Comments on

Model Uncertainty and Policy Evaluation:
Some Theory and Empirics

Brock, Durlauf and West
Basic Question

• Several models on the table
• Two strategies:
  1. Select a model using a statistical criterion and then choose optimal policy
  2. Average over models then choose optimal policy
• Explore intermediate alternatives
What was done

- Two model classes: backwards and hybrid. Both types of models contain distributed lags in inflation and output.
- Within a model class, different specifications of lag lengths. 64 different specifications per type. 128 specifications.
- Model averaging or partial averaging within classes using BIC adjusted likelihoods (do not average over parameters).
- Separate treatment across types or average treatment.
Within class analysis

- Empirically determined probabilities concentrated on a small number of specifications
- Suggest elimination of outlier models - why?
- Should be a more complete discussion of loss function misspecification
  1. Loss functions should be bounded?
  2. Discounting should be included? Timeless perspective? Learning?
Policy Rules

- Alternative Rules
  1. Taylor rule
  2. Optimized rule at (BIC adjusted) likelihood maxima within each model type (no model averaging)
  3. Optimization with full model averaging within classes is not featured. Natural benchmark. Computational problems?

- Taylor rule does okay across all specifications but is dominated noticeably over many of the models with a non-negligible empirical weights.

- Optimized rules perform extremely poorly over a small number of models with small empirical weights.
Conclusions?

- Loss function matters?
- Okay to engage in a two-step procedure? Pick specification within class according to BIC and optimize.
- Can you achieve multiple aims (no instability across models) and good performance over likely models by adopting a one step approach?
- Outcome dispersion? Intriguing, but why?
Related Approaches


- Robustness in hidden state models - perform reduction first via model averaging and then perturb - alternatively perturb each model (probability conditioned on a hidden state) and perturb weights across models, each in restrained ways.