Monetary Policy under Data Uncertainty

Interest-Rate Smoothing from a Cross-Country Perspective

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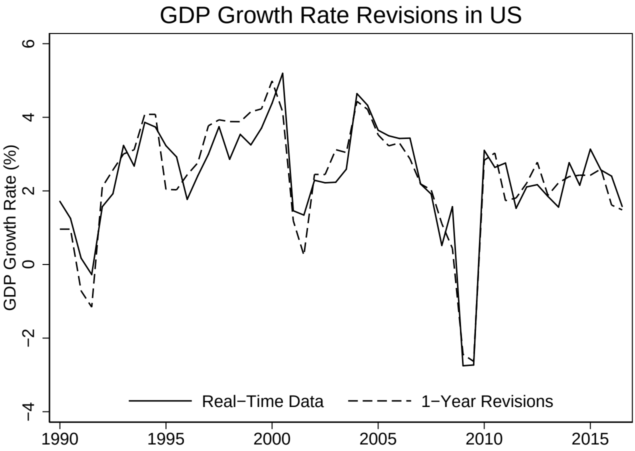
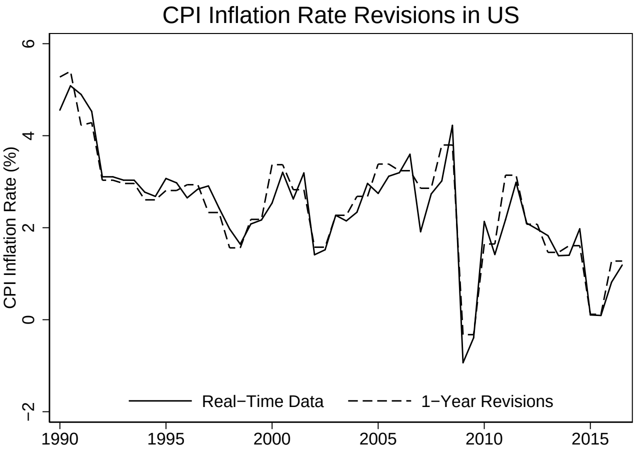
Motivation

Discrepancy between real-time data and their revisions in the United States



Motivation

Not only GDP growth rate but also CPI inflation rate



Research Question

"As a general rule, the Federal Reserve tends to adjust interest rates incrementally, in a series of small or moderate steps in the same direction. ... Relatively gradual policy adjustment produces better results in an uncertain economic environment." – Ben S. Bernanke, May 20, 2004.

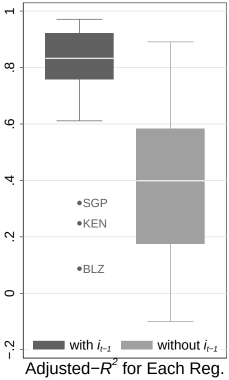
- What is the effect of data uncertainty on central banks' policy? Does it cause gradual adjustment of the interest rates?

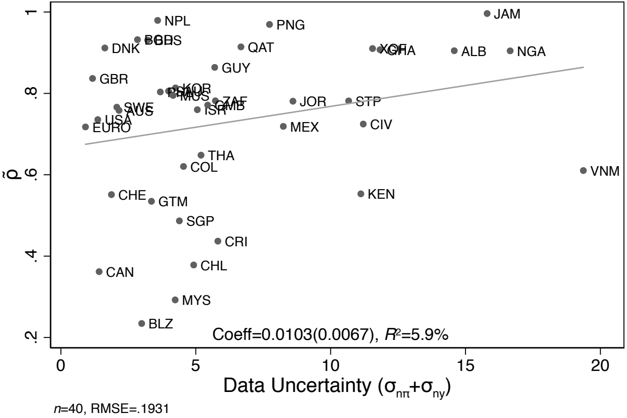
Key Results

- I examine differences in monetary policy across countries.
  $\rightarrow$ Interest rates are slow to adjust!
- Quality of the data matters.
- Countries with more data uncertainty are slower to adjust their interest rate.
- This is largely explained by the central banks' learning process.
- The central bank observes data with noise and makes inferences about the true data before making policy decisions.

Cross-Country Comparison of Interest-Rate Smoothing

$$i_t = (1 - \widetilde{\rho})[k + \widetilde{g_\pi} E_t \pi_{t+1} + \widetilde{g_y} y_t] + \widetilde{\rho} i_{t-1} + \varepsilon_t$$





→ Robust pattern controlling currency peg, income level, RER, or FFR.

