U.S. Monetary Policy and Indeterminacy

Giovanni Nicolò
Federal Reserve Board

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Motivation

Two common approaches to study role of U.S. monetary policy (MP) in post-war period:

1. Models with *stylized* structure (i.e. small-scale)
    - Use method of Lubik and Schorfheide (2004) (LS) to allow for 'passive' MP;

    $\rightarrow$ Before 1979: 'passive' MP $\rightarrow$ failure to stabilize inflation and output $\rightarrow$ indeterminacy

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   → Before 1979: 'passive' MP → failure to stabilize inflation and output → indeterminacy

2. Models with *rich* structure (i.e. medium-scale)

   - Few studies overcome technical challenges to implement LS and allow for 'passive' MP;

   → Contrasting results on role of MP (Justiniano & Primiceri, 2008; Hirose et al., 2021).

Motivation

However, two choices are relevant when studying the conduct of U.S. monetary policy:

1. The choice of small-scale models (Beyer and Farmer, 2007);
   - Under passive MP, expectations affect macroeconomy by introducing:
     - More persistence in the propagation of *all* shocks (expectations are fundamental drivers);
     - More volatility (due to newly-introduced sunspot shocks);

   → Stylized models may favor evidence of passive MP.

2. The choice of existing solution methods;
   - Technical and computational difficulties could challenge the search for a global maximum;

   → Alternative methods may deliver different results, especially in rich models.

This paper

1. I show that two features can have relevant empirical implications for findings:
   - Rich structural model + novel method of Bianchi and Nicolò (2021) (BN).
2. I study the systematic conduct of U.S. monetary policy in the post-war period;
   - Estimate the medium-scale, New Keynesian model of Smets and Wouters (SW, 2007);
   - Implement BN to allow for passive MP;
   - Use Hybrid Metropolis-Hastings algorithm to efficiently explore entire parameter space.
3. I verify robustness of results to alternative model specifications and data used.

Findings

1. The adoption of medium-scale model is key:
   - Simulate determinate version of SW model;
   - Estimation of small-scale model $\rightarrow$ incorrect evidence of indeterminacy
2. The adoption of BN is also key:
   - Simulate indeterminate version of SW model;
   - Estimation of SW model with LS $\rightarrow$ incorrect evidence of determinacy
3. Monetary policy was passive before 1979;
   - Robust to alternative specifications of SW model and data used.
4. The evidence of active monetary policy after 1979 is overturned if:
   - Volcker-disinflation period is excluded;
   - SW model allows for time-varying inflation target (also with data on infl. expectations).

Model, data, solution and estimation methods

- Smets and Wouters (2007) model (SW)
  - Medium-scale DSGE model with nominal and real frictions + seven exogenous shocks Details
- Three sub-samples
  - Pre-1979: 1955:Q4 - 1979:Q2
  - Post-1979: 1979:Q3 - 2007:Q3 (Boivin & Giannoni, 2006; Leduc et al., 2007)
  - Post-1982: 1982:Q4 - 2007:Q3 (as in LS)
- Solution method: Bianchi and Nicolò (2021)
  - Augmented representation to solve a LRE model over entire parameter space Details
- Estimation method: Hybrid Metropolis-Hastings algorithm in Bianchi and Nicolò (2021)
  - Explicitly accounts for local peaks in various regions of the parameter space Details

Feature #1: Relevance of adopting a medium-scale model

Under a passive monetary policy, the propagation of *all* shock is more persistent, and additional sunspot shocks are introduced.

These features may erroneously favor evidence of passive monetary policy, especially in small-scale models (Beyer and Farmer, 2007):

1. Richer *dynamic* structure could explain the *persistence* in macro data without recurring to the additional persistence due to role of expectations as fundamental business-cycle drivers;
2. Richer *stochastic* structure could explain the *volatility* in macro data without recurring to the additional sunspot shocks.

Analytic example

Feature #1: Relevance of adopting a medium-scale model

Consider small-scale Del Negro and Schorfheide (2004) model $\rightarrow$ Three main differences:

- Richness of the structural model;
- Taylor rules used in the two models;
- Additional time series used for the estimation of SW model.

DS model details

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Consider small-scale Del Negro and Schorfheide (2004) model $\rightarrow$ Three main differences:

- Richness of the structural model;
- Taylor rules used in the two models;
- Additional time series used for the estimation of SW model.

To disentangle these channels,

- Generate a long simulation using a determinate version of SW model;
- Use the last 500 observations to estimate the following models:
  1. Del Negro and Schorfheide (2004);
  2. Del Negro and Schorfheide (2004) with Taylor rule as in SW;
  3. SW model estimated using only the same three time series used for the small-scale model.

