

Sensitivity Analysis Toolbox for DYNARE

Marco Ratto

European Commission, Joint Research Centre

TP361, IPSC, via E. Fermi 1

21020 Ispra (VA) Italy

`marco.ratto@jrc.it` *

September 29, 2009

Abstract

The Sensitivity Analysis Toolbox for DYNARE is a set of MATLAB routines for the analysis of DSGE models with global sensitivity analysis. The routines are thought to be used within the DYNARE v4 environment.

Keywords: Stability Mapping , Reduced form solution, DSGE models, Monte Carlo filtering, Global Sensitivity Analysis.

*The author gratefully thanks Christophe Planas, Kenneth Judd, Michel Juillard, Alessandro Rossi, Frank Schorfheide and the participants to the Courses on Global Sensitivity Analysis for Macroeconomic Models (Ispra, 2006-2007-2008) for interesting discussions and helpful suggestions.

1 Introduction

The Sensitivity Analysis Toolbox for DYNARE is a collection of MATLAB routines implemented to answer the following questions: (i) Which is the domain of structural coefficients assuring the stability and determinacy of a DSGE model? (ii) Which parameters mostly drive the fit of, e.g., GDP and which the fit of inflation? Is there any conflict between the optimal fit of one observed series versus another one? (iii) How to represent in a direct, albeit approximated, form the relationship between structural parameters and the reduced form of a rational expectations model?

The discussion of the methodologies and their application is described in Ratto (2008).

2 Use of the Toolbox

The DYNARE parser now recognizes sensitivity analysis commands. The syntax is based on a single command:

```
dynare_sensitivity(option1=<opt1_val>,option2=<opt2_val>,...)
```

with a list of options described in the next section.

With respect to the previous version of the toolbox, in order to work properly, the sensitivity analysis Toolbox *no longer* needs that the DYNARE estimation environment is set-up.

Therefore, **`dynare_sensitivity`** is the only command to run to make a sensitivity analysis on a DSGE model¹.

¹Of course, when the user needs to perform the mapping of the fit with a posterior sample, a Bayesian estimation has to be performed beforehand

3 List of options

3.1 Sampling options

option name	default	description
Nsam	2048	Size of MC sample
ilptau	1	1 = use LP_τ quasi-Monte Carlo 0 = use LHS Monte Carlo
pprior	1	1 = sample from prior distributions 0 = sample from multivariate normal $N(\hat{\theta}, \Sigma)$, $\hat{\theta}$ is posterior mode $\Sigma = H^{-1}$, H is Hessian at the mode
prior_range	1	1 = sample <i>uniformly</i> from prior ranges 0 = sample from prior distributions: this requires MATLAB Statistics Toolbox
morris	0	0 = no Morris sampling for screening 1 = Morris sampling for screening
morris_nliv	6	number of levels in Morris design
morris_ntra	20	number of trajectories in Morris design
ppost	0	0 = don't use Metropolis posterior sample 1 = use Metropolis posterior sample: this overrides any other sampling option!

3.2 Stability mapping

option name	default	description
stab	1	1 = perform stability mapping 0 = no stability mapping is performed
load_stab	0	0 = generate a new sample 1 = load a previously created sample
alpha2_stab	0.4	critical value for correlations ρ in filtered samples: plot couples of parameters with $ \rho > \text{alpha2_stab}$
ksstat	0.1	critical value for Smirnov statistics d : plot parameters with $d > \text{ksstat}$

3.3 Reduced form mapping

The mapping of the reduced form solution forces the use of samples from prior ranges or prior distributions, i.e.:

```
options_.opt_gsa.pprior=1;
options_.opt_gsa.ppost=0;
```

It uses 250 samples to optimize smoothing parameters and 1000 samples to compute the fit. The rest of the sample is used for out-of-sample validation.