Rudebusch-Svensson Model

- Phillips & IS curves:

$$\pi_t = \alpha_0 + \alpha_{\pi 1}\pi_{t-1} + \alpha_{\pi 2}\pi_{t-2} + \alpha_{\pi 3}\pi_{t-3} + \alpha_{\pi 4}\pi_{t-4} + \alpha_y y_{t-1} + \varepsilon_t$$

$$y_t = \beta_0 + \beta_{y1} y_{t-1} + \beta_{y2} y_{t-2} + \beta_r(\bar{\iota}_{t-1} - \overline{\pi}_{t-1}) + \eta_t$$

- Loss function:

$$E[L_t] = Var[\overline{\pi}_t - \pi^*] + \lambda_y Var[y_t] + \lambda_i Var[\Delta i_t]$$

- Taylor rule:

$$i_t = (1-\rho)(k + g_\pi \pi_{t+1|t} + g_y y_{t|t}) + \rho i_{t-1}$$

Noise Structure

- Real-time noisy indicators on inflation and output gap:

$$\pi_t^n = \pi_t + n_t^\pi$$

$$y_t^n = y_t + n_t^y$$

Standard errors $\sigma_{n\pi}$ and σ_{ny} indicate data uncertainty.

- Noises are modeled as MA(1):

$$n_t^\pi = \epsilon_t^\pi + \theta^\pi \epsilon_{t-1}^\pi$$

$$n_t^y = \epsilon_t^y + \theta^y \epsilon_{t-1}^y$$

$$\epsilon_t^\pi \sim N(0, \sigma_{\epsilon\pi}^2),\ \epsilon_t^y \sim N(0, \sigma_{\epsilon y}^2)$$

Three Policy Types

$$i_t = (1-\rho)(k + g_\pi \pi_{t+1|t} + g_y y_{t|t}) + \rho i_{t-1}$$

- Case 1: Perfect Information
  Central Bank (CB) always observes true data.
- Case 2: Naive Policy
  CB takes face value of observed data without inference.
- Case 3: Learning Policy
  CB observes noisy data and forms inferences on the true data.

Cases 1 & 2: Benchmark Cases

Case 1: Perfect Information

- CB always observes true data (π_t and y_t).
- $\pi_{t|t} = \pi_t$ and $y_{t|t} = y_t$
- Central bank's policy rule:

$$i_t = (1-\rho^P)(k + g_\pi^P E_t[\pi_{t+1}|\pi_t] + g_y^P y_t) + \rho^P i_{t-1}$$

Case 2: Naive Policy

- CB takes face value of observed data without inference.
- $\pi_{t|t} = \pi_t^n$ and $y_{t|t} = y_t^n$
- Central bank's policy rule:

$$i_t = (1-\rho^N)(k + g_\pi^N E_t[\pi_{t+1}|\pi_t^n] + g_y^N y_t^n) + \rho^N i_{t-1}$$

Case 3: Learning Policy

- CB observes noisy data π_t^n and y_t^n and forms inferences on π_t and y_t by implementing Kalman filter.

$$X_{t+1} = AX_t + Bi_t + \boldsymbol{\nu}_{t+1}$$

$$X_t = [1 \ \pi_t \ \pi_{t-1} \ \pi_{t-2} \ \pi_{t-3} \ y_t \ y_{t-1} \ i_{t-1} \ i_{t-2} \ i_{t-3}]^T$$

$$Z_t = CX_t + \boldsymbol{w}_t$$

- Optimal Kalman gain and predicted error covariance are:

$$K = P_{t|t-1}C^T(CP_{t|t-1}C^T + V_w)^{-1}$$
$$P_{t|t-1} = A(P_{t|t-1} - KCP_{t|t-1})A^T + V_\nu$$

Case 3: Learning Policy

- Central bank's optimal inference is:

$$X_{t|t} = (I - KC)AX_{t-1|t-1} + (I - KC)Bi_{t-1} + KZ_t$$

- Central bank's policy rule is:

