Discussion of Estimated DSGE with Partial Dollarization

by Castillo, Montoro and Tuesta

Simon Potter

New York Fed

November 2006

The views expressed are not necessarily those of FRBNY or FRS.

Overview of Paper

- DSGE models for monetary policy in Peru including effects of dollarization
- State of art open economy DSGE model with new approach to dollarization
- Sophisticated Bayesian approach to estimation

Assessment

- Paper addresses a crucial issue for Peruvian monetary policy
- Makes new contribution to open economy DSGE literature
- Focus comments on use of Bayesian estimation and modeling issues

Simplified Description of Bayesian DSGE modeling for monetary policy

Contrast with old style large macro models

- Develop DSGE model that captures key features of the economy in a consistent way
  - Solve for general equilibrium vs. analyze each feature separately
  - DSGE model less vulnerable to Lucas critique
- Use recent macroeconomic data to estimate model by modern Bayesian methods
  - Estimate system, not equation by equation
  - Internally consistent treatment of parameter uncertainty for decisionmakers
  - Coherent methods of updating model estimates with new data
  - Possible to select or average across models

Why has movement to Bayesian DSGE modeling for monetary policy taken so long?

Is this too good to be true?

Some open issues

- How robust is the log linearization used in most studies?
  - Is dollarization a nonlinear phenomenon?
- Do we believe the marginal likelihood information on relative value of each model?
  - Do we really believe the priors?
  - How should we change priors across models? (recent work by Del Negro and Schorfheide)
  - Computational improvements possible over modified harmonic mean (see Meng and Wong Statistica Sinica 1996 + new papers)
- Great advantage of both Bayesian and DSGE approach is that we can make progress in a scientific way on the open issues

Log Linearization

- Rubio and Villaverde have shown problems with log linearization for likelihood based estimation
  - Particle filter is one solution but very fragile
  - Eventually increased computing power should allow workable solutions
- Is dollarization a steady state phenemonen?
  - Monetary policy and expectations of monetary policy effect degree of dollarization in a non-linear way
  - Lucas critique will still apply in model

Basic Model Choicc

Consider two models:

- Model 0 with parameter vector ψ, prior distribution $p_0(\psi)$ and likelihood $\ell(Y|\psi)$. For example, the standard open economy macro model
- Model 1 with parameter vector (ψ, θ),prior distribution $p_1(\psi, \theta)$ and likelihood $\ell(Y|\psi, \theta)$. For example, open economy model with dollarization etc, captured by parameter vector θ
- Assume the prior distribution for Model 0 is given by other sample information
- Prior distribution for Model 1 will depend on subjective views of investigator and "more objective prior information"

Marginal Likelihood and Bayes Factors

Bayes Factor is ratio of marginal likelihoods

The data Y allows updating on prior weights and parameters of each model.
The marginal likelihood is defined by

$$m(Y) = \int \ell(Y|\chi)p(\chi)d\chi,$$

$$\frac{m_0(Y)}{m_1(Y)} = \frac{\int \ell(Y|\psi)p_0(\psi)d\psi}{\int\int \ell(Y|\psi,\theta)p_1(\psi,\theta)d\psi d\theta}$$

This can be adjusted by prior model weights to form posterior model weights to construction predictions that average out over model uncertainty.

Priors on parameters and models might vary in model averaging exercise depending on the nature of the prediction: pure vs. policy projection

Simplification with Nested Models

Assume (with great loss of generality) that model 0 is nested within other model:

$$\ell(Y|\psi) = \ell(Y|\psi, \theta^*)$$

for $\theta = \theta^*$

Bayes factor comparisons with nested models simplify to Savage Dickey Density Ratio, similar to log likelihood ratio

Loss of generality because in practice models nested at boundary of parameter space and Savage Dickey Density ratio might not be valid. For example, dollarization!

