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1.1 What is Dynare?

Dynare is a software platform for handling a wide class of economic models, in particular dynamic stochastic general equilibrium (DSGE) and overlapping generations (OLG) models. The models solved by Dynare include those relying on the rational expectations hypothesis, wherein agents form their expectations about the future in a way consistent with the model. But Dynare is also able to handle models where expectations are formed differently: on one extreme, models where agents perfectly anticipate the future; on the other extreme, models where agents have limited rationality or imperfect knowledge of the state of the economy and, hence, form their expectations through a learning process. In terms of types of agents, models solved by Dynare can incorporate consumers, productive firms, governments, monetary authorities, investors and financial intermediaries. Some degree of heterogeneity can be achieved by including several distinct classes of agents in each of the aforementioned agent categories.

Dynare offers a user-friendly and intuitive way of describing these models. It is able to perform simulations of the model given a calibration of the model parameters and is also able to estimate these parameters given a dataset. In practice, the user will write a text file containing the list of model variables, the dynamic equations linking these variables together, the computing tasks to be performed and the desired graphical or numerical outputs.

A large panel of applied mathematics and computer science techniques are internally employed by Dynare: multivariate nonlinear solving and optimization, matrix factorizations, local functional approximation, Kalman filters and smoothers, MCMC techniques for Bayesian estimation, graph algorithms, optimal control, …

Various public bodies (central banks, ministries of economy and finance, international organisations) and some private financial institutions use Dynare for performing policy analysis exercises and as a support tool for forecasting exercises. In the academic world, Dynare is used for research and teaching purposes in postgraduate macroeconomics courses.

Dynare is a free software, which means that it can be downloaded free of charge, that its source code is freely available, and that it can be used for both non-profit and for-profit purposes. Most of the source files are covered by the GNU General Public Licence (GPL) version 3 or later (there are some exceptions to this, see the file license.txt in Dynare distribution). It is available for the Windows, macOS, and Linux platforms and is fully documented through a reference manual. Part of Dynare is programmed in C++, while the rest is written using the MATLAB programming language. The latter implies that commercially-available MATLAB software is required in order to run Dynare. However, as an alternative to MATLAB, Dynare is also able to run on top of GNU Octave (basically a free clone of MATLAB): this possibility is particularly interesting for students or institutions who cannot afford, or do not want to pay for, MATLAB and are willing to bear the concomitant performance loss.

The development of Dynare is mainly done at CEPREMAP by a core team of researchers who devote part of their time to software development. Increasingly, the developer base is expanding, as tools developed by researchers outside of CEPREMAP are integrated into Dynare. Financial support is provided by CEPREMAP, Banque de France and DSGE-net (an international research network for DSGE modeling).

Interaction between developers and users of Dynare is central to the project. A web forum is available for users who have questions about the usage of Dynare or who want to report bugs. Current known and fixed bugs are listed on the Dynare wiki. Issues or wishes can be reported on our Git repository. Training sessions are given through the Dynare Summer School, which is organized every year and is attended by about 40 people. Finally, priorities...
1.2 Documentation sources

The present document is the reference manual for Dynare. It documents all commands and features in a systematic fashion.

Other useful sources of information include the Dynare wiki and the Dynare forums.

1.3 Citing Dynare in your research

You should cite Dynare if you use it in your research. The recommended way to do this is to cite the present manual, as:


For convenience, you can copy and paste the following into your BibTeX file:

```bibtex
@TechReport{Adjemianetal2024,  
author = {Adjemian, St\'ephane and Juillard, Michel and Karam\'e, Fr\'ederic and Mutschler, Willi and Pfeifer, Johannes and Ratto, Marco and Rion, Normann and Villemot, S\'ebastien}, 
year = {2024}, 
institution = {CEPREMAP}, 
type = {Dynare Working Papers}, 
number = {80},
}
```

If you want to give a URL, use the address of the Dynare website: https://www.dynare.org.
CHAPTER TWO

INSTALLATION AND CONFIGURATION

2.1 Software requirements

Packaged versions of Dynare are available for Windows (10 and 11), several GNU/Linux distributions (Debian, Ubuntu, Linux Mint, Arch Linux), macOS (13 Ventura), and FreeBSD. Dynare should work on other systems, but some compilation steps are necessary in that case.

In order to run Dynare, you need one of the following:

• MATLAB, any version ranging from 9.5 (R2018b) to 24.1 (R2024a);
• GNU Octave, any version ranging from 7.1.0 to 9.1.0, with the statistics package from Octave-Forge. Note however that the Dynare installer for Windows requires a more specific version of Octave, as indicated on the download page.

The following optional extensions are also useful to benefit from extra features, but are in no way required:

• If under MATLAB: the Optimization Toolbox, the Statistics Toolbox, the Control System Toolbox;
• If under Octave, the following Octave-Forge packages: optim, io, control.

2.2 Installation of Dynare

After installation, Dynare can be used in any directory on your computer. It is best practice to keep your model files in directories different from the one containing the Dynare toolbox. That way you can upgrade Dynare and discard the previous version without having to worry about your own files.

2.2.1 On Windows

Execute the automated installer called dynare-x.y-win.exe (where x.y is the version number), and follow the instructions. The default installation directory is c:\dynare\x.y.

After installation, this directory will contain several sub-directories, among which are matlab, mex and doc.

The installer will also add an entry in your Start Menu with a shortcut to the documentation files and uninstaller.

Note that you can have several versions of Dynare coexisting (for example in c:\dynare), as long as you correctly adjust your path settings (see see Some words of warning).

Also note that it is possible to do a silent installation, by passing the /S flag to the installer on the command line. This can be useful when doing an unattended installation of Dynare on a computer pool.
2.2.2 On GNU/Linux

On Debian, Ubuntu and Linux Mint, the Dynare package can be installed with: `apt install dynare`. This will give a fully-functional Dynare installation usable with Octave. If you have MATLAB installed, you should also do: `apt install dynare-matlab` (under Debian, this package is in the contrib section). Documentation can be installed with `apt install dynare-doc`. The status of those packages can be checked at those pages:

- Package status in Debian
- Package status in Ubuntu
- Package status in Linux Mint

On Arch Linux, the Dynare package is not in the official repositories, but is available in the Arch User Repository. The needed sources can be downloaded from the package status in Arch Linux.

There is also a Dynare package for openSUSE, see the package status in openSUSE.

Dynare will be installed under `/usr/lib/dynare` (or `/usr/lib64/dynare` on openSUSE). Documentation will be under `/usr/share/doc/dynare` (only on Debian, Ubuntu and Linux Mint).

2.2.3 On macOS

2.2.3.1 With MATLAB

To install Dynare for use with MATLAB, execute the automated installer called `dynare-x.y-arch.pkg` (where `x.y` is the version number and `arch` is either arm64 for Apple Silicon or x86_64 for Intel architectures), and follow the instructions. This installation does not require administrative privileges. If for some reason admin rights are requested, use `Change Install Location` and select `Install for me only`. The default installation directory is `/Applications/Dynare/x.y-arch`. Installing into `/Applications/dynare` might fail if you have older versions of Dynare already installed in `/Applications/Dynare`. To fix this, modify the ownership by executing the following command in Terminal.app:

```sh
sudo chown -R "$USER":staff /Applications/Dynare
```

Alternatively, you can modify the installation path in the automated installed using Customize and Location. After installation, the folder will contain several sub-directories, among which are matlab, mex, and doc. Several versions of Dynare can coexist (by default in `/Applications/Dynare`), as long as you correctly adjust your path settings (see Some words of warning).

It is recommended to install the Xcode Command Line Tools (this is an Apple product) and GCC via Homebrew (see Prerequisites on macOS).

2.2.3.2 With Octave

We don’t provide Dynare packages for macOS with Octave support, but there is a Dynare package with Octave support in Homebrew.

Once Homebrew is installed, run a terminal and install Dynare (and Octave) by typing the following:

```sh
brew install dynare
```

Then open Octave by running the following in the same terminal:

```sh
octave --gui
```

Finally, at the Octave prompt, install some add-ons (you only have to do it once):

```sh
octave:1> pkg install -forge io statistics control struct optim
```
2.2.4 On FreeBSD

A FreeBSD port for Dynare is available. It can be installed with:

```
pkg install dynare
```

2.2.5 For other systems

You need to download Dynare source code from the Dynare website and unpack it somewhere. Then you will need to recompile the pre-processor and the dynamic loadable libraries. Please refer to README.md.

2.3 Compiler installation

2.3.1 Prerequisites on Windows

There are no prerequisites on Windows. Dynare now ships a compilation environment that can be used with the `use_dll` option.

2.3.2 Prerequisites on GNU/Linux

Users of MATLAB under GNU/Linux need a working compilation environment installed. Under Debian, Ubuntu or Linux Mint, it can be installed via `apt install build-essential`.

Users of Octave under GNU/Linux should install the package for MEX file compilation (under Debian, Ubuntu or Linux Mint, it can be done via `apt install liboctave-dev`).

2.3.3 Prerequisites on macOS

2.3.3.1 With MATLAB

Dynare now ships a compilation environment that can be used with the `use_dll` option. To install this environment correctly, the Dynare installer ensures that the Xcode Command Line Tools (an Apple product) have been installed on a system folder. To install the Xcode Command Line Tools yourself, simply type `xcode-select --install` into the terminal (`/Applications/Utilities/Terminal.app`) prompt. Additionally, to make MATLAB aware that you agree to the terms of Xcode, run the following two commands in the Terminal prompt:

```
CLT_VERSION=$(pkgutil --pkg-info=com.apple.pkg.CLTools_Executables | grep version | \n  \-awk '{print $2}' | cut -d'.' -f1-2) \ndefaults write com.apple.dt.Xcode IDEXcodeVersionForAgreedToGMLicense \n"${CLT_VERSION}" \ndefaults read com.apple.dt.Xcode IDEXcodeVersionForAgreedToGMLicense
```

Otherwise you will see a warning that Xcode is installed, but its license has not been accepted. You can check this e.g. by running the following command in the MATLAB command window:

```
mex -setup
```

Moreover, we recommend making use of optimized compilation flags when using `use_dll` and for this you need to install GCC via Homebrew:

```
brew install gcc
```
If you already have installed GCC, Dynare will automatically prefer it for `use_dll` if the binaries are either in `/opt/homebrew/bin` on Apple Silicon (arm64) or in `/usr/local/bin` on Intel (x86_64) systems. Otherwise, it will fall back to Clang in `/usr/bin/clang`, which works both on arm64 and x86_64 systems.

### 2.3.3.2 With Octave

The compiler can be installed via Homebrew. In a terminal, run:

```bash
brew install gcc
```

### 2.4 Configuration

#### 2.4.1 For MATLAB

You need to add the `matlab` subdirectory of your Dynare installation to MATLAB path. You have two options for doing that:

- Using the `addpath` command in the MATLAB command window:
  
  Under Windows, assuming that you have installed Dynare in the standard location, and replacing `x.y` with the correct version number, type:
  
  ```matlab
  >> addpath c:/dynare/x.y/matlab
  ```
  
  Under GNU/Linux, type:
  
  ```matlab
  >> addpath /usr/lib/dynare/matlab
  ```
  
  Under macOS, assuming that you have installed Dynare in the standard location, and replacing `x.y` with the correct version number, type:
  
  ```matlab
  >> addpath /Applications/Dynare/x.y/matlab
  ```

  MATLAB will not remember this setting next time you run it, and you will have to do it again.

- Via the menu entries:
  
  Select the “Set Path” entry in the “File” menu, then click on “Add Folder…”, and select the `matlab` subdirectory of your Dynare installation. Note that you should not use “Add with Subfolders…”. Apply the settings by clicking on “Save”. Note that MATLAB will remember this setting next time you run it.

#### 2.4.2 For Octave

You need to add the `matlab` subdirectory of your Dynare installation to Octave path, using the `addpath` at the Octave command prompt.

Under Windows, assuming that you have installed Dynare in the standard location, and replacing “x.y” with the correct version number, type:

```octave
octave:1> addpath c:/dynare/x.y/matlab
```

Under Debian, Ubuntu or Linux Mint, there is no need to use the `addpath` command; the packaging does it for you. Under Arch Linux, you need to do:

```octave
octave:1> addpath /usr/lib/dynare/matlab
```

Under macOS, assuming you have installed Dynare via Homebrew:
octave:1> addpath /usr/local/lib/dynare/matlab

If you don’t want to type this command every time you run Octave, you can put it in a file called .octaverc in your home directory (under Windows this will generally be c:\Users\USERNAME while under macOS it is /Users/USERNAME/). This file is run by Octave at every startup.

2.4.3 Some words of warning

You should be very careful about the content of your MATLAB or Octave path. You can display its content by simply typing path in the command window.

The path should normally contain system directories of MATLAB or Octave, and some subdirectories of your Dynare installation. You have to manually add the matlab subdirectory, and Dynare will automatically add a few other subdirectories at runtime (depending on your configuration). You must verify that there is no directory coming from another version of Dynare than the one you are planning to use.

You have to be aware that adding other directories (on top of the dynare folders) to your MATLAB or Octave path can potentially create problems if any of your M-files have the same name as a Dynare file. Your routine would then override the Dynare routine, making Dynare unusable.

**Warning:** Never add all the subdirectories of the matlab folder to the MATLAB or Octave path. You must let Dynare decide which subdirectories have to be added to the MATLAB or Octave path. Otherwise, you may end up with a non-optimal or un-useable installation of Dynare.
In order to give instructions to Dynare, the user has to write a *model file* whose filename extension must be `.mod` or `.dyn`. This file contains the description of the model and the computing tasks required by the user. Its contents are described in *The model file*.

### 3.1 Dynare invocation

Once the model file is written, Dynare is invoked using the `dynare` command at the MATLAB or Octave prompt (with the filename of the `.mod` given as argument).

In practice, the handling of the model file is done in two steps: in the first one, the model and the processing instructions written by the user in a *model file* are interpreted and the proper MATLAB or Octave instructions are generated; in the second step, the program actually runs the computations. Both steps are triggered automatically by the `dynare` command.

**MATLAB/Octave command:**

```
dynare FILENAME[.mod] [OPTIONS...]```

This command launches Dynare and executes the instructions included in `FILENAME.mod`. This user-supplied file contains the model and the processing instructions, as described in *The model file*. The options, listed below, can be passed on the command line, following the name of the `.mod` file or in the first line of the `.mod` file itself (see below).

* `FILENAME/driver.m`
  
  Contains variable declarations, and computing tasks.

* `FILENAME/dynamic.m`
  
  Contains the dynamic model equations. Note that Dynare might introduce auxiliary equations and variables (see *Auxiliary variables*). Outputs are the residuals of the dynamic model equations in the order the equations were declared and the Jacobian of the dynamic model equations. For higher order approximations also the Hessian and the third-order derivatives are provided. When computing the Jacobian of the dynamic model, the order of the endogenous variables in the columns is stored in `M_.lead_lag_incidence`. The rows of this matrix represent time periods: the first row denotes a lagged (time t-1) variable, the second row a contemporaneous (time t) variable, and the third row a leaded (time t+1) variable. The columns of the matrix represent the endogenous variables in their order of declaration. A zero in the matrix means that this endogenous does not appear in the model in this time period. The value in the `M_.lead_lag_incidence` matrix corresponds to the column of that variable in the Jacobian of the dynamic model. Example: Let the second declared variable be `c` and the (3,2) entry of `M_.lead_lag_incidence` be 15. Then the 15th column of the Jacobian is the derivative with respect to `c(+1)`.

* `FILENAME/static.m`
Contains the long run static model equations. Note that Dynare might introduce auxiliary equations and variables (see Auxiliary variables). Outputs are the residuals of the static model equations in the order the equations were declared and the Jacobian of the static equations. Entry \((i,j)\) of the Jacobian represents the derivative of the \(i\)th static model equation with respect to the \(j\)th model variable in declaration order.

These files may be looked at to understand errors reported at the simulation stage.

dynare will then run the computing tasks by executing \(+FILENAME/driver.m\). If a user needs to rerun the computing tasks without calling the preprocessor (or without calling the dynare command), for instance because he has modified the script, he just have to type the following on the command line:

```
>> FILENAME.driver
```

A few words of warning are warranted here: under Octave the filename of the .mod file should be chosen in such a way that the generated .m files described above do not conflict with .m files provided by Octave or by Dynare. Not respecting this rule could cause crashes or unexpected behaviour. In particular, it means that the .mod file cannot be given the name of an Octave or Dynare command. For instance, under Octave, it also means that the .mod file cannot be named test.mod or example.mod.

**Note:** Note on Quotes

When passing command line options that contains a space (or, under Octave, a double quote), you must surround the entire option (keyword and argument) with single quotes, as in the following example.

**Example**

Call Dynare with options containing spaces

```
>> dynare '<modfile.mod>' '-DA=[ i in [1,2,3] when i > 1 ]' 'conffile=C:\User\My Documents\config.txt'
```

**Options**

noclearall

By default, dynare will issue a clear all command to MATLAB (<R2015b) or Octave, thereby deleting all workspace variables and functions; this option instructs dynare not to clear the workspace. Note that starting with MATLAB 2015b dynare only deletes the global variables and the functions using persistent variables, in order to benefit from the JIT (Just In Time) compilation. In this case the option instructs dynare not to clear the globals and functions.

onlyclearglobals

By default, dynare will issue a clear all command to MATLAB versions before 2015b and to Octave, thereby deleting all workspace variables; this option instructs dynare to clear only the global variables (i.e. \(M_\), options_, oo_, estim_params_, bayestopt_, and dataset_), leaving the other variables in the workspace.

debug

Instructs the preprocessor to write some debugging information about the scanning and parsing of the .mod file.

notmpterms

Instructs the preprocessor to omit temporary terms in the static and dynamic files; this generally decreases performance, but is used for debugging purposes since it makes the static and dynamic files more readable.

savemacro[=FILENAME]

Instructs dynare to save the intermediary file which is obtained after macro processing (see Macro processing language); the saved output will go in the file specified, or if no file is specified...
in FILENAME-macroexp.mod. See the note on quotes for info on passing a FILENAME argument containing spaces.

onlymacro
Instructs the preprocessor to only perform the macro processing step, and stop just after. Useful for debugging purposes or for using the macro processor independently of the rest of Dynare toolbox.

linemacro
Instructs the macro preprocessor include @#line directives specifying the line on which macro directives were encountered and expanded from. Only useful in conjunction with savemacro.

onlymodel
Instructs the preprocessor to print only information about the model in the driver file; no Dynare commands (other than the shocks statement and parameter initializations) are printed and hence no computational tasks performed. The same ancillary files are created as would otherwise be created (dynamic, static files, etc.).

nolog
Instructs Dynare to no create a logfile of this run in FILENAME.log. The default is to create the logfile.

output=second|third
Instructs the preprocessor to output derivatives of the dynamic model at least up to the given order.

language=matlab|julia
Instructs the preprocessor to write output for MATLAB or Julia. Default: MATLAB

params_derivs_order=0|1|2
When identification, dynare_sensitivity (with identification), or estimation are present, this option is used to limit the order of the derivatives with respect to the parameters that are calculated by the preprocessor. 0 means no derivatives, 1 means first derivatives, and 2 means second derivatives. Default: 2

nowarn
Suppresses all warnings.

notime
Do not print the total computing time at the end of the driver, and do not save that total computing time to oo_.time.

transform_unary_ops
Transform the following operators in the model block into auxiliary variables: exp, log, log10, cos, sin, tan, acos, asin, atan, cosh, sinh, tanh, acosh, asinh, atanh, sqrt, cbrt, abs, sign, erf. Default: no obligatory transformation

json = parse|check|transform|compute
Causes the preprocessor to output a version of the .mod file in JSON format to <<M_.fname>>/model/json/. When the JSON output is created depends on the value passed. These values represent various steps of processing in the preprocessor.

If parse is passed, the output will be written after the parsing of the .mod file to a file called FILENAME.json but before file has been checked (e.g. if there are unused exogenous in the model block, the JSON output will be created before the preprocessor exits).

If check is passed, the output will be written to a file called FILENAME.json after the model has been checked.

If transform is passed, the JSON output of the transformed model (maximum lead of 1, minimum lag of -1, expectation operators substituted, etc.) will be written to a file called FILENAME.json and the original, untransformed model will be written in FILENAME_original.json.
And if `compute` is passed, the output is written after the computing pass. In this case, the transformed model is written to `FILENAME.json`, the original model is written to `FILENAME_original.json`, and the dynamic and static files are written to `FILENAME_dynamic.json` and `FILENAME_static.json`.

`jsonstdout`
Instead of writing output requested by `json` to files, write to standard out, i.e. to the MATLAB/Octave command window (and the log-file).

`onlyjson`
Quit processing once the output requested by `json` has been written.

`jsonderivsimple`
Print a simplified version (excluding variable name(s) and lag information) of the static and dynamic files in `FILENAME_static.json` and `FILENAME_dynamic.json`.

`warn_uninit`
Display a warning for each variable or parameter which is not initialized. See Parameter initialization, or `load_params_and_steady_state` for initialization of parameters. See Initial and terminal conditions, or `load_params_and_steady_state` for initialization of endogenous and exogenous variables.

`console`
Activate console mode. In addition to the behavior of `nodisplay`, Dynare will not use graphical waitbars for long computations.

`nograph`
Activate the `nograph` option (see `nograph`), so that Dynare will not produce any graph.

`nointeractive`
Instructs Dynare to not request user input.

`nopathchange`
By default Dynare will change MATLAB/Octave’s path if `dynare/matlab` directory is not on top and if Dynare’s routines are overridden by routines provided in other toolboxes. If one wishes to override Dynare’s routines, the `nopathchange` options can be used. Alternatively, the path can be temporarily modified by the user at the top of the `.mod` file (using MATLAB/Octave’s `addpath` command).

`nopreprocessoroutput`
Prevent Dynare from printing the output of the steps leading up to the preprocessor as well as the preprocessor output itself.

`mexext=mex|mexw64|mexmaci64|mexmaca64|mexa64`
The mex extension associated with your platform to be used when compiling output associated with `use_dll`. Dynare is able to set this automatically, so you should not need to set it yourself.

`matlabroot=<<path>>`
The path to the MATLAB installation for use with `use_dll`. Dynare is able to set this automatically, so you should not need to set it yourself. See the note on quotes for info on passing a `<<path>>` argument containing spaces.

`parallel[=CLUSTER_NAME]`
Tells Dynare to perform computations in parallel. If `CLUSTER_NAME` is passed, Dynare will use the specified cluster to perform parallel computations. Otherwise, Dynare will use the first cluster specified in the configuration file. See The configuration file, for more information about the configuration file.

`conffile=FILENAME`
Specifies the location of the configuration file if it differs from the default. See The configuration file, for more information about the configuration file and its default location. See the note on quotes for info on passing a `FILENAME` argument containing spaces.
**parallel_follower_open_mode**

Instructs Dynare to leave the connection to the follower node open after computation is complete, closing this connection only when Dynare finishes processing.

**parallel_test**

Tests the parallel setup specified in the configuration file without executing the `.mod` file. See *The configuration file*, for more information about the configuration file.

**parallel_use_psexec=true|false**

For local execution under Windows operating system, set `parallel_use_psexec=false` to use `start` instead of `psexec`, to properly allocate affinity when there are more than 32 cores in the local machine. This option is also helpful if `psexec` cannot be executed due to missing administrator privileges. [default=true]

**-DMACRO_VARIABLE [=MACRO_EXPRESSION]**

Defines a macro-variable from the command line (the same effect as using the Macro directive `@#define` in a model file, see *Macro processing language*). See the note on quotes for info on passing a MACRO_EXPRESSION argument containing spaces. Note that an expression passed on the command line can reference variables defined before it. If MACRO_EXPRESSION is omitted, the variable is assigned the true logical value. Strings assigned to a macro variable need to be enclosed in double quoted strings. This also allows for passing single quotes within the strings.

*Example*

Call dynare with command line defines

```bash
>> dynare <<modfile.mod>> -DA=true ' -DB="A string with space"' -
DC=[1,2,3] ' -DD=[ i in C when i > 1 ]' -DE -Ddatafile_name="'
→ 'my_data_file.mat'"
```

**-I<<path>>**

Defines a path to search for files to be included by the macro processor (using the `@#include` command). Multiple `-I` flags can be passed on the command line. The paths will be searched in the order that the `-I` flags are passed and the first matching file will be used. The flags passed here take priority over those passed to `@#includepath`. See the note on quotes for info on passing a <<path>> argument containing spaces.

**nostrict**

Allows Dynare to issue a warning and continue processing when

1. there are more endogenous variables than equations.
2. an undeclared symbol is assigned in `initval` or `endval`.
3. an undeclared symbol is found in the `model` block in this case, it is automatically declared exogenous.
4. exogenous variables were declared but not used in the `model` block.

**fast**

Don’t rewrite the output files otherwise written to the disk by the preprocessor when re-running the same model file while the lists of variables and the equations haven’t changed. Note that the whole model still needs to be preprocessed. This option is most useful with model option `use_dll`, because the time-consuming compilation of the MEX files will be skipped. We use a 32 bit checksum, stored in `<model filename>/checksum`. There is a very small probability that the preprocessor misses a change in the model. In case of doubt, re-run without the fast option.

**minimal_workspace**

Instructs Dynare not to write parameter assignments to parameter names in the `.m` file produced by the preprocessor. This is potentially useful when running `dynare` on a large `.mod` file that runs into workspace size limitations imposed by MATLAB.
compute_xrefs
Tells Dynare to compute the equation cross references, writing them to the output .m file.

stochastic
Tells Dynare that the model to be solved is stochastic. If no Dynare commands related to stochastic models (stoch_simul, estimation, ...) are present in the .mod file, Dynare understands by default that the model to be solved is deterministic.

exclude_eqs=<equation_tags_to_exclude>
Tells Dynare to exclude all equations specified by the argument. As a .mod file must have the same number of endogenous variables as equations, when exclude_eqs is passed, certain rules are followed for excluding endogenous variables. If the endogenous tag has been set for the excluded equation, the variable it specifies is excluded. Otherwise, if the left hand side of the excluded equation is an expression that contains only one endogenous variable, that variable is excluded. If neither of these conditions hold, processing stops with an error. If an endogenous variable has been excluded by the exclude_eqs option and it exists in an equation that has not been excluded, it is transformed into an exogenous variable.

To specify which equations to exclude, you must pass the argument <<equation_tags_to_exclude>>. This argument takes either a list of equation tags specifying the equations to be excluded or a filename that contains those tags.

If <<equation_tags_to_exclude>> is a list of equation tags, it can take one of the following forms:

1. Given a single argument, e.g. exclude_eqs=eq1, the equation with the tag [name='eq1'] will be excluded. Note that if there is a file called eq1 in the current directory, Dynare will instead try to open this and read equations to exclude from it (see info on filename argument to exclude_eqs below). Further note that if the tag value contains a space, you must use the variant specified in 2 below, i.e. exclude_eqs=[eq 1].

2. Given two or more arguments, e.g. exclude_eqs=[eq1, eq 2], the equations with the tags [name='eq1'] and [name='eq 2'] will be excluded.

3. If you’d like to exclude equations based on another tag name (as opposed to the default name), you can pass the argument as either e.g. exclude_eqs=[tagname='a tag'] if a single equation with tag [tagname='a tag'] is to be excluded or as e.g. exclude_eqs=[tagname=('a tag', 'a tag with a, comma')] if more than one equation with tags [tagname='a tag'] and [tagname='a tag with a, comma'] will be excluded (note the parenthesis, which are required when more than one equation is specified). Note that if the value of a tag contains a comma, it must be included inside single quotes.

If <<equation_tags_to_exclude>> is a filename, the file can take one of the following forms:

1. One equation per line of the file, where every line represents the value passed to the name tag. e.g., a file such as:

```
eq1
eq 2
```

would exclude equations with tags [name='eq1'] and [name='eq 2'].

2. One equation per line of the file, where every line after the first line represents the value passed to the tag specified by the first line. e.g., a file such as:

```
tagname=
a tag
a tag with a, comma
```

would exclude equations with tags [tagname='a tag'] and [tagname='a tag with a, comma']. Here note that the first line must end in an equal sign.
include_eqs=<equation_tags_to_include> 

Tells Dynare to run with only those equations specified by the argument; in other words, Dynare will exclude all equations not specified by the argument. The argument <equation_tags_to_include> is specified in the same way as the argument to exclude_eqs. The functionality of include_eqs is to find which equations to exclude then take actions in accord with exclude_eqs.

use_dll 

Instructs the preprocessor to create dynamic loadable libraries (DLL) containing the model equations and derivatives, instead of writing those in M-files. This is equivalent to the use_dll option of the model block.

nocommutativity 

This option tells the preprocessor not to use the commutativity of addition and multiplication when looking for common subexpressions. As a consequence, when using this option, equations in various outputs (LaTeX, JSON...) will appear as the user entered them (without terms or factors swapped). Note that using this option may have a performance impact on the preprocessing stage, though it is likely to be small.

These options can be passed to the preprocessor by listing them after the name of the .mod file. They can alternatively be defined in the first line of the .mod file, this avoids typing them on the command line each time a .mod file is to be run. This line must be a Dynare one-line comment (i.e. must begin with //) and the options must be whitespace separated between --- options: and ++-. Note that any text after the +++ will be discarded. As in the command line, if an option admits a value the equal symbol must not be surrounded by spaces. For instance json = compute is not correct, and should be written json=compute. The nopathchange option cannot be specified in this way, it must be passed on the command-line.

Output 

Depending on the computing tasks requested in the .mod file, executing the dynare command will leave variables containing results in the workspace available for further processing. More details are given under the relevant computing tasks. The M_, oo_, and options_ structures are saved in a file called FILENAME_results.mat located in the MODFILENAME/Output folder. If they exist, estim_params_, bayestopt_, dataset_, oo_recursive_ and estimation_info are saved in the same file. Note that MATLAB by default only allows .mat files up to 2GB. You can lift this restriction by enabling the save -v7.3 option in Preferences -> General -> MAT-Files.

MATLAB/Octave variable: M_ 
Structure containing various information about the model.

MATLAB/Octave variable: options_ 
Structure contains the values of the various options used by Dynare during the computation.

MATLAB/Octave variable: oo_ 
Structure containing the various results of the computations.

MATLAB/Octave variable: dataset_ 
A dseries object containing the data used for estimation.

MATLAB/Octave variable: oo_recursive_ 
Cell array containing the oo_ structures obtained when estimating the model for the different samples when performing recursive estimation and forecasting. The oo_ structure obtained for the sample ranging to the i-th observation is saved in the i-th field. The fields for non-estimated endpoints are empty.

MATLAB/Octave variable: oo_.time 
Total computing time of the Dynare run, in seconds. This field is not set if the notime option has been used.

Example 

Call dynare from the MATLAB or Octave prompt, without or with options:
Alternatively the options can be passed in the first line of `ramst.mod`:

```
// --+ options: savemacro, json=compute +--
```

and then dynare called without passing options on the command line:

```
>> dynare ramst
```

### 3.2 Dynare hooks

It is possible to call pre and post Dynare preprocessor hooks written as MATLAB scripts. The script `MODFILENAME/hooks/priorprocessing.m` is executed before the call to Dynare’s preprocessor, and can be used to programmatically transform the mod file that will be read by the preprocessor. The script `MODFILENAME/hooks/postprocessing.m` is executed just after the call to Dynare’s preprocessor, and can be used to programmatically transform the files generated by Dynare’s preprocessor before actual computations start. The pre and/or post dynare preprocessor hooks are executed if and only if the aforementioned scripts are detected in the same folder as the the model file, `FILENAME.mod`.

### 3.3 Understanding Preprocessor Error Messages

If the preprocessor runs into an error while processing your `.mod` file, it will issue an error. Due to the way that a parser works, sometimes these errors can be misleading. Here, we aim to demystify these error messages.

The preprocessor issues error messages of the form:

1. ERROR: `<file.mod>`: line A, col B: `<error message>`
2. ERROR: `<file.mod>`: line A, cols B-C: `<error message>`

The first two errors occur on a single line, with error two spanning multiple columns. Error three spans multiple rows.

Often, the line and column numbers are precise, leading you directly to the offending syntax. Infrequently however, because of the way the parser works, this is not the case. The most common example of misleading line and column numbers (and error message for that matter) is the case of a missing semicolon, as seen in the following example:

```
varexo a, b
parameters c, ...
```

In this case, the parser doesn’t know a semicolon is missing at the end of the `varexo` command until it begins parsing the second line and bumps into the `parameters` command. This is because we allow commands to span multiple lines and, hence, the parser cannot know that the second line will not have a semicolon on it until it gets there. Once the parser begins parsing the second line, it realizes that it has encountered a keyword, `parameters`, which it did not expect. Hence, it throws an error of the form: ERROR: `<file.mod>`: line 2, cols 0-9: syntax error, unexpected PARAMETERS. In this case, you would simply place a semicolon at the end of line one and the parser would continue processing.

It is also helpful to keep in mind that any piece of code that does not violate Dynare syntax, but at the same time is not recognized by the parser, is interpreted as native MATLAB code. This code will be directly passed to the driver script. Investigating the `driver.m` file then helps with debugging. Such problems most often occur when defined variable or parameter names have been misspelled so that Dynare’s parser is unable to recognize them.
4.1 Conventions

A model file contains a list of commands and of blocks. Each command and each element of a block is terminated by a semicolon (;). Blocks are terminated by `end;`.

If Dynare encounters an unknown expression at the beginning of a line or after a semicolon, it will parse the rest of that line as native MATLAB code, even if there are more statements separated by semicolons present. To prevent cryptic error messages, it is strongly recommended to always only put one statement/command into each line and start a new line after each semicolon.\(^1\)

Lines of codes can be commented out line by line or as a block. Single-line comments begin with `//` and stop at the end of the line. Multiline comments are introduced by `/*` and terminated by `*/`.

**Examples**

```
// This is a single line comment

var x; // This is a comment about x

/* This is another inline comment about alpha */  alpha = 0.3;

/*
   This comment is spanning
   two lines.
*/
```

Note that these comment marks should not be used in native MATLAB code regions where the `%` should be preferred instead to introduce a comment. In a `verbatim` block, see `Verbatim inclusion`, this would result in a crash since `//` is not a valid MATLAB statement).

Most Dynare commands have arguments and several accept options, indicated in parentheses after the command keyword. Several options are separated by commas. In the description of Dynare commands, the following conventions are observed:

- Optional arguments or options are indicated between square brackets: `['']`;
- Repeated arguments are indicated by ellipses: `"..."`;
- Mutually exclusive arguments are separated by vertical bars: `'|'`;
- `INTEGER` indicates an integer number;
- `INTEGER_VECTOR` indicates a vector of integers separated by spaces, enclosed by square brackets;

\(^1\) A `.mod` file must have lines that end with a line feed character, which is not commonly visible in text editors. Files created on Windows and Unix-based systems have always conformed to this requirement, as have files created on OS X and macOS. Files created on old, pre-OS X Macs used carriage returns as end of line characters. If you get a Dynare parsing error of the form `ERROR: <<mod file>>: line 1, cols 341–347: syntax error,...` and there’s more than one line in your `.mod` file, know that it uses the carriage return as an end of line character. To get more helpful error messages, the carriage returns should be changed to line feeds.
4.2 Variable declarations

While Dynare allows the user to choose their own variable names, there are some restrictions to be kept in mind. First, variables and parameters must not have the same name as Dynare commands or built-in functions. In this respect, Dynare is not case-sensitive. For example, do not use \texttt{Ln} or \texttt{shocks} to name your variable. Not conforming to this rule might yield hard-to-debug error messages or crashes. Second, when employing user-defined steady state files it is recommended to avoid using the name of MATLAB functions as this may cause conflicts. In particular, when working with user-defined steady state files, do not use correctly-spelled greek names like \texttt{alpha}, because there are MATLAB functions of the same name. Rather go for \texttt{alph} or \texttt{alph}. Lastly, please do not name a variable or parameter \texttt{i}. This may interfere with the imaginary number \texttt{i} and the index in many loops. Rather, name investment \texttt{invest}. Using \texttt{inv} is also not recommended as it already denotes the inverse operator. Commands for declaring variables and parameters are described below.

\textbf{Command:} \texttt{var} \texttt{VAR_NAME [\$TEX_NAME\$]} \[(long\_name=QUOTED\_STRING|NAME=QUOTED\_STRING)\]...;
\textbf{Command:}
\texttt{var(log) VAR_NAME [\$TEX_NAME\$]} \[(long\_name=QUOTED\_STRING|NAME=QUOTED\_STRING)\]...;
\textbf{Command:}
\texttt{var(deflator=MODEL\_EXPR) VAR_NAME (... same options apply)}
\textbf{Command:}
\texttt{var(log, deflator=MODEL\_EXPR) VAR_NAME (... same options apply)}
\texttt{Command:}
\texttt{var(log\_deflator=MODEL\_EXPR) VAR\_NAME (... same options apply)}

This required command declares the endogenous variables in the model. See \textit{Conventions} for the syntax of \texttt{VAR\_NAME} and \texttt{MODEL\_EXPR}. Optionally it is possible to give a LaTeX name to the variable or, if it is nonstationary, provide information regarding its deflator. The variables in the list can be separated by spaces or by commas, \texttt{var} commands can appear several times in the file and Dynare will concatenate them. Dynare stores the list of declared parameters, in the order of declaration, in a column cell array \texttt{M_.endo\_names}. If the model is nonstationary and is to be written as such in the model block, Dynare will need the trend deflator for the appropriate endogenous variables in order to stationaryize the model. The trend deflator must be provided alongside the variables that follow this trend.

\textit{Options}
log

In addition to the endogenous variable(s) thus declared, this option also triggers the creation of auxiliary variable(s) equal to the log of the corresponding endogenous variable(s). For example, given a var(log) y statement, two endogenous will be created (y and LOG_y), and an auxiliary equation linking the two will also be added (equal to LOG_y = log(y)). Moreover, every occurrence of y in the model will be replaced by exp(LOG_y). This option is for example useful when one wants to perform a loglinear approximation of some variable(s) in the context of a first-order stochastic approximation; or when one wants to ensure the variable(s) stay(s) in the definition domain of the function defining the steady state or the dynamic residuals when the nonlinear solver is used.

deflator = MODEL_EXPR

The expression used to detrend an endogenous variable. All trend variables, endogenous variables and parameters referenced in MODEL_EXPR must already have been declared by the trend_var, log_trend_var, var and parameters commands. The deflator is assumed to be multiplicative; for an additive deflator, use log_deflator. This option can be used together with the log option (the latter must come first).

log_deflator = MODEL_EXPR

Same as deflator, except that the deflator is assumed to be additive instead of multiplicative (or, to put it otherwise, the declared variable is equal to the log of a variable with a multiplicative trend). This option cannot be used together with the log option, because it would not make much sense from an economic point of view (the corresponding auxiliary variable would correspond to the log taken two times on a variable with a multiplicative trend).

long_name = QUOTED_STRING

This is the long version of the variable name. Its value is stored in M_.endo_names_long (a column cell array, in the same order as M_.endo_names). In case multiple long_name options are provided, the last one will be used. Default: VAR_NAME.

NAME = QUOTED_STRING

This is used to create a partitioning of variables. It results in the direct output in the .m file analogous to: M_.endo_partitions.NAME = QUOTED_STRING.

Example (variable partitioning)

