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Online Appendix:

A New Model of Trend Inflation Using Disaggregates, Survey Expectations, and Uncertainty

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Working Paper No. 26-08

March 2026

Suggested citation: Tallman, Ellis and Saeed Zaman. 2026. "A New Model of Trend Inflation Using Disaggregates, Survey Expectations, and Uncertainty." Working Paper No. 26-08. Federal Reserve Bank of Cleveland. <https://doi.org/10.26509/frbc-wp-202608>.

Federal Reserve Bank of Cleveland Working Paper Series

ISSN: 2573-7953

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Online Appendix

A New Model of Trend Inflation Using Disaggregates, Survey Expectations, and Uncertainty*

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Feb 27, 2026

*We thank Todd Clark, James Mitchell, and participants at the Advances in Econometrics Bayesian Macroeconometrics Workshop for helpful conversations and comments. The views expressed herein are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System.

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Contents

A1. Prior Elicitation	3
A2. MCMC Algorithm	5
A3. MCMC Convergence Diagnostics	20
A4. Prior and Posterior Distributions	27
A5.CBO Unemployment Rate Gap	29
A6.Trend Estimates: Sensitivity to Modeling Assumptions	30
A7.Uncertainty Estimates: Sensitivity to Modeling Assumptions	34
A8.Comparing Parameter Estimates: Baseline vs. Model with time-invariant parameters	35
A9.Comparing Parameter Estimates: Baseline vs. Model without Survey Expectations Data	36
A10. Trend Estimates: Single-Sector Model vs. Single-Sector Model without Survey data	37
A11. Trend estimates based on estimating models with data starting from 1980 onward	38

A1. Prior Elicitation

In the table below, the notation $N(a, b)$ denotes Normal distribution with mean a , and variance b ; and $IG(\nu, S)$ denotes Inverse Gamma distribution with degrees of freedom parameter ν , and scale parameter S .

Table 1: Prior settings for the Baseline Model

Parameter	Parameter Description	Prior
σ_{hS}^2	Var. of the Volatility – Services π measurement eq.	$IG(10, 0.25^2 \times 9)$
σ_{hG}^2	Var. of the Volatility – Goods π measurement eq.	$IG(10, 0.25^2 \times 9)$
$\sigma_{h\tau S}^2$	Var. of the Volatility – Trend Services π eq.	$IG(10, 0.05^2 \times 9)$
$\sigma_{h\tau G}^2$	Var. of the Volatility – Trend Goods π eq.	$IG(10, 0.05^2 \times 9)$
σ_{λ}^2	Var. of the shocks to TVP λ (Phillips curve slope)	$IG(10, 0.05^2 \times 9)$
$\sigma_{\alpha S}^2$	Var. of the shocks to TVP α^S	$IG(10, 0.1^2 \times 9)$
$\sigma_{\alpha G}^2$	Var. of the shocks to TVP α^G	$IG(10, 0.1^2 \times 9)$
$\sigma_{C\pi}^2$	Var. of the shocks to TVP C^π	$IG(10, 0.1^2 \times 9)$
$\sigma_{z\pi}^2$	Var. of the shocks to the eq. linking survey to π^*	$IG(10, 0.447^2 \times 9)$
β^π	Link between π^* and survey	$N(1, 0.05^2)$
λ_0	Initial value of λ , $t = 0$	$TN(-1, 0; 0, 1)$
α_0^S	Initial value of α^S , $t = 0$	$N(0, 1)$
α_0^G	Initial value of α^G , $t = 0$	$N(0, 1)$
C_0^π	Initial value of C^π , $t = 0$	$N(0, 0.1)$
h_0^{Ser}	Initial value of h^{Ser} , $t = 0$	$N(0, 1)$
h_0^{Goods}	Initial value of h^{Goods} , $t = 0$	$N(0, 1/5)$
$h_0^{\tau S}$	Initial value of $h^{\tau S}$, $t = 0$	$N(0, 1)$
$h_0^{\tau G}$	Initial value of $h^{\tau G}$, $t = 0$	$N(0, 1)$
τ_0^G	Initial value of τ^G , $t = 0$	$N(1, 100)$
τ_0^S	Initial value of τ^S , $t = 0$	$N(3, 100)$

Table 2: Prior settings for the Single-sector Model

Parameter	Parameter Description	Prior
σ_{hS}^2	Var. of the Volatility – aggregate π measurement eq.	$IG(10, 0.25^2 \times 9)$
$\sigma_{h\tau S}^2$	Var. of the Volatility – aggregate Trend π eq.	$IG(10, 0.05^2 \times 9)$
σ_{λ}^2	Var. of the shocks to TVP λ (Phillips curve slope)	$IG(10, 0.05^2 \times 9)$
$\sigma_{\alpha S}^2$	Var. of the shocks to TVP α	$IG(10, 0.1^2 \times 9)$
$\sigma_{c\pi}^2$	Var. of the shocks to TVP C^π	$IG(10, 0.1^2 \times 9)$
$\sigma_{z\pi}^2$	Var. of the shocks to the eq. linking survey to π^*	$IG(10, 0.447^2 \times 9)$
β^π	Link between π^* and survey	$N(1, 0.05^2)$
λ_0	Initial value of λ , $t = 0$	$TN(-1, 0; 0, 1)$
α_0	Initial value of α , $t = 0$	$N(0, 1)$
C_0^π	Initial value of C^π , $t = 0$	$N(0, 0.1)$
h_0	Initial value of h , $t = 0$	$N(0, 1)$
h_0^τ	Initial value of h^τ , $t = 0$	$N(0, 1)$
τ_0	Initial value of τ , $t = 0$	$N(2, 100)$

A2. MCMC Algorithm

The Baseline model is estimated by sampling from its joint posterior distribution, which entails sequentially drawing from a set of conditional posterior densities, some standard and some non-standard.

Collect all the time-invariant model parameters into θ :

$$\theta = (\sigma_{hS}^2, \sigma_{hG}^2, \sigma_{h\tau S}^2, \sigma_{h\tau G}^2, \sigma_\lambda^2, \sigma_{\alpha S}^2, \sigma_{\alpha G}^2, \sigma_{c\pi}^2, \sigma_{z\pi}^2, \beta^\pi)$$

Let's denote \bullet as representing all other model parameters. Then, the sequential steps to draw from the conditional posterior densities are:

1. $p(\alpha^S|Y, \bullet)$
2. $p(\alpha^G|Y, \bullet)$
3. $p(\lambda|Y, \bullet)$
4. $p(\tau^S|Y, \bullet)$
5. $p(\tau^G|Y, \bullet)$
6. $p(h^{Ser}|Y, \bullet)$
7. $p(h^{Goods}|Y, \bullet)$
8. $p(h^{\tau S}|Y, \bullet)$
9. $p(h^{\tau G}|Y, \bullet)$
10. $p(C^\pi|Y, \bullet)$
11. $p(\theta|Y, \bullet)$

In the steps below, $Y = \pi^S$ when sampling parameters defining dynamics of services inflation, and $Y = \pi^G$ when sampling parameters defining the dynamics of goods inflation.

Step 1. Derive the conditional distribution $p(\alpha^S|Y, \bullet)$

The information about α^S comes from two sources. Below, we derive an expression for each of these two sources.

First, some notation,

$$\begin{aligned}\tilde{\pi}_t^S &= \pi_t^S - \tau_t^S \\ \tilde{u}_t &= U_t - U_t^* \\ \tilde{v}_t &= e^{h_t^{Ser}} - e^{\bar{h}_t^{Ser}}\end{aligned}$$

The first source is the services inflation measurement equation. Rewrite it in a matrix notation,

$$N^{\alpha s} = X_v \alpha^S + \varepsilon^S \quad \varepsilon^S \sim N(0, \Omega_s), \quad \text{where } \Omega_s = \text{diag}(e^{h_1^{Ser}}, e^{h_2^{Ser}}, \dots, e^{h_T^{Ser}}) \quad (1)$$

where,

$$X_v = \text{diag}(\tilde{v}_1, \dots, \tilde{v}_T)$$

$$N^{\alpha s} = (\tilde{\pi}_1^S - \lambda_1 \tilde{u}_1, \dots, \tilde{\pi}_T^S - \lambda_T \tilde{u}_T)'$$

Ignoring any terms not involving α^S , the likelihood is

$$\log p(\pi^S | \alpha^S, \bullet) \propto -\frac{1}{2} (N^{\alpha s} - X_v \alpha^S)' \Omega_s^{-1} (N^{\alpha s} - X_v \alpha^S)$$

The second source comes from the state equation for α^S . We rewrite it in a matrix notation as follows,

$$H \alpha^S = \varepsilon^{\alpha s} \quad \varepsilon^{\alpha s} \sim N(0, \Omega_{\alpha s}), \quad \text{where } \Omega_{\alpha s} = \text{diag}(\omega_{\alpha s}^2, \sigma_{\alpha s}^2, \dots, \sigma_{\alpha s}^2) \quad (2)$$

Ignoring any terms not involving α^S , the prior density for α^S is given by

$$\log p(\alpha^S | \sigma_{\alpha s}^2, \Omega_{\alpha s}) \propto -\frac{1}{2} (\alpha^S)' H' \Omega_{\alpha s}^{-1} H (\alpha^S)$$

Combining the above two conditional densities we obtain,

$$\log p(\alpha^S | Y, \bullet) \propto -\frac{1}{2} (\alpha^S - \hat{\alpha}^S)' D_{\alpha s}^{-1} (\alpha^S - \hat{\alpha}^S)$$

where,

$$D_{\alpha s} = (H' \Omega_{\alpha s}^{-1} H + X_v' \Omega_s^{-1} X_v)^{-1}$$

$$\hat{\alpha}^S = D_{\alpha s} (X_v' \Omega_s^{-1} N^{\alpha s})$$

The candidate draws are sampled from $N(\hat{\alpha}^S, D_{\alpha s})$ using the precision-based algorithm.

Step 2. Derive the conditional distribution $p(\alpha^G | Y, \bullet)$

The information about α^G comes from two sources. Below, we derive an expression for each of these two sources.

First, some notation,

$$\begin{aligned}\tilde{\pi}_t^G &= \pi_t^G - \tau_t^G \\ \tilde{u}_t &= U_t - U_t^* \\ \tilde{v}g_t &= e^{h_t^{Goods}} - e^{\tilde{h}_t^{Goods}}\end{aligned}$$

The first source is the goods inflation measurement equation. Rewrite it in a matrix notation,

$$N^{\alpha g} = X_{vg}\alpha^G + \varepsilon^G \quad \varepsilon^G \sim N(0, \Omega_g), \quad \text{where } \Omega_g = \text{diag}(e^{h_1^{Goods}}, e^{h_2^{Goods}}, \dots, e^{h_T^{Goods}}) \quad (3)$$

where,

$$\begin{aligned}X_{vg} &= \text{diag}(\tilde{v}g_1, \dots, \tilde{v}g_T) \\ N^{\alpha g} &= (\tilde{\pi}_1^G, \dots, \tilde{\pi}_T^G)'\end{aligned}$$

Ignoring any terms not involving α^S , the likelihood is

$$\log p(\pi^G | \alpha^G, \bullet) \propto -\frac{1}{2}(N^{\alpha g} - X_{vg}\alpha^G)' \Omega_g^{-1} (N^{\alpha g} - X_{vg}\alpha^G)$$

The second source comes from the state equation for α^G . We rewrite it in a matrix notation as follows,

$$H\alpha^G = \varepsilon^{\alpha g} \quad \varepsilon^{\alpha g} \sim N(0, \Omega_{\alpha g}), \quad \text{where } \Omega_{\alpha g} = \text{diag}(\omega_{\alpha g}^2, \sigma_{\alpha g}^2, \dots, \sigma_{\alpha g}^2) \quad (4)$$

Ignoring any terms not involving α^G , the prior density for α^G is given by

$$\log p(\alpha^G | \sigma_{\alpha g}^2, \Omega_{\alpha g}) \propto -\frac{1}{2}(\alpha^G)' H' \Omega_{\alpha g}^{-1} H (\alpha^G)$$

Combining the above two conditional densities we obtain,

$$\log p(\alpha^G | Y, \bullet) \propto -\frac{1}{2}(\alpha^G - \hat{\alpha}^G)' D_{\alpha g}^{-1} (\alpha^G - \hat{\alpha}^G)$$

where,

$$D_{\alpha g} = (H' \Omega_{\alpha g}^{-1} H + X_{vg}' \Omega_g^{-1} X_{vg})^{-1}$$

$$\hat{\alpha}^G = D_{\alpha g}(X'_{vg}\Omega_g^{-1}N^{\alpha g})$$

The candidate draws are sampled from $N(\hat{\alpha}^G, D_{\alpha g})$ using the precision-based algorithm.

Step 3. Derive the conditional distribution $p(\lambda|Y, \bullet)$

The information about λ comes from two sources. Below, we derive an expression for each of these two sources.

