Back to the Future: What the 1970s Can Teach Us About Today's Economic Challenges

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Abstract

We investigate the importance of the monetary-fiscal policy mix during times of crisis by drawing insights from the Great Inflation of the 1960s and 1970s. Estimating a DSGE model with three monetary-fiscal policy regimes with a Sequential Monte Carlo (SMC) algorithm, we find that the macroeconomic dynamics during the Great Inflation were equally driven by passive monetary/passive fiscal policy and fiscal dominance. An analysis of the current macroeconomic milieu through the lens of our model shows that causes of inflation and the recipe to fight it depend on the policy regime in place. In a regime with monetary dominance, mark-up shocks mainly drive inflation and an increase in interest rate is effective, while in a fiscal dominant regime, transfers are the main cause of inflation and an increase in interest rates does not curb inflation.

JEL classification: C11, C15, E63, E65

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1 Introduction

We are currently living in the age of polycrisis, characterized by multiple severe and overlapping challenges. In advanced economies, sovereign debt levels have increased to record highs due to fiscal stimulus and rescue packages in response to the pandemic and the war in Ukraine. This has eroded the fiscal authorities' credibility in stabilizing the accumulated fiscal imbalances (Bianchi and Melosi, 2022). At the same time, inflation is surging, ending decades of generally stable prices. Navigating through this complex environment requires coordinated fiscal and monetary policy actions and a sound understanding of macroeconomic policy interactions. This paper aims to contribute to this debate by revisiting the historical episode of the Great Inflation in the U.S., which offers valuable macroeconomic lessons for the current high inflation period. Using a novel estimation method, we demonstrate that there was not one prevailing fiscal-monetary policy mix, and thus no single explanation for the observed macroeconomic dynamics in the pre-Volcker period. In a second step, we transfer these lessons to today's economic challenges, highlighting that the main drivers of post-pandemic inflation depend on the monetary-fiscal policy mix in place, as do the appropriate monetary and fiscal responses to contain them.

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).[1] 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

[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.

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, in particular government spending, were also an equally important driver of U.S. inflation in the 1960s and 1970s.

Through the lens of our model, we analyze the current macroeconomic situation and find that, much like during the Great Inflation, the main driver of post-pandemic inflation depends on the monetary-fiscal policy regime in place, as do the effects of monetary and fiscal policies. To demonstrate this, we filter U.S. data from 2020:Q1 - 2022:Q4 through the model, separately for each of the three estimated monetary-fiscal policy regimes. Although the smoothed shocks are similar in each parametrization, the contribution of each shock to inflation varies significantly across the policy regimes. In a regime of monetary dominance, the main driver of post-pandemic inflation are mark-up shocks. In a regime with two passive authorities, inflation is mainly caused by preference and tax shocks. In contrast, under fiscal dominance, transfers are the main cause of inflation. Consequently, while fiscal policy would be the main instrument to combat inflation in the latter two regimes, fiscal policy actions would not effectively bring down inflation in a regime of monetary dominance. We further illustrate the effectiveness of macroeconomic policy instruments in an impulse response analysis. While an increase in the nominal interest rate is effective in curbing inflation in a monetary policy-led regime, it is inflationary in a fiscal-led and a passive monetary/passive fiscal policy regime.

Our study contributes in three ways to the literature. First, our findings provide guidance in conquering post-pandemic inflation. We show that any discussion of potential causes of inflation must be accompanied by an assessment of the monetary-fiscal policy mix in place. Characterizing the drivers of post-pandemic inflation for each regime separately, we illustrate quantitatively how causes of inflation and recipes to fight it depend on the prevailing monetary-fiscal policy regime. In case of a regime of monetary dominance, the main driver of inflation is a mark-up shock. Thus an increase in interest rates is an appropriate policy to curb inflation. The same policy, however, would be inflationary in a regime of fiscal dominance. In the latter regime, the main cause of inflation is of fiscal nature, thus calling for lower fiscal activity. Therefore, policymakers must carefully assess the monetary-fiscal policy regime they are in to take informed decisions.

Second, 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, unable 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 finally dissolve the persisting dissonance between these two model classes. 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.

Third, our study provides methodological guidance on how to estimate DSGE models with monetary-fiscal policy interactions. As demonstrated by Herbst and Schorfheide (2014,

[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).

2015) and Cai et al. (2020), the SMC sampler outperforms the RWMH in the presence of multimodal posteriors, an outcome that is highly likely in a DSGE model with monetary-fiscal policy interactions. The model's different policy regimes exhibit different model dynamics and, hence, lead to discontinuous likelihood functions around the policy regimes. Compared to models with a single policy regime, this feature makes it harder for posterior samplers to transition between areas of the parameter space with similar fit. We contrast the RWMH's and SMC's performance in such a model and show that the choice of the posterior sampler determines the estimation outcome. While the SMC sampler can deal with the irregular posterior surface and can navigate through the entire parameter space, the RWMH produces posterior regime probabilities that highly depend on the sampler's starting value.[4]

The remainder of this paper is as follows. Section 2 describes the DSGE model with monetary-fiscal policy interactions and in Section 3, we outline our empirical approach. We describe the prior distributions and the dataset and contrast the two posterior sampler we employ, RWMH and SMC sampling. Section 4 provides the estimation results. We determine the monetary-fiscal policy mix in the pre-Volcker period sequentially with RWMH and SMC and compare the two samplers' performances, concluding that SMC sampling is the preferred approach for estimating DSGE models with monetary-fiscal policy interactions. In light of our new findings, in Section 5, we re-examine what caused the build-up of U.S. inflation in the 1960s and 1970s. In a second step, we link the findings on the pre-Volcker monetary-fiscal policy mix to the post-pandemic high inflation period to gain insights on causes and policy options in the current situation. The final section concludes the study.

[4]Bianchi and Nicolò (2021) 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. 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 exclusively examine the role of monetary policy and omit the fiscal side from the model.

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 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.[5] 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

[5] 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.

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

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:

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

$\hat{\pi}^*_t$ 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. $N(0,\sigma^2_R)$. 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. $N(0,\sigma^2_\tau)$. 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.[6] 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 $\Gamma_{0,\zeta}^*$.[7] Second, an exogenous sunspot shock ζ_t, unrelated to the fundamental shocks

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

[7] 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	$[-0.16, 0.16]$

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 Strategy

In this section, we present the Bayesian empirical strategy. We describe the prior distributions and the dataset, and motivate the procedures for posterior sampling we choose to determine the monetary-fiscal policy mix in the pre-Volcker period.

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.[8] 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.[9] In the following, we discuss only the key parameters of our analysis.

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

[9] In Appendix B.2 we show results from the prior predictive analysis. Specifically, 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.

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 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).[10] 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.

RWMH vs. SMC posterior sampling

Posterior inference in DSGE models relies on sampling techniques as the moments of the posterior cannot be characterized in closed forms. Compared to Bhattarai et al. (2016), our reference study, we do not estimate each regime separately with a RWMH, but choose the SMC algorithm introduced to the DSGE literature by Creal (2007), then further enhanced and theoretically justified by Herbst and Schorfheide (2014, 2015).[11] 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 that is highly likely in the case of the DSGE model with monetary-fiscal policy interactions with a discontinuous likelihood function.[12] 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]

To evaluate the RWMH's and SMC's performance explicitly in a model with monetary-

[10] 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.

[11] 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.

[12] In short, the RWMH is an iterative simulator that belongs to the class of Markov chain Monte Carlo (MCMC) techniques. Herbst and Schorfheide (2015, pp. 52-99), for instance, explain the sampler in detail.

[13] The SMC algorithm generates weighted draws from a sequence of easy-to-sample proposal densities. The weighted draws are called particles. Appendix D includes a more detailed description of the SMC algorithm and our choice of tuning parameters.

fiscal policy interactions, for comparison, we estimate the model over its unrestricted parameter space using RWMH and contrast the two samplers' findings. We choose a set-up that *a priori* puts the RWMH algorithm on equal grounds. In particular, we initialize (i) two chains à ten million draws at the mode of regime F and the indeterminacy regime, respectively, and pool these draws with (ii) four chains à ten million draws departing from a random value in the parameter space region of regime F and indeterminacy. Using the double number of draws from the randomly chosen starting values compared to the mode initialization, attributes the sampler a higher chance to explore the entire parameter space without getting stuck at a local mode and, hence, works in favor of the RWMH sampler. From this procedure, we obtain a total of 120 million posterior draws - an number much greater than usually computed for estimating medium-sized DSGE models.[14]

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

In this section, we determine the monetary-fiscal policy mix in the pre-Volcker period separately with the RWMH and the SMC and compare the performance of the two samplers. In the final discussion, we argue that the SMC, our preferred approach, is able to reconcile the empirical findings of the fixed-regime and regime-switching DSGE model literature, while also providing some intuition why restricting or not restricting the parameter space during estimation matters.

[14]From each chain we discard seven million draws as burn-in and use from the remainder each eighth draw to compute posterior results. In comparison, in Bhattarai et al. (2016), our reference study, a total of 21.6 million draws over all regimes is computed.

Posterior estimates

Figure 1 presents the posterior densities of the policy parameters ϕ_π and ψ_b from the unrestricted estimation with RWMH.[15] The values of ϕ_π and ψ_b determine the monetary-fiscal policy mix. $\phi_\pi < 1$ corresponds to a passive monetary authority, while $\phi_\pi > 1$ corresponds to an active central bank. The boundary of fiscal policy lies around zero. $\psi_b < 0$ refers to an active fiscal policy, while $\psi_b > 0$ is associated with a passive fiscal authority.

To evaluate the RWMH's performance, it is instructive to distinguish the posterior draws according to the initialization method described in Section 3. The blue solid and the blue dashed lines show the posterior draws obtained from initializing the RWMH at the mode of regime F and indeterminacy, respectively. The red solid line depicts the marginal posterior densities obtained from the runs started at random points in the parameter space of regime F and PMPF. The plot makes three points obvious. First, considering all draws jointly, the marginal posterior distribution of the policy parameters exhibit pronounced bimodalities. However, each initialization method taken individually generates a unimodal marginal posterior density that corresponds to a distinct policy regime. Second, starting the sampler at the mode of regime F results in posterior estimates corresponding to regime F, while starting the sampler at the mode of the indeterminacy regime produces draws exclusively from the indeterminacy region of the parameter space. Hence, initializing the RWMH at the mode of the policy regimes leads to posterior estimates that highly depend on the starting value as the sampler does not transition between regimes. Last, all runs started at random values, no matter if in regime F or PMPF, let the sampler draw uniquely from the indeterminacy region. This characteristic could lead to the conclusion that the indeterminacy region is the prevailing regime.

[15] For the RWMH, we monitored convergence by computing recursive means. Appendix E.2 provides the corresponding plots.

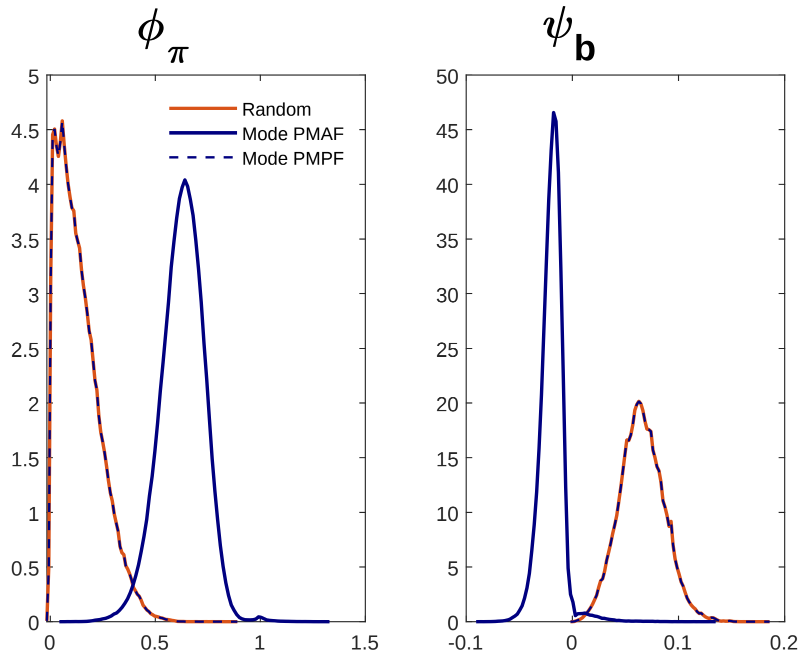


Figure 1: Posterior densities of the policy parameters obtained from RWMH sampling. The blue solid line depicts the posterior density obtained from initializing the sampler on the mode of regime F, the blue dashed line from initializing the sampler on the mode of regime PMPF, and the red solid line shows the posterior density obtained from the random initialization.

In Figure 2, we compare the marginal posterior densities of ϕ_π and ψ_b across the SMC and the RWMH samplers. The red dashed line corresponds to the posterior density obtained from SMC sampling,[16] while the blue solid line is the posterior density obtained from the pooled runs of the RWMH sampler. The black line shows the marginal prior distribution. Similar to the RWMH, the posterior densities of ϕ_π and ψ_b from SMC sampling display pronounced bimodalities around the policy regimes. However, while the RWMH generates draws mainly in the immediate vicinity of the policy regimes' modes, the SMC sampler transitions more frequently between regimes and assigns more probability mass to parameter values between the two modes of ϕ_π and ψ_b.[17] It is also noticeable that the probability mass below each

[16] To ensure convergence of the SMC, we follow the practical recommendations given in Herbst and Schorfheide (2014) and produced 50 independent runs with the SMC sampler. We pooled the draws over the 50 runs to compute parameter means, standard errors, and credible sets.

[17] 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

mode is unequally distributed across the samplers.

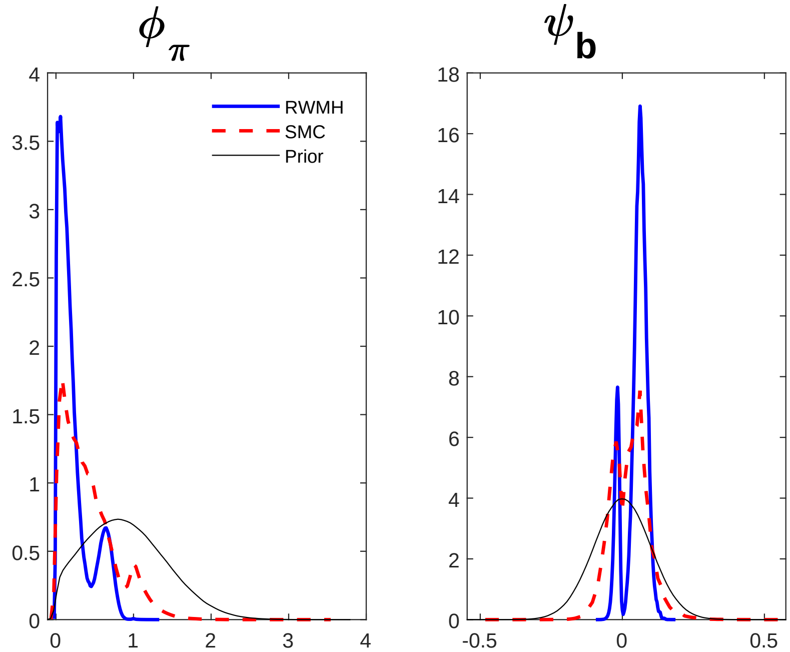


Figure 2: Posterior densities of the policy parameters obtained from SMC and RWMH sampling and prior densities. The blue solid line depicts the RWMH posterior density, the red dashed line the SMC posterior density, and the black line the prior density.

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). The two samplers agree that the dominant monetary-fiscal regime in the pre-Volcker period was the indeterminacy regime. However, while the RWMH attributes PMPF a posterior probability of 83.33 %, the SMC assigns the indeterminacy regime at 43.54 %, considerablye less. In contrast, regime F, receives in the SMC estimation, at 36.81 %, more than twice as much posterior probability as than in the RWMH estimation (16.32 %). In line with the literature, regime M obtaines for both samplers the least support from the data.[18]

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.

[18]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. Appendix E.3 contains posterior density plots of the unrestricted SMC estimation conditional on regime F and the PMPF regime.

Table 3: Posterior probability of pre-Volcker policy regimes

	AMPF	PMAF	PMPF
SMC	19.65	36.81	43.54
RWMH	0.35	16.32	83.33

Note: To obtain the posterior probabilities from SMC, 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 algorithm. For the RWMH, the posterior regime probabilities are computed over 120 million draws.

Discussion

The comparison of posterior estimates across the RWMH and the SMC shows that the choice of the sampler influences the estimation outcome in DSGE models with monetary-fiscal policy interactions. While the RWMH produces estimates that depend on the starting value and fails to transition between the policy regimes' distinct posterior modes, the SMC can deal with irregular-shaped posterior surfaces and explores the entire parameter space. Although the two sampler coincide in finding indeterminacy to be the dominant regime in the pre-Volcker period, the general conclusion drawn from the sampler comparison is that the RWMH overstates the posterior probability of the dominant regime and underrepresents the other regimes. For that reason, the SMC is our preferred sampler to estimate DSGE models with monetary-fiscal policy interactions, like the model of Bhattarai et al. (2016).

Compared to the restricted estimation in Bhattarai et al. (2016), using SMC to estimate the model over its unrestricted parameter space allows us to draw a more differentiated conclusion. In line with Bhattarai et al. (2016), we find that the regime with the highest posterior probability in the pre-Volcker period is the PMPF regime. However, in contrast to their analysis, we find that regime F scores only slightly worse. Based on our findings, we argue 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, on average, the 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 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.[19] Our findings support their view that an active U.S. fiscal policy played a substantial role in the build-up of pre-Volcker inflation.

The merit of our chosen SMC approach is that it can create new perspectives in a fixed-regime model environment. Since 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, using RWMH sampling to estimate the model in one step overrepresents the posterior probability of the dominant PMPF regime as the sampler takes draws mainly around the associated mode and does not transition frequently enough to other regions of the parameter space with less likelihood. Comparably, restricting the parameter space and estimating the model sequentially for each regime with RWMH 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 that, like Bhattarai et al. (2016), 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.

[19] 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.

5 From then to now - lessons from 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 second step, we link the findings on the pre-Volcker monetary-fiscal policy mix to the post-pandemic period to gain insights on causes and policy options in the recent inflation build-up.

Revisiting the causes of the Great Inflation

We use our findings to carry out a historical shock decomposition of pre-Volcker inflation and conduct a counterfactual analysis to quantify the importance of fiscal policy actions in the inflation build-up. We partition the draws from the posterior according to the corresponding policy regimes determined by the SMC and conduct the historical decomposition for the PMPF regime and regime F separately. Figure 3 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.[20]

[20] The fact that sunspot shocks did not play a substantial role in the pre-Volcker inflation build-up is, for instance, also confirmed in Nicolò (2020).