option name	default	description
redform	0	0 = don't prepare MC sample of reduced form matrices 1 = prepare MC sample of reduced form matrices
load_redform	0	0 = estimate the mapping of reduced form model 1 = load previously estimated mapping
logtrans_redform	0	0 = use raw entries 1 = use log-transformed entries
threshold_redform	[]	[] = don't filter MC entries of reduced form coefficients [max max] = analyse filtered entries within the range [max max]
ksstat_redform	0.1	critical value for Smirnov statistics d when reduced form entries are filtered
alpha2_redform	0.3	critical value for correlation ρ when reduced form entries are filtered
namendo	[]	list of endogenous variables
	:	jolly character to indicate ALL endogenous
namlagendo	[]	list of lagged endogenous variables: analyse entries [namendo×namlagendo]
	:	jolly character to indicate ALL endogenous
namexo	[]	list of exogenous variables: analyse entries [namendo×namexo]
	:	jolly character to indicate ALL exogenous

One can also load a previously estimated mapping with a new MC sample, to look at the forecast for the new MC sample.

3.4 Mapping the fit

The RMSE analysis can be performed with different types of sampling options:

1. when `pprior=1` and `ppost=0`, the Toolbox analyses the RMSE's for the MC sample obtained by sampling parameters from their prior distributions (or prior ranges): this analysis provides some hints about what parameter drives the fit of which observed series, prior to the full estimation;
2. when `pprior=0` and `ppost=0`, the Toolbox analyses the RMSE's for a multivariate normal MC sample, with covariance matrix based on the inverse Hessian at the optimum: this analysis is useful when ML estimation is done (i.e. no Bayesian estimation);
3. when `ppost=1` the Toolbox analyses the RMSE's for the posterior sample obtained by DYNARE's Metropolis procedure.

The use of cases 2. and 3. requires an estimation step beforehand! To facilitate the sensitivity analysis after estimation, the `dynare_sensitivity` command also allows to indicate some options of `dynare_estimation`. These are:

- `datafile`
- `mode_file`
- `first_obs`
- `nobs`
- `prefilter`
- `presample`
- `loglinear`

option name	default	description
<code>rmse</code>	0	0 = no RMSE analysis 1 = do RMSE analysis
<code>load_rmse</code>	0	0 = make a new RMSE analysis 1 = load previous RMSE analysis
<code>lik_only</code>	0	0 = compute RMSE's for all observed series 1 = compute only likelihood and posterior
<code>var_rmse</code>	<code>varobs</code>	list of observed series to be considered
<code>pfilt_rmse</code>	0.1	filtering threshold for RMSE's: default it to filter the best 10% for each observed series
<code>istart_rmse</code>	1	start computing RMSE's from <code>istart_rmse</code> : use 2 to avoid big initial error
<code>alpha_rmse</code>	0.002	critical value for Smirnov statistics d : plot parameters with $d > \text{alpha_rmse}$
<code>alpha2_rmse</code>	1	critical value for correlation ρ plot couples of parameters with $ \rho > \text{alpha2_rmse}$
<code>glue</code>	0	prepare for GLUE graphical interface

3.5 Screening analysis

The screening analysis does not require any additional options with respect to those listed in the ‘Sampling options’: `morris`, `morris_nliv`, `morris_ntra`. The Toolbox performs all the analyses required and displays results.

3.6 Identification analysis (under development)

Setting the option `identification=1`, an identification analysis based on theoretical moments is performed. Sensitivity plots are provided that allow to infer which parameters are most likely to be less identifiable.

Prerequisite for properly running all the identification routines, is the keyword `identification`; in the DYNARE model file. This keyword triggers the computation of analytic derivatives of the model with respect to estimated parameters and shocks. This is required for options `morris=0,2` below, which implement Iskrev (2009) identification analysis.

option name	default	description
<code>identification</code>	0	0 = no identification analysis 1 = performs identification analysis: this forces <code>redform=0</code> and <code>defaultmorris=1</code>
<code>morris</code>	1	1 = Screening analysis (Type II error) 0 = ANOVA Mapping (Type I error) and analytic derivatives 2 = Analytic derivatives (similar to Type II error)
<code>morris_nliv</code>	6	number of levels in Morris design
<code>morris_ntra</code>	20	number of trajectories in Morris design
<code>trans_ident</code>	0	data transformation for ANOVA Mapping 0 = no transformation 1 = log-transformation 2 = rank-transformation

For example, the following commands in the DYNARE model file

```
identification;
dynare_sensitivity(identification=1, morris=2);
```

trigger the identification analysis using analytic derivatives (Iskrev, 2009).

