Macroeconomic Shocks and their Propagation Under Rational Inattention

Etienne Briand
UQAM

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Adjustment frictions vs rational inattention

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Adj. frictions (New Keynesian) approach

[CEE, ACEL, Smets-Wouters . . .]

- habits, nominal rigidities, inv. adj. costs
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> *"My own view is that the best of these models ought to be regarded as proxies for better, harder-to-construct models . . . "*
>
> — Sims (1998, p.319)

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This paper confronts the two approaches in a **medium-scale DSGE**

Contributions & key ideas

- **Challenges**
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    - indirect estim: no formal comparison test, many untargeted shocks
    - direct estim: formal comparison test, noisy set of empirical IRFs

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- **What do we learn** from this exercise?

R1. today, **RI** $\approx$ **NK** iff capital is subject to a real friction (here **capital adj. costs**)
  - RI alone matches the data when there is no capital [Maćkowiak-Wiederholt 2015]
  - capital adj. costs needed for sluggish I in partial eq. [MWY 2022, Zorn 2018]

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  R2. **RI** responses: prompt to idiosyncratic shocks + slow to aggr. shocks

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adj. costs make I^* slow

RI makes I^{RI} **hump-shaped!**

This paper brings together three literatures

1. **Information frictions (in macro)**
   - **rational inattention:** Sims 1998, 2003, Maćkowiak-Wiederholt 2015, 2023, Afrouzi-Yang 2021, Miao-Wu-Young 2022, Song-Stern 2025
   - **others:** Lucas 1972, Mankiw-Reis 2002, Woodford 2003, Lorenzoni 2009 . . .
2. **Estimation of medium-scale DSGE models**
   - **limited info:** Chernozhukov-Hong 2003, Christiano-Eichenbaum-Evans 2005, Christiano-Eichenbaum-Trabandt 2015, Inoue-Shintani 2018, . . .
   - **full info:** Smets-Wouters 2007, Justiniano-Primiceri-Tambalotti 2010, 2011, . . .
3. **Micro-macro fit**
   - Nimark 2007, Maćkowiak-Wiederholt 2009, Boivin-Giannoni-Mihov 2009, Zorn 2018

Outline

1. Putting the RI in RI-DSGE
2. Medium-scale RI-DSGE model
3. Estimation
4. Results
5. Conclusion

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$$\sum_{t=0}^{\infty} \beta^t \, E_{\iota,-1}\Big\{ \underbrace{-\tfrac{1}{2}(x_{\iota t} - x_{\iota t}^*)' \, \Theta_\iota \, (x_{\iota t} - x_{\iota t}^*)}_{\text{losses from suboptimal actions}} - \underbrace{\lambda_\iota \overbrace{\big[H(\xi_t \mid \mathcal{I}_{\iota,t-1}) - H(\xi_t \mid \mathcal{I}_{\iota t})\big]}^{\text{uncertainty reduction}}}_{\text{attention cost}} \Big\}$$

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- aggregation: idiosyncratic noise washes out; **average responses are sluggish**

RI: one source of inertia that binds every action

For a given λ_ι, **three forces** determines the precision of $E_t[x^*_{\iota t}|\mathcal{I}_{\iota t}]$:

- **direct stakes**: the entries of $\mathbf{\Theta}_\iota$
  - larger $\mathbf{\Theta}_{\iota,nn} \Rightarrow$ bigger loss from mistracking the n^{th} element of $x^*_{\iota t}$

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$\Rightarrow x_{\iota t} = E_t[x^*_{\iota t}|\mathcal{I}_{\iota t}]$; depend on $\mathbf{\Theta}_\iota$ *and* the **covariance matrix** of $x^*_{\iota t}$

- $\mathbf{\Theta}_\iota$: derived from the microfoundations (curvature of profits/utility losses)
- $x^*_{\iota t}$: FOCs (GE endogenous feedback)