$$i_t = (1 - \rho)(k + GX_{t|t}) + \rho i_{t-1}$$

where

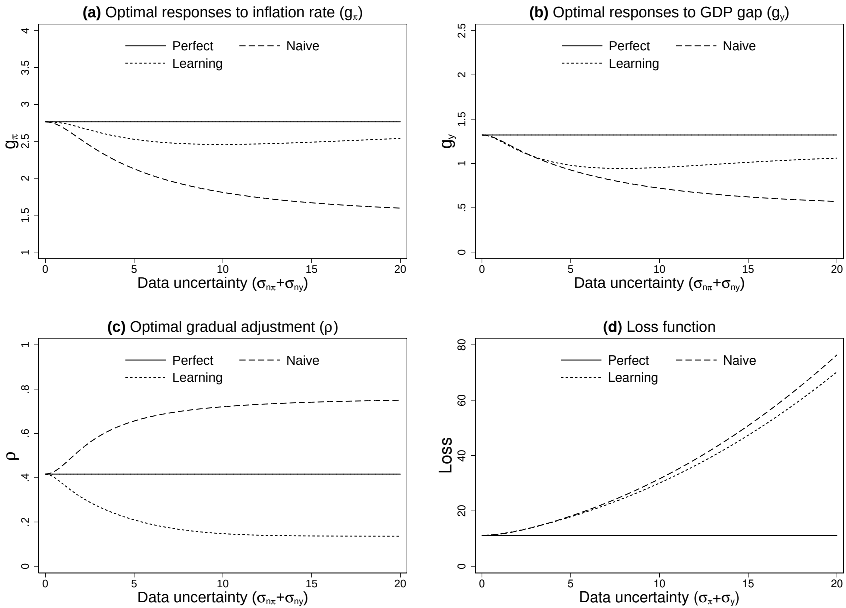
$$G = \begin{bmatrix} g_\pi & g_y \end{bmatrix} \begin{bmatrix} e_2 A \\ e_6 \end{bmatrix}$$

then

$$i_t = (1 - \rho)(k + G[(I - KC)AX_{t-1|t-1} + (I - KC)Bi_{t-1} + KZ_t]) + \rho i_{t-1}$$

Model Optimal Responses

$$i_t = (1-\rho)(k + g_\pi \pi_{t+1|t} + g_y y_{t|t}) + \rho i_{t-1}$$



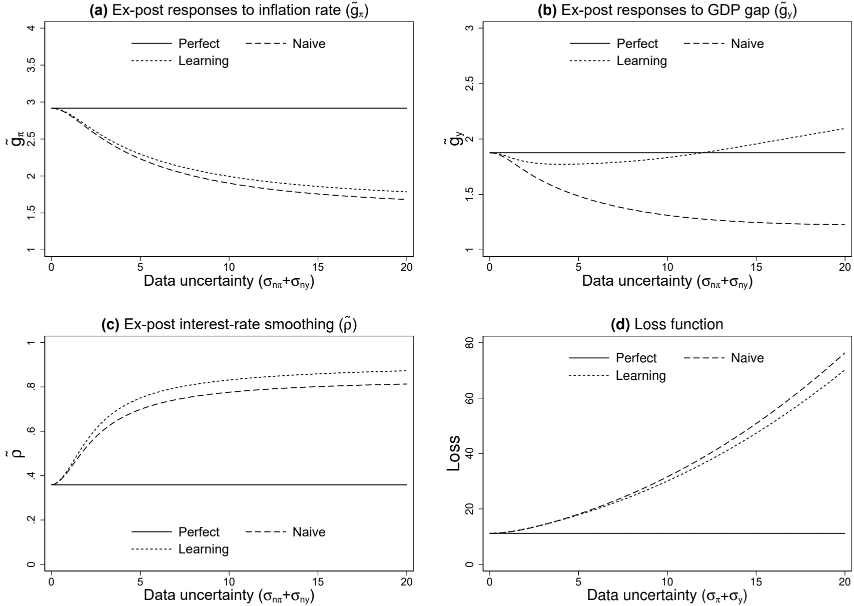
Ex-Post Estimates with Simulated Data

- Simulate the model and generate 100,000 obs given the optimal responses (first 20,000 obs dropped)
- Estimate Taylor rule with the simulated data:

$$i_t = (1 - \widetilde{\rho})[k + \widetilde{g_\pi} E_t \pi_{t+1} + \widetilde{g}_y y_t] + \widetilde{\rho} i_{t-1} + \varepsilon_t$$

- Repeat this varying level of data uncertainty for each policy type

Ex-Post Estimates with Simulated Data



Conclusion

- Countries with more data uncertainty tend to have more sluggish interest rates ($\widetilde{\rho}$).
- This is not because central banks put more weight (ρ) on lagged interest rates (i_{t-1}) but because of central banks' learning process.
- $\widetilde{\rho}$ in the reduced-form Taylor rule estimation with ex-post data is overestimated because the central bank's belief is not taken account. (Omitted variable bias!)
- Interest-rate smoothing can be endogenized by the learning process.

Thank you!

Full paper can be downloaded from

https://ssrn.com/abstract=3757399

Your questions and comments are welcome

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