

# "Assessing DSGE Model Nonlinearities "

Andrea Prestipino

NYU

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# Motivation

- Identify nonlinearities and evaluate nonlinear DSGE
  - State-space model

$$S_t = \Gamma (S_{t-1}, w_{t-1}; \theta)$$

$$Y_t^e = M (S_t, v_t; \theta)$$

- Statistical model

$$Y_t^s = f (Y_{t-1}^s, u_t)$$

- First order approximation
  - State-space model

$$S_t^1 = \Gamma^1 (\theta) S_{t-1} + H(\theta)w_t$$

$$Y_t^e = A (\theta) + B (\theta) S_t + v_t$$

- Statistical model

$$Y_t^s = CY_{t-1}^s + u_t$$

# Motivation

- What reference model for second order approximation?
  - QAR
- How to use this model to evaluate DSGE?
  - Posterior predictive checks

# Quadratic Autoregressive Model (QAR)

- Let

$$y_t^* = f(y_{t-1}^*, \omega u_t) \quad \text{where } u_t \sim N(0, 1)$$

- Second order approximation

$$y_t = y_t^0 + \omega y_t^{(1)} + \omega^2 y_t^{(2)}$$

- So that

$$\begin{aligned} y_t^* - \bar{y} &= f_y(y_{t-1}^* - \bar{y}) + f_u \omega u_t \\ &+ \frac{1}{2} f_{y,y}(y_{t-1}^* - \bar{y})^2 + f_{y,u}(y_{t-1}^* - \bar{y}) \omega u_t \\ &+ \frac{1}{2} f_{u,u}(\omega u_t)^2 + \text{higher order terms} \end{aligned}$$

- Substitute  $y_t$  and match coefficients

# QAR

- The resulting approximation is

$$y_t = \phi_0 + \phi_1 (y_{t-1} - \bar{y}) + \phi_2 s_{t-1}^2 + (1 + \gamma s_{t-1}) \sigma u_t + \frac{1}{2} \phi_3 \omega^2 u_t^2$$

$$s_t = \phi_1 s_{t-1} + \sigma u_t$$

- Unique steady state and non-explosive if  $|\phi_1| < 1$
- Not true for "standard" approximation

$$\hat{y}_t - \bar{y} = \phi_1 (\hat{y}_t - \bar{y}) + \phi_2 (\hat{y}_t - \bar{y})^2$$

# Why QAR?

- State dependent IRFs

$$IRF_t(h) = E_t [y_{t+h} | u_t = \mathbf{1}] - E_t [y_{t+h}]$$

$$IRF_t(0) = \sigma (1 + \gamma s_{t-1})$$

$$IRF_t(1) = \sigma \left( \phi_1 (1 + \gamma s_{t-1}) + 2\phi_1\phi_2\sqrt{1 - \phi_1^2} s_{t-1} \right)$$

- Conditional Heteroskedasticity

$$V_{t-1} [y_t] = (1 + \gamma s_{t-1})^2 \sigma^2$$

# How to use QAR?

- Estimate QAR
- Estimate 2nd order approximation to DSGE
- Use posterior on DSGE parameters to get a posterior predictive distribution on QAR estimates
- Check how far the actual QAR estimate lies in the tail of this distribution

# QAR: Estimation

- Computing

$$p(Y_{0:T}, \theta, s_0) = p(Y_{1:T} | y_0, s_0, \theta) p(y_0, s_0 | \theta) p(\theta)$$

- Factorize likelihood

$$p(Y_{1:T} | y_0, s_0, \theta) = \prod_{t=1}^T p(y_t | y_{0:t-1}, s_0, \theta)$$

- Computed recursively using

$$p(y_t | y_{t-1}, s_{t-1}) \sim N \quad s_t = g(y_t, y_{t-1}, s_{t-1})$$



# QAR Estimation

- Initialization

$$p(y_0, s_0 | \theta) = N \left( \begin{bmatrix} \mu_y \\ \mu_d \end{bmatrix}, \begin{bmatrix} \Sigma_{yy} & \Sigma_{ys} \\ \Sigma_{sy} & \Sigma_{ss} \end{bmatrix} \right)$$