Medium-scale RI-DSGE model

Model overview

- Discrete time with aggregate and idiosyncratic shocks
- Paying attention to each shock is a different activity
- Households consume c_{jt}, set a wage w_{jt} and invest in a mutual fund q_{jt} and bonds b_{jt}
- Firms choose capital k_{it} and set a price p_{it}
- Households and firms are subject to **RI**
  - 2nd-order log approx. of their intertemporal objectives $\rightarrow \Theta_\iota$
  - change of variable $\rightarrow x^*_{\iota t}$ (pure tracking problem)
- Standard policy side with a govt balanced budget and inertial Taylor rule

Households' problem

- Optimal actions reduce to:

$$x_{jt}^* = \begin{cases} c_{jt}^* = E_{jt}[c_{jt+1}^*] - \frac{1}{\gamma} E_{jt}[r_t - \pi_{t+1}] \\ w_{jt}^* = \frac{1}{1+\psi\vartheta_w} \left[\psi l_t + \psi\vartheta_w w_t + \gamma c_{jt}^*\right] \end{cases}$$

- Loss matrix:

$$\mathbf{\Theta}_j = C^{1-\gamma} \begin{bmatrix} \underbrace{\gamma}_{=1} & 0 \\ 0 & \underbrace{\vartheta_w \omega_W (1+\vartheta_w\psi)}_{49.1} \end{bmatrix}$$

Firms' problem

- Optimal actions reduce to:

$$x_{it}^* = \begin{cases} \zeta_{it}^* = p_t + \frac{(1-\alpha)\, y_t + \alpha\, w_t}{\vartheta_p + \alpha(1-\vartheta_p)} & \text{(optimal price given } k_{it-1}\text{)} \\ k_{it}^* = \alpha\ E_{it}\left[w_{t+1} + \frac{1}{\alpha} y_{t+1} - \frac{(r_t - \pi_{t+1})}{1-\beta(1-\delta)} \right] \\ \tilde{\boldsymbol{k}}_{\boldsymbol{it}}^{\boldsymbol{*}} = k_{it-1}^* + \nu^*\ k_{it}^* & \text{(adj. cost weighted optimal capital)} \end{cases}$$

- Loss matrix:

$$\boldsymbol{\Theta}_i = C^{-\gamma} Y \begin{bmatrix} \underbrace{\frac{\vartheta_p(\vartheta_p + \alpha(1-\vartheta_p))}{\alpha}}_{=24} & 0 \\ 0 & \underbrace{\frac{\beta\phi[\vartheta_p(1-\alpha-\phi)+\alpha+\phi]}{\vartheta_p + \alpha(1-\vartheta_p)}}_{=0.12} + \underbrace{\frac{\beta\phi(1+\beta)\,\chi_k}{1-\beta(1-\delta)}}_{\approx 284} \end{bmatrix}$$

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  - households solve their attention problem
  - firms solve their attention problem
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- **Key difficulty:** no direct way to solve **RICE** $\rightarrow$ guess-and-verify
  - solve two “partial equilibrium” RI problems for each iteration

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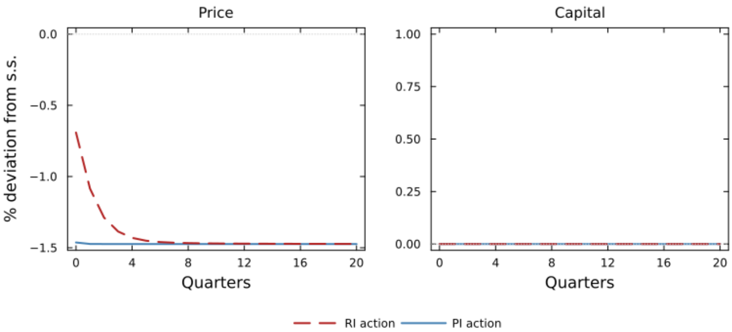
Firms at iter=1; mon. policy shock starting from the full-info solution



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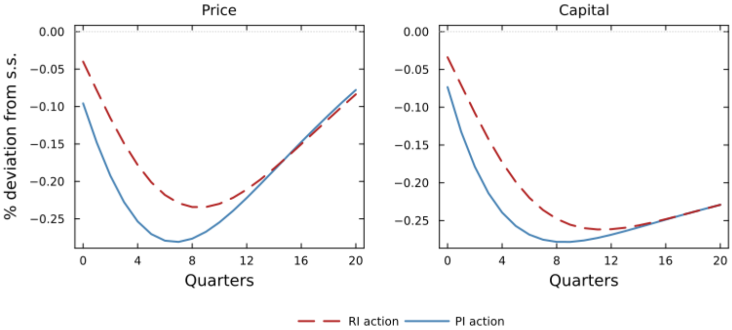