First, some notation,

$$\begin{aligned}\tilde{\pi}_t^S &= \pi_t^S - \tau_t^S \\ \tilde{u}_t &= U_t - U_t^* \\ \tilde{v}_t &= e^{h_t^{Ser}} - e^{\bar{h}_t^{Ser}} \\ NW &= (\tilde{\pi}_1^S - \alpha_1^S \tilde{v}_1, \dots, \tilde{\pi}_T^S - \alpha_T^S \tilde{v}_T)'\end{aligned}$$

The first source is the services inflation measurement equation. Rewrite it in a matrix notation,

$$NW = X_u \lambda + \varepsilon^S \quad \varepsilon^S \sim N(0, \Omega_s) \quad (5)$$

where,

$$X_u = \text{diag}(\tilde{u}_1, \dots, \tilde{u}_T)$$

Ignoring any terms not involving λ , the likelihood is

$$\log p(\pi^S | \lambda, \bullet) \propto -\frac{1}{2}(NW - X_u \lambda)' \Omega_s^{-1} (NW - X_u \lambda)$$

The second source comes from the state equation for λ . We rewrite it in a matrix notation as follows,

$$H\lambda = \varepsilon^\lambda \quad \varepsilon^\lambda \sim N(0, \Omega_\lambda), \quad \text{where } \Omega_\lambda = \text{diag}(\omega_\lambda^2, \sigma_\lambda^2, \dots, \sigma_\lambda^2) \quad (6)$$

$$-1 < \lambda_t < 0 \text{ for } t=1, \dots, T$$

Ignoring any terms not involving λ , the prior density for λ is given by

$$\log p(\lambda | \sigma_\lambda^2, \Omega_\lambda) \propto -\frac{1}{2}(\lambda)' H' \Omega_\lambda^{-1} H(\lambda) + g_\lambda(\lambda, \sigma_\lambda^2)$$

where,

$$g_\lambda(\lambda, \sigma_\lambda^2) = -\sum_{t=2}^T \log \left(\Phi \left(\frac{0 - \lambda_{t-1}}{\sigma_\lambda} \right) - \Phi \left(\frac{-1 - \lambda_{t-1}}{\sigma_\lambda} \right) \right)$$

Combining the above two conditional densities we obtain,

$$\log p(\lambda | Y, \bullet) \propto -\frac{1}{2}(\lambda - \hat{\lambda})' D_\lambda^{-1} (\lambda - \hat{\lambda}) + g_\lambda(\lambda, \sigma_\lambda^2)$$

where,

$$D_\lambda = (H' \Omega_\lambda^{-1} H + X_u' \Omega_s^{-1} X_u)^{-1}$$

$$\hat{\lambda} = D_\lambda (X_u' \Omega_s^{-1} N W)$$

The addition of the term $g_\lambda(\lambda, \sigma_\lambda^2)$ leads to a non-standard density. Accordingly, we sample λ using an independence-chain Metropolis-Hastings (MH) procedure. This involves first generating candidate draws from $N(\hat{\lambda}, D_\lambda)$ using the precision-based algorithm that are then accepted or rejected based on the accept-reject Metropolis-Hastings (ARMH) algorithm (discussed in Chan and Strachan, 2012).

Step 4. Derive the conditional distribution $p(\tau^S | Y, \bullet)$

The information about τ^S comes from three sources. Below, we derive an expression for each of these sources.

The first source is the services inflation measurement equation. Rewrite it in a matrix notation as,

$$\pi^S = \Phi_{\tau^S} + \tau^S + \varepsilon^S \quad \varepsilon^S \sim N(0, \Omega_S), \quad \text{where } \Omega_S = \text{diag}(e^{h_1^{Ser}}, e^{h_2^{Ser}}, \dots, e^{h_T^{Ser}}) \quad (7)$$

$$\text{where, } \Phi_{\tau^S} = \begin{pmatrix} \lambda_1(U_1 - U_1^*) + \alpha_1^S(e^{h_1^{Ser}} - e^{\bar{h}_1^{Ser}}) \\ \lambda_1(U_2 - U_2^*) + \alpha_2^S(e^{h_2^{Ser}} - e^{\bar{h}_2^{Ser}}) \\ \vdots \\ \lambda_1(U_T - U_T^*) + \alpha_T^S(e^{h_T^{Ser}} - e^{\bar{h}_T^{Ser}}) \end{pmatrix},$$

The likelihood is

$$\log p(\pi^S | U, U^*, \bullet) \propto -\frac{1}{2} \iota_T h^{Ser} - \frac{1}{2} (\pi^S - \Phi_{\tau^S})' \Omega_S^{-1} (\pi^S - \Phi_{\tau^S})$$

where ι_T is a $T \times 1$ column vector of ones.

The second source of information is from the state equation of τ^S . Rewrite it in a matrix notation,

$$H\tau^S = \mu_s + \varepsilon^{\tau^S} \quad \varepsilon^{\tau^S} \sim N(0, \Omega_{\tau^S}), \quad \text{where } \Omega_{\tau^S} = \text{diag}(\omega_{\tau^S}^2, e^{h_1^{\tau^S}}, \dots, e^{h_{T-1}^{\tau^S}}) \quad (8)$$

$$\text{where, } \mu_s = \begin{pmatrix} \tau_0^S \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

That is, the prior density for τ^S is given by

$$p(\tau^S | h^{\tau^S}) \propto -\frac{1}{2} (\tau^S - H^{-1}\mu_s)' H' \Omega_{\tau^S}^{-1} H (\tau^S - H^{-1}\mu_s)$$

The third source of information comes from the measurement equation that links surveys to τ^* . Rewrite the equation in a matrix notation,

$$F^{\pi^S} = \beta^\pi \tau^S + \varepsilon^{z\pi} \quad \varepsilon^{z\pi} \sim N(0, \Omega_{z\pi}) \quad (9)$$

where,

$$f_t^{\pi^S} = \frac{Z_t^\pi - C^\pi - \beta^\pi (w_t^G \tau^G)}{w_t^S}$$

$$F^{\pi^S} = (f_1^{\pi^S}, f_2^{\pi^S}, \dots, f_T^{\pi^S})'$$

$$\Omega_{z\pi} = \text{diag}(\sigma_{z\pi}^2, \dots, \sigma_{z\pi}^2)$$

Ignoring any terms not involving τ^S , we have

$$\log p(Z^\pi | \tau^S, \bullet) \propto -\frac{1}{2} (F^{\pi^S} - \beta^\pi \tau^S)' \Omega_{z\pi}^{-1} (F^{\pi^S} - \beta^\pi \tau^S)$$

Combining the above three conditional densities we obtain,

$$\log p(\tau^S|Y, \bullet) \propto -\frac{1}{2}(\tau^S - \hat{\tau}^S)' D_{\tau^S}^{-1}(\tau^S - \hat{\tau}^S)$$

where,

$$D_{\tau^S} = (\Omega_s^{-1} + H' \Omega_{\tau^S}^{-1} H + (\beta^\pi)^2 \Omega_{z^\pi}^{-1})^{-1}$$

$$\hat{\tau}^S = D_{\tau^S}(\Omega_s^{-1}(\pi^S - \Phi_{\tau^S}) + H' \Omega_{\tau^S}^{-1} \mu_s + \beta^\pi \Omega_{z^\pi}^{-1} F \pi^s)$$

The candidate draws are sampled from $N(\hat{\tau}^S, D_{\tau^S})$ using the precision-based algorithm.

Step 5. Derive the conditional distribution $p(\tau^G|Y, \bullet)$

The information about τ^G comes from three sources. Below, we derive an expression for each of these sources.

The first source is the services inflation measurement equation. Rewrite it in a matrix notation as,

$$\pi^S = \Phi_{\tau^G} + \tau^G + \varepsilon^G \quad \varepsilon^G \sim N(0, \Omega_G), \quad \text{where } \Omega_G = \text{diag}(e^{h_1^{Goods}}, e^{h_2^{Goods}}, \dots, e^{h_T^{Goods}}) \quad (10)$$

$$\text{where, } \Phi_{\tau^G} = \begin{pmatrix} \alpha_1^G (e^{h_1^{Goods}} - e^{\bar{h}_1^{Goods}}) \\ \alpha_2^G (e^{h_2^{Goods}} - e^{\bar{h}_2^{Goods}}) \\ \vdots \\ \alpha_T^G (e^{h_T^{Goods}} - e^{\bar{h}_T^{Goods}}) \end{pmatrix},$$

The likelihood is

$$\log p(\pi^G|U, U^*, \bullet) \propto -\frac{1}{2} \iota_T' h^{Goods} - \frac{1}{2} (\pi^G - \Phi_{\tau^G})' \Omega_G^{-1} (\pi^G - \Phi_{\tau^G})$$

where ι_T is a $T \times 1$ column vector of ones.

The second source of information is from the state equation of τ^G . Rewrite it in a matrix notation,

$$H \tau^G = \mu_g + \varepsilon^{\tau^G} \quad \varepsilon^{\tau^G} \sim N(0, \Omega_{\tau^G}), \quad \text{where } \Omega_{\tau^G} = \text{diag}(\omega_{\tau^G}^2, e^{h_1^{\tau^G}}, \dots, e^{h_{T-1}^{\tau^G}}) \quad (11)$$

$$\text{where, } \mu_g = \begin{pmatrix} \tau_0^G \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

That is, the prior density for τ^G is given by

$$p(\tau^G | h^{\tau^G}) \propto -\frac{1}{2}(\tau^G - H^{-1}\mu_g)' H' \Omega_{\tau^G}^{-1} H (\tau^G - H^{-1}\mu_g)$$

The third source of information comes from the measurement equation that links surveys to τ^* . Rewrite the equation in a matrix notation,

$$F^{\pi g} = \beta^\pi \tau^G + \varepsilon^{z\pi} \quad \varepsilon^{z\pi} \sim N(0, \Omega_{z\pi}) \quad (12)$$

where,

$$f_t^{\pi g} = \frac{Z_t^\pi - C^\pi - \beta^\pi (w_t^S \tau^S)}{w_t^G}$$

$$F^{\pi g} = (f_1^{\pi g}, f_2^{\pi g}, \dots, f_T^{\pi g})'$$

$$\Omega_{z\pi} = \text{diag}(\sigma_{z\pi}^2, \dots, \sigma_{z\pi}^2)$$

Ignoring any terms not involving τ^G , we have

$$\log p(Z^\pi | \tau^G, \bullet) \propto -\frac{1}{2}(F^{\pi g} - \beta^\pi \tau^G)' \Omega_{z\pi}^{-1} (F^{\pi g} - \beta^\pi \tau^G)$$

Combining the above three conditional densities we obtain,

$$\log p(\tau^G | Y, \bullet) \propto -\frac{1}{2}(\tau^G - \hat{\tau}^G)' D_{\tau^G}^{-1} (\tau^G - \hat{\tau}^G)$$

where,

$$D_{\tau^G} = (\Omega_G^{-1} + H' \Omega_{\tau^G}^{-1} H + (\beta^\pi)^2 \Omega_{z\pi}^{-1})^{-1}$$

$$\hat{\tau}^G = D_{\tau^G} (\Omega_G^{-1} (\pi^G - \Phi_{\tau^G}) + H' \Omega_{\tau^G}^{-1} \mu_s + \beta^\pi \Omega_{z\pi}^{-1} F^{\pi g})$$

The candidate draws are sampled from $N(\hat{\tau}^G, D_{\tau^G})$ using the precision-based algorithm.

Step 6. Derive the conditional distribution $p(h^{Ser} | Y, \bullet)$

This is a high-dimensional and non-standard density. To derive the conditional density $p(h^{Ser}|Y, \bullet)$, we follow the steps detailed in Chan (2017).

a. Obtain the gradient and Hessian of the log-density $\log p(h^{Ser}|Y, \alpha^S, \sigma_{hs}^2, \bullet)$

According to the Bayes's theorem

$$\log p(h^{Ser}|Y, \alpha^S, \sigma_{hs}^2, h_0^{Ser}) \propto p(Y|\alpha^S, h^{Ser}) p(h^{Ser}|\sigma_{hs}^2, h_0^{Ser})$$

The prior density of h^{Ser} , $p(h^{Ser}|\sigma_{hs}^2, h_0^{Ser})$ is Gaussian with log-density

$$\log p(h^{Ser}|\sigma_{hs}^2, h_0^{Ser}) = \frac{-1}{2\sigma_{hs}^2} (h^{Ser'} H' H h^{Ser} - 2h^{Ser'} H' H h_0^{Ser} \iota_T) + c_1$$

where c_1 is a constant independent of h^{Ser} .

The gradient and Hessian of the above log conditional density is

$$\frac{d}{dh^{Ser}} \log p(h^{Ser}|\sigma_{hs}^2, h_0^{Ser}) = \frac{-1}{\sigma_{hs}^2} H' H (h^{Ser} - h_0^{Ser} \iota_T)$$

$$\frac{d^2}{dh^{Ser} dh^{Ser'}} \log p(h^{Ser}|\sigma_{hs}^2, h_0^{Ser}) = \frac{-1}{\sigma_{hs}^2} H' H$$

Next, let f and G denote, respectively, the gradient and the negative Hessian of $\log p(Y|\alpha^S, h^{Ser})$

$$f = \frac{d}{dh^{Ser}} \log p(Y|\alpha^S, h^{Ser})$$

$$G = \frac{d^2}{dh^{Ser} dh^{Ser'}} \log p(Y|\alpha^S, h^{Ser})$$

Note that the log conditional likelihood $\log p(Y|\alpha^S, h^{Ser})$ has the form $\log p(Y|\alpha^S, h^{Ser}) = \sum_{t=1}^T \log p(\pi_t^S|\alpha_t^S, h_t^{Ser})$.