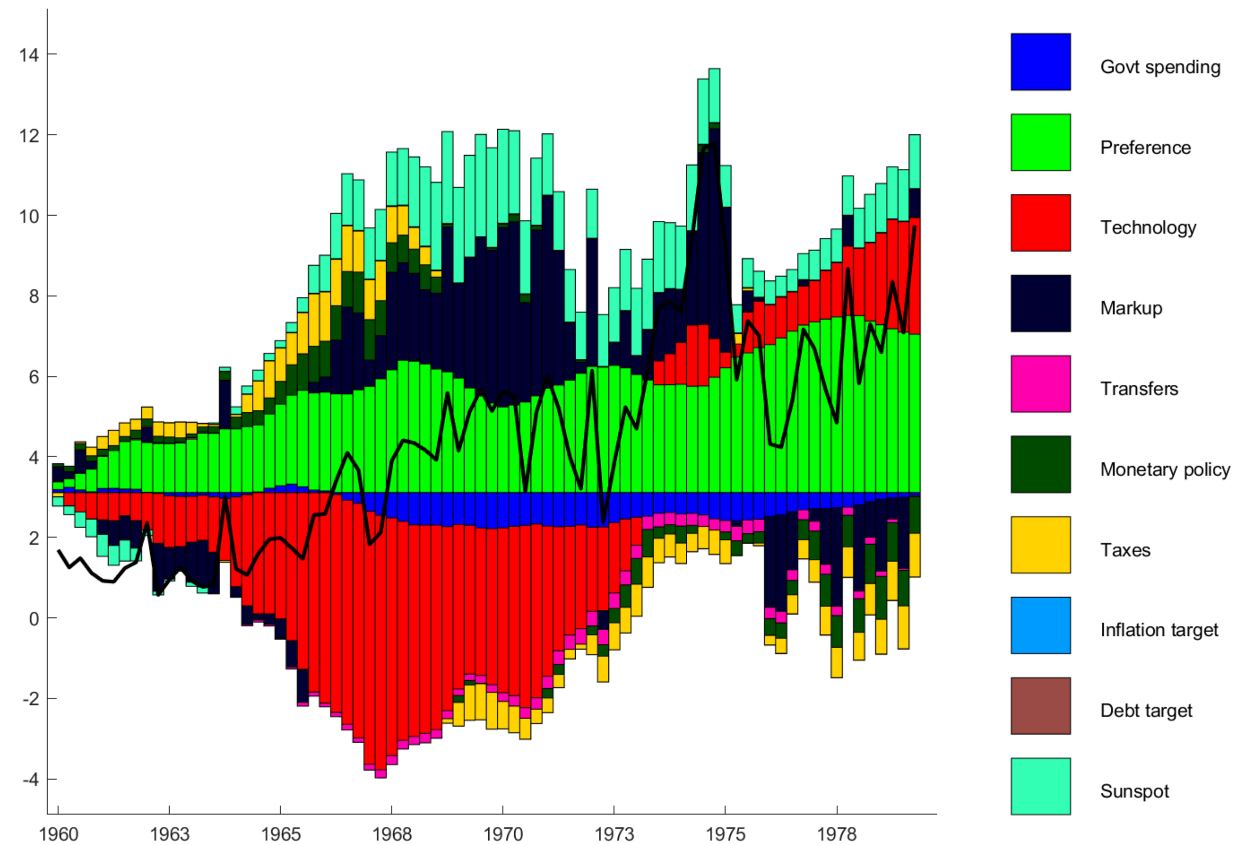


Figure 3: Contribution of each shock to inflation in the PMPF regime. The bold black line shows observed inflation. The historical decomposition is conducted at the posterior mean of the PMPF regime.

In regime F, the picture looks different. Figure 4 summarizes the findings. Technology and demand shocks played only a minor role in regime F. Instead, the mechanism of the fiscal theory of the price level (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 for the rising U.S. inflation in the pre-Volcker period in the literature. 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.

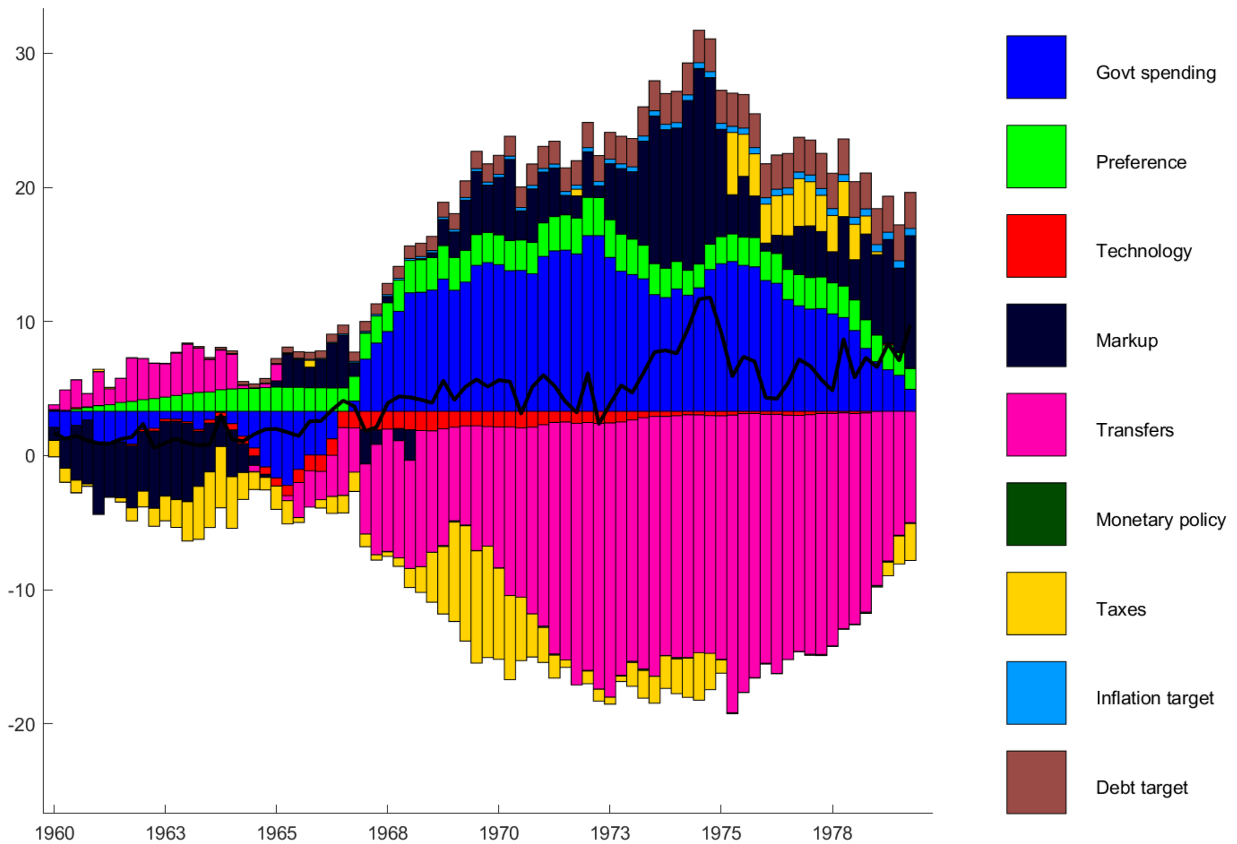


Figure 4: Contribution of each shock to inflation in regime F. The bold black line shows observed inflation. The historical decomposition is conducted at the posterior mean of regime F.

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 5 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.

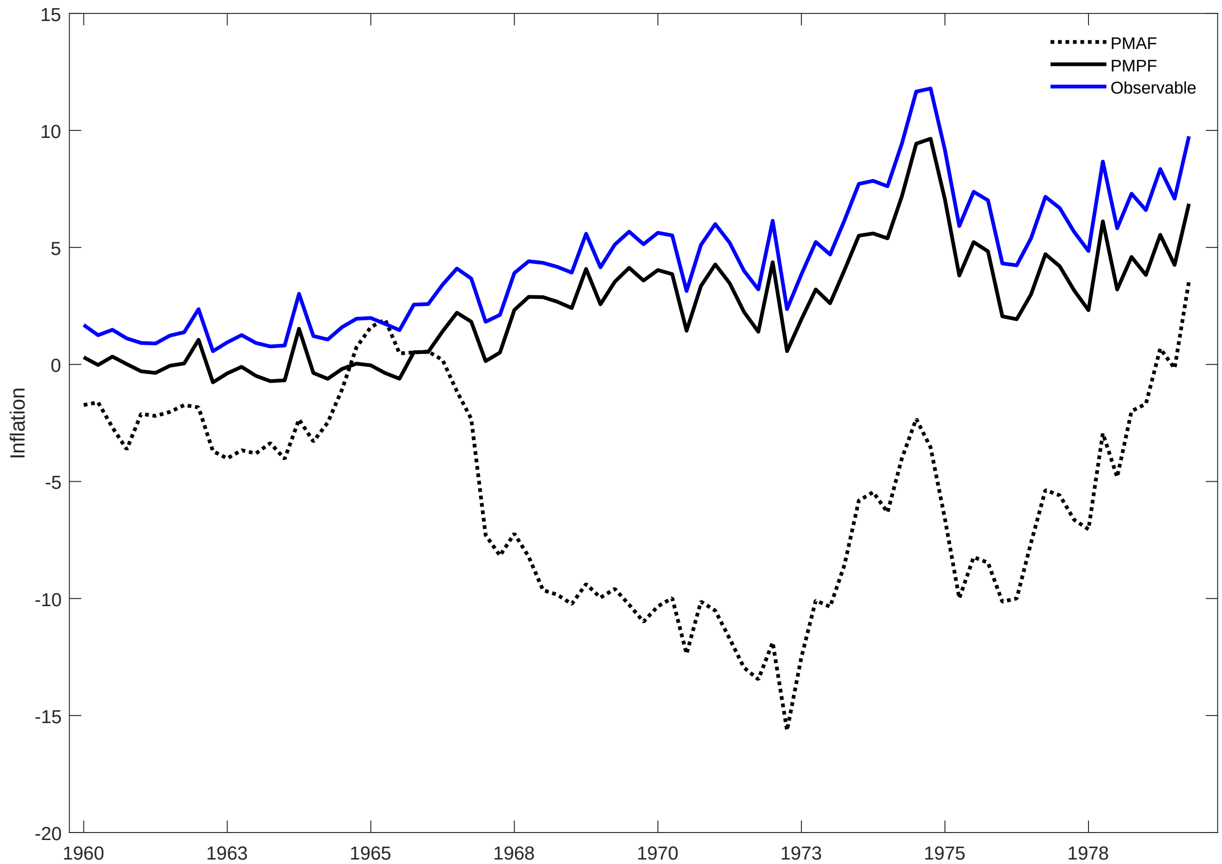


Figure 5: Evolution of inflation (in percentage points) without government spending shock in the PMPF regime and regime F. The counterfactual analysis is conducted at the posterior mean of each policy regime.

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 6 shows that, pre-Volcker, the smoothed government spending shocks of regime F and the PMPF regime are nearly congruent.[21] Hence, the differing evolution of inflation is induced by the regimes themselves.

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

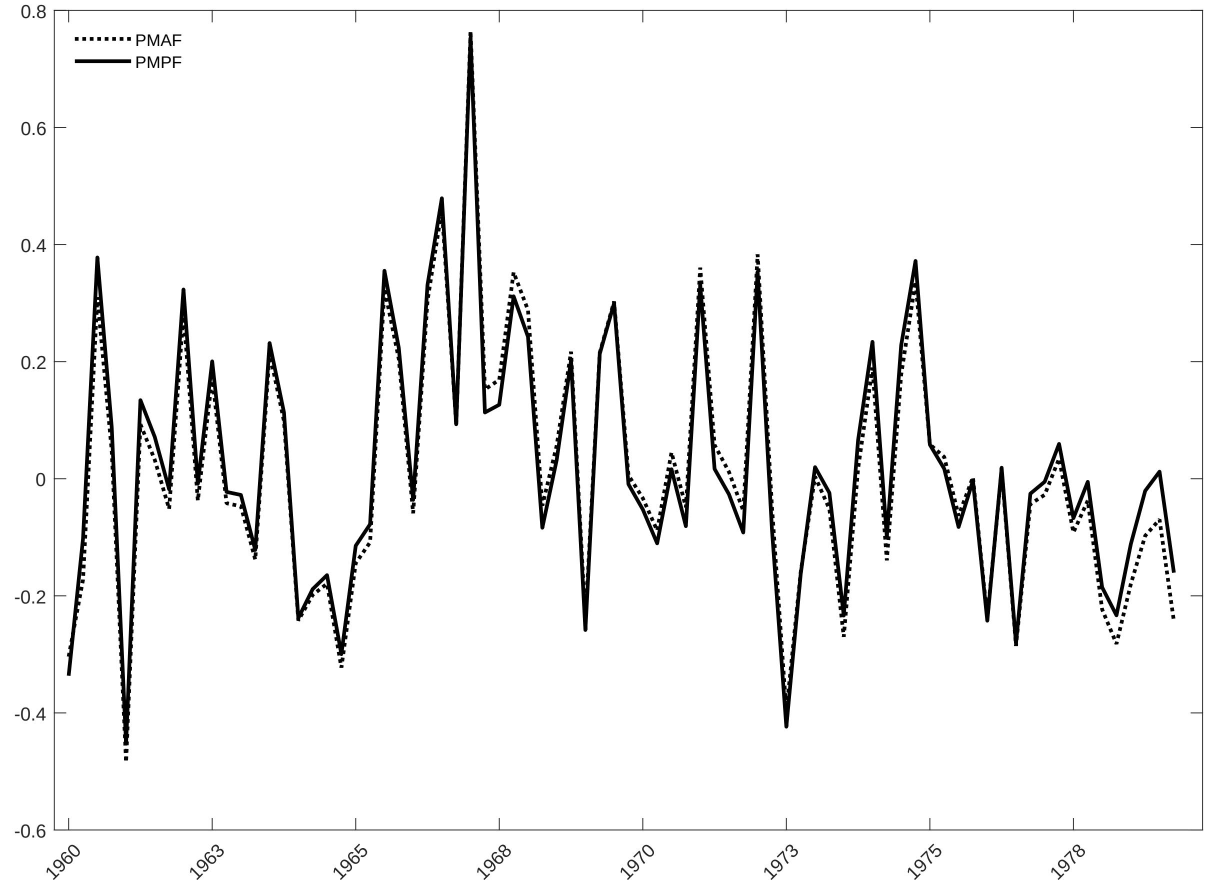


Figure 6: Smoothed government spending shock for 1960:Q1 to 1979:Q2 for regime F and the PMPF regime. The dotted line shows the shock computed at the posterior mean of regime F. The solid line shows the shock computed at the posterior mean of the PMPF regime.

The results of the counterfactual analysis are instructive for evaluating 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 5, 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.

Lessons for today

After decades of generally stable prices, the post-pandemic era marked a turning point with a global surge in inflation. In the U.S., shocks to energy prices and heavy fiscal stimulus in response to the pandemic, most notably U.S. President Biden's $ 1.9 trillion of federal government spending included in the American Rescue Plan Act, have evoked memories of the Great Inflation in the 1970s. In the last part of the study, we link our analysis of pre-Volcker inflation dynamics to the recent rise in inflation.

In particular, we use the insights from the estimated model in the previous sections to analyze causes and policy options in the inflation build-up since 2020. While the short period of the post-pandemic sample makes it impossible to determine the monetary-fiscal policy mix in our fixed-regime DSGE model framework, estimating the model on U.S. observables for the pre-Volcker period provides us a data-driven parametrization for the three relevant monetary/fiscal policy regimes.[22]

In a first step, we use these parametrizations to carry out a historical decomposition of U.S. inflation from 2020:Q1 - 2022:Q4. Figure 7 illustrates the drivers of post-pandemic inflation under an assumed regime of fiscal dominance. Over the period 2020:Q1 - 2022:Q4, positive transfer shocks are the main cause of inflation, echoing the conclusions in Bianchi and Melosi (2022) that the recent surge in inflation has a fiscal nature. Under a regime of monetary dominance, fiscal policy shocks play no role. Instead, Figure 8 shows that the main driver of post-pandemic inflation are mark-up (i.e., cost-push) shocks. Under assumed indeterminacy, post-pandemic inflation is mainly caused by preference and tax shocks (Figure 9). To summarize, in line with the recent narrative, the historical decomposition attributes mainly cost-push and fiscal shocks the role of driving post-pandemic inflation. Yet, depending on the regime, the quantitative importance of the shocks differ starkly.

[22]Bianchi and Melosi (2022) uses a Markov-switching model that is estimated on the sample 1954:Q4-2022:Q1. The authors conclude that in light of the unprecedented fiscal interventions implemented in response to the pandemic, a regime of fiscal dominance is considered more likely. However, the authors also point out the methodological limitations in getting robust predictions from models at the end of estimation samples.

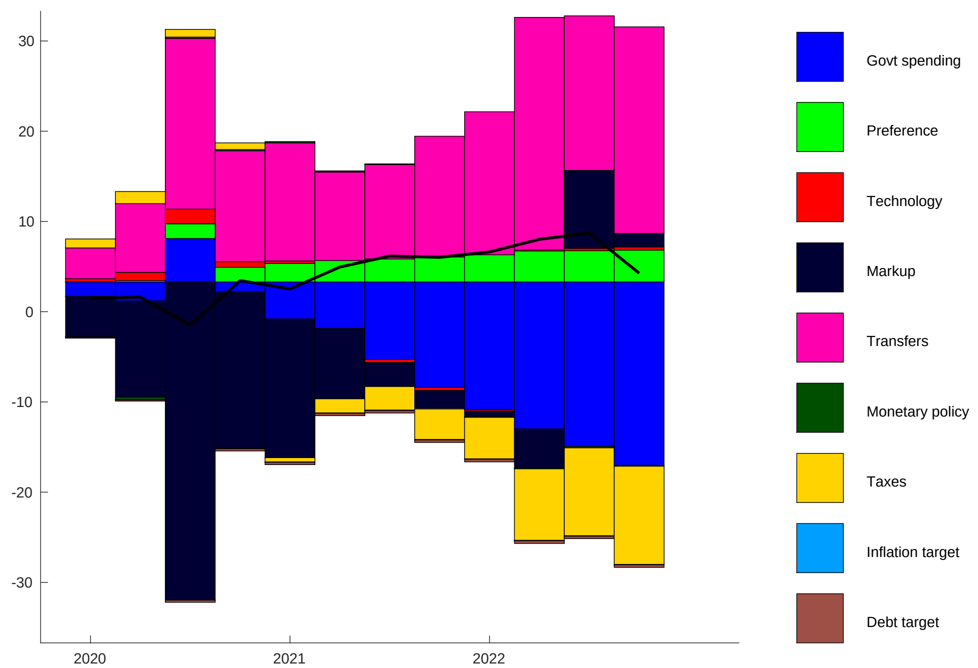


Figure 7: Contribution of each shock to post-pandemic inflation in regime F. The bold black line shows observed inflation. The historical decomposition is conducted at the posterior mean of draws from regime F in the pre-Volcker estimation.

In a second step, we investigate whether the recipe to get inflation back under control depends on the policy regime in place. To this end, we compare the effects of monetary and fiscal policy across the three different regimes. Panel a of Figure 10 shows the responses of output, inflation, and government debt to an increase in interest rates. On the one hand, in a regime of monetary dominance, an interest rate increase is indeed contractionary and leads to an increase in inflation. The debt-to-output ratio rises due to the decline in output. On the other hand, if the economy is in a regime of fiscal dominance, an increase in the interest rate causes an increase in inflation, after an initial contraction, an increase in output and, thus, a decline in the debt-to-output ratio. This counter-intuitive result is due to the muted response of the fiscal authority to an increase in debt service after an increase in interest rates. As the fiscal authority does not increase fiscal surpluses sufficiently to service the debt, the monetary policy has to let the price level adjust such that the equilibrium condition for government debt holds. The increase in inflation is higher than the one in the nominal interest rate, which leads to a negative real interest rates and thus to the positive output response. Inflation, together with the response of output, stabilizes the debt-to-output ratio. The third regime, the indeterminacy regime, shows similarities with regime F. As in regime F, monetary policy raises nominal interests less than inflation, which reduces the real interest rate and stimulates output. The impulse response functions in that regime a more pronounced due to a higher persistence in the estimated monetary policy rule.