- Substitute in steady state at  $t = -T^*$

- Find

$$E(s_j), E(y_j), V(s_j), V(y_j), cov(s_j, y_j), cov(s_j^2, y_j), V(s_j^2)$$

as a function of their lagged values using the QAR law of motions

# QAR Estimation

- Priors:

	GDP Growth	Wage Growth	Inflation	Fed Funds Rate
$\phi_0$	$N (.48, 2)$	$N (1.18, 2)$	$N (2.38, 2)$	$N (2.50, 2)$
$\phi_1$	$N^T (.36, .5)$	$N^T (-.02, .5)$	$N^T (0.00, .5)$	$N^T (0.66, .5)$
$\sigma$	$IG (1.42, 4)$	$IG (.82, 4)$	$IG (1.87, 4)$	$IG (.58, 4)$
$\phi_2$	$N (0, 0.1)$	$N (0, 0.1)$	$N (0, 0.1)$	$N (0, 0.1)$
$\gamma$	$N (0, 0.1)$	$N (0, 0.1)$	$N (0, 0.1)$	$N (0, 0.1)$

- Pre-sample information to parametrize priors

# QAR Estimation

- RWM Algorithm:
- Use prior to get a Cov matrix for parameters  $\Omega$
- Produce 100k draws using proposal density

$$\hat{\theta} = \theta_t + U_t \quad U_t \sim N(0, \Omega)$$

- Use last 50k to compute  $\Omega'$
- Produce 60k draws using new proposal density

$$\hat{\theta} = \theta_t + U'_t \quad U'_t \sim N(0, \Omega')$$

# DSGE

- New Keynesian DSGE with asymmetric price and wage adjustment costs
- 4 exogenous shocks: tfp; markup; government; monetary policy.
- Approximate solution using "standard" method
- Bayesian estimation using RWM and particle filter

# Particle Filter

- The goal is to approximate

$$p(y_t | Y^{t-1}, \theta) = \int p(y_t | s_t, \theta) p(s_t | Y^{t-1}, \theta) ds_t$$

- Start from  $p(s_0 | \theta)$  to draw  $\{s_0^i\}_{i=1}^N$ ; Assume we have  $\{s_{t-1}^i\}_{i=1}^N$  which approximate  $p(s_{t-1} | Y_{t-1}, \theta)$
- $p(s_t | Y_{t-1}, \theta)$  is approximated by

$$\begin{aligned} p(s_t | Y_{t-1}, \theta) &= \int p(s_t | s_{t-1}, \theta) p(s_{t-1} | Y^{t-1}, \theta) ds_{t-1} \\ &\approx \frac{1}{N} \sum p(s_t | s_{t-1}^i, \theta) \end{aligned}$$

## Particle Filter

- – Drawing  $\{\tilde{s}_t^i\}_{i=1}^N$  from  $p(s_t | s_{t-1}^i, \theta)$  approximates  $p(s_t | Y_{t-1}, \theta)$  hence

$$p(y_t | Y^{t-1}, \theta) = \int p(y_t | s_t, \theta) p(s_t | Y^{t-1}, \theta) ds_t \approx \frac{1}{N} \sum p(y_t | \tilde{s}_t^i, \theta)$$