```
var c gnp cva (country='US', state='VA')
    cca (country='US', state='CA', long_name='Consumption CA');
var (deflator=A) i b;
var c $C$ (long_name='Consumption');
```

Command:

varexo VAR_NAME [$TEX_NAME$] [(long_name=QUOTED_STRING|NAME=QUOTED_STRING)...];

This optional command declares the exogenous variables in the model. See Conventions for the syntax of VAR_NAME. Optionally it is possible to give a LaTeX name to the variable. Exogenous variables are required if the user wants to be able to apply shocks to her model. The variables in the list can be separated by spaces or by commas. varexo commands can appear several times in the file and Dynare will concatenate them.

Options

long_name = QUOTED_STRING

Like long_name but value stored in M_.exo_names_long.

NAME = QUOTED_STRING

Like partitioning but QUOTED_STRING stored in M_.exo_partitions.NAME.

Example

```
varexo m gov;
```

Remarks
An exogenous variable is an innovation, in the sense that this variable cannot be predicted from the knowledge of the current state of the economy. For instance, if logged TFP is a first order autoregressive process:

\[ a_t = \rho a_{t-1} + \varepsilon_t \]

then logged TFP \( a_t \) is an endogenous variable to be declared with var, its best prediction is \( \rho a_{t-1} \), while the innovation \( \varepsilon_t \) is to be declared with varexo.

**Command:**

```
varexo_det VAR_NAME \[\$TEX_NAME\] \[(long_name=QUOTED_STRING|NAME=QUOTED_STRING)\]...;
```

This optional command declares exogenous deterministic variables in a stochastic model. See *Conventions* for the syntax of VARIABLE_NAME. Optionally it is possible to give a LaTeX name to the variable. The variables in the list can be separated by spaces or by commas. varexo_det commands can appear several times in the file and Dynare will concatenate them.

It is possible to mix deterministic and stochastic shocks to build models where agents know from the start of the simulation about future exogenous changes. In that case stoch_simul will compute the rational expectation solution adding future information to the state space (nothing is shown in the output of stoch_simul) and forecast will compute a simulation conditional on initial conditions and future information.

Note that exogenous deterministic variables cannot appear with a lead or a lag in the model.

**Options**

- **long_name** = QUOTED_STRING
  - Like long_name but value stored in M_.exo_det_names_long.
- **NAME** = QUOTED_STRING
  - Like partitioning but QUOTED_STRING stored in M_.exo_det_partitions.NAME.

**Example**

```
varexo m gov;
varexo_det tau;
```

**Command:**

```
parameters PARAM_NAME \[\$TEX_NAME\] \[(long_name=QUOTED_STRING|NAME=QUOTED_STRING)\]...;
```

This command declares parameters used in the model, in variable initialization or in shocks declarations. See *Conventions* for the syntax of PARAM_NAME. Optionally it is possible to give a LaTeX name to the parameter. The parameters must subsequently be assigned values (see *Parameter initialization*).

The parameters in the list can be separated by spaces or by commas. parameters commands can appear several times in the file and Dynare will concatenate them.

**Options**

- **long_name** = QUOTED_STRING
  - Like long_name but value stored in M_.param_names_long.
- **NAME** = QUOTED_STRING
  - Like partitioning but QUOTED_STRING stored in M_.param_partitions.NAME.

**Example**

```
parameters alpha, bet;
```

**Command:**

```
change_type(var|varexo|varexo_det|parameters) VAR_NAME | PARAM_NAME...;
```

Changes the types of the specified variables/parameters to another type: endogenous, exogenous, exogenous deterministic or parameter. It is important to understand that this command has a global effect on the .mod file: the type change is effective after, but also before, the change_type command. This command is typically used when flipping some variables for steady state calibration: typically a separate model file is used for calibration, which includes the list of variable declarations with the macro processor, and flips some variable.
Example

```plaintext
var y, w;
parameters alpha, beta;
... change_type(var) alpha, beta;
change_type(parameters) y, w;
```

Here, in the whole model file, alpha and beta will be endogenous and y and w will be parameters.

Command: `var_remove VAR_NAME | PARAM_NAME...;`
Removes the listed variables (or parameters) from the model. Removing a variable that has already been used in a model equation or elsewhere will lead to an error.

Command: `predetermined_variables VAR_NAME...;`
In Dynare, the default convention is that the timing of a variable reflects when this variable is decided. The typical example is for capital stock: since the capital stock used at current period is actually decided at the previous period, then the capital stock entering the production function is \(k(-1)\), and the law of motion of capital must be written:

\[ k = i + (1-\delta)k(-1) \]

Put another way, for stock variables, the default in Dynare is to use a “stock at the end of the period” concept, instead of a “stock at the beginning of the period” convention.

The `predetermined_variables` is used to change that convention. The endogenous variables declared as predetermined variables are supposed to be decided one period ahead of all other endogenous variables. For stock variables, they are supposed to follow a “stock at the beginning of the period” convention.

Note that Dynare internally always uses the “stock at the end of the period” concept, even when the model has been entered using the `predetermined_variables` command. Thus, when plotting, computing or simulating variables, Dynare will follow the convention to use variables that are decided in the current period. For example, when generating impulse response functions for capital, Dynare will plot \(k\), which is the capital stock decided upon by investment today (and which will be used in tomorrow’s production function). This is the reason that capital is shown to be moving on impact, because it is \(k\) and not the predetermined \(k(-1)\) that is displayed. It is important to remember that this also affects simulated time series and output from smoother routines for predetermined variables. Compared to non-predetermined variables they might otherwise appear to be falsely shifted to the future by one period.

Example

The following two program snippets are strictly equivalent.

Using default Dynare timing convention:

```plaintext
var y, k, i;
... model;
y = k(-1)^alpha;
k = i + (1-delta)*k(-1);
... end;
```

Using the alternative timing convention:

```plaintext
var y, k, i;
predetermined_variables k;
... model;
y = k^alpha;
k(+1) = i + (1-delta)*k;
```

(continues on next page)
Command: trend_var(growth_factor = MODEL_EXPR) VAR_NAME \[$LATEX_NAME$\]...;

This optional command declares the trend variables in the model. See Conventions for the syntax of MODEL_EXPR and VAR_NAME. Optionally it is possible to give a LaTeX name to the variable.

The variable is assumed to have a multiplicative growth trend. For an additive growth trend, use log_trend_var instead.

Trend variables are required if the user wants to be able to write a nonstationary model in the model block. The trend_var command must appear before the var command that references the trend variable.

trend_var commands can appear several times in the file and Dynare will concatenate them.

If the model is nonstationary and is to be written as such in the model block, Dynare will need the growth factor of every trend variable in order to stationarize the model. The growth factor must be provided within the declaration of the trend variable, using the growth_factor keyword. All endogenous variables and parameters referenced in MODEL_EXPR must already have been declared by the var and parameters commands.

Example

\begin{verbatim}
  trend_var (growth_factor=gA) A;
\end{verbatim}

Command: log_trend_var(log_growth_factor = MODEL_EXPR) VAR_NAME \[$LATEX_NAME$\]...;

Same as trend_var, except that the variable is supposed to have an additive trend (or, to put it otherwise, to be equal to the log of a variable with a multiplicative trend).

Command: model_local_variable VARIABLE_NAME \[LATEX_NAME]\...;

This optional command declares a model local variable. See Conventions for the syntax of VARIABLE_NAME. As you can create model local variables on the fly in the model block (see Model declaration), the interest of this command is primarily to assign a LATEX_NAME to the model local variable.

Example

\begin{verbatim}
  model_local_variable GDP_US $GDPUS$;
\end{verbatim}

4.2.1 On-the-fly Model Variable Declaration

Endogenous variables, exogenous variables, and parameters can also be declared inside the model block. You can do this in two different ways: either via the equation tag (only for endogenous variables) or directly in an equation (for endogenous, exogenous or parameters).

To declare an endogenous variable on-the-fly in an equation tag, simply write endogenous followed by an equal sign and the variable name in single quotes. Hence, to declare a variable c as endogenous in an equation tag, you can type [endogenous='c'].

To perform on-the-fly variable declaration in an equation, simply follow the symbol name with a vertical line (|, pipe character) and either an e (for endogenous), an x (for exogenous), or a p (for parameter). For example, to declare a parameter named alpha in the model block, you could write alpha|p directly in an equation where it appears. Similarly, to declare an endogenous variable c in the model block you could write c|e. Note that in-equation on-the-fly variable declarations must be made on contemporaneous variables.

On-the-fly variable declarations do not have to appear in the first place where this variable is encountered.

Example

The following two snippets are equivalent:
Dynare distinguishes between two types of mathematical expressions: those that are used to describe the model, and those that are used outside the model block (e.g. for initializing parameters or variables, or as command options). In this manual, those two types of expressions are respectively denoted by MODEL_EXPRESSION and EXPRESSION.

Unlike MATLAB or Octave expressions, Dynare expressions are necessarily scalar ones: they cannot contain matrices or evaluate to matrices.

Expressions can be constructed using integers (INTEGER), floating point numbers (DOUBLE), parameter names (PARAMETER_NAME), variable names (VARIABLE_NAME), operators and functions.

The following special constants are also accepted in some contexts:

**Constant:** inf

Represents infinity.

**Constant:** nan

“Not a number”: represents an undefined or unrepresentable value.

### 4.3.1 Parameters and variables

Parameters and variables can be introduced in expressions by simply typing their names. The semantics of parameters and variables is quite different whether they are used inside or outside the model block.

---

2 Note that arbitrary MATLAB or Octave expressions can be put in a .mod file, but those expressions have to be on separate lines, generally at the end of the file for post-processing purposes. They are not interpreted by Dynare, and are simply passed on unmodified to MATLAB or Octave. Those constructions are not addressed in this section.
4.3.1.1 Inside the model

Parameters used inside the model refer to the value given through parameter initialization (see Parameter initialization) or homotopy_setup when doing a simulation, or are the estimated variables when doing an estimation.

Variables used in a MODEL_EXPRESSION denote current period values when neither a lead or a lag is given. A lead or a lag can be given by enclosing an integer between parenthesis just after the variable name: a positive integer means a lead, a negative one means a lag. Leads or lags of more than one period are allowed. For example, if c is an endogenous variable, then c(+1) is the variable one period ahead, and c(-2) is the variable two periods before.

When specifying the leads and lags of endogenous variables, it is important to respect the following convention: in Dynare, the timing of a variable reflects when that variable is decided. A control variable — which by definition is decided in the current period — must have no lead. A predetermined variable — which by definition has been decided in a previous period — must have a lag. A consequence of this is that all stock variables must use the "stock at the end of the period" convention.

Leads and lags are primarily used for endogenous variables, but can be used for exogenous variables. They have no effect on parameters and are forbidden for local model variables (see Model declaration).

4.3.1.2 Outside the model

When used in an expression outside the model block, a parameter or a variable simply refers to the last value given to that variable. More precisely, for a parameter it refers to the value given in the corresponding parameter initialization (see Parameter initialization); for an endogenous or exogenous variable, it refers to the value given in the most recent initval or endval block.

4.3.2 Operators

The following operators are allowed in both MODEL_EXPRESSION and EXPRESSION:

- Binary arithmetic operators: +, -, *, /, ^
- Unary arithmetic operators: +, -
- Binary comparison operators (which evaluate to either 0 or 1): <, >, <=, >=, ==, !=

Note the binary comparison operators are differentiable everywhere except on a line of the 2-dimensional real plane. However for facilitating convergence of Newton-type methods, Dynare assumes that, at the points of non-differentiability, the partial derivatives of these operators with respect to both arguments is equal to 0 (since this is the value of the partial derivatives everywhere else).

The following special operators are accepted in MODEL_EXPRESSION (but not in EXPRESSION):

**Operator: STEADY_STATE (MODEL_EXPRESSION)**

This operator is used to take the value of the enclosed expression at the steady state. A typical usage is in the Taylor rule, where you may want to use the value of GDP at steady state to compute the output gap.

Exogenous and exogenous deterministic variables may not appear in MODEL_EXPRESSION.

**Warning:** The concept of a steady state is ambiguous in a perfect foresight context with permament and potentially anticipated shocks occurring. Dynare will use the contents of oo_.steady_state as its reference for calls to the STEADY_STATE() operator. In the presence of endval, this implies that the terminal state provided by the user is used. This may be a steady state computed by Dynare (if endval is followed by steady) or simply the terminal state provided by the user (if endval is not followed by steady). Put differently, Dynare will not automatically compute the steady state conditional on the specified value of the exogenous variables in the respective periods.
Operator:  EXPECTATION (INTEGER) (MODEL_EXPRESSION)

This operator is used to take the expectation of some expression using a different information set than the information available at current period. For example, \( \text{EXPECTATION}(-1)(x(+1)) \) is equal to the expected value of variable \( x \) at next period, using the information set available at the previous period. See Auxiliary variables for an explanation of how this operator is handled internally and how this affects the output.

### 4.3.3 Functions

#### 4.3.3.1 Built-in functions

The following standard functions are supported internally for both MODEL_EXPRESSION and EXPRESSION:

**Function: \( \text{exp}(x) \)**
- Natural exponential.

**Function: \( \text{log}(x) \)**

**Function: \( \ln(x) \)**
- Natural logarithm.

**Function: \( \text{log10}(x) \)**
- Base 10 logarithm.

**Function: \( \text{sqrt}(x) \)**
- Square root.

**Function: \( \text{cbrt}(x) \)**
- Cube root.

**Function: \( \text{sign}(x) \)**
- Signum function, defined as:

\[
\text{sign}(x) = \begin{cases} 
-1 & \text{if } x < 0 \\
0 & \text{if } x = 0 \\
1 & \text{if } x > 0 
\end{cases}
\]

Note that this function is not continuous, hence not differentiable, at \( x = 0 \). However, for facilitating convergence of Newton-type methods, Dynare assumes that the derivative at \( x = 0 \) is equal to 0. This assumption comes from the observation that both the right- and left-derivatives at this point exist and are equal to 0, so we can remove the singularity by postulating that the derivative at \( x = 0 \) is 0.

**Function: \( \text{abs}(x) \)**
- Absolute value.

Note that this continuous function is not differentiable at \( x = 0 \). However, for facilitating convergence of Newton-type methods, Dynare assumes that the derivative at \( x = 0 \) is equal to 0 (even if the derivative does not exist). The rational for this mathematically unfounded definition, rely on the observation that the derivative of \( \text{abs}(x) \) is equal to \( \text{sign}(x) \) for any \( x \neq 0 \) in \( \mathbb{R} \) and from the convention for the value of \( \text{sign}(x) \) at \( x = 0 \).

**Function: \( \text{sin}(x) \)**

**Function: \( \text{cos}(x) \)**

**Function: \( \text{tan}(x) \)**

**Function: \( \text{asin}(x) \)**
Function: \( \text{acos}(x) \)

Function: \( \text{atan}(x) \)

Trigonometric functions.

Function: \( \text{sinh}(x) \)

Function: \( \text{cosh}(x) \)

Function: \( \text{tanh}(x) \)

Function: \( \text{asinh}(x) \)

Function: \( \text{acosh}(x) \)

Function: \( \text{atanh}(x) \)

Hyperbolic functions.

Function: \( \text{max}(a, b) \)

Function: \( \text{min}(a, b) \)

Maximum and minimum of two reals.

Note that these functions are differentiable everywhere except on a line of the 2-dimensional real plane defined by \( a = b \). However for facilitating convergence of Newton-type methods, Dynare assumes that, at the points of non-differentiability, the partial derivative of these functions with respect to the first (resp. the second) argument is equal to 1 (resp. to 0) (i.e. the derivatives at the kink are equal to the derivatives observed on the half-plane where the function is equal to its first argument).

Function: \( \text{normcdf}(x) \)

Function: \( \text{normcdf}(x, \mu, \sigma) \)

Gaussian cumulative density function, with mean \( \mu \) and standard deviation \( \sigma \). Note that \( \text{normcdf}(x) \) is equivalent to \( \text{normcdf}(x, 0, 1) \).

Function: \( \text{normpdf}(x) \)

Function: \( \text{normpdf}(x, \mu, \sigma) \)

Gaussian probability density function, with mean \( \mu \) and standard deviation \( \sigma \). Note that \( \text{normpdf}(x) \) is equivalent to \( \text{normpdf}(x, 0, 1) \).

Function: \( \text{erf}(x) \)

Gauss error function.

Function: \( \text{erfc}(x) \)

Complementary error function, i.e. \( \text{erfc}(x) = 1 - \text{erf}(x) \).

4.3.3.2 External functions

Any other user-defined (or built-in) MATLAB or Octave function may be used in both a MODEL_EXPRESSION and an EXPRESSION, provided that this function has a scalar argument as a return value.

To use an external function in a MODEL_EXPRESSION, one must declare the function using the \texttt{external_function} statement. This is not required for external functions used in an EXPRESSION outside of a model block or steady_state_model block.

Command: \texttt{external_function(OPTIONS...);} 

This command declares the external functions used in the model block. It is required for every unique function used in the model block.

\texttt{external_function} commands can appear several times in the file and must come before the model block.

Options
name = NAME
The name of the function, which must also be the name of the M-/MEX file implementing it. This option is mandatory.

nargs = INTEGER
The number of arguments of the function. If this option is not provided, Dynare assumes nargs = 1.

first_deriv_provided [= NAME]
If NAME is provided, this tells Dynare that the Jacobian is provided as the only output of the M-/MEX file given as the option argument. If NAME is not provided, this tells Dynare that the M-/MEX file specified by the argument passed to NAME returns the Jacobian as its second output argument. When this option is not provided, Dynare will use finite difference approximations for computing the derivatives of the function, whenever needed.

second_deriv_provided [= NAME]
If NAME is provided, this tells Dynare that the Hessian is provided as the only output of the M-/MEX file given as the option argument. If NAME is not provided, this tells Dynare that the M-/MEX file specified by the argument passed to NAME returns the Hessian as its third output argument. NB: This option can only be used if the first_deriv_provided option is used in the same external_function command. When this option is not provided, Dynare will use finite difference approximations for computing the Hessian derivatives of the function, whenever needed.

Example

```
external_function(name = funcname);
external_function(name = otherfuncname, nargs = 2, first_deriv_provided,...
   second_deriv_provided);
external_function(name = yetotherfuncname, nargs = 3, first_deriv_provided = funcname_deriv);
```

4.3.4 A few words of warning in stochastic context

The use of the following functions and operators is strongly discouraged in a stochastic context: max, min, abs, sign, <, >, <=, >=, ==, !=.

The reason is that the local approximation used by stoch_simul or estimation will by nature ignore the nonlinearities introduced by these functions if the steady state is away from the kink. And, if the steady state is exactly at the kink, then the approximation will be bogus because the derivative of these functions at the kink is bogus (as explained in the respective documentations of these functions and operators).

Note that extended_path is not affected by this problem, because it does not rely on a local approximation of the mode.

4.4 Parameter initialization

When using Dynare for computing simulations, it is necessary to calibrate the parameters of the model. This is done through parameter initialization.

The syntax is the following:

```
PARAMETER_NAME = EXPRESSION;
```

Here is an example of calibration:

```
parameters alpha, beta;
beta = 0.99;
```

(continues on next page)
alpha = 0.36;
A = 1-alpha^beta;

Internally, the parameter values are stored in $M_.params$:

**MATLAB/Octave variable: $M_.params$**
Contains the values of model parameters. The parameters are in the order that was used in the `parameters` command, hence ordered as in $M_.param_names$.

The parameter names are stored in $M_.param_names$:

**MATLAB/Octave variable: $M_.param_names$**
Cell array containing the names of the model parameters.

**MATLAB/Octave command: `get_param_by_name('PARAMETER_NAME')`**
Given the name of a parameter, returns its calibrated value as it is stored in $M_.params$.

**MATLAB/Octave command: `set_param_value('PARAMETER_NAME', MATLAB_EXPRESSION)`**
Sets the calibrated value of a parameter to the provided expression. This does essentially the same as the parameter initialization syntax described above, except that it accepts arbitrary MATLAB/Octave expressions, and that it works from MATLAB/Octave scripts.

## 4.5 Model declaration

The model is declared inside a `model` block:

**Block:**

```matlab
model
```

The equations of the model are written in a block delimited by `model` and `end` keywords.

There must be as many equations as there are endogenous variables in the model, except when computing the unconstrained optimal policy with `ramsey_model`, `ramsey_policy` or `discretionary_policy`.

The syntax of equations must follow the conventions for `MODEL_EXPRESSION` as described in Expressions. Each equation must be terminated by a semicolon (`;`). A normal equation looks like:

```
MODEL_EXPRESSION = MODEL_EXPRESSION;
```

When the equations are written in homogenous form, it is possible to omit the `'=0'` part and write only the left hand side of the equation. A homogenous equation looks like:

```
MODEL_EXPRESSION;
```

Inside the model block, Dynare allows the creation of `model-local variables`, which constitute a simple way to share a common expression between several equations. The syntax consists of a pound sign (`#`) followed by the name of the new model local variable (which must not be declared as in Variable declarations, but may have been declared by `model_local_variable`), an equal sign, and the expression for which this new variable will stand. Later on, every time this variable appears in the model, Dynare will substitute it by the expression assigned to the variable. Note that the scope of this variable is restricted to the model block; it cannot be used outside. To assign a LaTeX name to the model local variable, use the declaration syntax outlined by `model_local_variable`. A model local variable declaration looks like:

```
#VARIABLE_NAME = MODEL_EXPRESSION;
```

It is possible to tag equations written in the model block. A tag can serve different purposes by allowing the user to attach arbitrary informations to each equation and to recover them at runtime. For instance, it is possible to name the equations with a `name` tag, using a syntax like:
Here, name is the keyword indicating that the tag names the equation. If an equation of the model is tagged with a name, the resid command will display the name of the equations (which may be more informative than the equation numbers) in addition to the equation number. Several tags for one equation can be separated using a comma:

```latex
model;
[name = 'Budget constraint'];
c + k = k^{\theta}A;
end;
```

More information on tags is available at https://git.dynare.org/Dynare/dynare/-/wikis/Equations-Tags.

There can be several model blocks, in which case they are simply concatenated. The set of effective options is also the concatenation of the options declared in all the blocks, but in that case you may rather want to use the model_options command.

**Options**

**linear**

Declares the model as being linear. It spares oneself from having to declare initial values for computing the steady state of a stationary linear model. This option can’t be used with non-linear models, it will NOT trigger linearization of the model.

**use_dll**

Instructs the preprocessor to create dynamic loadable libraries (DLL) containing the model equations and derivatives, instead of writing those in M-files. You need a working compilation environment, i.e. a working mex command (see Compiler installation for more details). Using this option can result in faster simulations or estimations, at the expense of some initial compilation time. Alternatively, this option can be given to the dynare command (see Dynare invocation).³

**block**

Perform the block decomposition of the model, and exploit it in computations (steady-state, deterministic simulation, stochastic simulation with first order approximation and estimation). See https://archives.dynare.org/DynareWiki/FastDeterministicSimulationAndSteadyStateComputation for details on the algorithms used in deterministic simulation and steady-state computation.

**bytecode**

Instead of M-files, use a bytecode representation of the model, i.e. a binary file containing a compact representation of all the equations.

**cutoff** = DOUBLE

Threshold under which a jacobian element is considered as null during the model normalization. Only available with option block. Default: 1e-15

**mfs** = INTEGER

³ In particular, for big models, the compilation step can be very time-consuming, and use of this option may be counter-productive in those cases.
Controls the handling of minimum feedback set of endogenous variables for the dynamic model. Only available with option block. Possible values:

0
All the endogenous variables are considered as feedback variables.

1
The endogenous variables assigned to equation naturally normalized (i.e. of the form \( x = f(Y) \) where \( x \) does not appear in \( Y \)) are potentially recursive variables. All the other variables are forced to belong to the set of feedback variables.

2
In addition of variables with \( mfs = 1 \) the endogenous variables related to linear equations which could be normalized are potential recursive variables. All the other variables are forced to belong to the set of feedback variables.

3
In addition of variables with \( mfs = 2 \) the endogenous variables related to nonlinear equations which could be normalized are potential recursive variables. All the other variables are forced to belong to the set of feedback variables.

Default value is 1.

**static_mfs**

Controls the handling of minimum feedback set of endogenous variables for the static model. Only available with option block. See the \( mfs \) option for the possible values. Default value is 0.

**no_static**

Don’t create the static model file. This can be useful for models which don’t have a steady state.

**differentiate_forward_vars**

`differentiate_forward_vars = ( VARIABLE_NAME [VARIABLE_NAME ...] )`

Tells Dynare to create a new auxiliary variable for each endogenous variable that appears with a lead, such that the new variable is the time differentiate of the original one. More precisely, if the model contains \( x(+1) \), then a variable AUX_DIFF_VAR will be created such that \( AUX_{DIFF\_VAR} = x - x(-1) \), and \( x(+1) \) will be replaced with \( x + AUX_{DIFF\_VAR}(+1) \).

The transformation is applied to all endogenous variables with a lead if the option is given without a list of variables. If there is a list, the transformation is restricted to endogenous with a lead that also appear in the list.

This option can useful for some deterministic simulations where convergence is hard to obtain. Bad values for terminal conditions in the case of very persistent dynamics or permanent shocks can hinder correct solutions or any convergence. The new differentiated variables have obvious zero terminal conditions (if the terminal condition is a steady state) and this in many cases helps convergence of simulations.

**parallel_local_files = ( FILENAME [, FILENAME]... )**

Declares a list of extra files that should be transferred to follower nodes when doing a parallel computation (see Parallel Configuration).

**balanced_growth_test_tol = DOUBLE**

Tolerance used for determining whether cross-derivatives are zero in the test for balanced growth path (the latter is documented on https://archives.dynare.org/DynareWiki/RemovingTrends). Default: 1e-6

**Example** (Elementary RBC model)

```
var c k;
varxo x;
parameters aa alph bet delt gam;
```
Example (Use of model local variables)

The following program:

```plaintext
model;
# gamma = 1 - 1/sigma;
# print gamma;
# print u1;
# print u2;
u1 = c1^gamma/gamma;
u2 = c2^gamma/gamma;
end;
```

...is formally equivalent to:

```plaintext
model;
u1 = c1^(1-1/sigma)/(1-1/sigma);
u2 = c2^(1-1/sigma)/(1-1/sigma);
end;
```

Example (A linear model)

```plaintext
model(linear);
x = a*x(-1)+b*y(+1)+e_x;
y = d*y(-1)+e_y;
end;
```

Command: `model_options(OPTIONS...)`

This command accepts the same options as the `model` block.

The purpose of this statement is to specify the options that apply to the whole model, when there are several `model` blocks, so as to restore the symmetry between those blocks (since otherwise one `model` block would typically bear the options, while the other ones would typically have no option).

Command: `model_remove(TAGS...)`

This command removes equations that appeared in a previous `model` block.

The equations must be specified by a list of tag values, separated by commas. Each element of the list is either a simple quoted string, in which case it designates an equation by its name tag; or a tag name (without quotes), followed by an equal sign, then by the tag value (within quotes); or a list of tag-equals-value pairs separated by commas and enclosed within brackets, in which case this element removes the equation(s) that has all these tags with the corresponding values.

Each removed equation must either have an endogenous tag, or have a left hand side containing a single endogenous variable. The corresponding endogenous variable will be either turned into an exogenous (if it is still used in somewhere in the model at that point), otherwise it will be removed from the model.

Example

```plaintext
var c k dummy1 dummy2 dummy3;
model;
c + k - aa*x^k(-1)^alph - (1-delt)^k(-1) + dummy1;
c^(-gam) = (aa*alph*x(+1)^k^(alph-1) + 1 - delt)*c(+1)^(-gam)/
             (1+bet);
[ name = 'eq:dummy1', endogenous = 'dummy1' ]
```
In the above example, the last three equations will be removed, dummy1 will be turned into an exogenous, and dummy2 and dummy3 will be removed.

**Block: model_replace(TAGS...);**

This block replaces several equations in the model. It removes the equations given by the tags list (with the same syntax as in `model_remove`), and it adds equations given within the block (with the same syntax as `model`).

No variable is removed or has its type changed in the process.

**Example**

```plaintext
var c k;
model;
c + k - aa*x*k(-1)^alph - (1-delt)*k(-1);
  [ name = 'dummy' ]
c*k = 1;
end;
model_replace('dummy);
c^(-gam) = (1+bet)^(-1)*(aa*alph*x(+1)*k^(alph-1) + 1 - delt)*c(+1)^(-gam);
end;
```

In the above example, the dummy equation is replaced by a proper Euler equation.

Dynare has the ability to output the original list of model equations to a LaTeX file, using the `write_latex_original_model` command, the list of transformed model equations using the `write_latex_dynamic_model` command, and the list of static model equations using the `write_latex_static_model` command.

**Command:** `write_latex_original_model`;

**Command:** `write_latex_original_model(OPTIONS)`;

This command creates two LaTeX files: one containing the model as defined in the model block and one containing the LaTeX document header information.

If your .mod file is `FILENAME.mod`, then Dynare will create a file called `FILENAME/latex/original.tex`, which includes a file called `FILENAME/latex/original_content.tex` (also created by Dynare) containing the list of all the original model equations.

If LaTeX names were given for variables and parameters (see Variable declarations), then those will be used; otherwise, the plain text names will be used.

Time subscripts (t, t+1, t-1, ...) will be appended to the variable names, as LaTeX subscripts.

Compiling the TeX file requires the following LaTeX packages: geometry, fullpage, breqn.

**Options**

`write_equation_tags`

Write the equation tags in the LaTeX output. The equation tags will be interpreted with LaTeX markups.
Command: write_latex_dynamic_model ;
Command: write_latex_dynamic_model(OPTIONS);
This command creates two LaTeX files: one containing the dynamic model and one containing the LaTeX document header information.

If your .mod file is FILENAME.mod, then Dynare will create a file called FILENAME/latex/dynamic.tex, which includes a file called FILENAME/latex/dynamic_content.tex (also created by Dynare) containing the list of all the dynamic model equations.

If LaTeX names were given for variables and parameters (see Variable declarations), then those will be used; otherwise, the plain text names will be used.

Time subscripts (t, t+1, t-1, ...) will be appended to the variable names, as LaTeX subscripts.

Note that the model written in the TeX file will differ from the model declared by the user in the following dimensions:

• The timing convention of predetermined variables (see predetermined_variables) will have been changed to the default Dynare timing convention; in other words, variables declared as predetermined will be lagged on period back,

• The EXPECTATION operators will have been removed, replaced by auxiliary variables and new equations (as explained in the documentation of EXPECTATION),

• Endogenous variables with leads or lags greater or equal than two will have been removed, replaced by new auxiliary variables and equations,

• Exogenous variables with leads or lags will also have been replaced by new auxiliary variables and equations.

For the required LaTeX packages, see write_latex_original_model.

Options

write_equation_tags
See write_equation_tags

Command: write_latex_static_model ;
Command: write_latex_static_model(OPTIONS);
This command creates two LaTeX files: one containing the static model and one containing the LaTeX document header information.

If your .mod file is FILENAME.mod, then Dynare will create a file called FILENAME/latex/static.tex, which includes a file called FILENAME/latex/static_content.tex (also created by Dynare) containing the list of all the steady state model equations.

If LaTeX names were given for variables and parameters (see Variable declarations), then those will be used; otherwise, the plain text names will be used.

Note that the model written in the TeX file will differ from the model declared by the user in the some dimensions (see write_latex_dynamic_model for details).

Also note that this command will not output the contents of the optional steady_state_model block (see steady_state_model); it will rather output a static version (i.e. without leads and lags) of the dynamic model declared in the model block. To write the LaTeX contents of the steady_state_model see write_latex_steady_state_model.

For the required LaTeX packages, see write_latex_original_model.

Options

write_equation_tags
See write_equation_tags.
Command: write_latex_steady_state_model;

This command creates two LaTeX files: one containing the steady state model and one containing the LaTeX document header information.

If your .mod file is FILENAME.mod, then Dynare will create a file called FILENAME/latex/steady_state.tex, which includes a file called FILENAME/latex/steady_state_content.tex (also created by Dynare) containing the list of all the steady state model equations.

If LaTeX names were given for variables and parameters (see Variable declarations), then those will be used; otherwise, the plain text names will be used.

Note that the model written in the .tex file will differ from the model declared by the user in some dimensions (see write_latex_dynamic_model for details).

For the required LaTeX packages, see write_latex_original_model.

4.6 Auxiliary variables

The model which is solved internally by Dynare is not exactly the model declared by the user. In some cases, Dynare will introduce auxiliary endogenous variables—along with corresponding auxiliary equations—which will appear in the final output.

The main transformation concerns leads and lags. Dynare will perform a transformation of the model so that there is only one lead and one lag on endogenous variables and no leads/lags on exogenous variables.

This transformation is achieved by the creation of auxiliary variables and corresponding equations. For example, if $x(+2)$ exists in the model, Dynare will create one auxiliary variable $AUX\_ENDO\_LEAD = x(+1)$, and replace $x(+2)$ by $AUX\_ENDO\_LEAD(+1)$.

A similar transformation is done for lags greater than 2 on endogenous (auxiliary variables will have a name beginning with $AUX\_ENDO\_LAG$), and for exogenous with leads and lags (auxiliary variables will have a name beginning with $AUX\_EXO\_LEAD$ or $AUX\_EXO\_LAG$ respectively).

Another transformation is done for the $\text{EXPECTATION}$ operator. For each occurrence of this operator, Dynare creates an auxiliary variable defined by a new equation, and replaces the expectation operator by a reference to the new auxiliary variable. For example, the expression $\text{EXPECTATION}(-1)(x(+1))$ is replaced by $AUX\_EXPECT\_LAG\_1(-1)$, and the new auxiliary variable is declared as $AUX\_EXPECT\_LAG\_1 = x(+2)$.

Auxiliary variables are also introduced by the preprocessor for the $\text{ramsey\_model}$ and $\text{ramsey\_policy}$ commands. In this case, they are used to represent the Lagrange multipliers when first order conditions of the Ramsey problem are computed. The new variables take the form $MULT_i$, where $i$ represents the constraint with which the multiplier is associated (counted from the order of declaration in the model block).

Auxiliary variables are also introduced by the $\text{differentiate\_forward\_vars}$ option of the model block. The new variables take the form $AUX\_DIFF\_FWRD_{i}$, and are equal to $x-x(-1)$ for some endogenous variable $x$.

Finally, auxiliary variables will arise in the context of employing the $\text{diff}$ operator.

Once created, all auxiliary variables are included in the set of endogenous variables. The output of decision rules (see below) is such that auxiliary variable names are replaced by the original variables they refer to.

The number of endogenous variables before the creation of auxiliary variables is stored in $M\_.orig\_endo\_nbr$, and the number of endogenous variables after the creation of auxiliary variables is stored in $M\_.endo\_nbr$.

See https://git.dynare.org/Dynare/dynare/-/wikis/Auxiliary-variables for more technical details on auxiliary variables.
4.7 Initial and terminal conditions

For most simulation exercises, it is necessary to provide initial (and possibly terminal) conditions. It is also necessary to provide initial guess values for non-linear solvers. This section describes the statements used for those purposes.

In many contexts (deterministic or stochastic), it is necessary to compute the steady state of a non-linear model: `initval` then specifies numerical initial values for the non-linear solver. The command `resid` can be used to compute the equation residuals for the given initial values.

Used in perfect foresight mode, the types of forward-looking models for which Dynare was designed require both initial and terminal conditions. Most often these initial and terminal conditions are static equilibria, but not necessarily.

One typical application is to consider an economy at the equilibrium at time 0, trigger a shock in first period, and study the trajectory of return to the initial equilibrium. To do that, one needs `initval` and `shocks` (see Shocks on exogenous variables).

Another one is to study how an economy, starting from arbitrary initial conditions at time 0 converges towards equilibrium. In this case models, the command `histval` permits to specify different historical initial values for variables with lags for the periods before the beginning of the simulation. Due to the design of Dynare, in this case `initval` is used to specify the terminal conditions.

Block: initval
Block: initval(OPTIONS...);

The `initval` block has two main purposes: providing guess values for non-linear solvers in the context of perfect foresight simulations and providing guess values for steady state computations in both perfect foresight and stochastic simulations. Depending on the presence of `histval` and `endval` blocks it is also used for declaring the initial and terminal conditions in a perfect foresight simulation exercise. Because of this interaction of the meaning of an `initval` block with the presence of `histval` and `endval` blocks in perfect foresight simulations, it is strongly recommended to check that the constructed `oo_.endo_simul` and `oo_.exo_simul` variables contain the desired values after running `perfect_foresight_setup` and before running `perfect_foresight_solver`. In the presence of leads and lags, these subfields of the results structure will store the historical values for the lags in the first column/row and the terminal values for the leads in the last column/row.

The `initval` block is terminated by `end`; and contains lines of the form:

VARIABLE_NAME = EXPRESSION;

In a deterministic (i.e. perfect foresight) model

First, both the `oo_.endo_simul` and `oo_.exo_simul` variables storing the endogenous and exogenous variables will be filled with the values provided by this block. If there are no other blocks present, it will therefore provide the initial and terminal conditions for all the endogenous and exogenous variables, because it will also fill the last column/row of these matrices. For the intermediate simulation periods it thereby provides the starting values for the solver. In the presence of a `histval` block (and therefore absence of an `endval` block), this `histval` block will provide/overwrite the historical values for the state variables (lags) by setting the first column/row of `oo_.endo_simul` and `oo_.exo_simul`. This implies that the `initval` block in the presence of `histval` only sets the terminal values for the variables with leads and provides initial values for the perfect foresight solver.

Because of these various functions of `initval` it is often necessary to provide values for all the endogenous variables in an `initval` block. Initial and terminal conditions are strictly necessary for lagged/leaded variables, while feasible starting values are required for the solver. It is important to be aware that if some variables, endogenous or exogenous, are not mentioned in the `initval` block, a zero value is assumed. It is particularly important to keep this in mind when specifying exogenous variables using `varexo` that are not allowed to take on the value of zero, like e.g. TFP.

Note that if the `initval` block is immediately followed by a `steady` command, its semantics are slightly changed. The `steady` command will compute the steady state of the model for all the endogenous variables, assuming that exogenous variables are kept constant at the value declared in the `initval` block. These
steady state values conditional on the declared exogenous variables are then written into oo_.endo_simul and take up the potential roles as historical and terminal conditions as well as starting values for the solver. An initval block followed by steady is therefore formally equivalent to an initval block with the specified values for the exogenous variables, and the endogenous variables set to the associated steady state values conditional on the exogenous variables.

In a stochastic model

The main purpose of initval is to provide initial guess values for the non-linear solver in the steady state computation. Note that if the initval block is not followed by steady, the steady state computation will still be triggered by subsequent commands (stoch_simul, estimation...).

As such, initval allows specifying the initial instrument value for steady state finding when providing an analytical conditional steady state file for ramsey_model-computations.

It is not necessary to declare 0 as initial value for exogenous stochastic variables, since it is the only possible value.

The subsequently computed steady state (not the initial values, use histval for this) will be used as the initial condition at all the periods preceeding the first simulation period for the three possible types of simulations in stochastic mode:

- **stoch_simul**, if the periods option is specified.
- **forecast** as the initial point at which the forecasts are computed.
- **conditional_forecast** as the initial point at which the conditional forecasts are computed.

To start simulations at a particular set of starting values that are not a computed steady state, use histval.

Options

**all_values_required**

Issues an error and stops processing the .mod file if there is at least one endogenous or exogenous variable that has not been set in the initval block.

Example

