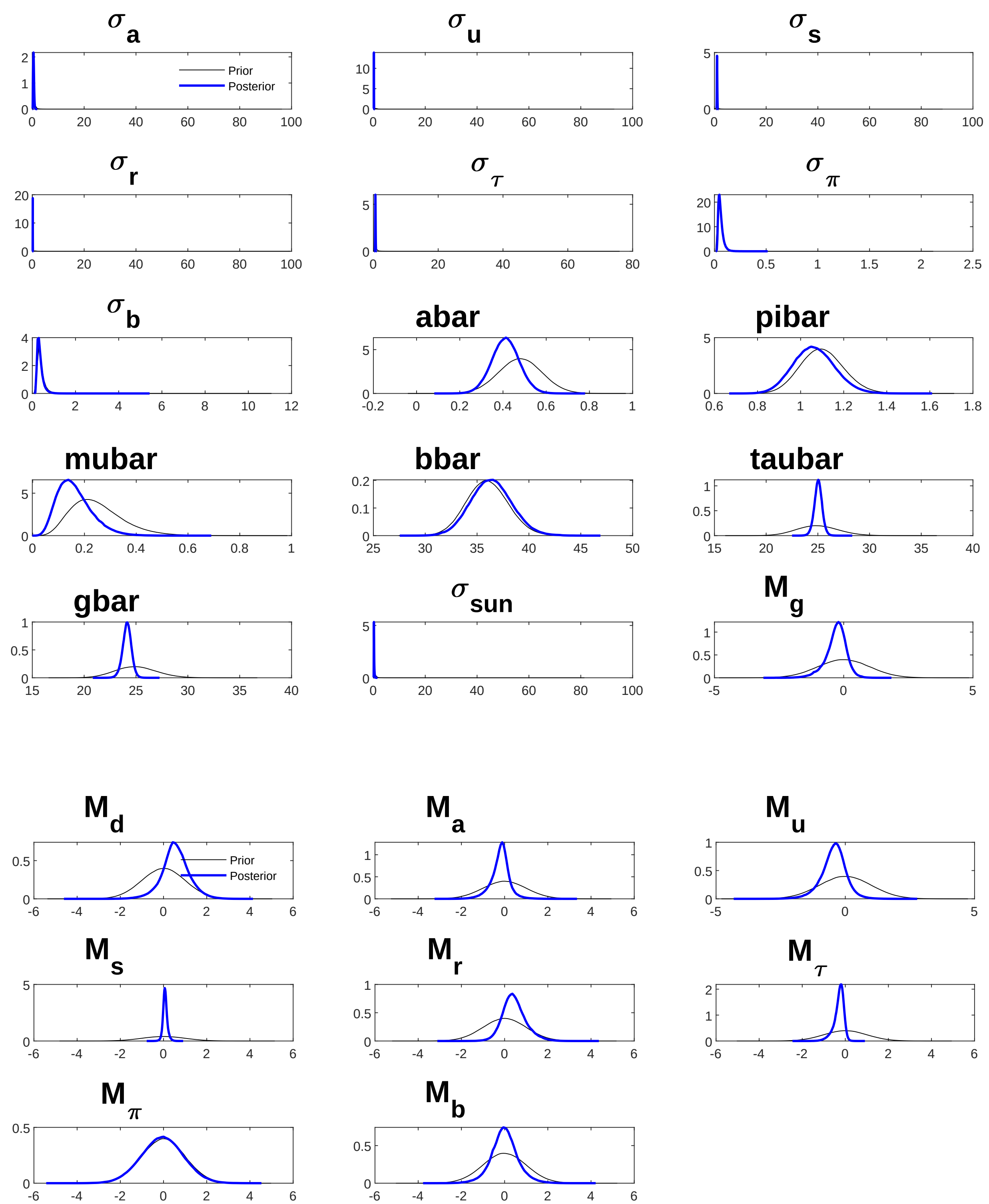


Figure 11: Prior and posterior densities of the estimated model parameters for the PMPF regime. The blue bold line depicts the posterior density, the black line the prior density. The prior densities are specified as in Bhattarai et al. (2016).

Table 7: Posterior distributions for estimated parameters (PMPF regime)

Parameter	Posterior Mean	SD	90 percent credible set
Monetary policy			
ϕ_π, interest rate response to inflation	0.31	0.15	[0.06, 0.56]
ϕ_π^*, distance to monetary boundary	0.71	0.05	[0.66, 0.79]
ϕ_Y, interest rate response to output	0.28	0.02	[0.25, 0.31]
ρ_R, response to lagged interest rate	0.7	0.03	[0.66, 0.74]
Fiscal policy			
ψ_b, tax response to lagged debt	0.05	0.02	[0.008, 0.08]
ψ_b^*, distance to fiscal boundary	0.05	0.01	[0.039, 0.055]
ψ_Y, tax response to output	0.71	0.03	[0.66, 0.77]
χ_Y, govt spending response to lagged output	0.44	0.07	[0.33, 0.54]
ρ_g, response to lagged govt spending	0.96	0.004	[0.957, 0.967]
ρ_τ, response to lagged taxes	0.5	0.03	[0.44, 0.54]
Preference and HHs			
η, habit formation	0.23	0.02	[0.21, 0.28]
$\mu := 100(\beta^{-1} - 1)$, discount factor	0.16	0.01	[0.14, 0.18]
Frictions			
α, price stickiness	0.68	0.02	[0.65, 0.72]
γ, price indexation	0.4	0.08	[0.3, 0.49]
Shocks			
ρ_d, preference	0.85	0.02	[0.82, 0.88]
ρ_a, technology	0.37	0.06	[0.27, 0.44]
ρ_u, cost-push	0.33	0.05	[0.27, 0.41]
ρ_s, transfers	0.75	0.02	[0.73, 0.77]
σ_g, govt spending	0.23	0.002	[0.226, 0.23]
σ_d, preference	0.29	0.02	[0.26, 0.32]
σ_a, technology	0.52	0.07	[0.42, 0.61]
σ_u, cost-push	0.21	0.006	[0.2, 0.21]
σ_s, transfers	1.02	0.008	[1, 1.03]
σ_R, monetary policy	0.18	0.006	[0.17, 0.19]
σ_τ, tax	0.62	0.01	[0.6, 0.64]
σ_π, inflation target	0.06	0.004	[0.05, 0.06]
σ_b, debt/output target	0.36	0.02	[0.32, 0.39]
Steady state			
$a := 100(\bar{a} - 1)$, technology	0.41	0.01	[0.39, 0.42]
$\pi := 100(\bar{\pi} - 1)$, inflation	1.06	0.02	[1.03, 1.07]

Table 7: Posterior distributions for estimated parameters (PMPF regime) - continued

Parameter	Posterior Mean	SD	90 percent credible set
$b := 100\bar{b}$, debt/output	36.4	0.31	[35.97, 36.77]
$\tau := 100\bar{\tau}$, tax/output	25.06	0.09	[24.94, 25.17]
$g := 100\bar{g}$, govt spending/output	24.13	0.08	[24.04, 24.28]
Indeterminacy			
σ_ζ, sunspot shock	0.26	0.05	[0.22, 0.3]
$M_{g\zeta}$	-0.29	0.11	[-0.43, -0.13]
$M_{d\zeta}$	0.6	0.2	[0.42, 0.92]
$M_{a\zeta}$	-0.2	0.08	[-0.34, -0.1]
$M_{u\zeta}$	-0.44	0.15	[-0.59, -0.25]
$M_{s\zeta}$	0.08	0.03	[0.03, 0.12]
$M_{R\zeta}$	0.43	0.18	[0.22, 0.68]
$M_{\tau\zeta}$	-0.3	0.1	[-0.46, -0.2]
$M_{\pi\zeta}$	-0.05	0.16	[-0.28, 0.26]
$M_{b\zeta}$	-0.006	0.13	[-0.18, 0.12]

Note: Means, and standard deviations are over 50 independent runs of the SMC algorithm with $N = 14,000$, $N_\delta = 500$, $\lambda = 2.5$, $N_{blocks} = 6$, and $M_{MH} = 1$. We compute 90 % highest posterior density intervals.