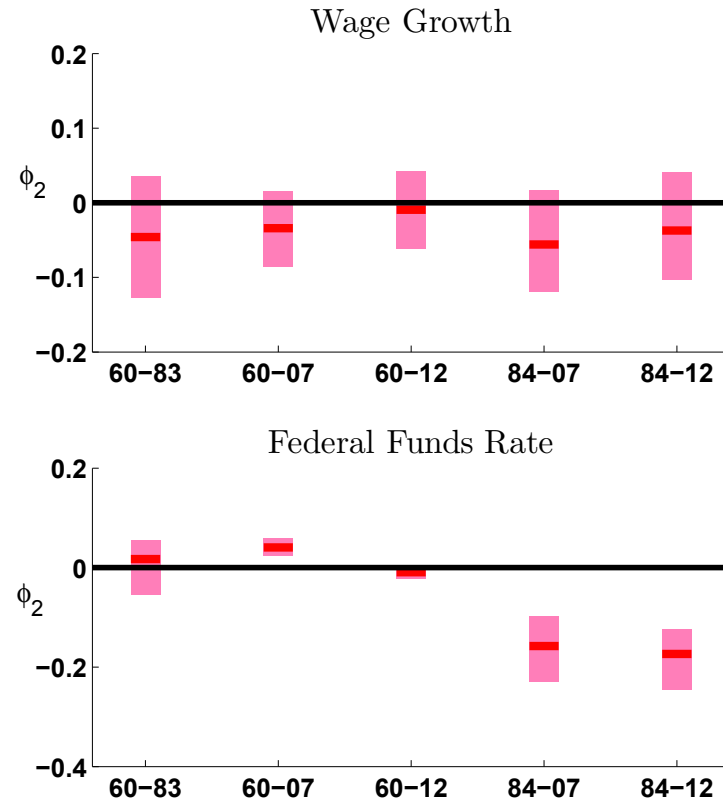
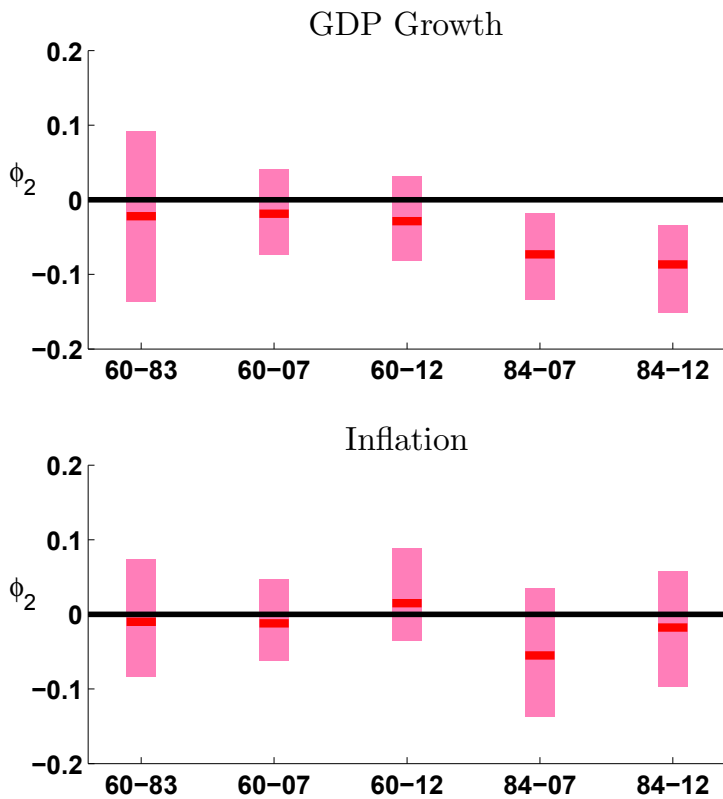
- Finally get an approximation  $\{s_t^i\}_{i=1}^N$  of  $p(s_t | Y_t, \theta)$  by drawing with replacement from  $\{\tilde{s}_t^i\}_{i=1}^N$  with pmf given by

$$\pi_t^i = \frac{p(y_t | \tilde{s}_t^i, \theta)}{\sum p(y_t | \tilde{s}_t^i, \theta)}$$

## Posterior predictive checks

- Draw  $\theta^i$  from posterior of the DSGE parameters
- Simulate Data from the DSGE  $\{Y_{-T^*:T}^i\}$  and obtain median estimate of QAR parameters  $S^i$
- Examine how far the median estimate from actual US data lie in the tail of the empirical distribution of  $S^i$