```plaintext
initval;
c = 1.2;
k = 12;
x = 1;
end;
steady;
```

Block: endval;

This block is terminated by end; and contains lines of the form:

```plaintext
VARIABLE_NAME = EXPRESSION;
```

The endval block makes only sense in a deterministic model and cannot be used together with histval. Similar to the initval command, it will fill both the oo_.endo_simul and oo_.exo_simul variables storing the endogenous and exogenous variables with the values provided by this block. If no initval block is present, it will fill the whole matrices, therefore providing the initial and terminal conditions for all the endogenous and exogenous variables, because it will also fill the first and last column/row of these matrices. Due to also filling the intermediate simulation periods it will provide the starting values for the solver as well.

If an initval block is present, initval will provide the historical values for the variables (if there are states/lags), while endval will fill the remainder of the matrices, thereby still providing i) the terminal conditions for variables entering the model with a lead and ii) the initial guess values for all endogenous variables at all the simulation dates for the perfect foresight solver.
Note that if some variables, endogenous or exogenous, are NOT mentioned in the endval block, the value assumed is that of the last initval block or steady command (if present). Therefore, in contrast to initval, omitted variables are not automatically assumed to be 0 in this case. Again, it is strongly recommended to check the constructed oo_.endo_simul and oo_.exo_simul variables after running perfect_foresight_setup and before running perfect_foresight_solver to see whether the desired outcome has been achieved.

Like initval, if the endval block is immediately followed by a steady command, its semantics are slightly changed. The steady command will compute the steady state of the model for all the endogenous variables, assuming that exogenous variables are kept constant to the value declared in the endval block. These steady state values conditional on the declared exogenous variables are then written into oo_.endo_simul and therefore take up the potential roles as historical and terminal conditions as well as starting values for the solver. An endval block followed by steady is therefore formally equivalent to an endval block with the specified values for the exogenous variables, and the endogenous variables set to the associated steady state values.

Options

all_values_required

See all_values_required.

Example

\[
\text{\bf var} \ c \ k; \\
\text{\bf varexo} \ x; \\
\text{\bf model}; \\
c + k - aa*x^k(-1)^alph - (1-delt)*k(-1); \\
c^(-gam) - (1+bet)^(-1)*(aa^alph*x(+1)^k*(alph-1) + 1 - delt)*c(+1)^(- \rightarrow gam); \\
\text{end}; \\
\text{\bf initval}; \\
c = 1.2; \\
k = 12; \\
x = 1; \\
\text{end}; \\
\text{\bf steady}; \\
\text{\bf endval}; \\
c = 2; \\
k = 20; \\
x = 2; \\
\text{end}; \\
\text{\bf steady}; \\
\text{\bf perfect_foresight_setup(periods=200)}; \\
\text{\bf perfect_foresight_solver};
\]

In this example, the problem is finding the optimal path for consumption and capital for the periods \( t = 1 \) to \( T = 200 \), given the path of the exogenous technology level \( x \). \( c \) is a forward-looking variable and the exogenous variable \( x \) appears with a lead in the expected return of physical capital, while \( k \) is a purely backward-looking (state) variable.

The initial equilibrium is computed by steady conditional on \( x=1 \), and the terminal one conditional on \( x=2 \). The initval block sets the initial condition for \( k \) (since it is the only backward-looking variable), while the endval block sets the terminal condition for \( c \) (since it is the only forward-looking endogenous variable). The starting values for the perfect foresight solver are given by the endval block. See below for more details.
Example

```plaintext
var c k;
varexo x;

model;
c + k - aa^x*k(-1)^alph - (1-delt)*k(-1);
c^(-gam) - (1+bet)^(-1)*(aa*alph*x(+1)*k^(alph-1) + 1 - delt)*c(+1)^(-gam);
end;

initval;
k = 12;
end;

derval;
c = 2;
x = 1.1;
end;

perfect_fore Osborne_setup(periods=200);
perfect_fore Osborne_solver;
```

In this example, there is no `steady` command, hence the conditions are exactly those specified in the `initval` and `endval` blocks. We need terminal conditions for `c` and `x`, since both appear with a lead, and an initial condition for `k`, since it appears with a lag.

Setting `x=1.1` in the `endval` block without a `shocks` block implies that technology is at `1.1` in `t = 1` and stays there forever, because `endval` is filling all entries of `oo_.endo_simul` and `oo_.exo_simul` except for the very first one, which stores the initial conditions and was set to 0 by the `initval` block when not explicitly specifying a value for it.

Because the law of motion for capital is backward-looking, we need an initial condition for `k` at time 0. Due to the presence of `endval`, this cannot be done via a `histval` block, but rather must be specified in the `initval` block. Similarly, because the Euler equation is forward-looking, we need a terminal condition for `c` at `t = 201`, which is specified in the `endval` block.

As can be seen, it is not necessary to specify `c` and `x` in the `initval` block and `k` in the `endval` block, because they have no impact on the results. Due to the optimization problem in the first period being to choose `c,k` at `t = 1` given the predetermined capital stock `k` inherited from `t = 0` as well as the current and future values for technology `x`, the values for `c` and `x` at time `t = 0` play no role. The same applies to the choice of `c,k` at time `t = 200`, which does not depend on `k` at `t = 201`. As the Euler equation shows, that choice only depends on current capital as well as future consumption `c` and technology `x`, but not on future capital `k`. The intuitive reason is that those variables are the consequence of optimization problems taking place in at periods `t = 0` and `t = 201`, respectively, which are not modeled here.

Example

```plaintext
initval;
c = 1.2;
k = 12;
x = 1;
end;

derval;
c = 2;
k = 20;
x = 1.1;
end;
```
In this example, initial conditions for the forward-looking variables \( x \) and \( c \) are provided, together with a terminal condition for the backward-looking variable \( k \). As shown in the previous example, these values will not affect the simulation results. Dynare simply takes them as given and basically assumes that there were realizations of exogenous variables and states that make those choices equilibrium values (basically initial/terminal conditions at the unspecified time periods \( t < 0 \) and \( t > 201 \)).

The above example suggests another way of looking at the use of \texttt{steady after initval and endval}. Instead of saying that the implicit unspecified conditions before and after the simulation range have to fit the initial/terminal conditions of the endogenous variables in those blocks, \texttt{steady} specifies that those conditions at \( t < 0 \) and \( t > 201 \) are equal to being at the steady state given the exogenous variables in the \texttt{initval} and \texttt{endval} blocks. The endogenous variables at \( t = 0 \) and \( t = 201 \) are then set to the corresponding steady state equilibrium values.

The fact that \( c \) at \( t = 0 \) and \( k \) at \( t = 201 \) specified in \texttt{initval} and \texttt{endval} are taken as given has an important implication for plotting the simulated vector for the endogenous variables, i.e. the rows of \texttt{oo_.endo_simul}: this vector will also contain the initial and terminal conditions and thus is 202 periods long in the example. When you specify arbitrary values for the initial and terminal conditions for forward- and backward-looking variables, respectively, these values can be very far away from the endogenously determined values at \( t = 1 \) and \( t = 200 \). While the values at \( t = 0 \) and \( t = 201 \) are unrelated to the dynamics for \( 0 < t < 201 \), they may result in strange-looking large jumps. In the example above, consumption will display a large jump from \( t = 0 \) to \( t = 1 \) and capital will jump from \( t = 200 \) to \( t = 201 \) when using \texttt{rplot} or manually plotting \texttt{oo_.endo_simul}.

\textbf{Block: histval ;}
\textbf{Block: histval(OPTIONS...);}

\emph{In a deterministic perfect foresight context}

In models with lags on more than one period, the \texttt{histval} block permits to specify different historical initial values for different periods of the state variables. In this case, the \texttt{initval} block takes over the role of specifying terminal conditions and starting values for the solver. Note that the \texttt{histval} block does not take non-state variables.

This block is terminated by \texttt{end;} and contains lines of the form:

\begin{verbatim}
VARIABLE_NAME(INTEGER) = EXPRESSION;
\end{verbatim}

\texttt{EXPRESSION} is any valid expression returning a numerical value and can contain already initialized variable names.

By convention in Dynare, period 1 is the first period of the simulation. Going backward in time, the first period before the start of the simulation is period 0, then period -1, and so on.

State variables not initialized in the \texttt{histval} block are assumed to have a value of zero at period 0 and before. Note that \texttt{histval} cannot be followed by \texttt{steady}.

\textit{Example}

\begin{verbatim}
model;
x=1.5*x(-1)-0.6*x(-2)+epsilon;
log(c)=0.5*x+0.5*log(c(+1));
end;

histval;
x(0)=-1;
x(-1)=0.2;
end;

initval;
c=1;
\end{verbatim}

(continues on next page)
In this example, **histval** is used to set the historical conditions for the two lags of the endogenous variable \( x \), stored in the first column of `oo_.endo_simul`. The **initval** block is used to set the terminal condition for the forward looking variable \( c \), stored in the last column of `oo_.endo_simul`. Moreover, the **initval** block defines the starting values for the perfect foresight solver for both endogenous variables \( c \) and \( x \).

**In a stochastic simulation context**

In the context of stochastic simulations, **histval** allows setting the starting point of those simulations in the state space. As for the case of perfect foresight simulations, all not explicitly specified variables are set to 0. Moreover, as only states enter the recursive policy functions, all values specified for control variables will be ignored. This can be used

- In **stoch_simul**, if the **periods** option is specified. Note that this only affects the starting point for the simulation, but not for the impulse response functions. When using the **loglinear** option, the **histval** block nevertheless takes the unlogged starting values.
- In **forecast** as the initial point at which the forecasts are computed. When using the **loglinear** option, the **histval** block nevertheless takes the unlogged starting values.
- In **conditional_forecast** for a calibrated model as the initial point at which the conditional forecasts are computed. When using the **loglinear** option, the **histval** block nevertheless takes the unlogged starting values.
- In **Ramsey policy**, where it also specifies the values of the endogenous states (including lagged exogenous) at which the objective function of the planner is computed. Note that the initial values of the Lagrange multipliers associated with the planner’s problem cannot be set (see `evaluate_planner_objective`).

**Options**

**all_values_required**

See **all_values_required**.

**Example**

```plaintext
var x y;
varx e;

define:
x = y(-1)^alpha*y(-2)^*(1-alpha)+e;
end;

initval;
x = 1;
y = 1;
e = 0.5;
end;

steady;

histval;
y(0) = 1.1;
y(-1) = 0.9;
end;

stoch_simul(periods=100);
```

(continued from previous page)
**Command:** resid \\
This command will display the residuals of the static equations of the model, using the values given for the endogenous in the last `initval` or `endval` block (or the steady state file if you provided one, see *Steady state*).

**Options**

*non_zero*

Only display non-zero residuals.

**Command:** `initval_file(OPTIONS...);`

In a deterministic setup, this command is used to specify a path for all endogenous and exogenous variables. The length of these paths must be equal to the number of simulation periods, plus the number of leads and the number of lags of the model (for example, with 50 simulation periods, in a model with 2 lags and 1 lead, the paths must have a length of 53). Note that these paths cover two different things:

- The constraints of the problem, which are given by the path for exogenous and the initial and terminal values for endogenous
- The initial guess for the non-linear solver, which is given by the path for endogenous variables for the simulation periods (excluding initial and terminal conditions)

In perfect foresight and stochastic contexts, `steady` uses the first observation loaded by `initval_file` as guess value to solve for the steady state of the model. This first observation is determined by the `first_obs` option when it is used.

Don’t mix `initval_file` with `initval` statements. However, after `initval_file`, you can modify the historical initial values with `histval` or `histval_file` statement.

There can be several `initval_file` statements in a model file. Each statement resets `oo_.initval_series`.

**Options**

*datafile = FILENAME*

*filename = FILENAME (deprecated)*

The name of the file containing the data. It must be included in quotes if the filename contains a path or an extension. The command accepts the following file formats:

- M-file (extension `.m`): for each endogenous and exogenous variable, the file must contain a row or column vector of the same name.
- MAT-file (extension `.mat`): same as for M-files.
- Excel file (extension `.xls` or `.xlsx`): for each endogenous and exogenous variable, the file must contain a column of the same name. NB: Octave only supports the `.xlsx` file extension and must have the `io` package installed (easily done via octave by typing `pkg install -forge io`). The first column may contain the date of each observation.
- CSV files (extension `.csv`): for each endogenous and exogenous variable, the file must contain a column of the same name. The first column may contain the date of each observation.

*first_obs = {INTEGER | DATE}*

The observation number or the date (see *The dates class*) of the first observation to be used in the file

*first_simulation_period = {INTEGER | DATE}*

The observation number in the file or the date (see `dates`) at which the simulation (or the forecast) is starting. This option avoids to have to compute the maximum number of lags in the model. The observation corresponding to the first period of simulation doesn’t need to exist in the file as the only dates necessary for initialization are before that date.

*last_simulation_period = {INTEGER | DATE}*

The observation number in the file or the date (see `dates`) at which the simulation (or the forecast) is ending. This option avoids to have to compute the maximum number of leads in the model.

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last_obs = {INTEGER | DATE}

The observation number or the date (see The dates class) of the last observation to be used in the file.

nobs = INTEGER

The number of observations to be used in the file (starting with first of first_obs observation).

series = DSERIES NAME

The name of a DSERIES containing the data (see The dseries class)

Example 1

```matlab
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

initval_file(datafile=mydata.csv);
perfect_foresight_setup(periods=200);
perfect_foresight_solver;
```

The initial and terminal values are taken from file mydata.csv (nothing guarantees that these values are the steady state of the model). The guess value for the trajectories are also taken from the file. The file must contain at least 203 observations of variables c, x and e. If there are more than 203 observations available in the file, the first 203 are used by perfect_foresight_setup(periods=200). Note that the values for the auxiliary variable corresponding to x(-2) are automatically computed by initval_file.

Example 2

```matlab
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

initval_file(datafile=mydata.csv,
             first_obs=10);
perfect_foresight_setup(periods=200);
perfect_foresight_solver;
```
The initial and terminal values are taken from file mydata.csv starting with the 10th observation in the file. There must be at least 212 observations in the file.

**Example 3**

```plaintext
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

ds = dseries(mydata.csv);
lds = log(ds);
initval_file(series=lds,
   first_obs=2010Q1);
perfect_foresight_setup(periods=200);
perfect_foresight_solver;
```

The initial and terminal values are taken from dseries lds. All observations are loaded starting with the 1st quarter of 2010 until the end of the file. There must be data available at least until 2050Q3.

**Example 4**

```plaintext
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

initval_file(datafile=mydata.csv,
   first_simulation_period=2010Q1);
perfect_foresight_setup(periods=200);
perfect_foresight_solver;
```

The initial and terminal values are taken from file mydata.csv. The observations in the file must have dates. All observations are loaded from the 3rd quarter of 2009 until the end of the file. There must be data available in the file at least until 2050Q3.

**Example 5**

```plaintext

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```
\begin{verbatim}
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

initval_file(datafile=mydata.csv, last_obs = 212);

perfect_foresight_setup(periods=200);
perfect_foresight_solver;
\end{verbatim}

The initial and terminal values are taken from file mydata.csv. The first 212 observations are loaded and the first 203 observations will be used by perfect_foresight_setup(periods=200).

Example 6

\begin{verbatim}
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

initval_file(datafile=mydata.csv, first_obs = 10, nobs = 203);

perfect_foresight_setup(periods=200);
perfect_foresight_solver;
\end{verbatim}

The initial and terminal values are taken from file mydata.csv. Observations 10 to 212 are loaded.

Example 7

\begin{verbatim}
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
\end{verbatim}

(continues on next page)
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

initval_file(datafile=mydata.csv,
   first_obs = 10);

steady;

The values of the 10th observation of mydata.csv are used as guess value to compute the steady state. The exogenous variables are set to values found in the file or zero if these variables aren’t present.

Command: histval_file(OPTIONS...);

This command is equivalent to histval, except that it reads its input from a file, and is typically used in conjunction with smoother2histval.

Options

datafile = FILENAME

filename = FILENAME (deprecated)

The name of the file containing the data. The command accepts the following file formats:

- M-file (extension .m): for each endogenous and exogenous variable, the file must contain a row or column vector of the same name.
- MAT-file (extension .mat): same as for M-files.
- Excel file (extension .xls or .xlsx): for each endogenous and exogenous variable, the file must contain a column of the same name. NB: Octave only supports the .xlsx file extension and must have the io package installed (easily done via octave by typing ‘pkg install -forge io’). The first column may contain the date of each observation.
- CSV files (extension .csv): for each endogenous and exogenous variable, the file must contain a column of the same name. The first column may contain the date of each observation.

first_obs = {INTEGER | DATE}

The observation number or the date (see The dates class) of the first observation to be used in the file

first_simulation_period = {INTEGER | DATE}

The observation number in the file or the date (see The dates class) at which the simulation (or the forecast) is starting. This option avoids to have to compute the maximum number of lags in the model. The observation corresponding to the first period of simulation doesn’t need to exist in the file as the only dates necessary for initialization are before that date.

last_simulation_period = {INTEGER | DATE}

The observation number in the file or the date (see dates) at which the simulation (or the forecast) is ending. This option avoids to have to compute the maximum number of leads in the model.

last_obs = {INTEGER | DATE}

The observation number or the date (see The dates class) of the last observation to be used in the file.

nobs = INTEGER

The number of observations to be used in the file (starting with first of first_obs observation).

series = DSERIES NAME

The name of a DSERIES containing the data (see The dseries class)
Example 1

```markdown
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

steady_state_model;
x = 0;
c = exp(c*x/(1 - d));
end;

histval_file(datafile=mydata.csv);

stoch_simul(order=1, periods=100);
```

The initial values for the stochastic simulation are taken from the two first rows of file mydata.csv.

Example 2

```markdown
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

histval_file(datafile=mydata.csv,
             first_obs=10);

stoch_simul(order=1, periods=100);
```

The initial values for the stochastic simulation are taken from rows 10 and 11 of file mydata.csv.

Example 3

```markdown
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
```

(continues on next page)
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(continued from previous page)

c = 0.5;  
d = 0.5;  

model;  
x = a*x(-1) + b*x(-2) + e;  
log(c) = c*x + d*log(c(+1));  
end;  

histval_file(datafile=mydata.csv,  
    first_obs=2010Q1);  

stoch_simul(order=1, periods=100);  

The initial values for the stochastic simulation are taken from observations 2010Q1 and 2010Q2 of file mydata.csv.

Example 4

var c x;  
varexo e;  
parameters a b c d;  

a = 1.5;  
b = -0.6;  
c = 0.5;  
d = 0.5;  

model;  
x = a*x(-1) + b*x(-2) + e;  
log(c) = c*x + d*log(c(+1));  
end;  

histval_file(datafile=mydata.csv,  
    first_simulation_period=2010Q1)  

stoch_simul(order=1, periods=100);  

The initial values for the stochastic simulation are taken from observations 2009Q3 and 2009Q4 of file mydata.csv.

Example 5

var c x;  
varexo e;  
parameters a b c d;  

a = 1.5;  
b = -0.6;  
c = 0.5;  
d = 0.5;  

model;  
x = a*x(-1) + b*x(-2) + e;  
log(c) = c*x + d*log(c(+1));  
end;  

histval_file(datafile=mydata.csv,  
    last_obs = 4);  

(continues on next page)

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The initial values for the stochastic simulation are taken from the two first rows of file `mydata.csv`.

**Example 6**

```plaintext
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

initval_file(datafile=mydata.csv,
             first_obs = 10,
             nobs = 4);

stoch_simul(order=1, periods=100);
```

The initial values for the stochastic simulation are taken from rows 10 and 11 of file `mydata.csv`.

**Example 7**

```plaintext
var c x;
varexo e;
parameters a b c d;

a = 1.5;
b = -0.6;
c = 0.5;
d = 0.5;

model;
x = a*x(-1) + b*x(-2) + e;
log(c) = c*x + d*log(c(+1));
end;

initval_file(datafile=mydata.csv,
             first_obs = 10);

histval_file(datafile=myotherdata.csv);

perfect_foresight_setup(periods=200);
perfect_foresight_solver;
```

Historical initial values for the simulation are taken from the two first rows of file `myotherdata.csv`.

Terminal values and guess values for the simulation are taken from file `mydata.csv` starting with the 12th observation in the file. There must be at least 212 observations in the file.
4.8 Shocks on exogenous variables

In a deterministic context, when one wants to study the transition of one equilibrium position to another, it is equivalent to analyze the consequences of a permanent shock and this is done in Dynare through the proper use of initval and endval.

Another typical experiment is to study the effects of a temporary shock after which the system goes back to the original equilibrium (if the model is stable...). A temporary shock is a temporary change of value of one or several exogenous variables in the model. Temporary shocks are specified with the command shocks.

In a stochastic framework, the exogenous variables take random values in each period. In Dynare, these random values follow a normal distribution with zero mean, but it belongs to the user to specify the variability of these shocks. The non-zero elements of the matrix of variance-covariance of the shocks can be entered with the shocks command.

If the variance of an exogenous variable is set to zero, this variable will appear in the report on policy and transition functions, but isn’t used in the computation of moments and of Impulse Response Functions. Setting a variance to zero is an easy way of removing an exogenous shock.

Note that, by default, if there are several shocks or mshocks blocks in the same .mod file, then they are cumulative: all the shocks declared in all the blocks are considered; however, if a shocks or mshocks block is declared with the overwrite option, then it replaces all the previous shocks and mshocks blocks.

Block: shocks;

Block: shocks(overwrite);

See above for the meaning of the overwrite option.

In deterministic context

For deterministic simulations, the shocks block specifies temporary changes in the value of exogenous variables. For permanent shocks, use an endval block.

The block should contain one or more occurrences of the following group of three lines:

```
var VARIABLE_NAME;
periods INTEGER[:INTEGER] [[,] INTEGER[:INTEGER]]...;
values DOUBLE | (EXPRESSION) [[,] DOUBLE | (EXPRESSION) ]...;
```

It is possible to specify shocks which last several periods and which can vary over time. The periods keyword accepts a list of several dates or date ranges, which must be matched by as many shock values in the values keyword. Note that a range in the periods keyword can be matched by only one value in the values keyword. If values represents a scalar, the same value applies to the whole range. If values represents a vector, it must have as many elements as there are periods in the range.

Note that shock values are not restricted to numerical constants: arbitrary expressions are also allowed, but you have to enclose them inside parentheses.

The feasible range of periods is from 0 to the number of periods specified in perfect_foresight_setup.

**Warning:** Note that the first endogenous simulation period is period 1. Thus, a shock value specified for the initial period 0 may conflict with (i.e. may overwrite or be overwritten by) values for the initial period specified with initval or endval (depending on the exact context). Users should always verify the correct setting of oo_.exo_simul after perfect_foresight_setup.

Example (with scalar values)

```
shocks;
var e;
```

(continues on next page)
Example (with vector values)

\[ xx = [1.2; 1.3; 1]; \]

```
shocks;
var e; 
periods 1:3;
values (xx);
end;
```

In stochastic context

For stochastic simulations, the `shocks` block specifies the non-zero elements of the covariance matrix of the shocks of exogenous variables.

You can use the following types of entries in the block:

- Specification of the standard error of an exogenous variable.

```
var VARIABLE_NAME; stderr EXPRESSION;
```

- Specification of the variance of an exogenous variable.

```
var VARIABLE_NAME = EXPRESSION;
```

- Specification of the covariance of two exogenous variables.

```
var VARIABLE_NAME, VARIABLE_NAME = EXPRESSION;
```

- Specification of the correlation of two exogenous variables.

```
corr VARIABLE_NAME, VARIABLE_NAME = EXPRESSION;
```

In an estimation context, it is also possible to specify variances and covariances on endogenous variables: in that case, these values are interpreted as the calibration of the measurement errors on these variables. This requires the `varobs` command to be specified before the `shocks` block.

Example

```
shocks;
var e = 0.000081;
var u; stderr 0.009;
corr e, u = 0.8;
var v, w = 2;
end;
```
In stochastic optimal policy context

When computing conditional welfare in a `ramsey_model` or `discretionary_policy` context, welfare is conditional on the state values inherited by planner when making choices in the first period. The information set of the first period includes the respective exogenous shock realizations. Thus, their known value can be specified using the perfect foresight syntax. Note that i) all other values specified for periods than period 1 will be ignored and ii) the value of lagged shocks (e.g. in the case of news shocks) is specified with `histval`.

Example

```plaintext
shocks;
  var u; stderr 0.008;
  var u;
  periods 1;
  values 1;
end;
```

Mixing deterministic and stochastic shocks

It is possible to mix deterministic and stochastic shocks to build models where agents know from the start of the simulation about future exogenous changes. In that case `stoch_simul` will compute the rational expectation solution adding future information to the state space (nothing is shown in the output of `stoch_simul`) and `forecast` will compute a simulation conditional on initial conditions and future information.

Example

```plaintext
varexo_det tau;
varexo e;
...
shocks;
  var e; stderr 0.01;
  var tau;
  periods 1:9;
  values -0.15;
end;

stoch_simul(irf=0);
forecast;
```

Block: `mshocks`

Block: `mshocks(OPTIONS...)`

The purpose of this block is similar to that of the `shocks` block for deterministic shocks, except that the numeric values given will be interpreted in a multiplicative way. For example, if a value of 1.05 is given as shock value for some exogenous at some date, it means 5% above its steady state value.

If no `endval` block is present, the steady state as specified in the `initval` block is used as the basis for the multiplication. If an `endval` block is present, the terminal steady state as specified in the `endval` block will be used as the basis for the multiplication (unless the `relative_to_initval` option is passed).

The syntax is the same as `shocks` in a deterministic context.

This command is only meaningful in two situations:

- on exogenous variables with a non-zero steady state, in a deterministic setup,
- on deterministic exogenous variables with a non-zero steady state, in a stochastic setup.

Options

- `overwrite`
  Same meaning as in the `shocks` block.
relative_to_initval

If an endval block is present, the initial steady state as specified in the initval block will be used as the basis for multiplication (instead of the terminal steady state).

Block: heteroskedastic_shocks;
Block: heteroskedastic_shocks(overwrite);

In estimation context, it implements heteroskedastic filters, where the standard error of shocks may unexpectedly change in every period. The standard deviation of shocks may be either provided directly or set/modified in each observed period by a scale factor. If \( \text{std0} \) is the usual standard error for shock1, then:

- using a scale factor in period \( t \) implies: \( \text{std} \text{(shock1|t)} = \text{std0}(\text{shock1}) \times \text{scale}(t) \)
- using a provided value in period \( t \) implies: \( \text{std} \text{(shock1|t)} = \text{value}(t) \).

The block has a similar syntax as the shocks block in a perfect foresight context. It should contain one or more occurrences of the following group of three lines (for setting values):

```
var VARIABLE_NAME;
periods INTEGER[:INTEGER] [, INTEGER[:INTEGER]]...;
values DOUBLE | (EXPRESSION) [, DOUBLE | (EXPRESSION)] ...;
```

OR (for setting scale factors):

```
var VARIABLE_NAME;
periods INTEGER[:INTEGER] [, INTEGER[:INTEGER]]...;
scales DOUBLE | (EXPRESSION) [, DOUBLE | (EXPRESSION)] ...;
```

NOTE: scales and values cannot be simultaneously set for the same shock in the same period, but it is possible to set values for some periods and scales for other periods for the same shock. There can be only one scales and values directive each for a given shock, so all affected periods must be set in one statement.

Example

```
heteroskedastic_shocks;

var e1;
periods 86:87, 89:97;
scales 0.5, 0;

var e1;
periods 88;
values 0.1;

var e2;
periods 86:87 88:97;
values 0.04 0.01;

end;
```

MATLAB/Octave command: `get_shock_stderr_by_name('EXOGENOUS_NAME');`

Given the name of an exogenous variable, returns its standard deviation, as set by a previous shocks block.

MATLAB/Octave command: `set_shock_stderr_value('EXOGENOUS_NAME', MATLAB_EXPRESSION);`

Sets the standard deviation of an exogenous variable. This does essentially the same as setting the standard error via a shocks block, except that it accepts arbitrary MATLAB/Octave expressions, and that it works from MATLAB/Octave scripts.
4.9 Other general declarations

Command: \texttt{dsample INTEGER [INTEGER]};

Reduces the number of periods considered in subsequent output commands.

4.10 Steady state

There are two ways of computing the steady state (i.e. the static equilibrium) of a model. The first way is to let Dynare compute the steady state using a nonlinear Newton-type solver; this should work for most models, and is relatively simple to use. The second way is to give more guidance to Dynare, using your knowledge of the model, by providing it with a method to compute the steady state, either using a \texttt{steady\_state\_model} block or writing matlab routine.

4.10.1 Finding the steady state with Dynare nonlinear solver

Command: \texttt{steady ;}
Command: \texttt{steady(OPTIONS...);}

This command computes the steady state of a model using a nonlinear Newton-type solver and displays it. When a steady state file is used \texttt{steady} displays the steady state and checks that it is a solution of the static model.

More precisely, it computes the equilibrium value of the endogenous variables for the value of the exogenous variables specified in the previous \texttt{initval} or \texttt{endval} block.

\texttt{steady} uses an iterative procedure and takes as initial guess the value of the endogenous variables set in the previous \texttt{initval} or \texttt{endval} block.

For complicated models, finding good numerical initial values for the endogenous variables is the trickiest part of finding the equilibrium of that model. Often, it is better to start with a smaller model and add new variables one by one.

Options

\texttt{maxit = INTEGER}

Determines the maximum number of iterations used in the non-linear solver. The default value of \texttt{maxit} is 50.

\texttt{tolf = DOUBLE}

Convergence criterion for termination based on the function value. Iteration will cease when the residuals are smaller than \texttt{tolf}. Default: $\epsilon^{1/3}$

\texttt{tolx = DOUBLE}

Convergence criterion for termination based on the step tolerance along. Iteration will cease when the attempted step size is smaller than \texttt{tolx}. Default: $\epsilon^{2/3}$

\texttt{solve\_algo = INTEGER}

Determines the non-linear solver to use. Possible values for the option are:

0

Use \texttt{fsolve} (under MATLAB, only available if you have the Optimization Toolbox; always available under Octave).

1

Use a Newton-like algorithm with line-search.

2
Splits the model into recursive blocks and solves each block in turn using the same solver as value 1.

3

Use Chris Sims’ solver.

4

Splits the model into recursive blocks and solves each block in turn using a trust-region solver with autoscaling.

5

Newton algorithm with a sparse Gaussian elimination (SPE) solver at each iteration (requires bytecode option, see Model declaration).

6

Newton algorithm with a sparse LU solver at each iteration (requires bytecode and/or block option, see Model declaration).

7

Newton algorithm with a Generalized Minimal Residual (GMRES) solver at each iteration (requires bytecode and/or block option, see Model declaration).

8

Newton algorithm with a Stabilized Bi-Conjugate Gradient (BiCGStab) solver at each iteration (requires bytecode and/or block option, see Model declaration).

9

Trust-region algorithm with autoscaling (same as value 4, but applied to the entire model, without splitting).

10

Levenberg-Marquardt mixed complementarity problem (LMMCP) solver (Kanzow and Petra (2004)). The complementarity conditions are specified with an mcp equation tag, see lmmcp.

11

PATH mixed complementarity problem solver of Ferris and Munson (1999). The complementarity conditions are specified with an mcp equation tag, see lmmcp. Dynare only provides the interface for using the solver. Due to licence restrictions, you have to download the solver’s most current version yourself from http://pages.cs.wisc.edu/~ferris/path.html and place it in MATLAB’s search path.

12

Computes a block decomposition and then applies a Newton-type solver on those smaller blocks rather than on the full nonlinear system. This is similar to 2, but is typically more efficient. The block decomposition is done at the preprocessor level, which brings two benefits: it identifies blocks that can be evaluated rather than solved; and evaluations of the residual and Jacobian of the model are more efficient because only the relevant elements are recomputed at every iteration. This option is typically used with the perfect_forest_solver command with purely backward, forward or static models, or with routines for semi-structural models, and it must not be combined with option block of the model block. Also note that for those models, the block decomposition is performed as if mfs=3 had been passed to the model block, and the decomposition is slightly different because it is computed in a time-recursive fashion (i.e. in such a way that the simulation is meant to be done with the outer loop on periods and the inner loop on blocks; while for models with both leads and lags, the outer loop is on blocks and the inner loop is on periods).
Same as 12, except that it applies a trust region solver (similar to 4) to the blocks. Default value is 4.

**homotopy_mode = INTEGER**
Use a homotopy (or divide-and-conquer) technique to solve for the steady state. If you use this option, you must specify a homotopy_setup block. This option can take three possible values:

0  
Do not use homotopy.

1  
In this mode, all the parameters are changed simultaneously, and the distance between the boundaries for each parameter is divided in as many intervals as there are steps (as defined by the homotopy_steps option); the problem is solved as many times as there are steps.

2  
Same as mode 1, except that only one parameter is changed at a time; the problem is solved as many times as steps times number of parameters.

3  
Dynare tries first the most extreme values. If it fails to compute the steady state, the interval between initial and desired values is divided by two for all parameters. Every time that it is impossible to find a steady state, the previous interval is divided by two. When it succeeds to find a steady state, the previous interval is multiplied by two. In that last case homotopy_steps contains the maximum number of computations attempted before giving up.

Default value is 0.

**homotopy_steps = INTEGER**
Defines the number of steps when performing a homotopy. See homotopy_mode option for more details. Default is 10.

**homotopy_force_continue = INTEGER**
This option controls what happens when homotopy fails.

0  
steady fails with an error message

1  
steady keeps the values of the last homotopy step that was successful and continues. BE CAREFUL: parameters and/or exogenous variables are NOT at the value expected by the user.

Default is 0.

**nocheck**
Don’t check the steady state values when they are provided explicitly either by a steady state file or a steady_state_model block. This is useful for models with unit roots as, in this case, the steady state is not unique or doesn’t exist.

**markowitz = DOUBLE**
Value of the Markowitz criterion (in the interval $(0, \infty)$) used to select the pivot with sparse Gaussian elimination (solve_algo = 5). This criterion governs the tradeoff between selecting the pivot resulting in the most accurate solution (low markowitz values) and the one that preserves maximum sparsity (high markowitz values). Default: 0.5.
fsolve_options = (NAME, VALUE, ...)

A list of NAME and VALUE pairs. Can be used to set options for the fsolve routine, which is selected when solve_algo = 0 (this option has no effect for other values of solve_algo). For the list of available name/value pairs, see the documentation of fsolve in the MATLAB or Octave manual. Note that Dynare already uses the values of the maxit, tolf and tolx options of the steady command for initializing the corresponding options passed to fsolve, so you should not need to override those. Also note that you should not try to override the value of the Jacobian or SpecifyObjectiveGradient option.

Example

See Initial and terminal conditions.

After computation, the steady state is available in the following variable:

MATLAB/Octave variable: oo_.steady_state

Contains the computed steady state. Endogenous variables are ordered in the order of declaration used in the var command (which is also the order used in M_.endo_names).

MATLAB/Octave variable: oo_.exo_steady_state

Contains the steady state of the exogenous variables, as declared by the previous initval or endval block. Exogenous variables are ordered in the order of declaration used in the varexo command (which is also the order used in M_.exo_names).

MATLAB/Octave command: get_mean(’ENDOGENOUS_NAME’ [, ’ENDOGENOUS_NAME’]... );

Returns the steady state of the given endogenous variable(s), as it is stored in oo_.steady_state. Note that, if the steady state has not yet been computed with steady, it will first try to compute it.

Block: homotopy_setup ;

Block: homotopy_setup(from_initval_to_endval) ;

This block is used to declare initial and final values when using a homotopy method. It is used in conjunction with the option homotopy_mode of the steady command.

The idea of homotopy (also called divide-and-conquer by some authors) is to subdivide the problem of finding the steady state into smaller problems. It assumes that you know how to compute the steady state for a given set of parameters, and it helps you finding the steady state for another set of parameters, by incrementally moving from one to another set of parameters.

The purpose of the homotopy_setup block is to declare the final (and possibly also the initial) values for the parameters or exogenous that will be changed during the homotopy. It should contain lines of the form:

VARIABLE_NAME, EXPRESSION, EXPRESSION;

This syntax specifies the initial and final values of a given parameter/exogenous.

There is an alternative syntax:

VARIABLE_NAME, EXPRESSION;

Here only the final value is specified for a given parameter/exogenous; the initial value is taken from the preceeding initval block (or from the preceeding endval block if there is one before the homotopy_setup block).

A necessary condition for a successful homotopy is that Dynare must be able to solve the steady state for the initial parameters/exogenous without additional help (using the guess values given in the initval or endval block).