Restricted estimation - prior as in Section 3.1 with renormalized policy parameters

In a next step, we conduct the restricted SMC estimation with the prior specification as outlined in Section 3.1. One exception is the prior specifications for the policy parameters ϕ_π and ψ_b. To ensure that we completely impose a particular policy regime during estimation, we again follow Bhattarai et al. (2016) and estimate the model with the reparameterized policy parameters ϕ_π^* and ψ_b^*. ϕ_π^* follows a Gamma distribution with a mean of 0.5 and a standard deviation of 0.2. ψ_b^* is also Gamma-distributed and has a mean of 0.05 and a standard deviation of 0.04. The prior densities of the remaining parameters are specified as in Section 3.1.

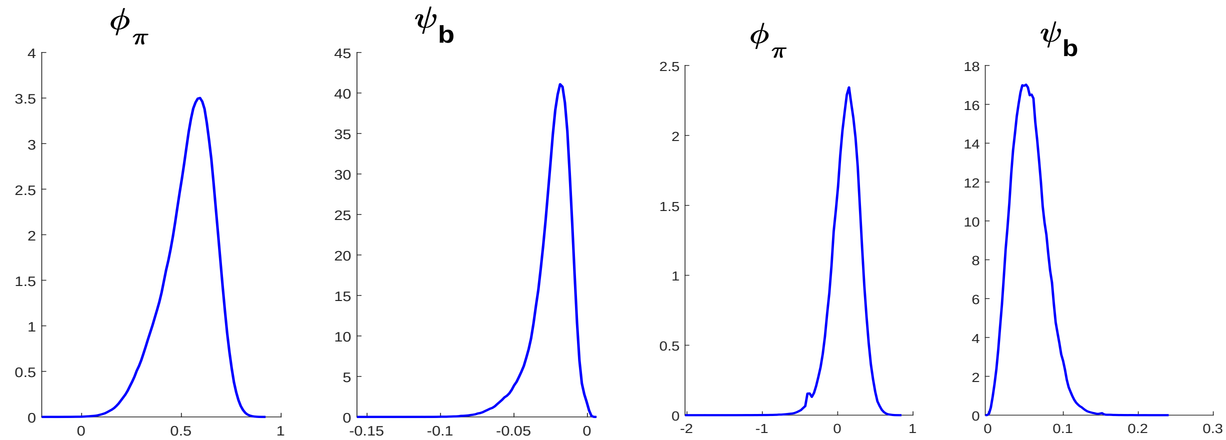
Table 8 shows the estimated marginal data densities of each regime. Also, with the prior specification of Section 3.1, we come to the conclusion that in the U.S. in the pre-Volcker period the PMPF regime receives the best support from the data.

Table 8: Log marginal data densities for each policy regime from restricted estimation

	AMPF	PMAF	PMPF
Log MDD	-548.72	-542.72	-523.17

Note: 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. For each regime, its mean is computed over 50 independent runs of the SMC algorithm.

Figure 12 shows plots of the posterior densities of the policy parameters for regime F and the PMPF regime. The shapes of the posterior densities are comparable to the findings in the previous subsection. The mean estimates for the Taylor-coefficient ϕ_π (regime F: 0.54; PMPF: 0.11) and ψ_b (regime F: -0.02; PMPF: 0.05) change only slightly. Hence, using, a for our exercise more suitable, prior specification together with SMC posterior sampling does not influence the estimation results.



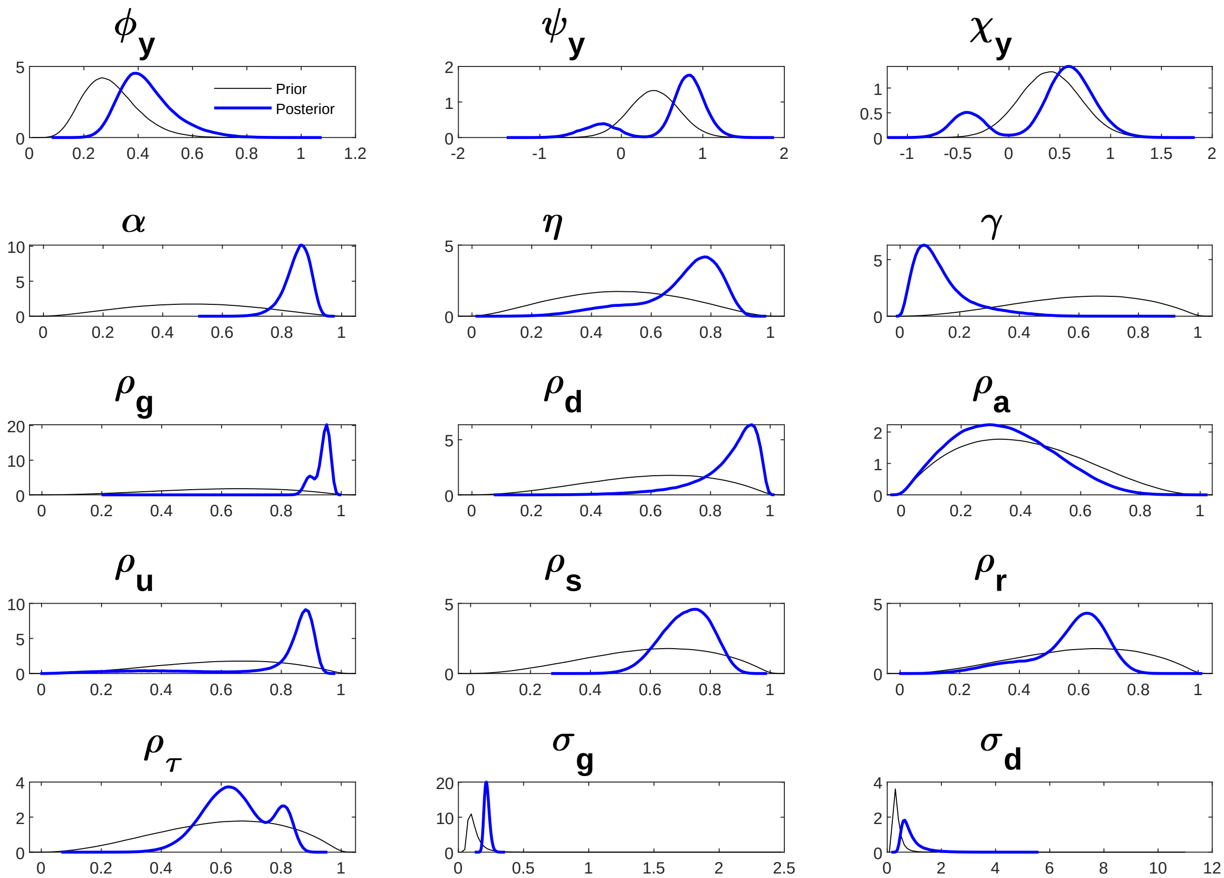
(a) Regime F

(b) PMPF regime

Figure 12: Posterior densities of the policy parameters ϕ_π and ψ_b for regime F and the PMPF regime.

To make the results of the restricted estimation more comparable to the unrestricted estimation, we renormalized the policy parameters ϕ^*_π and ψ^*_b to ϕ_π and ψ_b in the density plots.