DS model details

Feature #1: Relevance of adopting a medium-scale model

Model	Posterior mode		Prob.Determ.
	Determinacy	Indeterminacy	
Del Negro and Schorfheide	-623.5	-581.7	0
Del Negro and Schorfheide + Taylor rule as in SW	-621.7	-581.6	0
SW model + time series as in Del Negro and Schorfheide	-523.1	-534.5	1

→ The two versions of the small-scale model erroneously favor evidence of a passive monetary policy.

→ When a richer model structure is considered, the results correctly indicate that the simulated data is consistent with an active monetary policy.

Feature #2: Relevance of adopting BN

- Most studies that allow for passive monetary policy adopt the solution method of LS;
- Because of the technical and computational challenges to implement this method, small-scale models are generally adopted;
- Few exceptions:
  - → Contrasting evidence (Justiniano and Primiceri, 2008; Hirose et al., 2021);
  - → Adopt method of LS.
- However, the choice of solution method/baseline solution is relevant for the study of the conduct of monetary policy, especially in rich models.

Details

Feature #2: Relevance of adopting BN

To show the empirical relevance of the choice of solution method,

- Generate a long simulation using an indeterminate version of SW model;
- Use the last 500 observations to estimate the SW model using both alternative methods.

Feature #2: Relevance of adopting BN

To show the empirical relevant of the choice of solution method,

- Generate a long simulation using SW model + posterior means from pre-Volcker period;
- Use the last 500 observations to estimate the SW model using both alternative methods.

Model	Posterior mode		Prob.Determ.
	Determinacy	Indeterminacy	
SW model + Bianchi and Nicolò	-2663.3	-2590.9	0
SW model + Lubik and Schorfheide	-2661.7	-2769.6	1

→ The model estimation using LS erroneously favors evidence of an active monetary policy.

→ When the model is estimated using BN, the results correctly indicate that the simulated data is consistent with a passive monetary policy.

U.S. Monetary policy in the post-war period

Three sub-samples:

- Pre-1979: 1955:Q4 - 1979:Q2
- Post-1979: 1979:Q3 - 2007:Q3 (Boivin & Giannoni, 2006; Leduc et al., 2007)
- Post-1982: 1982:Q4 - 2007:Q3 (as in LS)

	Posterior mode		Prob. Determ.
	Determinacy	Indeterminacy	
Pre-1979	-546.3	-525.1	0
Post-1979	-567.1	-584.8	1
Post-1982	-377.1	-375.3	0

$\rightarrow$ Pre-1979: indeterminacy result carries over to medium-scale SW model.

$\rightarrow$ Post-1979: determinacy result overturned if Volcker-disinflation period is excluded.

U.S. Monetary policy in the post-war period

Coefficient	Description	Pre-1979 Mean	Pre-1979 [5 , 95]	Post-1979 Mean	Post-1979 [5 , 95]	Post-1982 Mean	Post-1982 [5 , 95]
r_π	Taylor rule inflation	0.86	[0.68,0.97]	2.10	[1.76,2.47]	0.75	[0.34,0.96]
r_y	Taylor rule output gap	0.14	[0.08,0.21]	0.07	[0.03,0.11]	0.10	[0.03,0.18]
$r_{\Delta y}$	Taylor rule Δ(output gap)	0.16	[0.12,0.21]	0.20	[0.15,0.25]	0.14	[0.09,0.20]
ρ	Taylor rule smoothing	0.85	[0.78,0.92]	0.78	[0.73,0.82]	0.88	[0.81,0.93]

$\rightarrow$ Relative to pre-1979, MP response in post-1979: $\uparrow r_\pi$, $\downarrow r_y$ and $\downarrow \rho$

$\rightarrow$ Relative to post-1979, MP response in post-1982: $\downarrow r_\pi$ and $\uparrow \rho$

$\rightarrow$ Similar estimates of Taylor-rule coefficients for pre-1979 and post-1982.