# Estimation of QAR(1,1) Model on U.S. Data – $\phi_2$

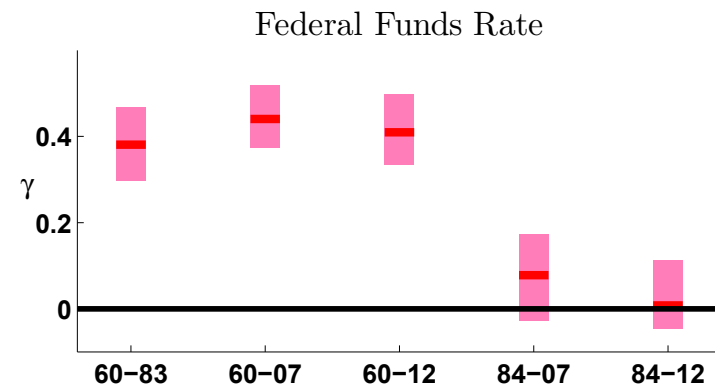
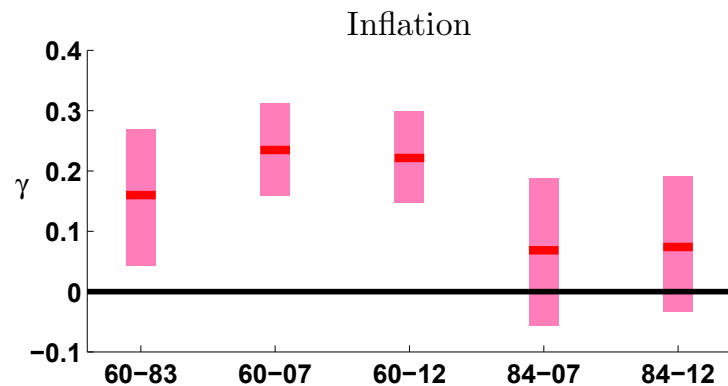
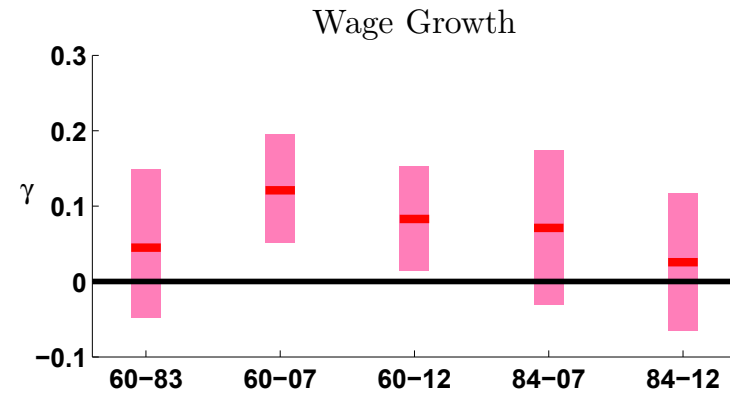
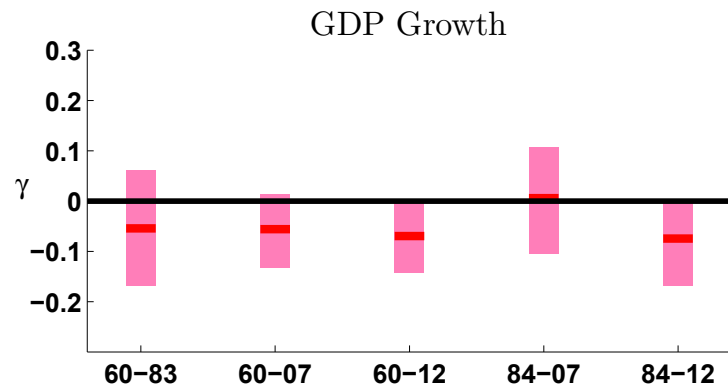


$$y_t = \phi_0 + \phi_1(y_{t-1} - \phi_0) + \phi_2 s_{t-1}^2 + (1 + \gamma s_{t-1})\sigma u_t$$

$$s_t = \phi_1 s_{t-1} + \sigma u_t \quad u_t \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1)$$