Regime F



ϕ_y
ψ_y
χ_y
Prior
Posterior
α
η
γ
ρ_g
ρ_d
ρ_a
ρ_u
ρ_s
ρ_r
ρ_τ
σ_g
σ_d

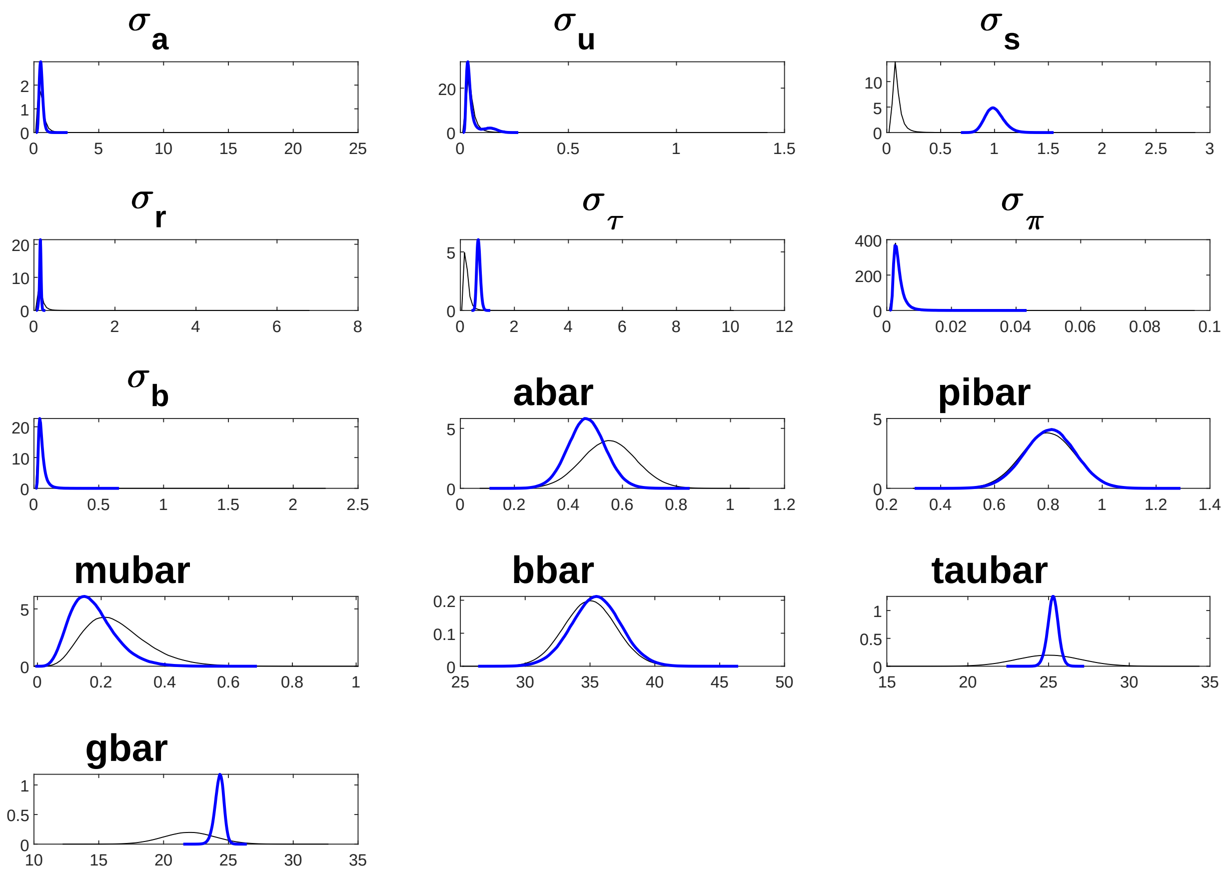


Figure 13: Prior and posterior densities of the estimated model parameters for regime F. The blue bold line depicts the posterior density, the black line the prior density. The densities of ϕ_π^* and ψ_b^* are specified as in Bhattarai et al. (2016), the remaining parameters as in Section 3.1.

Table 9: Posterior distributions for estimated parameters (Regime F)

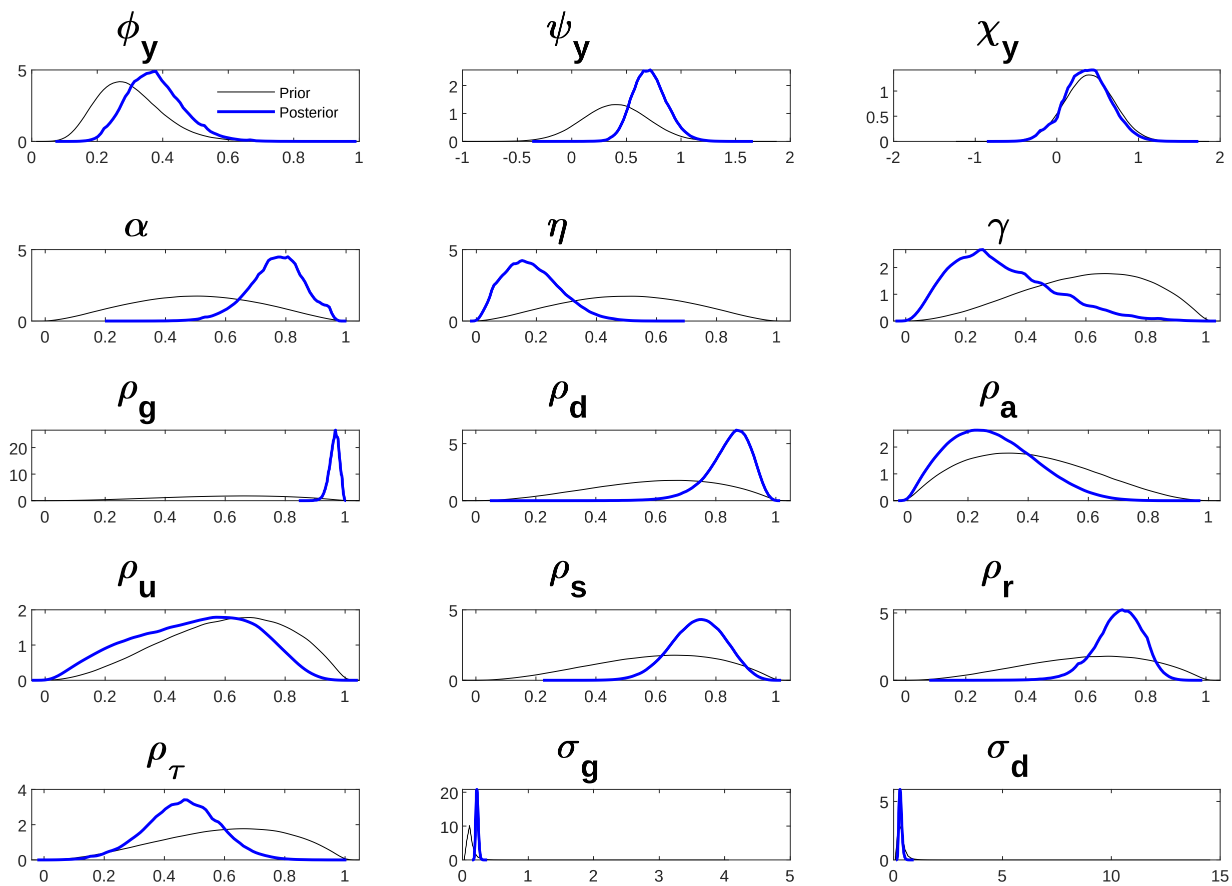
	Posterior		
Parameter	Mean	SD	90 percent credible set
Monetary policy			
ϕ_π, interest rate response to inflation	0.54	0.12	[0.33, 0.73]
ϕ_π^*, distance to monetary boundary	0.35	0.05	[0.31, 0.43]
ϕ_Y, interest rate response to output	0.44	0.06	[0.4, 0.54]
ρ_R, response to lagged interest rate	0.56	0.09	[0.38, 0.63]
Fiscal policy			
ψ_b, tax response to lagged debt	-0.02	0.01	[-0.04, -0.005]
ψ_b^*, distance to fiscal boundary	0.027	0.007	[0.02, 0.04]
ψ_Y, tax response to output	0.58	0.39	[-0.25, 0.86]
χ_Y, govt spending response to lagged output	0.38	0.36	[-0.38, 0.63]

Table 9: Posterior distributions for estimated parameters (Regime F) - continued

	Posterior		
Parameter	Mean	SD	90 percent credible set
ρ_g, response to lagged govt spending	0.93	0.02	[0.9, 0.95]
ρ_τ, response to lagged taxes	0.66	0.07	[0.61, 0.79]
Preference and HHs			
η, habit formation	0.69	0.1	[0.49, 0.78]
$\mu \coloneqq 100(\beta^{-1} - 1)$, discount factor	0.17	0.01	[0.16, 0.19]
Frictions			
α, price stickiness	0.85	0.02	[0.83, 0.86]
γ, price indexation	0.13	0.06	[0.09, 0.22]
Shocks			
ρ_d, preference	0.86	0.03	[0.82, 0.9]
ρ_a, technology	0.33	0.04	[0.26, 0.37]
ρ_u, cost-push	0.77	0.17	[0.45, 0.88]
ρ_s, transfers	0.72	0.03	[0.65, 0.74]
σ_g, govt spending	0.22	0.006	[0.21, 0.23]
σ_d, preference	0.87	0.14	[0.58, 1.03]
σ_a, technology	0.56	0.01	[0.55, 0.58]
σ_u, cost-push	0.06	0.03	[0.04, 0.12]
σ_s, transfers	1	0.003	[0.997, 1.01]
σ_R, monetary policy	0.15	0.01	[0.13, 0.16]
σ_τ, tax	0.68	0.03	[0.66, 0.72]
σ_π, inflation target	0.004	0	[0.0036, 0.0039]
σ_b, debt/output target	0.06	0.001	[0.059, 0.064]
Steady state			
$a \coloneqq 100(\bar{a} - 1)$, technology	0.47	0.007	[0.46, 0.48]
$\pi \coloneqq 100(\bar{\pi} - 1)$, inflation	0.81	0.02	[0.79, 0.83]
$b \coloneqq 100\bar{b}$, debt/output	35.5	0.16	[35.28, 35.62]
$\tau \coloneqq 100\bar{\tau}$, tax/output	25.26	0.12	[25.05, 25.36]
$g \coloneqq 100\bar{g}$, govt spending/output	24.31	0.09	[24.24, 24.45]