4 Directory structure

Sensitivity analysis results are saved on the hard-disk of the computer. The Toolbox uses a dedicated folder called **GSA**, located in

`<DYNARE_file>\GSA,`

where `<DYNARE_file>.mod` is the name of the DYNARE model file.

4.1 Binary data files

A set of binary data files is saved in the **GSA** folder:

`<DYNARE_file>_prior.mat`: this file stores information about the analyses performed sampling from the prior ranges, i.e. `pprior=1` and `ppost=0`;

`<DYNARE_file>_mc.mat`: this file stores information about the analyses performed sampling from multivariate normal, i.e. `pprior=0` and `ppost=0`;

`<DYNARE_file>_post.mat`: this file stores information about analyses performed using the Metropolis posterior sample, i.e. `ppost=1`.

`<DYNARE_file>_prior_*.mat`: these files store the filtered and smoothed variables for the prior MC sample, generated when doing RMSE analysis (`pprior=1` and `ppost=0`);

`<DYNARE_file>_mc_*.mat`: these files store the filtered and smoothed variables for the multivariate normal MC sample, generated when doing RMSE analysis (`pprior=0` and `ppost=0`).

4.2 Stability analysis

Figure files `<DYNARE_file>_prior_*.fig` store results for the stability mapping from prior MC samples:

`<DYNARE_file>_prior_stab_SA_*.fig`: plots of the Smirnov test analyses confronting the cdf of the sample fulfilling Blanchard-Kahn conditions with the cdf of the rest of the sample;

`<DYNARE_file>_prior_stab_indet_SA_*.fig`: plots of the Smirnov test analyses confronting the cdf of the sample producing indeterminacy with the cdf of the original prior sample;

<DYNARE_file>_prior_stab_unst_SA_*.fig: plots of the Smirnov test analyses confronting the cdf of the sample producing unstable (explosive roots) behaviour with the cdf of the original prior sample;

<DYNARE_file>_prior_stable_corr_*.fig: plots of bivariate projections of the sample fulfilling Blanchard-Kahn conditions;

<DYNARE_file>_prior_indeterm_corr_*.fig: plots of bivariate projections of the sample producing indeterminacy;

<DYNARE_file>_prior_unstable_corr_*.fig: plots of bivariate projections of the sample producing instability;

<DYNARE_file>_prior_unacceptable_corr_*.fig: plots of bivariate projections of the sample producing unacceptable solutions, i.e. either instability or indeterminacy or the solution could not be found (e.g. the steady state solution could not be found by the solver).

Similar conventions apply for <DYNARE_file>_mc_*.fig files, obtained when samples from multivariate normal are used.

4.3 RMSE analysis

Figure files <DYNARE_file>_rmse_*.fig store results for the RMSE analysis.

<DYNARE_file>_rmse_prior_*.fig: save results for the analysis using prior MC samples;

<DYNARE_file>_rmse_mc_*.fig: save results for the analysis using multivariate normal MC samples;

<DYNARE_file>_rmse_post_*.fig: save results for the analysis using Metropolis posterior samples.

The following types of figures are saved (we show prior sample to fix ideas, but the same conventions are used for multivariate normal and posterior):

<DYNARE_file>_rmse_prior_*.fig: for each parameter, plots the cdf's corresponding to the best 10% RMES's of each observed series;

<DYNARE_file>_rmse_prior_dens_*.fig: for each parameter, plots the pdf's corresponding to the best 10% RMES's of each observed series;

<DYNARE_file>_rmse_prior_<name of observedseries>_corr_*.fig: for each observed series plots the bi-dimensional projections of samples with the best 10% RMSE's, when the correlation is significant;

<DYNARE_file>_rmse_prior_lnlik*.fig: for each observed series, plots *in red* the cdf of the log-likelihood corresponding to the best 10% RMSE's, *in green* the cdf of the rest of the sample and *in blue* the cdf of the full sample; this allows to see the presence of some idiosyncratic behaviour;