Priors

U.S. Monetary policy in the post-war period

		Pre-1979		Post-1979		Post-1982	
Coefficient	Description	Mean	[5 , 95]	Mean	[5 , 95]	Mean	[5 , 95]
σ_a	Technology shock	0.56	[0.49,0.64]	0.39	[0.34,0.44]	0.38	[0.33,0.42]
σ_b	Risk premium shock	0.17	[0.11,0.23]	0.22	[0.19,0.26]	0.17	[0.06,0.22]
σ_g	Government sp. shock	0.52	[0.46,0.59]	0.47	[0.42,0.52]	0.40	[0.35,0.45]
σ_I	Investment-specific shock	0.52	[0.40,0.65]	0.39	[0.32,0.46]	0.38	[0.28,0.51]
σ_r	Monetary policy shock	0.18	[0.15,0.20]	0.23	[0.20,0.26]	0.12	[0.10,0.14]
σ_p	Price mark-up shock	0.30	[0.25,0.35]	0.10	[0.07,0.12]	0.14	[0.10,0.18]
σ_w	Wage mark-up shock	0.28	[0.23,0.32]	0.31	[0.25,0.37]	0.30	[0.24,0.37]
σ_ν	Sunspot shock	0.13	[0.03,0.22]	0.50	[0.05,0.95]	0.14	[0.08,0.21]

- Relative to pre-1979:
  - Some exog. shocks in post-1979 have smaller std. dev. (vs higher: risk premium and MP).
  - *All* exog. shocks in post-1982 have similar or smaller std. dev.
  - Std. dev. of sunspot shock is only identified in pre-1979 and post-1982. Posterior distributions

Conclusions

1. Two key features for the study of the systematic conduct of U.S. monetary policy:
   - *Both* a rich structural model and the method of BN.

2. Evidence of passive monetary policy before 1979 is strong and robust.

3. Evidence of active monetary policy after 1979 is weak and sensitive to:
   - Exclusion of Volcker-disinflation period;
   - Adoption of time-varying inflation target (even when using data on inflation expectations).

The Smets-Wouters Model in a Nutshell

- Medium-scale DSGE model with both nominal and real frictions:
  - External habit formation in consumption;
  - Variable capital utilization;
  - Investment adjustment cost;
  - Fixed cost in production
  - Sticky nominal prices and wages;
  - Indexation to past inflation.
- Seven exogenous shocks to match the seven observables used in the estimation:
  - "Demand" shocks: Exogenous gov. spending, risk-premium and investment-specific;
  - "Supply" shocks: Productivity, price mark-up and wage mark-up;
  - Monetary policy shock:

$$R_t = \rho R_{t-1} + (1-\rho)\{r_\pi \pi_t + r_Y(y_t - y_t^p)\} + r_{\Delta y}[(y_t - y_t^p) - (y_{t-1} - y_{t-1}^p)] + \varepsilon_t^r$$

Back

Data and Measurement Equations

- The measurement equation used to estimate the data is:

$$Y_t^{obs} = \begin{bmatrix} dlGDP_t \\ dlCONS_t \\ dlINV_t \\ dlWAG_t \\ lHours_t \\ dlP_t \\ FEDFUNDS_t \end{bmatrix} = \begin{bmatrix} \bar{\gamma} \\ \bar{\gamma} \\ \bar{\gamma} \\ \bar{\gamma} \\ \bar{l} \\ \bar{\pi} \\ \bar{r} \end{bmatrix} + \begin{bmatrix} y_t - y_{t-1} \\ c_t - c_{t-1} \\ i_t - i_{t-1} \\ w_t - w_{t-1} \\ l_t \\ \pi_t \\ r_t \end{bmatrix}$$

- Three sub-samples:
  - Pre-1979: 1955:Q4 - 1979:Q2
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Solution method: BN

I solve the SW model by implementing the novel method of BN.

The approach proposes an augmented representation of a LRE model and:

- Solves the model over the *entire* parameter space;
- Is applicable when region of determinacy and degrees of indeterminacy are *unknown*;
- Can be easily combined with standard as well as sophisticated estimation algorithms.

◂ Back

Solution Method: Building the Intuition

Consider a classical monetary model described by the Fisher Equation

$$R_t = r_t + E_t(\pi_{t+1}), \qquad r_t \sim \mathcal{N}(0, \sigma_r^2) \tag{1}$$

the Taylor rule

$$R_t = \phi_\pi \pi_t \tag{2}$$

and $\eta_t \equiv \pi_t - E_{t-1}(\pi_t)$.

Combining (1) and (2), the model becomes a univariate LRE model

$$\begin{cases} E_t(\pi_{t+1}) = \phi_\pi \pi_t - r_t \\ \\ \eta_t = \pi_t - E_{t-1}(\pi_t) \end{cases}$$

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Augmented Representation

The approach proposes to solve the augmented system:

$$\begin{cases} E_t(\pi_{t+1}) = \phi_\pi \pi_t - r_t \\ \\ \omega_t = \left(\frac{1}{\alpha}\right) \omega_{t-1} - \nu_t + \eta_t \end{cases}$$

Back

Solution in Augmented Model

The approach proposes to solve the augmented system:

$$\begin{cases} E_t(\pi_{t+1}) = \phi_\pi \pi_t - r_t \\ \omega_t \quad = \left(\frac{1}{\alpha}\right)\omega_{t-1} - \nu_t + \eta_t \end{cases}$$

Suppose $|\phi_\pi| > 1$.