The from_initval_to_endval option can be used in the context of a permanent shock, when the initial steady state has already been computed. This option can be used following the endval block that describes the terminal steady state. In that case, in the subsequent steady command, Dynare will perform a homotopy from the initial to the terminal steady state (technically, using this option is equivalent to writing a homotopy_setup block where all exogenous variables are asked to transition from their values in the initval to their values in the endval block). When this option is used, the homotopy_setup block is
typically empty (but it’s nevertheless possible to add explicit directives for moving exogenous or parameters; these will be added on top of those implicitly generated by the from_initval_to_endval option).

If the homotopy fails, a possible solution is to increase the number of steps (given in homotopy_steps option of steady).

Example

In the following example, Dynare will first compute the steady state for the initial values (gam=0.5 and x=1), and then subdivide the problem into 50 smaller problems to find the steady state for the final values (gam=2 and x=2):

```matlab
var c k;
varexo x;
parameters alph gam delt bet aa;
alph=0.5;
delt=0.02;
aa=0.5;
bet=0.05;
model;
c + k - aa*x*k(-1)^alph - (1-delt)*k(-1);
c^(-gam) - (1+bet)^(-1)*(aa*alph*x(+1)*k^(alph-1) + 1 - delt)*c(+1)^(-gam);
end;

initval;
x = 1;
k = ((delt+bet)/(aa*x*alph))^(1/(alph-1));
c = aa*x*k^alph-delt*k;
end;

homotopy_setup;
gam, 0.5, 2;
x, 2;
end;

steady(homotopy_mode = 1, homotopy_steps = 50);
```

4.10.2 Providing the steady state to Dynare

If you know how to compute the steady state for your model, you can provide a MATLAB/Octave function doing the computation instead of using steady. Again, there are two options for doing that:

- The easiest way is to write a steady_state_model block, which is described below in more details. See also fs2000.mod in the examples directory for an example. The steady state file generated by Dynare will be called `FILENAME/steadystate.m`.

- You can write the corresponding MATLAB function by hand. If your .mod file is called `FILENAME.mod`, the steady state file must be called `FILENAME_steadystate.m` in the examples directory for an example. This option gives a bit more flexibility (loops and conditional structures can be used), at the expense of a heavier programming burden and a lesser efficiency.

Note that both files allow to update parameters in each call of the function. This allows for example to calibrate a model to a labor supply of 0.2 in steady state by setting the labor disutility parameter to a corresponding value (see NK_baseline_steadystate.m in the examples directory). They can also be used in estimation where some parameter may be a function of an estimated parameter and needs to be updated for every parameter draw. For example, one might want to set the capital utilization cost parameter as a function of the discount rate to ensure that capacity utilization is 1 in steady state. Treating both parameters as independent or not updating one as a
function of the other would lead to wrong results. But this also means that care is required. Do not accidentally overwrite your parameters with new values as it will lead to wrong results.

**Block: steady_state_model**

When the analytical solution of the model is known, this command can be used to help Dynare find the steady state in a more efficient and reliable way, especially during estimation where the steady state has to be recomputed for every point in the parameter space.

Each line of this block consists of a variable (either an endogenous, a temporary variable or a parameter) which is assigned an expression (which can contain parameters, exogenous at the steady state, or any endogenous or temporary variable already declared above). Each line therefore looks like:

\[ \text{VARIABLE\_NAME} = \text{EXPRESSION}; \]

Note that it is also possible to assign several variables at the same time, if the main function in the right hand side is a MATLAB/Octave function returning several arguments:

\[ [ \text{VARIABLE\_NAME}, \text{VARIABLE\_NAME}, \ldots ] = \text{EXPRESSION}; \]

Dynare will automatically generate a steady state file (of the form +FILENAME/steadystate.m) using the information provided in this block.

**Steady state file for deterministic models**

The `steady_state_model` block also works with deterministic models. An `initval` block and, when necessary, an `endval` block, is used to set the value of the exogenous variables. Each `initval` or `endval` block must be followed by `steady` to execute the function created by `steady_state_model` and set the initial, respectively terminal, steady state.

**Example**

```plaintext
var m P c e W R k d n l gy_obs gp_obs y dA;
varexo e_a e_m;
parameters alp bet gam mst rho psi del;
...
// parameter calibration, (dynamic) model declaration, shock calibration.
...

steady_state_model;

dA = exp(gam);
gst = 1/dA; // A temporary variable
m = mst;

// Three other temporary variables
khst = ( (1-gst^bet*(1-del)) / (alp^gst^alp^bet) )^(1/(alp-1));
xist = ( ((khst^gst)^alp - (1-gst*(1-del))*khst)/mst )^(-1);
nust = psi*mst^2/( (1-alp)*(1-psi)*bet*gst^alp*khst^alp );

n = xist/(nust+xist);
P = xist + nust;
k = khst^n;

l = psi*mst^2/( (1-psi)^2 );
c = mst/P;
d = l - mst + 1;
y = k^alp^n*(1-psi)*gst^alp;
R = mst/bet;
```

(continues on next page)
4.10.3 Replace some equations during steady state computations

When there is no steady state file, Dynare computes the steady state by solving the static model, i.e. the model from the .mod file from which leads and lags have been removed.

In some specific cases, one may want to have more control over the way this static model is created. Dynare therefore offers the possibility to explicitly give the form of equations that should be in the static model.

More precisely, if an equation is prepended by a [static] tag, then it will appear in the static model used for steady state computation, but that equation will not be used for other computations. For every equation tagged in this way, you must tag another equation with [dynamic]: that equation will not be used for steady state computation, but will be used for other computations.

This functionality can be useful on models with a unit root, where there is an infinity of steady states. An equation (tagged [dynamic]) would give the law of motion of the nonstationary variable (like a random walk). To pin down one specific steady state, an equation tagged [static] would affect a constant value to the nonstationary variable.

Another situation where the [static] tag can be useful is when one has only a partial closed form solution for the steady state.

Example

This is a trivial example with two endogenous variables. The second equation takes a different form in the static model:

```matlab
var c k;
varexo x;
...
model;
c + k - aa*x^k(-1)^alph - (1-delt)*k(-1);
[dynamic] c^(-gam) - (1+bet)^(-1)*(aa*alph*x(+1)*k^(alph-1) + 1 - delt)*c(+1)^(-gam);
[static] k = ((delt+bet)/(x^aa*alph))^(1/(alph-1));
end;
```

4.11 Getting information about the model

**Command:** check;
**Command:** check(OPTIONS...);

Computes the eigenvalues of the model linearized around the values specified by the last `initval`, `endval` or `steady` statement. Generally, the eigenvalues are only meaningful if the linearization is done around a steady state of the model. It is a device for local analysis in the neighborhood of this steady state.

A necessary condition for the uniqueness of a stable equilibrium in the neighborhood of the steady state is that there are as many eigenvalues larger than one in modulus as there are forward looking variables in the system.

An additional rank condition requires that the square submatrix of the right Schur vectors corresponding to the forward looking variables (jumpers) and to the explosive eigenvalues must have full rank.
Note that the outcome may be different from what would be suggested by \( \text{sum}(\text{abs}(\text{oo}_-.\text{dr.eigval})) \) when eigenvalues are very close to \text{qz_criterium}.

**Options**

\texttt{solve_algo = INTEGER}

See \texttt{solve_algo}, for the possible values and their meaning.

\texttt{qz_zero_threshold = DOUBLE}

Value used to test if a generalized eigenvalue is \(0/0\) in the generalized Schur decomposition (in which case the model does not admit a unique solution). Default: 1e-6.

**Output**

\texttt{check} returns the eigenvalues in the global variable \texttt{oo_.dr.eigval}.

**MATLAB/Octave variable: oo_.dr.eigval**

Contains the eigenvalues of the model, as computed by the check command.

**Command:** \texttt{model_diagostics ;}

This command performs various sanity checks on the model, and prints a message if a problem is detected (missing variables at current period, invalid steady state, singular Jacobian of static model).

**Command:** \texttt{model_info ;}

**Command:** \texttt{model_info(OPTIONS...);}

This command provides information about the model. By default, it will provide a list of predetermined state variables, forward-looking variables, and purely static variables.

The command also allows to display information on the dynamic and static versions of the block decomposition of the model:

- The normalization of the model: an endogenous variable is attributed to each equation of the model (the dependent variable);
- The block structure of the model: for each block \texttt{model_info} indicates its type, size as well as the equation number(s) or name tags and endogenous variables belonging to this block.

There are five different types of blocks depending on the simulation method used:

- **EVALUATE FORWARD**

  In this case the block contains only equations where the dependent variable \( j \) attributed to the equation appears contemporaneously on the left hand side and where no forward looking endogenous variables appear. The block has the form: \( y_{j,t} = f_j(y_{t}, y_{t-1}, \ldots, y_{t-k}) \).

- **EVALUATE BACKWARD**

  The block contains only equations where the dependent variable \( j \) attributed to the equation appears contemporaneously on the left hand side and where no backward looking endogenous variables appear. The block has the form: \( y_{j,t} = f_j(y_{t}, y_{t+1}, \ldots, y_{t+k}) \).

- **SOLVE BACKWARD x**

  The block contains only equations where the dependent variable \( j \) attributed to the equation does not appear contemporaneously on the left hand side and where no forward looking endogenous variables appear. The block has the form: \( g_j(y_{j,t}, y_{t}, y_{t-1}, \ldots, y_{t-k}) = 0 \). Here, \( x \) denotes the subtype of the block. \( x \) is equal to SIMPLE if the block has only one equation. If several equations appear in the block, \( x \) is equal to COMPLETE.

- **SOLVE FORWARD x**

  The block contains only equations where the dependent variable \( j \) attributed to the equation does not appear contemporaneously on the left hand side and where no backward looking endogenous variables appear. The block has the form: \( g_j(y_{j,t}, y_{t}, y_{t+1}, \ldots, y_{t+k}) = 0 \). Here, \( x \) denotes the subtype of the block. \( x \) is equal to SIMPLE if the block has only one equation. If several equations appear in the block, \( x \) is equal to COMPLETE.
• SOLVE TWO BOUNDARIES x

The block contains equations depending on both forward and backward variables. The block looks like:

\[ g_j(y_{j,t}, y_{t-1}, \ldots, y_{t-k}, y_{t-1}, y_{t+1}, \ldots, y_{t+k}) = 0. \]

Here, \( x \) denotes the subtype of the block. \( x \) is equal to SIMPLE if the block has only one equation. If several equations appear in the block, \( x \) is equal to COMPLETE.

**Options**

- **block_static**
  Prints out the block decomposition of the static model.

- **block_dynamic**
  Prints out the block decomposition of the dynamic model.

- **incidence**
  Displays the gross incidence matrix and the reordered incidence matrix of the block decomposed model for the block_dynamic or block_static options.

**Command:** print_bytecode_dynamic_model;

Prints the equations and the Jacobian matrix of the dynamic model stored in the bytecode binary format file. Can only be used in conjunction with the bytecode option of the model block.

**Command:** print_bytecode_static_model;

Prints the equations and the Jacobian matrix of the static model stored in the bytecode binary format file. Can only be used in conjunction with the bytecode option of the model block.

### 4.12 Deterministic simulation

#### 4.12.1 Perfect foresight

When the framework is deterministic, Dynare can be used for models with the assumption of perfect foresight. Typically, the system is supposed to be in a state of equilibrium before a period 1 when the news of a contemporaneous or of a future shock is learned by the agents in the model. The purpose of the simulation is to describe the reaction in anticipation of, then in reaction to the shock, until the system returns to the old or to a new state of equilibrium. In most models, this return to equilibrium is only an asymptotic phenomenon, which one must approximate by an horizon of simulation far enough in the future. Another exercise for which Dynare is well suited is to study the transition path to a new equilibrium following a permanent shock. For deterministic simulations, the numerical problem consists of solving a nonlinear system of simultaneous equations in \( n \) endogenous variables in \( T \) periods. Dynare offers several algorithms for solving this problem, which can be chosen via the stack_solve_algo option. By default (stack_solve_algo=0), Dynare uses a Newton-type method to solve the simultaneous equation system. Because the resulting Jacobian is in the order of \( n \) by \( T \) and hence will be very large for long simulations with many variables, Dynare makes use of the sparse matrix capacities of MATLAB/Octave. A slower but potentially less memory consuming alternative (stack_solve_algo=1) is based on a Newton-type algorithm first proposed by Laffargue (1990) and Boucekkine (1995), which avoids ever storing the full Jacobian. The details of the algorithm can be found in Juillard (1996). The third type of algorithms makes use of block decomposition techniques (divide-and-conquer methods) that exploit the structure of the model. The principle is to identify recursive and simultaneous blocks in the model structure and use this information to aid the solution process. These solution algorithms can provide a significant speed-up on large models.

**Warning:** Be careful when employing auxiliary variables in the context of perfect foresight computations. The same model may work for stochastic simulations, but fail for perfect foresight simulations. The issue arises when an equation suddenly only contains variables dated \( t+1 \) (or \( t-1 \) for that matter). In this case, the derivative in the last (first) period with respect to all variables will be 0, rendering the stacked Jacobian singular.

**Example**

Consider the following specification of an Euler equation with log utility:
\[
\Lambda = \beta C(-1)/C; \\
\Lambda(+1)^*R(+1) = 1;
\]

Clearly, the derivative of the second equation with respect to all endogenous variables at time \(t\) is zero, causing `perfect_foresight_solver` to generally fail. This is due to the use of the Lagrange multiplier \(\Lambda\) as an auxiliary variable. Instead, employing the identical

\[
\beta^*C/C(+1)^*R(+1) = 1;
\]

will work.

**Command:** `perfect_foresight_setup`;

**Command:** `perfect_foresight_setup(OPTIONS...)`;

Prepares a perfect foresight simulation, by extracting the information in the `initval`, `endval` and `shocks` blocks and converting them into simulation paths for exogenous and endogenous variables.

This command must always be called before running the simulation with `perfect_foresight_solver`.

**Options**

`periods = INTEGER`

Number of periods of the simulation.

`datafile = FILENAME`

Used to specify path for all endogenous and exogenous variables. Strictly equivalent to `initval_file`.

`endval_steady`

In scenarios with a permanent shock, specifies that the terminal condition is a steady state, even if the `steady` command has not been called after the `endval` block. As a consequence, the subsequent `perfect_foresight_solver` command will compute the terminal steady state itself (given the value of the exogenous variables given in the `endval` block). In practice, this option is useful when the permanent shock is very large, in which case the homotopy procedure inside `perfect_foresight_solver` will find both the terminal steady state and the transitional dynamics within the same loop (which is less costly than first computing the terminal steady state by homotopy, then computing the transitional dynamics by homotopy).

**Output**

The paths for the exogenous variables are stored into `oo_.exo_simul`.

The initial and terminal conditions for the endogenous variables and the initial guess for the path of endogenous variables are stored into `oo_.endo_simul`.

**Command:** `perfect_foresight_solver`;

**Command:** `perfect_foresight_solver(OPTIONS...)`;

Computes the perfect foresight (or deterministic) simulation of the model.

Note that `perfect_foresight_setup` must be called before this command, in order to setup the environment for the simulation.

If the perfect foresight solver cannot directly find the solution of the problem, it subsequently tries a homotopy technique (unless the `no_homotopy` option is given). Concretely, this technique consists in dividing the problem into smaller steps by diminishing the size of shocks and increasing them progressively until the problem converges.

**Options**

`maxit = INTEGER`

Determines the maximum number of iterations used in the non-linear solver. The default value of `maxit` is 50.
**tolf = DOUBLE**

Convergence criterion for termination based on the function value. Iteration will cease when it proves impossible to improve the function value by more than tolf. Default: 1e-5

**tolx = DOUBLE**

Convergence criterion for termination based on the change in the function argument. Iteration will cease when the solver attempts to take a step that is smaller than tolx. Default: 1e-5

**noprint**

Don’t print anything. Useful for loops.

**print**

Print results (opposite of noprint).

**stack_solve_algo = INTEGER**

Algorithm used for computing the solution. Possible values are:

0

Use a Newton algorithm with a direct sparse LU solver at each iteration, applied to the stacked system of all equations in all periods (Default).

1

Use the Laffargue-Boucekkine-Juillard (LBJ) algorithm proposed in Juillard (1996) on top of a LU solver. It is slower than stack_solve_algo=0, but may be less memory consuming on big models. Note that if the block option is used (see Model declaration), a simple Newton algorithm with sparse matrices, applied to the stacked system of all block equations in all periods, is used for blocks which are purely backward or forward (of type SOLVE BACKWARD or SOLVE FORWARD, see model_info), since LBJ only makes sense on blocks with both leads and lags (of type SOLVE TWO BOUNDARIES).

2

Use a Newton algorithm with a Generalized Minimal Residual (GMRES) solver at each iteration, applied on the stacked system of all equations in all periods (requires bytecode and/or block option, see Model declaration)

3

Use a Newton algorithm with a Stabilized Bi-Conjugate Gradient (BiCGStab) solver at each iteration, applied on the stacked system of all equations in all periods (requires bytecode and/or block option, see Model declaration).

4

Use a Newton algorithm with a direct sparse LU solver and an optimal path length at each iteration, applied on the stacked system of all equations in all periods (requires bytecode and/or block option, see Model declaration).

5

Use the Laffargue-Boucekkine-Juillard (LBJ) algorithm proposed in Juillard (1996) on top of a sparse Gaussian elimination (SPE) solver. The latter takes advantage of the similarity of the Jacobian across periods when searching for the pivots (requires bytecode option, see Model declaration).

6

Synonymous for stack_solve_algo=1. Kept for backward compatibility.

7

Allows the user to solve the perfect foresight model with the solvers available through option solve_algo, applied on the stacked system of all equations in all periods (See solve_algo for a list of possible values, note that values 5, 6, 7 and 8, which require
bytecode and/or block options, are not allowed). For instance, the following commands:

```plaintext
perfect_foresight_setup(periods=400);
perfect_foresight_solver(stack_solve_algo=7, solve_algo=9)
```

trigger the computation of the solution with a trust region algorithm.

**robust_lin_solve**
Triggers the use of a robust linear solver for the default stack_solve_algo=0.

**solve_algo**
See `solve_algo`. Allows selecting the solver used with stack_solve_algo=7. Also used for purely backward, forward and static models (when neither the block nor the bytecode option of the model block is specified); for those models, the values 12 and 14 are especially relevant.

**no_homotopy**
This option tells Dynare to not try a homotopy technique (as described above) if the problem cannot be solved directly.

**homotopy_initial_step_size** = DOUBLE
Specifies which share of the shock should be applied in the first iteration of the homotopy procedure. This option is useful when it is known that immediately trying 100% of the shock will fail, so as to save computing time. Must be between 0 and 1. Default: 1.

**homotopy_min_step_size** = DOUBLE
The homotopy procedure halves the size of the step whenever there is a failure. This option specifies the minimum step size under which the homotopy procedure is considered to have failed. Default: 0.001.

**homotopy_step_size_increase_success_count** = INTEGER
Specifies after how many consecutive successful iterations the homotopy procedure should double the size of the step. A zero value means that the step size should never be increased. Default: 3.

**homotopy_linearization_fallback**
Whenever the homotopy procedure is not able to find a solution for 100% of the shock, but is able to find one for a smaller share, instructs Dynare to compute an approximate solution by rescaling the solution obtained for a fraction of the shock, as if the reaction of the model to the shock was a linear function of the size of that shock. More formally, if \( s \) is the share of the shock applied (between 0 and 1), \( y(s) \) is the value of a given endogenous variable at a given period as a function of \( s \) (in particular, \( y(1) \) corresponds to the exact solution of the problem), and \( s^* \) is the greatest share of the shock for which the homotopy procedure has been able to find a solution, then the approximate solution returned is \( \frac{y(s^*) - y(0)}{s^*} \).

**homotopy_marginal_linearization_fallback** [= DOUBLE]
Whenever the homotopy procedure is not able to find a solution for 100% of the shock, but is able to find one for a smaller share, instructs Dynare to compute an approximate solution obtained by rescaling the solution obtained for a fraction of the shock, obtained as if the reaction of the model to the shock was, at the margin, a linear function of the size of that shock. More formally, if \( s \) is the share of the shock applied (between 0 and 1), \( y(s) \) is the value of a given endogenous variable at a given period as a function of \( s \) (in particular, \( y(1) \) corresponds to the exact solution of the problem), \( s^* \) is the greatest share of the shock for which the homotopy procedure has been able to find a solution, and \( \epsilon \) is a small step size, then the approximate solution returned is \( y(s^*) + (1 - s^*) \frac{y(s^*) - y(s^* - \epsilon)}{\epsilon} \). The value of \( \epsilon \) is 0.01 by default, but can be modified by passing some other value to the option.

**homotopy_max_completion_share** = DOUBLE
Instructs Dynare, within the homotopy procedure, to not try to compute the solution for a greater share than the one given as the option value. This option only makes sense when used in conjunction with either the `homotopy_linearization_fallback` or the `homotopy_marginal_linearization_fallback` option. It is typically used in situations...
where it is known that homotopy will fail to go beyond a certain point, so as to save computing time, while at the same time getting an approximate solution.

**homotopy_exclude_varexo = (VARIABLE_NAME...)**

A list of exogenous variables which are to be excluded from the homotopy procedure, i.e. which must be kept at their value corresponding to 100% of the shock during all homotopy iterations.

**markowitz = DOUBLE**

Value of the Markowitz criterion, used to select the pivot. Only used when `stack_solve_algo = 5`. Default: 0.5.

**minimal_solving_periods = INTEGER**

Specify the minimal number of periods where the model has to be solved, before using a constant set of operations for the remaining periods. Only used when `stack_solve_algo = 5`. Default: 1.

**lmmcp**

Solves the perfect foresight model with a Levenberg-Marquardt mixed complementarity problem (LMMCP) solver (Kanzow and Petra, 2004), which allows to consider inequality constraints on the endogenous variables (such as a zero lower bound, henceforth ZLB, on the nominal interest rate or a model with irreversible investment). This option is equivalent to `stack_solve_algo=7 and solve_algo=10`. Using the LMMCP solver avoids the need for min/max operators and explicit complementary slackness conditions in the model as they will typically introduce a singularity into the Jacobian. This is done by setting the problem up as a mixed complementarity problem (MCP) of the form:

\[
LB = X \Rightarrow F(X) > 0
\]

\[
LB \leq X \leq UB \Rightarrow F(X) = 0
\]

\[
X = UB \Rightarrow F(X) < 0
\]

where \(X\) denotes the vector of endogenous variables, \(F(X)\) the equations of the model, \(LB\) denotes a lower bound, and \(UB\) an upper bound. Such a setup is implemented by attaching an equation tag (see Model declaration) with the \texttt{mcp} keyword to the affected equations. This tag states that the equation to which the tag is attached has to hold unless the inequality constraint within the tag is binding.

For instance, a ZLB on the nominal interest rate would be specified as follows in the model block:

```plaintext
model;
...
[mcp = 'r > -1.94478']
r = rho*r(-1) + (1-rho)*(gpi*Infl+gy*YGap) + e;
...
end;
```

where 1.94478 is the steady state level of the nominal interest rate and \(r\) is the nominal interest rate in deviation from the steady state. This construct implies that the Taylor rule is operative, unless the implied interest rate \(r<=-1.94478\), in which case the \(r\) is fixed at \(-1.94478\) (thereby being equivalent to a complementary slackness condition). By restricting the value of \(r\) coming out of this equation, the \texttt{mcp} tag also avoids using \texttt{max(r, -1.94478)} for other occurrences of \(r\) in the rest of the model. Two things are important to keep in mind. First, because the \texttt{mcp} tag effectively replaces a complementary slackness condition, it cannot be simply attached to any equation. Rather, it must be attached to the correct affected equation as otherwise the solver will solve a different problem than originally intended. Second, the sign of the residual of the dynamic equation must conform to the MCP setup outlined above. In case of the ZLB, we are dealing with a lower bound. Consequently, the dynamic equation needs to return a positive residual. Dynare by default computes the residual of an equation \texttt{LHS=RHS} as \texttt{residual=LHS-RHS}, while an implicit equation \texttt{LHS} is interpreted as \texttt{LHS=0}. For the above equation this implies

\[
\text{residual} = r - (rho*r(-1) + (1-rho)*(gpi*Infl+gy*YGap) + e);
\]
which is correct, since it will be positive if the implied interest rate \( \rho \cdot r(-1) + (1-\rho)\cdot(gpi^*Infl+gy^*YGap) + e \) is below \( r=-1.94478 \). In contrast, specifying the equation as

\[
\rho \cdot r(-1) + (1-\rho)\cdot(gpi^*Infl+gy^*YGap) + e = r;
\]

would be wrong.

Note that in the current implementation, the content of the \texttt{mcp} equation tag is not parsed by the preprocessor. The inequalities must therefore be as simple as possible: an endogenous variable, followed by a relational operator, followed by a number (not a variable, parameter or expression).

\textbf{endogenous\_terminal\_period}

The number of periods is not constant across Newton iterations when solving the perfect foresight model. The size of the nonlinear system of equations is reduced by removing the portion of the paths (and associated equations) for which the solution has already been identified (up to the tolerance parameter). This strategy can be interpreted as a mix of the shooting and relaxation approaches. Note that round off errors are more important with this mixed strategy (user should check the reported value of the maximum absolute error). Only available with option \texttt{stack\_solve\_algo==0}.

\textbf{linear\_approximation}

Solves the linearized version of the perfect foresight model. The model must be stationary and a steady state needs to be provided. Linearization is conducted about the last defined steady state, which can derive from \texttt{initval}, \texttt{endval} or a subsequent steady. Only available with option \texttt{stack\_solve\_algo==0} or \texttt{stack\_solve\_algo==7}.

\textbf{steady\_solve\_algo = INTEGER}

See \texttt{solve\_algo}. Used when computing the terminal steady state when option \texttt{endval\_steady} has been specified to the \texttt{perfect\_foresight\_setup} command.

\textbf{steady\_tolf = DOUBLE}

See \texttt{tolf}. Used when computing the terminal steady state when option \texttt{endval\_steady} has been specified to the \texttt{perfect\_foresight\_setup} command.

\textbf{steady\_tolx = DOUBLE}

See \texttt{tolx}. Used when computing the terminal steady state when option \texttt{endval\_steady} has been specified to the \texttt{perfect\_foresight\_setup} command.

\textbf{steady\_maxit = INTEGER}

See \texttt{maxit}. Used when computing the terminal steady state when option \texttt{endval\_steady} has been specified to the \texttt{perfect\_foresight\_setup} command.

\textbf{steady\_markowitz = DOUBLE}

See \texttt{markowitz}. Used when computing the terminal steady state when option \texttt{endval\_steady} has been specified to the \texttt{perfect\_foresight\_setup} command.

\textit{Output}

The simulated endogenous variables are available in global matrix \texttt{oo\_.endo\_simul}.

\textbf{Command: simul ;}

\textbf{Command: simul(OPTIONS...)};

This command is deprecated. It is strictly equivalent to a call to \texttt{perfect\_foresight\_setup} followed by a call to \texttt{perfect\_foresight\_solver}.

\textbf{Options}

Accepts all the options of \texttt{perfect\_foresight\_setup} and \texttt{perfect\_foresight\_solver}.

\textbf{MATLAB/Octave variable: oo\_.endo\_simul}

This variable stores the result of a deterministic simulation (computed by \texttt{perfect\_foresight\_solver} or \texttt{simul}) or of a stochastic simulation (computed by \texttt{stoch\_simul} with the periods option or by \texttt{extended\_path}). The variables are arranged row by row, in order of declaration (as in \texttt{M\_.endo\_names}). Note that this variable also contains initial and terminal conditions, so it has more columns than the value of
the periods option: the first simulation period is in column 1+M_.maximum_lag, and the total number of columns is M_.maximum_lag+periods+M_.maximum_lead.

MATLAB/Octave variable: oo_.exo_simul
This variable stores the path of exogenous variables during a simulation (computed by perfect_foresight_solver, simul, stoch_simul or extended_path). The variables are arranged in columns, in order of declaration (as in M_.exo_names). Periods are in rows. Note that this convention regarding columns and rows is the opposite of the convention for oo_.endo_simul! Also note that this variable also contains initial and terminal conditions, so it has more rows than the value of the periods option: the first simulation period is in row 1+M_.maximum_lag, and the total number of rows is M_.maximum_lag+periods+M_.maximum_lead.

MATLAB/Octave variable: oo_.initial_steady_state
If a permanent shock is simulated through the use of both initval and endval blocks, this variable contains the initial steady state, as determined by the initval block (when followed by a steady command). This variable has the same structure as oo_.steady_state (and this latter variable contains the terminal steady state, if the endval block is followed by a steady command).

MATLAB/Octave variable: oo_.initial_exo_steady_state
If a permanent shock is simulated through the use of both initval and endval blocks, this variable contains the initial steady state of the exogenous variables, as specified in the initval block. This variable has the same structure as oo_.exo_steady_state (and this latter variable contains the terminal steady state of the exogenous variables).

MATLAB/Octave variable: M_.maximum_lag
The maximum number of lags in the model. Note that this value is computed on the model after the transformations related to auxiliary variables, so in practice it is either 1 or 0 (the latter value corresponds to a purely forward or static model).

MATLAB/Octave variable: M_.maximum_lead
The maximum number of leads in the model. Note that this value is computed on the model after the transformations related to auxiliary variables, so in practice it is either 1 or 0 (the latter value corresponds to a purely backward or static model).

4.12.2 Perfect foresight with expectation errors

The solution under perfect foresight that was presented in the previous section makes the assumption that agents learn the complete path of future shocks in period 1, without making any expectation errors.

One may however want to study a scenario where it turns out that agents make expectation errors, in the sense that the path they had anticipated in period 1 does not realize exactly. More precisely, in some simulation periods, they may receive new information that makes them revise their anticipation for the path of future shocks. Also, under this scenario, it is assumed that agents behave as under perfect foresight, i.e. they take their decisions as if there was no uncertainty and they knew exactly the path of future shocks; the new information that they may receive comes as a total surprise to them.

Such a scenario can be solved by Dynare using the perfect_foresight_with_expectation_errors_setup and perfect_foresight_with_expectation_errors_solver commands, alongside shocks and endval blocks which are given a special learnt_in option.

Block: shocks(learnt_in=INTEGER) ;
Block: shocks(learnt_in=INTEGER,overwrite) ;

The shocks(learnt_in=INTEGER) syntax can be used to specify temporary shocks that are learnt in a specific period. It should contain one or more occurrences of the following group of three lines, with the same semantics as a regular shocks block:

var VARIABLE_NAME;
periods INTEGER[:INTEGER] [[,] INTEGER[:INTEGER]]...;
values DOUBLE | (EXPRESSION) [[,] DOUBLE | (EXPRESSION)]...;
If the period in which information is learnt is greater or equal than 2, then it is possible to specify the shock values in deviation with respect to the values that were expected from the perspective of the previous period. If the new information consists of an addition to the previously-anticipated value, the values keyword can be replaced by the add keyword; similarly, if the new information consists of a multiplication of the previously-anticipated value, the values keyword can be replaced by the multiply keyword.

The overwrite option says that this block cancels and replaces previous shocks and mshocks blocks that have the same learnt_in option.

Note that a shocks(learnt_in=1) block is equivalent to a regular shocks block.

Example

```
shocks(learnt_in=1);
  var x;
  periods 1:2 3:4 5;
  values 1 1.2 1.4;
end;

shocks(learnt_in=2);
  var x;
  periods 3:4;
  add 0.1;
end;

shocks(learnt_in=4);
  var x;
  periods 5;
  multiply 2;
end;
```

This syntax means that:

- from the perspective of period 1, x is expected to be equal to 1 in periods 1 and 2, to 1.2 in periods 3 and 4, and to 1.4 in period 5;
- from the perspective of periods 2 (and 3), x is expected to be equal to 1 in period 2, to 1.3 in periods 3 and 4, and to 1.4 in period 5;
- from the perspective of periods 4 (and following), x is expected to be equal to 1.3 in period 4, and to 2.8 in period 5.

Block: endval(learnt_in=INTEGER) ;

The endval(learnt_in=INTEGER) can be used to specify terminal conditions that are learnt in a specific period.

Note that an endval(learnt_in=1) block is equivalent to a regular endval block.

Also note that, similarly to the regular endval block, any variable specified in this block will jump to its new value in the same period as the one in which the information is learnt; and, from the perspective of that period, the variable is expected by agents to remain to that value until the end of the simulation. In particular, this means that any temporary shock that may have been anticipated on that variable (as specified through a shocks(learnt_in=...) block for a previous informational period) will be overridden; if this is not the desired behaviour, then the temporary shock will have to be reinstated through another shocks(learnt_in=...) block.

It is possible to express the terminal condition by specifying the level of the exogenous variable (using an equal symbol, as in a regular endval blocks without the learnt_in option). But it is also possible to express the terminal condition as an addition to the value expected from the perspective of the previous previous period (using the += operator), or as a multiplicative factor over that previously expected value (using the *= operator).

Example
This syntax means that, in period 3, the agents learn that:

- the terminal condition for $x$ will be 1.1;
- the terminal condition for $y$ will be 0.1 above the terminal condition for $y$ that was expected from the perspective of period 2;
- the terminal condition for $z$ will be 2 times the terminal condition for $z$ that was expected from the perspective of period 2.

Those values will be the realized ones, unless there is another `endval(learnt_in=p)` block with $p > 3$.

The three variables will jump to their new value in period 3 and, from the perspective of period 3, they are expected by agents to remain there until the end of the simulation. In particular, any temporary shock on either $x$, $y$ or $z$ specified through a regular `shocks` block or through a `shocks(learnt_in=2)` block will be overridden. If this is not the desired behaviour, a `shocks(learnt_in=3)` block will have to be added to reinstate the temporary shock.

**Block:** `mshocks(learnt_in=INTEGER) ;`

**Block:** `mshocks(learnt_in=INTEGER,OPTIONS...) ;`

The `mshocks(learnt_in=INTEGER)` syntax can be used to specify temporary shocks that are learnt in a specific period, specified in a multiplicative way. It should contain one or more occurrences of the following group of three lines, with the same semantics as a regular `mshocks` block:

```
var VARIABLE_NAME;
periods INTEGER[:INTEGER] [[,] INTEGER[:INTEGER]]...;
values DOUBLE | (EXPRESSION) [[,] DOUBLE | (EXPRESSION)]...;
```

As in the regular `mshocks` block (without the `learnt_in` option), the values are interpreted as a multiplicative factor over the steady state value of the exogenous variable (the latter being taken either from the `initval` or `endval`, see `mshocks` for the details).

If the terminal steady state as specified in the `endval` block is used as a basis for the multiplication, its value as anticipated from the period given in the `learnt_in` option will be used.

Note that a `mshocks(learnt_in=1)` block is equivalent to a regular `mshocks` block.

**Options**

- `overwrite`
  This block cancels and replaces previous shocks and `mshocks` blocks that have the same `learnt_in` option.

- `relative_to_initval`
  Same meaning as in the regular `mshocks` block.

**Example**

```
mshocks(learnt_in=2);
  var x;
  periods 3:4;
  values 1.1;
end;
```

This syntax means that from the perspective of period 2, $x$ in periods 3 and 4 is expected to be equal to 1.1 times its steady state. If there is no `endval` block, the initial steady state as given by `initval` is used; if
there is an endval block, the terminal steady state as anticipated from the perspective of period 2 is used (as specified in the relevant endval(learnt_in=... block)).

**Command:** `perfect_foresight_with_expectation_errors_setup`;

**Command:** `perfect_foresight_with_expectation_errors_setup(OPTIONS...)`;

Prepares a perfect foresight simulation with expectation errors, by extracting the contents of the initval, endval and shocks blocks (the latter two types of blocks typically used with the learnt_in option); alternatively, the information about future shocks can be given in a CSV file using the datafile option.

This command must always be called before running the simulation with `perfect_foresight_with_expectation_errors_solver`.

Note that this command makes the assumption that the terminal condition is always a steady state. Hence, it will recompute the terminal steady state as many times as the anticipation about the terminal condition changes. In particular, the information about endogenous variables that may be given in the endval block is ignored. Said otherwise, the equivalent of option endval_steady of the `perfect_foresight_setup` command is always implicitly enabled.

**Options**

`periods = INTEGER`

Number of periods of the simulation.

`datafile = FILENAME`

Used to specify the information about future shocks and their anticipation through a CSV file, as an alternative to shocks and endval blocks.

The file has the following format:

- the first column is ignored (can be used to add descriptive labels)
- the first line contains names of exogenous variables
- the second line contains, in columns, indices of periods at which expectations are formed; the information set used in a given period is described by all the columns for which that line is equal to the period index
- the subsequent lines correspond to the periods for which expectations are formed, one period per line; each line gives the values of present and future exogenous variables, as seen from the period given in the second line
- the last line corresponds to the terminal condition for exogenous variables, as anticipated in the various informational periods

If `p` is the value of the `periods` option and `k` is the number of exogenous variables, then the CSV file has `p+3` lines and `k×p+1` columns.

Concretely, the value of a given exogenous in period `t`, as anticipated from period `s`, is given in line `t+2`, and in the column which has the name of the variable on the first line and `s` on the second line. Of course, values in cells corresponding to `t<s` are ignored.

**Output**

`oo_.exo_simul` and `oo_.endo_simul` are initialized before the simulation. Temporary shocks are stored in `oo_.pfwee.shocks_info`, terminal conditions for exogenous variables are stored in `oo_.pfwee.terminal_info`.

**Example**

Here is a CSV file example that could be given to the `datafile` option (adding some extra padding space for clarity):

<table>
<thead>
<tr>
<th>Exogenous</th>
<th>x</th>
<th>x</th>
<th>x</th>
<th>x</th>
<th>x</th>
<th>x</th>
<th>x</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period (info)</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Period 1 (real)</td>
<td>1.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Period 2 (real)</td>
<td>1</td>
<td>1.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(continues on next page)
In this example, there is only one exogenous variable ($x$), and 7 simulation periods. In the first period, agents learn a contemporary shock (1.2), but anticipate no further shock. In period 2, they learn an unexpected contemporary shock (1.3), and also a change in the terminal condition (1.1). In period 3 again there is an unexpected contemporary shock and a change in the terminal condition. No new information comes in period 4 and 5. In period 6, an unexpected permanent shock is learnt. No new information comes in period 7.