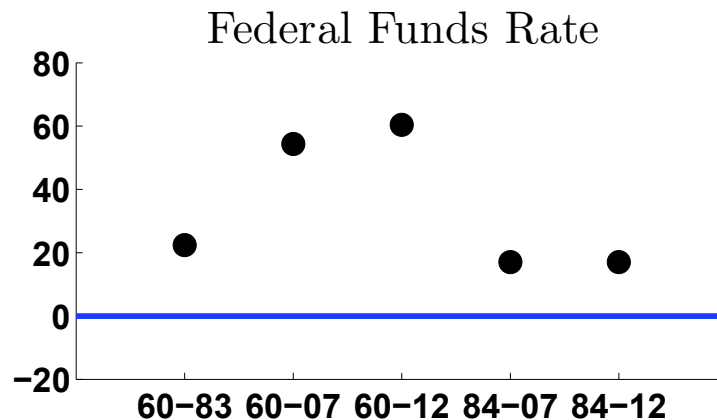
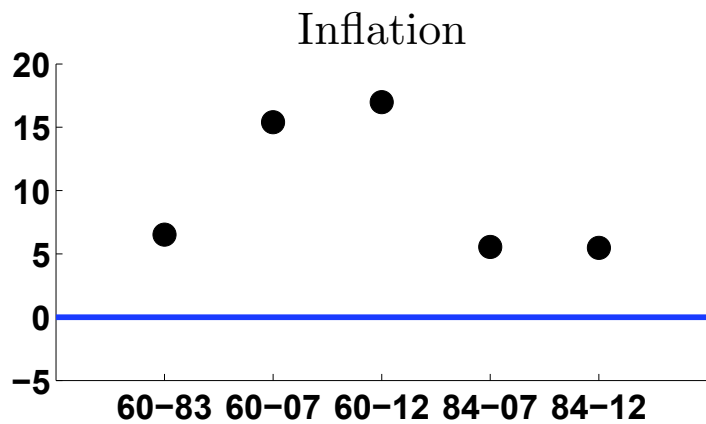
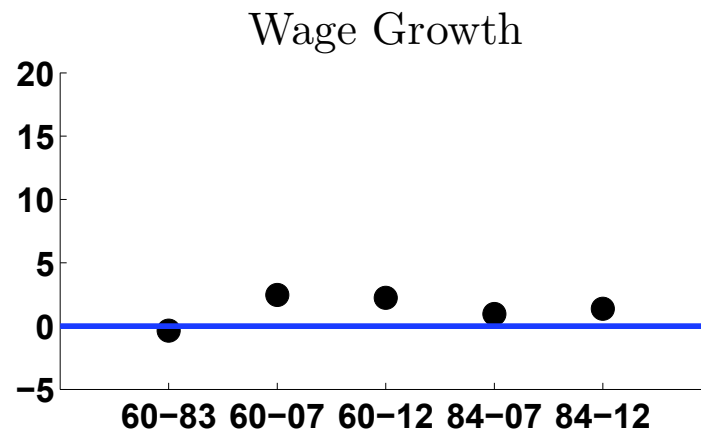
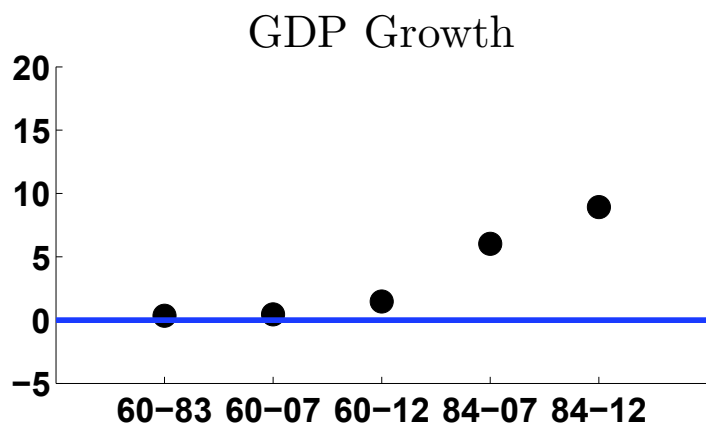
# Estimation of QAR(1,1) Model on U.S. Data – $\gamma$



