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Monetary policy design under uncertainty

Workshop on Prudent Risk Management Approach to Monetary Policy January 12, 2024



THE FEDERAL RESERVE BOARD OF GOVERNORS

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Disclaimer: The analysis and conclusions in these slides are those of the author only and should not be attributed to the Board of Governors of the Federal Reserve System or other members of its staff.

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Sketch of my remarks

- **1.** Some musings on FPAS Mark II
- **2.** Standard practice for optimal policy
 - LQG control, single simulation, single set of policymaker preferences
 - Multiple simulations, multiple preferences
- 3. Bayesian approaches to model uncertainty
 - Multiple models, averaged.
- 4. Departures from quadratic preferences:
 - Linear-exponential loss function
 - Robust control & ambiguity aversion



On FPAS Mark II Prudent Risk Management

On FPAS Mark II and Prudent Risk Management There is a lot to like!:

- Putting risk and uncertainty at the center
- No undue emphasis on uncertainty measures
- Ruling out "dark corners"

Operational issues:

- Policymakers don't know what they want
- "Least regrets" is hard to operationalize
- Case A v. B conveys impression of symmetry

Deeper questions:

- Bilateral communications and learning.
- The central bank as a part of the DGP.

Linear-quadratic Gaussian control

Policymaker preferences: standard practice

LQG problems:

- Linear models
- Quadratic preferences
- Gaussian disturbances

Advantages:

- Certainty equivalence (CE) holds
- Separation theorem holds.
- Simple to compute and simple to explain

Disadvantages:

• Risk disappears (corollary of CE)

The Federal Reserve staff loss function:

- L= policymaker loss
- *I* = felicity (periodic loss)
- *p* = *policy choice*
- s = economic state
- z^t = history of variable z to period t.
- X = mandate variable streams

$$\min_{R^* \mid t} L_t(X; s^t) = \min_{R \mid t} \left\{ \underbrace{\left(\underbrace{\pi_t^2 + \lambda_u u_t^2 + \lambda_{\Delta R} \left(\Delta R_t \right)^2}_{X} \right) + \beta E \left[L_{t+1}(X) \right]}_{X} \right\}$$

subject to the law of motion for s,X; p.

Tealbook Optimal Control (2017)



Authorized for Public Release

January 23, 2017

Class II FOMC - Restricted (FR)

Note: Each set of lines corresponds to an optimal control policy under commitment in which policymakers minimize a discounted weighted sum of squared deviations of four-quarter headline PCE inflation from the Committee's 2 percent objective, of squared deviations of the unemployment rate from the staffs estimate of the natural rate, and of squared changes in the federal funds rate. The weights vary across simulations. See the appendix for technical details and the box "Optimal Control and the Loss Function" in the June 2016 Tealbook B for a motivation.

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Tealbook Fanchart (2017)





The Bayesian approach to uncertainty

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Multiple models, the Bayesian case:

$$X_{t+1} = outcome to predict$$

 $D^t = data sequence from period 0 to t.$
 $P = policy rule$
 $m = model$

Standard econometric approach is to formulate conditional probability densities of x_{t+1} .

$$Pr\left(X_{t+1} | D^t, p, m\right)$$

key question: which model? $m \in M$

A

Bayesian multi-model analogues

- The inclusion of the model, m, as a conditioning element reflects the practice of assuming away model uncertainty
- A natural solution to this problem is to generalize uncertainty by integrating over (candidate) models.

$$Pr(X_{t+1}|D^t, p, \mathbf{M}) = \sum_{m \in \mathbf{M}} Pr(m|D^t) Pr(X_{t+1}|D^t, p, m)$$

Operationalizing

- Integrating over (econometric) models is an exercise in Bayesian decision theory.
- With statistical integration it's Bayesian model averaging.