Alternatively, instead of using a CSV file, the same sequence of information sets could be described using the following blocks:

```plaintext
initval;
x = 1;
end;

steady;

shocks(learnt_in = 1);
  var x;
  periods 1;
  values 1.2;
end;

shocks(learnt_in = 2);
  var x;
  periods 2;
  values 1.3;
end;

dendval(learnt_in = 2);
x = 1.1;
end;

shocks(learnt_in = 3);
  var x;
  periods 3;
  values 1.4;
end;

dendval(learnt_in = 3);
x = 1.2;
end;

shocks(learnt_in = 6);
  var x;
  periods 6:7;
  values 1.1;
end;

dendval(learnt_in = 6);
x = 1.1;
end;
```
Command: perfect_foresight_with_expectation_errors_solver;

Command: perfect_foresight_with_expectation_errors_solver(OPTIONS...);

Computes the perfect foresight simulation with expectation errors of the model.

Note that perfect_foresight_with_expectation_errors_setup must be called before this command, in order to setup the environment for the simulation.

Options

This command accepts all the options of perfect_foresight_solver, with the same semantics, plus the following one:

constant_simulation_length

By default, every time the information set changes, the simulation with the new information set is shorter than the previous one (because the terminal date is getting closer). When this option is set, every new simulation has the same length (as specified by the periods option of perfect_foresight_with_expectation_errors_setup). as a consequence, the simulated paths as stored in oo_.endo_simul will be longer when this option is set (if s is the last period in which the information set is modified, then they will contain s+periods-1 periods, excluding initial and terminal conditions).

Output

The simulated paths of endogenous variables are available in oo_.endo_simul. The terminal steady state values corresponding to the last period of the information set are available in oo_.steady_state and oo_.exo_steady_state.

MATLAB/Octave variable: oo_.pfwee.shocks_info

This variable stores the temporary shocks used during perfect foresight simulations with expectation errors, after perfect_foresight_with_expectation_errors_setup has been run. It is a three-dimensional matrix: first dimension correspond to exogenous variables (in declaration order); second dimension corresponds to real time; third dimension corresponds to informational time. In other words, the value of exogenous indexed k in period t, as anticipated from period s, is stored in oo_.pfwee.shocks_info(k,t,s).

MATLAB/Octave variable: oo_.pfwee.terminal_info

This variable stores the terminal conditions for exogenous variables used during perfect foresight simulations with expectation errors, after perfect_foresight_with_expectation_errors_setup has been run. It is a matrix, whose lines correspond to exogenous variables (in declaration order), and whose columns correspond to informational time. In other words, the terminal condition for exogenous indexed k, as anticipated from period s, is stored in oo_.pfwee.terminal_info(k,s).

4.13 Stochastic solution and simulation

In a stochastic context, Dynare computes one or several simulations corresponding to a random draw of the shocks.

The main algorithm for solving stochastic models relies on a Taylor approximation, up to third order, of the expectation functions (see Judd (1996), Collard and Juillard (2001a, 2001b), and Schmitt-Grohé and Uribe (2004)). The details of the Dynare implementation of the first order solution are given in Villemot (2011). Such a solution is computed using the stoch_simul command.

As an alternative, it is possible to compute a simulation to a stochastic model using the extended path method presented by Fair and Taylor (1983). This method is especially useful when there are strong nonlinearities or binding constraints. Such a solution is computed using the extended_path command.
4.13.1 Computing the stochastic solution

Command: stoch_simul [VARIABLE_NAME...];
Command: stoch_simul(OPTIONS...) [VARIABLE_NAME...];

Solves a stochastic (i.e., rational expectations) model, using perturbation techniques.

More precisely, stoch_simul computes a Taylor approximation of the model around the deterministic steady state and solves of the the decision and transition functions for the approximated model. Using this, it computes impulse response functions and various descriptive statistics (moments, variance decomposition, correlation and autocorrelation coefficients). For correlated shocks, the variance decomposition is computed as in the VAR literature through a Cholesky decomposition of the covariance matrix of the exogenous variables. When the shocks are correlated, the variance decomposition depends upon the order of the variables in the varexo command.

The Taylor approximation is computed around the steady state (see Steady state).

The IRFs are computed as the difference between the trajectory of a variable following a shock at the beginning of period 1 and its steady state value. More details on the computation of IRFs can be found at https://archives.dynare.org/DynareWiki/IrFs.

Variance decomposition, correlation, autocorrelation are only displayed for variables with strictly positive variance. Impulse response functions are only plotted for variables with response larger than $10^{-10}$.

Variance decomposition is computed relative to the sum of the contribution of each shock. Normally, this is of course equal to aggregate variance, but if a model generates very large variances, it may happen that, due to numerical error, the two differ by a significant amount. Dynare issues a warning if the maximum relative difference between the sum of the contribution of each shock and aggregate variance is larger than 0.01%.

The covariance matrix of the shocks is specified with the shocks command (see Shocks on exogenous variables).

When a list of VARIABLE_NAME is specified, results are displayed only for these variables.

Options

ar = INTEGER
  Order of autocorrelation coefficients to compute and to print. Default: 5.

drop = INTEGER
  Number of points (burnin) dropped at the beginning of simulation before computing the summary statistics. Note that this option does not affect the simulated series stored in oo_.endo_simul and the workspace. Here, no periods are dropped. Default: 100.

hp_filter = DOUBLE
  Uses HP filter with $\lambda = \text{DOUBLE}$ before computing moments. If theoretical moments are requested, the spectrum of the model solution is filtered following the approach outlined in Uhlig (2001). Default: no filter.

one_sided_hp_filter = DOUBLE
  Uses the one-sided HP filter with $\lambda = \text{DOUBLE}$ described in Stock and Watson (1999) before computing moments. This option is only available with simulated moments. Default: no filter.

bandpass_filter
  Uses a bandpass filter with the default passband before computing moments. If theoretical moments are requested, the spectrum of the model solution is filtered using an ideal bandpass filter. If empirical moments are requested, the Baxter and King (1999) filter is used. Default: no filter.

bandpass_filter = [HIGHEST_PERIODICITY LOWEST_PERIODICITY]
  Uses a bandpass filter before computing moments. The passband is set to a periodicity of to LOWEST_PERIODICITY, e.g. 6 to 32 quarters if the model frequency is quarterly. Default: [6, 32].
filtered_theoretical_moments_grid = INTEGER
When computing filtered theoretical moments (with either option hp_filter or option bandpass_filter), this option governs the number of points in the grid for the discrete In-verse Fast Fourier Transform. It may be necessary to increase it for highly autocorrelated processes. Default: 512.

irf = INTEGER
Number of periods on which to compute the IRFs. Setting irf=0 suppresses the plotting of IRFs. Default: 40.

irf_shocks = ( VARIABLE_NAME [[[,] VARIABLE_NAME ...]] ]
The exogenous variables for which to compute IRFs. Default: all.

relative_irf
Requests the computation of normalized IRFs. At first order, the normal shock vector of size one standard deviation is divided by the standard deviation of the current shock and multiplied by 100. The impulse responses are hence the responses to a unit shock of size 1 (as opposed to the regular shock size of one standard deviation), multiplied by 100. Thus, for a loglinearized model where the variables are measured in percent, the IRFs have the interpretation of the percent responses to a 100 percent shock. For example, a response of 400 of output to a TFP shock shows that output increases by 400 percent after a 100 percent TFP shock (you will see that TFP increases by 100 on impact). Given linearity at order=1, it is straightforward to rescale the IRFs stored in oo_.irfs to any desired size. At higher order, the interpretation is different. The relative_irf option then triggers the generation of IRFs as the response to a 0.01 unit shock (corresponding to 1 percent for shocks measured in percent) and no multiplication with 100 is performed. That is, the normal shock vector of size one standard deviation is divided by the standard deviation of the current shock and divided by 100. For example, a response of 0.04 of log output (thus measured in percent of the steady state output level) to a TFP shock also measured in percent then shows that output increases by 4 percent after a 1 percent TFP shock (you will see that TFP increases by 0.01 on impact).

irf_plot_threshold = DOUBLE
Threshold size for plotting IRFs. All IRFs for a particular variable with a maximum absolute deviation from the steady state smaller than this value are not displayed. Default: 1e-10.

corr
Don’t print the correlation matrix (printing them is the default).

decomposition
Don’t compute (and don’t print) unconditional variance decomposition.

functions
Don’t print the coefficients of the approximated solution (printing them is the default).

moments
Don’t print moments of the endogenous variables (printing them is the default).

modelsummary
Don’t print the model summary and the covariance of the exogenous shocks (printing them is the de-fault).

graph
Do not create graphs (which implies that they are not saved to the disk nor displayed). If this option is not used, graphs will be saved to disk (to the format specified by graph_format option, except if graph_format=none) and displayed to screen (unless nodisplay option is used).

graph
Re-enables the generation of graphs previously shut off with nograph.

nodisplay
Do not display the graphs, but still save them to disk (unless nograph is used).

graph_format = FORMAT
graph_format = ( FORMAT, FORMAT... )

Specify the file format(s) for graphs saved to disk. Possible values are eps (the default), pdf, fig and none. Under Octave, fig will use Octave’s ofig format. If the file format is set equal to none, the graphs are displayed but not saved to the disk.

noprint

See noprint.

print

See print.

order = INTEGER

Order of Taylor approximation. Note that for third order and above, the k_order_solver option is implied and only empirical moments are available (you must provide a value for periods option). Default: 2 (except after an estimation command, in which case the default is the value used for the estimation).

k_order_solver

Use a k-order solver (implemented in C++) instead of the default Dynare solver. This option is not yet compatible with the bytecode option (see Model declaration). Default: disabled for order 1 and 2, enabled for order 3 and above.

periods = INTEGER

If different from zero, empirical moments will be computed instead of theoretical moments. The value of the option specifies the number of periods to use in the simulations. Values of the initval block, possibly recomputed by steady, will be used as starting point for the simulation. The simulated endogenous variables are made available to the user in a vector for each variable and in the global matrix oo_.endo_simul (see oo_.endo_simul). The simulated exogenous variables are made available in oo_.exo_simul (see oo_.exo_simul). Default: 0.

qz_criterium = DOUBLE

Value used to split stable from unstable eigenvalues in reordering the Generalized Schur decomposition used for solving first order problems. Default: 1.000001 (except when estimating with lik_init option equal to 1: the default is 0.999999 in that case; see Estimation based on likelihood).

qz_zero_threshold = DOUBLE

See qz_zero_threshold.

replic = INTEGER

Number of simulated series used to compute the IRFs. Default: 1 if order=1, and 50 otherwise.

simul_replic = INTEGER

Number of series to simulate when empirical moments are requested (i.e. periods > 0). Note that if this option is greater than 1, the additional series will not be used for computing the empirical moments but will simply be saved in binary form to the file FILENAME_simul in the FILENAME/Output folder. Default: 1.

solve_algo = INTEGER

See solve_algo, for the possible values and their meaning.

aim_solver

Use the Anderson-Moore Algorithm (AIM) to compute the decision rules, instead of using Dynare’s default method based on a generalized Schur decomposition. This option is only valid for first order approximation. See AIM website for more details on the algorithm.

conditional_variance_decomposition = INTEGER

Computes a conditional variance decomposition for the specified period(s). The periods must be strictly positive. Conditional variances are given by \( \text{var}(y_{t+k}|t) \). For period 1, the conditional variance decomposition provides the decomposition of the effects of shocks upon impact.
The results are stored in `oo_.conditional_variance_decomposition` (see `oo_.conditional_variance_decomposition`). In the presence of measurement error, the `oo_.conditional_variance_decomposition` field will contain the variance contribution after measurement error has been taken out, i.e., the decomposition will be conducted of the actual as opposed to the measured variables. The variance decomposition of the measured variables will be stored in `oo_.conditional_variance_decomposition_ME` (see `oo_.conditional_variance_decomposition_ME`). The variance decomposition is only conducted, if theoretical moments are requested, i.e., using the `periods=0` option. Only available at `order<3` and without `pruning`. In case of `order=2`, Dynare provides a second-order accurate approximation to the true second moments based on the linear terms of the second-order solution (see Kim, Kim, Schaumburg and Sims (2008)). Note that the unconditional variance decomposition i.e., at horizon infinity is automatically conducted if theoretical moments are requested and if `nodecomposition` is not set (see `oo_.variance_decomposition`).

**pruning**

Discard higher order terms when iteratively computing simulations of the solution. At second order, Dynare uses the algorithm of Kim, Kim, Schaumburg and Sims (2008), while at third order and higher its generalization by Andreasen, Fernández-Villaverde and Rubio-Ramírez (2018) is used. When specified, theoretical moments are based on the pruned state space, i.e., the computation of second moments uses all terms as in Andreasen, Fernández-Villaverde and Rubio-Ramírez (2018), page 10 as opposed to simply providing a second-order accurate result based on the linear solution as in Kim, Kim, Schaumburg and Sims (2008).

**partial_information**

Computes the solution of the model under partial information, along the lines of Pearlman, Currie and Levine (1986). Agents are supposed to observe only some variables of the economy. The set of observed variables is declared using the `varobs` command. Note that if `varobs` is not present or contains all endogenous variables, then this is the full information case and this option has no effect. More references can be found here.

**dr = OPTION**

Determines the method used to compute the decision rule. Possible values for OPTION are:

- **default**
  
  Uses the default method to compute the decision rule based on the generalized Schur decomposition (see Villemot (2011) for more information).

- **cycle_reduction**
  
  Uses the cycle reduction algorithm of Bini et al. (2002) to solve the polynomial equation for retrieving the coefficients associated to the endogenous variables in the decision rule. This method is faster than the default one for large scale models.

- **logarithmic_reduction**
  
  Uses the logarithmic reduction algorithm of Bini et al. (2002) to solve the polynomial equation for retrieving the coefficients associated to the endogenous variables in the decision rule. This method is in general slower than the cycle_reduction.

Default value is `default`.

**dr_cycle_reduction_tol = DOUBLE**

The convergence criterion used in the cycle reduction algorithm. Its default value is `1e-7`.

**dr_logarithmic_reduction_tol = DOUBLE**

The convergence criterion used in the logarithmic reduction algorithm. Its default value is `1e-12`.

**dr_logarithmic_reduction_maxiter = INTEGER**

The maximum number of iterations used in the logarithmic reduction algorithm. Its default value is 100.
loglinear

See loglinear. Note that ALL variables are log-transformed by using the Jacobian transformation, not only selected ones. Thus, you have to make sure that your variables have strictly positive steady states. stoch_simul will display the moments, decision rules, and impulse responses for the log-linearized variables. The decision rules saved in oo_.dr and the simulated variables will also be the ones for the log-linear variables.

tex

Requests the printing of results and graphs in TeX tables and graphics that can be later directly included in LaTeX files.

dr_display_tol = DOUBLE

Tolerance for the suppression of small terms in the display of decision rules. Rows where all terms are smaller than dr_display_tol are not displayed. Default value: 1e-6.

contemporaneous_correlation

Saves the contemporaneous correlation between the endogenous variables in oo_.contemporaneous_correlation. Requires the nocorr option not to be set.

spectral_density

Triggers the computation and display of the theoretical spectral density of the (filtered) model variables. Results are stored in oo_.SpectralDensity, defined below. Default: do not request spectral density estimates.

hp_ngrid = INTEGER

Deprecated option. It has the same effect as filtered_theoretical_moments_grid.

Output

This command sets oo_.dr, oo_.mean, oo_.var, oo_.var_list, and oo_.autocorr, which are described below.

If the periods option is present, sets oo_.skewness, oo_.kurtosis, and oo_.endo_simul (see oo_.endo_simul).

If option irf is different from zero, sets oo_.irfs (see below).

If the option contemporaneous_correlation is different from 0, sets oo_.contemporaneous_correlation, which is described below.

Example

```
shocks;
var e;
stderr 0.0348;
end;

stoch_simul;
```

Performs the simulation of the 2nd-order approximation of a model with a single stochastic shock e, with a standard error of 0.0348.

Example

```
stoch_simul(irf=60) y k;
```

Performs the simulation of a model and displays impulse response functions on 60 periods for variables y and k.

MATLAB/Octave variable: oo_.mean

After a run of stoch_simul, contains the mean of the endogenous variables. Contains theoretical mean if the periods option is not present, and simulated mean otherwise. The variables are arranged in declaration order.
MATLAB/Octave variable: `oo_.var`

After a run of `stoch_simul`, contains the variance-covariance of the endogenous variables. Contains theoretical variance if the `periods` option is not present and simulated variance otherwise. Only available for `order<4`. At `order=2` it will be a second-order accurate approximation (i.e., ignoring terms of order 3 and 4 that would arise when using the full second-order policy function). At `order=3`, theoretical moments are only available with pruning. The variables are arranged in declaration order.

MATLAB/Octave variable: `oo_.var_list`

The list of variables for which results are displayed.

MATLAB/Octave variable: `oo_.skewness`

After a run of `stoch_simul` contains the skewness (standardized third moment) of the simulated variables if the `periods` option is present. The variables are arranged in declaration order.

MATLAB/Octave variable: `oo_.kurtosis`

After a run of `stoch_simul` contains the excess kurtosis (standardized fourth moment) of the simulated variables if the `periods` option is present. The variables are arranged in declaration order.

MATLAB/Octave variable: `oo_.autocorr`

After a run of `stoch_simul`, contains a cell array of the autocorrelation matrices of the endogenous variables. The element number of the matrix in the cell array corresponds to the order of autocorrelation. The option `ar` specifies the number of autocorrelation matrices available. Contains theoretical autocorrelations if the `periods` option is not present and simulated autocorrelations otherwise. Only available for `order<4`. At `order=2` it will be a second-order accurate approximation. At `order=3`, theoretical moments are only available with pruning. The field is only created if stationary variables are present.

The element `oo_.autocorr{i}(k,l)` is equal to the correlation between $y_k^i$ and $y_{l-i}^i$, where $y_k^i$ (resp. $y_l^i$) is the $k$-th (resp. $l$-th) endogenous variable in the declaration order.

Note that if theoretical moments have been requested, `oo_.autocorr{i}` is the same than `oo_.gamma_y{i+1}`.

MATLAB/Octave variable: `oo_.gamma_y`

After a run of `stoch_simul`, if theoretical moments have been requested (i.e., if the `periods` option is not present), this variable contains a cell array with the following values (where `ar` is the value of the option of the same name):

- `oo_.gamma{1}`: Variance/covariance matrix.
- `oo_.gamma{i+1}` (for `i=1:ar`): Autocorrelation function. See `oo_.autocorr` for more details. Beware, this is the autocorrelation function, not the autocovariance function.
- `oo_.gamma{ar+2}`: Unconditional variance decomposition, see `oo_.variance_decomposition`.
- `oo_.gamma{ar+3}`: If a second order approximation has been requested, contains the vector of the mean correction terms. Only available at `order<4`. In case `order=2`, the theoretical second moments are a second order accurate approximation of the true second moments. See conditional_variance_decomposition. At `order=3`, theoretical moments are only available with pruning.

MATLAB/Octave variable: `oo_.variance_decomposition`

After a run of `stoch_simul` when requesting theoretical moments (`periods=0`), contains a matrix with the result of the unconditional variance decomposition (i.e., at horizon infinity). The first dimension corresponds to the endogenous variables (in the order of declaration after the command or in `M_.endo_names`) and the second dimension corresponds to exogenous variables (in the order of declaration). Numbers are in percent.
and sum up to 100 across columns. In the presence of measurement error, the field will contain the variance contribution after measurement error has been taken out, i.e. the decomposition will be conducted of the actual as opposed to the measured variables.

**MATLAB/Octave variable: oo_.variance_decomposition_ME**

Field set after a run of `stoch_simul` when requesting theoretical moments (periods=0) if measurement error is present. It is similar to `oo_.variance_decomposition`, but the decomposition will be conducted of the measured variables. The field contains a matrix with the result of the unconditional variance decomposition (i.e. at horizon infinity). The first dimension corresponds to the observed endogenous variables (in the order of declaration after the command) and the second dimension corresponds to exogenous variables (in the order of declaration), with the last column corresponding to the contribution of measurement error. Numbers are in percent and sum up to 100 across columns.

**MATLAB/Octave variable: oo_.conditional_variance_decomposition**

After a run of `stoch_simul` with the `conditional_variance_decomposition` option, contains a three-dimensional array with the result of the decomposition. The first dimension corresponds to the endogenous variables (in the order of declaration after the command or in `M_.endo_names` if not specified), the second dimension corresponds to the forecast horizons (as declared with the option), and the third dimension corresponds to the exogenous variables (in the order of declaration). In the presence of measurement error, the field will contain the variance contribution after measurement error has been taken out, i.e. the decomposition will be conducted of the actual as opposed to the measured variables.

**MATLAB/Octave variable: oo_.conditional_variance_decomposition_ME**

Field set after a run of `stoch_simul` with the `conditional_variance_decomposition` option if measurement error is present. It is similar to `oo_.conditional_variance_decomposition`, but the decomposition will be conducted of the measured variables. It contains a three-dimensional array with the result of the decomposition. The first dimension corresponds to the endogenous variables (in the order of declaration after the command or in `M_.endo_names` if not specified), the second dimension corresponds to the forecast horizons (as declared with the option), and the third dimension corresponds to the exogenous variables (in the order of declaration), with the last column corresponding to the contribution of the measurement error.

**MATLAB/Octave variable: oo_.contemporaneous_correlation**

After a run of `stoch_simul` with the `contemporaneous_correlation` option, contains theoretical contemporaneous correlations if the `periods` option is not present, and simulated contemporaneous correlations otherwise. Only available for order<4. At order=2 it will be a second-order accurate approximation. At order=3, theoretical moments are only available with pruning. The variables are arranged in declaration order.

**MATLAB/Octave variable: oo_.SpectralDensity**

After a run of `stoch_simul` with option `spectral_density`, contains the spectral density of the model variables. There will be a `nvars` by `nfrequencies` subfield `freqs` storing the respective frequency grid points ranging from 0 to $2\pi$ and a same sized subfield `density` storing the corresponding density.

**MATLAB/Octave variable: oo_.irfs**

After a run of `stoch_simul` with option `irf` different from zero, contains the impulse responses, with the following naming convention: `VARIABLE_NAME_SHOCK_NAME`.

For example, `oo_.irfs.gnp_ea` contains the effect on `gnp` of a one-standard deviation shock on `ea`.

**MATLAB/Octave command:**

```
IRF_MATRIX=get_irf(’EXOGENOUS_NAME’ [, ’ENDOGENOUS_NAME’]... );
```

Given the name of an exogenous variable, returns the IRFs for the requested endogenous variable(s) (as they are stored in `oo_.irfs`) in the output `IRF_MATRIX`. The periods are stored along the first dimension, with the steady state in the first row. The variables are stored along the second dimension. If no endogenous variables were specified, the matrix contains all variables stored in `oo_.irfs`.

The approximated solution of a model takes the form of a set of decision rules or transition equations expressing the current value of the endogenous variables of the model as function of the previous state of the model and shocks observed at the beginning of the period. The decision rules are stored in the structure `oo_.dr` which is described below.
MATLAB/Octave variable: oo_.dr

Structure storing the decision rules. The subfields for different orders of approximation are explained below.

Command: extended_path;
Command: extended_path(OPTIONS...);

Simulates a stochastic (i.e. rational expectations) model, using the extended path method presented by Fair and Taylor (1983). Time series for the endogenous variables are generated by assuming that the agents believe that there will no more shocks in the following periods.

This function first computes a random path for the exogenous variables (stored in oo_.exo_simul, see oo_.exo_simul) and then computes the corresponding path for endogenous variables, taking the steady state as starting point. The result of the simulation is stored in oo_.endo_simul (see oo_.endo_simul). Note that this simulation approach does not solve for the policy and transition equations but for paths for the endogenous variables.

Options

periods = INTEGER

The number of periods for which the simulation is to be computed. No default value, mandatory option.

solver_periods = INTEGER

The number of periods used to compute the solution of the perfect foresight at every iteration of the algorithm. Default: 200.

order = INTEGER

If order is greater than 0 Dynare uses a gaussian quadrature to take into account the effects of future uncertainty. If order = \( S \) then the time series for the endogenous variables are generated by assuming that the agents believe that there will no more shocks after period \( t + S \). This is an experimental feature and can be quite slow. A non-zero value is not compatible with the bytecode option of the model block. Default: 0.

hybrid

Use the constant of the second order perturbation reduced form to correct the paths generated by the (stochastic) extended path algorithm.

lmmcp

Solves the perfect foresight model with a Levenberg-Marquardt mixed complementarity problem (LMMCP) solver (Kanzow and Petra (2004)), which allows to consider inequality constraints on the endogenous variables (such as a ZLB on the nominal interest rate or a model with irreversible investment). For specifying the necessary mcp tag, see lmmcp.

4.13.2 Typology and ordering of variables

Dynare distinguishes four types of endogenous variables:

*Purely backward (or purely predetermined) variables*

Those that appear only at current and past period in the model, but not at future period (i.e. at \( t \) and \( t - 1 \) but not \( t + 1 \)). The number of such variables is equal to \( M_.npred \).

*Purely forward variables*

Those that appear only at current and future period in the model, but not at past period (i.e. at \( t \) and \( t + 1 \) but not \( t - 1 \)). The number of such variables is stored in \( M_.nfwrd \).

*Mixed variables*

Those that appear at current, past and future period in the model (i.e. at \( t, t + 1 \) and \( t - 1 \)). The number of such variables is stored in \( M_.nboth \).

*Static variables*

Those that appear only at current, not past and future period in the model (i.e. only at \( t \), not at \( t + 1 \) or \( t - 1 \)). The number of such variables is stored in \( M_.nstatic \).
Note that all endogenous variables fall into one of these four categories, since after the creation of auxiliary variables (see Auxiliary variables), all endogenous have at most one lead and one lag. We therefore have the following identity:

\[ M_.npred + M_.both + M_.nfwd + M_.nstatic = M_.endo_nbr \]

**MATLAB/Octave variable: M_.state_var**

Vector of numerical indices identifying the state variables in the vector of declared variables. \( M_.\) endo_names(M_.state_var) therefore yields the name of all variables that are states in the model declaration, i.e. that show up with a lag.

Internally, Dynare uses two orderings of the endogenous variables: the order of declaration (which is reflected in \( M_.\) endo_names), and an order based on the four types described above, which we will call the DR-order (“DR” stands for decision rules). Most of the time, the declaration order is used, but for elements of the decision rules, the DR-order is used.

The DR-order is the following: static variables appear first, then purely backward variables, then mixed variables, and finally purely forward variables. Inside each category, variables are arranged according to the declaration order.

**MATLAB/Octave variable: oo_.dr.order_var**

This variables maps DR-order to declaration order.

**MATLAB/Octave variable: oo_.dr.inv_order_var**

This variable contains the inverse map.

In other words, the k-th variable in the DR-order corresponds to the endogenous variable numbered oo_.dr.order_var(k) in declaration order. Conversely, k-th declared variable is numbered oo_.dr.inv_order_var(k) in DR-order.

Finally, the state variables of the model are the purely backward variables and the mixed variables. They are ordered in DR-order when they appear in decision rules elements. There are \( M_.nspred = M_.npred + M_.nboth \) such variables. Similarly, one has \( M_.nsfwrd = M_.nfwd + M_.nboth \), and \( M_.ndynamic = M_.nfwd + M_.nboth + M_.npred \).

### 4.13.3 First-order approximation

The approximation has the stylized form:

\[ y_t = y^s + Ay_{t-1}^h + Bu_t \]

where \( y^s \) is the steady state value of \( y \) and \( y_t^h = y_t - y^s \).

**MATLAB/Octave variable: oo_.dr.state_var**

Vector of numerical indices identifying the state variables in the vector of declared variables, given the current parameter values for which the decision rules have been computed. It may differ from \( M_.\) state_var in case a state variable drops from the model given the current parameterization, because it only gets 0 coefficients in the decision rules. See \( M_.\) state_var.

The coefficients of the decision rules are stored as follows:

- \( y^s \) is stored in oo_.dr.ys. The vector rows correspond to all endogenous in the declaration order.
- \( A \) is stored in oo_.dr.ghx. The matrix rows correspond to all endogenous in DR-order. The matrix columns correspond to state variables in DR-order, as given by oo_.dr.state_var.
- \( B \) is stored oo_.dr.ghu. The matrix rows correspond to all endogenous in DR-order. The matrix columns correspond to exogenous variables in declaration order.

Of course, the shown form of the approximation is only stylized, because it neglects the required different ordering in \( y^s \) and \( y_t^h \). The precise form of the approximation that shows the way Dynare deals with differences between declaration and DR-order, is:

\[ y_t(oo_.dr.order_var) = y^s(oo_.dr.order_var) + A \cdot y_{t-1}(oo_.dr.order_var(k2)) - y^s(oo_.dr.order_var(k2)) + B \cdot u_t \]
where \( k_2 \) selects the state variables, \( y_t \) and \( y^* \) are in declaration order and the coefficient matrices are in DR-order. Effectively, all variables on the right hand side are brought into DR order for computations and then assigned to \( y_t \) in declaration order.

### 4.13.4 Second-order approximation

The approximation has the form:

\[
y_t = y^* + 0.5 \Delta^2 + Ay_{t-1}^h + Bu_t + 0.5C(y_{t-1}^h \otimes y_{t-1}^h) + 0.5D(u_t \otimes u_t) + E(y_{t-1}^h \otimes u_t)
\]

where \( y^* \) is the steady state value of \( y \), \( y^h_t = y_t - y^* \), and \( \Delta^2 \) is the shift effect of the variance of future shocks. For the reordering required due to differences in declaration and DR order, see the first order approximation.

The coefficients of the decision rules are stored in the variables described for first order approximation, plus the following variables:

- \( \Delta^2 \) is stored in \( oo_.dr.ghs2 \). The vector rows correspond to all endogenous in DR-order.
- \( C \) is stored in \( oo_.dr.ghxx \). The matrix rows correspond to all endogenous in DR-order. The matrix columns correspond to the Kronecker product of the vector of state variables in DR-order.
- \( D \) is stored in \( oo_.dr.ghuu \). The matrix rows correspond to all endogenous in DR-order. The matrix columns correspond to the Kronecker product of exogenous variables in declaration order.
- \( E \) is stored in \( oo_.dr.ghxu \). The matrix rows correspond to all endogenous in DR-order. The matrix columns correspond to the Kronecker product of the vector of state variables (in DR-order) by the vector of exogenous variables (in declaration order).

### 4.13.5 Third-order approximation

The approximation has the form:

\[
y_t = y^* + G_0 + G_1 z_t + G_2(z_t \otimes z_t) + G_3(z_t \otimes z_t \otimes z_t)
\]

where \( y^* \) is the steady state value of \( y \), and \( z_t \) is a vector consisting of the deviation from the steady state of the state variables (in DR-order) at date \( t-1 \) followed by the exogenous variables at date \( t \) (in declaration order). The vector \( z_t \) is therefore of size \( n_z = M_.nspred + M_.exo_nbr \).

The coefficients of the decision rules are stored as follows:

- \( y^* \) is stored in \( oo_.dr.yxs \). The vector rows correspond to all endogenous in the declaration order.
- \( G_0 \) is stored in \( oo_.dr.g_0 \). The vector rows correspond to all endogenous in DR-order.
- \( G_1 \) is stored in \( oo_.dr.g_1 \). The matrix rows correspond to all endogenous in DR-order. The matrix columns correspond to state variables in DR-order, followed by exogenous in declaration order.
- \( G_2 \) is stored in \( oo_.dr.g_2 \). The matrix rows correspond to all endogenous in DR-order. The matrix columns correspond to the Kronecker product of state variables (in DR-order), followed by exogenous (in declaration order). Note that the Kronecker product is stored in a folded way, i.e. symmetric elements are stored only once, which implies that the matrix has \( n_z(n_z+1)/2 \) columns. More precisely, each column of this matrix corresponds to a pair \((i_1, i_2)\) where each index represents an element of \( z_t \) and is therefore between 1 and \( n_z \). Only non-decreasing pairs are stored, i.e. those for which \( i_1 \leq i_2 \). The columns are arranged in the lexicographical order of non-decreasing pairs. Also note that for those pairs where \( i_1 \neq i_2 \), since the element is stored only once but appears two times in the unfolded \( G_2 \) matrix, it must be multiplied by 2 when computing the decision rules.
- \( G_3 \) is stored in \( oo_.dr.g_3 \). The matrix rows correspond to all endogenous in DR-order. The matrix columns correspond to the third Kronecker power of state variables (in DR-order), followed by exogenous (in declaration order). Note that the third Kronecker power is stored in a folded way, i.e. symmetric elements are stored only once, which implies that the matrix has \( n_z(n_z+1)(n_z+2)/6 \) columns. More precisely, each column of this matrix corresponds to a tuple \((i_1, i_2, i_3)\) where each index represents an element of \( z_t \) and is
therefore between 1 and \( n \). Only non-decreasing tuples are stored, i.e. those for which \( i_1 \leq i_2 \leq i_3 \). The columns are arranged in the lexicographical order of non-decreasing tuples. Also note that for tuples that have three distinct indices (i.e. \( i_1 \neq i_2 \) and \( i_1 \neq i_3 \) and \( i_2 \neq i_3 \)), since these elements are stored only once but appears six times in the unfolded \( G_3 \) matrix, they must be multiplied by 6 when computing the decision rules. Similarly, for those tuples that have two equal indices (i.e. of the form \((a, a, b)\) or \((a, b, a)\) or \((b, a, a)\)), since these elements are stored only once but appears three times in the unfolded \( G_3 \) matrix, they must be multiplied by 3 when computing the decision rules.

### 4.13.6 Higher-order approximation

Higher-order approximations are simply a generalization of what is done at order 3. The steady state is stored in \( oo_.dr.ys \) and the constant correction is stored in \( oo_.dr.g_0 \). The coefficient for orders 1, 2, 3, 4... are respectively stored in \( oo_.dr.g_0 \), \( oo_.dr.g_1 \), \( oo_.dr.g_2 \), \( oo_.dr.g_3 \), \( oo_.dr.g_4 \)... The columns of those matrices correspond to multidimensional indices of state variables, in such a way that symmetric elements are never repeated (for more details, see the description of \( oo_.dr.g_3 \) in the third-order case).

### 4.14 Occasionally binding constraints (OCCBIN)

Dynare allows simulating models with up to two occasionally-binding constraints by relying on a piecewise linear solution as in Guerrieri and Iacoviello (2015). It also allows estimating such models employing either the inversion filter of Cuba-Borda, Guerrieri, Iacoviello, and Zhong (2019) or the piecewise Kalman filter of Giovannini, Pfeiffer, and Ratto (2021). To trigger computations involving occasionally-binding constraints requires

1. defining and naming the occasionally-binding constraints using an `occbin_constraints` block
2. specifying the model equations for the respective regimes in the `model` block using appropriate equation tags.
3. potentially specifying a sequence of surprise shocks using a `shocks(surprise)` block
4. setting up Occbin simulations or estimation with `occbin_setup`
5. triggering a simulation with `occbin_solver` or running `estimation` or `calib_smoother`.

All of these elements are discussed in the following.

**Block: occbin_constraints**

The `occbin_constraints` block specifies the occasionally-binding constraints. It contains one or two of the following lines:

```plaintext
name 'STRING'; bind EXPRESSION; [relax EXPRESSION;] [error_bind EXPRESSION;] [error_relax EXPRESSION;]
```

`STRING` is the name of constraint that is used to reference the constraint in `relax` / `bind` equation tags to identify the respective regime (see below). The `bind` expression is mandatory and defines a logical condition that is evaluated in the baseline/steady state regime to check whether the specified constraint becomes binding. In contrast, the `relax` expression is optional and specifies a logical condition that is evaluated in the binding regime to check whether the regime returns to the baseline/steady state regime. If not specified, Dynare will simply check in the binding regime whether the `bind` expression evaluates to false. However, there are cases where the `bind` expression cannot be evaluated in the binding regime(s), because the variables involved are constant by definition so that e.g. the value of the Lagrange multiplier on the complementary slackness condition needs to be checked. In these cases, it is necessary to provide an explicit condition that can be evaluated in the binding regime that allows to check whether it should be left.

Note that the baseline regime denotes the steady state of the model where the economy will settle in the long-run without shocks. For that matter, it may be one where e.g. a borrowing constraint is binding. In that type of setup, the `bind` condition is used to specify the condition when this borrowing constraint becomes non-binding so that the alternative regime is entered.
Three things are important to keep in mind when specifying the expressions. First, feasible expressions may only contain contemporaneous endogenous variables. If you want to include leads/lags or exogenous variables, you need to define an auxiliary variable. Second, Dynare will at the current stage not linearly approximate the entered expressions. Because Occbin will work with a linearized model, consistency will often require the user to enter a linearized constraint. Otherwise, the condition employed for checking constraint violations may differ from the one employed within model simulations based on the piecewise-linear model solution. Third, in contrast to the original Occbin replication codes, the variables used in expressions are not automatically demeaned, i.e., they refer to the levels, not deviations from the steady state. To access the steady state level of a variable, the \texttt{STEADY\_STATE()} operator can be used.

Finally, it’s worth keeping in mind that for each simulation period, Occbin will check the respective conditions for whether the current regime should be left. Small numerical differences from the cutoff point for a regime can sometimes lead to oscillations between regimes and cause a spurious periodic solution. Such cases may be prevented by introducing a small buffer between the two regimes, e.g.

\begin{verbatim}
occbin_constraints;
    name 'ELB'; bind inom <= iss-le8; relax inom > iss+le-8;
end;
\end{verbatim}

The \texttt{error\_bind} and \texttt{error\_relax} options are optional and allow specifying numerical criteria for the size of the respective constraint violations employed in numerical routines. By default, Dynare will simply use the absolute value of the \texttt{bind} and \texttt{relax} inequalities. But occasionally, user-specified expressions perform better.

Example

\begin{verbatim}
occbin_constraints;
    name 'IRR'; bind log_Invest-log(steady_state(Invest))<log(phi);
        relax Lambda<0;
    name 'INEG'; bind log_Invest-log(steady_state(Invest))<0;
end;
\end{verbatim}

\texttt{IRR} is a constraint for irreversible investment that becomes binding if investment drops below its steady state by more than 0.025 percent in the non-binding regime. The constraint will be relaxed whenever the associated Lagrange multiplier \texttt{Lambda} in the binding regime becomes negative. Note that the constraint here takes on a linear form to be consistent with a piecewise linear model solution.

The specification of the model equations belonging to the respective regimes is done in the \texttt{model} block, with equation tags indicating to which regime a particular equation belongs. All equations that differ across regimes must have a \texttt{name} tag attached to them that allows uniquely identifying different versions of the same equation. The name of the constraints specified is then used in conjunction with a \texttt{bind} or \texttt{relax} tag to indicate to which regime a particular equation belongs. In case of more than one occasionally-binding constraint, if an equation belongs to several regimes (e.g. both constraints binding), the constraint name tags must be separated by a comma. If only one name tag is present, the respective equation is assumed to hold for both states of the other constraint.