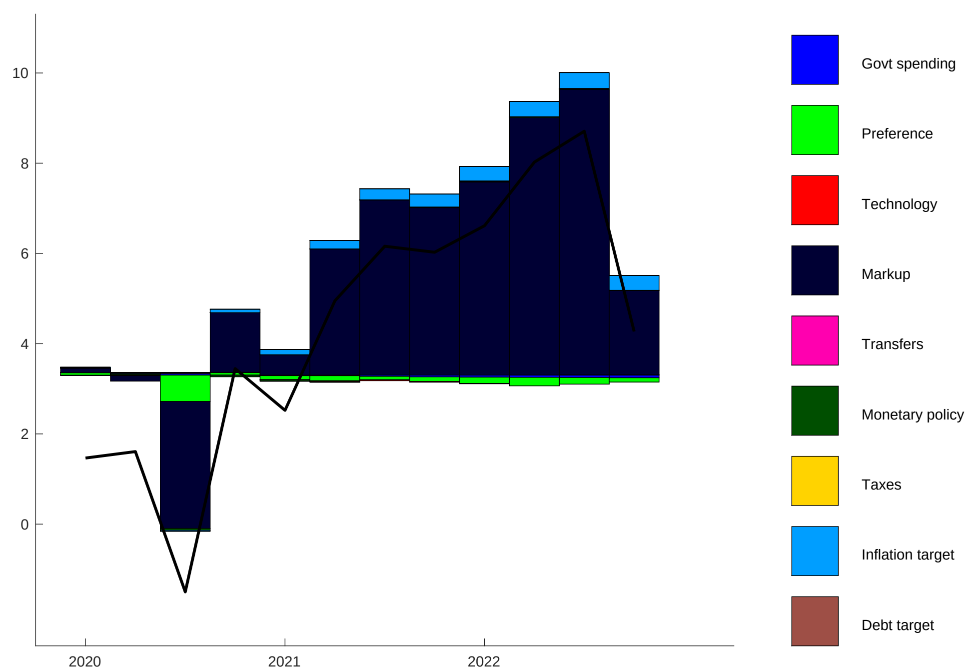


Figure 8: Contribution of each shock to post-pandemic inflation in regime M. The bold black line shows observed inflation. The historical decomposition is conducted at the posterior mean of draws from regime M in the pre-Volcker estimation.

The differences between the regimes also appear in the impulse response functions after a shock to government spending (Panel b of Figure 10). In regime F, an increase in government spending is inflationary and due to the muted response of monetary policy and the reduction of real rates expansionary. These effects are not present in the other regimes. Here, an increase in government spending only slightly moves inflation and output. The increase in spending is driving the debt-to-output ratio persistently up though.

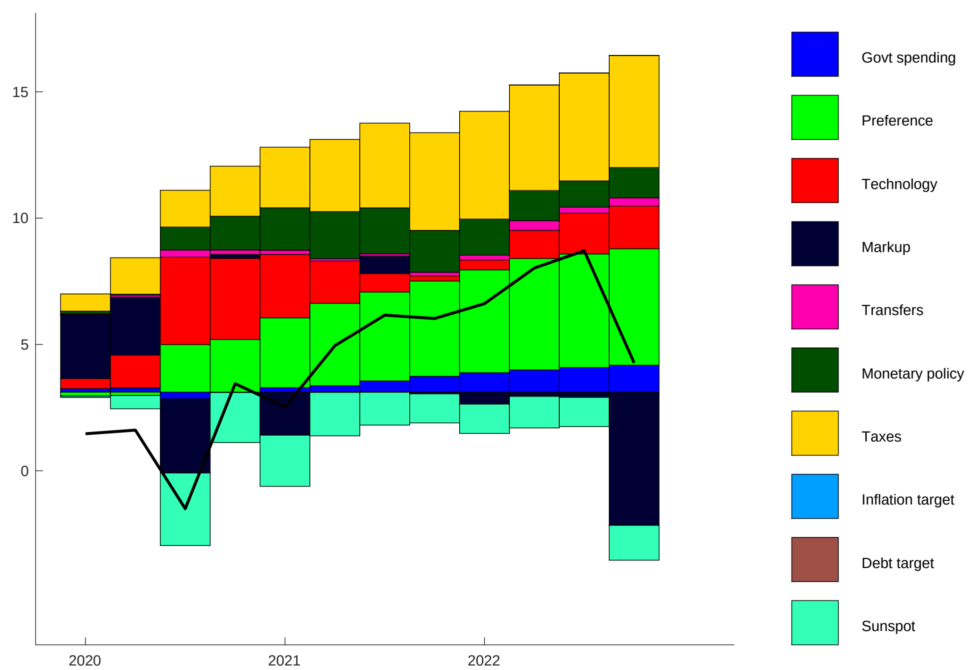
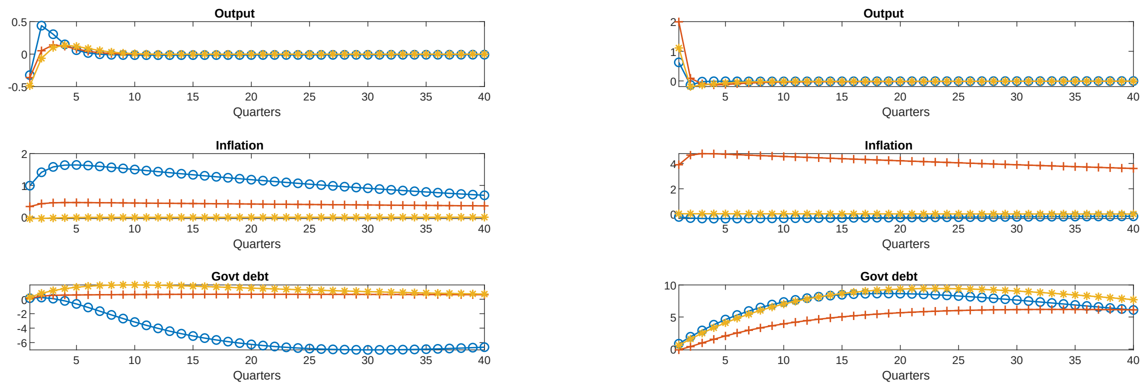


Figure 9: Contribution of each shock to post-pandemic inflation in the indeterminacy regime. The bold black line shows observed inflation. The historical decomposition is conducted at the posterior mean of draws from the indeterminacy regime in the pre-Volcker estimation.

Taken together, both investigations stress the importance of monetary-fiscal policy interactions. Not only does the main driver of the recent surge in inflation depend on the policy regime in place, but so does the effect the different policy measures have on the economy. An increase in inflation due to a cost-push shock calls for an increase in the interest rate. Yet, a "contractionary" monetary policy shock, which also curbs inflation is only in regime

M worthy of his name. In regime F, that shock would be inflationary. At the same time, inflation in regime F is primarily driven by fiscal policy. Here, a decrease in government spending is strongly deflationary and contractionary, while this is not the case in regime M nor in the indeterminacy regime.



(a) Monetary policy shock

(b) Government spending shock

Figure 10: Impulse response functions to a monetary policy and a government spending shock. The line with circles corresponds to the indeterminacy regime, the line with stars to regime M, and the line with crosses to regime F.

6 Conclusion

What can we learn from going back to a past that seems to resemble a possible future? At least three lessons. First, the macroeconomic dynamics during the pre-Volcker period were almost similarly driven by two different policy regimes, a passive monetary/passive fiscal policy regime and one of fiscal dominance. The implication of the result is that the Great Inflation was not only caused by non-policy shocks, but that fiscal policy shocks were an equally important driver. Second, applying the insights to today's situation we find that the main driving forces behind the rise in inflation also depend on the policy regime in place. In case of a regime of monetary dominance, the historical decomposition connects mainly cost-push shocks to the increase in inflation. In case of a fiscally-led regime, the causes of inflation are of fiscal nature. But not only the causes differ and call for different policy actions, so do the effects of the policy tools. In particular, a monetary policy shock is inflationary in a regime of fiscal dominance. Third, the SMC algorithm is suited better than the standard RWMH algorithm to estimate models with distinct monetary/fiscal policy regimes.

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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. Additionally, 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 as capturing 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, then 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[23]

$$min\left[\sum_{j=1}^{9}||d^M_j||_2, \sum_{j=1}^{9}||d^F_j||_2\right].$$

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

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

from the prior distribution outlined in Section 3 and, with each draw, solve the model. If a 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 11 and 12 show that the impulse responses (IRFs) are nearly congruent.

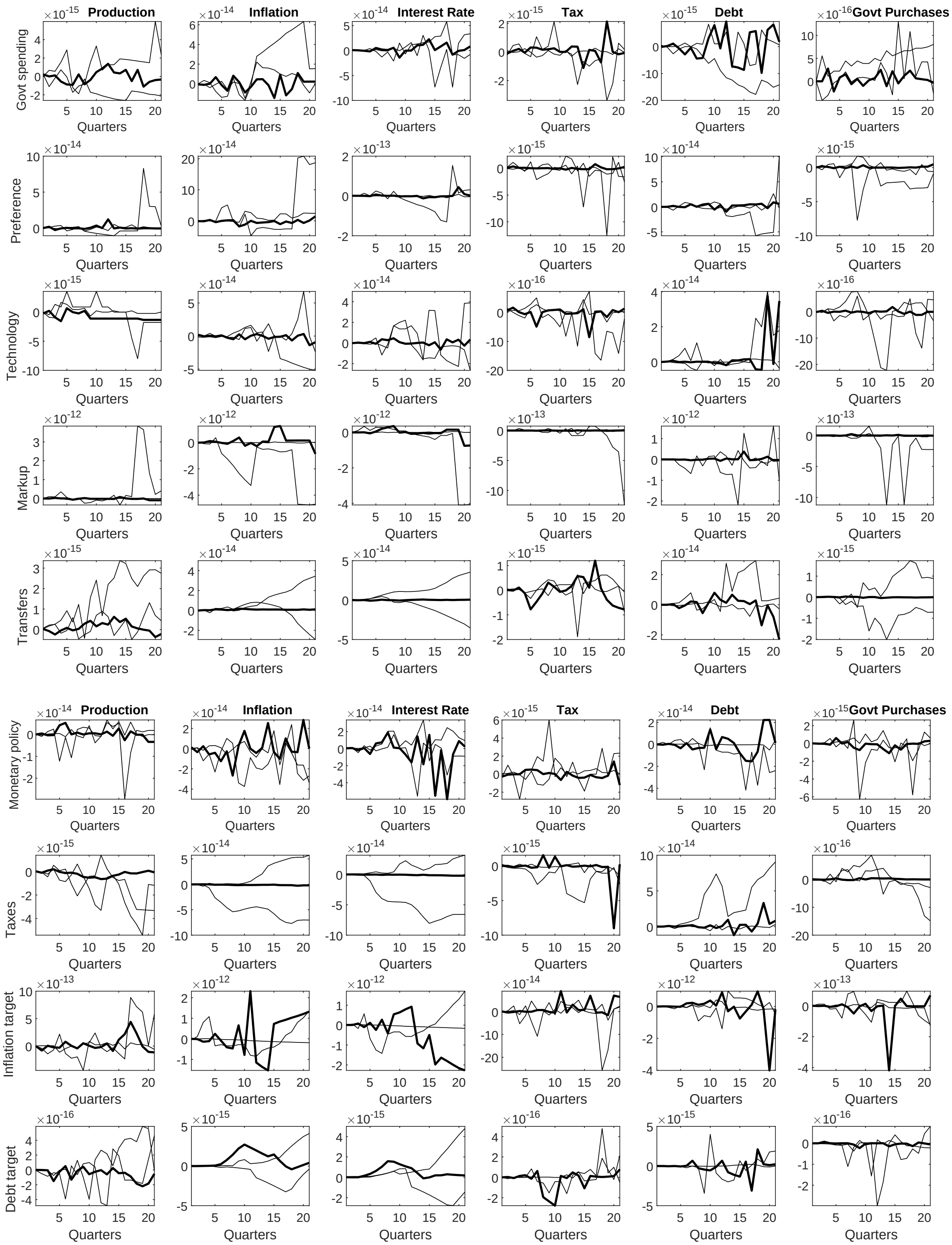


Figure 11: Difference of IRFs computed in the determinacy and the indeterminacy region around the monetary boundary. The bold line shows posterior means and the solid line 90 % credible sets.

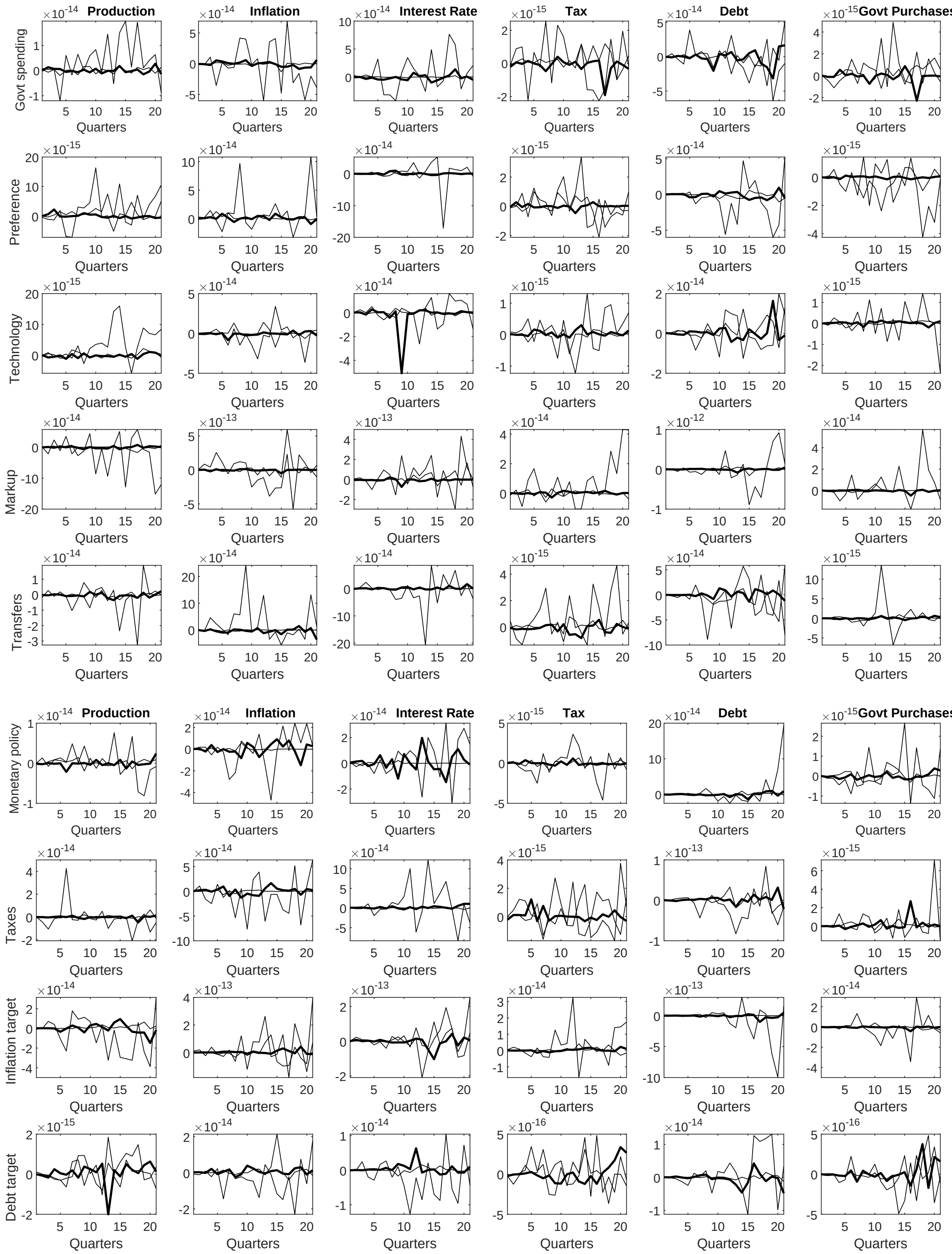


Figure 12: Difference of IRFs computed in the determinacy and the indeterminacy region around the fiscal boundary. The bold line shows posterior means and the solid line 90 % credible sets.

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

	Prior				
Parameter	Range	Distribution	Mean	SD	90 percent int.
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. Specifically, we take 20,000 draws from the prior and simulate with these draws 20,000 times the model's observables.

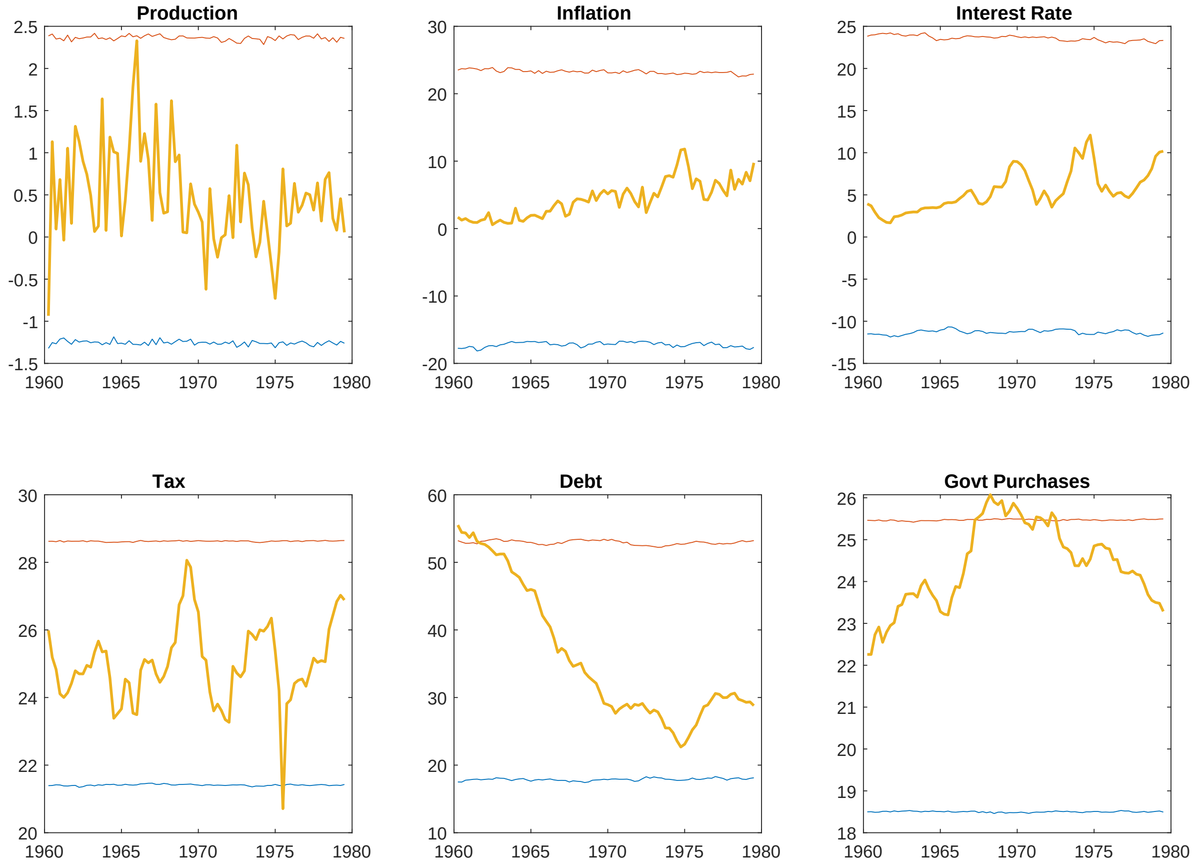


Figure 13: Simulated model observables vs. real data for 1960:Q1 to 1979:Q2. The bold yellow line shows the actual time series we use for estimating the model. The blue and the red line show the 90 % interval of the simulated time series.

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. For the period 2020:Q1 to 2022:Q4, we update the dataset of Bhattarai et al. (2016) from the same sources.

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

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

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. This 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 $M_{MH} = 2$ insured 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.[24]

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

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

[24]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 splitting it into N_{blocks} blocks, thus making it easier to approximate the target density in each of the RWMH's M_{MH} steps.[25] 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:**

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

`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.[26] It is only in terms of posterior sampling that we do not rely on RWMH sampling; rather we 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 US-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.