- If $|\frac{1}{\alpha}| \leq 1 \quad \rightarrow \quad$ the solution for the augmented representation is

$$\begin{cases} \pi_t = \frac{1}{\phi_\pi} r_t \\ \omega_t \ = \left(\frac{1}{\alpha}\right)\omega_{t-1} - \nu_t + \eta_t \end{cases}$$

- If $|\frac{1}{\alpha}| > 1 \quad \rightarrow \quad$ *No solution for the augmented representation (boundedness is violated).*

◂ Back

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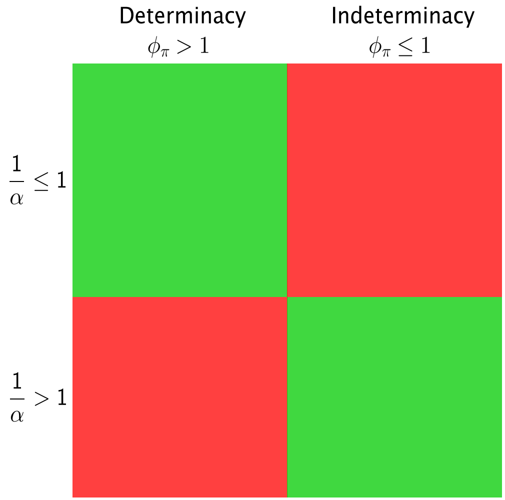
Suppose $|\phi_\pi| \leq 1$.

- If $|\frac{1}{\alpha}| \leq 1$ $\rightarrow$ *No solution for the augmented representation (BK condition).*
- If $|\frac{1}{\alpha}| > 1$ $\rightarrow$ the solution for the augmented representation is

$$\begin{cases} \pi_t = \phi_\pi \pi_{t-1} - r_{t-1} + \eta_t \\ \omega_t = 0 \end{cases}$$

Choose α Back

Solution in Augmented Model



Back

Solution in Augmented Model

	Determinacy $\phi_\pi > 1$	Indeterminacy $\phi_\pi \leq 1$
$\frac{1}{\alpha} \leq 1$	$\begin{cases} \pi_t = \frac{1}{\phi_\pi} r_t \\ \omega_t = \frac{1}{\alpha}\omega_{t-1} - \nu_t + r_t \end{cases}$	
$\frac{1}{\alpha} > 1$		$\begin{cases} \pi_t = \phi_\pi \pi_{t-1} - r_{t-1} + \eta_t \\ \omega_t = 0 \end{cases}$

Back

How to choose α

Consider the following two cases:

1. The researcher knows the region of determinacy ($\phi_\pi > 1$)

   $\rightarrow$ Set $\alpha \equiv \phi_\pi$.

2. The region of determinacy is completely unknown

   $\rightarrow$ Set uniform prior for α over the interval $[1 - a, 1 + a]$, where $a \in (0, 1)$.

Back

Estimation method: Hybrid Metropolis-Hastings algorithm

- At the boundaries between the regions of (in)determinacy, the posterior often presents possibly severe discontinuities.

- Also, these models often have local peaks in the posterior.

- Methods, such as the sequential Monte Carlo algorithm (Herbst and Schorfheide, 2015), tend to overcome these challenges.

$\rightarrow$ In this paper, I adopt the Hybrid Metropolis-Hastings algorithm developed in BN.

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Hybrid Metropolis-Hastings algorithm: Steps

1. In each region of (in)determinacy $j = 1, ..., J$, apply a numerical optimization procedure to search for modes $\widetilde{\theta}_{(j)}$ of the posterior density and compute the inverse of the Hessian, $\widetilde{\Sigma}_{(j)}$.