The t -th element of f is simply $f_t = \frac{d \log p(\pi_t^S|\alpha_t^S, h_t^{Ser})}{dh_t^{Ser}}$

And the negative Hessian G is diagonal, where the t -th diagonal element is

$$G_t = \frac{-d^2 \log p(\pi_t^S|\alpha_t^S, h_t^{Ser})}{(dh_t^{Ser})^2}$$

Putting all these together, the gradient and Hessian of $\log p(h^{Ser}|Y, \alpha^S, \sigma_{hs}^2, h_0^{Ser})$ are

$$S(h^{Ser}) = \frac{d}{dh^{Ser}} \log p(h^{Ser}|Y, \alpha^S, \sigma_{hs}^2, h_0^{Ser}) = \frac{-1}{\sigma_{hs}^2} H' H (h^{Ser} - h_0^{Ser} \iota_T) + f$$

$$F(h^{Ser}) = \frac{d^2}{dh^{Ser} dh^{Ser'}} \log p(h^{Ser}|Y, \alpha^S, \sigma_{hs}^2, h_0^{Ser}) = -(\frac{1}{\sigma_{hs}^2} H' H + G)$$

Solve the above using the Newton-Raphson method:

1. Initialize the algorithm with $h^{Ser} = h^{Ser(1)}$ for some constant vector $h^{Ser(1)}$
2. For $t=1,2,\dots$, use $h^{Ser} = h^{Ser(t)}$ in the evaluation of $S(h^{Ser})$ and $F(h^{Ser})$, and compute the Newton-Raphson recursion $h^{Ser(t+1)} = h^{Ser(t)} - F(h^{Ser(t)})S(h^{Ser(t)})$
3. Repeat this procedure until some convergence criterion is reached, e.g., when $\|h^{Ser(t+1)} - h^{Ser(t)}\| < \epsilon$ for some prefixed tolerance level ϵ .

The convergence is very fast because the Hessian is globally negative definite.

Let \hat{h}^{Ser} be the mode obtained from the Newton-Raphson method and let K_{hs} denote the negative Hessian evaluated at the mode, i.e., $K_{hs} = \frac{H'H}{\sigma_{hs}^2} + G$

Then use $N(\hat{h}^{Ser}, K_{hs}^{-1})$ as the proposal density in an independence-chain MH step. Since the precision matrix is again a band matrix, we rely on the precision sampler to obtain candidate draws from $N(\hat{h}^{Ser}, K_{hs}^{-1})$ efficiently.

The candidate draw is then accepted with a probability, which is computed in the MH step.

Step 7. Derive the conditional distribution $p(h^{Goods}|Y, \bullet)$

Same procedure as discussed in the previous step, but applied to goods inflation.

Step 8. Derive the conditional distribution $p(h^{\tau S}|Y, \bullet)$

Following, Chan, Koop, and Potter (2013; 2016), we draw $h^{\tau S}$ using the accept-reject independence-chain Metropolis Hastings (ARMH) algorithm of Chan and Strachan (2012; page 32-34).

Step 9. Derive the conditional distribution $p(h^{\tau G}|Y, \bullet)$

As done in the previous step, we follow Chan, Koop, and Potter (2013; 2016) to draw $h^{\tau G}$ using the accept-reject independence-chain Metropolis Hastings (ARMH) algorithm of Chan and Strachan (2012; page 32-34).

Step 10. Derive the conditional distribution $p(C^\pi|Y, \bullet)$

The information about C^π comes from two sources. Below, we derive an expression for each of these two sources.

The first source is the measurement equation linking survey to τ^* . Rewrite it in a matrix notation,

$$N^{z\pi} = C^\pi + \varepsilon^{z\pi} \quad \varepsilon^{z\pi} \sim N(0, \Omega_{z\pi}) \quad (13)$$

where,

$$\begin{aligned} n_t^{z\pi} &= Z_t^\pi - \beta^\pi \tau^* \\ N^{z\pi} &= (n_1^{z\pi}, n_2^{z\pi}, \dots, n_T^{z\pi})' \\ \Omega_{z\pi} &= \text{diag}(\sigma_{z\pi}^2, \dots, \sigma_{z\pi}^2) \end{aligned}$$

Ignoring any terms not involving C^π , the likelihood is

$$\log p(Z^\pi|C^\pi, \bullet) \propto -\frac{1}{2}(N^{z\pi} - C^\pi)' \Omega_{z\pi}^{-1} (N^{z\pi} - C^\pi)$$

The second source comes from the state equation for C^π . We rewrite it in a matrix notation as follows,

$$HC^\pi = \mu_{c\pi} + \varepsilon^{c\pi} \quad \varepsilon^{c\pi} \sim N(0, \Omega_{c\pi}), \quad \text{where } \Omega_{c\pi} = \text{diag}(\omega_{c\pi}^2, \sigma_{c\pi}^2, \dots, \sigma_{c\pi}^2) \quad (14)$$

where,

$$\mu_{c\pi} = \begin{pmatrix} C_0^\pi \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

Ignoring any terms not involving C^π , the prior density for C^π is given by

$$\log p(C^\pi | \sigma_{c\pi}^2, \Omega_{c\pi}) \propto -\frac{1}{2}(C^\pi - H^{-1}\mu_{c\pi})' H' \Omega_{c\pi}^{-1} H (C^\pi - H^{-1}\mu_{c\pi})$$

Combining the above two conditional densities we obtain,

$$\log p(C^\pi | Y, \bullet) \propto -\frac{1}{2}(C^\pi - \hat{C}^\pi)' D_{C^\pi}^{-1} (C^\pi - \hat{C}^\pi)$$

where,

$$D_{C^\pi} = (H' \Omega_{c\pi}^{-1} H + \Omega_{z\pi}^{-1})^{-1}$$

$$\hat{C}^\pi = D_{C^\pi} (H' \Omega_{c\pi}^{-1} \mu_{c\pi} + \Omega_{z\pi}^{-1} N^{z\pi})$$

The candidate draws are sampled from $N(\hat{C}^\pi, D_{C^\pi})$ using the precision-based algorithm.

Step 11. Derive the conditional distribution $p(\theta|Y, \bullet)$

There are 10 parameters in the vector θ . These parameters are drawn in 10 separate blocks using standard regression procedures.

Substep 11.1 Derive the conditional distribution $p(\beta^\pi|Y, \bullet)$

Candidate draws are sampled from $N(\hat{\beta}^\pi, D_{\beta\pi})$ using the precision-based algorithm.

where,

$$D_{\beta\pi} = (V_{\beta\pi}^{-1} + X^{z\pi'} \Omega_{z\pi}^{-1} X^{z\pi})^{-1}$$

$$\hat{\beta}^\pi = D_{\beta\pi} (V_{\beta\pi}^{-1} \beta_0^\pi + X^{z\pi'} \Omega_{z\pi}^{-1} J^{z\pi})$$

$$\begin{aligned}
j_t^{z\pi} &= Z_t^\pi - C_t^\pi \\
J^{z\pi} &= (j_1^{z\pi}, \dots, j_T^{z\pi})' \\
x_t^{z\pi} &= w_t^S \tau_t^S + w_t^G \tau_t^G \\
X^{z\pi} &= (x_1^{z\pi}, \dots, x_T^{z\pi})'
\end{aligned}$$

$V_{\beta^\pi}^{-1}$ is the prior variance and β_0^π is the prior mean for β^π

Substep 11.2 Derive the conditional distribution $p(\sigma_{c\pi}^2|Y, \bullet)$

$p(\sigma_{c\pi}^2|Y, \bullet)$ is a standard inverse-Gamma density,

Candidate draws are sampled from

$$p(\sigma_{c\pi}^2|Y, \bullet) \sim IG(\nu_{c\pi 0} + \frac{T-1}{2}, S_{c\pi 0} + \frac{1}{2} \sum_{t=2}^T (C_t^\pi - C_{t-1}^\pi)^2)$$

Substep 11.3 Derive the conditional distribution $p(\sigma_{z\pi}^2|Y, \bullet)$

$p(\sigma_{z\pi}^2|Y, \bullet)$ is a standard inverse-Gamma density,

Candidate draws are sampled from

$$p(\sigma_{z\pi}^2|Y, \bullet) \sim IG(\nu_{z\pi 0} + \frac{T}{2}, S_{z\pi 0} + \frac{1}{2} \sum_{t=1}^T (Z_t^\pi - C_t^\pi - \beta^\pi \tau_t^*)^2)$$

Substep 11.4 Derive the conditional distribution $p(\sigma_{\alpha s}^2|Y, \bullet)$

$p(\sigma_{\alpha s}^2|Y, \bullet)$ is a standard inverse-Gamma density,

Candidate draws are sampled from

$$p(\sigma_{\alpha s}^2|Y, \bullet) \sim IG(\nu_{\alpha s 0} + \frac{T-1}{2}, S_{\alpha s 0} + \frac{1}{2} \sum_{t=2}^T (\alpha_t^S - \alpha_{t-1}^S)^2)$$

Substep 11.5 Derive the conditional distribution $p(\sigma_{\alpha G}^2|Y, \bullet)$

$p(\sigma_{\alpha G}^2|Y, \bullet)$ is a standard inverse-Gamma density,

Candidate draws are sampled from

$$p(\sigma_{\alpha G}^2|Y, \bullet) \sim IG(\nu_{\alpha g0} + \frac{T-1}{2}, S_{\alpha g0} + \frac{1}{2} \sum_{t=2}^T (\alpha_t^G - \alpha_{t-1}^G)^2)$$

Substep 11.6 Derive the conditional distribution $p(\sigma_{hs}^2|Y, \bullet)$

$p(\sigma_{hs}^2|Y, \bullet)$ is a standard inverse-Gamma density,

Candidate draws are sampled from

$$p(\sigma_{hs}^2|Y, \bullet) \sim IG(\nu_{hs0} + \frac{T-1}{2}, S_{hs0} + \frac{1}{2} \sum_{t=2}^T (h_t^{Ser} - h_{t-1}^{Ser})^2)$$

Substep 11.7 Derive the conditional distribution $p(\sigma_{hG}^2|Y, \bullet)$

$p(\sigma_{hG}^2|Y, \bullet)$ is a standard inverse-Gamma density,

Candidate draws are sampled from

$$p(\sigma_{hG}^2|Y, \bullet) \sim IG(\nu_{hg0} + \frac{T-1}{2}, S_{hg0} + \frac{1}{2} \sum_{t=2}^T (h_t^{Goods} - h_{t-1}^{Goods})^2)$$

Substep 11.8 Derive the conditional distribution $p(\sigma_{h\tau s}^2|Y, \bullet)$

$p(\sigma_{h\tau s}^2|Y, \bullet)$ is a standard inverse-Gamma density,

Candidate draws are sampled from

$$p(\sigma_{h\tau s}^2|Y, \bullet) \sim IG(\nu_{h\tau s0} + \frac{T-1}{2}, S_{h\tau s0} + \frac{1}{2} \sum_{t=2}^T (h_t^{\tau S} - h_{t-1}^{\tau S})^2)$$

Substep 11.9 Derive the conditional distribution $p(\sigma_{h\tau G}^2|Y, \bullet)$

$p(\sigma_{h\tau G}^2|Y, \bullet)$ is a standard inverse-Gamma density,

Candidate draws are sampled from

$$p(\sigma_{h\tau G}^2|Y, \bullet) \sim IG(\nu_{h\tau g0} + \frac{T-1}{2}, S_{h\tau g0} + \frac{1}{2} \sum_{t=2}^T (h_t^{\tau G} - h_{t-1}^{\tau G})^2)$$

Substep 11.10 Derive the conditional distribution $p(\sigma_\lambda^2|Y, \bullet)$

$p(\sigma_\lambda^2|Y, \bullet)$ is a non-standard density because of the constraints on λ ,

$$\log p(\sigma_\lambda^2|Y, \bullet) \propto -(\nu_{\lambda 0} + 1) \log \sigma_\lambda^2 - \frac{S_{\lambda 0}}{\sigma_\lambda^2} - \frac{T-1}{2} \log \sigma_\lambda^2 - \frac{1}{2\sigma_\lambda^2} \sum_{t=2}^T (\lambda_t - \lambda_{t-1})^2 + g_\lambda(\lambda, \sigma_\lambda^2)$$

The candidate draws from $p(\sigma_\lambda^2|Y, \bullet)$ are obtained via the MH step with the proposal density $IG(\nu_{\lambda 0} + \frac{T-1}{2}, S_{\lambda 0} + \frac{1}{2} \sum_{t=2}^T (\lambda_t - \lambda_{t-1})^2)$

A3. MCMC Convergence Diagnostics

This section documents the diagnostic properties of the Base model’s MCMC algorithm. Following Koop, Leon-Gonzalez, and Strachan (2010), among others, we report the autocorrelation functions of the posterior draws (10th and 50th order sample autocorrelation), inefficiency factors (IFs), and convergence diagnostic (CD) of Geweke (1992) of the model parameters.¹

One of the most common metrics examined to assess the efficiency of the MCMC sampler is to look at the autocorrelation function of the draws, which indicates how well the chain is mixing. Low autocorrelations are preferred to higher because the lower the autocorrelation, the closer the draws are to being independent and the higher the efficiency of the algorithm. The plots shown in the left panels of Figures 1,...,5 correspond to the 10th and 50th order autocorrelations in the draws, and as can be seen, they indicate very low autocorrelation. In the case of the 50th order autocorrelation, most indicate correlation less than 0.1, and in the case of 10th order except for a few, most indicate correlation below 0.3.

To assess whether the MCMC sampler has converged, a rough rule of thumb is to look at the CDs and see whether 95% of them are less than 2. If they are, then convergence is likely achieved. Based on the plots in the right panels of Figures 1,...,5, majority of CDs are within +/- 2.