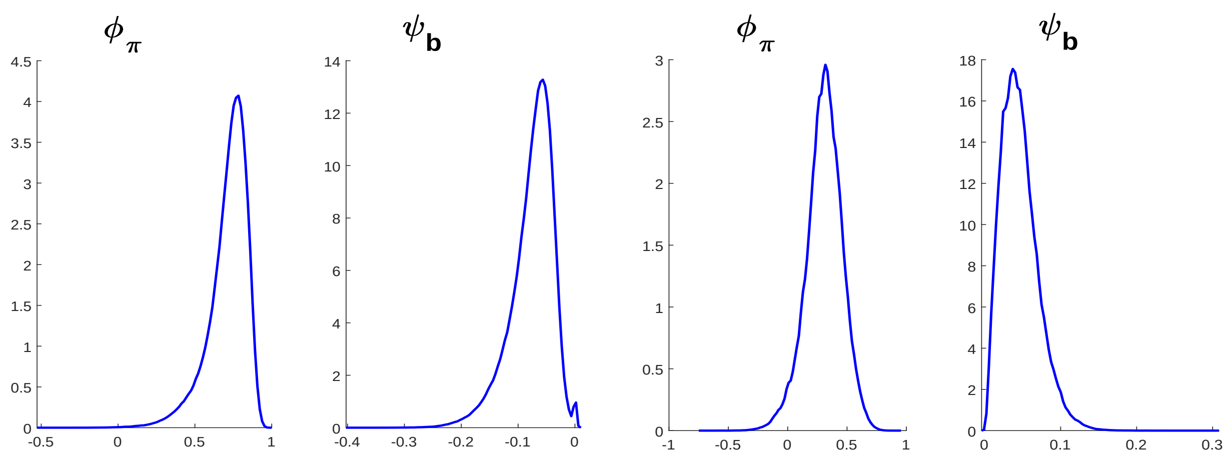
[26]For details on this prior specification, we refer the reader to the Online Appendix of the original study.

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 14 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.



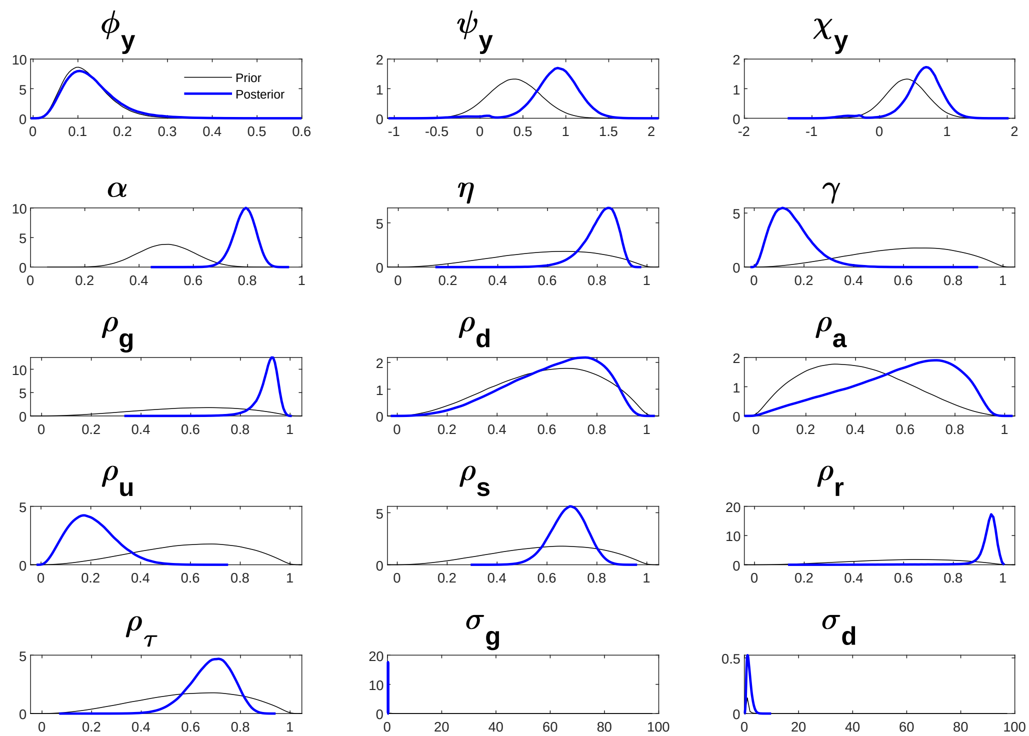
(a) Regime F

(b) PMPF regime

Figure 14: 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
α
η
γ
ρ_g
ρ_d
ρ_a
ρ_u
ρ_s
ρ_r
ρ_τ
σ_g
σ_d
Prior
Posterior

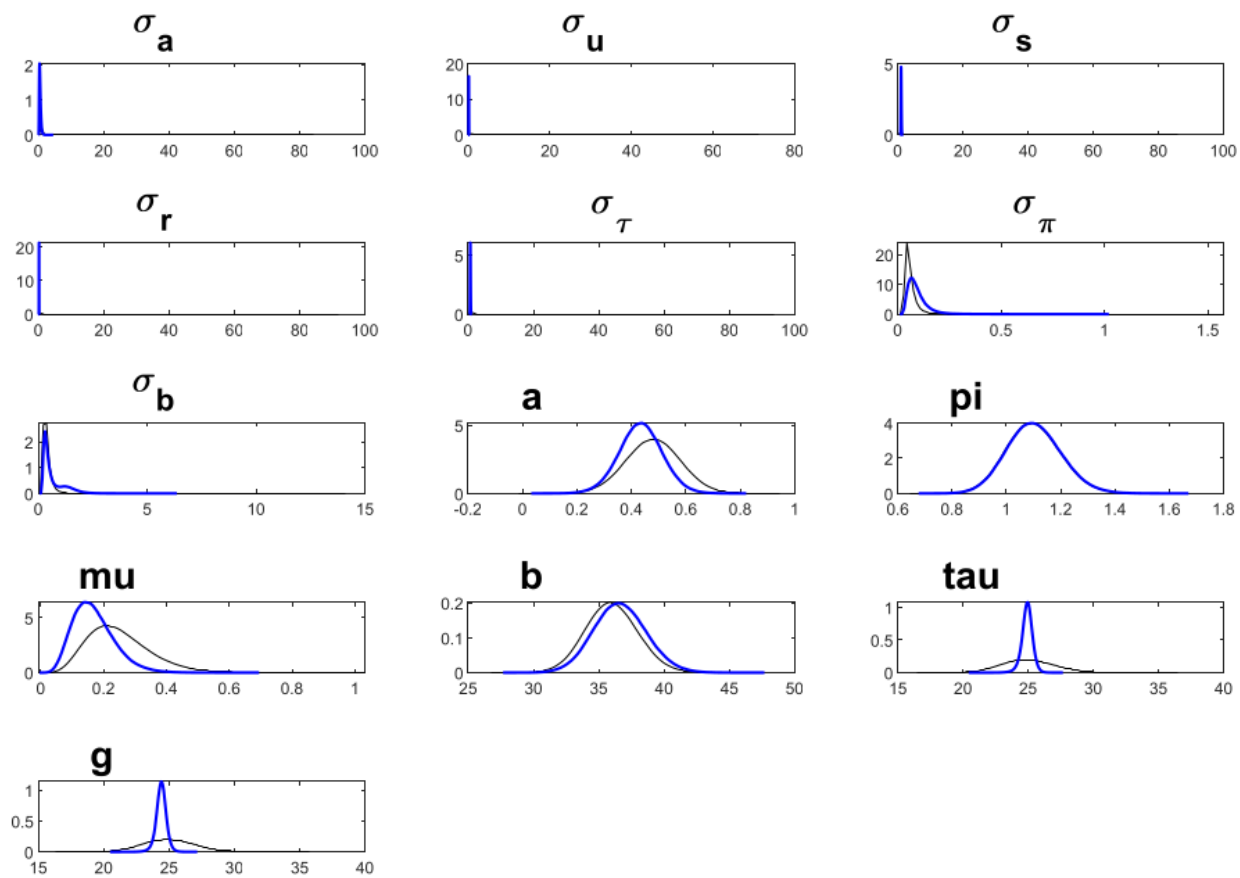


Figure 15: Prior and posterior densities of the estimated model parameters for regime F. The blue bold line depicts the posterior density, the black line the prior density. The prior densities are specified as in Bhattarai et al. (2016).

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

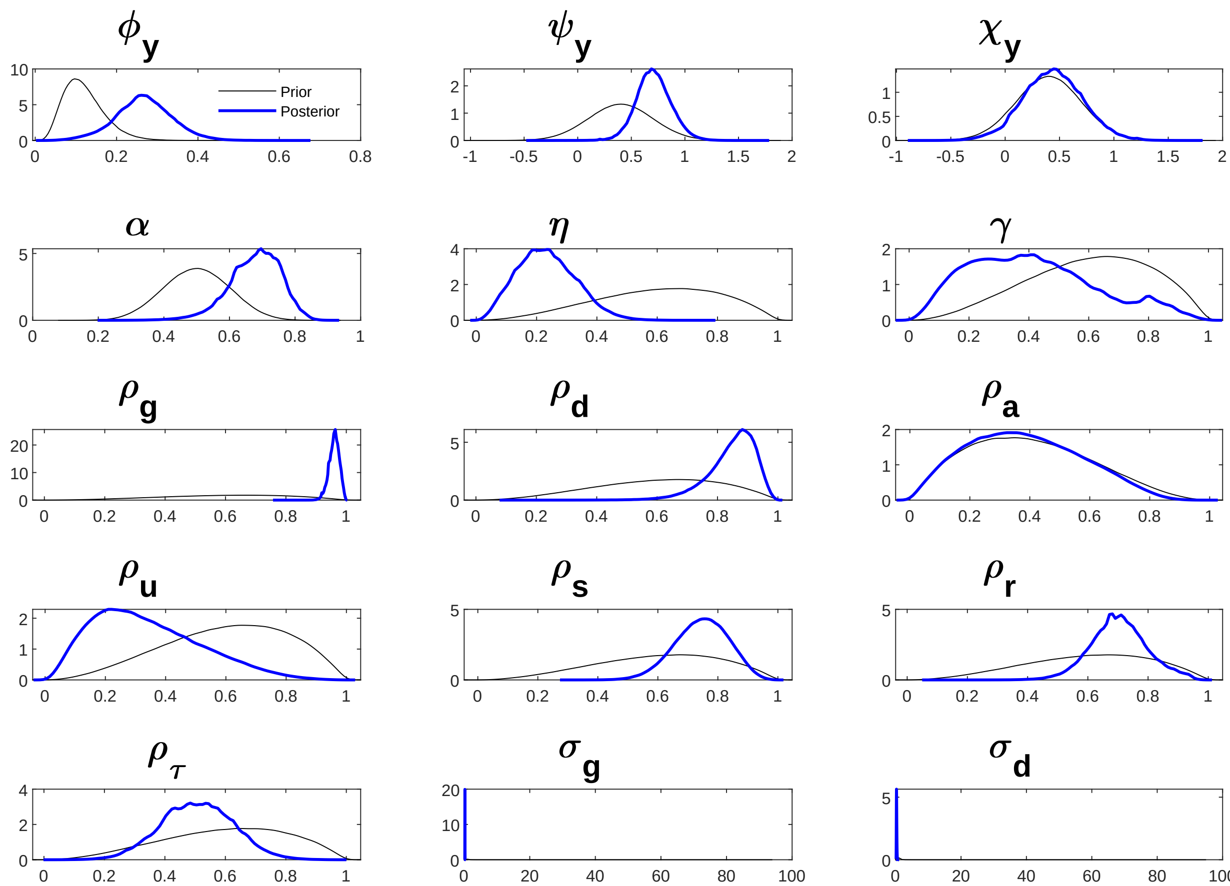
Parameter	Posterior Mean	SD	90 percent credible set
Monetary policy			
ϕ_π, interest rate response to inflation	0.71	0.13	[0.53, 0.9]
ϕ_π^*, distance to monetary boundary	0.27	0.13	[0.09, 0.46]
ϕ_Y, interest rate response to output	0.13	0.06	[0.04, 0.21]
ρ_R, response to lagged interest rate	0.93	0.07	[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

	Posterior		
Parameter	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
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

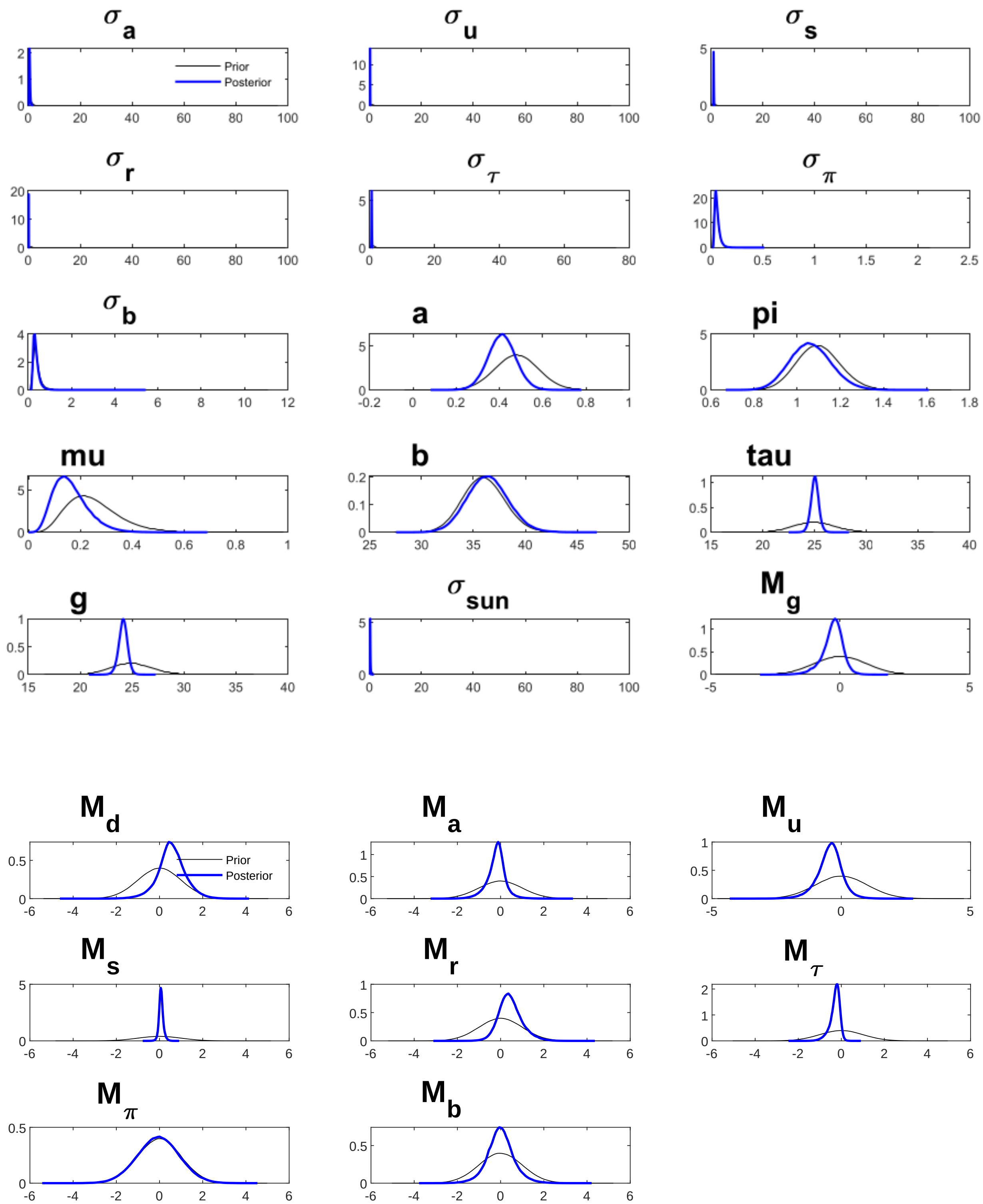


Figure 16: Prior and posterior densities of the estimated model parameters for the PMPF regime. The blue bold line depicts the posterior density, the black line the prior density. The prior densities are specified as in Bhattarai et al. (2016).

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]
$\mu \coloneqq 100(\beta^{-1} - 1)$, 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			
$a \coloneqq 100(\bar{a} - 1)$, technology	0.41	0.01	[0.39, 0.42]
$\pi \coloneqq 100(\bar{\pi} - 1)$, 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 with renormalized policy parameters

In a next step, we conduct the restricted SMC estimation with the prior specification as outlined in Section 3. 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.

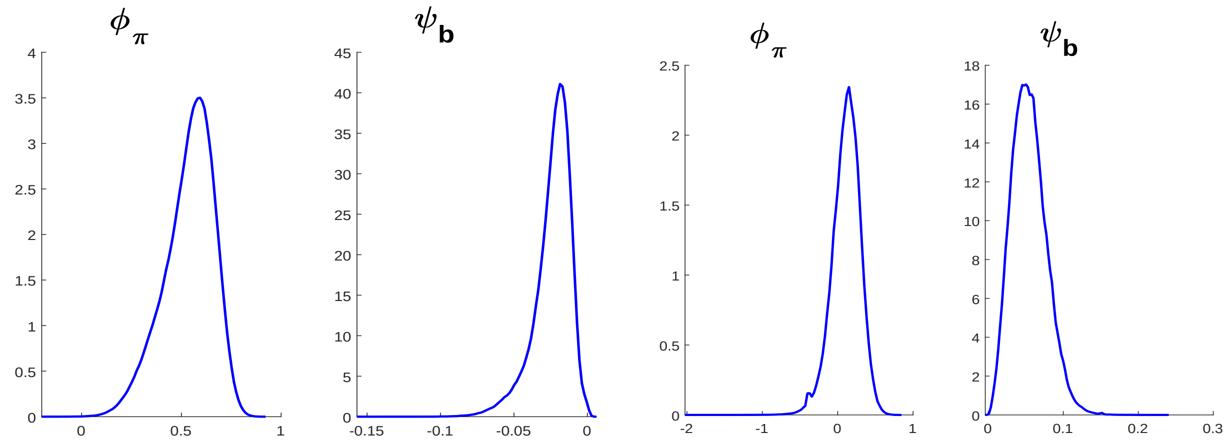
Table 8 shows the estimated marginal data densities of each regime. Also, with the prior specification of Section 3, we come to the conclusion, that in the US, in the pre-Volcker period, the PMPF regime receives the best support from the data.

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 17 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.