◂ Back

Hybrid Metropolis-Hastings algorithm: Steps

1. In each region of (in)determinacy $j = 1, ..., J$, apply a numerical optimization procedure to search for modes $\widetilde{\theta}_{(j)}$ of the posterior density and compute the inverse of the Hessian, $\widetilde{\Sigma}_{(j)}$.
2. Let $q_j(\theta)$ be the density of a multivariate distribution obtained mixing two normals:

$$q_j(\theta) = z^l N\left(\widetilde{\theta}_{(j)}, c_j^l \widetilde{\Sigma}_{(j)}\right) + \left(1 - z^l\right) N\left(\widetilde{\theta}_{(j)}, c_j^s \widetilde{\Sigma}_{(j)}\right), \qquad c_j^s < c_j^l \textit{ and } z^l \in [0, 1].$$

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3. After choosing a starting value $\theta^{(0)}$, follow these steps for $s = 1, \dots, nsim$:
   1. Defining $q(\theta) \equiv \sum_{j=1}^{J} \pi_j q_j(\theta)$, make a draw ϑ from the following proposal distribution:

$$\widetilde{q}(\vartheta|\theta^{(s-1)}) = w^{RW} N\left(\theta^{(s-1)}, c^{RW} \widetilde{\Sigma}_{(j)}\right) + \left(1 - w^{RW}\right) q(\theta), \quad w^{RW} \in [0, 1].$$

   2. Accept the jump from $\theta^{(s-1)}$ to ϑ $\left(\theta^{(s)} = \vartheta\right)$ with probability $\min\left\{1, r_j\left(\theta^{(s-1)}, \vartheta|Y\right)\right\}$, otherwise reject the proposed draw and set $\theta^{(s)} = \theta^{(s-1)}$, where

$$r_j\left(\theta^{(s-1)}, \vartheta|Y\right) = \frac{\mathcal{L}\left(\vartheta|Y\right) p\left(\vartheta\right) / \widetilde{q}(\vartheta|\theta^{(s-1)})}{\mathcal{L}\left(\theta^{(s-1)}|Y\right) p\left(\theta^{(s-1)}\right) / \widetilde{q}(\theta^{(s-1)}|\vartheta)}$$

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Identification Problem

Suppose a researcher uses two alternative models to study the dynamics of the inflation rate.

Model 1:

$$\pi_t = a\, E_t(\pi_{t+1}),$$

where the forecast error is

$$\eta_t \equiv \pi_t - E_{t-1}(\pi_t).$$

Back

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BK condition: Unique, determinate sol if # unstable roots equals # expectational variables.

The roots of the system are 0 and $\lambda \equiv a^{-1}$.

When $|\lambda| > 1 \Rightarrow$ Unique, determinate solution: $\pi_t = 0$.

When $|\lambda| \leq 1 \Rightarrow$ Multiple, indeterminate solution defined by any process of the form

$$\pi_t = \lambda \pi_{t-1} + \eta_t.$$

Back

Identification Problem

Suppose a researcher uses two alternative models to study the dynamics of the inflation rate.

Model 2:

$$\pi_t = a\, E_t(\pi_{t+1}) + b\, \pi_{t-1} + \varepsilon_t, \qquad \varepsilon_t \overset{iid}{\sim} \mathcal{N}(0, \sigma_\varepsilon^2)$$

where the forecast error is

$$\eta_t \equiv \pi_t - E_{t-1}(\pi_t).$$

Back

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$$\pi_t = a\, E_t(\pi_{t+1}) + b\, \pi_{t-1} + \varepsilon_t, \qquad \varepsilon_t \overset{iid}{\sim} \mathcal{N}(0, \sigma_\varepsilon^2)$$

where the forecast error is

$$\eta_t \equiv \pi_t - E_{t-1}(\pi_t).$$

Denote the two roots of the system by $\{\lambda, \theta\}$ as a function of the structural parameters $\{a, b\}$.

Consider the case, $|\lambda| < 1$ and $|\theta| > 1$.

$\Rightarrow$ Unique, determinate solution defined by

$$\pi_t = \lambda \pi_{t-1} + \frac{\lambda + \theta}{\theta} \varepsilon_t.$$

Back

Identification Problem

The two models are *observationally equivalent*.

Model 1:

$$\pi_t = a\, E_t(\pi_{t+1}).$$

→ Indeterminate solution

$$\pi_t = \lambda \pi_{t-1} + \eta_t.$$

Model 2:

$$\pi_t = a\, E_t(\pi_{t+1}) + b\, \pi_{t-1} + \varepsilon_t.$$

→ Determinate solution

$$\pi_t = \lambda \pi_{t-1} + \frac{\lambda + \theta}{\theta} \varepsilon_t.$$

⇒ The adoption of the richer Model 2 overturns the results.

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Identification Problem

The univariate model provides an analytical example of the identification problem due to observational equivalence.

A similar example *cannot* be analytically derived for more complicated models.