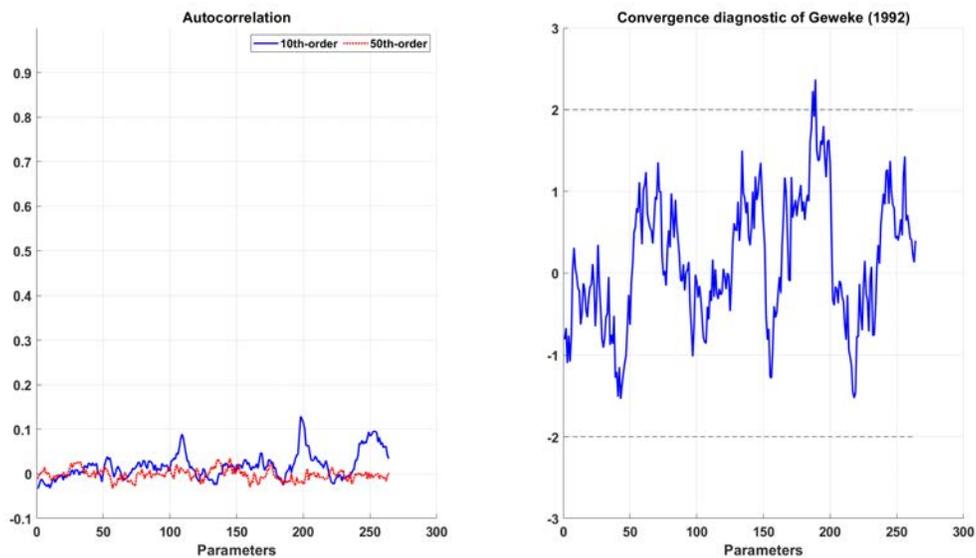
The inefficiency factor related to the autocorrelation functions is the inverse of Geweke’s (1992) relative numerical efficiency measure (RNE). It is computed using the following formula, $(1 + 2 \sum_{i=1}^{\infty} \rho_i)$, where ρ_i refers to the $k - th$ order autocorrelation of the chain. Figure 6 plots the IF for all the model parameters of the Baseline model. The values lower than or close to 20 are considered desirable. As shown, most of the IFs are below 20. (Note: IFs are computed using the default setting in LeSage’s toolbox: estimation of spectral density at frequency zero uses a tapered window of 4%.)

Overall, these diagnostic measures suggest good convergence properties of the MCMC algorithm developed for the Baseline model.

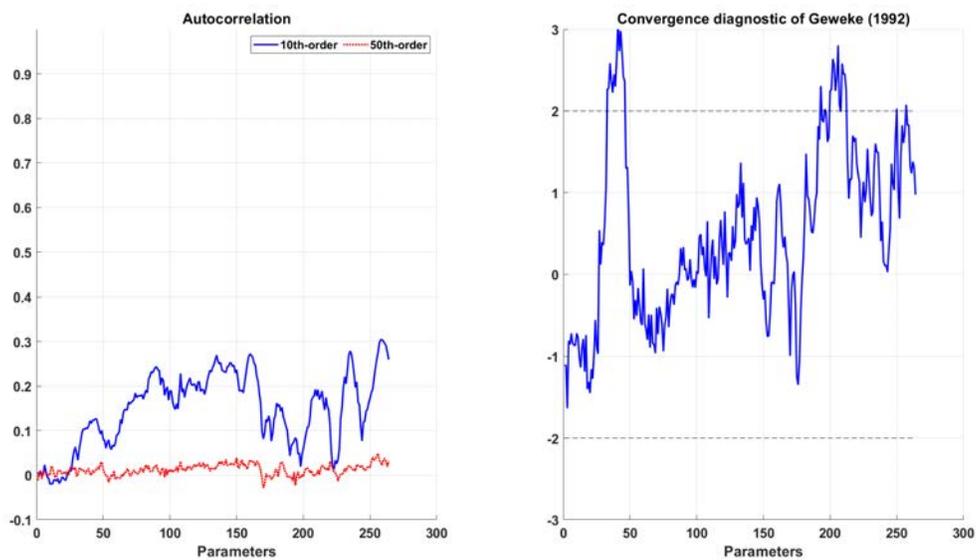
¹In computing some of these metrics, we have benefitted from the Matlab toolbox developed by James P. LeSage. A detailed explanation, including intuition for these convergence diagnostics, is provided in Koop (2003; page 67-68) and Chan et al. (2019; page 209).

Figure 1: MCMC Diagnostics: Autocorrelation and CDs

SV parameter: h^{Ser}



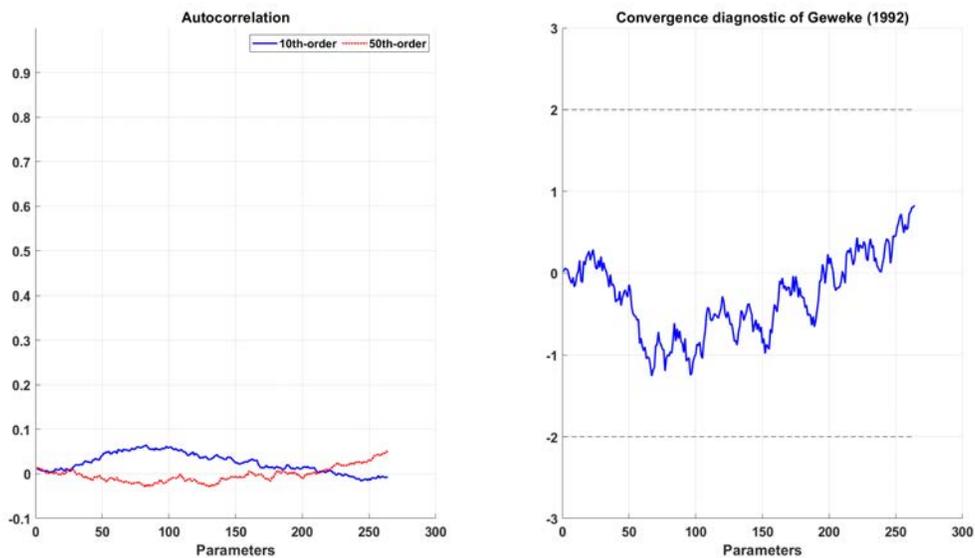
SV parameter: h^{Goods}



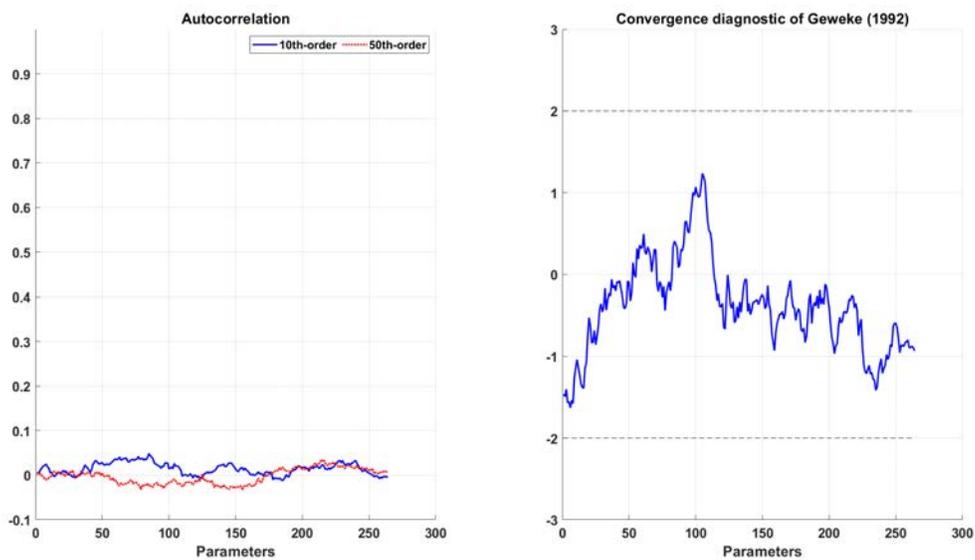
Note: Diagnostics based on estimating data from 1959Q3 through 2025Q2.

Figure 2: MCMC Diagnostics: Autocorrelation and CDs

SV parameter: $h^{\tau S}$



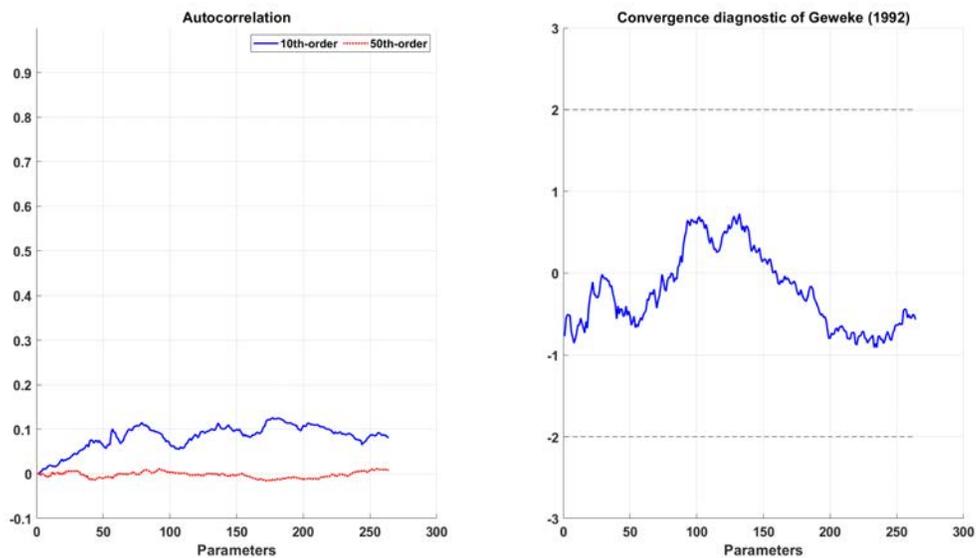
SV parameter: $h^{\tau G}$



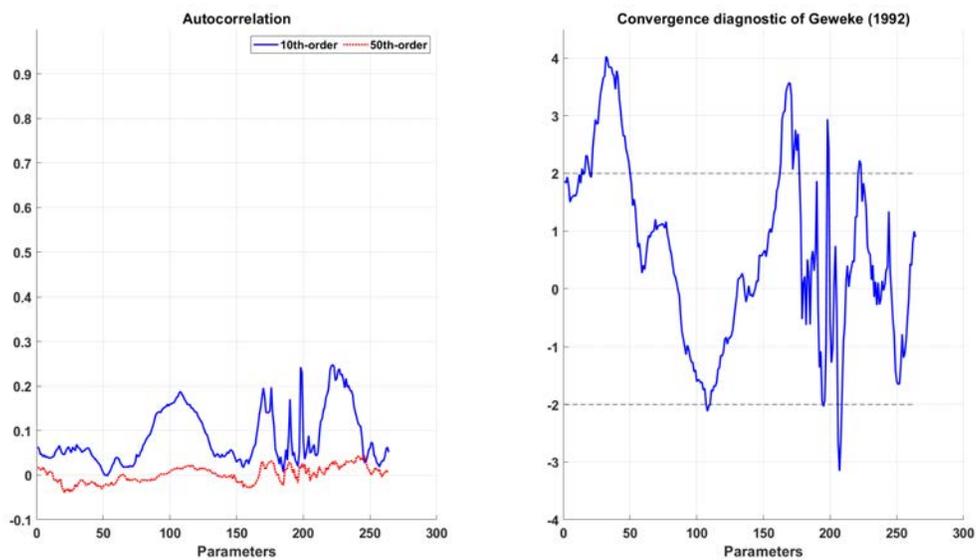
Note: Diagnostics based on estimating data from 1959Q3 through 2025Q2.

Figure 3: MCMC Diagnostics: Autocorrelation and CDs

TVP parameter: α^S



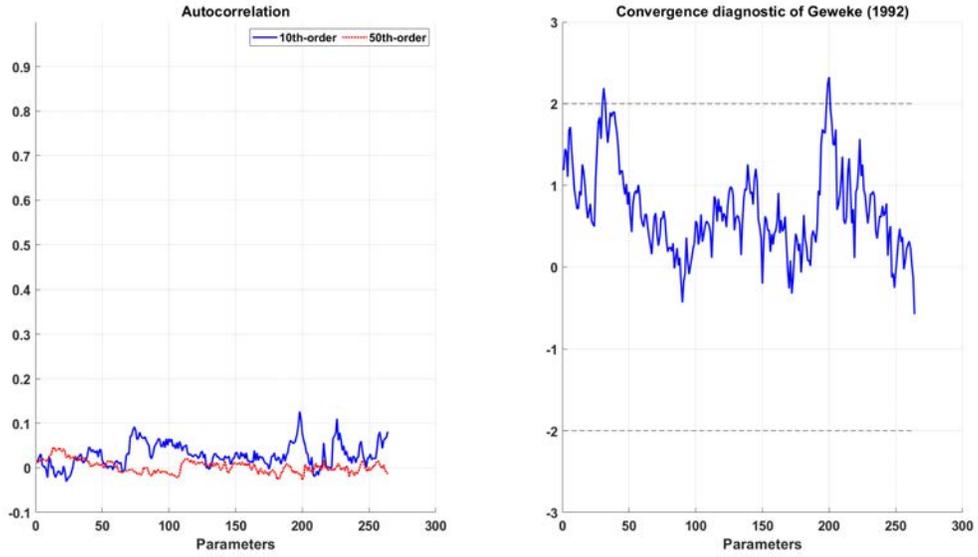
TVP parameter: α^G



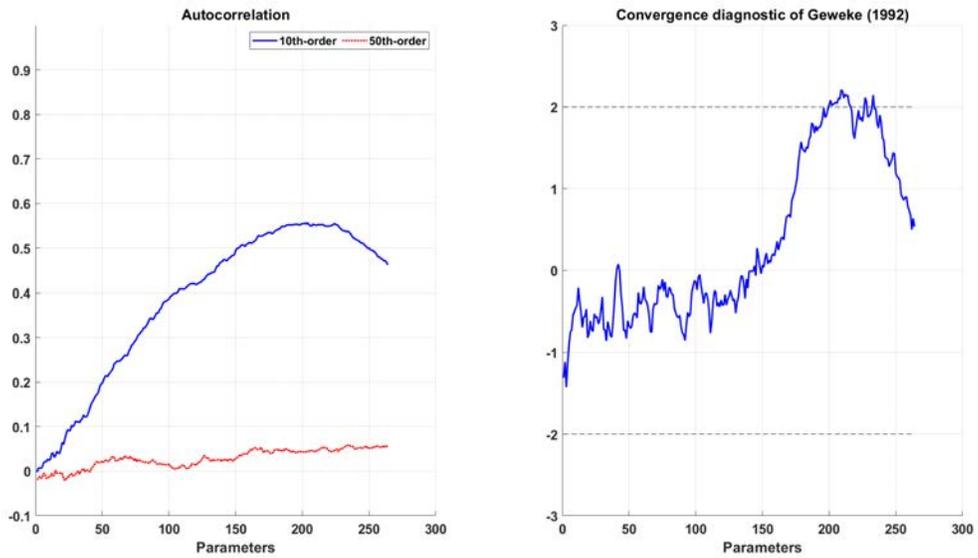
Note: Diagnostics based on estimating data from 1959Q3 through 2025Q2.