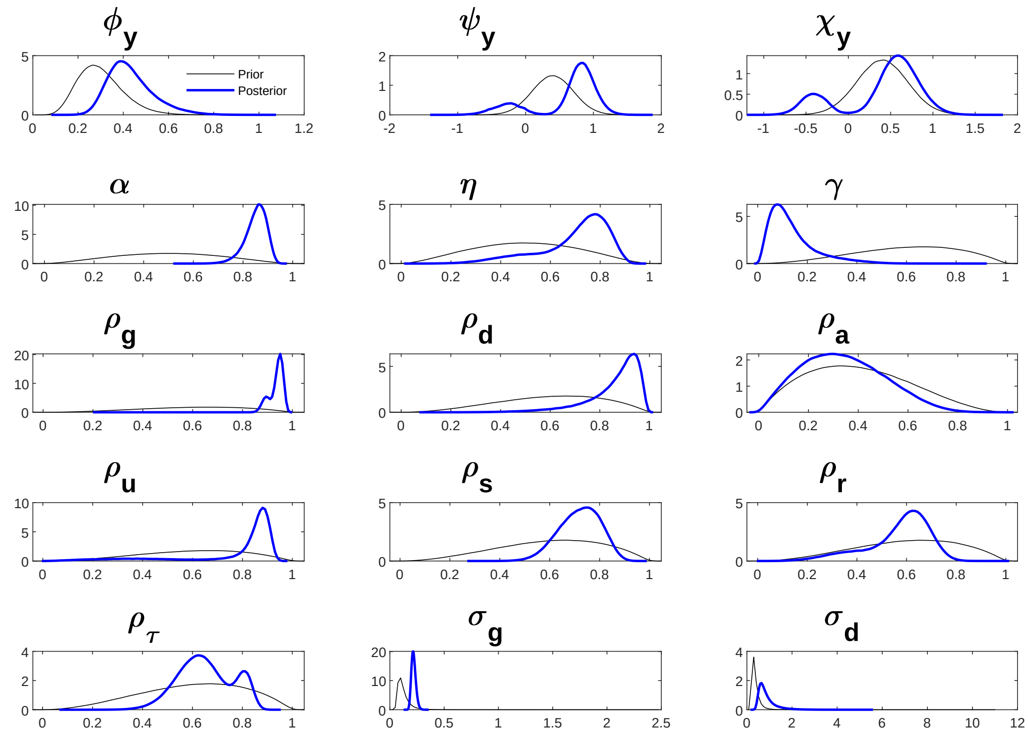


(a) Regime F (b) PMPF regime

Figure 17: 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
Prior
Posterior
ψ_y
χ_y
α
η
γ
ρ_g
ρ_d
ρ_a
ρ_u
ρ_s
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ρ_τ
σ_g
σ_d

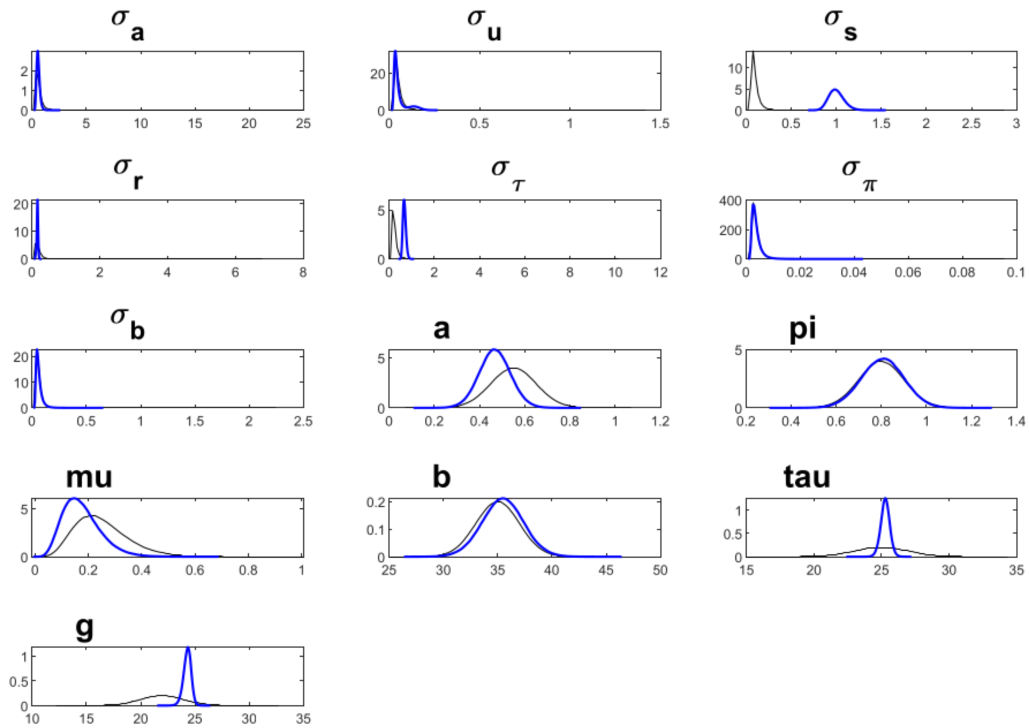


Figure 18: Prior and posterior densities of the estimated model parameters for regime F. The blue bold line depicts the posterior density, the black line the prior density. The densities of ϕ_π^* and ψ_b^* are specified as in Bhattarai et al. (2016), the remaining parameters as in Section 3.

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

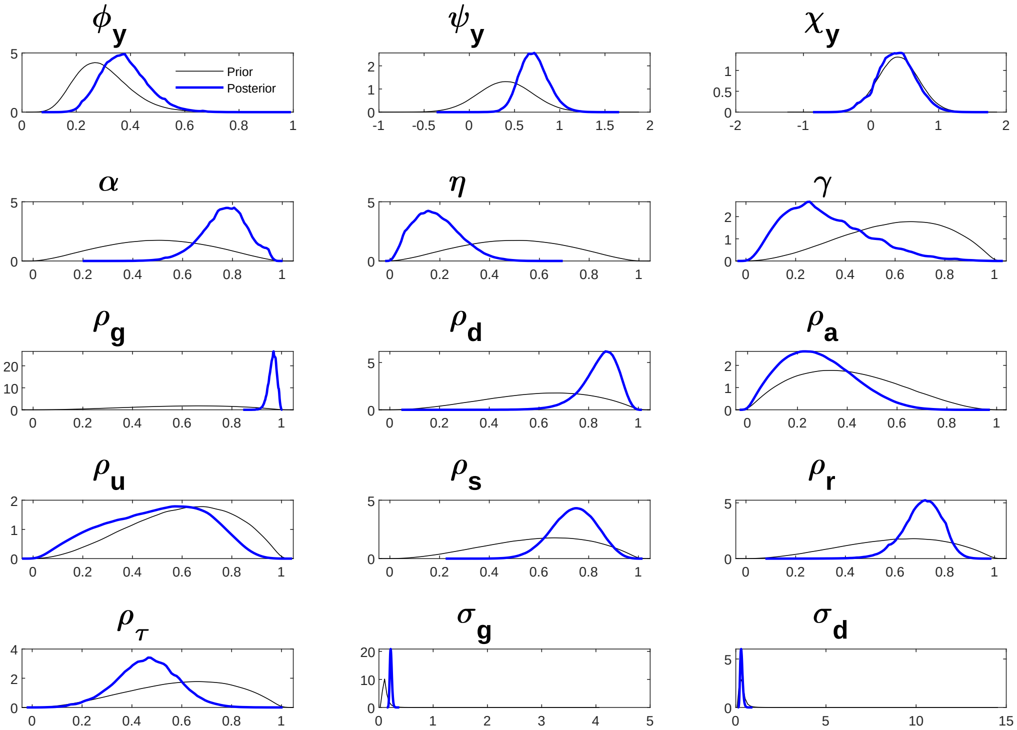
	Posterior		
Parameter	Mean	SD	90 percent credible set
Monetary policy			
ϕ_π, interest rate response to inflation	0.54	0.12	[0.33, 0.73]
ϕ_π^*, distance to monetary boundary	0.35	0.05	[0.31, 0.43]
ϕ_Y, interest rate response to output	0.44	0.06	[0.4, 0.54]
ρ_R, response to lagged interest rate	0.56	0.09	[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]
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]

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

Parameter	Posterior		
	Mean	SD	90 percent credible set
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
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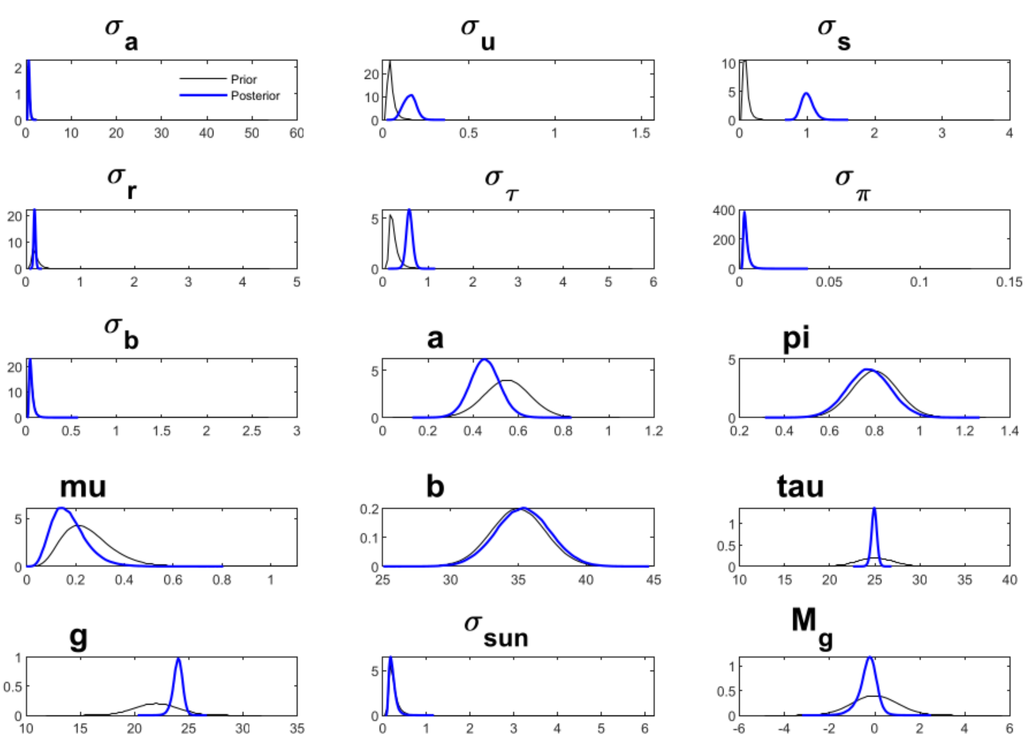
ρ_τ
σ_g
σ_d


σ_a
Prior
Posterior
σ_u
σ_s
σ_r
σ_τ
σ_π
σ_b
a
pi
mu
b
tau
g
σ_{sun}
M_g

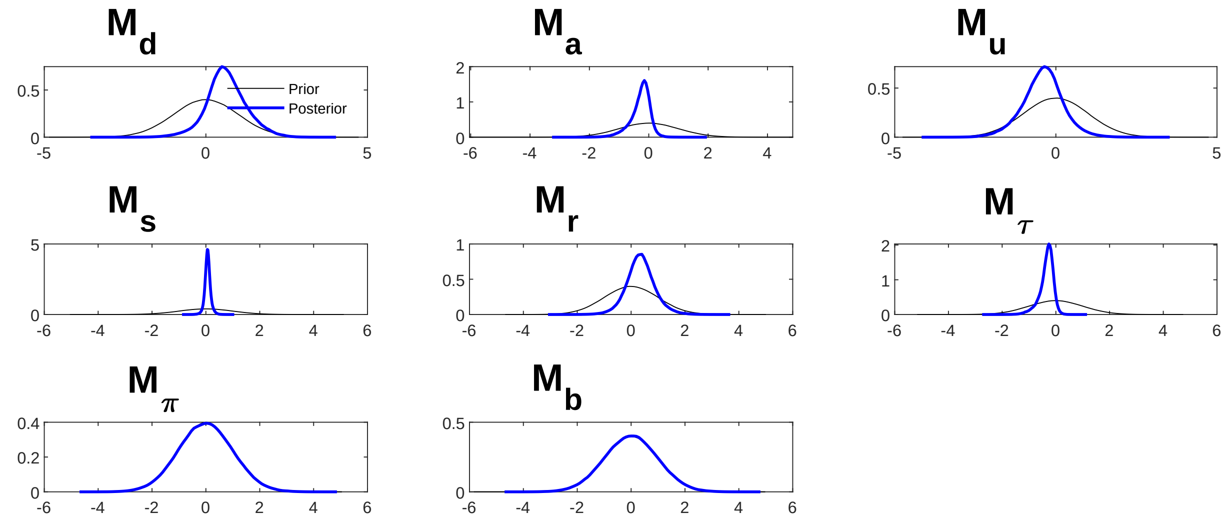


Figure 19: Prior and posterior densities of the estimated model parameters for the PMPF regime. The blue bold line depicts the posterior density, the black line the prior density. The densities of ϕ_π^* and ψ_b^* are specified as in Bhattarai et al. (2016), the remaining parameters as in Section 3.

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

	Posterior		
Parameter	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]

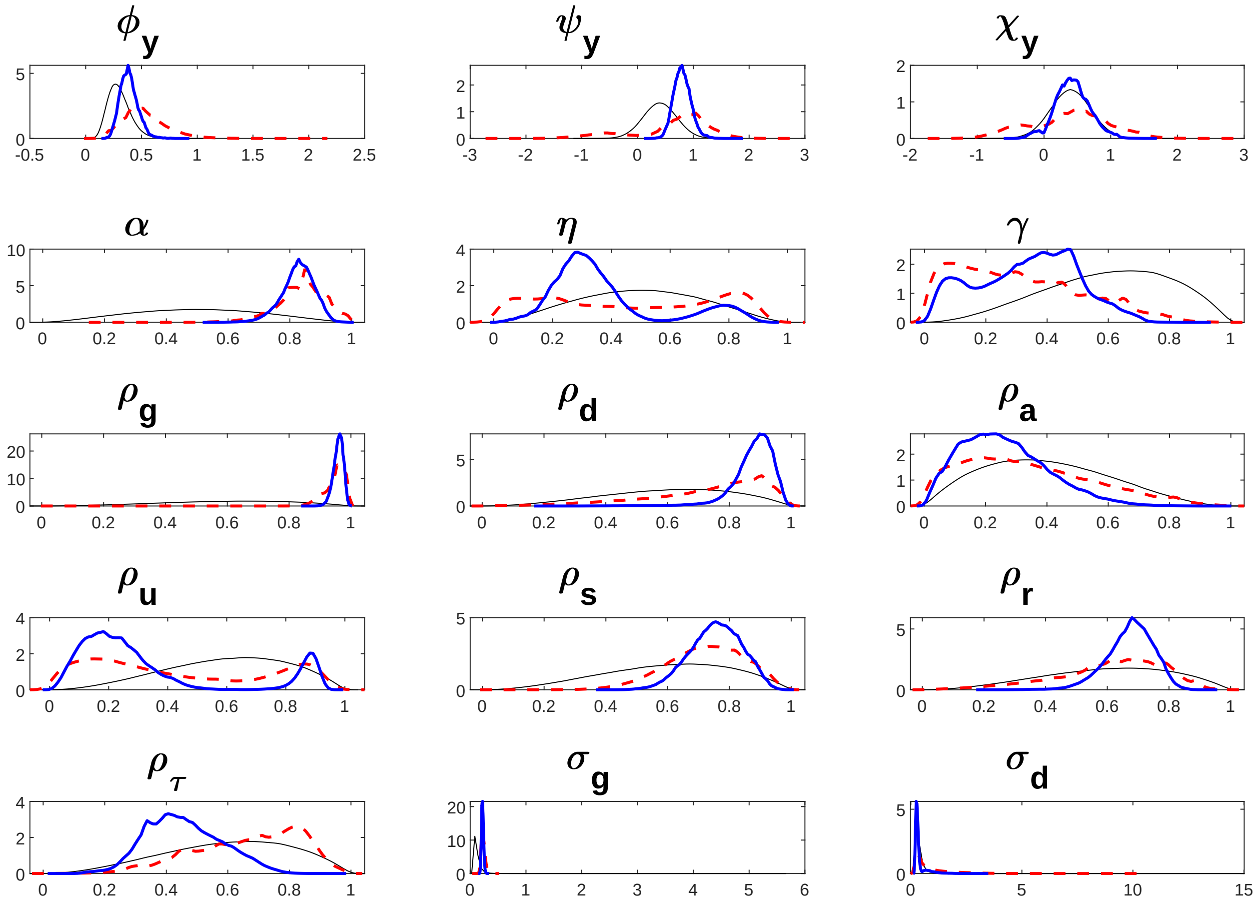
Table 10: Posterior distributions for estimated parameters (PMPF regime) - continued

	Posterior		
Parameter	Mean	SD	90 percent credible set
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]
$b := 100\bar{b}$, 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 and RWMH sampler and tables that summarize the estimation results. Here, the prior specification and the estimation approach corresponds to the description in Section 3.



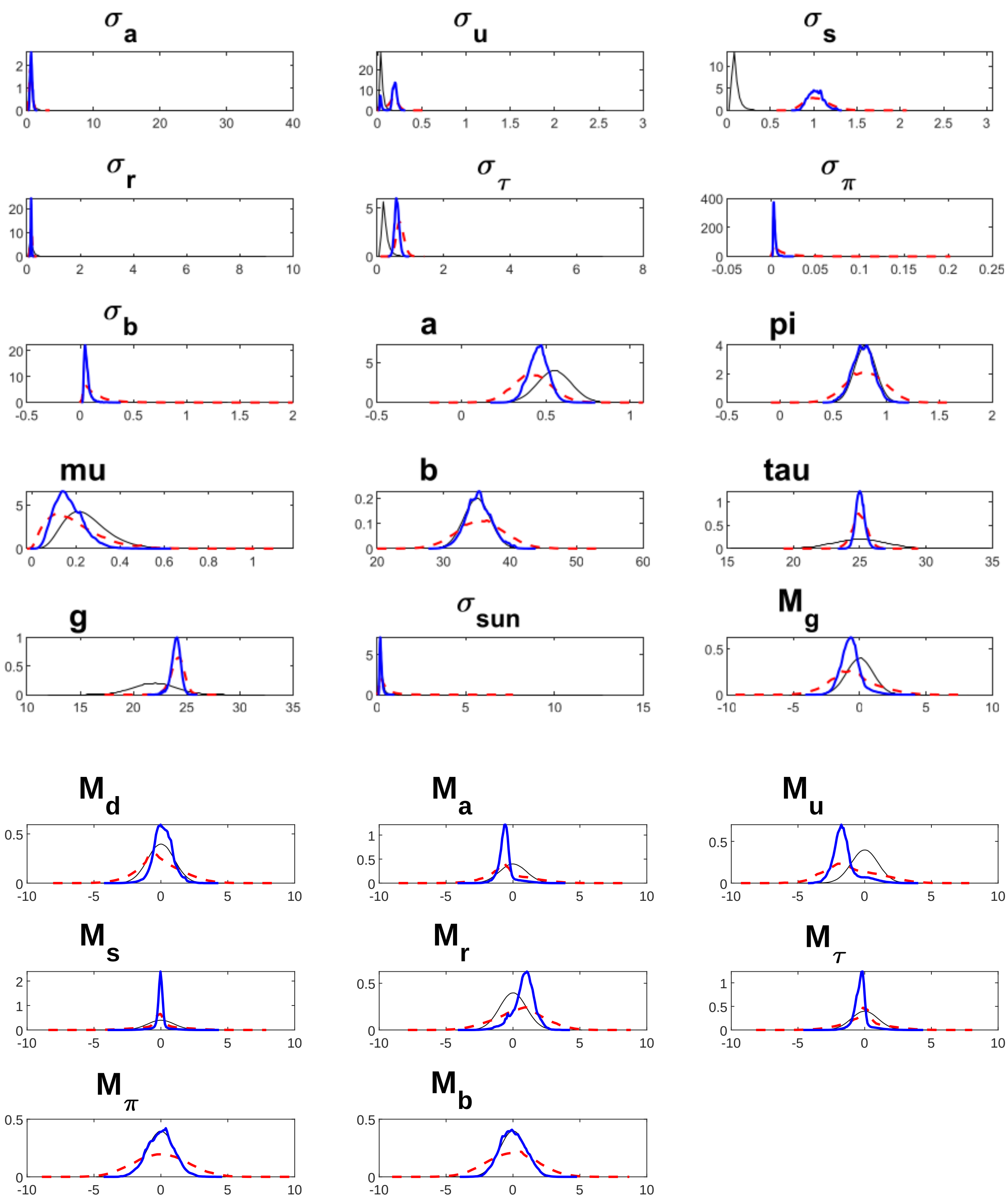


Figure 20: Prior and posterior densities of the estimated model parameters from the unrestricted estimation with SMC and RWMH. The red dashed line depicts the SMC posterior density, the blue solid line depicts the posterior density from RWMH sampling, and the black line the prior density.