(Generalized) Savage Dickey Density Ratio

$$\frac{m_0(Y)}{m_1(Y)} = \frac{p_1(\theta^*|Y)}{p_1(\theta^*)c_1}.$$

$$c_1 = \int \frac{p_1(\psi|\theta^*)}{p_0(\psi)} p_0(\psi|Y) d\psi,$$

While $p_1(\theta^*|Y)$ depends on the choice for $p_1(\psi)$ and $p_1(\theta|\psi)$, the data as viewed through the likelihood for model 1 will dominate as the sample size grows

If $p_1(\psi|\theta^*) \neq p_0(\psi)$ then the Bayes Factor will be effected by prior choices over ψ as viewed through the likelihood of model 0 in the value of c_1

Simple Example: Mean of AR(1)

$$y_t = \psi + \theta y_{t-1} + \varepsilon_t, \ \varepsilon_t \sim N(0,1).$$

At $\theta = \theta^* = 0$ models are nested.
Interested in assessing whether the data has dependence

If we assume that ψ and θ are a priori independent then $p_1(\psi|\theta^*) = p_1(\psi)$

If we further assume that $p_1(\psi) = p_0(\psi)$ then sample information on the location μ of Y rather than persistence of the observed sample can dominate the Bayes Factor

Prior Construction to Avoid Problem

Change of variable argument assuming common belief across models about location,

$$\frac{\psi}{1-\theta} = \mu \sim N(\underline{\mu}, \underline{\lambda}^2),$$

and $\theta \sim U(-1, 1)$. Thus

$$\psi|\theta \sim N(\underline{\mu}(1-\theta), \underline{\lambda}^2(1-\theta)^2),$$

Now ψ and θ are *a priori* DEPENDENT and

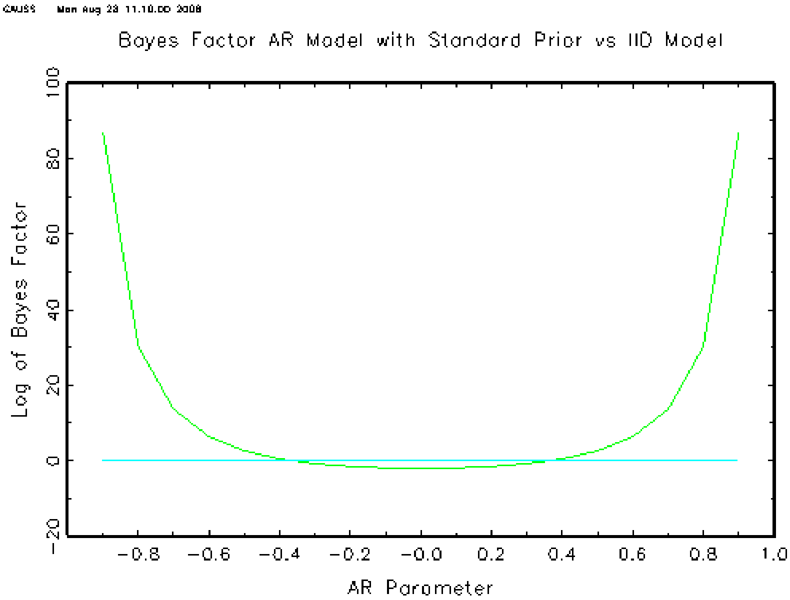
$$p_1(\psi|\theta) \neq p_0(\psi) \text{ if } \theta \neq \theta^*,$$