Note: Means, and standard deviations are over 50 independent runs of the SMC algorithm with $N = 14,000$, $N_\delta = 500$, $\lambda = 2.5$, $N_{blocks} = 6$, and $M_{MH} = 1$. We compute 90 % highest posterior density intervals.

PMPF regime



ϕ_y
Prior
Posterior
ψ_y
χ_y
α
η
γ
ρ_g
ρ_d
ρ_a
ρ_u
ρ_s
ρ_r
ρ_τ
σ_g
σ_d

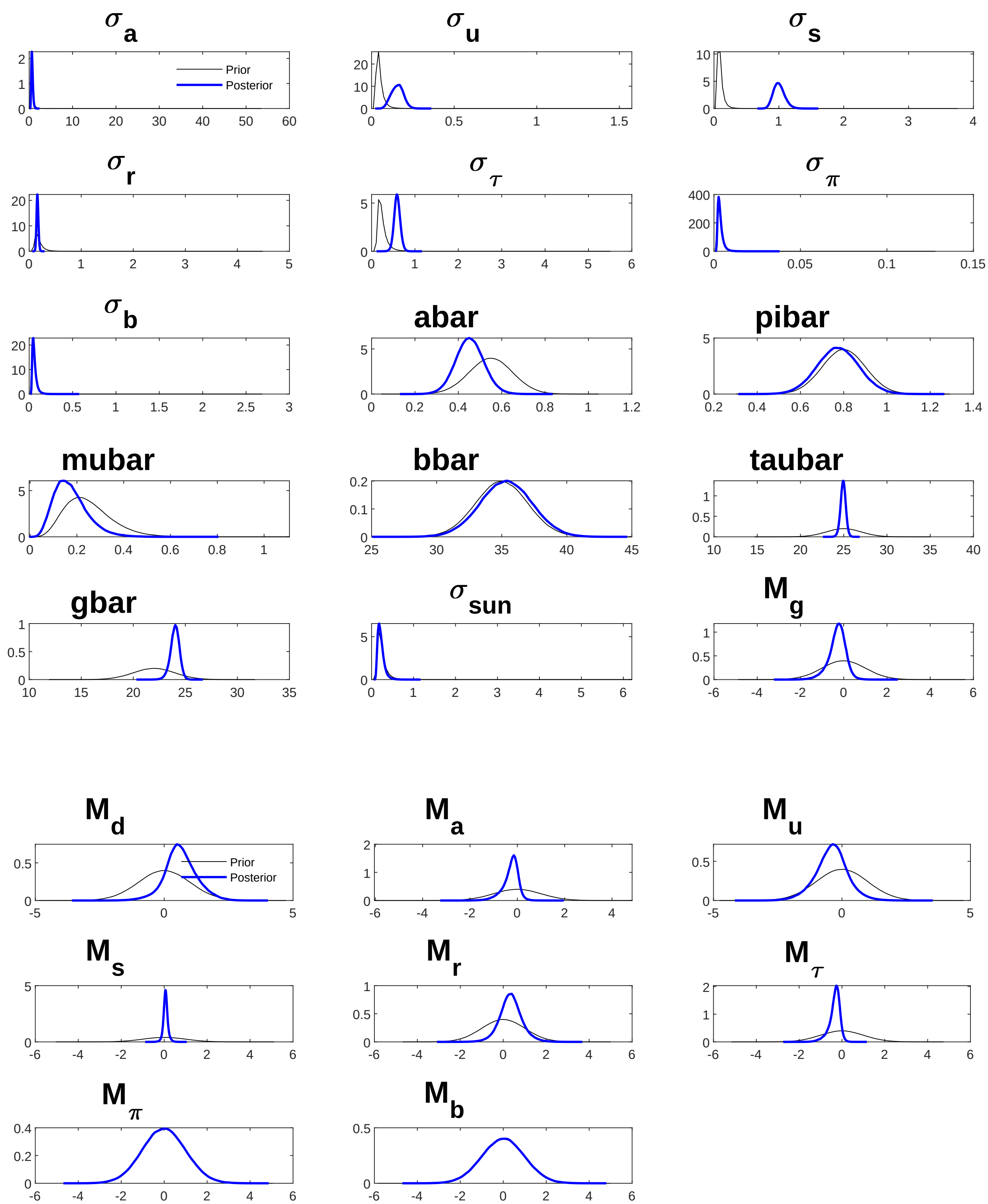


Figure 14: Prior and posterior densities of the estimated model parameters for the PMPF regime. The blue bold line depicts the posterior density, the black line the prior density. The densities of ϕ_π^* and ψ_b^* are specified as in Bhattarai et al. (2016), the remaining parameters as in Section 3.1.

Table 10: Posterior distributions for estimated parameters (PMPF regime)

Parameter	Posterior		
	Mean	SD	90 percent credible set
Monetary policy			
ϕ_π, interest rate response to inflation	0.11	0.19	[-0.18, 0.42]
ϕ_π^*, interest rate response to inflation	0.87	0.05	[0.83, 0.95]
ϕ_Y, interest rate response to output	0.39	0.02	[0.36, 0.41]
ρ_R, response to lagged interest rate	0.71	0.02	[0.69, 0.73]
Fiscal policy			
ψ_b, tax response to lagged debt	0.05	0.02	[0.02, 0.09]
ψ_b^*, distance to fiscal boundary	0.06	0.004	[0.05, 0.06]
ψ_Y, tax response to output	0.73	0.03	[0.7, 0.78]
χ_Y, govt spending response to lagged output	0.37	0.05	[0.29, 0.45]
ρ_g, response to lagged govt spending	0.97	0.002	[0.962, 0.969]
ρ_τ, response to lagged taxes	0.45	0.03	[0.4, 0.49]
Preference and HHs			
η, habit formation	0.19	0.02	[0.16, 0.21]
$\mu := 100(\beta^{-1} - 1)$, discount factor	0.17	0.01	[0.16, 0.19]
Frictions			
α, price stickiness	0.77	0.02	[0.74, 0.79]
γ, price indexation	0.31	0.04	[0.22, 0.35]
Shocks			
ρ_d, preference	0.85	0.01	[0.83, 0.87]
ρ_a, technology	0.26	0.02	[0.22, 0.29]
ρ_u, cost-push	0.48	0.07	[0.38, 0.59]
ρ_s, transfers	0.74	0.01	[0.73, 0.76]
σ_g, govt spending	0.22	0.001	[0.219, 0.222]
σ_d, preference	0.31	0.01	[0.29, 0.33]
σ_a, technology	0.69	0.05	[0.63, 0.73]
σ_u, cost-push	0.16	0.01	[0.15, 0.18]
σ_s, transfers	1.01	0.006	[0.99, 1.01]
σ_R, monetary policy	0.16	0.003	[0.155, 0.163]
σ_τ, tax	0.59	0.01	[0.57, 0.6]
σ_π, inflation target	0.004	0	[0.003, 0.004]
σ_b, debt/output target	0.06	0.004	[0.056, 0.068]
Steady state			
$a := 100(\bar{a} - 1)$, technology	0.45	0.008	[0.44, 0.46]
$\pi := 100(\bar{\pi} - 1)$, inflation	0.77	0.01	[0.75, 0.79]