Table 11: Posterior distributions, SMC estimation (Unrestricted)

Parameter	Posterior		
	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, SMC estimation (Unrestricted) - continued

Parameter	Posterior		
	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]

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

Table 12: Posterior distributions, RWMH estimation (Unrestricted)

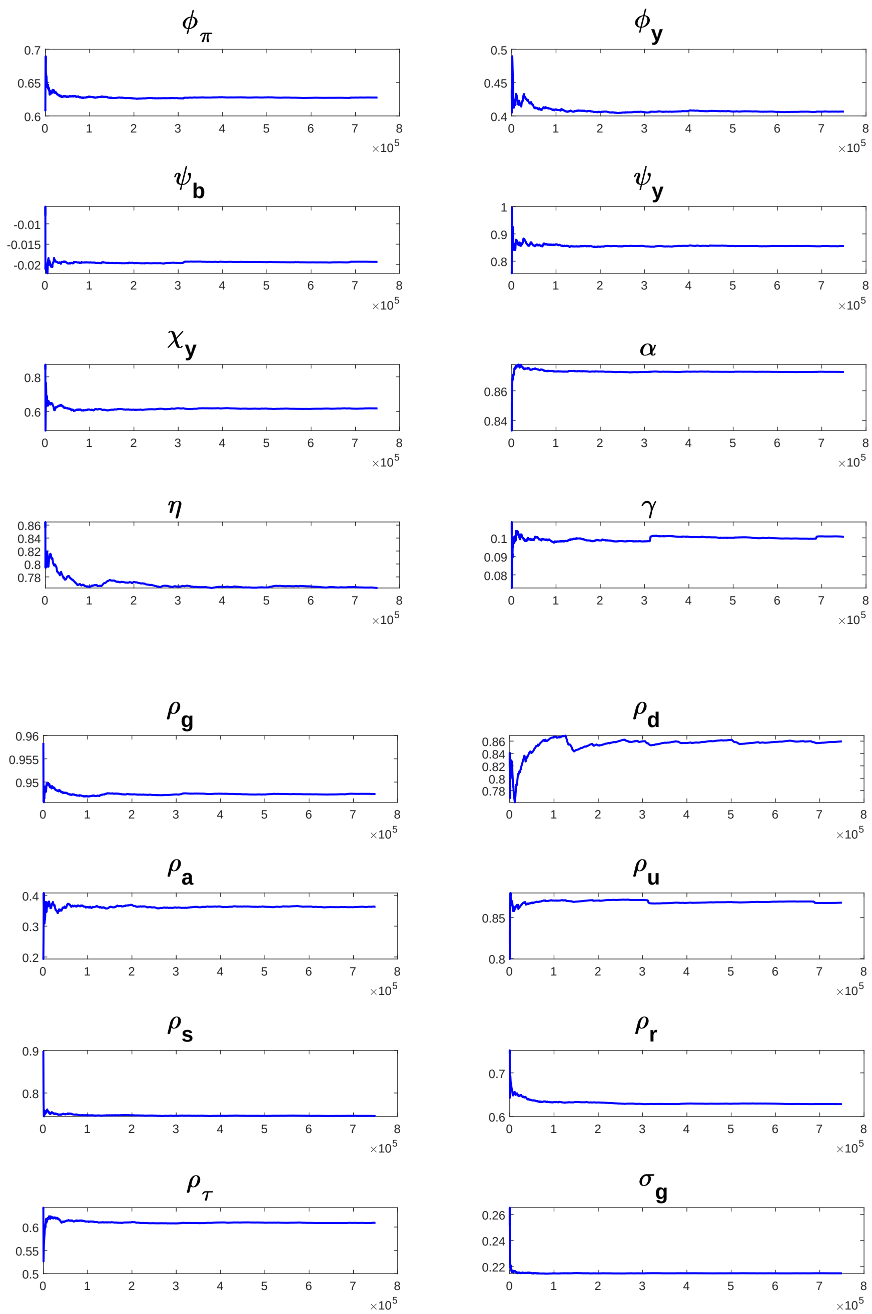
Parameter	Posterior		
	Mean	SD	90 percent credible set
Monetary policy			
ϕ_π, interest rate response to inflation	0.22	0.21	[0.00, 0.61]
ϕ_Y, interest rate response to output	0.39	0.08	[0.26, 0.52]
ρ_R, response to lagged interest rate	0.67	0.076	[0.56, 0.8]
Fiscal policy			
ψ_b, tax response to lagged debt	0.051	0.037	[-0.026, 0.096]
ψ_Y, tax response to output	0.8	0.15	[0.55, 1.051]
χ_Y, govt spending response to lagged output	0.43	0.26	[0.036, 0.88]
ρ_g, response to lagged govt spending	0.96	0.016	[0.93, 0.99]
ρ_τ, response to lagged taxes	0.46	0.12	[0.26, 0.66]
Preference and HHs			
η, habit formation	0.38	0.19	[0.16, 0.8]
$\mu \coloneqq 100(\beta^{-1} - 1)$, discount factor	0.17	0.065	[0.062, 0.26]

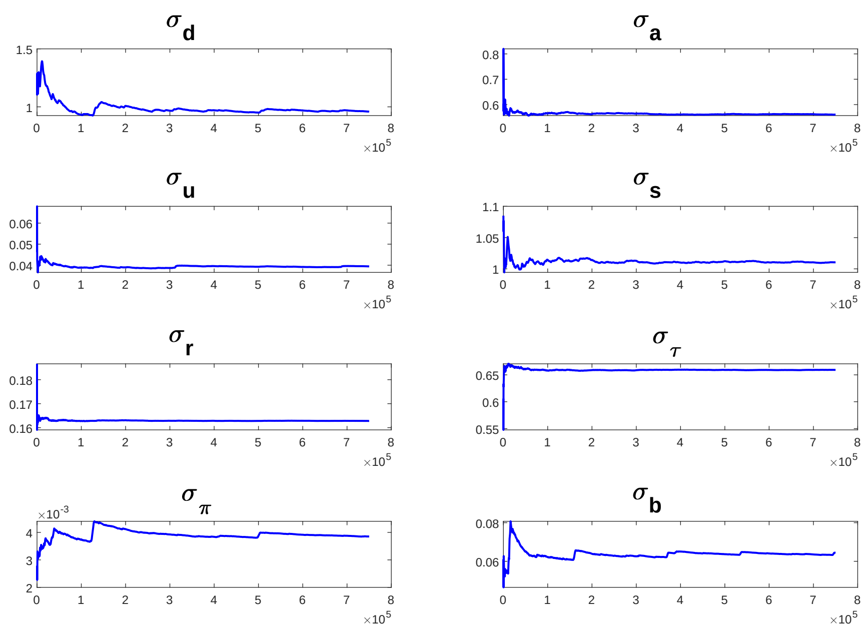
Table 12: Posterior distributions, RWMH estimation (Unrestricted) - continued

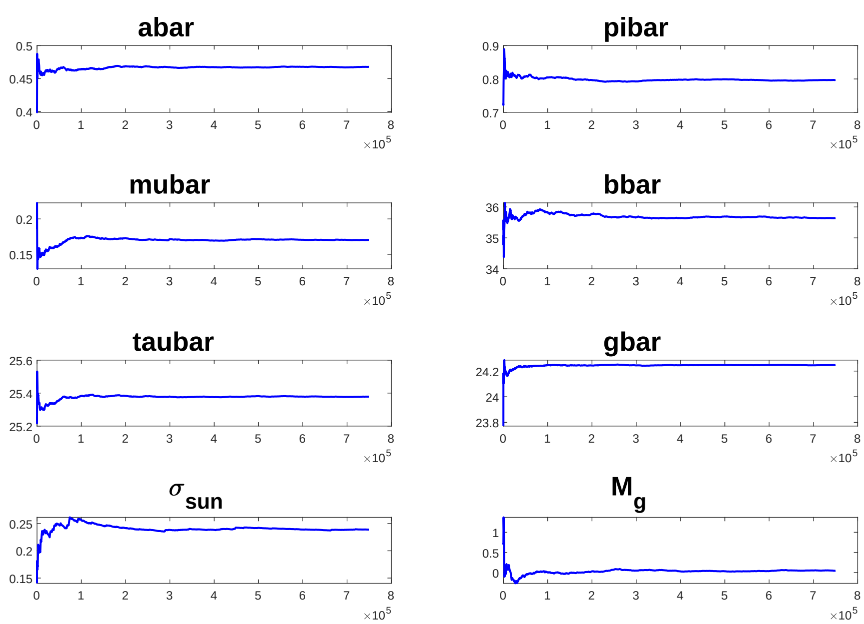
	Posterior		
Parameter	Mean	SD	90 percent credible set
Frictions			
α, price stickiness	0.83	0.052	[0.74, 0.91]
γ, price indexation	0.34	0.16	[0.034, 0.55]
Shocks			
ρ_d, preference	0.88	0.067	[0.79, 0.97]
ρ_a, technology	0.26	0.14	[0.031, 0.47]
ρ_u, cost-push	0.32	0.26	[0.077, 0.9]
ρ_s, transfers	0.76	0.083	[0.62, 0.9]
σ_g, govt spending	0.22	0.019	[0.19, 0.25]
σ_d, preference	0.39	0.31	[0.16, 0.78]
σ_a, technology	0.65	0.17	[0.39, 0.92]
σ_u, cost-push	0.17	0.063	[0.027, 0.23]
σ_s, transfers	1.03	0.087	[0.87, 1.15]
σ_R, monetary policy	0.16	0.02	[0.13, 0.19]
σ_τ, tax	0.6	0.07	[0.48, 0.71]
σ_π, inflation target	0.0037	0.0019	[0.0016, 0.0058]
σ_b, debt/output target	0.064	0.033	[0.027, 0.1]
Steady state			
$a := 100(\bar{a} - 1)$, technology	0.46	0.059	[0.36, 0.55]
$\pi := 100(\bar{\pi} - 1)$, inflation	0.78	0.1	[0.62, 0.95]
$b := 100\bar{b}$, debt/output	35.27	1.96	[31.98, 38.46]
$\tau := 100\bar{\tau}$, tax/output	25.03	0.33	[24.49, 25.58]
$g := 100\bar{g}$, govt spending/output	23.99	0.44	[23.3, 24.7]
Indeterminacy			
σ_ζ, sunspot shock	0.22	0.08	[0.11, 0.32]
$M_{g\zeta}$	-0.69	0.74	[-1.95, 0.37]
$M_{d\zeta}$	0.16	0.71	[-0.96, 1.33]
$M_{a\zeta}$	-0.57	0.57	[-1.56, 0.14]
$M_{u\zeta}$	-1.53	0.91	[-2.96, 0.0072]
$M_{s\zeta}$	-0.034	0.42	[-0.59, 0.52]
$M_{R\zeta}$	0.8	0.79	[-0.57, 2]
$M_{\tau\zeta}$	-0.32	0.53	[-1.23, 0.34]
$M_{\pi\zeta}$	-0.0095	0.99	[-1.62, 1.63]
$M_{b\zeta}$	-0.0053	0.95	[-1.51, 1.6]

Note: Means, standard deviations, and 90 % highest posterior density intervals are over 12 independent RWMH runs à ten million draws from which we discard seven million respectively as burn-in.

RWMH convergence diagnostics - mode initialization in regime F




σd
σa
σu
σs
σr
στ
σπ
σb
×10^5


abar
pibar
mubar
bbar
taubar
gbar
σsun
Mg
×10^5

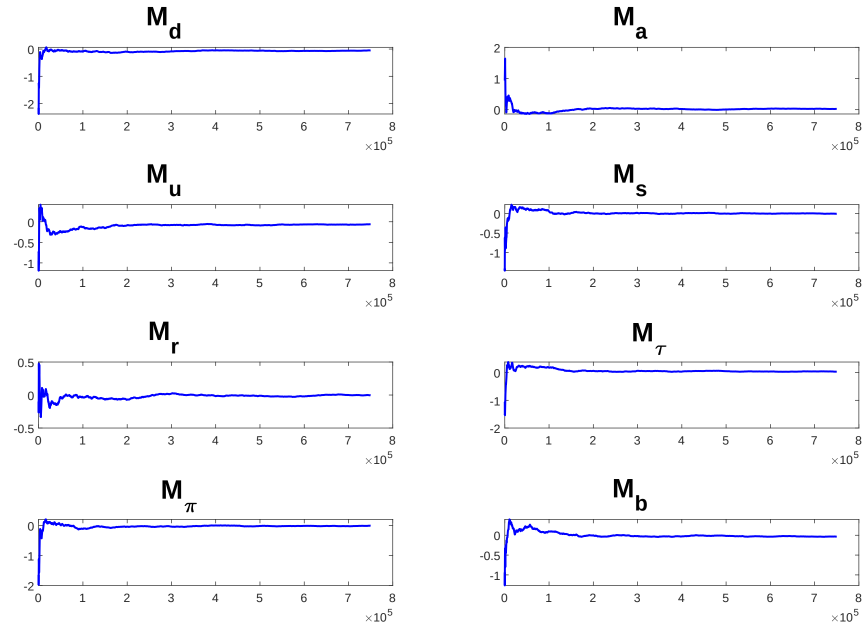
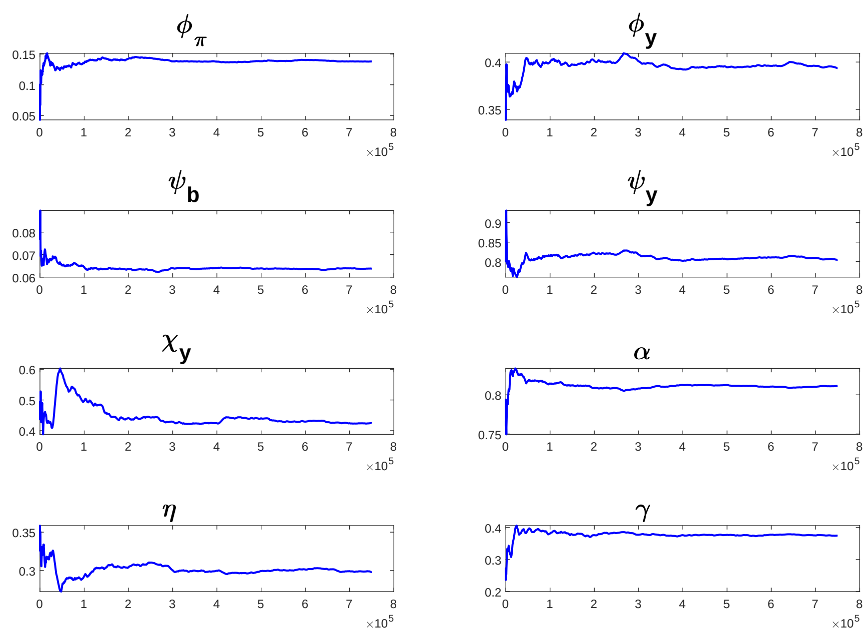
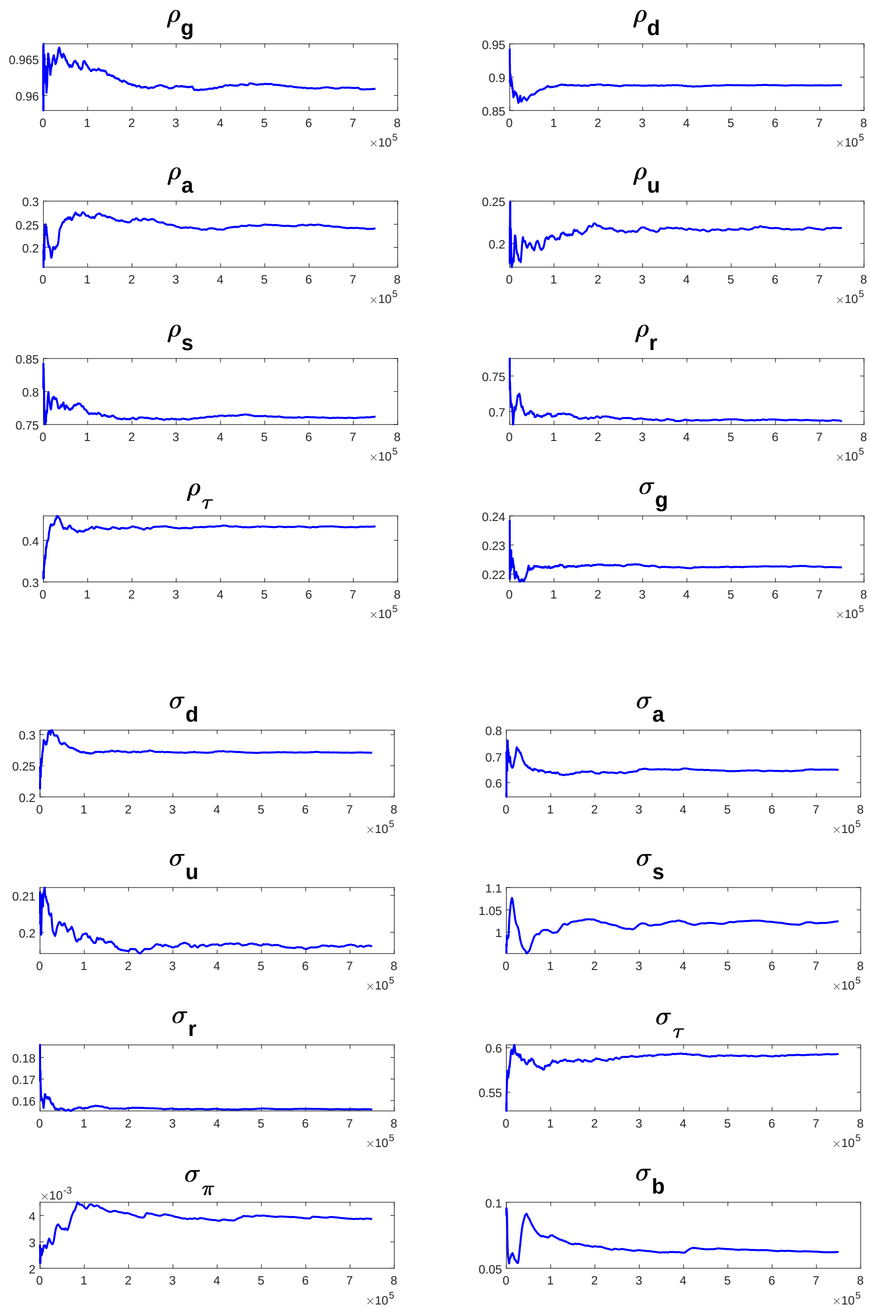