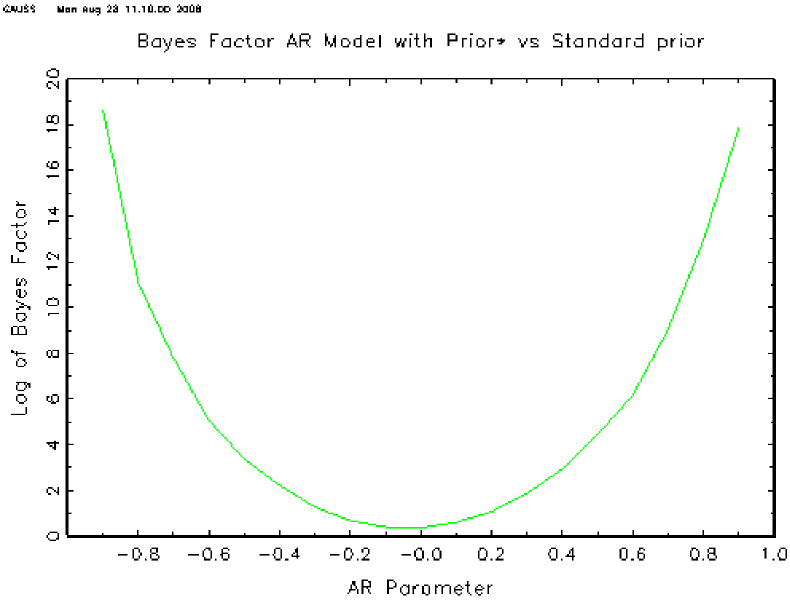
BUT with equality at θ^*.

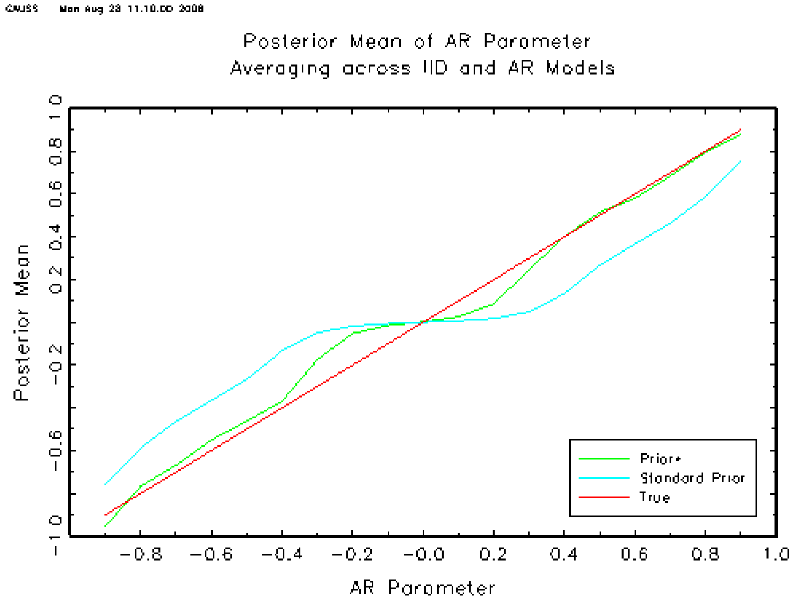
Call this prior: $p_1^*(\psi, \theta)$

Experiment

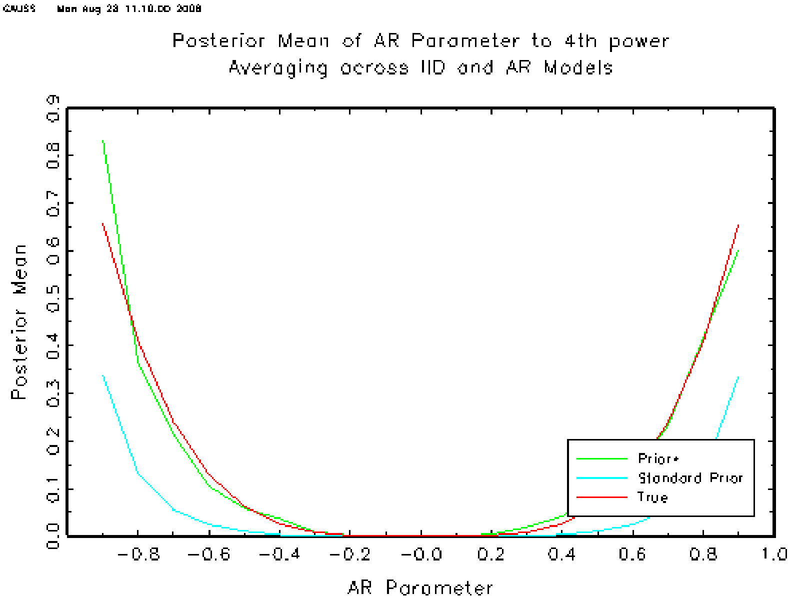
- $\underline{\mu} = 3$, $\underline{\lambda} = 0.4$, $T = 50$
- Vary θ from -0.9 to $+0.9$
- Use population moments for sufficient statistics in updating prior to posterior
- Use posterior under standard prior for AR model to average importance weights of other priors