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- **Representation:** min. # of stoch. processes entering hhs and firms problems (IRFs)
  - $\mathcal{J}_{endo} = \{\mathcal{J}_{c}, \mathcal{J}_{inv}, \mathcal{J}_{inf}, \mathcal{J}_{w}\}$
  - $\mathcal{J}_{exo} = \{\mathcal{J}_{m}, \ldots\}$

Estimation

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   - adj. frictions parameters: $\kappa_p, \kappa_w, h, \chi_i$
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3. Limited info estimation (quasi-Bayesian) of the **RI** model on the **NK** mon. policy IRFs
   - marginal attention costs: λ_i, λ_j
   - **capital adj. costs**: χ_k
   - **reuse the posterior mode's solution to warm start new proposals** ($\approx$ 2sec)

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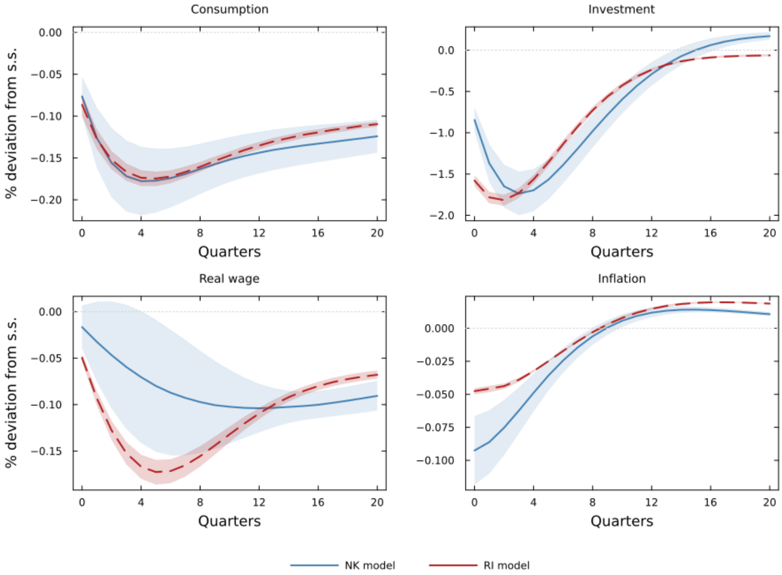
   - marginal attention costs: λ_i, λ_j
   - **capital adj. costs**: χ_k
   - **reuse the posterior mode's solution to warm start new proposals** ($\approx$ 2sec)

$\Rightarrow$ Posterior dist. of the mon. policy IRFs

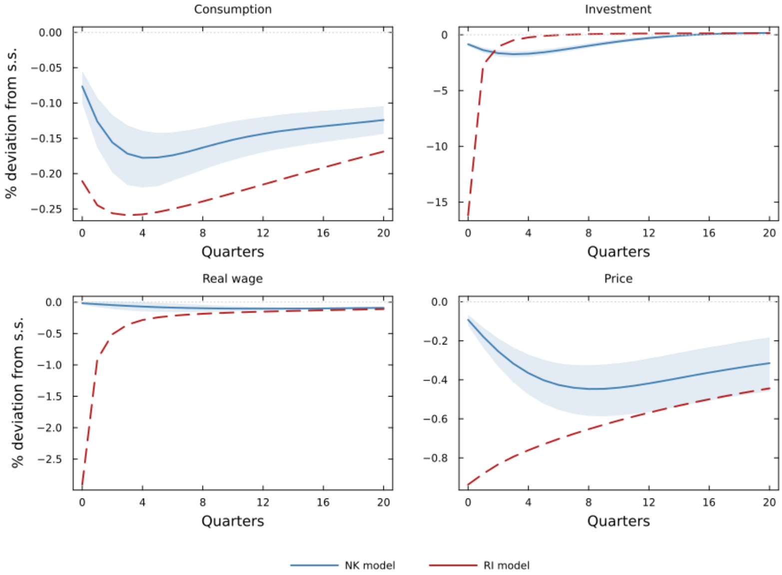
- directly comparable: models share the same core **and** stoch. processes
- step 2's uncertainty is accounted for in step 3
- 6 untargeted shocks