Example

\begin{verbatim}
[name='investment',bind='IRR,INEG']
(log_Invest - log(phi*steady_state(Invest))) = 0;
[name='investment',relax='IRR']
Lambda=0;
[name='investment',bind='IRR',relax='INEG']
(log_Invest - log(phi*steady_state(Invest))) = 0;
\end{verbatim}

The three entered equations for the investment condition define the model equation for all four possible combinations of the two constraints. The first equation defines the model equation in the regime where both the IRR and INEG constraint are binding. The second equation defines the model equation for the regimes where the IRR constraint is non-binding, regardless of whether...
the INEG constraint is binding or not. Finally, the last equation defines the model equation for the final regime where the IRR constraint is binding, but the INEG one is not.

Block: shocks(surprise);

Block: shocks(surprise, overwrite);

The shocks(surprise) block allows specifying a sequence of temporary changes in the value of exogenous variables that in each period come as a surprise to agents, i.e. are not anticipated. Note that to actually use the specified shocks in subsequent commands like occbin_solver, the block needs to be followed by a call to occbin_setup.

The block mirrors the perfect foresight syntax in that it should contain one or more occurrences of the following group of three lines:

```
var VARIABLE_NAME;
periods INTEGER[:INTEGER] [[,] INTEGER[:INTEGER]]...;
values DOUBLE | (EXPRESSION) [[,] DOUBLE | (EXPRESSION)]...;
```

Example (with vector values and overwrite option)

```
shockssequence = randn(100,1)*0.02;

shocks(surprise, overwrite);
var epsilon;
periods 1:100;
values (shockssequence);
end;
```

Command: occbin_setup;

Command: occbin_setup(OPTIONS...);

Prepares a simulation with occasionally binding constraints. This command will also translate the contents of a shocks(surprise) block for use in subsequent commands.

In order to conduct estimation with occasionally binding constraints, it needs to be prefaced by a call to occbin_setup to trigger the use of either the inversion filter or the piecewise Kalman filter (default). An issue that can arise in the context of estimation is a structural shock dropping out of the model in a particular regime. For example, at the zero lower bound on interest rates, the monetary policy shock in the Taylor rule will not appear anymore. This may create a problem if there are then more observables than shocks. The way to handle this issue depends on the type of filter used. The first step is to set the data points for the zero interest rate period to NaN. For the piecewise Kalman filter, the standard deviation of the associated shock needs to be set to 0 for the corresponding periods using the heteroskedastic_shocks block. This avoids stochastic singularity. However, this approach does not work for the inversion filter as the heteroskedastic_shocks block does not do anything here. For the inversion filter, as many shocks as observables are required at each point in time. Dynare assumes a one-to-one mapping between the declared shocks in varexo and declared observables in varobs. For example, if the second declared observable is NaN in a given period, Dynare will drop the second declared shock.

Warning: If there are missing values, it is imperative for the inversion filter that the declaration order of shocks and observables is conformable. Sticking with our example, if the nominal interest is the second varobs and is set to NaN, the inversion filter will drop the second declared shock. If that second declared shock is, e.g., a TFP shock, it will be dropped instead of the intended monetary policy shock.

Note that models with unit roots will require the user to specify the diffuse_filter option as otherwise Blanchard-Kahn errors will be triggered. For the piecewise Kalman filter, the initialization steps in the diffuse filter will always rely on the model solved for the baseline regime, without checking whether this is the actual regime in the first period(s).
Example

```matlab
ocbin_setup(likelihood_inversion_filter, smoother_inversion_filter);
estimation(smoother, heteroskedastic_filter, ...);
```

The above piece of code sets up an estimation employing the inversion filter for both the likelihood evaluation and the smoother, while also accounting for heteroskedastic shocks using the heteroskedastic_filter option.

Be aware that Occbin has largely command-specific options, i.e. there are separate options to control the behavior of Occbin when called by the smoother or when computing the likelihood. These latter commands will not inherit the options potentially previously set for simulations.

Options

```matlab
simul_periods = INTEGER

Number of periods of the simulation. Default: 100.
```

```matlab
simul_maxit = INTEGER

Maximum number of iterations when trying to find the regimes of the piecewise solution. Default: 30.
```

```matlab
simul_check_ahead_periods = INTEGER

Number of periods for which to check ahead for return to the baseline regime. This number should be chosen large enough, because Occbin requires the simulation to return to the baseline regime at the end of time. Default: 200.
```

```matlab
simul_reset_check_ahead_periods

Allows to reset `simul_check_ahead_periods` to its specified value at the beginning of each simulation period. Otherwise, the original value may permanently increase endogenously at some point due to regimes that last very long in expectations. This may considerably slow down convergence in subsequent periods. Default: not enabled.
```

```matlab
simul_max_check_ahead_periods = INTEGER

If set to a finite number, it enforces the OccBin algorithm to check ahead only for the maximum number of periods (i.e. when we want agents to be myopic beyond some future period) instead of potentially endogenously increasing `simul_check_ahead_periods` ever further. Default: Inf.
```

```matlab
simul_curb_retrench

Instead of basing the initial regime guess for the current iteration on the last iteration, update the guess only one period at a time. This will slow down the iterations, but may lead to more robust convergence behavior. Default: not enabled.
```

```matlab
simul_periodic_solution

Accept a periodic solution where the solution alternates between two sets of results across iterations, i.e. is not found to be unique. This is sometimes caused by spurious numerical errors that lead to oscillations between regimes and may be prevented by allowing for a small buffer in regime transitions. Default: not enabled.
```

```matlab
simul_debug

Provide additional debugging information during solving. Default: not enabled.
```

```matlab
smoother_periods = INTEGER

Number of periods employed during the simulation when called by the smoother (equivalent of `simul_periods`). Default: 100.
```

```matlab
smoother_maxit = INTEGER

Maximum number of iterations employed during the simulation when called by the smoother (equivalent of `simul_maxit`). Default: 30.
```
smoother_check_ahead_periods = INTEGER
   Number of periods for which to check ahead for return to the baseline regime during the
   simulation when called by the smoother (equivalent of simul_check_ahead_periods).
   Default: 200.

smoother_max_check_ahead_periods = INTEGER
   If set to a finite number, it enforces the OccBin algorithm to check ahead only for the maxi-
   mum number of periods (i.e. when we want agents to be myopic beyond some future period)
   instead of potentially endogenously increasing smoother_check_ahead_periods ever fur-
   ther. Equivalent of simul_max_check_ahead_periods. Default: Inf.

smoother_curb_retrench
   Have the smoother invoke the simul_curb_retrench option during simulations. Default: not enabled.

smoother_periodic_solution
   Accept periodic solution where solution alternates between two sets of results (equivalent of
   simul_periodic_solution). Default: not enabled.

likelihood_periods = INTEGER
   Number of periods employed during the simulation when computing the likelihood (equiv-
   alent of simul_periods). Default: 100.

likelihood_maxit = INTEGER
   Maximum number of iterations employed during the simulation when computing the likeli-
   hood (equivalent of simul_maxit). Default: 30.

likelihood_check_ahead_periods = INTEGER
   Number of periods for which to check ahead for return to the baseline regime during the
   simulation when computing the likelihood (equivalent of simul_check_ahead_periods). Default: 200.

smoother_max_check_ahead_periods = INTEGER
   If set to a finite number, it enforces the OccBin algorithm to check ahead only for the maxi-
   mum number of periods (i.e. when we want agents to be myopic beyond some future period)
   instead of potentially endogenously increasing likelihood_check_ahead_periods ever further. Equivalent of simul_max_check_ahead_periods. Default: Inf.

likelihood_curb_retrench
   Have the likelihood computation invoke the simul_curb_retrench option during simulations. Default: not enabled.

likelihood_periodic_solution
   Accept periodic solution where solution alternates between two sets of results (equivalent of
   simul_periodic_solution). Default: not enabled.

likelihood_inversion_filter
   Employ the inversion filter of Cuba-Borda, Guerrieri, Iacoviello, and Zhong (2019) when
   estimating the model. Default: not enabled.

likelihood_piecewise_kalman_filter
   Employ the piecewise Kalman filter of Giovannini, Pfeiffer, and Ratto (2021) when esti-
   mating the model. Note that this filter is incompatible with univariate Kalman filters, i.e.
   kalman_algo=2,4. Default: enabled.

likelihood_max_kalman_iterations
   Maximum number of iterations of the outer loop for the piecewise Kalman filter. Default: 10.
**smoother_inversion_filter**

Employ the inversion filter of *Cuba-Borda, Guerrieri, Iacoviello, and Zhong (2019)* when running the smoother. The underlying assumption is that the system starts at the steady state. In this case, the inversion filter will provide the required smoother output. Default: not enabled.

**smoother_piecewise_kalman_filter**

Employ the piecewise Kalman filter of *Giovannini, Pfeiffer, and Ratto (2021)* when running the smoother. Default: enabled.

**filter_use_relaxation**

Triggers relaxation within the guess and verify algorithm used in the update step of the piecewise Kalman filter. When old and new guess regime differ to much, use a new guess closer to the previous guess. In case of multiple solutions, tends to provide an occasionally binding regime with a shorter duration (typically preferable). Specifying this option may slow down convergence. Default: not enabled.

**Output**

The paths for the exogenous variables are stored into `options_.occbin.simul.SHOCKS`.

**Command:** `occbin_solver ;`

**Command:** `occbin_solver(OPTIONS...) ;`

Computes a simulation with occasionally-binding constraints based on a piecewise-linear solution.

Note that `occbin_setup` must be called before this command in order for the simulation to take into account previous shocks(surprise) blocks.

**Options**

**simul_periods =** INTEGER

See `simul_periods`.

**simul_maxit =** INTEGER

See `simul_maxit`.

**simul_check_ahead_periods =** INTEGER

See `simul_check_ahead_periods`.

**simul_reset_check_ahead_periods**

See `simul_reset_check_ahead_periods`.

**simul_max_check_ahead_periods**

See `simul_max_check_ahead_periods`.

**simul_curb_retrench**

See `simul_curb_retrench`.

**simul_debug**

See `simul_debug`.

**Output**

The command outputs various objects into `oo_.occbin`.

**MATLAB/Octave variable: oo_.occbin.simul.piecewise**

Matrix storing the simulations based on the piecewise-linear solution. The variables are arranged by column, in order of declaration (as in `M_.endo_names`), while the the rows correspond to the `simul_periods`.

**MATLAB/Octave variable: oo_.occbin.simul.linear**

Matrix storing the simulations based on the linear solution, i.e. ignoring the occasionally binding constraint(s). The variables are arranged by column, in order of declaration (as in `M_.endo_names`), while the rows correspond to the `simul_periods`.
MATLAB/Octave variable: oo_.occbin.simul.shocks_sequence

Matrix storing the shock sequence employed during the simulation. The shocks are arranged column by column, with their order in M_.exo_names stored in oo_.occbin.exo_pos. The the rows correspond to the number of shock periods specified in a shocks(surprise) block, which may be smaller than simul_periods.

MATLAB/Octave variable: oo_.occbin.simul.regime_history

Structure storing information on the regime history, conditional on the shock that happened in the respective period (stored along the rows). type is equal to either smoother or simul, depending on whether the output comes from a run of simulations or the smoother. The subfield regime contains a vector storing the regime state, while the the subfield regimestart indicates the expected start of the respective regime state. For example, if row 40 contains [1,0] for regime2 and [1,6] for regimestart2, it indicates that - after the shock in period 40 has occurred - the second constraint became binding (1) and is expected to revert to non-binding (0) after six periods including the current one, i.e. period 45.

MATLAB/Octave variable: oo_.occbin.simul.ys

Vector of steady state values

Command: occbin_graph [VARIABLE_NAME...];
Command: occbin_graph(OPTIONS...) [VARIABLE_NAME...];

Plots a graph comparing the simulation results of the piecewise-linear solution with the occasionally binding contraints to the linear solution ignoring the constraint.

Options

noconstant

Omit the steady state in the graphs.

Command: occbin_write_regimes ;
Command: occbin_write_regimes(OPTIONS...);

Write the information on the regime history stored in oo_.occbin.simul.regime_history or oo_.occbin.smoother.regime_history into an Excel file stored in the FILENAME/Output folder.

Options

periods = INTEGER

Number of periods for which to write the expected regime durations. Default: write all available periods.

filename = FILENAME

Name of the Excel file to write. Default: FILENAME_occbin_regimes.

simul

Selects the regime history from the last run of simulations. Default: enabled.

smoother

Selects the regime history from the last run of the smoother. Default: use simul.

4.15 Estimation based on likelihood

Provided that you have observations on some endogenous variables, it is possible to use Dynare to estimate some or all parameters. Both maximum likelihood (as in Ireland (2004)) and Bayesian techniques (as in Fernández-Villaverde and Rubio-Ramírez (2004), Rabanal and Rubio-Ramírez (2003), Schorfheide (2000) or Smets and Wouters (2003)) are available. Using Bayesian methods, it is possible to estimate DSGE models, VAR models, or a combination of the two techniques called DSGE-VAR.

Note that in order to avoid stochastic singularity, you must have at least as many shocks or measurement errors in your model as you have observed variables.
Command: `varobs` VARIABLE_NAME...;
This command lists the name of observed endogenous variables for the estimation procedure. These variables must be available in the data file (see `estimation`).

Alternatively, this command is also used in conjunction with the `partial_information` option of `stoch_simul`, for declaring the set of observed variables when solving the model under partial information.

Only one instance of `varobs` is allowed in a model file. If one needs to declare observed variables in a loop, the macro processor can be used as shown in the second example below.

Example

```
varobs C y rr;
```
Declares endogenous variables C, y and rr as observed variables.

Example (with a macro processor loop)

```
varobs#
  @#for co in countries
  GDP_{@co}
  @#endfor
#
```

Block: `observation_trends`;
This block specifies linear trends for observed variables as functions of model parameters. In case the `loglinear` option is used, this corresponds to a linear trend in the logged observables, i.e. an exponential trend in the level of the observables.

Each line inside of the block should be of the form:

```
VARIABLE_NAME(EXPRSSION);
```

In most cases, variables shouldn't be centered when `observation_trends` is used.

Example

```
observation_trends;
Y (eta);
P (mu/eta);
end;
```

Block: `estimated_params`;

This block lists all parameters to be estimated and specifies bounds and priors as necessary.

Each line corresponds to an estimated parameter.

In a maximum likelihood or a method of moments estimation, each line follows this syntax:

```
stderr VARIABLE_NAME | corr VARIABLE_NAME_1, VARIABLE_NAME_2 | PARAMETER_NAME, INITIAL_VALUE [, LOWER_BOUND, UPPER_BOUND ];
```

In a Bayesian MCMC or a penalized method of moments estimation, each line follows this syntax:

```
stderr VARIABLE_NAME | corr VARIABLE_NAME_1, VARIABLE_NAME_2 | PARAMETER_NAME | ←DSGE_PRIOR_WEIGHT
[, INITIAL_VALUE [, LOWER_BOUND, UPPER_BOUND]], PRIOR_SHAPE, PRIOR_MEAN, PRIOR_STANDARD_ERROR [, PRIOR_3RD_PARAMETER [, PRIOR_4TH_PARAMETER [, SCALE_PARAMETER ] ] ]
```
The first part of the line consists of one of the four following alternatives:

- **stderr VARIABLE_NAME**
  Indicates that the standard error of the exogenous variable VARIABLE_NAME, or of the observation error/measurement errors associated with endogenous observed variable VARIABLE_NAME, is to be estimated.

- **corr VARIABLE_NAME1, VARIABLE_NAME2**
  Indicates that the correlation between the exogenous variables VARIABLE_NAME1 and VARIABLE_NAME2, or the correlation of the observation errors/measurement errors associated with endogenous observed variables VARIABLE_NAME1 and VARIABLE_NAME2, is to be estimated. Note that correlations set by previous shocks blocks or estimation commands are kept at their value set prior to estimation if they are not estimated again subsequently. Thus, the treatment is the same as in the case of deep parameters set during model calibration and not estimated.

- **PARAMETER_NAME**
  The name of a model parameter to be estimated

- **DSGE_PRIOR_WEIGHT**
  Special name for the weight of the DSGE model in DSGE-VAR model.

The rest of the line consists of the following fields, some of them being optional:

**INITIAL_VALUE**
Specifies a starting value for the posterior mode optimizer or the maximum likelihood estimation. If unset, defaults to the prior mean.

**LOWER_BOUND**
Specifies a lower bound for the parameter value in maximum likelihood estimation. In a Bayesian estimation context, sets a lower bound only effective while maximizing the posterior kernel. This lower bound does not modify the shape of the prior density, and is only aimed at helping the optimizer in identifying the posterior mode (no consequences for the MCMC). For some prior densities (namely inverse gamma, gamma, uniform, beta or Weibull) it is possible to shift the support of the prior distributions to the left or the right using **prior_3rd_parameter**. In this case the prior density is effectively modified (note that the truncated Gaussian density is not implemented in Dynare). If unset, defaults to minus infinity (ML) or the natural lower bound of the prior (Bayesian estimation).

**UPPER_BOUND**
Same as **lower_bound**, but specifying an upper bound instead.

**PRIOR_SHAPE**
A keyword specifying the shape of the prior density. The possible values are: beta_pdf, gamma_pdf, normal_pdf, uniform_pdf, inv_gamma_pdf, inv_gamma1_pdf, inv_gamma2_pdf and weibull_pdf. Note that inv_gamma_pdf is equivalent to inv_gamma1_pdf.

**PRIOR_MEAN**
The mean of the prior distribution.

**PRIOR_STANDARD_ERROR**
The standard error of the prior distribution.

**PRIOR_3RD_PARAMETER**
A third parameter of the prior used for generalized beta distribution, generalized gamma, generalized Weibull, the truncated normal, and for the uniform distribution. Default: -Inf for normal distribution, 0 otherwise.

**PRIOR_4TH_PARAMETER**
A fourth parameter of the prior used for generalized beta distribution, the truncated normal, and for the uniform distribution. Default: Inf for normal distribution, 1 otherwise.
**SCALE_PARAMETER**

A parameter specific scale parameter for the jumping distribution’s covariance matrix of the Metropolis-Hasting algorithm.

Note that INITIAL_VALUE, LOWER_BOUND, UPPER_BOUND, PRIOR_MEAN, PRIOR_STANDARD_ERROR, PRIOR_3RD_PARAMETER, PRIOR_4TH_PARAMETER and SCALE_PARAMETER can be any valid EXPRESSION. Some of them can be empty, in which Dynare will select a default value depending on the context and the prior shape.

In case of the uniform distribution, it can be specified either by providing an upper and a lower bound using PRIOR_3RD_PARAMETER and PRIOR_4TH_PARAMETER or via mean and standard deviation using PRIOR_MEAN, PRIOR_STANDARD_ERROR. The other two will automatically be filled out. Note that providing both sets of hyperparameters will yield an error message.

As one uses options more towards the end of the list, all previous options must be filled: for example, if you want to specify SCALE_PARAMETER, you must specify PRIOR_3RD_PARAMETER and PRIOR_4TH_PARAMETER. Use empty values, if these parameters don’t apply.

**Example**

```
corr eps_1, eps_2, 0.5, , , beta_pdf, 0, 0.3, -1, 1;
```

Sets a generalized beta prior for the correlation between eps_1 and eps_2 with mean 0 and variance 0.3. By setting PRIOR_3RD_PARAMETER to -1 and PRIOR_4TH_PARAMETER to 1 the standard beta distribution with support [0, 1] is changed to a generalized beta with support [-1, 1]. Note that LOWER_BOUND and UPPER_BOUND are left empty and thus default to -1 and 1, respectively. The initial value is set to 0.5.

**Example**

```
corr eps_1, eps_2, 0.5, -0.5, 1, beta_pdf, 0, 0.3, -1, 1;
```

Sets the same generalized beta distribution as before, but now truncates this distribution to [-0.5, 1] through the use of LOWER_BOUND and UPPER_BOUND.

**Parameter transformation**

Sometimes, it is desirable to estimate a transformation of a parameter appearing in the model, rather than the parameter itself. It is of course possible to replace the original parameter by a function of the estimated parameter everywhere is the model, but it is often unpractical.

In such a case, it is possible to declare the parameter to be estimated in the parameters statement and to define the transformation, using a pound sign (#) expression (see *Model declaration*).

**Example**

```
parameters bet;

model;
  # sig = 1/bet;
  c = sig*c(+1)*mpk;
end;

estimated_params;
  bet, normal_pdf, 1, 0.05;
end;
```

It is possible to have several estimated_params blocks. By default, subsequent blocks are concatenated with the previous ones; this can be useful when building models in a modular fashion (see also estimated_params_remove for that use case). However, if an estimated_params block has the overwrite option, its contents becomes the new list of estimated parameters, cancelling previous blocks; this can be useful when doing several estimations in a single .mod file.

**Block: estimated_params_init ;**
Block: `estimated_params_init` (OPTIONS...);

This block declares numerical initial values for the optimizer when these ones are different from the prior mean. It should be specified after the `estimated_params` block as otherwise the specified starting values are overwritten by the latter.

Each line has the following syntax:

```plaintext
stderr VARIABLE_NAME | corr VARIABLE_NAME_1, VARIABLE_NAME_2 | PARAMETER_NAME, INITIAL_VALUE;
```

Options

**use_calibration**

For not specifically initialized parameters, use the deep parameters and the elements of the covariance matrix specified in the `shocks` block from calibration as starting values for estimation. For components of the shocks block that were not explicitly specified during calibration or which violate the prior, the prior mean is used.

See `estimated_params`, for the meaning and syntax of the various components.

Block: `estimated_params_bounds`;

This block declares lower and upper bounds for parameters in maximum likelihood estimation.

Each line has the following syntax:

```plaintext
stderr VARIABLE_NAME | corr VARIABLE_NAME_1, VARIABLE_NAME_2 | PARAMETER_NAME, LOWER_BOUND, UPPER_BOUND;
```

See `estimated_params`, for the meaning and syntax of the various components.

Block: `estimated_params_remove`;

This block partially undoes the effect of a previous `estimated_params` block, by removing some parameters from the estimation.

Each line has the following syntax:

```plaintext
stderr VARIABLE_NAME | corr VARIABLE_NAME_1, VARIABLE_NAME_2 | PARAMETER_NAME;
```

Command: `estimation` [VARIABLE_NAME...];

Command: `estimation` (OPTIONS...) [VARIABLE_NAME...];

This command runs Bayesian or maximum likelihood estimation.

The following information will be displayed by the command:

- Results from posterior optimization (also for maximum likelihood)
- Marginal log data density
- Posterior mean and highest posterior density interval (shortest credible set) from posterior simulation
- Convergence diagnostic table when only one MCM chain is used or Metropolis-Hastings convergence graphs documented in Pfeifer (2014) in case of multiple MCM chains
- Table with numerical inefficiency factors of the MCMC
- Graphs with prior, posterior, and mode
- Graphs of smoothed shocks, smoothed observation errors, smoothed and historical variables

Note that the posterior moments, smoothed variables, k-step ahead filtered variables and forecasts (when requested) will only be computed on the variables listed after the estimation command. Alternatively, one can choose to compute these quantities on all endogenous or on all observed variables (see `consider_all_endogenous`, `consider_all_endogenous_and_auxiliary`, and `consider_only_observed` options below). If no variable is listed after the estimation command, then Dynare will interactively ask which variable set to use.
Also, during the MCMC (Bayesian estimation with $\text{mh\_replic} > 0$) a (graphical or text) waiting bar is displayed showing the progress of the Monte-Carlo and the current value of the acceptance ratio. Note that if the $\text{load\_mh\_file}$ option is used (see below) the reported acceptance ratio does not take into account the draws from the previous MCMC. In the literature there is a general agreement for saying that the acceptance ratio should be close to one third or one quarter. If this not the case, you can stop the MCMC ($\text{Ctrl-C}$) and change the value of option $\text{mh\_jscale}$ (see below).

Note that by default Dynare generates random numbers using the algorithm $\text{mt199937ar}$ (i.e. Mersenne Twister method) with a seed set equal to 0. Consequently the MCMCs in Dynare are deterministic: one will get exactly the same results across different Dynare runs ($\text{ceteris paribus}$). For instance, the posterior moments or posterior densities will be exactly the same. This behaviour allows to easily identify the consequences of a change on the model, the priors or the estimation options. But one may also want to check that across multiple runs, with different sequences of proposals, the returned results are almost identical. This should be true if the number of iterations (i.e. the value of $\text{mh\_replic}$) is important enough to ensure the convergence of the MCMC to its ergodic distribution. In this case the default behaviour of the random number generators in not wanted, and the user should set the seed according to the system clock before the estimation command using the following command:

```
set_dynare_seed('clock');
```

so that the sequence of proposals will be different across different runs.

Finally, Dynare does not always properly distinguish between maximum likelihood and Bayesian estimation in its field names. While there is an important conceptual distinction between frequentist confidence intervals and Bayesian highest posterior density intervals (HPDI) as well as between posterior density and likelihood, Dynare sometimes uses the Bayesian terms as a stand-in in its display of maximum likelihood results. An example is the storage of the output of the $\text{forecast}$ option of $\text{estimation}$ with $\text{ML}$, which will use $\text{HPDinf}/\text{HPDsup}$ to denote the confidence interval.

Algorithms

The Monte Carlo Markov Chain (MCMC) diagnostics are generated by the estimation command if $\text{mh\_replic}$ is larger than 2000 and if option $\text{nodiagnostic}$ is not used. By default, the convergence diagnostics of Geweke ($\text{block\_iter1992,1999}$) is computed for each chain. It uses a chi-square test to compare the means of the first and last draws specified by $\text{geweke\_interval}$ after discarding the burn-in of $\text{mh\_drop}$. The test is computed using variance estimates under the assumption of no serial correlation as well as using tapering windows specified in $\text{taper\_steps}$. If $\text{mh\_nbblocks}$ is larger than 1, the convergence diagnostics of Brooks and Gelman (1998) are also provided. As described in section 3 of Brooks and Gelman (1998) the univariate convergence diagnostics are based on comparing pooled and within MCMC moments (Dynare displays the second and third order moments, and the length of the Highest Probability Density interval covering 80% of the posterior distribution). Due to computational reasons, the multivariate convergence diagnostic does not follow Brooks and Gelman (1998) strictly, but rather applies their idea for univariate convergence diagnostics to the range of the posterior likelihood function instead of the individual parameters. The posterior kernel is used to aggregate the parameters into a scalar statistic whose convergence is then checked using the Brooks and Gelman (1998) univariate convergence diagnostic.

The inefficiency factors are computed as in Giordano et al. (2011) based on Parzen windows as in e.g. Andrews (1991).

Options

**datafile = FILENAME**

The datafile: a .m file, a .mat file, a .csv file, or a .xls/.xlsx file (under Octave, the io package from Octave-Forge is required for the .csv and .xls formats and the .xlsx file extension is not supported). Note that the base name (i.e. without extension) of the datafile has to be different from the base name of the model file. If there are several files named FILENAME, but with different file endings, the file name must be included in quoted strings and provide the file ending like:

```
estimation(datafile='..//fsdat_simul.mat',...);
dirname = FILENAME
```
Directory in which to store estimation output. To pass a subdirectory of a directory, you must quote the argument. Default: `<mod_file>`.

**xls_sheet** = QUOTED_STRING

The name of the sheet with the data in an Excel file.

**xls_range** = RANGE

The range with the data in an Excel file. For example, `xls_range=B2:D200`.

**nobs** = INTEGER

The number of observations following `first_obs` to be used. Default: all observations in the file after `first_obs`.

**nobs** = [INTEGER1:INTEGER2]

Runs a recursive estimation and forecast for samples of size ranging from `INTEGER1` to `INTEGER2`. Option `forecast` must also be specified. The forecasts are stored in the `RecursiveForecast` field of the results structure (see `RecursiveForecast`). The respective results structures `oo_` are saved in `oo_recursive_` (see `oo_recursive_`) and are indexed with the respective sample length.

**first_obs** = INTEGER

The number of the first observation to be used. In case of estimating a DSGE-VAR, `first_obs` needs to be larger than the number of lags. Default: 1.

**first_obs** = [INTEGER1:INTEGER2]

Runs a rolling window estimation and forecast for samples of fixed size `nobs` starting with the first observation ranging from `INTEGER1` to `INTEGER2`. Option `forecast` must also be specified. This option is incompatible with requesting recursive forecasts using an expanding window (see `nobs`). The respective results structures `oo_` are saved in `oo_recursive_` (see `oo_recursive_`) and are indexed with the respective first observation of the rolling window.

**prefilter** = INTEGER

A value of 1 means that the estimation procedure will demean each data series by its empirical mean. If the `loglinear` option without the `logdata` option is requested, the data will first be logged and then demeaned. Default: 0, i.e. no prefiltering.

**presample** = INTEGER

The number of observations after `first_obs` to be skipped before evaluating the likelihood. These presample observations do not enter the likelihood, but are used as a training sample for starting the Kalman filter iterations. This option is incompatible with estimating a DSGE-VAR. Default: 0.

**loglinear**

Computes a log-linear approximation of the model instead of a linear approximation. As always in the context of estimation, the data must correspond to the definition of the variables used in the model (see Pfeifer (2013) for more details on how to correctly specify observation equations linking model variables and the data). If you specify the loglinear option, Dynare will take the logarithm of both your model variables and of your data as it assumes the data to correspond to the original non-logged model variables. The displayed posterior results like impulse responses, smoothed variables, and moments will be for the logged variables, not the original un-logged ones. Default: computes a linear approximation.

**logdata**

Dynare applies the log transformation to the provided data if a log-linearization of the model is requested (`loglinear`) unless `logdata` option is used. This option is necessary if the user provides data already in logs, otherwise the log transformation will be applied twice (this may result in complex data).

**plot_priors** = INTEGER

Control the plotting of priors.

0
No prior plot.

1

Prior density for each estimated parameter is plotted. It is important to check that the actual shape of prior densities matches what you have in mind. Ill-chosen values for the prior standard density can result in absurd prior densities.

Default value is 1.

nograph
See nograph.

posterior_nograph
Suppresses the generation of graphs associated with Bayesian IRFs (bayesian_irf), posterior smoothed objects (smoother), and posterior forecasts (forecast).

posterior_graph
Re-enables the generation of graphs previously shut off with posterior_nograph.

nodisplay
See nodisplay.

graph_format = FORMAT
See graph_format.

no_init_estimation_check_first_obs
Do not check for stochastic singularity in first period. If used, ESTIMATION CHECKS does not return an error if the check fails only in first observation. This should only be used when observing stock variables (e.g. capital) in first period, on top of their associated flow (e.g. investment). Using this option may lead to a crash or provide undesired/wrong results for badly specified problems (e.g. the additional variable observed in first period is not predetermined).

For advanced use only.

lik_init = INTEGER
Type of initialization of Kalman filter:

1

For stationary models, the initial matrix of variance of the error of forecast is set equal to the unconditional variance of the state variables.

2

For nonstationary models: a wide prior is used with an initial matrix of variance of the error of forecast diagonal with 10 on the diagonal (follows the suggestion of Harvey and Phillips(1979)).

3

For nonstationary models: use a diffuse filter (use rather the diffuse_filter option).

4

The filter is initialized with the fixed point of the Riccati equation.

5

Use i) option 2 for the non-stationary elements by setting their initial variance in the forecast error matrix to 10 on the diagonal and all covariances to 0 and ii) option 1 for the stationary elements.

Default value is 1. For advanced use only.
conditional_likelihood

Do not use the kalman filter to evaluate the likelihood, but instead evaluate the conditional likelihood, based on the first order reduced form of the model, by assuming that the initial state vector is at its steady state. This approach requires that:

1. The number of structural innovations be equal to the number of observed variables.
2. The absence of measurement errors (as introduced by the Dynare interface, see documentation about the estimated_params block).
3. The absence of missing observations.

The evaluation of the conditional likelihood is faster and more stable than the evaluation of the likelihood with the Kalman filter. Also this approach does not require special treatment for models with unit roots. Note however that the conditional likelihood is sensitive to the choice for the initial condition, which can be an issue if the data are initially far from the steady state. This option is not compatible with analytic_derivation.

conf_sig = DOUBLE
Level of significance of the confidence interval used for classical forecasting after estimation. Default: 0.9.

mh_conf_sig = DOUBLE
Confidence/HPD interval used for the computation of prior and posterior statistics like: parameter distributions, prior/posterior moments, conditional variance decomposition, impulse response functions, Bayesian forecasting. Default: 0.9.

mh_repl = INTEGER
Number of replications for each chain of the Metropolis-Hastings algorithm. The number of draws should be sufficient to achieve convergence of the MCMC and to meaningfully compute posterior objects. Default: 20000.

sub_draws = INTEGER
Number of draws from the MCMC that are used to compute posterior distribution of various objects (smoothed variable, smoothed shocks, forecast, moments, IRF). The draws used to compute these posterior moments are sampled uniformly in the estimated empirical posterior distribution (i.e. draws of the MCMC). sub_draws should be smaller than the total number of MCMC draws available. Default: min(posterior_max_subsample_draws, (Total number of draws)*(number of chains) ).

posterior_max_subsample_draws = INTEGER
Maximum number of draws from the MCMC used to compute posterior distribution of various objects (smoothed variable, smoothed shocks, forecast, moments, IRF), if not overridden by option sub_draws. Default: 1200.

mh_nblocks = INTEGER

mh_drop = DOUBLE
The fraction of initially generated parameter vectors to be dropped as a burn-in before using posterior simulations. Default: 0.5.

mh_jscale = DOUBLE
The scale parameter of the jumping distribution’s covariance matrix (Metropolis-Hastings or TaRB-algorithm). This option must be tuned to obtain, ideally, an acceptance ratio of 25%-33%. Basically, the idea is to increase the variance of the jumping distribution if the acceptance ratio is too high, and decrease the same variance if the acceptance ratio is too low. In some situations it may help to consider parameter-specific values for this scale parameter. This can be done in the estimated_params block. Note that mode_compute=6 will tune the scale parameter to achieve an acceptance rate of AcceptanceRateTarget. The resulting scale parameter will be saved into a file named MODEL_FILENAME_mh_scale.mat in the FILENAME/Output folder. This file can be loaded in subsequent runs via the
posterior_sampler_options option \textit{scale\_file}. Both \textit{mode\_compute}=6 and \textit{scale\_file} will overwrite any value specified in \textit{estimated\_params} with the tuned value. Default: \(2.38/\sqrt{n}\).

Note also that for the Random Walk Metropolis Hastings algorithm, it is possible to use option \textit{mh\_tune\_jscale}, to automatically tune the value of \textit{mh\_jscale}. In this case, the \textit{mh\_jscale} option must not be used.

\textbf{mh\_init\_scale = DOUBLE (deprecated)}

The scale to be used for drawing the initial value of the Metropolis-Hastings chain. Generally, the starting points should be overdispersed for the \textit{Brooks and Gelman (1998)} convergence diagnostics to be meaningful. Default: \(2 \times \textit{mh\_jscale}\).

It is important to keep in mind that \textit{mh\_init\_scale} is set at the beginning of Dynare execution, i.e. the default will not take into account potential changes in \textit{mh\_jscale} introduced by either \textit{mode\_compute}=6 or the \textit{posterior\_sampler\_options} option \textit{scale\_file}. If \textit{mh\_init\_scale} is too wide during initialization of the posterior sampler so that 100 tested draws are inadmissible (e.g. Blanchard-Kahn conditions are always violated), Dynare will request user input of a new \textit{mh\_init\_scale} value with which the next 100 draws will be drawn and tested. If the \textit{nointeractive} option has been invoked, the program will instead automatically decrease \textit{mh\_init\_scale} by 10 percent after 100 futile draws and try another 100 draws. This iterative procedure will take place at most 10 times, at which point Dynare will abort with an error message.

\textbf{mh\_init\_scale\_factor = DOUBLE}

The multiple of \textit{mh\_jscale} used for drawing the initial value of the Metropolis-Hastings chain. Generally, the starting points should be overdispersed for the \textit{Brooks and Gelman (1998)} convergence diagnostics to be meaningful. Default: \(2\).

If \textit{mh\_init\_scale\_factor} is too wide during initialization of the posterior sampler so that 100 tested draws are inadmissible (e.g. Blanchard-Kahn conditions are always violated), Dynare will request user input of a new \textit{mh\_init\_scale\_factor} value with which the next 100 draws will be drawn and tested. If the \textit{nointeractive} option has been invoked, the program will instead automatically decrease \textit{mh\_init\_scale\_factor} by 10 percent after 100 futile draws and try another 100 draws. This iterative procedure will take place at most 10 times, at which point Dynare will abort with an error message.

\textbf{mh\_tune\_jscale [= DOUBLE]}

Automatically tunes the scale parameter of the jumping distribution’s covariance matrix (Metropolis-Hastings), so that the overall acceptance ratio is close to the desired level. Default value is \(0.33\). It is not possible to match exactly the desired acceptance ratio because of the stochastic nature of the algorithm (the proposals and the initial conditions of the markov chains if \textit{mh\_nblocks}>1). This option is only available for the Random Walk Metropolis Hastings algorithm. Must not be used in conjunction with \textit{mh\_jscale = DOUBLE}.

\textbf{mh\_tune\_guess = DOUBLE}

Specifies the initial value for the \textit{mh\_tune\_jscale} option. Default: \(2.38/\sqrt{n}\). Must not be set if \textit{mh\_tune\_jscale} is not used.

\textbf{mh\_recover}

Attempts to recover a Metropolis-Hastings simulation that crashed prematurely, starting with the last available saved \textit{mh\_file}. Shouldn’t be used together with \textit{load\_mh\_file} or a different \textit{mh\_replic} than in the crashed run. Since Dynare 4.5 the proposal density from the previous run will automatically be loaded. In older versions, to assure a neat continuation of the chain with the same proposal density, you should provide the \textit{mode\_file} used in the previous run or the same user-defined \textit{mcmc\_jumping\_covariance} when using this option. Note that under Octave, a neat continuation of the crashed chain with the respective last random number generator state is currently not supported.

\textbf{mh\_posterior\_mode\_estimation}

Skip optimizer-based mode-finding and instead compute the mode based on a run of a MCMC. The MCMC will start at the prior mode and use the prior variances to compute the inverse Hessian.
**mode_file = FILENAME**

Name of the file containing previous value for the mode. When computing the mode, Dynare stores the mode (xparam1) and the hessian (hh, only if `cova_compute=1`) in a file called `MODEL_FILENAME_mode.mat` in the `FILENAME/Output` folder. After a successful run of the estimation command, the `mode_file` will be disabled to prevent other function calls from implicitly using an updated mode file. Thus, if the `.mod` file contains subsequent estimation commands, the `mode_file` option, if desired, needs to be specified again.