$\Rightarrow$ In this paper, I show empirically that the choice of the model structure impacts the conclusions on the conduct of monetary policy.

Back

Del Negro and Schorfheide (2004) model

The Del Negro and Schorfheide (2004) model allows for a BGP and is described by:

- Dynamic IS curve

$$y_t = E_t(y_{t+1}) - \tau^{-1}(R_t - E_t(\pi_{t+1})) + (1-\rho_g)g_t + \rho_z \tau^{-1} z_t$$

- NKPC

$$\pi_t = \beta E_t(\pi_{t+1}) + \kappa\left(y_t - g_t\right), \qquad \beta = \frac{\gamma}{r^*}$$

- Monetary policy

$$R_t = \rho_R R_{t-1} + (1-\rho_R)(\phi_\pi \pi_t + \phi_y y_t) + \varepsilon_{R,t}$$

- Demand and supply shocks: $g_t = \rho_g g_{t-1} + \varepsilon_{g,t}$ and $z_t = \rho_z z_{t-1} + \varepsilon_{z,t}$.

◂ Back

Feature #2: Relevance of adopting BN

Consider a classical monetary model described by the Fisher Equation

$$R_t = r_t + E_t(\pi_{t+1}), \qquad r_t \sim \mathcal{N}(0, \sigma_r^2) \tag{3}$$

the Taylor rule

$$R_t = \phi_\pi \pi_t \tag{4}$$

and $\eta_t \equiv \pi_t - E_{t-1}(\pi_t)$.

Combining (1) and (2), the model becomes a univariate LRE model

$$\begin{cases} E_t(\pi_{t+1}) = \phi_\pi \pi_t - r_t \\ \\ \eta_t = \pi_t - E_{t-1}(\pi_t) \end{cases}$$

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Feature #2: Relevance of adopting BN

$$\begin{cases} E_t(\pi_{t+1}) = \phi_\pi \pi_t - r_t, & r_t \sim \mathcal{N}(0, \sigma_r^2) \\ \eta_t = \pi_t - E_{t-1}(\pi_t) \end{cases}$$

- If $|\phi_\pi| > 1 \quad \rightarrow \quad$ Active monetary policy: $\left\{ \pi_t = \frac{1}{\phi_\pi} r_t, \;\; E_{t-1}(\pi_t) = 0, \;\; \eta_t = \frac{1}{\phi_\pi} r_t \right\}$.
- If $|\phi_\pi| \leq 1 \quad \rightarrow \quad$ Passive monetary policy:

Back

Feature #2: Relevance of adopting BN

$$\begin{cases} E_t(\pi_{t+1}) = \phi_\pi \pi_t - r_t, & r_t \sim \mathcal{N}(0, \sigma_r^2) \\ \eta_t = \pi_t - E_{t-1}(\pi_t) \end{cases}$$

- If $|\phi_\pi| > 1 \quad \rightarrow \quad$ Active monetary policy: $\left\{\pi_t = \frac{1}{\phi_\pi} r_t, \;\; E_{t-1}(\pi_t) = 0, \;\; \eta_t = \frac{1}{\phi_\pi} r_t \right\}$.
- If $|\phi_\pi| \leq 1 \quad \rightarrow \quad$ Passive monetary policy:
  1. Using BN:

$$\begin{cases} \pi_t = \phi_\pi \pi_{t-1} - r_{t-1} + \nu_t \\ \eta_t \equiv \nu_t \end{cases} \qquad \begin{pmatrix} r_t \\ \nu_t \end{pmatrix} \sim \mathcal{MVN}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_r^2 & \rho_{r,\nu} \\ \rho_{r,\nu} & \sigma_\nu^2 \end{pmatrix} \right).$$

  2. Using LS:

$$\begin{cases} \pi_t = \phi_\pi \pi_{t-1} - r_{t-1} + \eta_t \\ \eta_t \equiv M_r r_t + \zeta_t \end{cases} \qquad \begin{pmatrix} r_t \\ \zeta_t \end{pmatrix} \sim \mathcal{MVN}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\zeta^2 \end{pmatrix} \right).$$

◂ Back

Feature #2: Relevance of adopting BN

1. Using BN:

$$\begin{cases} \pi_t = \phi_\pi \pi_{t-1} - r_{t-1} + \nu_t \\ \eta_t \equiv \nu_t \end{cases} \qquad \begin{pmatrix} r_t \\ \nu_t \end{pmatrix} \sim \mathcal{MVN}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_r^2 & \rho_{r,\nu} \\ \rho_{r,\nu} & \sigma_\nu^2 \end{pmatrix} \right).$$

2. Using LS:

$$\begin{cases} \pi_t = \phi_\pi \pi_{t-1} - r_{t-1} + \eta_t \\ \eta_t \equiv M_r r_t + \zeta_t \end{cases} \qquad \begin{pmatrix} r_t \\ \zeta_t \end{pmatrix} \sim \mathcal{MVN}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\zeta^2 \end{pmatrix} \right).$$

The methods have two important differences:

1. In BN, the correlation $\rho_{r,\nu}$ has a well-defined domain.
2. In LS, the centering of the baseline solution around the determinate solution ($M_r = 1/\phi_\pi$) poses technical and computational difficulties, especially in rich models.

