

Kalman Filter Learning Versus Bounded Rationality in a Heterogeneous Agent NK Model

Szabolcs Deák, Paul Levine, Joseph Pearlman, Bo Yang

Yifan Zhang

University of Oxford

Behavioural Macro and Finance Workshop, January, 2024

KF Learning versus Bounded Rationality

Motivation:

- FIRE models often struggle to reproduce the persistence observed in actual macroeconomic data
- Agents in FIRE models are assumed to know the *model* (RE) and *state variables* (FI)
- Recent literature relaxes RE or FI or both, improves model fit

KF Learning versus Bounded Rationality

Motivation:

- FIRE models often struggle to reproduce the persistence observed in actual macroeconomic data
- Agents in FIRE models are assumed to know the *model* (RE) and *state variables* (FI)
- Recent literature relaxes RE or FI or both, improves model fit

Question: *Which fits better with the data?*

KF Learning versus Bounded Rationality

Motivation:

- FIRE models often struggle to reproduce the persistence observed in actual macroeconomic data
- Agents in FIRE models are assumed to know the *model* (RE) and *state variables* (FI)
- Recent literature relaxes RE or FI or both, improves model fit

Question: *Which fits better with the data?*

This Paper: Propose a NK model with RE and bounded rationality agents
⇒ Comparison among different models
⇒ Information assumption is important

A Bird's Eye View

Model Setup: A standard NK model with heterogeneous agents:

- BR agents: AU learning + adaptive expectations about *external* variables
 - Observe local variables and nominal interest rate with no lag, aggregate with a lag

A Bird's Eye View

Model Setup: A standard NK model with heterogeneous agents:

- BR agents: AU learning + adaptive expectations about *external* variables
 - Observe local variables and nominal interest rate with no lag, aggregate with a lag
- RE agents: a) perfect information; b) *imperfect information* (KF learning)

A Bird's Eye View

Model Setup: A standard NK model with heterogeneous agents:

- BR agents: AU learning + adaptive expectations about *external* variables
 - Observe local variables and nominal interest rate with no lag, aggregate with a lag
- RE agents: a) perfect information; b) *imperfect information* (KF learning)
- Shocks: 4 Exog. AR(1) Shock: $A_t, G_t, MS_t, \Pi_{targ,t}$; 4 i.i.d shocks

A Bird's Eye View

Model Setup: A standard NK model with heterogeneous agents:

- BR agents: AU learning + adaptive expectations about *external* variables
 - Observe local variables and nominal interest rate with no lag, aggregate with a lag
- RE agents: a) perfect information; b) *imperfect information* (KF learning)
- Shocks: 4 Exog. AR(1) Shock: $A_t, G_t, MS_t, \Pi_{targ,t}$; 4 i.i.d shocks

Information Consistency: *Common imperfect information assumptions for RE and BR*

A Bird's Eye View

Model Setup: A standard NK model with heterogeneous agents:

- BR agents: AU learning + adaptive expectations about *external* variables
 - Observe local variables and nominal interest rate with no lag, aggregate with a lag
- RE agents: a) perfect information; b) *imperfect information* (KF learning)
- Shocks: 4 Exog. AR(1) Shock: $A_t, G_t, MS_t, \Pi_{targ,t}$; 4 i.i.d shocks

Information Consistency: *Common imperfect information assumptions for RE and BR*

⇒ Agents cannot back out the shock processes – wedge between PI and II

A Bird's Eye View

Model Setup: A standard NK model with heterogeneous agents:

- BR agents: AU learning + adaptive expectations about *external* variables
 - Observe local variables and nominal interest rate with no lag, aggregate with a lag
- RE agents: a) perfect information; b) *imperfect information* (KF learning)
- Shocks: 4 Exog. AR(1) Shock: $A_t, G_t, MS_t, \Pi_{targ,t}$; 4 i.i.d shocks

Information Consistency: *Common imperfect information assumptions for RE and BR*

⇒ Agents cannot back out the shock processes – wedge between PI and II

⇒ **Fair comparison between BR and RE (II)**

A Bird's Eye View

Model Setup: A standard NK model with heterogeneous agents:

- BR agents: AU learning + adaptive expectations about *external* variables
 - Observe local variables and nominal interest rate with no lag, aggregate with a lag
- RE agents: a) perfect information; b) *imperfect information* (KF learning)
- Shocks: 4 Exog. AR(1) Shock: $A_t, G_t, MS_t, \Pi_{targ,t}$; 4 i.i.d shocks

Information Consistency: *Common imperfect information assumptions for RE and BR*

⇒ Agents cannot back out the shock processes – wedge between PI and II

⇒ **Fair comparison between BR and RE (II)**

Bayesian Estimation: estimate the models with macroeconomic data

⇒ BR and RE with II improve the model fit and the persistence of the model

⇒ RE(II)-BR > Pure RE(II) > RE(PI)-BR > Pure BR > Pure RE

Comment # 1: Alternative misspecified forecasting rules?