**mode_compute = INTEGER | FUNCTION_NAME**

Specifies the optimizer for the mode computation:

0

The mode isn't computed. When the `mode_file` option is specified, the mode is simply read from that file.

When `mode_file` option is not specified, Dynare reports the value of the log posterior (log likelihood) evaluated at the initial value of the parameters.

When `mode_file` is not specified and there is no `estimated_params` block, but the `smoother` option is used, it is a roundabout way to compute the smoothed value of the variables of a model with calibrated parameters.

1

Uses `fmincon` optimization routine (available under MATLAB if the Optimization Toolbox is installed; available under Octave if the `optim` package from Octave-Forge, version 1.6 or above, is installed).

2

Uses the continuous simulated annealing global optimization algorithm described in Corana et al.(1987) and Goffe et al.(1994).

3

Uses `fminunc` optimization routine (available under MATLAB if the Optimization Toolbox is installed; available under Octave if the `optim` package from Octave-Forge is installed).

4

Uses Chris Sims’s `csminwel`.

5

Uses Marco Ratto’s `newrat`. This value is not compatible with non linear filters or DSGE-VAR models. This is a slice optimizer: most iterations are a sequence of univariate optimization step, one for each estimated parameter or shock. Uses `csminwel` for line search in each step.

6

Uses a Monte-Carlo based optimization routine (see https://archives.dynare.org/DynareWiki/MonteCarloOptimization for more details).

7

Uses `fminsearch`, a simplex-based optimization routine (available under MATLAB if the Optimization Toolbox is installed; available under Octave if the `optim` package from Octave-Forge is installed).

8

Uses Dynare implementation of the Nelder-Mead simplex-based optimization routine (generally more efficient than the MATLAB or Octave implementation available with `mode_compute=7`).

9

4.15. Estimation based on likelihood

10 Uses the simpsa algorithm, based on the combination of the non-linear simplex and simulated annealing algorithms as proposed by Cardoso, Salcedo and Feyo de Azevedo (1996).

11 This is not strictly speaking an optimization algorithm. The (estimated) parameters are treated as state variables and estimated jointly with the original state variables of the model using a nonlinear filter. The algorithm implemented in Dynare is described in Liu and West (2001), and works with k order local approximations of the model.

12 Uses the particleswarm optimization routine (available under MATLAB if the Global Optimization Toolbox is installed; not available under Octave).

13 Uses the lsqnonlin non-linear least squares optimization routine (available under MATLAB if the Optimization Toolbox is installed; available under Octave if the optim package from Octave-Forge is installed). Only supported for method_of_moments.


102 Uses simulannealbnd optimization routine (available under MATLAB if the Global Optimization Toolbox is installed; not available under Octave)

FUNCTION_NAME
It is also possible to give a FUNCTION_NAME to this option, instead of an INTEGER. In that case, Dynare takes the return value of that function as the posterior mode.

Default value is 5.

additional_optimizer_steps = [INTEGER]
additional_optimizer_steps = [INTEGER1:INTEGER2]
additional_optimizer_steps = [INTEGER1 INTEGER2 ...]
Vector of additional minimization algorithms run after mode_compute. Default: no additional optimization iterations.

silent_optimizer
Instructs Dynare to run mode computing/optimization silently without displaying results or saving files in between. Useful when running loops.

mcmc_jumping_covariance = OPTION
Tells Dynare which covariance to use for the proposal density of the MCMC sampler. OPTION can be one of the following:

hessian
Uses the Hessian matrix computed at the mode.

prior_variance
Uses the prior variances. No infinite prior variances are allowed in this case.
identity_matrix

Uses an identity matrix.

FILENAME

Loads an arbitrary user-specified covariance matrix from `FILENAME.mat`. The covariance matrix must be saved in a variable named `jumping_covariance`, must be square, positive definite, and have the same dimension as the number of estimated parameters.

Note that the covariance matrices are still scaled with `mh_jscale`. Default value is `hessian`.

mode_check

Tells Dynare to plot the posterior density for values around the computed mode for each estimated parameter in turn. This is helpful to diagnose problems with the optimizer. Note that for order>1 the likelihood function resulting from the particle filter is not differentiable anymore due to the resampling step. For this reason, the `mode_check` plot may look wiggly.

mode_check_neighbourhood_size = DOUBLE

Used in conjunction with option `mode_check`, gives the width of the window around the posterior mode to be displayed on the diagnostic plots. This width is expressed in percentage deviation. The Inf value is allowed, and will trigger a plot over the entire domain (see also `mode_check_symmetric_plots`). Default: 0.5.

mode_check_symmetric_plots = INTEGER

Used in conjunction with option `mode_check`, if set to 1, tells Dynare to ensure that the check plots are symmetric around the posterior mode. A value of 0 allows to have asymmetric plots, which can be useful if the posterior mode is close to a domain boundary, or in conjunction with `mode_check_neighbourhood_size = Inf` when the domain is not the entire real line. Default: 1.

mode_check_number_of_points = INTEGER

Number of points around the posterior mode where the posterior kernel is evaluated (for each parameter). Default is 20.

prior_trunc = DOUBLE

Probability of extreme values of the prior density that is ignored when computing bounds for the parameters. Default: `1e-32`.

huge_number = DOUBLE

Value for replacing infinite values in the definition of (prior) bounds when finite values are required for computational reasons. Default: `1e7`.

load_mh_file

Tells Dynare to add to previous Metropolis-Hastings simulations instead of starting from scratch. Since Dynare 4.5 the proposal density from the previous run will automatically be loaded. In older versions, to assure a neat continuation of the chain with the same proposal density, you should provide the `mode_file` used in the previous run or the same user-defined `mcmc_jumping_covariance` when using this option. Shouldn’t be used together with `mh_recover`. Note that under Octave, a neat continuation of the chain with the last random number generator state of the already present draws is currently not supported.

load_results_after_load_mh

This option is available when loading a previous MCMC run without adding additional draws, i.e. when `load_mh_file` is specified with `mh_replic=0`. It tells Dynare to load the previously computed convergence diagnostics, marginal data density, and posterior statistics from an existing _results file instead of recomputing them.

mh_initialize_from_previous_mcmc

This option allows to pick initial values for new MCMC from a previous one, where the model specification, the number of estimated parameters, (some) prior might have changed (so a situation where
load mh file would not work). If an additional parameter is estimated, it is automatically initialized from prior_draw. Note that, if this option is used to skip the optimization step, you should use a sampling method which does not require a proposal density, like slice. Otherwise, optimization should always be done beforehand or a mode file with an appropriate posterior covariance matrix should be used.

**mh_initialize_from_previous_mcmc_directory = FILENAME**

If `mh_initialize_from_previous_mcmc` is set, users must provide here the path to the standard FNAME folder from where to load prior definitions and last MCMC values to be used to initialize the new MCMC.

Example: if previous project directory is `/my_previous_dir` and FNAME is mymodel, users should set the option as

```
mh_initialize_from_previous_mcmc_directory = '/my_previous_dir/mymodel'
```

Dynare will then look for the last record file into

```
/my_previous_dir/mymodel/metropolis/mymodel_mh_history_<LAST>.mat
```

and for the prior definition file into

```
/my_previous_dir/mymodel/prior/definition.mat
```

**mh_initialize_from_previous_mcmc_record = FILENAME**

If `mh_initialize_from_previous_mcmc` is set, and whenever the standard file or directory tree is not applicable to load initial values, users may directly provide here the path to the record file from which to load values to be used to initialize the new MCMC.

**mh_initialize_from_previous_mcmc_prior = FILENAME**

If `mh_initialize_from_previous_mcmc` is set, and whenever the standard file or directory tree is not applicable to load initial values, users may directly provide here the path to the prior definition file, to get info in the priors used in previous MCMC.

**optim = (NAME, VALUE, ...)**

A list of NAME and VALUE pairs. Can be used to set options for the optimization routines. The set of available options depends on the selected optimization routine (i.e. on the value of option `mode_compute`):

```
1, 3, 7, 12, 13
```

Available options are given in the documentation of the MATLAB Optimization Toolbox or in Octave’s documentation.

```
2
```

Available options are:

- `'initial_step_length'`
  Initial step length. Default: 1.

- `'initial_temperature'`
  Initial temperature. Default: 15.

- `'MaxIter'`
  Maximum number of function evaluations. Default: 100000.

- `'neps'`
  Number of final function values used to decide upon termination. Default: 10.

- `'ns'`
  Number of cycles. Default: 10.

- `'nt'`
Number of iterations before temperature reduction. Default: 10.

'step_length_c'
Step length adjustment. Default: 0.1.

'TolFun'

'rt'
Temperature reduction factor. Default: 0.1.

'verbosity'
Controls verbosity of display during optimization, ranging from 0 (silent) to 3 (each function evaluation). Default: 1

Available options are:

'InitialInverseHessian'
Initial approximation for the inverse of the Hessian matrix of the posterior kernel (or likelihood). Obviously this approximation has to be a square, positive definite and symmetric matrix. Default: '1e-4*eye(nx)', where nx is the number of parameters to be estimated.

'MaxIter'
Maximum number of iterations. Default: 1000.

'NumgradAlgorithm'
Possible values are 2, 3 and 5, respectively, corresponding to the two, three and five points formula used to compute the gradient of the objective function (see Abramowitz and Stegun (1964)). Values 13 and 15 are more experimental. If perturbations on the right and the left increase the value of the objective function (we minimize this function) then we force the corresponding element of the gradient to be zero. The idea is to temporarily reduce the size of the optimization problem. Default: 2.

'NumgradEpsilon'
Size of the perturbation used to compute numerically the gradient of the objective function. Default: 1e-6.

'TolFun'

'verbosity'
Controls verbosity of display during optimization. Set to 0 to set to silent. Default: 1.

'SaveFiles'
Controls saving of intermediate results during optimization. Set to 0 to shut off saving. Default: 1.

Available options are:

'Hessian'
Triggers three types of Hessian computations. 0: outer product gradient; 1: default Dynare Hessian routine; 2: 'mixed' outer product gradient, where diagonal elements are obtained using second order derivation formula and outer product
is used for correlation structure. Both [0] and [2] options require univariate filters, to ensure using maximum number of individual densities and a positive definite Hessian. Both [0] and [2] are quicker than default Dynare numeric Hessian, but provide decent starting values for Metropolis for large models (option [2] being more accurate than [0]). Default: 1.

'MaxIter'
Maximum number of iterations. Default: 1000.

'TolFun'
Stopping criteria. Default: $10^{-5}$ for numerical derivatives, $10^{-7}$ for analytic derivatives.

'robust'
Trigger more robust but computationally more expensive line search. Default: false.

'TolGstep'
Tolerance parameter used for tuning gradient step. Default: same value as TolFun.

'TolGstepRel'
Parameter used for tuning gradient step, governing the tolerance relative to the functions value. Default: not triggered.

'verbosity'
Controls verbosity of display during optimization. Set to 0 to set to silent. Default: 1.

'SaveFiles'
Controls saving of intermediate results during optimization. Set to 0 to shut off saving. Default: 1.

Available options are:

'AcceptanceRateTarget'
A real number between zero and one. The scale parameter of the jumping distribution is adjusted so that the effective acceptance rate matches the value of option 'AcceptanceRateTarget'. Default: 1.0/3.0.

'InitialCovarianceMatrix'
Initial covariance matrix of the jumping distribution. It is also used to initialize the covariance matrix during recursive updating. Default is 'previous' if option mode_file is used, 'prior' otherwise. The user can also specify 'identity', which will use an identity matrix with a diagonal of 0.1.

'nclimb-mh'
Number of iterations in the last MCMC (climbing mode). Default: 200000.

'ncov-mh'
Number of iterations used for updating the covariance matrix of the jumping distribution. Default: 20000.

'nscale-mh'
Maximum number of iterations used for adjusting the scale parameter of the jumping distribution. Default: 200000.

'NumberOfMh'
Number of MCMC run sequentially. Default: 3.

Available options are:

'InitialSimplexSize'
Initial size of the simplex, expressed as percentage deviation from the provided initial guess in each direction. Default: .05.

'MaxIter'
Maximum number of iterations. Default: 5000.

'MaxFunEvals'
Maximum number of objective function evaluations. No default.

'MaxFunEvalFactor'
Set MaxFunEvals equal to MaxFunEvalFactor times the number of estimated parameters. Default: 500.

'TolFun'
Tolerance parameter (w.r.t the objective function). Default: 1e-4.

'TolX'
Tolerance parameter (w.r.t the instruments). Default: 1e-4.

'verbosity'
Controls verbosity of display during optimization. Set to 0 to set to silent. Default: 1.

Available options are:

'CMAESResume'
Resume previous run. Requires the variablescmaes.mat from the last run. Set to 1 to enable. Default: 0.

'MaxIter'
Maximum number of iterations.

'MaxFunEvals'
Maximum number of objective function evaluations. Default: Inf.

'TolFun'
Tolerance parameter (w.r.t the objective function). Default: 1e-7.

'TolX'
Tolerance parameter (w.r.t the instruments). Default: 1e-7.

'verbosity'
Controls verbosity of display during optimization. Set to 0 to set to silent. Default: 1.

'SaveFiles'
Controls saving of intermediate results during optimization. Set to 0 to shut off saving. Default: 1.

Available options are:

'EndTemperature'
Terminal condition w.r.t the temperature. When the temperature reaches EndTemperature, the temperature is set to zero and the algorithm falls back into a standard simplex algorithm. Default: 0.1.

'MaxIter'
Maximum number of iterations. Default: 5000.

'MaxFunvEvals'
Maximum number of objective function evaluations. No default.

'TolFun'
Tolerance parameter (w.r.t the objective function). Default: 1e-4.

'TolX'
Tolerance parameter (w.r.t the instruments). Default: 1e-4.

'verbosity'
Controls verbosity of display during optimization. Set to 0 to set to silent. Default: 1.

Available options are:

'LBGradientStep'
Lower bound for the stepsize used for the difference approximation of gradients. Default: 1e-11.

'MaxIter'
Maximum number of iterations. Default: 15000.

'SpaceDilation'
Coefficient of space dilation. Default: 2.5.

'TolFun'
Tolerance parameter (w.r.t the objective function). Default: 1e-6.

'TolX'
Tolerance parameter (w.r.t the instruments). Default: 1e-6.

'verbosity'
Controls verbosity of display during optimization. Set to 0 to set to silent. Default: 1.

Available options are given in the documentation of the MATLAB Global Optimization Toolbox.

Example
To change the defaults of csminwel (mode_compute=4):
nodiagnostic

Does not compute the convergence diagnostics for Metropolis-Hastings. Default: diagnostics are computed and displayed.

bayesian_irf

Triggers the computation of the posterior distribution of IRFs. The length of the IRFs are controlled by the irf option. Results are stored in oo_.PosteriorIRF.dsge (see below for a description of this variable).

relative_irf

See relative_irf.

dsge_var = DOUBLE

Triggers the estimation of a DSGE-VAR model, where the weight of the DSGE prior of the VAR model is calibrated to the value passed (see Del Negro and Schorfheide (2004)). It represents the ratio of dummy over actual observations. To assure that the prior is proper, the value must be bigger than $(k + n)/T$, where $k$ is the number of estimated parameters, $n$ is the number of observables, and $T$ is the number of observations.

NB: The previous method of declaring dsge_prior_weight as a parameter and then calibrating it is now deprecated and will be removed in a future release of Dynare. Some of objects arising during estimation are stored with their values at the mode in oo_.dsge_var. posterior_mode.

dsge_varlag = INTEGER

The number of lags used to estimate a DSGE-VAR model. Default: 4.

posterior_sampling_method = NAME

Selects the sampler used to sample from the posterior distribution during Bayesian estimation. Default: 'random_walk_metropolis_hastings'.

'random_walk_metropolis_hastings'

Instructs Dynare to use the Random-Walk Metropolis-Hastings. In this algorithm, the proposal density is recentered to the previous draw in every step.

'tailored_random_block_metropolis_hastings'

Instructs Dynare to use the Tailored randomized block (TaRB) Metropolis-Hastings algorithm proposed by Chib and Ramamurthy (2010) instead of the standard Random-Walk Metropolis-Hastings. In this algorithm, at each iteration the estimated parameters are randomly assigned to different blocks. For each of these blocks a mode-finding step is conducted. The inverse Hessian at this mode is then used as the covariance of the proposal density for a Random-Walk Metropolis-Hastings step. If the numerical Hessian is not positive definite, the generalized Cholesky decomposition of Schnabel and Eskow (1990) is used, but without pivoting. The TaRB-MH algorithm massively reduces the autocorrelation in the MH draws and thus reduces the number of draws required to representatively sample from the posterior. However, this comes at a computational cost as the algorithm takes more time to run.

'independent_metropolis_hastings'
Use the Independent Metropolis-Hastings algorithm where the proposal distribution - in contrast to the Random Walk Metropolis-Hastings algorithm - does not depend on the state of the chain.

'slice'

Instructs Dynare to use the Slice sampler of Planas, Ratto, and Rossi (2015). Note that 'slice' is incompatible with prior_trunc=0.

Whereas one Metropolis-Hastings iteration requires one evaluation of the posterior, one slice iteration requires $neval$ evaluations, where as a rule of thumb $neval = 7 \times npar$ with $npar$ denoting the number of estimated parameters. Spending the same computational budget of $N$ posterior evaluations in the slice sampler then implies setting $mh\_replic=N/neval$.

Note that the slice sampler will typically return less autocorrelated Monte Carlo Markov Chain draws than the MH-algorithm. Its relative (in)efficiency can be investigated via the reported inefficiency factors.

'hssmc'


**posterior_sampler_options = (NAME, VALUE, ...)**

A list of NAME and VALUE pairs. Can be used to set options for the posterior sampling methods. The set of available options depends on the selected posterior sampling routine (i.e. on the value of option *posterior_sampling_method*):

'select random_walk_metropolis_hastings'

Available options are:

'proposal_distribution'

Specifies the statistical distribution used for the proposal density.

'rand_multivariate_normal'

Use a multivariate normal distribution. This is the default.

'rand_multivariate_student'

Use a multivariate student distribution.

'student_degrees_of_freedom'

Specifies the degrees of freedom to be used with the multivariate student distribution. Default: 3.

'use_mh_covariance_matrix'

Indicates to use the covariance matrix of the draws from a previous MCMC run to define the covariance of the proposal distribution. Requires the load_mh_file option to be specified. Default: 0.

'scale_file'

Provides the name of a _mh_scale.mat file storing the tuned scale factor from a previous run of mode_compute=6.

'save_tmp_file'

Save the MCMC draws into a _mh_tmp_blck file at the refresh rate of the status bar instead of just saving the draws when the current _mh*_blck file is full. Default: 0

'independent_metropolis_hastings'
Takes the same options as in the case of random_walk_metropolis_hastings. 'slice'

Available options are:

'slice' (rotated)
Triggers rotated slice iterations using a covariance matrix from initial burn-in iterations. Requires either use_mh_covariance_matrix or slice_initialize_with_mode. Default: 0.

'mode_files'
For multimodal posteriors, provide the name of a file containing a nparam by nmodes variable called xparams storing the different modes. This array must have one column vector per mode and the estimated parameters along the row dimension. With this info, the code will automatically trigger the rotated and mode options. Default: [].

'slice_initialize_with_mode'
The default for slice is to set mode_compute=0 and start the chain(s) from a random location in the prior space. This option first runs the mode-finder and then starts the chain from the mode. Together with rotated, it will use the inverse Hessian from the mode to perform rotated slice iterations. Default: 0.

'initial_step_size'
Sets the initial size of the interval in the stepping-out procedure as fraction of the prior support, i.e. the size will be initial_step_size * (UB-LB). initial_step_size must be a real number in the interval [0,1]. Default: 0.8.

'use_mh_covariance_matrix'
See use_mh_covariance_matrix. Must be used with 'rotated'. Default: 0.

'save_tmp_file'

tailored_random_block_metropolis_hastings

Available options are:

'proposal_distribution'
Specifies the statistical distribution used for the proposal density. See proposal_distribution.

new_block_probability = DOUBLE
Specifies the probability of the next parameter belonging to a new block when the random blocking in the TaRB Metropolis-Hastings algorithm is conducted. The higher this number, the smaller is the average block size and the more random blocks are formed during each parameter sweep. Default: 0.25.

mode_compute = INTEGER
Specifies the mode-finder run in every iteration for every block of the TaRB Metropolis-Hastings algorithm. See mode_compute. Default: 4.

optim = (NAME, VALUE,..)
Specifies the options for the mode-finder used in the TaRB Metropolis-Hastings algorithm. See optim.

'scale_file'
See scale_file.
'save_tmp_file'
'hssmc'
Available options are:
'particles'
Number of particles. Default value is: 20000.
'steps'
Number of weights \( \phi_i \in [0, 1] \) on the likelihood function used to define a sequence of tempered likelihoods. This parameter is denoted \( N_{\phi} \) in Herbst and Schorfheide (2014), and we have \( \phi_1 = 0 \) and \( \phi_{N_{\phi}} = 1 \). Default value is: 25.
'lambda'
Positive parameter controlling the sequence of weights \( \phi_i \), Default value is: 2. Weights are defined by:
\[
\phi_i = \left( \frac{i - 1}{N_{\phi} - 1} \right)^\lambda
\]
for \( i = 1, \ldots, N_{\phi} \). Usually we set \( \lambda > 1 \), so that \( \Delta \phi_i = \phi_i - \phi_{i-1} \) is increasing with \( i \).
'target'
Acceptance rate target. Default value is: .25.
'scale'
Scale parameter in the mutation step (on the proposal covariance matrix of the MH iteration). Default value is: .5.

`moments_varendo`
Triggers the computation of the posterior distribution of the theoretical moments of the endogenous variables. Results are stored in `oo_.PosteriorTheoreticalMoments` (see `oo_.PosteriorTheoreticalMoments`). The number of lags in the autocorrelation function is controlled by the `ar` option.

`contemporaneous_correlation`
See `contemporaneous_correlation`. Results are stored in `oo_.PosteriorTheoreticalMoments`. Note that the nocorr option has no effect.

`no_posterior_kernel_density`
Shuts off the computation of the kernel density estimator for the posterior objects (see `density` field).

`conditional_variance_decomposition = INTEGER`
`conditional_variance_decomposition = [INTEGER1:INTEGER2]`
`conditional_variance_decomposition = [INTEGER1 INTEGER2 ...]`
Computes the posterior distribution of the conditional variance decomposition for the specified period(s). The periods must be strictly positive. Conditional variances are given by \( \text{var}(y_{t+k}|t) \). For period 1, the conditional variance decomposition provides the decomposition of the effects of shocks upon impact. The results are stored in `oo_.PosteriorTheoreticalMoments.dsge.ConditionalVarianceDecomposition`. Note that this option requires the option `moments_varendo` to be specified. In the presence of measurement error, the field will contain the variance contribution after measurement error has been taken out, i.e. the decomposition will be conducted of the actual as opposed to the measured variables. The variance decomposition of the measured variables will be stored in `oo_.PosteriorTheoreticalMoments.dsge.ConditionalVarianceDecompositionME`. 
**filtered_vars**

Triggers the computation of the posterior distribution of filtered endogenous variables/one-step ahead forecasts, i.e. $E_{t}y_{t+1}$. Results are stored in `oo_.FilteredVariables` (see below for a description of this variable).

**smoother**

Triggers the computation of the posterior distribution of smoothed endogenous variables and shocks, i.e. the expected value of variables and shocks given the information available in all observations up to the final date ($E_{T}y_{t}$). Results are stored in `oo_.SmoothedVariables`, `oo_.SmoothedShocks` and `oo_.SmoothedMeasurementErrors`. Also triggers the computation of `oo_.UpdatedVariables`, which contains the estimation of the expected value of variables given the information available at the current date ($E_{t}y_{t}$). See below for a description of all these variables.

**smoother Redux**

Triggers a faster computation of the smoothed endogenous variables and shocks for large models. It runs the smoother only for the state variables (i.e. with the same representation used for likelihood computations) and computes the remaining variables ex-post. Static unobserved objects (filtered, smoothed, updated, k-step ahead) are recovered, but there are exceptions to a full recovery, depending on how static unobserved variables depend on the restricted state space adopted. For example, lagged shocks which are ONLY used to recover NON-observed static variables will not be recovered. For such exceptions, only the following output is provided:

- `FilteredVariablesKStepAhead`: will be fully recovered
- `SmoothedVariables, FilteredVariables, UpdatedVariables`: recovered for all periods beyond period $d+1$.
  where $d$ denotes the number of diffuse filtering steps.
- `FilteredVariablesKStepAheadVariances`, `Variance`, and `State_uncertainty` cannot be recovered, and ZERO is provided as output.

If you need variances for those variables, either do not set the option, or declare the variable as observed, using NaNs as data points.

**forecast = INTEGER**

Computes the posterior distribution of a forecast on INTEGER periods after the end of the sample used in estimation. If no Metropolis-Hastings is computed, the result is stored in variable `oo_.forecast` and corresponds to the forecast at the posterior mode. If a Metropolis-Hastings is computed, the distribution of forecasts is stored in variables `oo_.PointForecast` and `oo_.MeanForecast`. See `Forecasting`, for a description of these variables.

**tex**

See `tex`.

**kalman_algo = INTEGER**

- 0: Automatically use the Multivariate Kalman Filter for stationary models and the Multivariate Diffuse Kalman Filter for non-stationary models.
- 1: Use the Multivariate Kalman Filter.
- 2: Use the Univariate Kalman Filter.
- 3: Use the Multivariate Diffuse Kalman Filter.
- 4: Use the Univariate Diffuse Kalman Filter.
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Default value is 0. In case of missing observations of single or all series, Dynare treats those missing values as unobserved states and uses the Kalman filter to infer their value (see e.g. Durbin and Koopman (2012), Ch. 4.10) This procedure has the advantage of being capable of dealing with observations where the forecast error variance matrix becomes singular for some variable(s). If this happens, the respective observation enters with a weight of zero in the log-likelihood, i.e. this observation for the respective variable(s) is dropped from the likelihood computations (for details see Durbin and Koopman (2012), Ch. 6.4 and 7.2.5 and Koopman and Durbin (2000)). If the use of a multivariate Kalman filter is specified and a singularity is encountered, Dynare by default automatically switches to the univariate Kalman filter for this parameter draw. This behavior can be changed via the use_univariate_filters_if_singularity_is_detected option.

\texttt{fast\_kalman\_filter}

Select the fast Kalman filter using Chandrasekhar recursions as described by Herbst (2015). This setting is only used with kalman\_algo=1 or kalman\_algo=3. In case of using the diffuse Kalman filter (kalman\_algo=3/lik\_init=3), the observables must be stationary. This option is not yet compatible with analytic\_derivation.

\texttt{kalman\_tol = DOUBLE}

Numerical tolerance for determining the singularity of the covariance matrix of the prediction errors during the Kalman filter (minimum allowed reciprocal of the matrix condition number). Default value is 1e-10.

\texttt{diffuse\_kalman\_tol = DOUBLE}

Numerical tolerance for determining the singularity of the covariance matrix of the prediction errors ($F_\infty$) and the rank of the covariance matrix of the non-stationary state variables ($P_\infty$) during the Diffuse Kalman filter. Default value is 1e-6.

\texttt{filter\_covariance}

Saves the series of one step ahead error of forecast covariance matrices. With Metropolis, they are saved in \texttt{oo\_.FilterCovariance}, otherwise in \texttt{oo\_.Smooother.Variance}. Saves also k-step ahead error of forecast covariance matrices if filter\_step\_ahead is set.

\texttt{filter\_step\_ahead = [INTEGER1:INTEGER2]}

Triggers the computation k-step ahead filtered values, i.e. $E_T y_{t+k}$. Stores results in \texttt{oo\_.FilteredVariablesKStepAhead}. Also stores 1-step ahead values in \texttt{oo\_.FilteredVariables}. \texttt{oo\_.FilteredVariablesKStepAheadVariances} is stored if filter\_covariance.

\texttt{filter\_decomposition}

Triggers the computation of the shock decomposition of the above k-step ahead filtered values. Stores results in \texttt{oo\_.FilteredVariablesShockDecomposition}.

\texttt{smoothed\_state\_uncertainty}

Triggers the computation of the variance of smoothed estimates, i.e. $\text{var}_T(y_t)$. Stores results in \texttt{oo\_.Smooother.State\_uncertainty}.

\texttt{diffuse\_filter}

Uses the diffuse Kalman filter (as described in Durbin and Koopman (2012) and Koopman and Durbin (2003) for the multivariate and Koopman and Durbin (2000) for the univariate filter) to estimate models with non-stationary observed variables. This option will also reset the qz\_criterium to count unit root variables towards the stable variables. Trying to estimate a model with unit roots will otherwise result in a Blanchard-Kahn error.

When \texttt{diffuse\_filter} is used the lik\_init option of estimation has no effect.

When there are nonstationary exogenous variables in a model, there is no unique deterministic steady state. For instance, if productivity is a pure random walk:

$$a_t = a_{t-1} + \epsilon_t$$
any value of \( \bar{a} \) of \( a \) is a deterministic steady state for productivity. Consequently, the model admits an infinity of steady states. In this situation, the user must help Dynare in selecting one steady state, except if zero is a trivial model’s steady state, which happens when the linear option is used in the model declaration. The user can either provide the steady state to Dynare using a steady_state_model block (or writing a steady state file) if a closed form solution is available, see steady_state_model, or specify some constraints on the steady state, see equation_tag_for_conditional_steady_state, so that Dynare computes the steady state conditionally on some predefined levels for the non stationary variables. In both cases, the idea is to use dummy values for the steady state level of the exogenous non stationary variables. Note that the nonstationary variables in the model must be integrated processes (their first difference or k-difference must be stationary).

**heteroskedastic_filter**

Runs filter, likelihood, and smoother using heteroskedastic definitions provided in a heteroskedastic_shocks block.

**selected_variables_only**

Only run the classical smoother on the variables listed just after the estimation command. This option is incompatible with requesting classical frequentist forecasts and will be overridden in this case. When using Bayesian estimation, the smoother is by default only run on the declared endogenous variables. Default: run the smoother on all the declared endogenous variables.

**cova_compute = INTEGER**

When \( 0 \), the covariance matrix of estimated parameters is not computed after the computation of posterior mode (or maximum likelihood). This increases speed of computation in large models during development, when this information is not always necessary. Of course, it will break all successive computations that would require this covariance matrix. Otherwise, if this option is equal to 1, the covariance matrix is computed and stored in variable \( hh \) of MODEL_FILENAME_mode.mat. Default is 1.

**solve_algo = INTEGER**

See solve_algo.

**order = INTEGER**

Order of approximation around the deterministic steady state. When greater than 1, the likelihood is evaluated with a particle or nonlinear filter (see Fernández-Villaverde and Rubio-Ramírez (2005)). Default is 1, i.e. the likelihood of the linearized model is evaluated using a standard Kalman filter.

**irf = INTEGER**

See irf. Only used if bayesian_irf is passed.

**irf_shocks = ( VARIABLE_NAME [[,] VARIABLE_NAME ...] )**

See irf_shocks. Only used if bayesian_irf is passed.

**irf_plot_threshold = DOUBLE**

See irf_plot_threshold. Only used if bayesian_irf is passed.

**aim_solver**

See aim_solver.

**lyapunov = OPTION**

Determines the algorithm used to solve the Lyapunov equation to initialized the variance-covariance matrix of the Kalman filter using the steady-state value of state variables. Possible values for OPTION are:

- default
  - Uses the default solver for Lyapunov equations based on Bartels-Stewart algorithm.
- fixed_point
Uses a fixed point algorithm to solve the Lyapunov equation. This method is faster than the default one for large scale models, but it could require a large amount of iterations.

doubling

Uses a doubling algorithm to solve the Lyapunov equation (\texttt{disclyap\_fast}). This method is faster than the two previous one for large scale models.

\texttt{square\_root\_solver}

Uses a square-root solver for Lyapunov equations (\texttt{dlyapchol}). This method is fast for large scale models (available under MATLAB if the Control System Toolbox is installed; available under Octave if the control package from Octave-Forge is installed)

Default value is default.

\texttt{lyapunov\_fixed\_point\_tol} = \texttt{DOUBLE}

This is the convergence criterion used in the fixed point Lyapunov solver. Its default value is $1 \times 10^{-10}$.

\texttt{lyapunov\_doubling\_tol} = \texttt{DOUBLE}

This is the convergence criterion used in the doubling algorithm to solve the Lyapunov equation. Its default value is $1 \times 10^{-16}$.

\texttt{use\_penalized\_objective\_for\_hessian}

Use the penalized objective instead of the objective function to compute numerically the hessian matrix at the mode. The penalties decrease the value of the posterior density (or likelihood) when, for some perturbations, Dynare is not able to solve the model (issues with steady state existence, Blanchard and Kahn conditions, ...). In practice, the penalized and original objectives will only differ if the posterior mode is found to be near a region where the model is ill-behaved. By default the original objective function is used.

\texttt{analytic\_derivation}

Triggers estimation with analytic gradient at order=1. The final hessian at the mode is also computed analytically. Only works for stationary models without missing observations, i.e. for \texttt{kalman\_algo<3}. Optimizers that rely on analytic gradients are \texttt{mode\_compute=1,3,4,5,101}.

\texttt{ar} = \texttt{INTEGER}

See \texttt{ar}. Only useful in conjunction with option \texttt{moments\_varendo}.

\texttt{endogenous\_prior}

Use endogenous priors as in Christiano, Trabandt and Walentin (2011). The procedure is motivated by sequential Bayesian learning. Starting from independent initial priors on the parameters, specified in the \texttt{estimated\_params} block, the standard deviations observed in a “pre-sample”, taken to be the actual sample, are used to update the initial priors. Thus, the product of the initial priors and the pre-sample likelihood of the standard deviations of the observables is used as the new prior (for more information, see the technical appendix of Christiano, Trabandt and Walentin (2011)). This procedure helps in cases where the regular posterior estimates, which minimize in-sample forecast errors, result in a large overprediction of model variable variances (a statistic that is not explicitly targeted, but often of particular interest to researchers).

\texttt{use\_univariate\_filters\_if\_singularity\_is\_detected} = \texttt{INTEGER}

Decide whether Dynare should automatically switch to univariate filter if a singularity is encountered in the likelihood computation (this is the behaviour if the option is equal to 1). Alternatively, if the option is equal to 0, Dynare will not automatically change the filter, but rather use a penalty value for the likelihood when such a singularity is encountered. Default: 1.

\texttt{keep\_kalman\_algo\_if\_singularity\_is\_detected}

With the default \texttt{use\_univariate\_filters\_if\_singularity\_is\_detected=1}, Dynare will switch to the univariate Kalman filter when it encounters a singular forecast error variance matrix during Kalman filtering. Upon encountering such a singularity for the first time, all subsequent parameter draws and computations will automatically rely on univariate filter, i.e. Dynare will never try the multivariate filter again. Use the \texttt{keep\_kalman\_algo\_if\_singularity\_is\_detected} option
to have the `use_univariate_filters_if_singularity_is_detected` only affect the behavior for the current draw/computation.

**rescale_prediction_error_covariance**

Rescales the prediction error covariance in the Kalman filter to avoid badly scaled matrix and reduce the probability of a switch to univariate Kalman filters (which are slower). By default no rescaling is done.

*rescale_prediction_error_covariance = DOUBLE*

See `rescale_prediction_error_covariance`.

**qz_zero_threshold = DOUBLE**

See `qz_zero_threshold`.

**taper_steps = [INTEGER1 INTEGER2 ...]**

Percent tapering used for the spectral window in the Geweke (1992,1999) convergence diagnostics (requires `mh_nblocks=1`). The tapering is used to take the serial correlation of the posterior draws into account. Default: [4 8 15].

**brooks_gelman_plotrows = INTEGER**

Number of parameters to depict along the rows of the figures depicting the Brooks and Gelman (1998) convergence diagnostics. Default: 3.

**geweke_interval = [DOUBLE DOUBLE]**

Percentage of MCMC draws at the beginning and end of the MCMC chain taken to compute the Geweke (1992,1999) convergence diagnostics (requires `mh_nblocks=1`) after discarding the first `mh_drop` percent of draws as a burnin. Default: [0.2 0.5].

**raftery_lewis_diagnostics**

Triggers the computation of the Raftery and Lewis (1992) convergence diagnostics. The goal is deliver the number of draws required to estimate a particular quantile of the CDF q with precision r with a probability s. Typically, one wants to estimate the q=0.025 percentile (corresponding to a 95 percent HPDI) with a precision of 0.5 percent (r=0.005) with 95 percent certainty (s=0.95). The defaults can be changed via `raftery_lewis_qrs`. Based on the theory of first order Markov Chains, the diagnostics will provide a required burn-in (M), the number of draws after the burnin (N) as well as a thinning factor that would deliver a first order chain (k). The last line of the table will also deliver the maximum over all parameters for the respective values.

**raftery_lewis_qrs = [DOUBLE DOUBLE DOUBLE]**

Sets the quantile of the CDF q that is estimated with precision r with a probability s in the Raftery and Lewis (1992) convergence diagnostics. Default: [0.025 0.005 0.95].

**consider_all_endogenous**

Compute the posterior moments, smoothed variables, k-step ahead filtered variables and forecasts (when requested) on all the endogenous variables. This is equivalent to manually listing all the endogenous variables after the estimation command.

**consider_all_endogenous_and_auxiliary**

Compute the posterior moments, smoothed variables, k-step ahead filtered variables and forecasts (when requested) on all the endogenous variables and the auxiliary variables introduced by the pre-processor. This option is useful when e.g. running `smoother2histval` on the results of the Kalman smoother.

**consider_only_observed**

Compute the posterior moments, smoothed variables, k-step ahead filtered variables and forecasts (when requested) on all the observed variables. This is equivalent to manually listing all the observed variables after the estimation command.

**number_of_particles = INTEGER**

Number of particles used when evaluating the likelihood of a non linear state space model. Default: 1000.

