Negotiating the Wilderness of Bounded Rationality through Robust Policy

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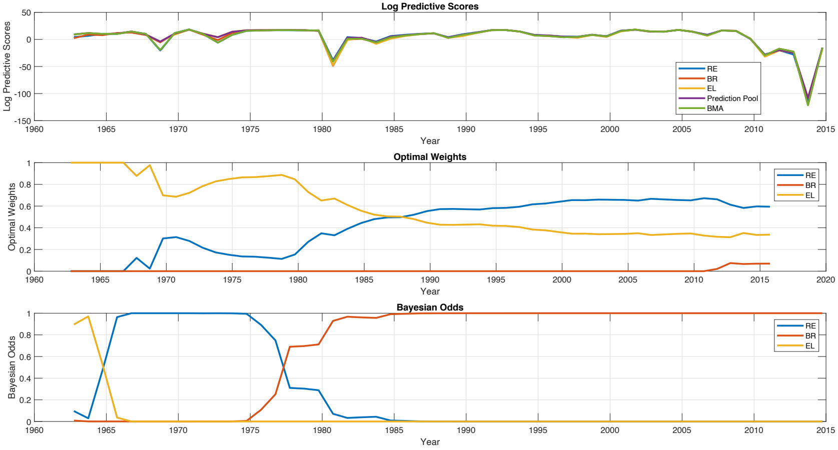
Context

- Many different behavioural models :
  - Sims (1980) warned that leaving the rational expectations equilibrium concept sends us into a “wilderness”
- Each may be valuable at potentially different points in time.
- How can forward-looking policy makers combine insights across models to inform the design of monetary policy when?
  - No one model is believed to be the true DGP (renders Bayesian model averaging (BMA) inapplicable).
  - Some may only provide limited insight (i.e. in certain states).
  - Future shocks are uncertain.
  - Within-model parameter uncertainty persists.
  - Policy makers must adhere to a strict mandate.

This Paper

- We **estimate** two leading behavioural models and compare their predictive performance with a RE NK model.
- We consider a model with "Euler learning" and another with myopic boundedly rational agents exhibiting limited attention.
- We design robust simple rules that address across-model uncertainty in a novel way:
  - We measure the usefulness of models by **their relative forecasting accuracy**.
  - Models combined on this basis form a **prediction pool** (Geweke and Amisano, 2012). Why?
    1. Current model combination techniques such as BMA assume that one of the models is *the* true DGP.
    2. Prediction pools relax this assumption, allowing competing misspecified models to be useful at different times.
    3. Modern monetary policy by central banks is forward-looking relying heavily on forecasts.

Model Weights: Relative Predictive Performance



A Mandate Framework

We assume the policy maker employs the following type of rule:

$$\log\left(\frac{R_{n,t}}{R_n}\right) = \rho_r \log\left(\frac{R_{n,t-1}}{R_n}\right) + \alpha_\pi \log\left(\frac{\Pi_t}{\Pi}\right) + \alpha_y \log\left(\frac{Y_t}{Y}\right) + \alpha_{dy} \log\left(\frac{Y_t}{Y_{t-1}}\right) \quad (1)$$

Let $\rho = [\rho_r, \alpha_\pi, \alpha_y, \alpha_{dy}]$. The equilibrium is solved by backward induction in the following three-stage delegation game.

1. **Stage 1**: The policymaker chooses a per period probability of hitting the ZLB and sets the optimal loss function in mandate.
2. **Stage 2**: The optimal steady state inflation rate consistent with stage 1 is chosen.
3. **Stage 3**: The CB receives the mandate in the form of a welfare criterion and rule of the form (1). Welfare is then optimized with respect to ρ resulting in an optimized rule.

Optimized Rules with a ZLB: Price-Level Rules

	Optimal ZLB Mandate Across Models ($\bar{p} = 0.01$)								
Models	ρ_r^*	α_π^*	α_y^*	α_{dy}^*	Π^*	Act welfare	CEV	p_zlb	w_r^*
RE	1.0	0.24	0.00	0.00	1.0034	-2315.4	-0.1523	0.01	200
BR	1.0	0.15	0.0	0.012	1.0185	-3266.8	-0.1827	0.01	20
EL	1.0	100.38	1.0	0.00	1.0219	-2622.8	-0.6447	0.01	80
Pool of models	1.0	3.72	0.006	0.02	1.0184	-2609.1	-2.0761	0.01	40
	Optimal ZLB Mandate Across Models ($\bar{p} = 0.096$)								
Models	ρ_r^*	α_π^*	α_y^*	α_{dy}^*	Π^*	Act welfare	CEV	p_zlb	w_r^*
RE	1.0	1.59	0.00	0.06	1.0015	-2312.7	-0.0152	0.096	20
BR	0.83	5.08	0.03	0.50	1.0111	-3264.3	-0.0558	0.096	0
EL	1.0	101.73	1.0	0.32	1.0102	-2612.3	-0.1117	0.096	20
Pool of models	1.0	1.59	0.00	0.00	1.0048	-2569.9	-0.0883	0.096	60

- To avoid the ZLB optimized rules must have $\rho_r^* = 1$ and $\alpha_y \approx 0$ and $\alpha_{dy}^* \approx 0$; i.e., they are close to a price-level rule.