Figure 21: Recursive means - for RWMH runs initialized at the mode of regime F

RWMH convergence diagnostics - mode initialization in the indeterminacy regime




ρg
ρd
ρa
ρu
ρs
ρr
ρτ
σg
σd
σa
σu
σs
σr
στ
σπ
σb

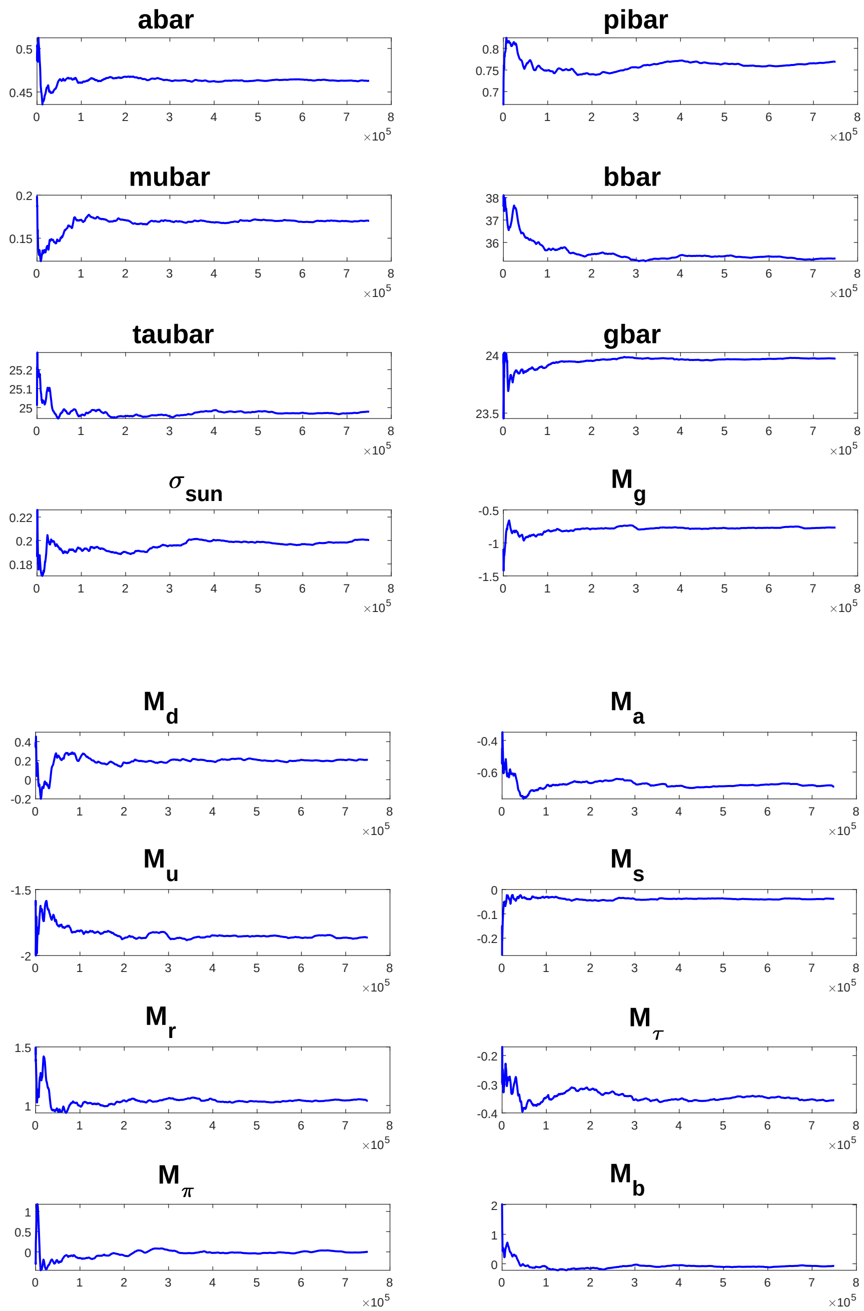
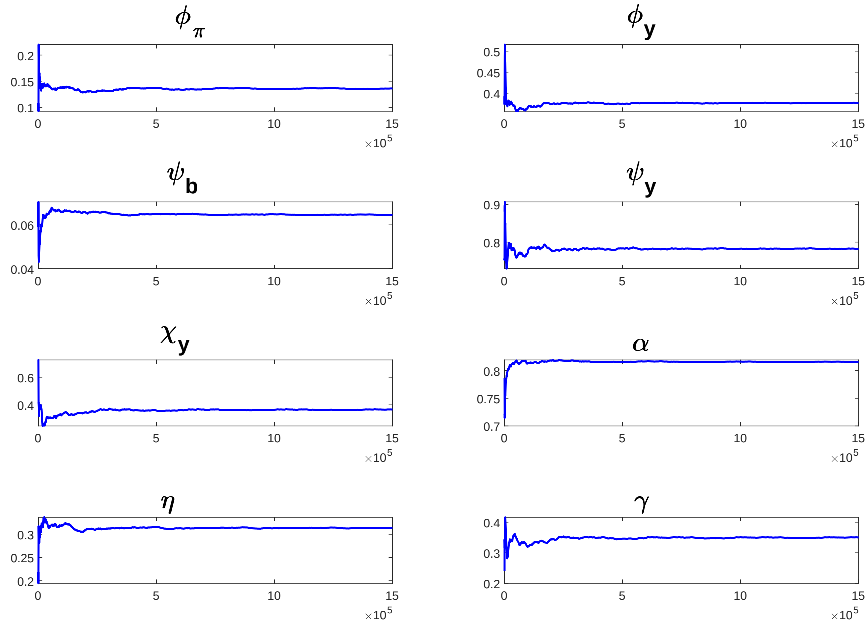
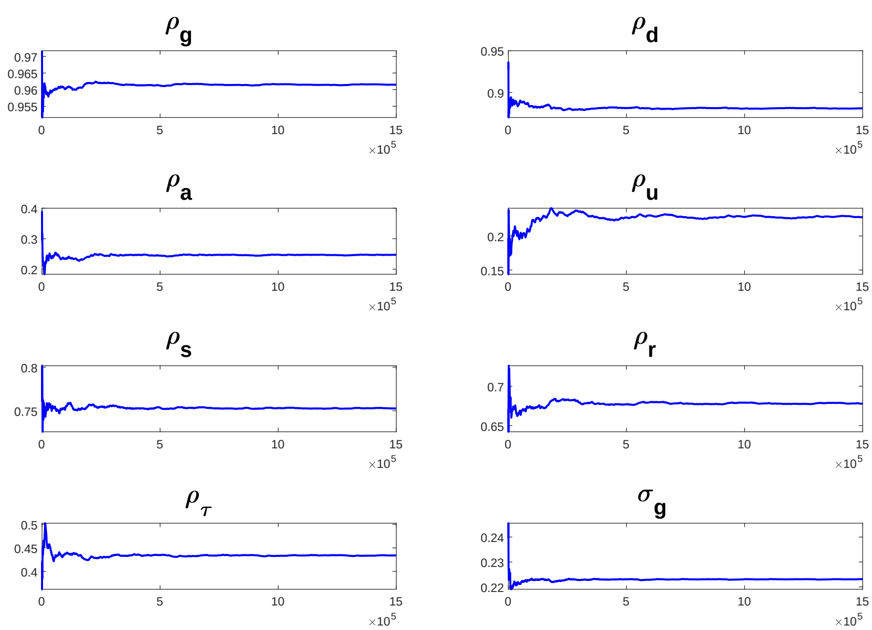
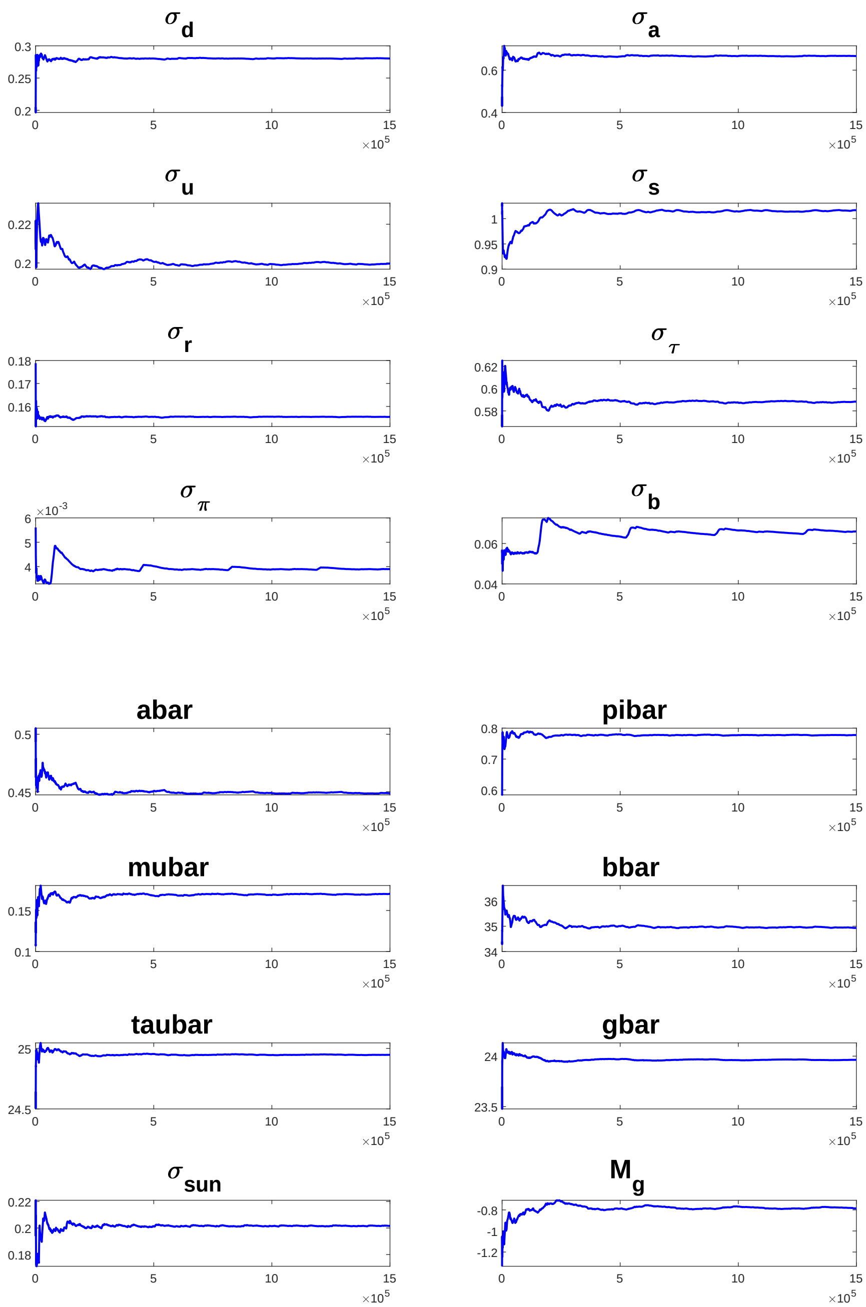


Figure 22: Recursive means - for RWMH runs initialized at the mode of regime PMPF

RWMH convergence diagnostics - random initialization in regime F






σd
σa
σu
σs
σr
στ
σπ
σb
abar
pibar
mubar
bbar
taubar
gbar
σsun
Mg
×10^5

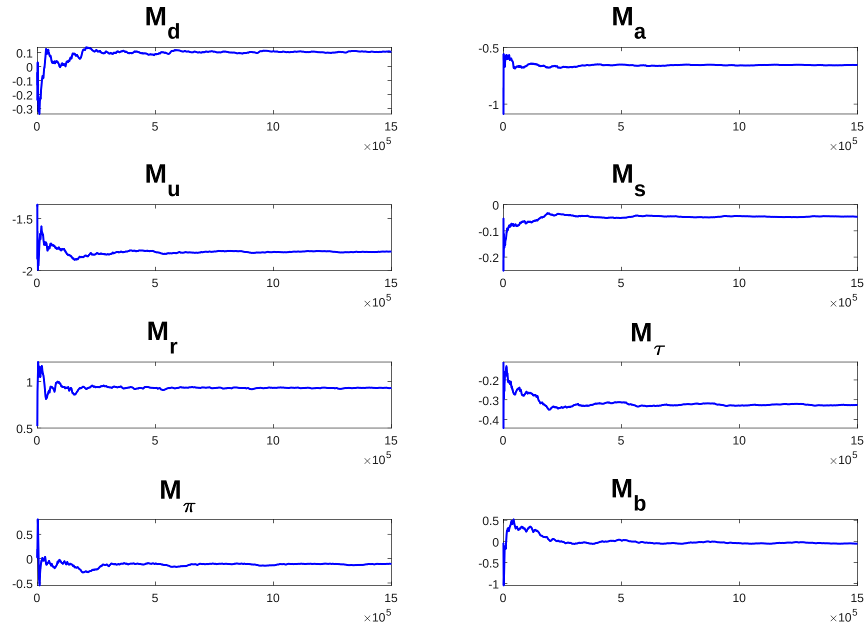
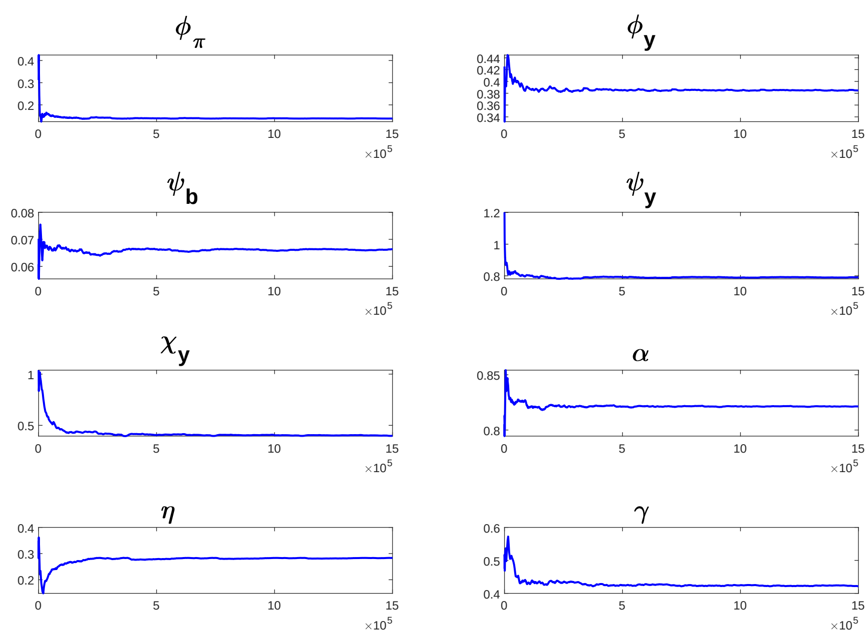
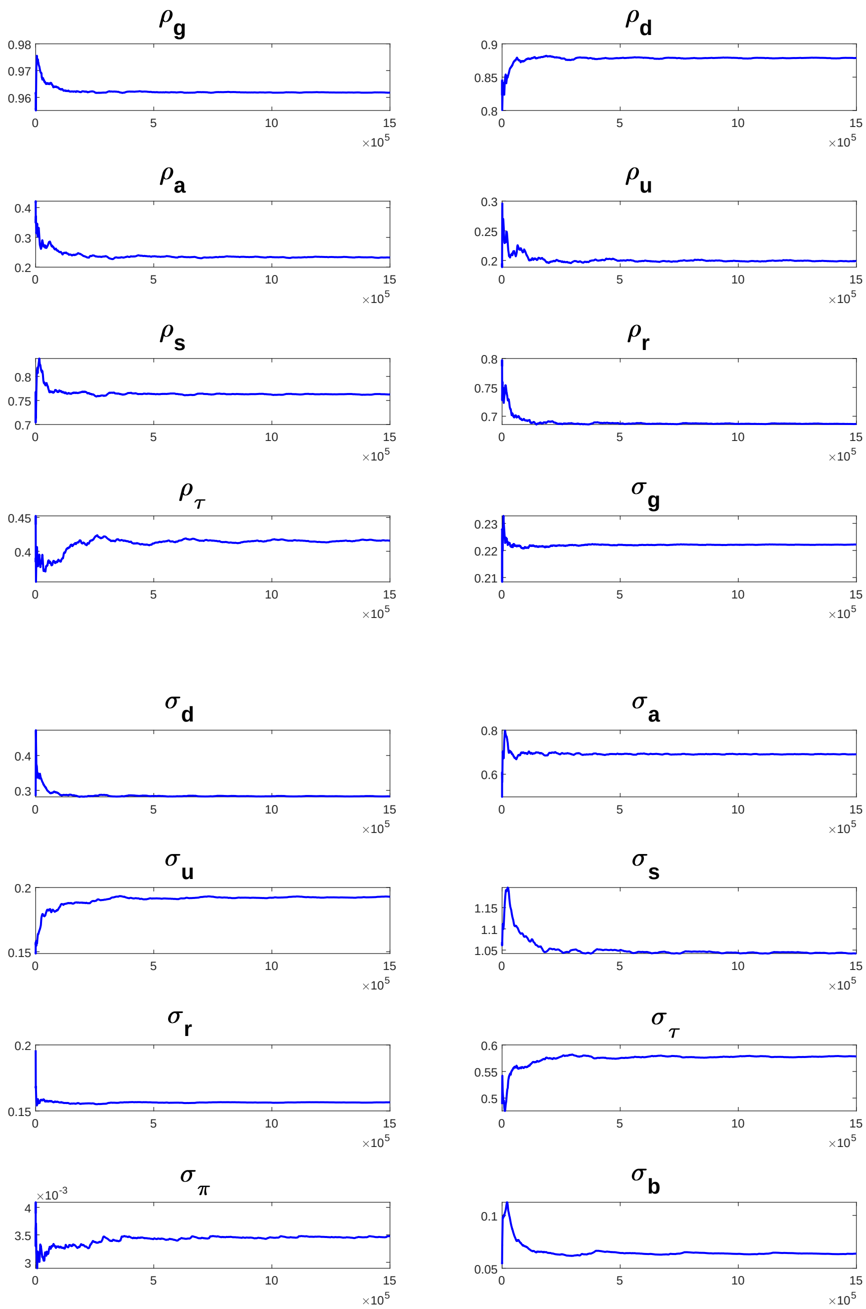


Figure 23: Recursive means - for RWMH runs initialized at a random value in regime F

RWMH convergence diagnostics - random initialization in the indeterminacy regime




ρg
ρd
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ρu
ρs
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ρτ
σg
σd
σa
σu
σs
σr
στ
σπ
σb