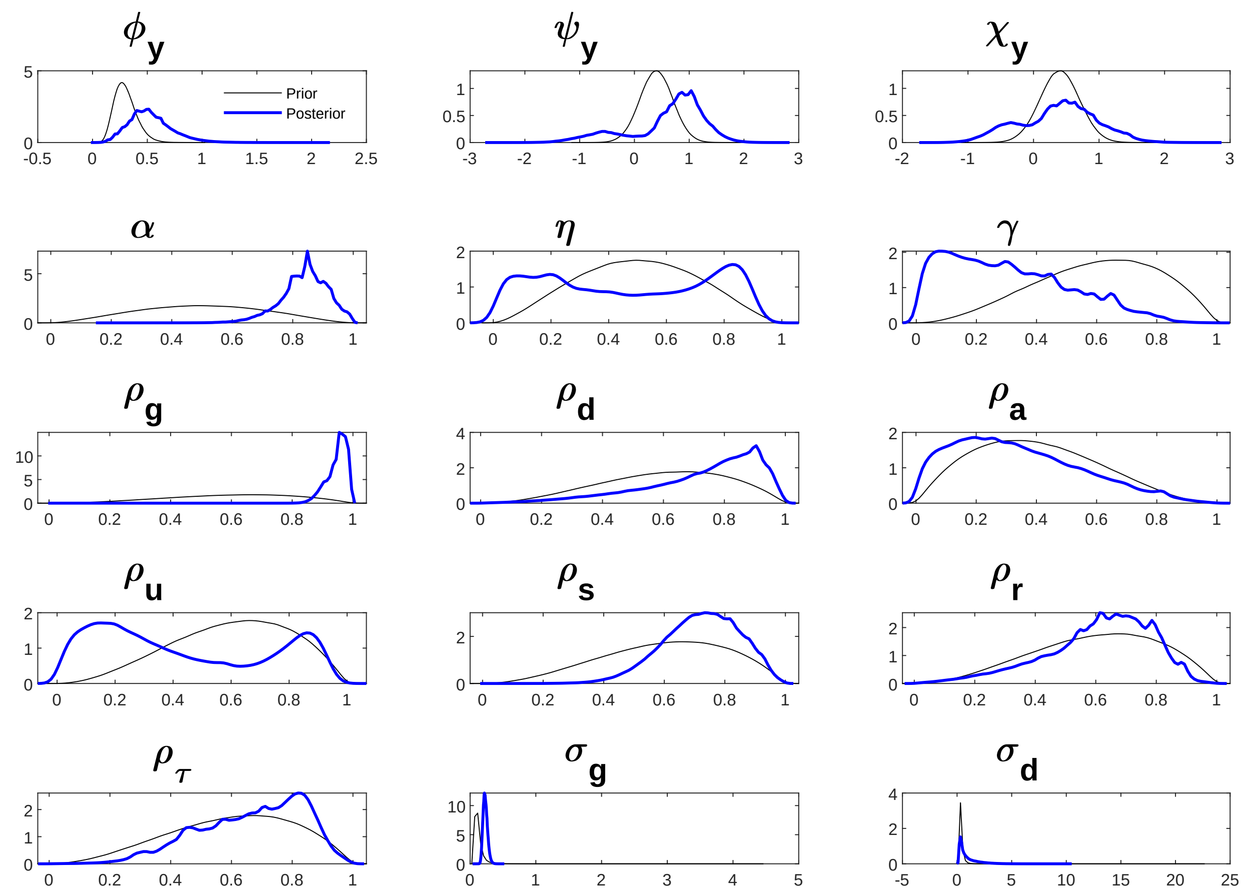
Table 10: Posterior distributions for estimated parameters (PMPF regime) - continued

	Posterior		
Parameter	Mean	SD	90 percent credible set
$b := 100\bar{b}$, debt/output	35.4	0.26	[35.02, 35.75]
$\tau := 100\bar{\tau}$, tax/output	24.01	0.06	[24.82, 24.99]
$g := 100\bar{g}$, govt spending/output	23.99	0.05	[23.93, 24.08]
Indeterminacy			
σ_ζ, sunspot shock	0.22	0.01	[0.21, 0.23]
$M_{g\zeta}$	-0.28	0.06	[-0.37, -0.2]
$M_{d\zeta}$	0.67	0.13	[0.48, 0.85]
$M_{a\zeta}$	-0.26	0.07	[-0.35, -0.19]
$M_{u\zeta}$	-0.41	0.09	[-0.54, -0.4]
$M_{s\zeta}$	0.07	0.02	[0.04, 0.09]
$M_{R\zeta}$	0.34	0.08	[0.24, 0.47]
$M_{\tau\zeta}$	-0.35	0.08	[-0.46, -0.25]
$M_{\pi\zeta}$	-0.02	0.1	[-0.18, 0.15]
$M_{b\zeta}$	0	0.03	[-0.11, 0.14]

Note: Means, and standard deviations are over 50 independent runs of the SMC algorithm with $N = 14,000$, $N_\delta = 500$, $\lambda = 2.5$, $N_{blocks} = 6$, and $M_{MH} = 1$. We compute 90 % highest posterior density intervals.

Appendix E.2 Unrestricted estimation

Here, we show plots of the prior and posterior densities for the remaining parameters from the unrestricted estimation with the SMC sampler and tables that summarize the estimation results. Here, the prior specification and the estimation approach corresponds to the description in Section 3.



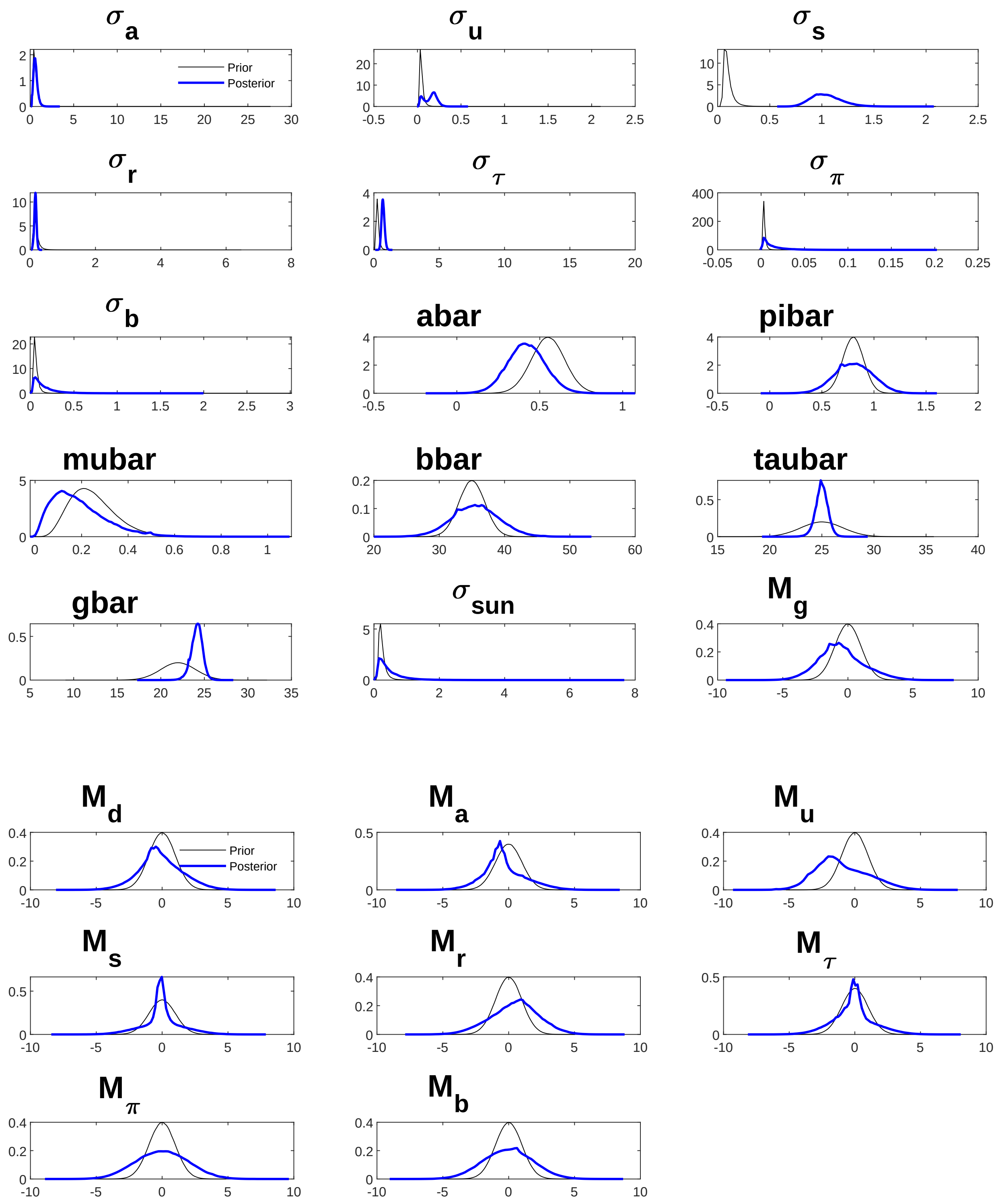


Figure 15: Prior and posterior densities of the estimated model parameters from the unrestricted estimation. The blue bold line depicts the posterior density, the black line the prior density.