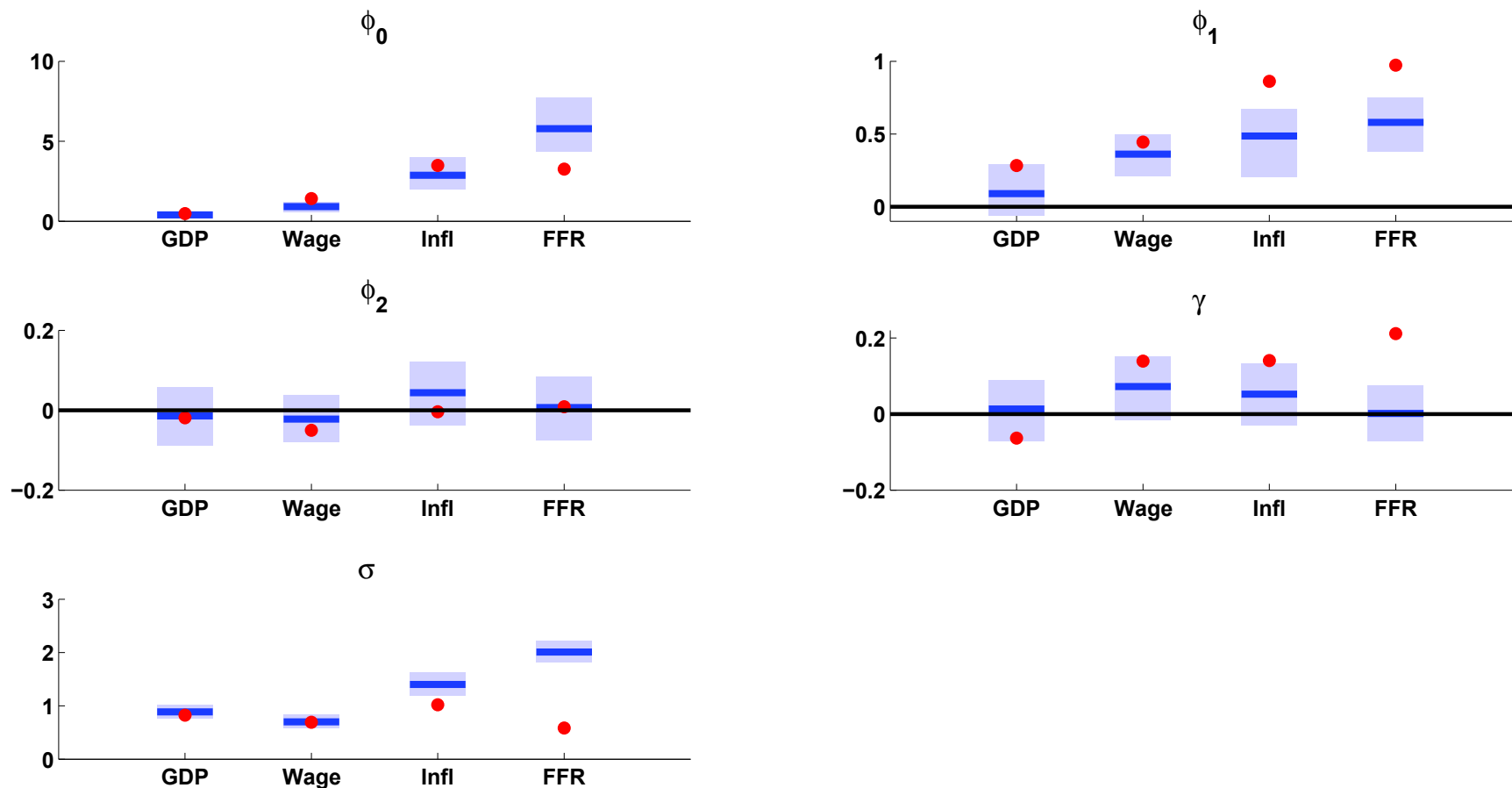
$$y_t = \phi_0 + \phi_1(y_{t-1} - \phi_0) + \phi_2 s_{t-1}^2 + (1 + \gamma s_{t-1})\sigma u_t$$

$$s_t = \phi_1 s_{t-1} + \sigma u_t \quad u_t \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1)$$