Results

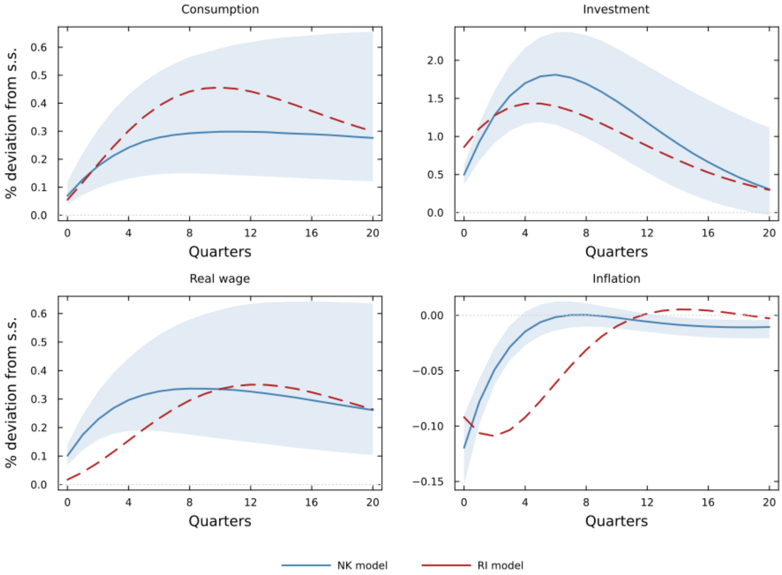
Model's fit: RI $\approx$ NK for mon. policy shock



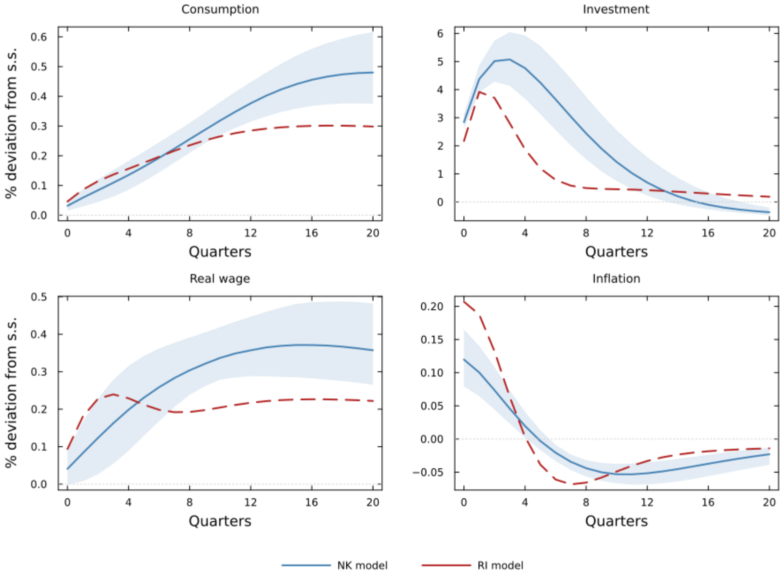
Capital adj. costs are essential for the fit: $\chi_K = 0$



Untargeted shock: TFP



Untargeted shock: MEI



Conclusion

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$$\textbf{RI} + \underbrace{\textbf{capital adj. costs}}_{\text{proxy for?}} \approx \underbrace{\left(\textbf{habits} + \textbf{Calvo} + \textbf{inv. adj. costs}\right)}_{\text{adj. frictions (NK core)}}$$

Conclusion

$$\text{RI} + \underbrace{\text{capital adj. costs}}_{\text{proxy for?}} \approx \underbrace{(\text{habits} + \text{Calvo} + \text{inv. adj. costs})}_{\text{adj. frictions (NK core)}}$$

$\Rightarrow$ maybe not *more* frictions, but *better* microfoundations

Thank you!