Table 11: Posterior distributions for estimated parameters (Unrestricted)

	Posterior		
Parameter	Mean	SD	90 percent credible set
Monetary policy			
ϕ_π, interest rate response to inflation	0.4	0.22	[0.13, 0.73]
ϕ_Y, interest rate response to output	0.53	0.1	[0.4, 0.67]
ρ_R, response to lagged interest rate	0.61	0.11	[0.38, 0.74]
Fiscal policy			
ψ_b, tax response to lagged debt	0.026	0.04	[-0.05, 0.08]
ψ_Y, tax response to output	0.62	0.5	[-0.51, 1.05]
χ_Y, govt spending response to lagged output	0.38	0.35	[-0.25, 0.86]
ρ_g, response to lagged govt spending	0.95	0.02	[0.91, 0.97]
ρ_τ, response to lagged taxes	0.66	0.11	[0.5, 0.81]
Preference and HHs			
η, habit formation	0.45	0.23	[0.20, 0.81]
$\mu := 100(\beta^{-1} - 1)$, discount factor	0.19	0.04	[0.14, 0.22]
Frictions			
α, price stickiness	0.84	0.04	[0.8, 0.92]
γ, price indexation	0.31	0.12	[0.12, 0.44]
Shocks			
ρ_d, preference	0.73	0.11	[0.52, 0.87]
ρ_a, technology	0.33	0.08	[0.22, 0.41]
ρ_u, cost-push	0.41	0.2	[0.15, 0.71]
ρ_s, transfers	0.72	0.04	[0.64, 0.77]
σ_g, govt spending	0.23	0.01	[0.22, 0.24]
σ_d, preference	0.88	0.61	[0.31, 1.78]
σ_a, technology	0.62	0.09	[0.52, 0.72]
σ_u, cost-push	0.15	0.05	[0.09, 0.22]
σ_s, transfers	1.04	0.02	[1, 1.06]
σ_R, monetary policy	0.16	0.02	[0.13, 0.18]
σ_τ, tax	0.7	0.05	[0.64, 0.77]
σ_π, inflation target	0.006	0.006	[0.008, 0.02]
σ_b, debt/output target	0.15	0.05	[0.11, 0.2]
Steady state			
$a := 100(\bar{a} - 1)$, technology	0.42	0.03	[0.39, 0.45]
$\pi := 100(\bar{\pi} - 1)$, inflation	0.8	0.05	[0.74, 0.87]
$b := 100\bar{b}$, debt/output	35.62	0.79	[34.74, 36.44]
$\tau := 100\bar{\tau}$, tax/output	24.97	0.18	[24.68, 25.2]

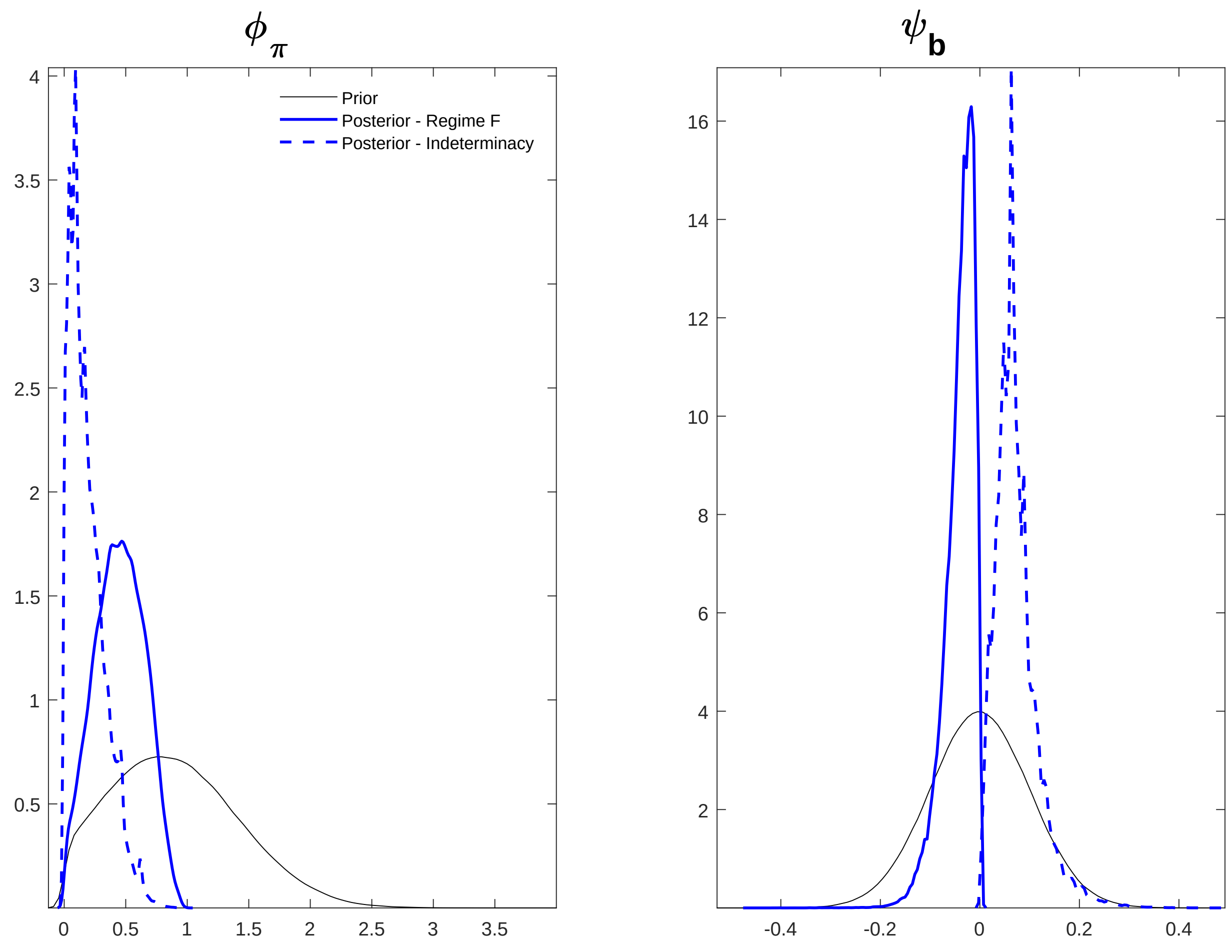
Table 11: Posterior distributions for estimated parameters (Unrestricted) - continued