Figure 4: MCMC Diagnostics: Autocorrelation and CDs

TVP parameter: λ



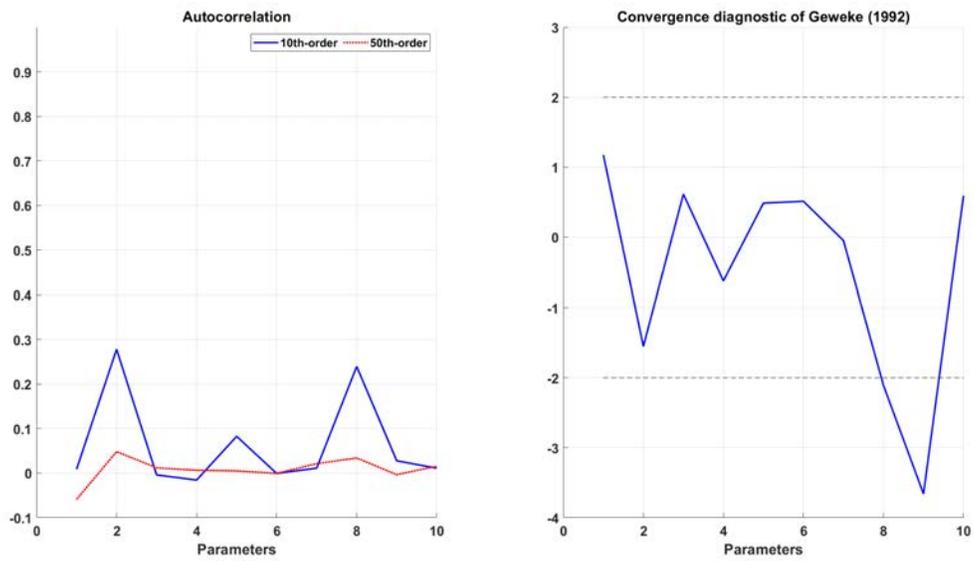
TVP parameter: C^π



Note: Diagnostics based on estimating data from 1959Q3 through 2025Q2.

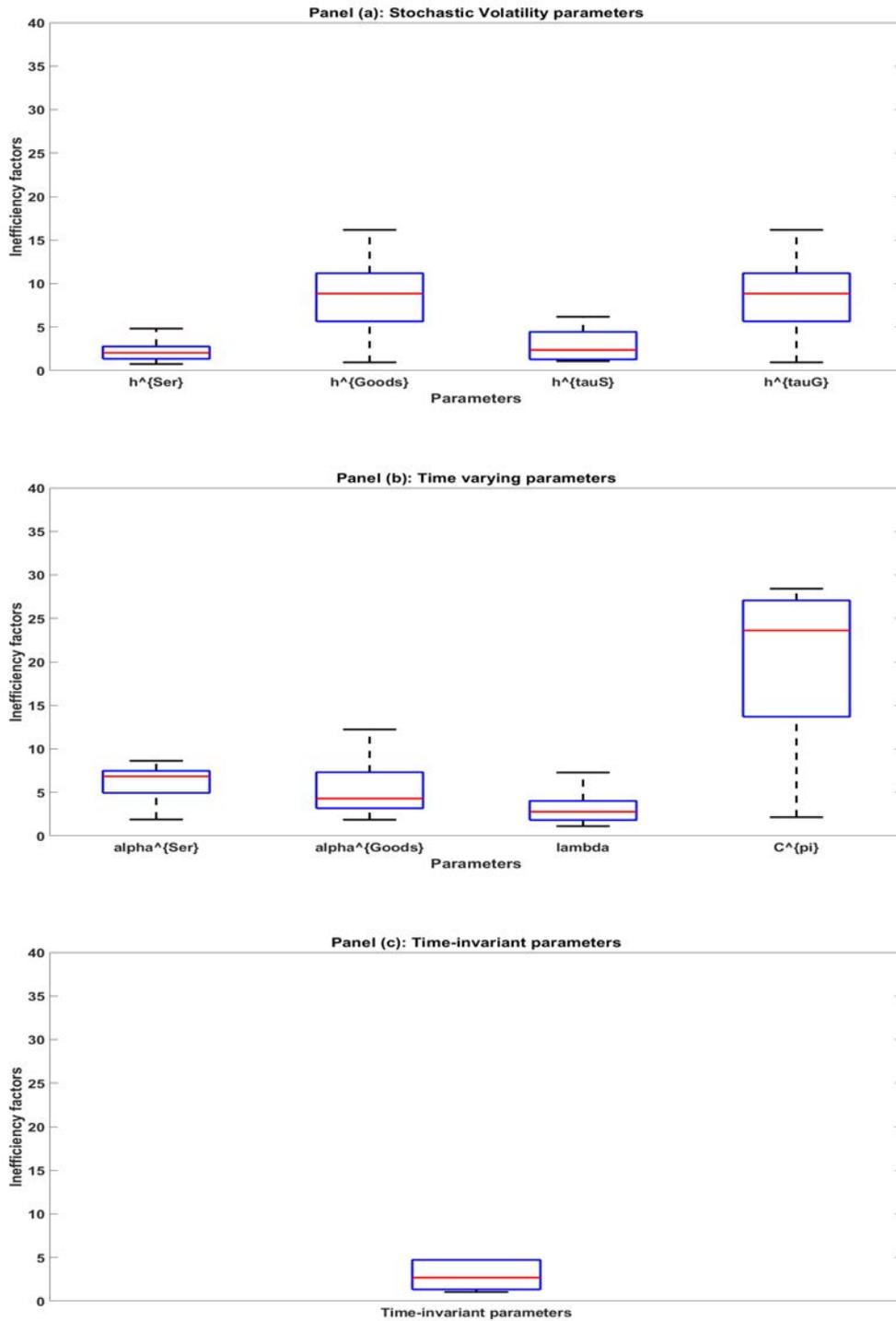
Figure 5: MCMC Diagnostics: Autocorrelation and CDs

Time-invariant parameters



Note: Diagnostics based on estimating data from 1959Q3 through 2025Q2.

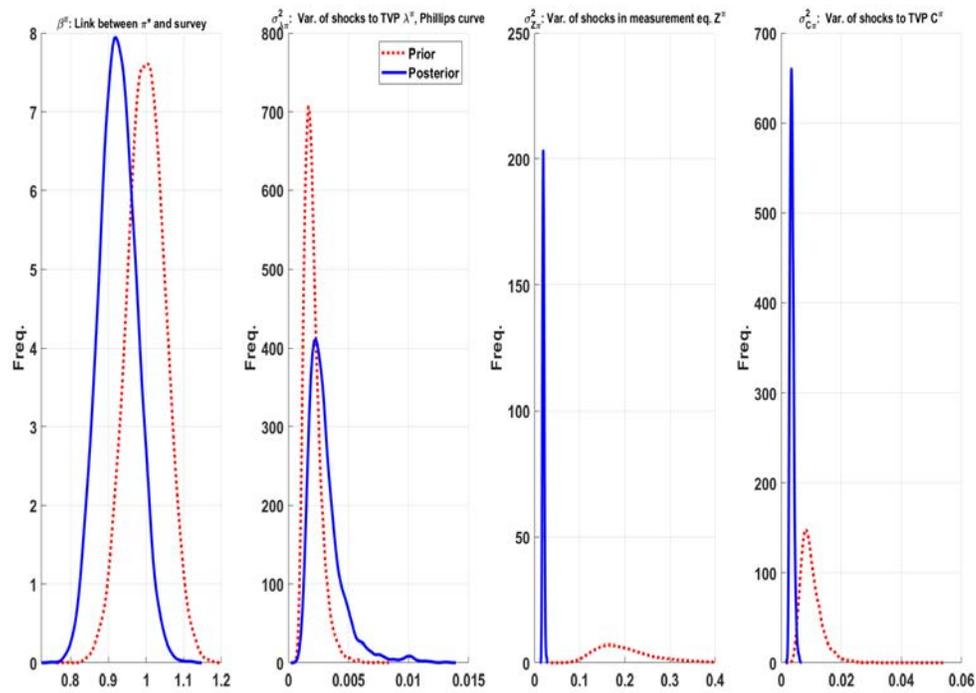
Figure 6: MCMC Diagnostics: Inefficiency Factors



Note: Diagnostics based on estimating data from 1959Q3 through 2025Q2. The red line represents the median, the lower and upper lines represent the 25th and 75th percentiles, respectively. The whiskers extend to the maximum and minimum.

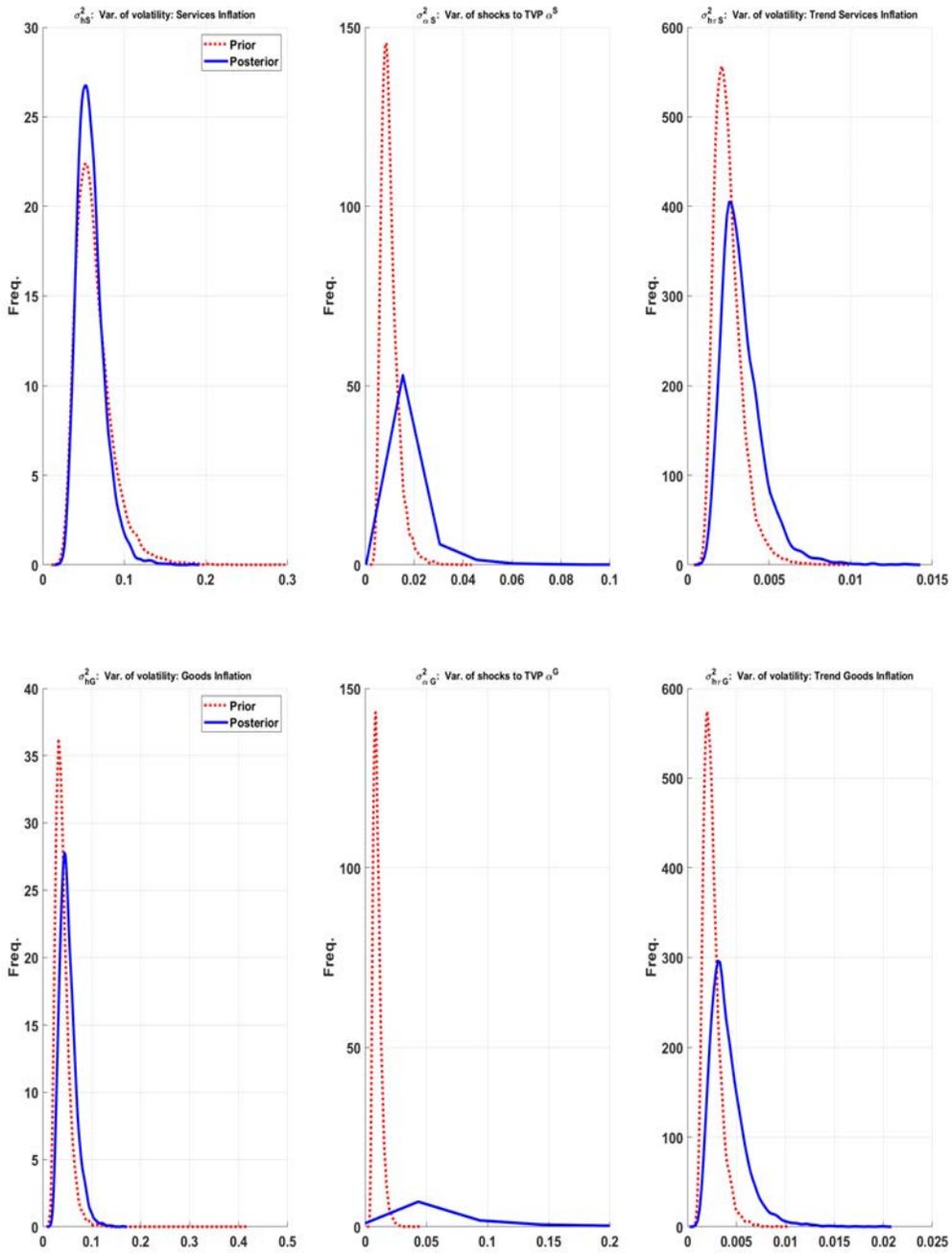
A4. Prior and Posterior Distributions of the Parameters: Baseline Model

Figure 7: Prior and Posterior Distributions of the Parameters: Baseline Model



Note: Plotted in dotted red lines are the prior distributions, in blue are the posterior distributions based on estimating data from 1959Q3 through 2025Q2.

