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

GDP Growth Rate Revisions in US

- Real-Time Data
- 1-Year Revisions
Motivation

Not only GDP growth rate but also CPI inflation rate

CPI Inflation Rate Revisions in US

- Real-Time Data
- 1-Year Revisions
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. → 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

\[ i_t = (1 - \tilde{\rho})[k + \tilde{\gamma}_\pi E_t \pi_{t+1} + \tilde{\gamma}_y y_t] + \tilde{\rho} i_{t-1} + \varepsilon_t \]

→ Robust pattern controlling currency peg, income level, RER, or FFR.
Rudebusch-Svensson Model

- Phillips & IS curves:
  \[ \pi_t = \alpha_0 + \alpha_{\pi 1}\pi_{t-1} + \alpha_{\pi 2}\pi_{t-2} + \alpha_{\pi 3}\pi_{t-3} + \alpha_{\pi 4}\pi_{t-4} + \alpha_y y_{t-1} + \varepsilon_t \]
  \[ y_t = \beta_0 + \beta_{y 1}y_{t-1} + \beta_{y 2}y_{t-2} + \beta_r (\bar{i}_{t-1} - \bar{\pi}_{t-1}) + \eta_t \]

- Loss function:
  \[ E[L_t] = \text{Var}[\pi_t - \pi^*] + \lambda_y \text{Var}[y_t] + \lambda_i \text{Var}[\Delta i_t] \]

- 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:

\[ \pi^n_t = \pi_t + n^\pi_t \]

\[ y^n_t = y_t + n^y_t \]

Standard errors \( \sigma_{n\pi} \) and \( \sigma_{ny} \) indicate data uncertainty.

- Noises are modeled as MA(1):

\[ n^\pi_t = \epsilon^\pi_t + \theta^\pi \epsilon^\pi_{t-1} \]

\[ n^y_t = \epsilon^y_t + \theta^y \epsilon^y_{t-1} \]

\( \epsilon^\pi_t \sim N(0, \sigma^2_{\epsilon\pi}) \), \( \epsilon^y_t \sim N(0, \sigma^2_{\epsilon y}) \)
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 ($\pi_t$ 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 $\pi^n_t$ and $y^n_t$ and forms inferences on $\pi_t$ and $y_t$ by implementing Kalman filter.

\[
X_{t+1} = AX_t + Bi_t + \nu_{t+1}
\]
\[
X_t = [1 \pi_t \pi_{t-1} \pi_{t-2} \pi_{t-3} y_t y_{t-1} i_{t-1} i_{t-2} i_{t-3}]^T
\]
\[
Z_t = CX_t + w_t
\]

- 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
\[ G = \begin{bmatrix} g_\pi & g_y \\ e_2A \\ e_6 \end{bmatrix} \]

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

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

(a) Optimal responses to inflation rate \((g_\pi)\)

(b) Optimal responses to GDP gap \((g_y)\)

(c) Optimal gradual adjustment \((\rho)\)

(d) Loss function

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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:

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

- Repeat this varying level of data uncertainty for each policy type
Ex-Post Estimates with Simulated Data

(a) Ex-post responses to inflation rate ($\tilde{g}_\pi$)

(b) Ex-post responses to GDP gap ($\tilde{g}_y$)

(c) Ex-post interest-rate smoothing ($\tilde{\rho}$)

(d) Loss function

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Conclusion

- Countries with more data uncertainty tend to have more sluggish interest rates ($\tilde{\rho}$).

- This is not because central banks put more weight ($\rho$) on lagged interest rates ($i_{t-1}$) but because of central banks’ learning process.

- $\tilde{\rho}$ 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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