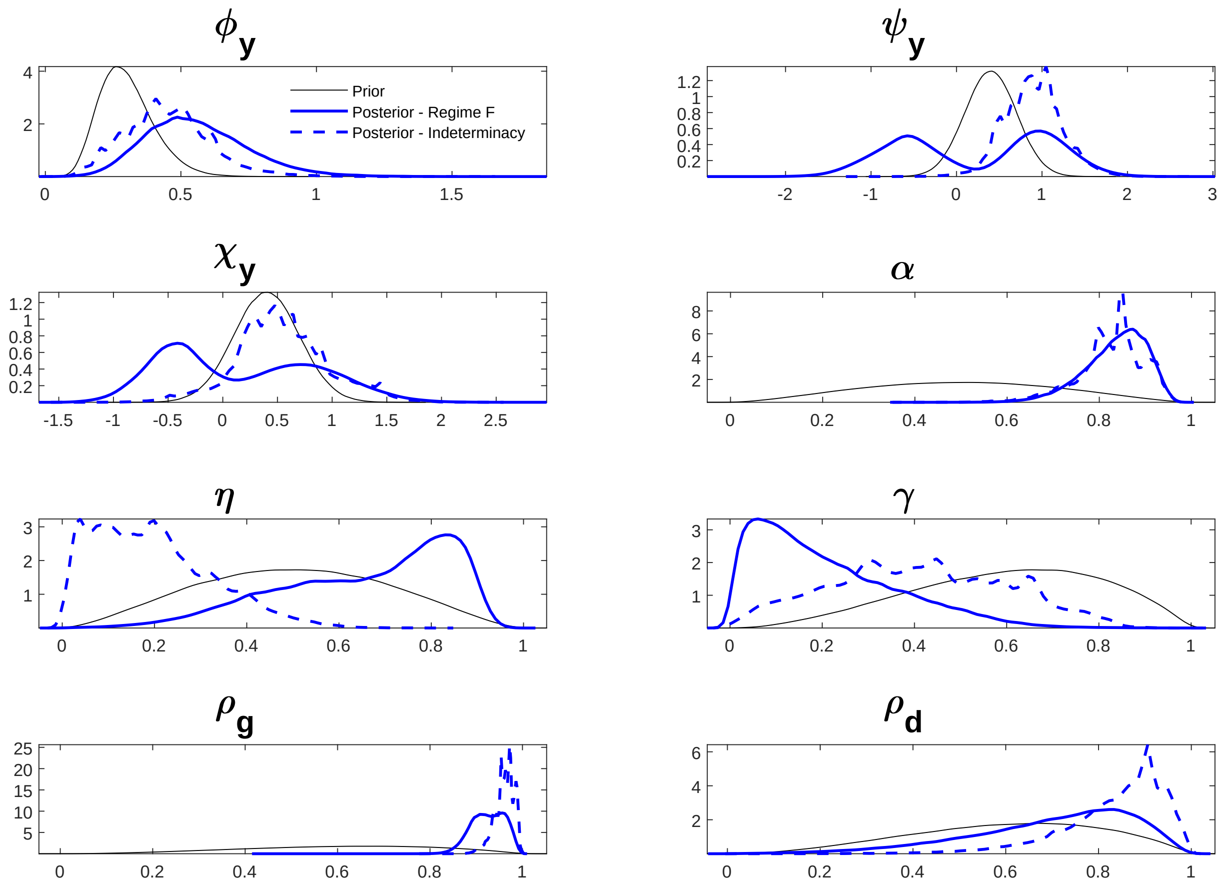
	Posterior		
Parameter	Mean	SD	90 percent credible set
$g \coloneqq 100\bar{g}$, govt spending/output	24.12	0.21	[23.82, 24.48]
Indeterminacy			
σ_ζ, sunspot shock	0.49	0.14	[0.27, 0.68]
$M_{g\zeta}$	-0.58	0.58	[-1.43, 0.03]
$M_{d\zeta}$	-0.11	0.35	[-0.69, 0.33]
$M_{a\zeta}$	-0.41	0.43	[-0.94, 0.17]
$M_{u\zeta}$	-1.09	0.98	[-2.37, 0.03]
$M_{s\zeta}$	-0.04	0.14	[-0.28, 0.16]
$M_{R\zeta}$	0.5	0.64	[-0.21, 1.22]
$M_{\tau\zeta}$	-0.13	0.38	[-0.7, 0.22]
$M_{\pi\zeta}$	0	0.45	[-0.54, 0.46]
$M_{b\zeta}$	-0.07	0.29	[-0.34, 0.45]
Log Marginal data density	-558.84		

Note: Means, standard deviations, and estimates of the log marginal data density are over 50 independent runs of the SMC algorithm with $N = 20,000$, $N_\delta = 600$, $\lambda = 2.4$, $N_{blocks} = 10$, and $M_{MH} = 2$. We compute 90 % highest posterior density intervals. 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.

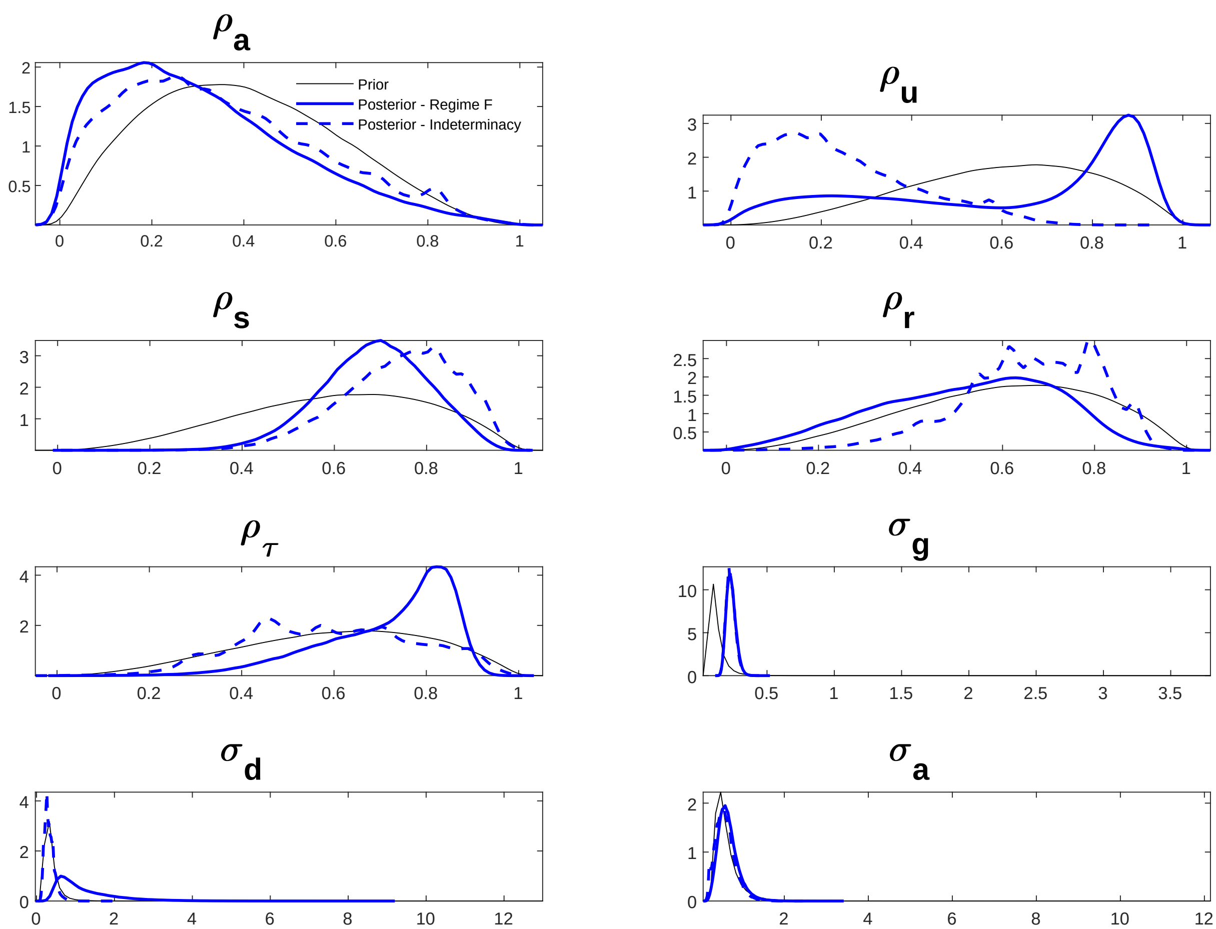
Appendix E.3 Unrestricted estimation - posterior densities conditional on regime F and the PMPF regime

Here, we show plots of the prior and posterior densities conditional on regime F and indeterminacy from the unrestricted estimation with the SMC sampler for the policy parameters ϕ_π and ψ_b, and the remaining parameters.