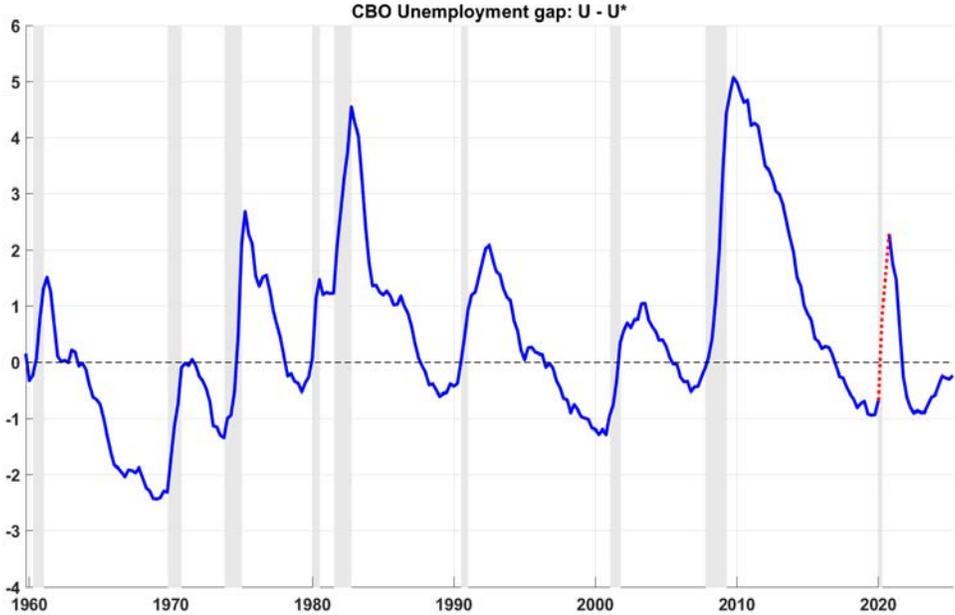
Figure 8: Prior and Posterior Distributions of the Parameters: Baseline Model



Note: Plotted in dotted red lines are the prior distributions, in blue are the posterior distributions based on estimating data from 1959Q3 through 2025Q2.

A5. CBO Unemployment Rate Gap

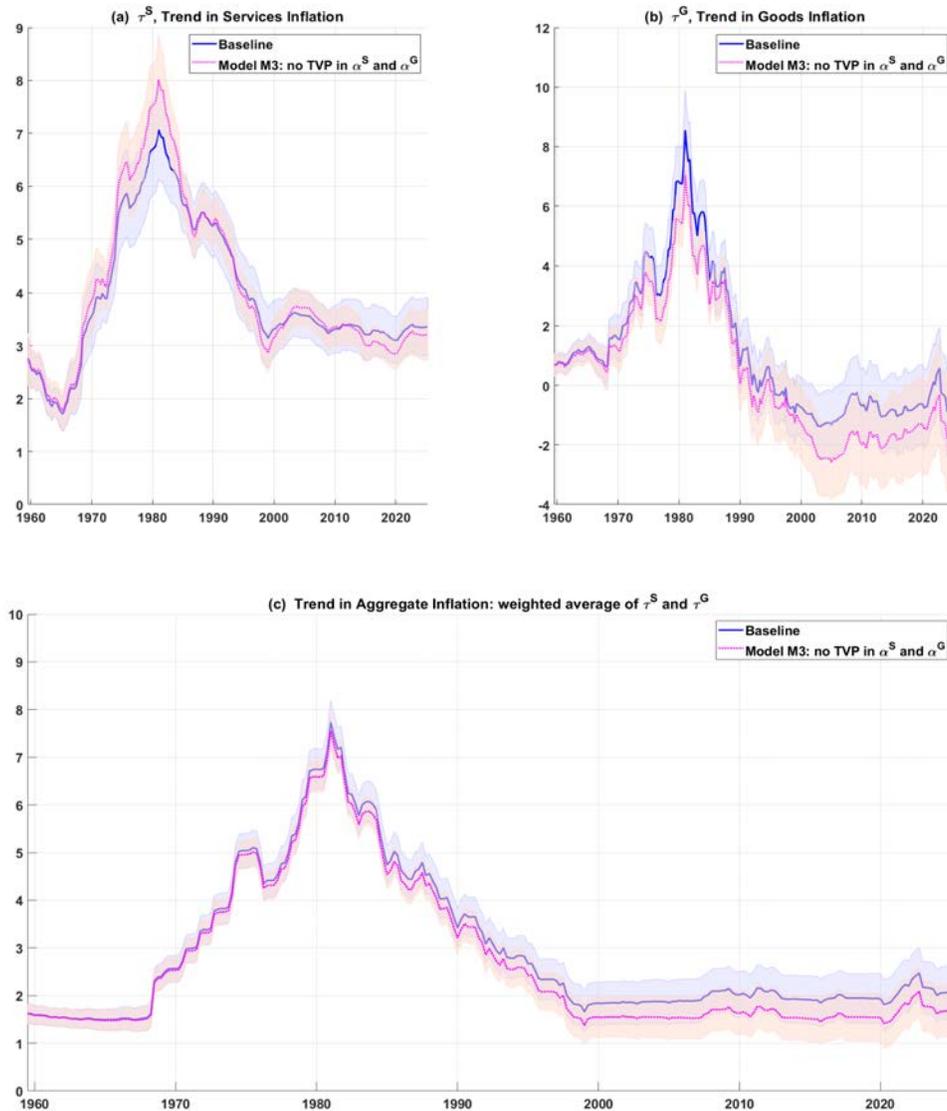
Figure 9: Congressional Budget Office estimate of the Unemployment Gap



Note: The plot in blue represents the Congressional Budget Office (CBO) estimate of the Unemployment gap, defined as the difference between the unemployment rate and the CBO estimate of the natural rate of unemployment. The plot in red represents the inferred value of the unemployment gap for 2020Q2 and 2020Q3, the COVID-pandemic quarters; the inferred value for 2020Q2 is based on averaging the actual unemployment gap values for 2020Q1 and 2020Q4, and for 2020Q3 is based on averaging the inferred 2020Q2 value and the actual 2020Q4 value. The shaded bars represent the NBER-defined recession bars.

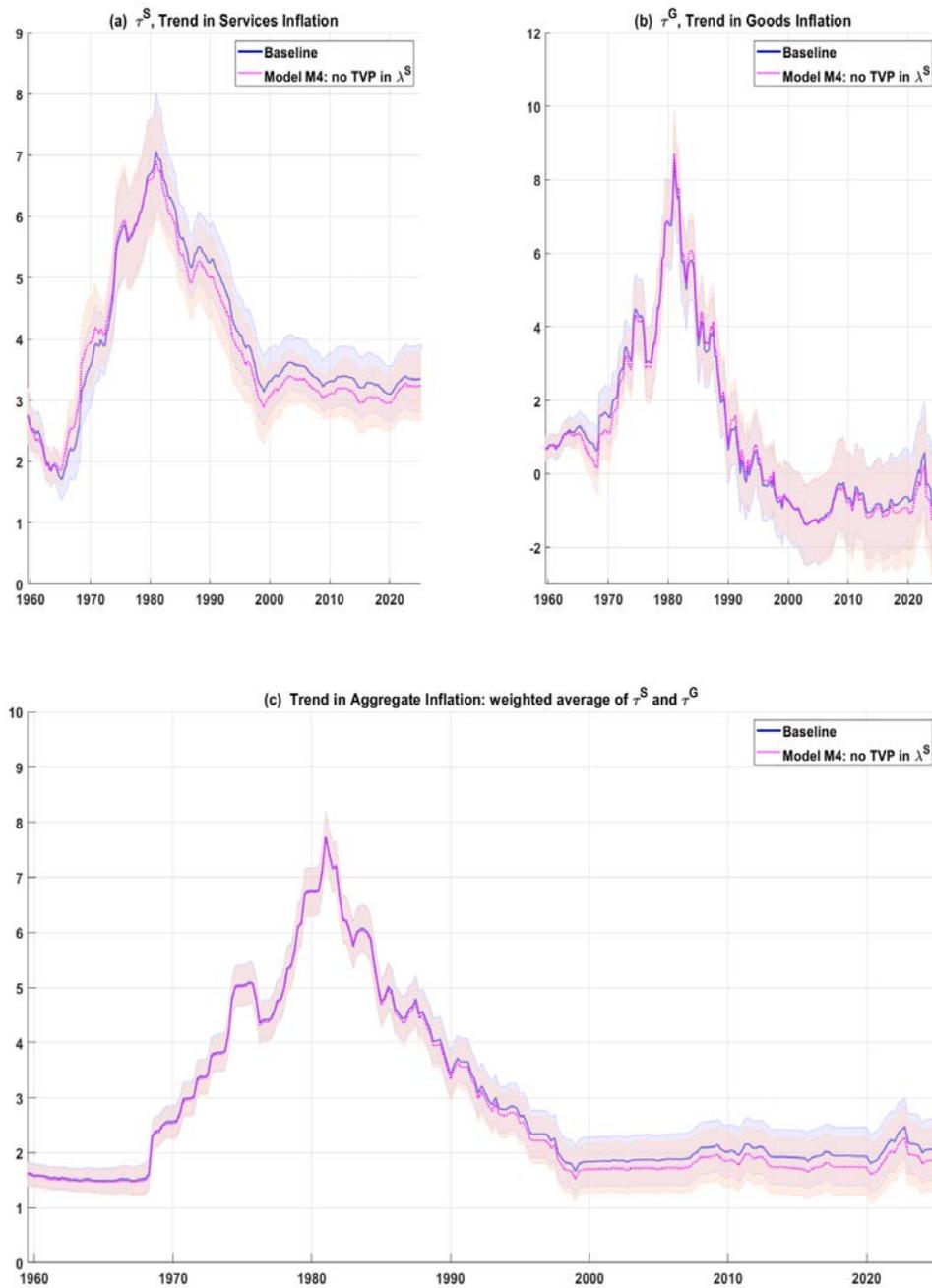
A6. Trend Estimates: Sensitivity to Modeling Assumptions

Figure 10: Trend Inflation: Baseline vs. Variant with time-invariant Uncertainty effects



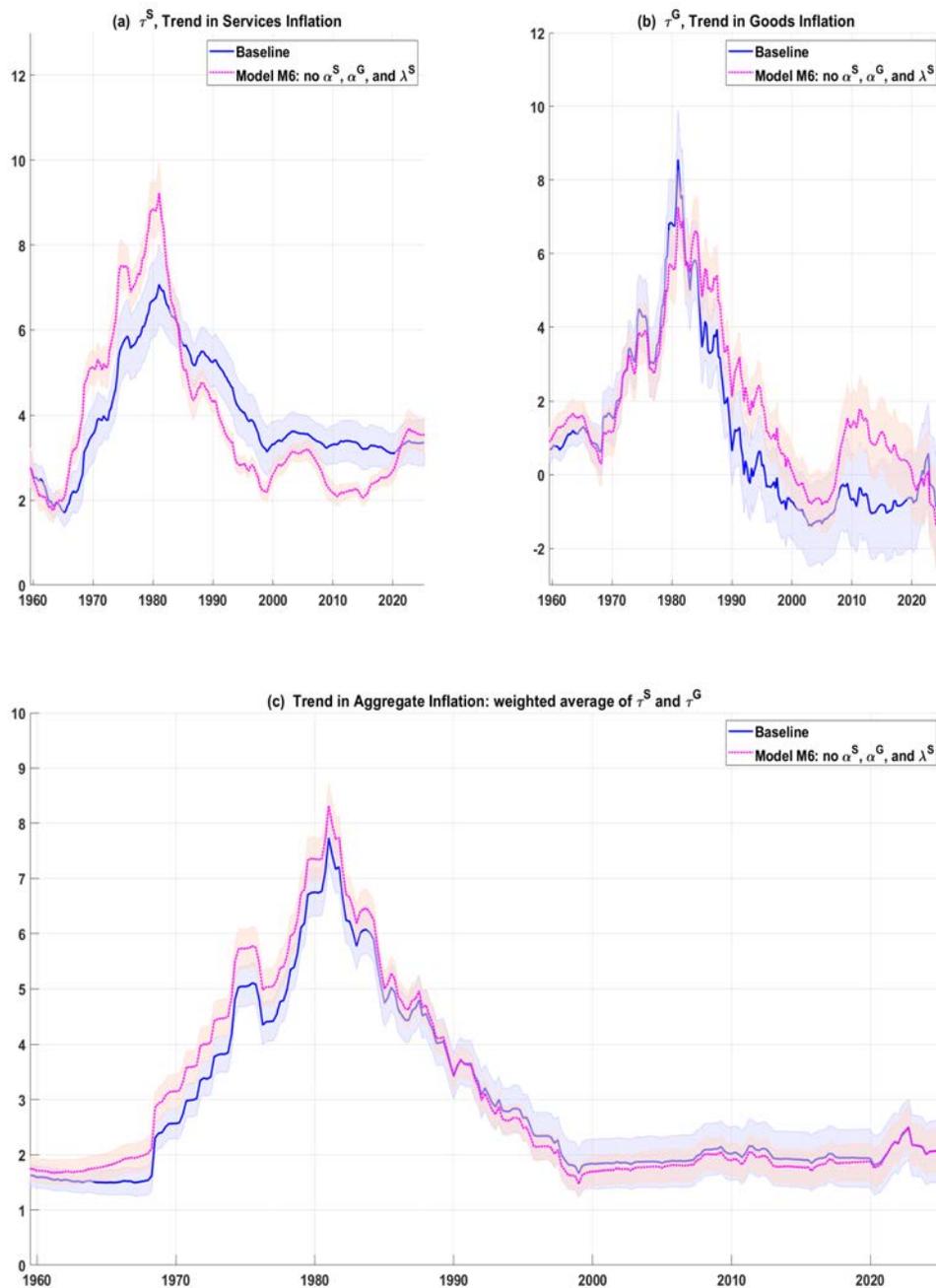
Note: The posterior estimates are based on the full sample (from 1959Q3 through 2025Q2). The shaded area represents the 68% posterior coverage interval. Panel (a), posterior estimates of the trend in services PCE inflation. Panel (b), posterior estimates of the trend in goods PCE inflation. Panel (c), posterior estimates of the trend in aggregate PCE inflation, constructed as a weighted average of the trends in services and goods PCE inflation.