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Prior distributions

Coefficient	Description	Distr.	Mean	Std. Dev
ϕ	Adjustment cost	Normal	4.00	1.50
σ_c	IES	Normal	1.50	0.37
h	Habit Persistence	Beta	0.70	0.10
σ_l	Labor supply elasticity	Normal	2.00	0.75
ξ_w	Wage stickiness	Beta	0.50	0.10
ξ_p	Price Stickiness	Beta	0.50	0.10
ι_w	Wage Indexation	Beta	0.50	0.15
ι_p	Price Indexation	Beta	0.50	0.15
ψ	Capacity utilization elasticity	Beta	0.50	0.15
Φ	Share of fixed costs	Normal	1.25	0.12
α	Share of capital	Normal	0.30	0.05
$\bar{\pi}$	S.S. inflation rate (quart.)	Gamma	0.62	0.10
$100(\beta^{-1} - 1)$	Discount factor	Gamma	0.25	0.10
$\bar{l}$	S.S. hours worked	Normal	0.00	2.00
$\bar{\gamma}$	Trend growth rate	Normal	0.40	0.10
r_π	Taylor rule inflation	Normal	***1.00***	***0.35***
r_y	Taylor rule output gap	Normal	0.12	0.05
$r_{\Delta y}$	Taylor rule Δ(output gap)	Normal	0.12	0.05
ρ	Taylor rule smoothing	Beta	0.75	0.10

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Prior distributions

Coefficient	Description	Distr.	Mean	Std. Dev
σ_a	Technology shock	Invgamma	0.10	2.00
σ_b	Risk premium shock	Invgamma	0.10	2.00
σ_g	Government sp. shock	Invgamma	0.10	2.00
σ_I	Investment-specific shock	Invgamma	0.10	2.00
σ_r	Monetary policy shock	Invgamma	0.10	2.00
σ_p	Price mark-up shock	Invgamma	0.10	2.00
σ_w	Wage mark-up shock	Invgamma	0.10	2.00
σ_ν	Sunspot shock	Uniform[0,1]	0.50	0.29
ρ_a	Persistence technology	Beta	0.50	0.20
ρ_b	Persistence risk premium	Beta	0.50	0.20
ρ_g	Persistence government sp.	Beta	0.50	0.20
ρ_I	Persistence investment-specific	Beta	0.50	0.20
ρ_r	Persistence monetary policy	Beta	0.50	0.20
ρ_p	Persistence price mark-up	Beta	0.50	0.20
ρ_w	Persistence wage mark-up	Beta	0.50	0.20
μ_p	Mov. Avg. term, price mark-up	Beta	0.50	0.20
μ_w	Mov. Avg. term, wage mark-up	Beta	0.50	0.20
ρ_{ga}	$Cov(\sigma_a, \sigma_g)$	Normal	0.50	0.25
$\rho_{\nu p}$	$Corr(\sigma_\nu, \sigma_p)$	Uniform[-1,1]	0	0.57

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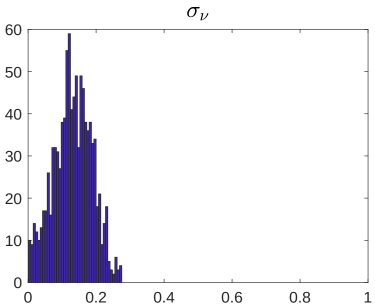
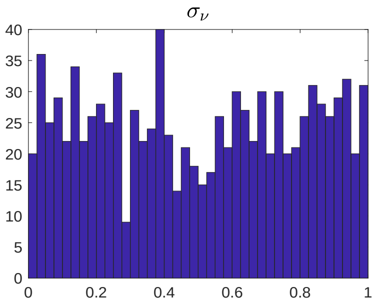
U.S. Monetary policy in the post-war period



(a) Pre-1979



(b) Post-1979

→ Std. dev. of sunspot shock is only identified in pre-1979 and post-1982 (not shown).