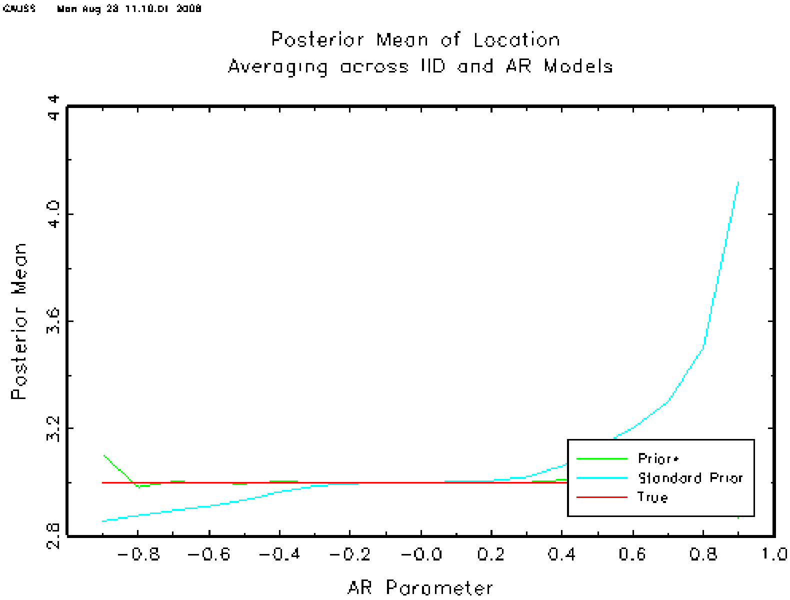

GAUSS Mon Aug 28 11:10:00 2008
Bayes Factor AR Model with Standard Prior vs IID Model
Log of Bayes Factor
-20
0
20
40
60
80
100
-0.8
-0.6
-0.4
-0.2
-0.0
0.2
0.4
0.6
0.8
1.0
AR Parameter


GAUSS Mon Aug 28 11:10:00 2008
Bayes Factor AR Model with Prior* vs Standard prior
Log of Bayes Factor
0
2
4
6
8
10
12
14
16
18
20
-0.8
-0.6
-0.4
-0.2
-0.0
0.2
0.4
0.6
0.8
1.0
AR Parameter



Posterior Mean of AR Parameter
Averaging across IID and AR Models
Posterior Mean
-1.0
-0.6
-0.2
0.2
0.4
0.6
0.8
1.0
-0.8
-0.6
-0.4
-0.2
-0.0
0.2
0.4
0.6
0.8
1.0
AR Parameter
Prior*
Standard Prior
True


GAUSS Mon Aug 28 11:10:00 2006
Posterior Mean of AR Parameter to 4th power
Averaging across IID and AR Models
Posterior Mean
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
-0.8
-0.6
-0.4
-0.2
-0.0
0.2
0.4
0.6
0.8
1.0
AR Parameter
Prior*
Standard Prior
True


GAUSS Mon Aug 28 11:10:01 2006
Posterior Mean of Location
Averaging across IID and AR Models
Posterior Mean
4.4
4.0
3.6
3.2
2.8
-0.8
-0.6
-0.4
-0.2
-0.0
0.2
0.4
0.6
0.8
1.0
AR Parameter
Prior*
Standard Prior
True

Conclusions

- Impressive contribution to open economy Bayesian DSGE literature
- Priors matter for Bayesian analysis of DSGE model
- More care needs to be taken with constructing priors without and with dollarization
  - Particularly true with short data samples due to regime change