$$\operatorname{var}\left(X_{t+1} \mid D^{t}, p, M\right) = \sum_{m \in M} Pr(m \mid D^{t}) \operatorname{var}\left(X_{t+1} \mid D^{t}, p, m\right) + \sum_{m \in M} Pr(m \mid D^{t}) \left(E\left(X_{t+1} \mid D^{t}, p, m\right) - E\left(X_{t+1} \mid D^{t}, p, M\right)\right)^{2}$$

effect of intermodal uncertainty

Alternative preference specifications

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Linear-exponential loss-averse preferences:

Li= policymakers' linex loss function X = objective function variables g_{t+j} = optimal predictor of X_{t+j}

$$Li_t(X;\alpha) = \left\{ (\exp(\alpha X) - \alpha X - 1) + \beta E[Li_{t+1}(X;\alpha)] \right\}$$

Varian (1974), Zellner (1986), Christofferson and Diebold (1997). Anatolyev (2009). For clarity, lets take $X=\pi$:

$$g_{t+1} = \alpha^{-1} \log E \left[\exp(\alpha \pi_{t+1}) \right]$$
$$= E \overline{\pi}_{t+1} + (\alpha / 2) E_t \sigma_{\pi,t+1}^2$$

The linex function

J. Kim, F.J. Ruge-Murcia / Journal of Monetary Economics 56 (2009) 365-377





The robust approach to uncertainty

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Uncertainty in macroeconomics

A century old question: Knight (1921), Keynes (1921). Modern models typically employ strong assumptions:

- Model consistent expectations
- Complete knowledge of the model and shocks
- Full commitment of policymakers

Risk-sensitive control and Ambiguity aversion take uncertainty seriously

- Origins from engineering: robust control theory (e.g., Hansen & Sargent, 2008)
- Also: axiomatic theory (Gilboa & Schmeidler, 1989; Epstein and Schneider, 2003)

Uncertainty in macroeconomics, II

The Ellsberg (1961) Paradox





Risky decision

Ambiguous decision

Uncertainty in macroeconomics: Ambiguity Aversion

Ambiguity aversion:

- Puts decisionmakers and econometricians on the same footing
- Entertains doubts by both about their models
- Ambiguity means uncertainty in the sense of Knight.
- Preference for known odds over unknown
- Decisions avoid the local worst-case outcome
- But the local worst case is endogenous.

Bayesian control problem:

$$L_{t}(X;s^{t}) = l(X_{t}(s^{t})) + \beta \sum_{m \in M} \Pr(m | D^{t}) E\left[L_{t+1}(X;s^{t+1})\right]$$

Ambiguity averse problem:

- Recursive multiple priors (Epstein & Schneider, 2003)
- Size of belief set captures lack of confidence $b_m \in M_t(s^t)$
- Foundation: preference for known over unknown odds.
- Leads to a criterion of minimizing the (local) worst case

$$L_{t}(X;s^{t}) = l(X_{t}(s^{t})) + \beta \min_{b_{m} \in M_{t}(s^{t})} E^{b} \left[L_{t+1}(X;s^{t+1}) \right]$$

In Conclusion....

On MPAS Mark II:

- Lots to like with this project!
- Poised to put the CB of Armenia on a good path...
- ...even if there are a few issues to work out.

On loss functions for modeling uncertainty:

• Methods for modeling uncertainty exist that could be helpful.

Thank you!



Appendix

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Uncertainty in macroeconomics: Risk-sensitive LQ control:

Recall the quadratic loss function:

$$L_{t}(\pi_{t}, y_{t}) = \underbrace{\left(\pi_{t}^{2} + \lambda y_{t}^{2}\right)}_{l(.)} + \beta E \Big[L_{t+1}(\pi_{t+1}, y_{t+1})\Big]$$

The risk-sensitive extension twists the quadratic criterion:

$$l(\theta) = \frac{2}{\theta} \log E \left[\exp \left(\frac{1}{2} \theta (\pi_t^2 + \lambda y_t^2) \right) \right], \quad \theta > 0$$