◂ Back

Robustness Analysis

- Time-varying inflation target.
- Time-varying inflation target with inflation expectations.
- Real-time data.

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Time-varying Inflation Target

- A time-varying inflation target better captures low-frequency movements in inflation.

- Haque (2021): a time-varying target rules out indeterminacy with a small scale model.
  - Response to inflation gap is more aggressive when target is time-varying rather than fixed.

→ Add a time-varying inflation target to the SW model (Del Negro and Schorfheide, 2013):

$$R_t = \rho R_{t-1} + (1-\rho)\{r_\pi(\pi_t - \pi_t^*) + r_y(y_t - y_t^p)\} + r_{\Delta y}\left[(y_t - y_t^p) - (y_{t-1} - y_{t-1}^p)\right] + u_{R,t}$$

where

$$\pi_t^* = \rho_{\pi^*}\pi_{t-1}^* + \varepsilon_{\pi^*,t} \qquad 0 < \rho_{\pi^*} < 1$$

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Time-varying Inflation Target

Model	Pre-1979			Post-1979		
	Posterior mode		Prob.Det.	Posterior mode		Prob.Det.
	Det.	Indet.		Det.	Indet.	
SW model	-546.3	-525.1	0	-567.1	-584.8	1
SWπ^*	-534.4	-520.5	0	-564.4	-557.1	0

$\rightarrow$ Model with time-varying inflation target fits the data better.

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Time-varying Inflation Target

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→ Model with time-varying inflation target better fits the data.

→ Inclusion of time-varying target can affect findings on stance of U.S. monetary policy:

- Pre-1979: indeterminacy result persists.
- Post-1979: determinacy result is overturned.

→ Differences from Haque (2021) can be attributed to model scale and solution method.

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Time-varying Inflation Target and Inflation Expectations

- Data on inflation expectations can improve measurement of π_t^*.

→ Augment measurement equation of SWπ^* model as in Del Negro and Schorfheide (2013):

$$\pi_t^{e,J} = \bar{\pi} + \mathbb{E}_t \left[\frac{1}{J} \sum_{k=1}^{J} \pi_{t+k} \right]$$

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Time-varying Inflation Target and Inflation Expectations

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- Short-term inflation expectations ($\pi_t^{e,4}$):
  - Survey Professional Forecasters (SPF): 1-year-ahead avg. GDP price infl. (since 1970:Q2)
- Longer-term inflation expectations ($\pi_t^{e,40}$):
  - Blue Chip Economic Indicators survey: 10-year-ahead avg. CPI infl. (since 1979:Q4)
  - SPF: 10-year-ahead avg. GDP price infl. (since 1991:Q4)

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Time-varying Inflation Target and Inflation Expectations

Model	Pre-1979			Post-1979		
	Posterior mode		Prob.Det.	Posterior mode		Prob.Det.
	Det.	Indet.		Det.	Indet.	
SW model	-546.3	-525.1	0	-567.1	-584.8	1
$SW\pi^*$	-534.4	-520.5	0	-564.4	-557.1	0
$SW\pi^* + \pi^{e,4}$	-584.8	-571.1	0	-485.2	-451.0	0
$SW\pi^* + \pi^{e,40}$	-	-	-	-472.2	-466.6	0

- Both periods: Estimation of $SW\pi^*$ model with $\pi^{e,4}$ points to indeterminacy.
- Post-1979: same conclusion can be reached with $\pi^{e,40}$.

→ Relative to $SW\pi^*$ model, inclusion of short- or longer-term inflation expectations does not affect the indeterminacy result.

◂ Back

Real-Time Data

- Orphanides (2001): use of real-time data can affect conclusions about conduct of MP.
  - Policymakers overestimated potential output in the 1970s (Orphanides 2002, 2003).

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→ Estimate the SW model using real-time data.

- Real-time data sourced from Philadelphia Fed's Real-Time Data Research Center.
- Pre- and post-1979 vintages of real-time data (as available at the end of the sample):
  - Real output, personal consumption expenditure, non-residential private domestic investment, and output price index.
- Remaining time series use most recent data available.

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Real-Time Data

Model	Pre-1979			Post-1979		
	Posterior mode		Prob.Det.	Posterior mode		Prob.Det.
	Det.	Indet.		Det.	Indet.	
SW model	-546.3	-525.1	0	-567.1	-584.8	1
SW model + Real-time data	-543.9	-522.8	0	-598.2	-605.7	1

→ Results with real-time data support findings of baseline SW model with most recent data.

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