AU learning: agents only have knowledge of their own objectives and constraints, do not have economic model of determination of aggregate variables

A simple example:

$$c_t = \sum_{s=t}^{\infty} [(1 - \beta) E_t^* y_s - \sigma \beta E_t^* r_s]$$

Comment # 1: Alternative misspecified forecasting rules?

AU learning: agents only have knowledge of their own objectives and constraints, do not have economic model of determination of aggregate variables

A simple example:

$$c_t = \sum_{s=t}^{\infty} [(1 - \beta) E_t^* y_s - \sigma \beta E_t^* r_s]$$

Heuristic expectation rule: $E_t^* x_{t+1} = E_{t-1}^* x_t + \lambda_x (x_{t-j} - E_{t-1}^* x_t)$

Comment # 1: Alternative misspecified forecasting rules?

AU learning: agents only have knowledge of their own objectives and constraints, do not have economic model of determination of aggregate variables

A simple example:

$$c_t = \sum_{s=t}^{\infty} [(1 - \beta) E_t^* y_s - \sigma \beta E_t^* r_s]$$

Heuristic expectation rule: $E_t^* x_{t+1} = E_{t-1}^* x_t + \lambda_x (x_{t-j} - E_{t-1}^* x_t)$

– Convenient approach. Are the findings dependent on this particular forecasting rules?

Comment #2: More to be understood beyond Bayes Factor

Incorporate BR or RE(II) improve models' ability to match the macroeconomic data

Comment #2: More to be understood beyond Bayes Factor

Incorporate BR or RE(II) improve models' ability to match the macroeconomic data

Bayesian Estimation: Likelihood Race Ranking:

$\text{RE(II)-BR} > \text{Pure RE(II)} > \text{RE(PI)-BR} > \text{Pure BR} > \text{Pure RE}$

Comment #2: More to be understood beyond Bayes Factor

Incorporate BR or RE(II) improve models' ability to match the macroeconomic data

Bayesian Estimation: Likelihood Race Ranking:

$\text{RE(II)-BR} > \text{Pure RE(II)} > \text{RE(PI)-BR} > \text{Pure BR} > \text{Pure RE}$

- Understand the marginal contribution of BR to RE(II)-BR

Comment #2: More to be understood beyond Bayes Factor

Incorporate BR or RE(II) improve models' ability to match the macroeconomic data

Bayesian Estimation: Likelihood Race Ranking:

$\text{RE(II)-BR} > \text{Pure RE(II)} > \text{RE(PI)-BR} > \text{Pure BR} > \text{Pure RE}$

- Understand the marginal contribution of BR to RE(II)-BR
- Estimated shock persistence are quite different across models
 - ▶ Lower exog. persistence in RE(II) and BR models – Expectation more persistent

Comment #2: More to be understood beyond Bayes Factor

Incorporate BR or RE(II) improve models' ability to match the macroeconomic data

Bayesian Estimation: Likelihood Race Ranking:

RE(II)-BR > Pure RE(II) > RE(PI)-BR > Pure BR > Pure RE

- Understand the marginal contribution of BR to RE(II)-BR
- Estimated shock persistence are quite different across models
 - ▶ Lower exog. persistence in RE(II) and BR models – Expectation more persistent
 - ▶ But..., price mark-up ρ_{MS} is estimated to be 0.39 in Pure RE (PI), 0.97 in all other models

Comment #3: Survey information serves as an additional restriction

- Survey information serves as an *additional restriction* and helps differentiate between models
- Ormeño and Molnár (2015): adaptive learning fares similarly to RE in fitting macro data, but *clearly outperforms* RE in fitting macro and survey data simultaneously

Comment #3: Survey information serves as an additional restriction

- Survey information serves as an *additional restriction* and helps differentiate between models
- Ormeño and Molnár (2015): adaptive learning fares similarly to RE in fitting macro data, but *clearly outperforms* RE in fitting macro and survey data simultaneously

– *Estimate the models with macroeconomic and **survey** data simultaneously, if substantial differences in the likelihood (e.g. Hommes et al. (2023))*

Final remarks

- Growing literature on deviations from FIRE
- This paper: **information assumption** is important in the empirical comparison of RE and BR NK models
- Potential for policy implications