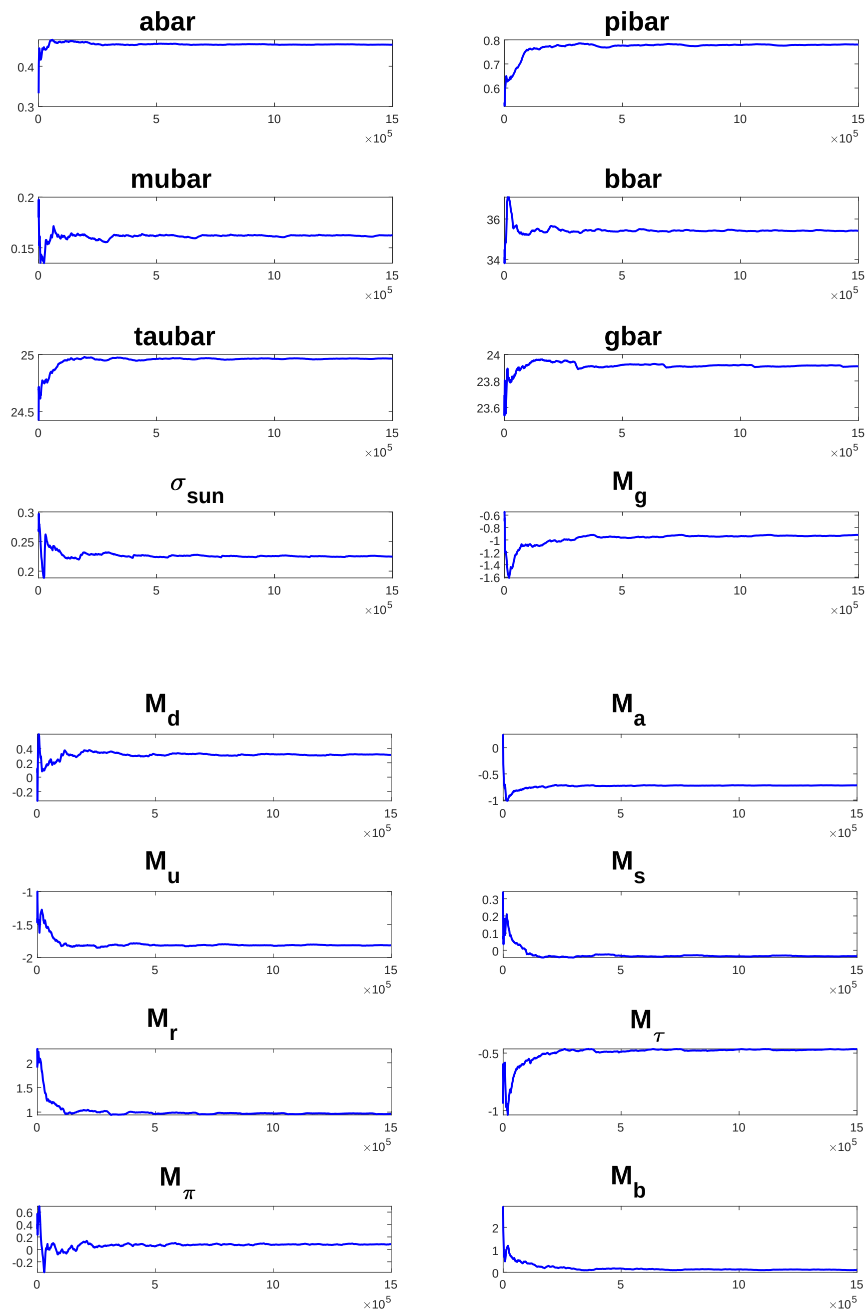
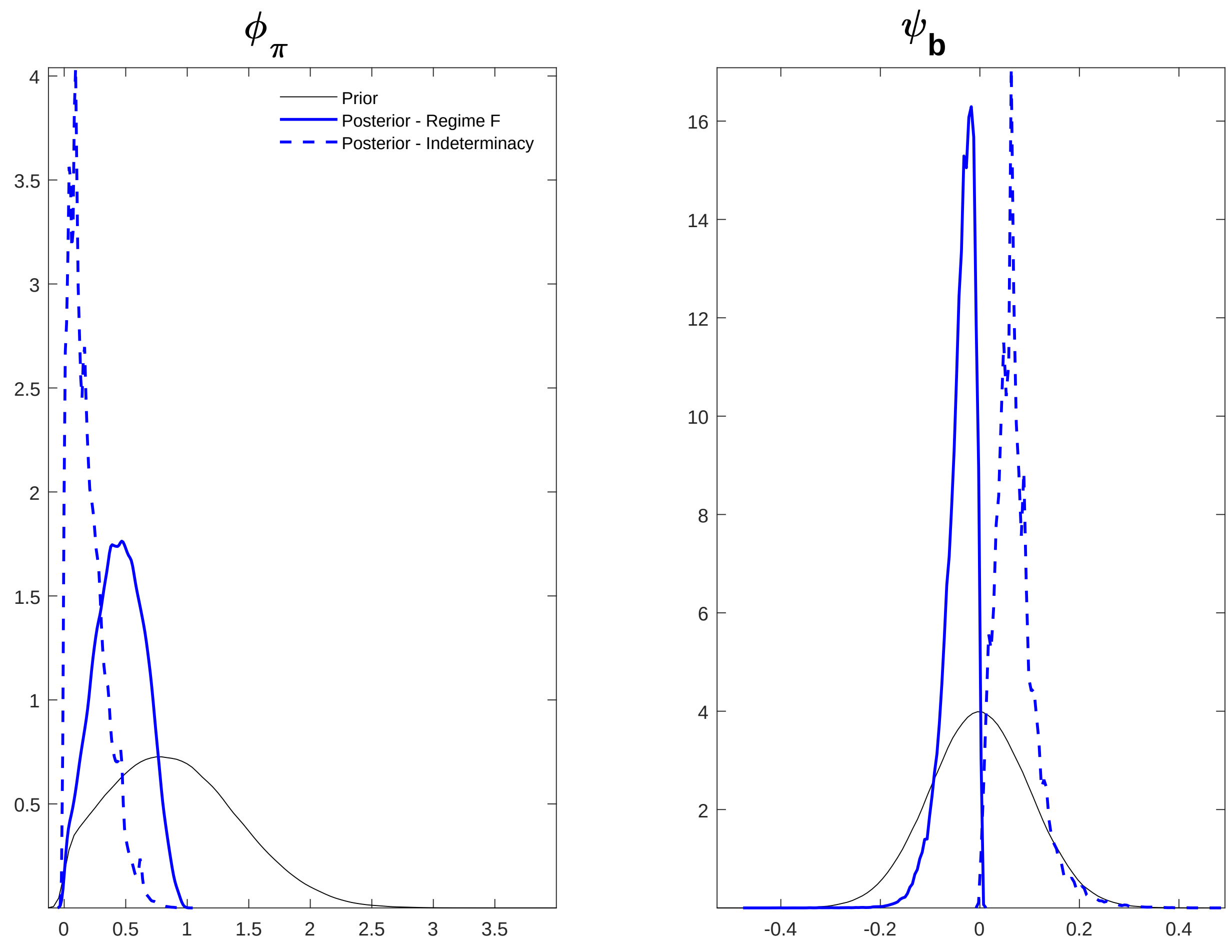
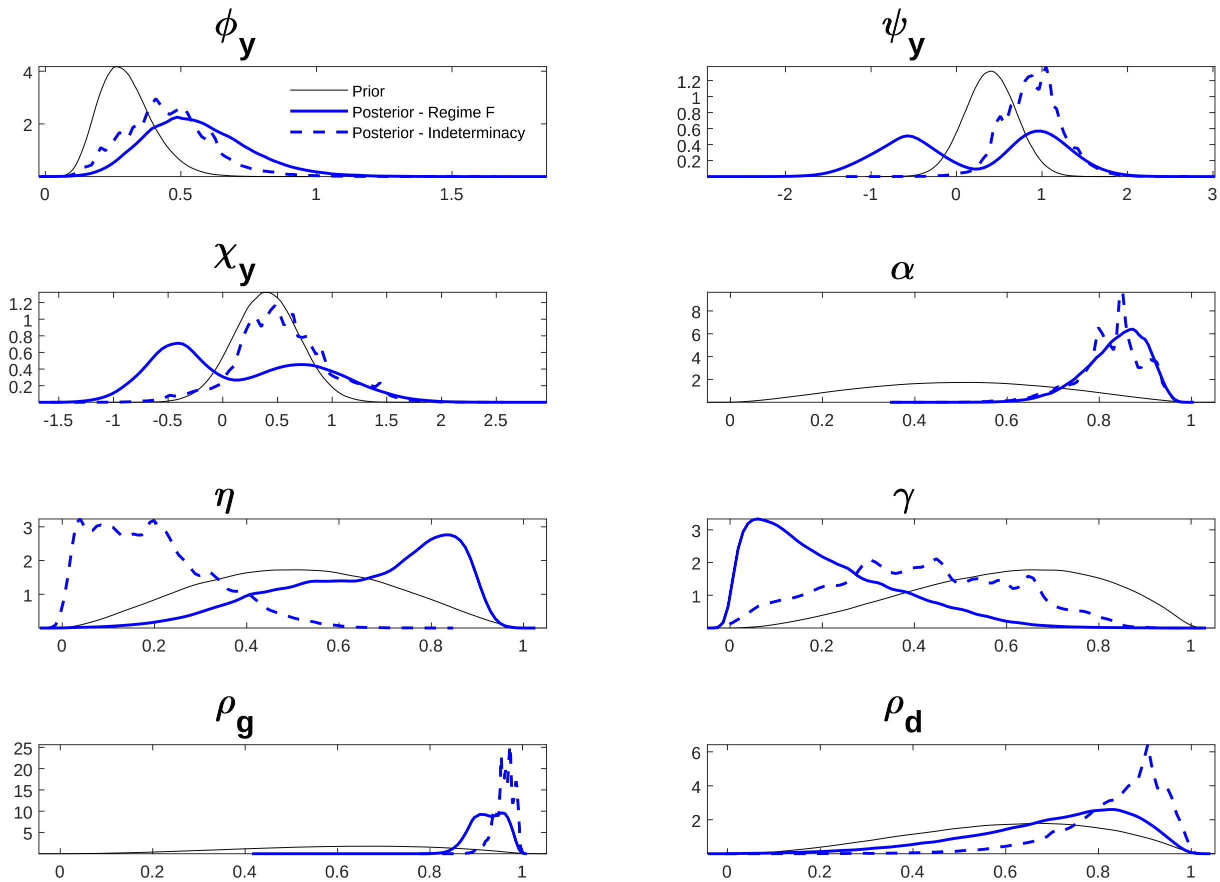


Figure 24: Recursive means - for RWMH runs initialized at a random value in regime PMPF

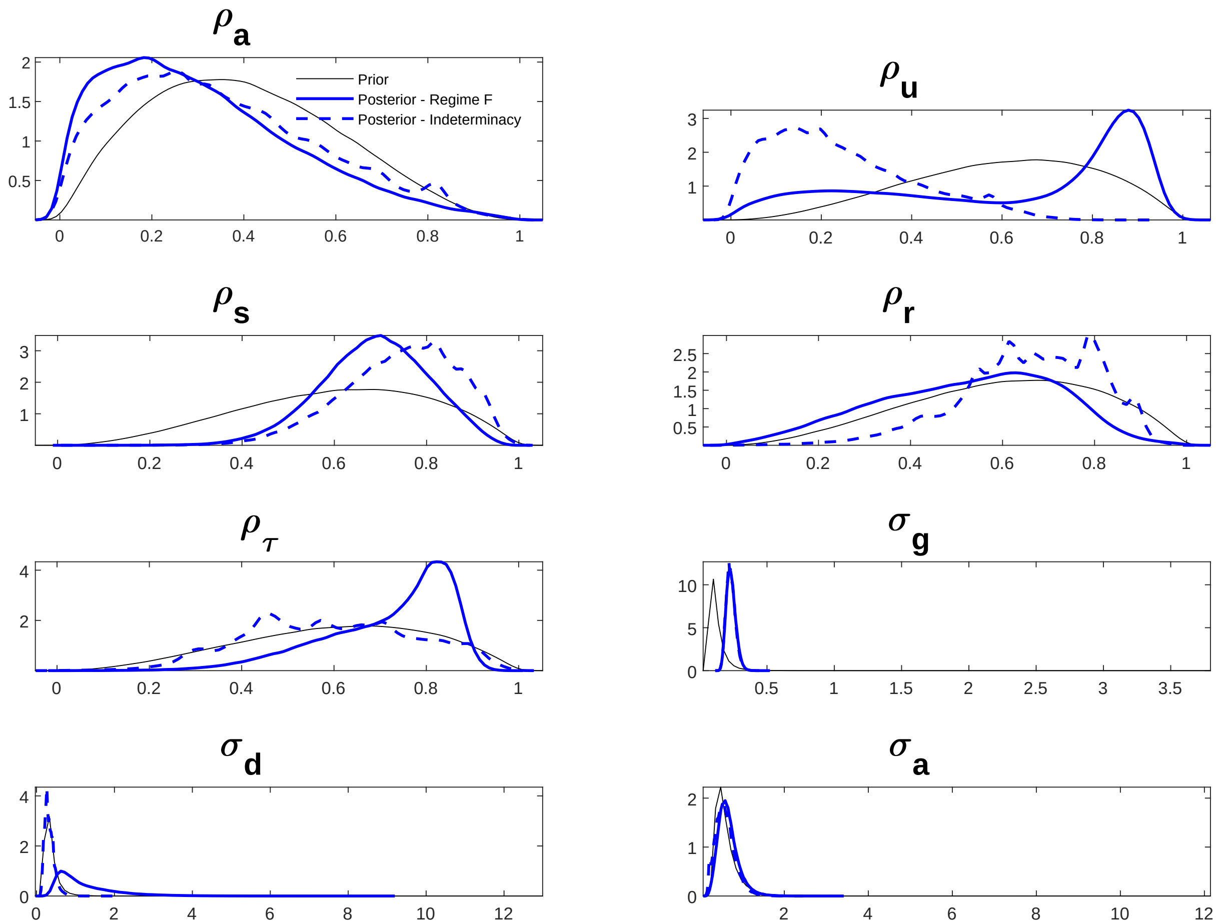
Appendix E.3 Unrestricted estimation - posterior densities conditional on regime F and the PMPF regime

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

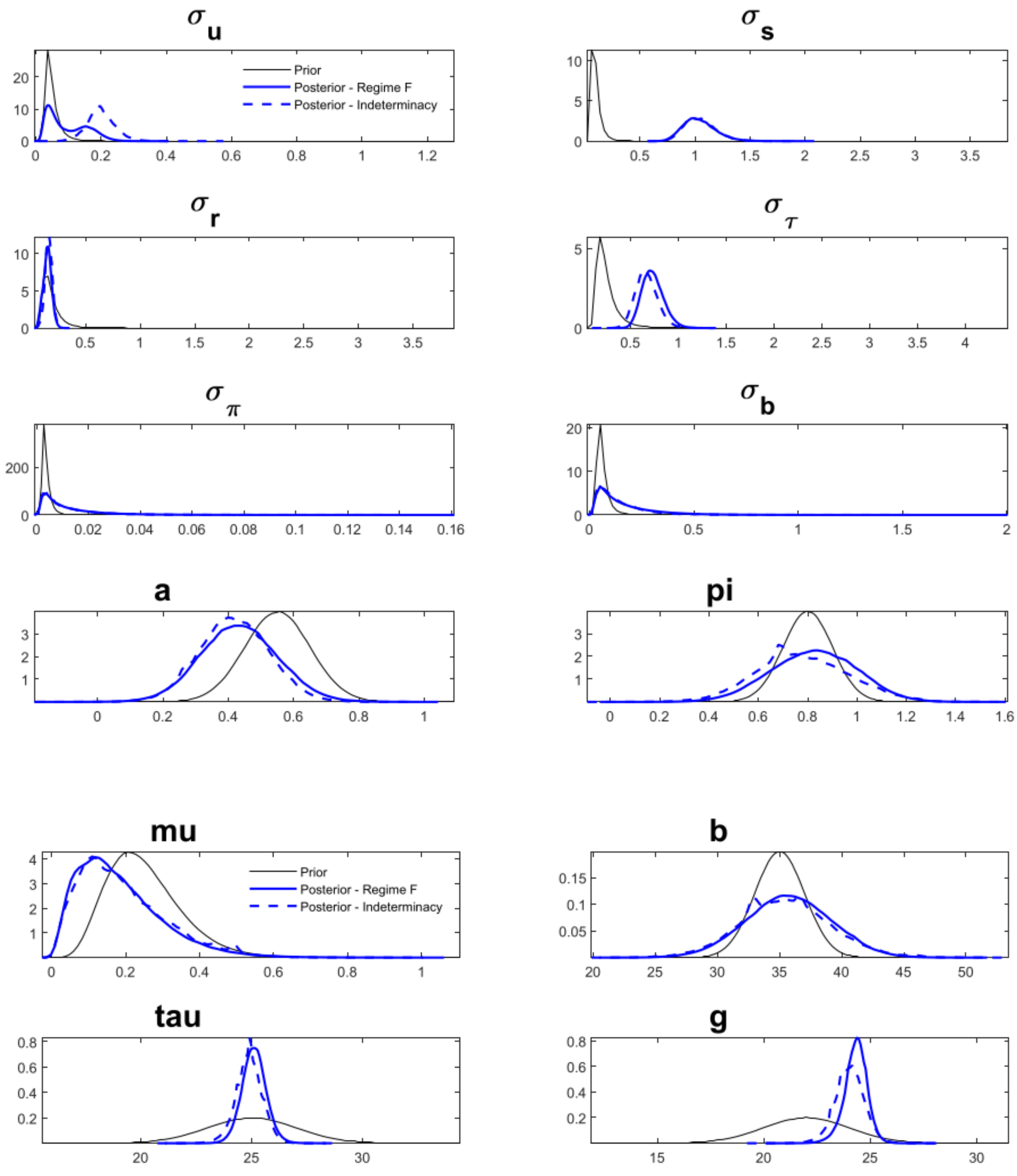


Figure 25: Prior and conditional posterior densities of the estimated model parameters from the unrestricted estimation. The blue bold line depicts the posterior density conditional on regime F, the dashed blue line the posterior density conditional on the PMPF regime, and the black line the prior density.

Appendix F Smoothed shocks

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

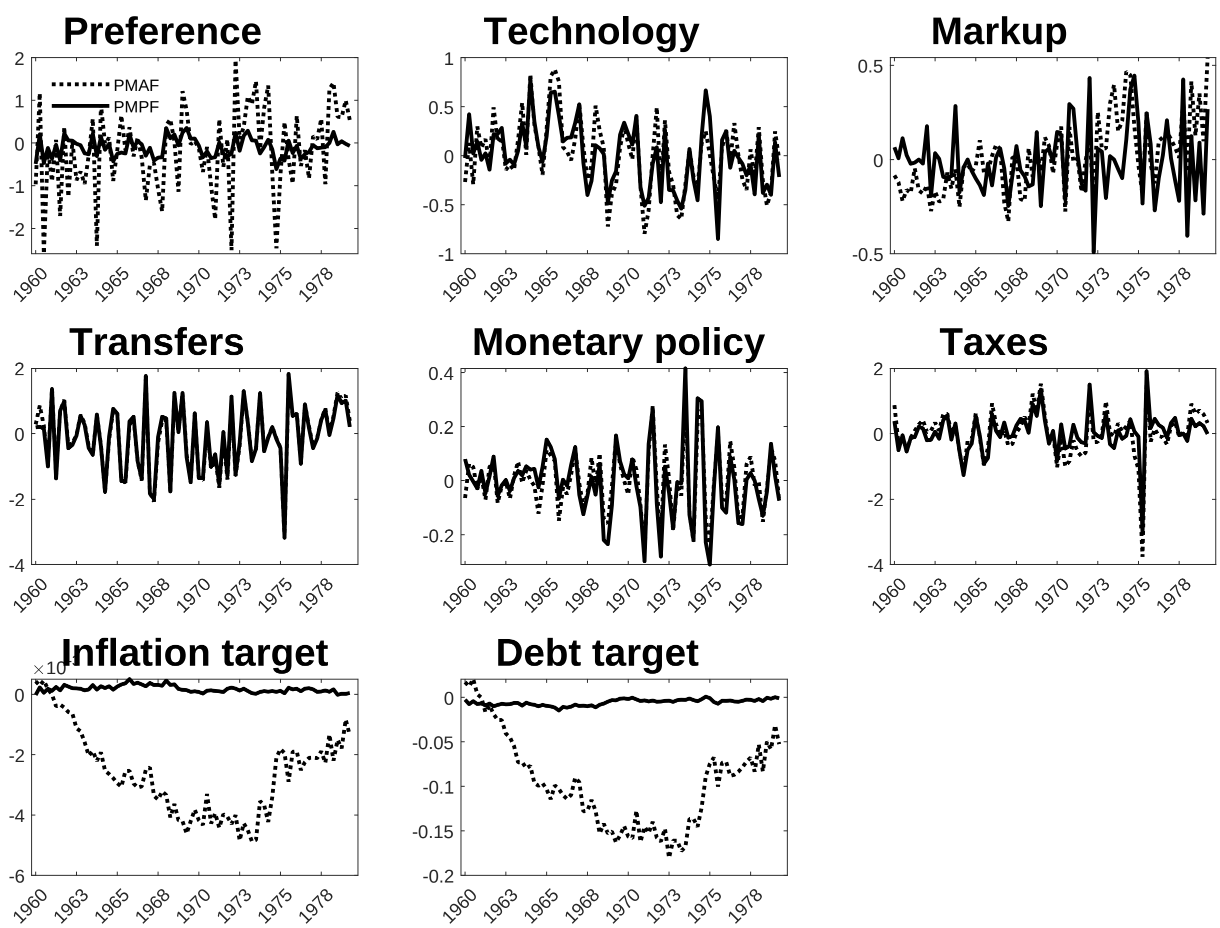


Figure 26: Smoothed shocks for 1960:Q1 to 1979:Q2 for regime F and the PMPF regime. The dashed line shows shocks computed at the mean of the posterior density from the unrestricted estimation conditional on regime F. The solid line shows shocks computed at the mean of the posterior density from the unrestricted estimation conditional on the PMPF regime.