# Log Marginal Data Density Differentials: QAR(1,1) versus AR(1)

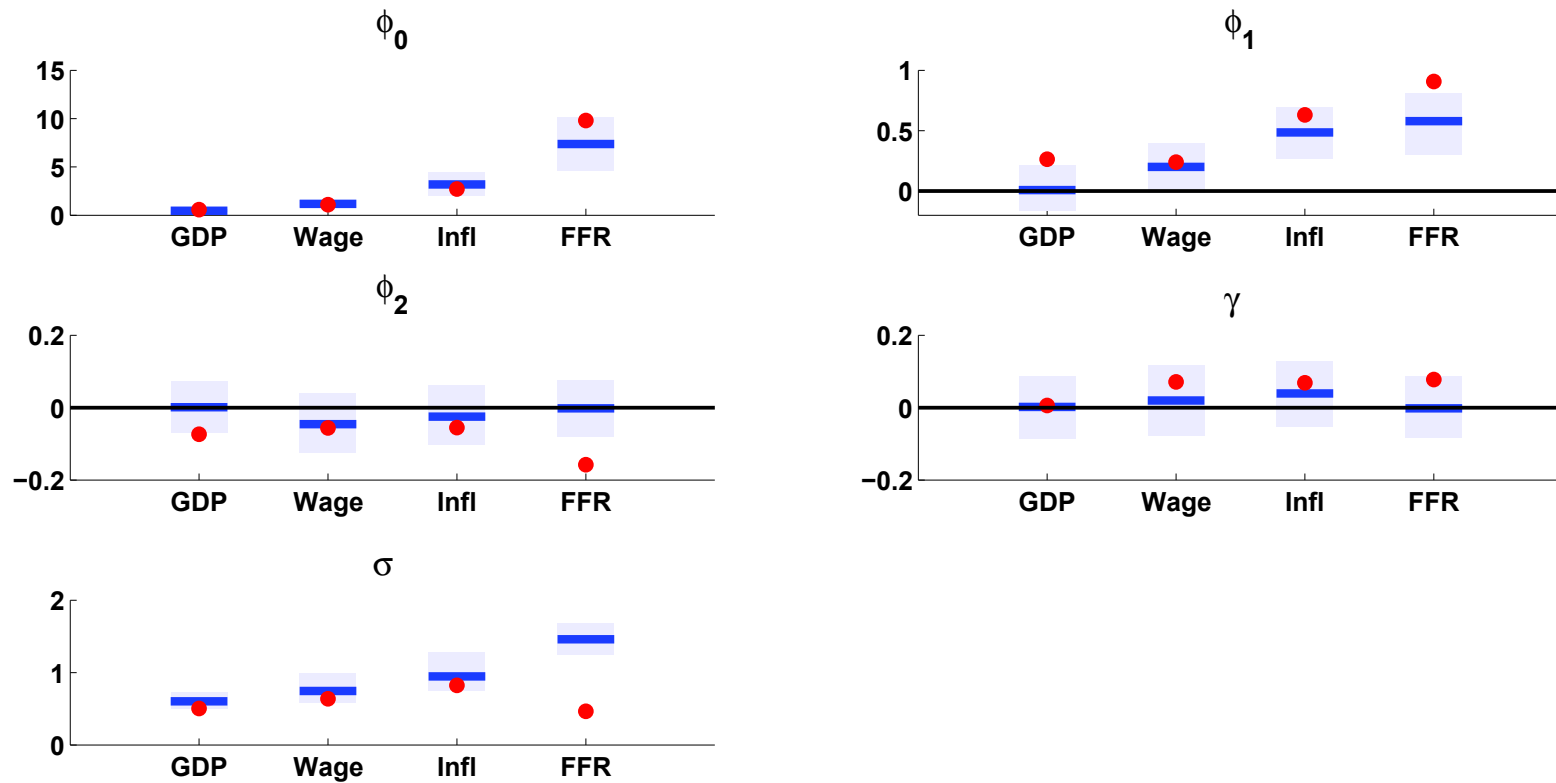


# Posterior Predictive Checks: 1960-2007 Sample



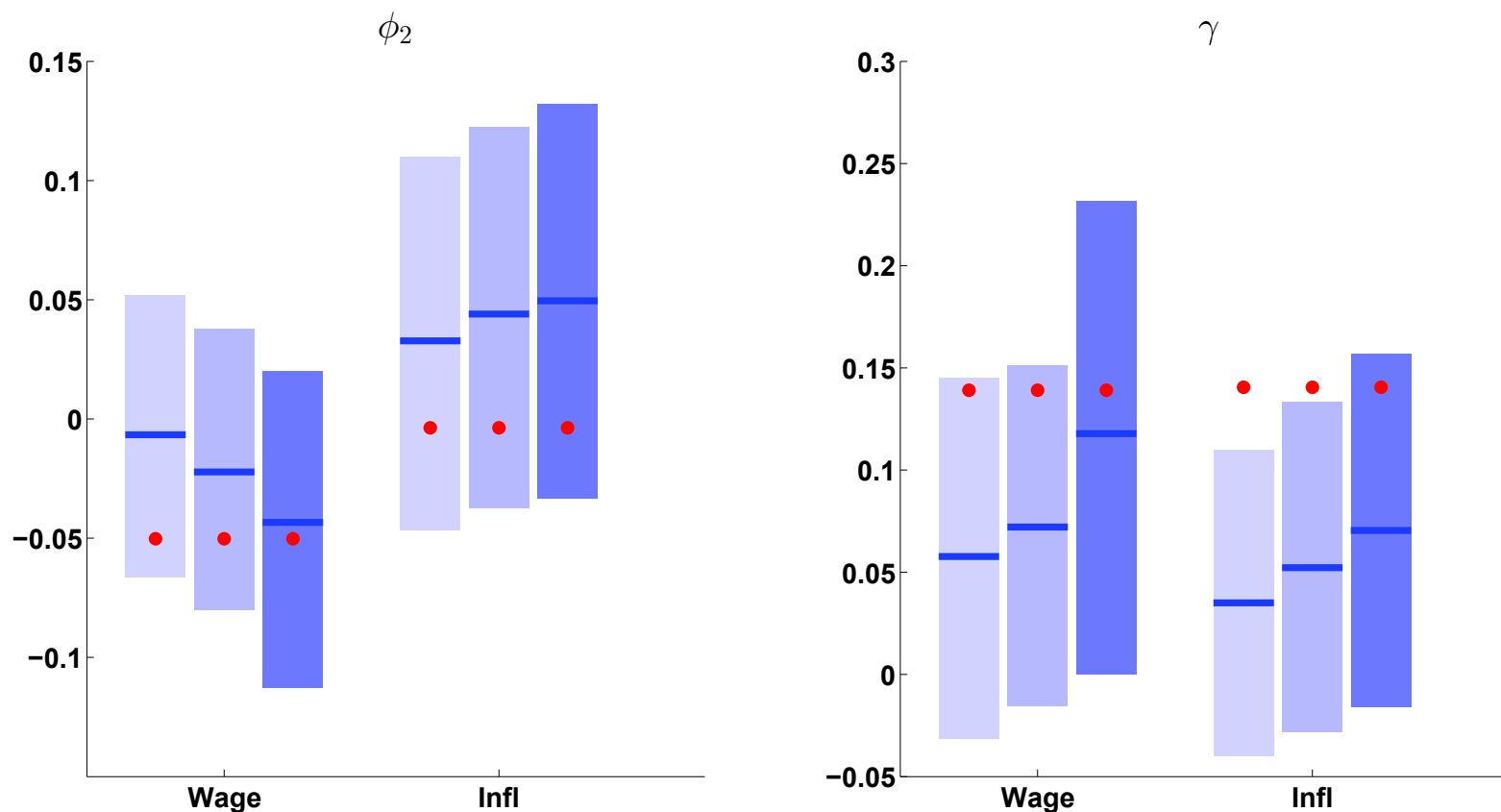
- ▶ QAR estimates from actual and model-generated data are similar.
- ▶ Only interest rates exhibit noticeable differences.
- ▶ Except for wage and inflation  $\hat{\gamma}$ , nonlinearities are generally weak.

# Posterior Predictive Checks: 1984-2007 Sample



- ▶ Model does not generate nonlinearity ( $\hat{\phi}_2$ ) in GDP dynamics.

# Effect of Adjustment Costs on Nonlinearities: 1960-2007 Sample



No asymmetric costs is  $\psi_p = \psi_w = 0$  (light blue); high asymmetric costs is  $\psi_p = \psi_w = 300$  (dark blue). Large dots correspond to posterior median estimates based on U.S. data.