Figure 11: Trend Inflation: Baseline vs. Variant with time-invariant Phillips curve



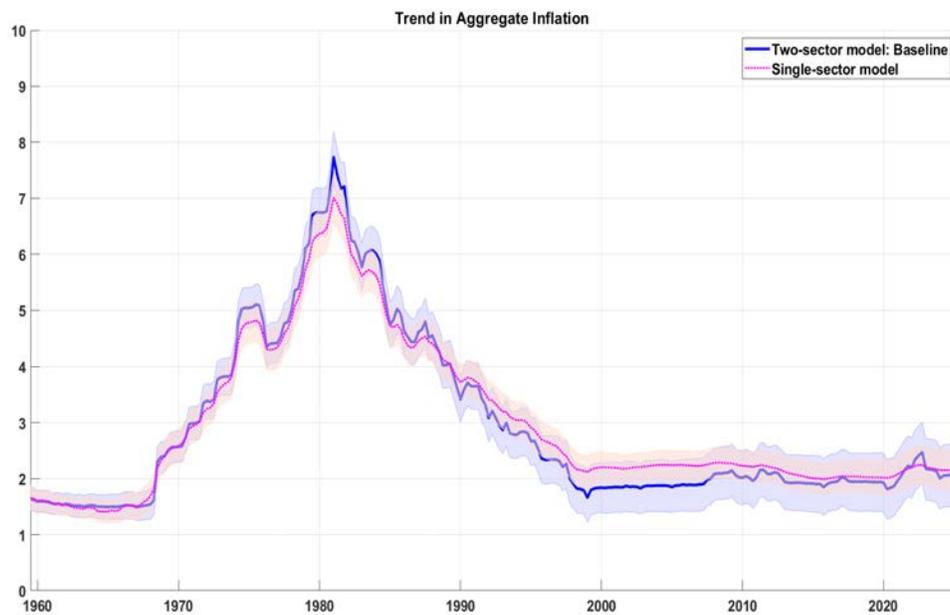
Note: The posterior estimates are based on the full sample (from 1959Q3 through 2025Q2). The shaded area represents the 68% posterior coverage interval. Panel (a), posterior estimates of the trend in services PCE inflation. Panel (b), posterior estimates of the trend in goods PCE inflation. Panel (c), posterior estimates of the trend in aggregate PCE inflation, constructed as a weighted average of the trends in services and goods PCE inflation.

Figure 12: Trend Inflation: Baseline vs. Variant with No Uncertainty and Phillips Curve



Note: The posterior estimates are based on the full sample (from 1959Q3 through 2025Q2). The shaded area represents the 68% posterior coverage interval. Panel (a), posterior estimates of the trend in services PCE inflation. Panel (b), posterior estimates of the trend in goods PCE inflation. Panel (c), posterior estimates of the trend in aggregate PCE inflation, constructed as a weighted average of the trends in services and goods PCE inflation.

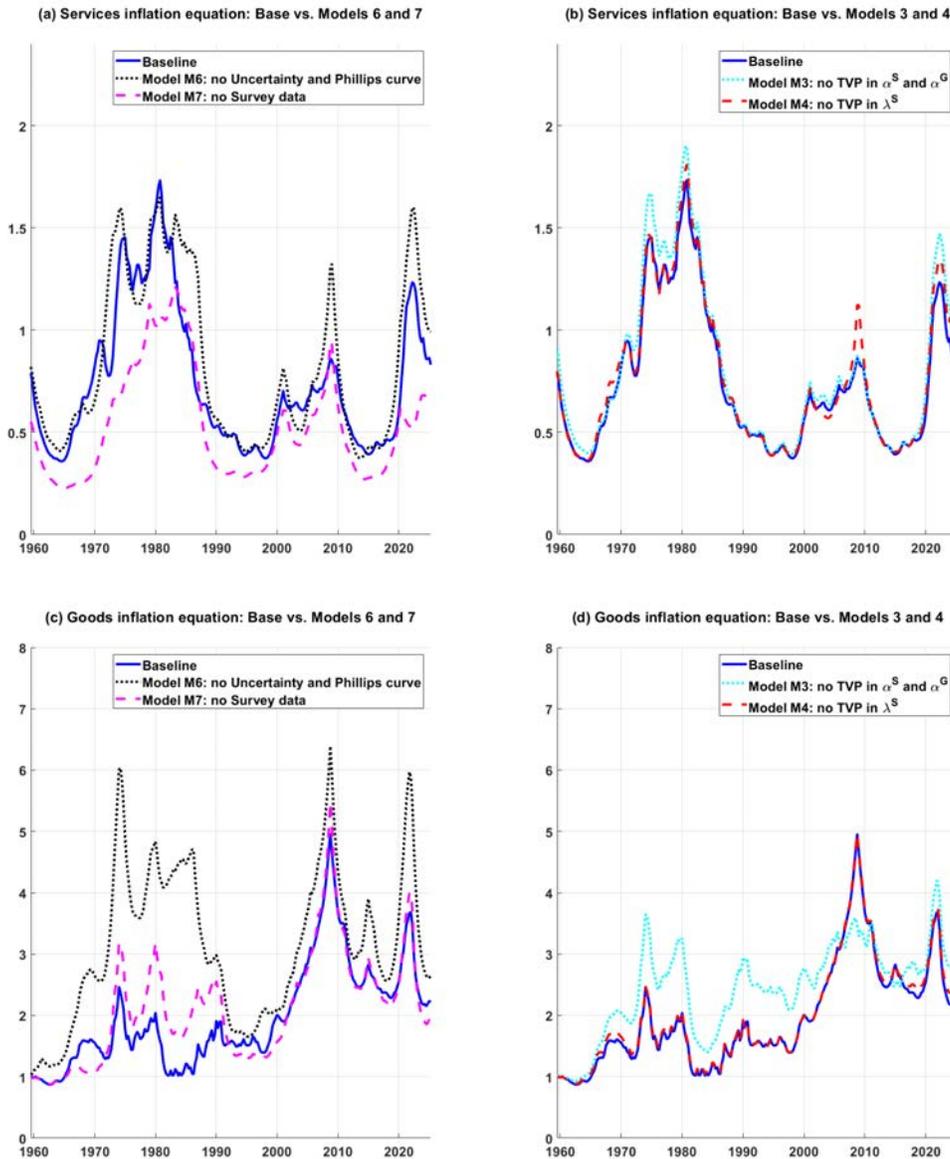
Figure 13: Trend Inflation: Baseline vs. Single-Sector Model



Note: The posterior estimates are based on the full sample (from 1959Q3 through 2025Q2). The shaded area represents the 68% posterior coverage interval. The solid and dashed lines represent the posterior mean estimates from the (two-sector) baseline model and single-sector models, respectively (posterior estimates of the trend in services PCE inflation).

A7. Uncertainty Estimates: Sensitivity to Modeling Assumptions

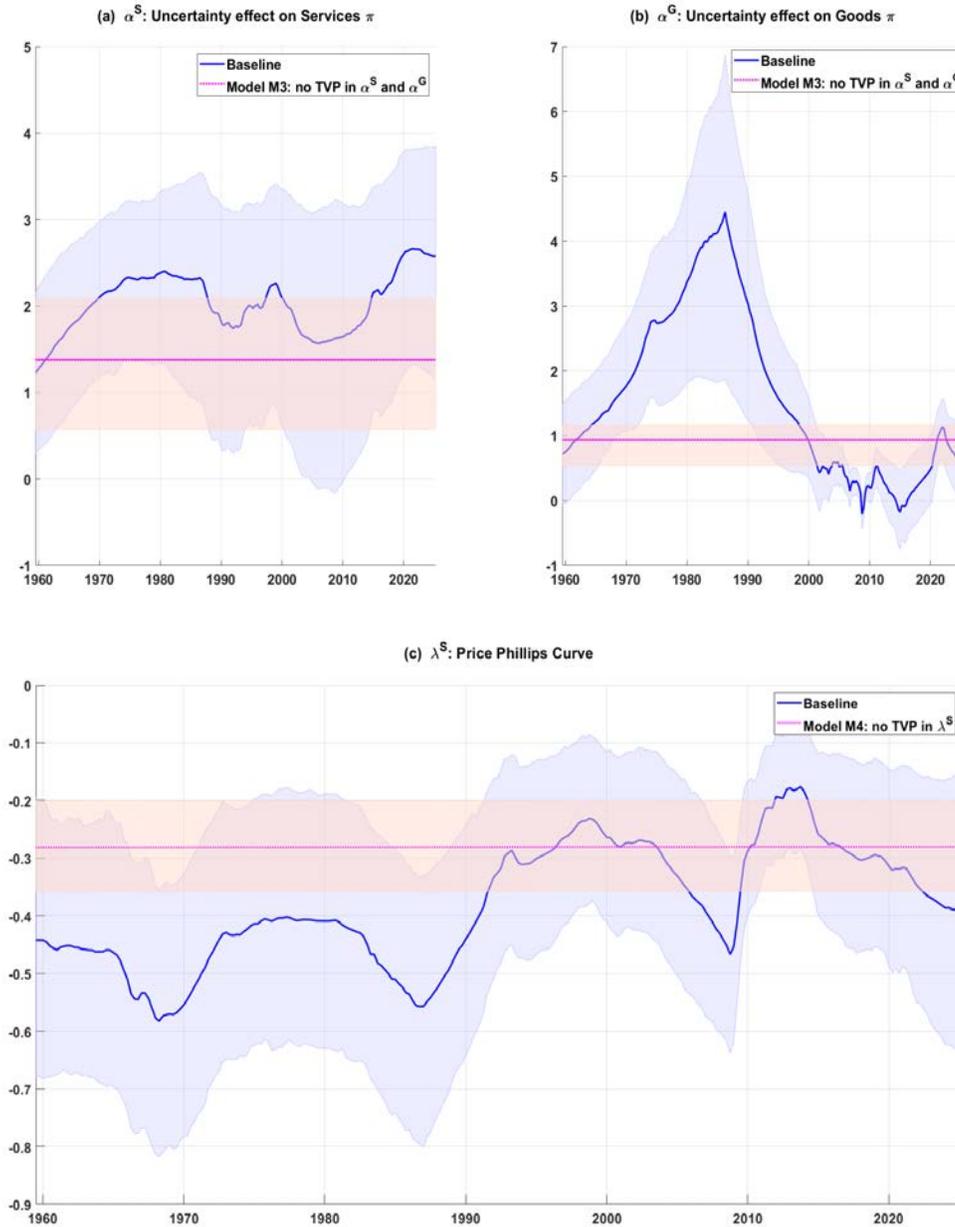
Figure 14: Estimates of Stochastic Volatility



Note: Panel (a) and Panel (b) present the uncertainty estimates associated with services inflation, i.e., the posterior median estimates of the standard deviation (sd) of the shocks defining the services inflation measurement equation. Panel (c) and Panel (d) present the uncertainty estimates associated with goods inflation. The estimates are computed using the full sample (from 1959Q3 through 2025Q2).

A8. Comparing Parameter Estimates: Baseline vs. Model with time-invariant parameters

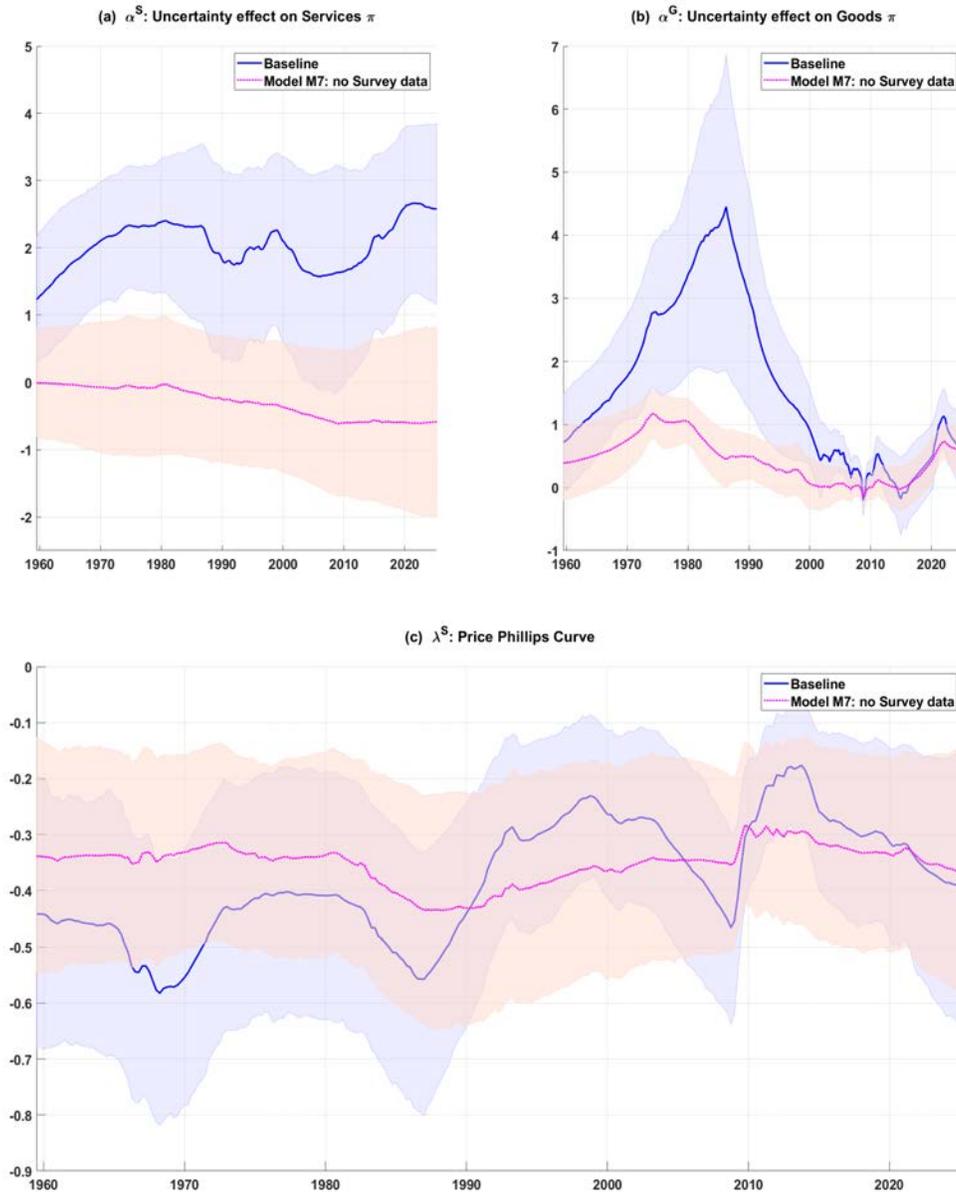
Figure 15: Estimates of TVPs: Base vs. Variant with time-invariant parameters



Note: Plotted are the posterior estimates of the parameters computed using the full sample (from 1959Q3 through 2025Q2). The solid lines represent the posterior mean, and the shaded area represents the 68% credible intervals.