<DYNARE_file>_rmse_prior_lnpost*.fig: for each observed series, plots *in red* the cdf of the log-posterior corresponding to the best 10% RMSE's, *in green* the cdf of the rest of the sample and *in blue* the cdf of the full sample; this allows to see idiosyncratic behaviour;

<DYNARE_file>_rmse_prior_lnprior*.fig: for each observed series, plots *in red* the cdf of the log-prior corresponding to the best 10% RMSE's, *in green* the cdf of the rest of the sample and *in blue* the cdf of the full sample; this allows to see idiosyncratic behaviour;

<DYNARE_file>_rmse_prior_lik_SA_*.fig: when lik_only=1, this shows the Smirnov tests for the filtering of the best 10% log-likelihood values;

<DYNARE_file>_rmse_prior_post_SA_*.fig: when lik_only=1, this shows the Smirnov test for the filtering of the best 10% log-posterior values.

4.4 Reduced form mapping

In the case of the mapping of the reduced form solution, synthetic figures are saved in the \GSA folder:

<DYNARE_file>_redform_<endo name>_vs_lags_*.fig: shows bar charts of the sensitivity indices for the *ten most important* parameters driving the reduced form coefficients of the selected endogenous variables (**namendo**) versus lagged endogenous variables (**namlagendo**); suffix **log** indicates the results for log-transformed entries;

<DYNARE_file>_redform_<endo name>_vs_shocks_*.fig: shows bar charts of the sensitivity indices for the *ten most important* parameters driving the reduced form coefficients of the selected endogenous variables (**namendo**) versus exogenous variables (**namexo**); suffix **log** indicates the results for log-transformed entries;

<DYNARE_file>_redform_GSA(_log).fig: shows bar chart of all sensitivity indices for each parameter: this allows to notice parameters that have a minor effect for *any* of the reduced form coefficients,

Detailed results of the analyses are shown in the subfolder `\GSA\redform_stab`, where the detailed results of the estimation of the single functional relationships between parameters θ and reduced form coefficient are stored in separate directories named as:

`<namendo>_vs_<namlagendo>`: for the entries of the transition matrix;

`<namendo>_vs_<namexo>`: for entries of the matrix of the shocks.

Moreover, analyses for log-transformed entries are denoted with the following suffixes (y denotes the generic reduced form coefficient):

`log`: $y^* = \log(y)$;

`minuslog`: $y^* = \log(-y)$;

`logsquared`: $y^* = \log(y^2)$ for symmetric fat tails;

`logskew`: $y^* = \log(|y + \lambda|)$ for asymmetric fat tails.

The optimal type of transformation is automatically selected without the need of any user's intervention.

4.5 Screening analysis

The results of the screening analysis with Morris sampling design are stored in the subfolder `\GSA\SCREEN`. The data file `<DYNARE_file>_prior` stores all the information of the analysis (Morris sample, reduced form coefficients, etc.).

Screening analysis merely concerns reduced form coefficients. Similar synthetic bar charts as for the reduced form analysis with MC samples are saved:

`<DYNARE_file>_redform_<endo name>_vs_lags_*.fig`: shows bar charts of the elementary effect tests for the *ten most important* parameters driving the reduced form coefficients of the selected endogenous variables (`namendo`) versus lagged endogenous variables (`namlagendo`);

`<DYNARE_file>_redform_<endo name>_vs_shocks_*.fig`: shows bar charts of the elementary effect tests for the *ten most important* parameters driving the reduced form coefficients of the selected endogenous variables (`namendo`) versus exogenous variables (`namexo`);

`<DYNARE_file>_redform_screen.fig`: shows bar chart of all elementary effect tests for each parameter: this allows to identify parameters that have a minor effect for *any* of the reduced form coefficients.

References

- Nikolay Iskrev. Local identification in DSGE models. mimeo, 2009.
- M. Ratto. Analysing dsge models with global sensitivity analysis. *Computational Economics*, 31:115–139, 2008.