ϕ_y
Prior
Posterior - Regime F
Posterior - Indeterminacy
ψ_y
χ_y
α
η
γ
ρ_g
ρ_d



ρ_a
Prior
Posterior - Regime F
Posterior - Indeterminacy
ρ_u
ρ_s
ρ_r
ρ_τ
σ_g
σ_d
σ_a

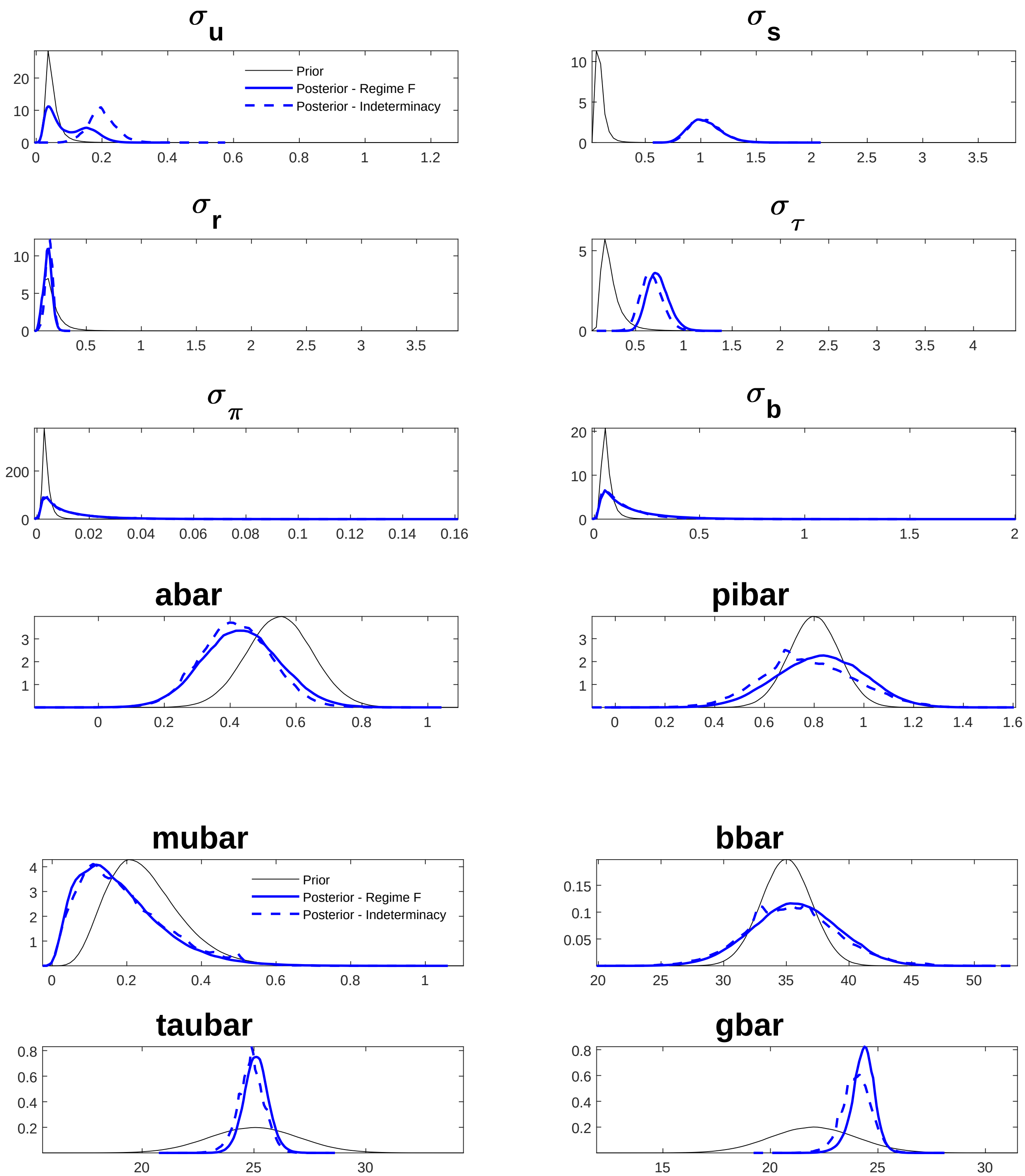


Figure 16: Prior and conditional posterior densities of the estimated model parameters from the unrestricted estimation. The blue bold line depicts the posterior density conditional on regime F, the dashed blue line the posterior density conditional on the PMPF regime, and the black line the prior density.

Appendix F Smoothed shocks

Here, we show plots of the remaining smoothed shocks for regime F and the PMPF regime, respectively.

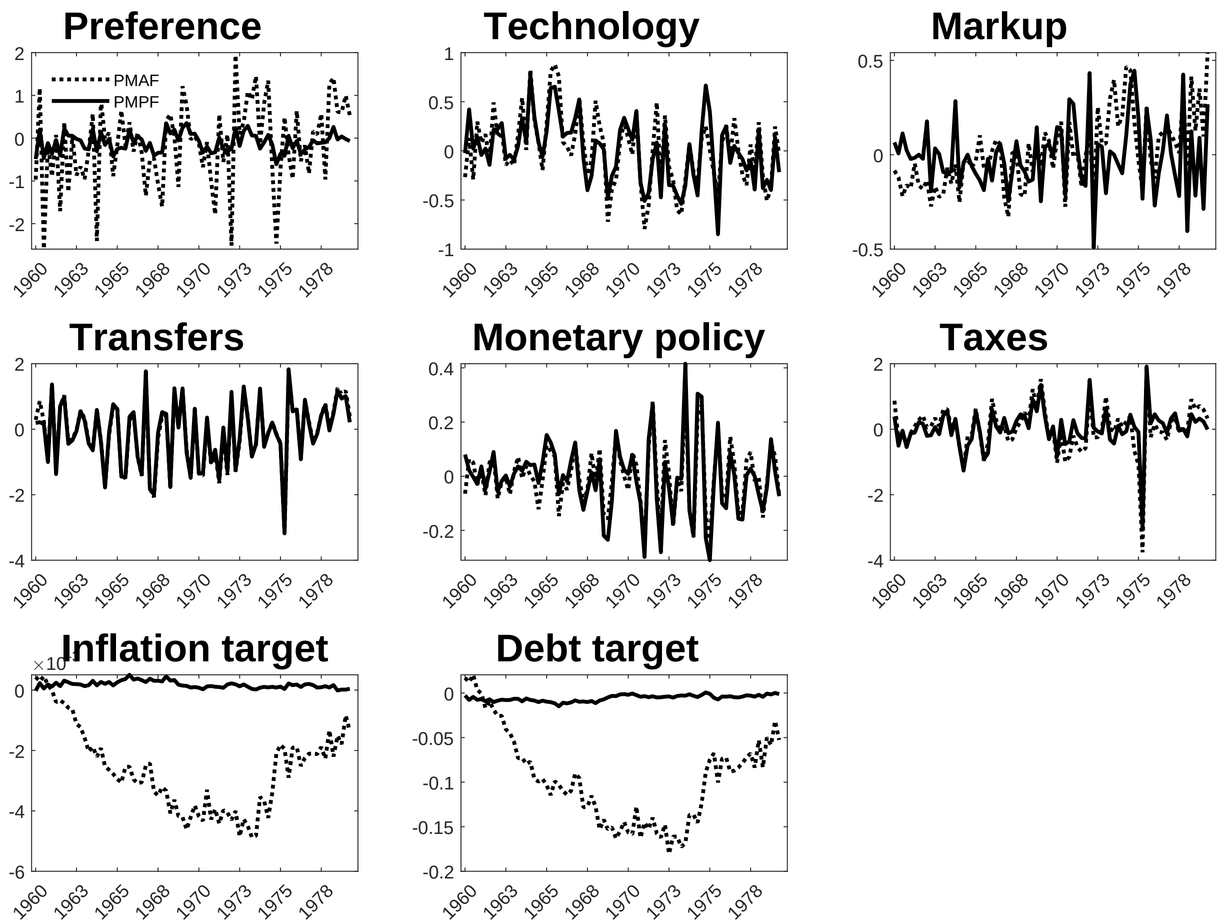


Figure 17: Smoothed shocks for 1960:Q1 to 1979:Q2 for regime F and the PMPF regime. The dashed line shows shocks computed at the mean of the posterior density from the unrestricted estimation conditional on regime F. The solid line shows shocks computed at the mean of the posterior density from the unrestricted estimation conditional on the PMPF regime.