A9. Comparing Parameter Estimates: Baseline vs. Model without Survey Expectations Data

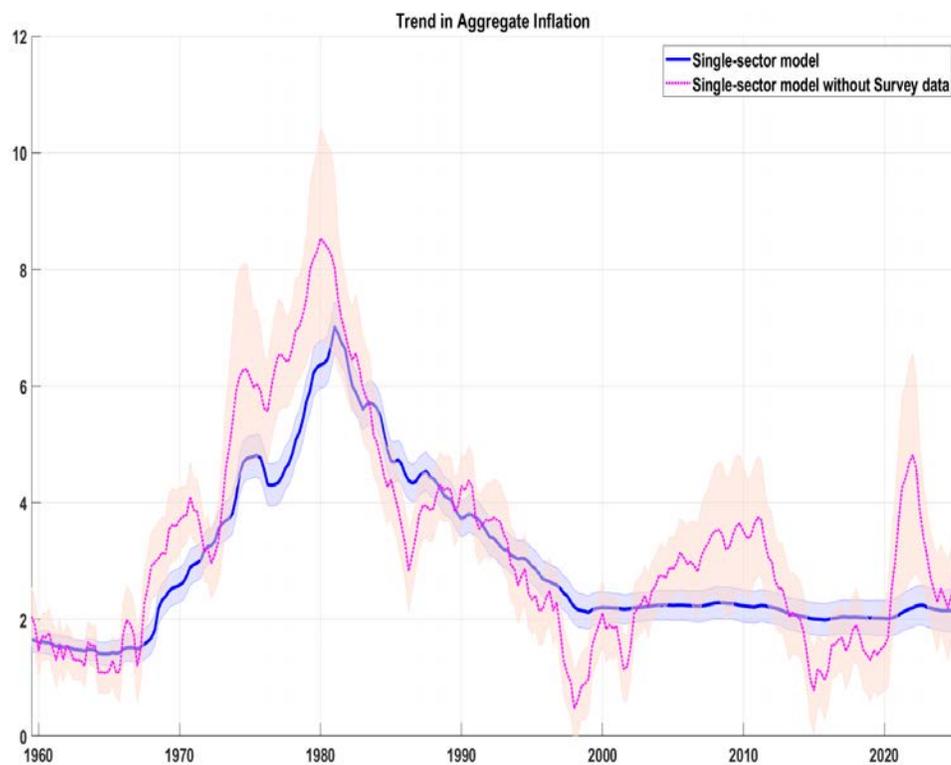
Figure 16: Estimates of TVPs: Base vs. Variant with no Survey data



Note: Plotted are the posterior estimates of the parameters computed using the full sample (from 1959Q3 through 2025Q2). The solid lines represent the posterior mean, and the shaded area represents the 68% credible intervals.

A10. Trend Estimates: Single-Sector Model vs. Single-Sector Model without Survey data

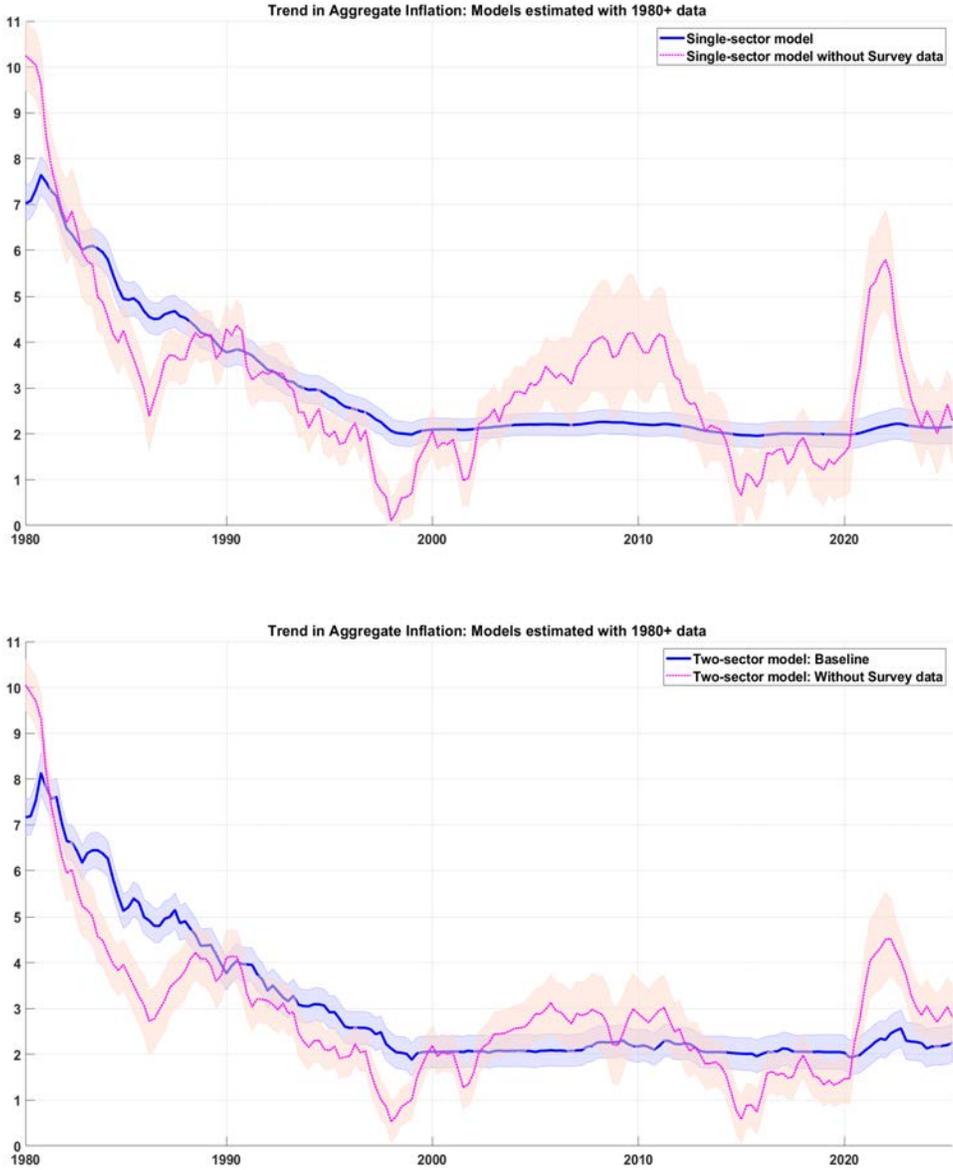
Figure 17: Trend Inflation: Single-Sector Model



Note: The posterior estimates are based on the full sample (from 1959Q3 through 2025Q2). The shaded area represents the 68% posterior coverage interval.

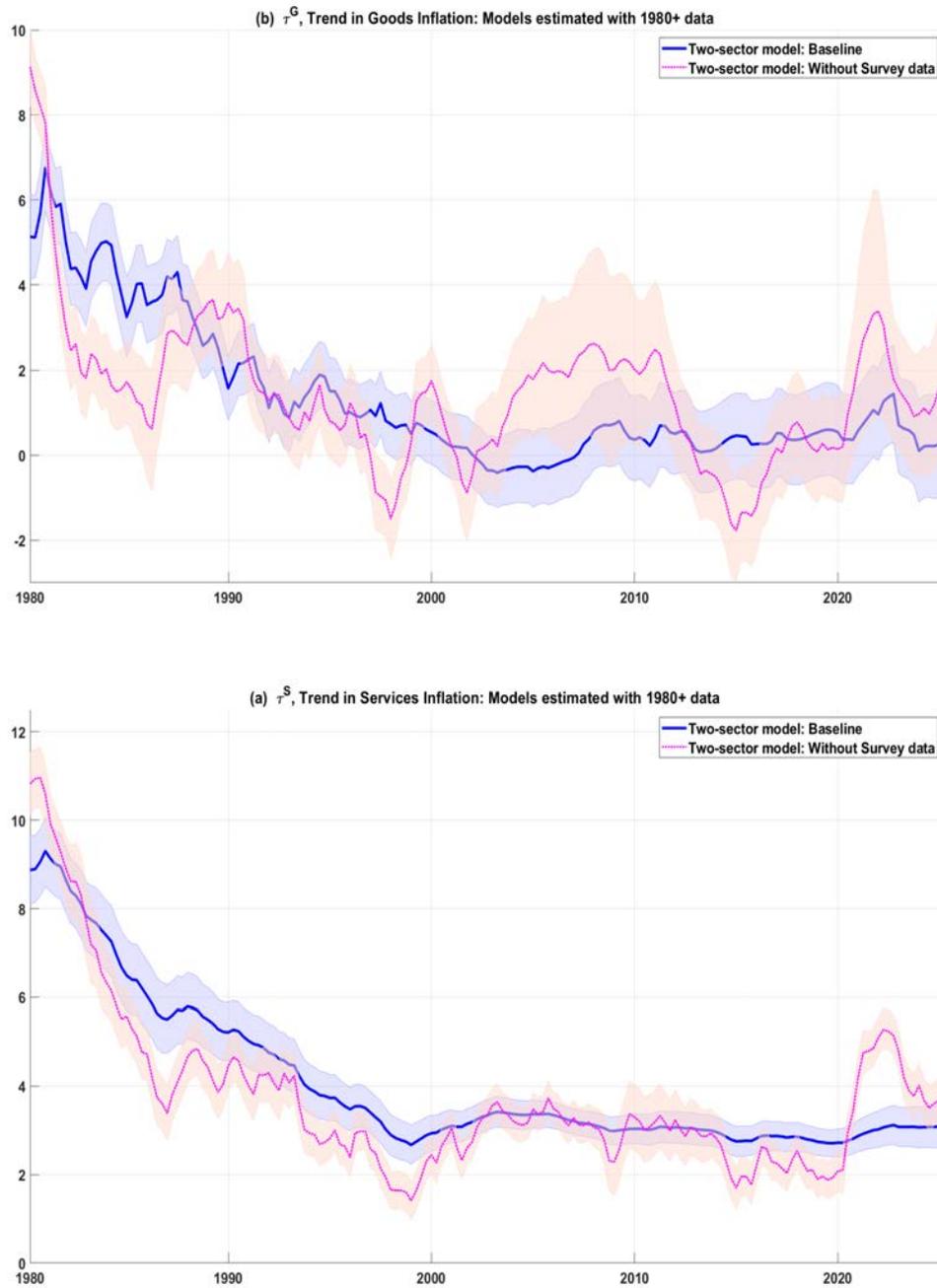
A11. Trend estimates based on estimating models with data starting from 1980 onward

Figure 18: Trend Estimates: Baseline and Single-Sector Models



Note: Plotted are the posterior estimates of the parameters computed using the full sample (from 1980Q2 through 2025Q2). The solid lines represent the posterior mean, and the shaded area represents the 68% credible intervals.

Figure 19: Goods and Services Trend Estimates: Base vs. Variant with no Survey data



Note: Plotted are the posterior estimates of the parameters computed using the full sample (from 1980Q2 through 2025Q2). The solid lines represent the posterior mean, and the shaded area represents the 68% credible intervals.

Table 3: Bayesian Model Comparison: Models estimated with data 1980+

*Panel A: Baseline (Two-sector model) vs. Variant without Survey data

Model	1980-2025Q2, MDD		1980-2019, MDD	
	Services π	Goods π	Services π	Goods π
M1: Baseline	-204.3	-437.8	-168.5	-379.8
M7: Baseline but No Survey data	-192.0	-418.0	-163.7	-362.6

*Panel B: Baseline, Single-sector, and Variants without Survey data

Model	MDD Aggregate PCE π	
	1980-2025Q2 sample	1980-2019 sample
M1: Baseline	-287.1	-246.1
M7: Baseline but No Survey data	-267.9	-230.3
M8: Single-sector	-290.2	-246.1
M10: Single-sector but No Survey data	-273.2	-236.0

Note: MDD refers to the log of the marginal data density, which measures the model's fit to the services inflation data and to goods inflation data. The top panel reports the model's fit to the data over the entire sample (1980Q4-2025Q2) and the pre-COVID sample (1980Q4-2019Q4). The bottom panel reports the model fit to the aggregate PCE inflation for the single-sector model (which models directly the aggregate PCE inflation) and its variants, to facilitate comparison, the implied model fit for the Baseline model and Baseline model without survey data are also reported.