**resampling = OPTION**

Determines if resampling of the particles is done. Possible values for `OPTION` are:
none
No resampling.
systematic
Resampling at each iteration, this is the default value.
generic
Resampling if and only if the effective sample size is below a certain level defined by resampling_threshold * number_of_particles.

resampling_threshold = DOUBLE
A real number between zero and one. The resampling step is triggered as soon as the effective number of particles is less than this number times the total number of particles (as set by number_of_particles). This option is effective if and only if option resampling has value generic.

resampling_method = OPTION
Sets the resampling method. Possible values for OPTION are: kitagawa, stratified and smooth.

filter_algorithm = OPTION
Sets the particle filter algorithm. Possible values for OPTION are:
sis
Sequential importance sampling algorithm, this is the default value.
apf
Auxiliary particle filter.
gf
Gaussian filter.
gmf
Gaussian mixture filter.
cpf
Conditional particle filter.
nlkf
Use a standard (linear) Kalman filter algorithm with the nonlinear measurement and state equations.

proposal_approximation = OPTION
Sets the method for approximating the proposal distribution. Possible values for OPTION are: cubature, montecarlo and unscented. Default value is unscented.

distribution_approximation = OPTION
Sets the method for approximating the particle distribution. Possible values for OPTION are: cubature, montecarlo and unscented. Default value is unscented.

cpf_weights = OPTION
Controls the method used to update the weights in conditional particle filter, possible values are amisanotristani (Amisano et al. (2010)) or murrayjonesparslow (Murray et al. (2013)). Default value is amisanotristani.

nonlinear_filter_initialization = INTEGER
Sets the initial condition of the nonlinear filters. By default the nonlinear filters are initialized with the unconditional covariance matrix of the state variables, computed with the reduced form solution of the first order approximation of the model. If nonlinear_filter_initialization=2, the nonlinear filter is instead initialized with a covariance matrix estimated with a stochastic simulation of the reduced form solution of the second order approximation of the model. Both these
initializations assume that the model is stationary, and cannot be used if the model has unit roots (which can be seen with the check command prior to estimation). If the model has stochastic trends, user must use nonlinear_filter_initialization=3, the filters are then initialized with an identity matrix for the covariance matrix of the state variables. Default value is nonlinear_filter_initialization=1 (initialization based on the first order approximation of the model).

\textbf{particle_filter_options = (NAME, VALUE, ...)}

A list of NAME and VALUE pairs. Can be used to set some fine-grained options for the particle filter routines. The set of available options depends on the selected filter routine.

More information on particle filter options is available at https://git.dynare.org/Dynare/dynare/-/wikis/Particle-filters.

Available options are:

'pruning'

Enable pruning for particle filter-related simulations. Default: false.

'liu_west_delta'

Set the value for delta for the Liu/West online filter. Default: 0.99.

'unstcetved_alpha'

Set the value for alpha for unscented transforms. Default: 1.

'unstctved_beta'

Set the value for beta for unscented transforms. Default: 2.

'unstctved_kappa'

Set the value for kappa for unscented transforms. Default: 1.

'initial_state_prior_std'

Value of the diagonal elements for the initial covariance of the state variables when employing nonlinear_filter_initialization=3. Default: 1.

'mixture_state_variables'

Number of mixture components in the Gaussian-mixture filter (gmf) for the state variables. Default: 5.

'mixture_structural_shocks'

Number of mixture components in the Gaussian-mixture filter (gmf) for the structural shocks. Default: 1.

'mixture_measurement_shocks'

Number of mixture components in the Gaussian-mixture filter (gmf) for the measurement errors. Default: 1.

\textit{Note}

If no \texttt{mh_jscale} parameter is used for a parameter in \texttt{estimated_params}, the procedure uses \texttt{mh_jscale} for all parameters. If \texttt{mh_jscale} option isn’t set, the procedure uses 0.2 for all parameters. Note that if \texttt{mode_compute}=6 is used or the \texttt{posterior_sampler_option} called \texttt{scale_file} is specified, the values set in \texttt{estimated_params} will be overwritten.

\textit{“Endogenous” prior restrictions}

It is also possible to impose implicit “endogenous” priors about IRFs and moments on the model during estimation. For example, one can specify that all valid parameter draws for the model must generate fiscal multipliers that are bigger than 1 by specifying how the IRF to a government spending shock must look like. The prior restrictions can be imposed via \texttt{irf_calibration} and \texttt{moment_calibration} blocks (see \textit{IRF/Moment calibration}). The way it works internally is that any parameter draw that is inconsistent with
the “calibration” provided in these blocks is discarded, i.e. assigned a prior density of 0. When specifying these blocks, it is important to keep in mind that one won’t be able to easily do model comparison in this case, because the prior density will not integrate to 1.

**Output**

After running estimation, the parameters `M_.params` and the variance matrix `M_.Sigma_e` of the shocks are set to the mode for maximum likelihood estimation or posterior mode computation without Metropolis iterations. After estimation with Metropolis iterations (option `mh_replic > 0` or option `load_mh_file` set) the parameters `M_.params` and the variance matrix `M_.Sigma_e` of the shocks are set to the posterior mean.

Depending on the options, estimation stores results in various fields of the oo_.structure, described below. In the following variables, we will adopt the following shortcuts for specific field names:

### MOMENT_NAME

This field can take the following values:

- **HPDinf**
  - Lower bound of a 90% HPD interval.\(^4\)

- **HPDsup**
  - Upper bound of a 90% HPD interval.

- **HPDinf_ME**
  - Lower bound of a 90% HPD interval for observables when taking measurement error into account (see e.g. Christoffel et al. (2010), p.17).

- **HPDsup_ME**
  - Upper bound of a 90% HPD interval for observables when taking measurement error into account.

- **Mean**
  - Mean of the posterior distribution.

- **Median**
  - Median of the posterior distribution.

- **Std**
  - Standard deviation of the posterior distribution.

- **Variance**
  - Variance of the posterior distribution.

- **deciles**
  - Deciles of the distribution.

- **density**
  - Non parametric estimate of the posterior density following the approach outlined in Skoeld and Roberts (2003). First and second columns are respectively abscissa and ordinate coordinates.

### ESTIMATED_OBJECT

This field can take the following values:

- **measurement_errors_corr**
  - Correlation between two measurement errors.

---

\(^4\) See options `conf_sig` and `mh_conf_sig` to change the size of the HPD interval.

\(^5\) See options `conf_sig()` and `mh_conf_sig()` to change the size of the HPD interval.
measurement_errors_std
   Standard deviation of measurement errors.
parameters
   Parameters.
shocks_corr
   Correlation between two structural shocks.
shocks_std
   Standard deviation of structural shocks.

MATLAB/Octave variable: oo_.MarginalDensity.LaplaceApproximation
   Variable set by the estimation command. Stores the marginal data density based on the Laplace Approximation.

MATLAB/Octave variable: oo_.MarginalDensity.ModifiedHarmonicMean
   Variable set by the estimation command, if it is used with mh_replic > 0 or load_mh_file option. Stores the marginal data density based on Geweke (1999) Modified Harmonic Mean estimator.

MATLAB/Octave variable: oo_.posterior.optimization
   Variable set by the estimation command if mode-finding is used. Stores the results at the mode. Fields are of the form:

   oo_.posterior.optimization.OBJECT

   where OBJECT is one of the following:

   mode
      Parameter vector at the mode.
   Variance
      Inverse Hessian matrix at the mode or MCMC jumping covariance matrix when used with the MCMC_jumping_covariance option.
   log_density
      Log likelihood (ML)/log posterior density (Bayesian) at the mode when used with mode_compute>0.

MATLAB/Octave variable: oo_.posterior.metropolis
   Variable set by the estimation command if mh_replic>0 is used. Fields are of the form:

   oo_.posterior.metropolis.OBJECT

   where OBJECT is one of the following:

   mean
      Mean parameter vector from the MCMC.
   Variance
      Covariance matrix of the parameter draws in the MCMC.

MATLAB/Octave variable: oo_.FilteredVariables
   Variable set by the estimation command, if it is used with the filtered_vars option. After an estimation without Metropolis, fields are of the form:

   oo_.FilteredVariables.VARIABLE_NAME

   After an estimation with Metropolis, fields are of the form:
MATLAB/Octave variable: `oo_.FilteredVariablesKStepAhead`

Variable set by the `estimation` command, if it is used with the `filter_step_ahead` option. The k-steps are stored along the rows while the columns indicate the respective variables. The third dimension of the array provides the observation for which the forecast has been made. For example, if `filter_step_ahead=[1 2 4]` and `nobs=200`, the element `(3,5,204)` stores the four period ahead filtered value of variable 5 computed at time `t=200` for time `t=204`. The periods at the beginning and end of the sample for which no forecasts can be made, e.g. entries `(1,5,1)` and `(1,5,204)` in the example, are set to zero. Note that in case of Bayesian estimation the variables will be ordered in the order of declaration after the estimation command (or in general declaration order if no variables are specified here). In case of running the classical smoother, the variables will always be ordered in general declaration order. If the `selected_variables_only` option is specified with the classical smoother, non-requested variables will be simply left out in this order.

MATLAB/Octave variable: `oo_.FilteredVariablesKStepAheadVariances`

Variable set by the `estimation` command, if it is used with the `filter_step_ahead` option. It is a 4 dimensional array where the k-steps are stored along the first dimension, while the fourth dimension of the array provides the observation for which the forecast has been made. The second and third dimension provide the respective variables. For example, if `filter_step_ahead=[1 2 4]` and `nobs=200`, the element `(3,4,5,204)` stores the four period ahead forecast error covariance between variable 4 and variable 5, computed at time `t=200` for time `t=204`. Padding with zeros and variable ordering is analogous to `oo_.FilteredVariablesKStepAhead`.

MATLAB/Octave variable: `oo_.Filtered_Variables_X_step_ahead`

Variable set by the `estimation` command, if it is used with the `filter_step_ahead` option in the context of Bayesian estimation. Fields are of the form:

`oo_.Filtered_Variables_X_step_ahead.VARIABLE_NAME`

The n-th entry stores the k-step ahead filtered variable computed at time `n` for time `n+k`.

MATLAB/Octave variable: `oo_.FilteredVariablesShockDecomposition`

Variable set by the `estimation` command, if it is used with the `filter_step_ahead` option. The k-steps are stored along the rows while the columns indicate the respective variables. The third dimension corresponds to the shocks in declaration order. The fourth dimension of the array provides the observation for which the forecast has been made. For example, if `filter_step_ahead=[1 2 4]` and `nobs=200`, the element `(3,5,2,204)` stores the contribution of the second shock to the four period ahead filtered value of variable 5 (in deviations from the mean) computed at time `t=200` for time `t=204`. The periods at the beginning and end of the sample for which no forecasts can be made, e.g. entries `(1,5,1)` and `(1,5,204)` in the example, are set to zero. Padding with zeros and variable ordering is analogous to `oo_.FilteredVariablesKStepAhead`.

MATLAB/Octave variable: `oo_.PosteriorIRF.dsge`

Variable set by the `estimation` command, if it is used with the `bayesian_irf` option. Fields are of the form:

`oo_.PosteriorIRF.dsge.MOMENT_NAME.VARIABLE_NAME_SHOCK_NAME`

MATLAB/Octave variable: `oo_.SmoothedMeasurementErrors`

Variable set by the `estimation` command, if it is used with the `smoother` option. Fields are of the form:

`oo_.SmoothedMeasurementErrors.VARIABLE_NAME`

MATLAB/Octave variable: `oo_.SmoothedShocks`

Variable set by the `estimation` command (if used with the `smoother` option), or by the `calib_smoother` command.
After an estimation without Metropolis, or if computed by calib_smoother, fields are of the form:

```
oo_.SmoothedShocks.VARIABLE_NAME
```

After an estimation with Metropolis, fields are of the form:

```
oo_.SmoothedShocks.MOMENT_NAME.VARIABLE_NAME
```

**MATLAB/Octave variable: oo_.SmoothedVariables**

Variable set by the estimation command (if used with the smoother option), or by the calib_smoother command.

After an estimation without Metropolis, or if computed by calib_smoother, fields are of the form:

```
oo_.SmoothedVariables.VARIABLE_NAME
```

After an estimation with Metropolis, fields are of the form:

```
oo_.SmoothedVariables.MOMENT_NAME.VARIABLE_NAME
```

**MATLAB/Octave command: get_smooth('VARIABLE_NAME' [, 'VARIABLE_NAME']...);**

Returns the smoothed values of the given endogenous or exogenous variable(s), as they are stored in the oo_.SmoothedVariables and oo_.SmoothedShocks variables.

**MATLAB/Octave variable: oo_.UpdatedVariables**

Variable set by the estimation command (if used with the smoother option), or by the calib_smoother command. Contains the estimation of the expected value of variables given the information available at the current date.

After an estimation without Metropolis, or if computed by calib_smoother, fields are of the form:

```
oo_.UpdatedVariables.VARIABLE_NAME
```

After an estimation with Metropolis, fields are of the form:

```
oo_.UpdatedVariables.MOMENT_NAME.VARIABLE_NAME
```

**MATLAB/Octave command: get_update('VARIABLE_NAME' [, 'VARIABLE_NAME']...);**

Returns the updated values of the given variable(s), as they are stored in the oo_.UpdatedVariables variable.

**MATLAB/Octave variable: oo_.FilterCovariance**

Three-dimensional array set by the estimation command if used with the smoother and Metropolis, if the filter_covariance option has been requested. Contains the series of one-step ahead forecast error covariance matrices from the Kalman smoother. The $M_.endo_nbr$ times $M_.endo_nbr$ times $T+1$ array contains the variables in declaration order along the first two dimensions. The third dimension of the array provides the observation for which the forecast has been made. Fields are of the form:

```
oo_.FilterCovariance.MOMENT_NAME
```

Note that density estimation is not supported.

**MATLAB/Octave variable: oo_.Smoother.Variance**

Three-dimensional array set by the estimation command (if used with the smoother) without Metropolis, or by the calib_smoother command, if the filter_covariance option has been requested. Contains the series of one-step ahead forecast error covariance matrices from the Kalman smoother. The $M_.endo_nbr$ times $M_.endo_nbr$ times $T+1$ array contains the variables in declaration order along the first two dimensions. The third dimension of the array provides the observation for which the forecast has been made.

4.15. Estimation based on likelihood
MATLAB/Octave variable: oo_.Smoother.State_uncertainty

Three-dimensional array set by the estimation command (if used with the smoother option) without Metropolis, or by the calib_smoother command, if the smoothed_state_uncertainty option has been requested. Contains the series of covariance matrices for the state estimate given the full data from the Kalman smoother. The M_.endo_nbr times M_.endo_nbr times T array contains the variables in declaration order along the first two dimensions. The third dimension of the array provides the observation for which the smoothed estimate has been made.

MATLAB/Octave variable: oo_.Smoother.SteadyState

Variable set by the estimation command (if used with the smoother) without Metropolis, or by the calib_smoother command. Contains the steady state component of the endogenous variables used in the smoother in order of variable declaration.

MATLAB/Octave variable: oo_.Smoother.TrendCoeffs

Variable set by the estimation command (if used with the smoother) without Metropolis, or by the calib_smoother command. Contains the trend coefficients of the observed variables used in the smoother in order of declaration of the observed variables.

MATLAB/Octave variable: oo_.Smoother.Trend

Variable set by the estimation command (if used with the smoother option), or by the calib_smoother command. Contains the trend component of the variables used in the smoother.

Fields are of the form:

| oo_.Smoother.Trend.VARIABLE_NAME |

MATLAB/Octave variable: oo_.Smoother.Constant

Variable set by the estimation command (if used with the smoother option), or by the calib_smoother command. Contains the constant part of the endogenous variables used in the smoother, accounting e.g. for the data mean when using the prefilter option.

Fields are of the form:

| oo_.Smoother.Constant.VARIABLE_NAME |

MATLAB/Octave variable: oo_.Smoother.loglinear

Indicator keeping track of whether the smoother was run with the loglinear option and thus whether stored smoothed objects are in logs.

MATLAB/Octave variable: oo_.PosteriorTheoreticalMoments

Variable set by the estimation command, if it is used with the moments_varendo option. Fields are of the form:

| oo_.PosteriorTheoreticalMoments.dsge.THEORETICAL_MOMENT.ESTIMATED_OBJECT._MOMENT_NAME.VARIABLE_NAME |

where THEORETICAL_MOMENT is one of the following:

- covariance
  - Variance-covariance of endogenous variables.
- contemporaneous_correlation
  - Contemporaneous correlation of endogenous variables when the contemporaneous_correlation option is specified.
- correlation
  - Auto- and cross-correlation of endogenous variables. Fields are vectors with correlations from 1 up to order options_.ar.
- VarianceDecomposition
Decomposition of variance (unconditional variance, i.e. at horizon infinity).\(^6\)

**VarianceDecompositionME**

Same as **VarianceDecomposition**, but contains the decomposition of the measured as opposed to the actual variable. The joint contribution of the measurement error will be saved in a field named **ME**.

**ConditionalVarianceDecomposition**

Only if the **conditional_variance_decomposition** option has been specified. In the presence of measurement error, the field will contain the variance contribution after measurement error has been taken out, i.e. the decomposition will be conducted of the actual as opposed to the measured variables.

**ConditionalVarianceDecompositionME**

Only if the **conditional_variance_decomposition** option has been specified. Same as **ConditionalVarianceDecomposition**, but contains the decomposition of the measured as opposed to the actual variable. The joint contribution of the measurement error will be saved in a field names **ME**.

**MATLAB/Octave variable: oo_.posterior_density**

Variable set by the estimation command, if it is used with \( mh\_replic > 0 \) or \( load\_mh\_file \) option. Fields are of the form:

\[
\text{oo\_.posterior\_density.\text{PARAMETER\_NAME}}
\]

**MATLAB/Octave variable: oo_.posterior_hpdinf**

Variable set by the estimation command, if it is used with \( mh\_replic > 0 \) or \( load\_mh\_file \) option. Fields are of the form:

\[
\text{oo\_.posterior\_hpdinf.\text{ESTIMATED\_OBJECT.VARIABLE\_NAME}}
\]

**MATLAB/Octave variable: oo_.posterior_hpdsup**

Variable set by the estimation command, if it is used with \( mh\_replic > 0 \) or \( load\_mh\_file \) option. Fields are of the form:

\[
\text{oo\_.posterior\_hpdsup.\text{ESTIMATED\_OBJECT.VARIABLE\_NAME}}
\]

**MATLAB/Octave variable: oo_.posterior_mean**

Variable set by the estimation command, if it is used with \( mh\_replic > 0 \) or \( load\_mh\_file \) option. Fields are of the form:

\[
\text{oo\_.posterior\_mean.\text{ESTIMATED\_OBJECT.VARIABLE\_NAME}}
\]

**MATLAB/Octave variable: oo_.posterior_mode**

Variable set by the estimation command during mode-finding. Fields are of the form:

\[
\text{oo\_.posterior\_mode.\text{ESTIMATED\_OBJECT.VARIABLE\_NAME}}
\]

**MATLAB/Octave variable: oo_.posterior_std_at_mode**

Variable set by the estimation command during mode-finding. It is based on the inverse Hessian at \( oo\_.posterior\_mode \). Fields are of the form:

\[
\text{oo\_.posterior\_std\_at\_mode.\text{ESTIMATED\_OBJECT.VARIABLE\_NAME}}
\]

---

\(^6\) When the shocks are correlated, it is the decomposition of orthogonalized shocks via Cholesky decomposition according to the order of declaration of shocks (see **Variable declarations**).
**MATLAB/Octave variable: oo_.posterior_std**

Variable set by the estimation command, if it is used with `mh_replic > 0` or `load_mh_file` option. Fields are of the form:

```
oo_.posterior_std.ESTIMATED_OBJECT.VARIABLE_NAME
```

**MATLAB/Octave variable: oo_.posterior_var**

Variable set by the estimation command, if it is used with `mh_replic > 0` or `load_mh_file` option. Fields are of the form:

```
oo_.posterior_var.ESTIMATED_OBJECT.VARIABLE_NAME
```

**MATLAB/Octave variable: oo_.posterior_median**

Variable set by the estimation command, if it is used with `mh_replic > 0` or `load_mh_file` option. Fields are of the form:

```
oo_.posterior_median.ESTIMATED_OBJECT.VARIABLE_NAME
```

**Example**

Here are some examples of generated variables:

```
oo_.posterior_mode.parameters.alp
oo_.posterior_mean.shocks_std.ex
oo_.posterior_hpdsup.measurement_errors_corr.gdp_conso
```

**MATLAB/Octave variable: oo_.dsge_var.posterior_mode**

Structure set by the `dsge_var` option of the estimation command after `mode_compute`.

The following fields are saved:

- `PHI_tilde`
  Stacked posterior DSGE-BVAR autoregressive matrices at the mode (equation (28) of Del Negro and Schorfheide (2004)).

- `SIGMA_u_tilde`
  Posterior covariance matrix of the DSGE-BVAR at the mode (equation (29) of Del Negro and Schorfheide (2004)).

- `iXX`
  Posterior population moments in the DSGE-BVAR at the mode ($inv(\lambda T)_{XX} + X'X$).

- `prior`
  Structure storing the DSGE-BVAR prior.

- `PHI_star`
  Stacked prior DSGE-BVAR autoregressive matrices at the mode (equation (22) of Del Negro and Schorfheide (2004)).

- `SIGMA_star`
  Prior covariance matrix of the DSGE-BVAR at the mode (equation (23) of Del Negro and Schorfheide (2004)).

- `ArtificialSampleSize`
  Size of the artificial prior sample ($inv(\lambda T)$).

- `DF`
  Prior degrees of freedom ($inv(\lambda T − k − n)$).
iGXX_star

Inverse of the theoretical prior “covariance” between X and X ($\Gamma_{\alpha}^{-1}$ in Del Negro and Schorfheide (2004)).

**MATLAB/Octave variable: oo_.RecursiveForecast**

Variable set by the forecast option of the estimation command when used with the `nobs` = [INTEGER1:INTEGER2] option (see `nobs`).

Fields are of the form:

\[
\text{oo_.RecursiveForecast.FORECAST_OBJECT.VARIABLE_NAME}
\]

where FORECAST_OBJECT is one of the following:

- **Mean**
  Mean of the posterior forecast distribution.

- **HPDinf/HPDsup**
  Upper/lower bound of the 90% HPD interval taking into account only parameter uncertainty (corresponding to `oo_.MeanForecast`).

- **HPDTotalinf/HPDTotalsup**
  Upper/lower bound of the 90% HPD interval taking into account both parameter and future shock uncertainty (corresponding to `oo_.PointForecast`).

VARIABLE_NAME contains a matrix of the following size: number of time periods for which forecasts are requested using the `nobs` = [INTEGER1:INTEGER2] option times the number of forecast horizons requested by the forecast option. i.e., the row indicates the period at which the forecast is performed and the column the respective k-step ahead forecast. The starting periods are sorted in ascending order, not in declaration order.

**MATLAB/Octave variable: oo_.convergence.geweke**

Variable set by the convergence diagnostics of the estimation command. There is a subfield in the struct array for each MCMC chain.

Fields are of the form:

\[
\text{oo_.convergence.geweke.VARIABLE_NAME.DIAGNOSTIC_OBJECT}
\]

where DIAGNOSTIC_OBJECT is one of the following:

- **posteriormean**
  Mean of the posterior parameter distribution.

- **posteriorstd**
  Standard deviation of the posterior parameter distribution.

- **nse_iid**
  Numerical standard error (NSE) under the assumption of iid draws.

- **rne_iid**
  Relative numerical efficiency (RNE) under the assumption of iid draws.

- **nse_taper_x**
  Numerical standard error (NSE) when using an x% taper.

- **rne_taper_x**
  Relative numerical efficiency (RNE) when using an x% taper.

---

7 See `forecast` for more information.
pooled_mean

Mean of the parameter when pooling the beginning and end parts of the chain specified in geweke_interval and weighting them with their relative precision. It is a vector containing the results under the iid assumption followed by the ones using the taper_steps option (see taper_steps).

pooled_nse

NSE of the parameter when pooling the beginning and end parts of the chain and weighting them with their relative precision. See pooled_mean.

prob_chi2_test

p-value of a chi-squared test for equality of means in the beginning and the end of the MCMC chain. See pooled_mean. A value above 0.05 indicates that the null hypothesis of equal means and thus convergence cannot be rejected at the 5 percent level. Differing values along the taper_steps signal the presence of significant autocorrelation in draws. In this case, the estimates using a higher tapering are usually more reliable.

MATLAB/Octave variable: oo_.convergence.raftery_lewis

Variable set by the convergence diagnostics of the estimation command when used with raftery_lewis_diagnostics option (see raftery_lewis_diagnostics). There is a subfield in the struct array for each MCMC chain. Contains the results of the test in individual fields.

Command: unit_root_vars VARIABLE_NAME...;

This command is deprecated. Use estimation option diffuse_filter instead for estimating a model with non-stationary observed variables or steady option nocheck to prevent steady to check the steady state returned by your steady state file.

Dynare also has the ability to estimate Bayesian VARs:

Command: bvar_density;

Computes the marginal density of an estimated BVAR model, using Minnesota priors.
See bvar-a-la-sims.pdf, which comes with Dynare distribution, for more information on this command.

Command: bvar_irf;

Computes the impulse responses of an estimated BVAR model, using Minnesota priors.
See bvar-a-la-sims.pdf, which comes with Dynare distribution, for more information on this command.

4.16 Estimation based on moments

Provided that you have observations on some endogenous variables or their dynamic behavior following structural shocks, Dynare provides a suite of tools for parameter estimation utilizing the method of moments approach. This includes the Simulated Method of Moments (SMM), the Generalized Method of Moments (GMM), and ImpulseResponseFunctionMatching(IRFmatching). Each of these methods offers a distinct strategy for estimating some or all parameters by minimizing the distances between unconditional model objects (moments or impulse responses) and their empirical counterparts.

GMM and SMM estimation

For SMM Dynare computes model moments via stochastic simulations based on the perturbation approximation up to any order, whereas for GMM model moments are computed in closed-form based on the pruned state-space representation of the perturbation solution up to third order. The implementation of SMM is inspired by Born and Pfeifer (2014) and Ruge-Murcia (2012), whereas the one for GMM is adapted from Andreasen, Fernández-Villaverde and Rubio-Ramírez (2018) and Mutschler (2018). Successful estimation heavily relies on the accuracy and efficiency of the perturbation approximation, so it is advised to tune this as much as possible (see Computing the stochastic solution). The method of moments estimator is consistent and asymptotically normally distributed given certain regularity conditions (see Duffie and Singleton (1993) for SMM and Hansen (1982) for GMM). For instance, it is required to have at least as many moment conditions as estimated parameters (over-identified or just
identified). Moreover, the Jacobian of the moments with respect to the estimated parameters needs to have full rank. Performing identification analysis helps to check this regularity condition.

In the over-identified case of declaring more moment conditions than estimated parameters, the choice of `weighting_matrix` matters for the efficiency of the estimation, because the estimated orthogonality conditions are random variables with unequal variances and usually non-zero cross-moment covariances. A weighting matrix allows to re-weight moments to put more emphasis on moment conditions that are more informative or better measured (in the sense of having a smaller variance). To achieve asymptotic efficiency, the weighting matrix needs to be chosen such that, after appropriate scaling, it has a probability limit proportional to the inverse of the covariance matrix of the limiting distribution of the vector of orthogonality conditions. Dynare uses a Newey-West-type estimator with a Bartlett kernel to compute an estimate of this so-called optimal weighting matrix. Note that in this over-identified case, it is advised to perform the estimation in at least two stages by setting e.g. `weighting_matrix=['DIAGONAL','DIAGONAL']` so that the computation of the optimal weighting matrix benefits from the consistent estimation of the previous stages. The optimal weighting matrix is used to compute standard errors and the J-test of overidentifying restrictions, which tests whether the model and selection of moment conditions fits the data sufficiently well. If the null hypothesis of a “valid” model is rejected, then something is (most likely) wrong with either your model or selection of orthogonality conditions.

In case the (presumed) global minimum of the moment distance function is located in a region of the parameter space that is typically considered unlikely (dilemma of absurd parameters), you may opt to choose the `penalized_estimator` option. Similar to adding priors to the likelihood, this option incorporates prior knowledge (i.e. the prior mean) as additional moment restrictions and weights them by their prior precision to guide the minimization algorithm to more plausible regions of the parameter space. Ideally, these regions are characterized by only slightly worse values of the objective function. Note that adding prior information comes at the cost of a loss in efficiency of the estimator.

**IRF matching**

Dynare employs a user-specified `simulation_method` to compute the impulse response function (IRF) for observable variables with respect to the structural shocks. Currently, only stochastic simulations based on the perturbation method are supported and it is advised to fine-tune the perturbation approximation as much as possible for optimal results (see Computing the stochastic solution for guidance).

The core idea of IRF matching is then to treat empirical impulse responses (e.g. given from a SVAR or local projection estimation) as data and select model parameters that align the model’s IRFs closely with their empirical counterparts. Dynare supports both Frequentist and Bayesian IRF matching approaches, using the same optimization and sampling techniques as those applied in likelihood-based estimation (sharing many options with the `estimation command`). The Frequentist approach to this is inspired by the work of Christiano, Eichenbaum, and Evans (2005), while the Bayesian method adapts from Christiano, Trabandt, and Walentin (2010). A crucial element in IRF matching is the choice of the weighting matrix, which influences how the distances between model-generated and empirical IRFs are weighted in the estimation process. It is common practice to employ a diagonal weighting matrix, with the diagonal elements set to the inverse of the estimated variance of the respective empirical impulse response, thereby prioritizing more precisely estimated IRFs. While it’s possible to also specify weights using covariances between different IRF components (possibly with shrinking), this is less common due to the complex interpretation involved (cross effects of different variables or different shocks or both).

Importantly, it is the user’s responsibility to supply (1) the values of the empirical IRFs intended for matching and (2) their importance by choosing an appropriate weighting matrix. Dynare does not perform the SVAR or local projection estimation, it treats the empirical IRFs as given.
4.16.1 Method of moments specific blocks

Command: varobs VARIABLE_NAME...;

Required. All variables used in the matched_moments, matched_irfs, or matched_irfs_weights block need to be observable. See varobs for more details.

Block: matched_moments;

This block specifies the product moments which are used in estimation. Currently, only linear product moments (e.g. $E[y_t], E[y_t^2], E[x_t y_t], E[y_t y_{t-1}], E[y_t^2 x_t^2]$) are supported. For other functions like $E[\log(y_t) e^{x_t}]$ you need to declare auxiliary endogenous variables.

Each line inside of the block should be of the form:

```
VARIABLE_NAME(LEAD/LAG)^POWER*VARIABLE_NAME(LEAD/LAG)^POWER*...*VARIABLE_NAME(LEAD/LAG)^POWER;
```

where VARIABLE_NAME is the name of a declared observable variable, LEAD/LAG is either a negative integer for lags or a positive one for leads, and POWER is a positive integer indicating the exponent on the variable. You can omit LEAD/LAG equal to 0 or POWER equal to 1.

Example

For $E[c_t], E[y_t], E[c_t^2], E[c_t y_t], E[y_t^2], E[c_t c_{t+3}], E[y_t^2 c_t^2], E[c_t^2 y_t^2]$, use the following block:

```
matched_moments;
c;
y;
c*c;
c*y;
y^2;
c*c(3);
y(1)^2*c(-4)^3;
c(-5)^3*y(0)^2;
end;
```

Limitations

1. For GMM, Dynare can only compute the theoretical mean, covariance, and autocovariances (i.e. first and second moments). Higher-order moments are only supported for SMM.

2. By default, the product moments are not demeaned, unless the prefilteter option is set to 1. That is, by default, $c^c$ corresponds to $E[c_t^2]$ and not to $Var[c_t] = E[c_t^2] - E[c_t]^2$.

Output

Dynare translates the matched_moments block into a cell array M_.matched_moments where:

- the first column contains a vector of indices for the chosen variables in declaration order
- the second column contains the corresponding vector of leads and lags
- the third column contains the corresponding vector of powers

During the estimation phase, Dynare will eliminate all redundant or duplicate orthogonality conditions in M_.matched_moments and display which conditions were removed. In the example above, this would be the case for the last row, which is the same as the second-to-last one. The original block is saved in M_.matched_moments_orig.

Block: matched_irfs;

Block: matched_irfs(overwrite);

This block specifies the values and diagonal weights of the empirical IRFs that are matched in estimation. The overwrite option replaces the current matched_irfs block with the new one.

Each line inside of the block should be of the form:
\begin{verbatim}
var ENDOGENOUS_NAME;
varxo EXOGENOUS_NAME;
periods INTEGER[:INTEGER] [, INTEGER[:INTEGER]]...;
values DOUBLE | (EXPRESSION) [, DOUBLE | (EXPRESSION)]...;
weights DOUBLE | (EXPRESSION) [, DOUBLE | (EXPRESSION)]...;
\end{verbatim}

ENDOGENOUS_NAME is the name of a declared observable variable, whereas EXOGENOUS_NAME is the name of an exogenous variable. It is possible to specify individual horizons or a range of specified periods as lists with the periods keyword. Note that for each entry a corresponding entry in values needs to be provided; that is values is a list of the same length as periods. If only one value is specified, it is used at all corresponding periods in the list. weights are optional and specify the diagonal element of the corresponding entry in the weighting matrix. Typically, these are set to the inverse of the variance of the empirical IRF. If only one weight is specified, it is used at all corresponding periods in the list. If not specified, the weight defaults to 1. For values and weights you can use expressions (e.g. variables or anonymous functions in the workspace) by putting paranthesis around them. A new statement is started with either the var or varexo keyword.

Example You can either enter the values directly or load them from variables in the workspace.

\begin{verbatim}
::
  \% MATLAB expressions that can be used xx = [23,24,25]; ww = [51,52]; irfs_eR = @(j) IRFFF(2:15,j); \% gdp is the 3th column of IRFFF weights_eR = @(j) 1./(IRFFFSE(2:15,j).^2); R_eR = IRFFF(1:15,3); weight_R_eR = 1./(IRFFFSE(1:15,3).^2);
  matched_irfs; var gdp; varexo eR; periods 2:15; values (irfs_eR(3)); weights (weights_eR(3));
  var R; varexo eR; periods 1:15; values (R_eR); weights (weight_R_eR);
  var y; varexo eD; periods 5; values 7; weights 25;
  var r; varexo eD; periods 1:2; values 17,18; weights 37,38;
  var c; varexo eA; periods 3:5; values (xx);
  var y; varexo eA; periods 1:2; values 30; weights (ww);
  varexo eR; var w; periods 1, 13:15, 2:12; values 2, (xx), 15; weights 3, (xx), 4; end;
\end{verbatim}

Limitations

Output

Dynare translates the matched_irfs block into a cell array where the rows correspond to the statements in the block M_.matched_irfs where:

- the first column contains the names of the endogenous variables
- the second column contains the names of the exogenous variables
- the third column contains a nested cell array that contains

the list of horizons, values and weights.

Block: matched_irfs_weights

Block: matched_irfs_weights(overwrite);

This optional block specifies elements of the weighting matrix used for IRF matching. The overwrite option replaces the current matched_irfs_weights block with the new one.

The weighting matrix is initialized as a diagonal matrix with ones on the diagonal. Each line inside of the block should be of the form:

\begin{verbatim}
  ENDOGENOUS_NAME_1(HORIZON_1), EXOGENOUS_NAME_1, ENDOGENOUS_NAME_2(HORIZON_2), ...
  \_EXOGENOUS_NAME_2, WEIGHT;
\end{verbatim}

where ENDOGENOUS_NAME_1 and ENDOGENOUS_NAME_2 are the names of declared observable variables, EXOGENOUS_NAME_1 and EXOGENOUS_NAME_2 are the names of exogenous variables, HORIZON_1 and HORIZON_2 are integers indicating the horizon of the IRFs and WEIGHT is a double value of the weight one wants to assign to the covariance between the two specified IRFs.

Example You can either enter the values directly or load them from variables in the workspace.
Limitations

Output

Dynare translates the `matched_irfs_weights` block into a cell array `M_.matched_irfs_weights` where:

- the first column contains the names of the first endogenous variables
- the second column contains the names of the first exogenous variables
- the third column contains the horizons of the IRFs for the first endogenous variable
- the fourth column contains the names of the second endogenous variables
- the fifth column contains the names of the second exogenous variables
- the sixth column contains the horizons of IRFs for the second endogenous variable
- the seventh column contains the vector of weights

All values that are not specified will be either one (if they are on the diagonal) or zero (if they are not on the diagonal). Symmetry is respected, so one does not need to specify both `c(1), e_A, y(3), e_R, WEIGHT` and `y(3), e_R, c(1), e_A, WEIGHT`. Default: empty cell.

Block: `estimated_params`

Required. This block lists all parameters to be estimated and specifies bounds and priors as necessary. See `estimated_params` for details and syntax.

Block: `estimated_params_init`

Optional. This block declares numerical initial values for the optimizer when these ones are different from the prior mean. See `estimated_params_init` for details and syntax.

Block: `estimated_params_bounds`

Optional. This block declares lower and upper bounds for parameters in maximum likelihood estimation. See `estimated_params_bounds` for details and syntax.

4.16.2 method_of_moments command

Command: `method_of_moments(OPTIONS...)`

This command runs the method of moments estimation. The following information will be displayed in the command window:

- Overview of options chosen by the user
- Estimation results for each stage and iteration
- Value of minimized moment distance objective function
- Result of the J-test (for SMM/GMM)
- Comparison plot of model IRFs and empirical IRFs (for IRF matching)
- Table of data moments/IRFs and estimated model moments/IRFs
4.16.2.1 Necessary Options

\[ \text{mom\_method} = \text{SMM|GMM|IRF\_MATCHING} \]

“Simulated Method of Moments” is triggered by SMM, “Generalized Method of Moments” by GMM and “Impulse Response Function Matching” by IRF\_MATCHING.

\[ \text{datafile} = \text{FILENAME} \]

The name of the file containing the data (for GMM and SMM only). See datafile for the meaning and syntax. For IRF matching, the data is specified in the matched\_irfs block.

4.16.2.2 Common Options

\[ \text{order} = \text{INTEGER} \]

Order of perturbation approximation. For GMM only orders 1|2|3 are supported. For SMM and IRF matching, you can choose an arbitrary order. Note that the order set in other functions will not overwrite the default. Default: 1.

\[ \text{pruning} \]

Discard higher order terms when iteratively computing simulations of the solution. See pruning for more details. Default: not set for SMM and IRF matching, always set for GMM.

\[ \text{verbose} \]

Display and store intermediate estimation results in oo_.mom. Default: not set.

Common options for SMM and GMM

\[ \text{penalized\_estimator} \]

This option includes deviations of the estimated parameters from the prior mean as additional moment restrictions and weights them by their prior precision. Default: not set.

\[ \text{weighting\_matrix} = [\text{WM1}', \text{WM2}', \ldots, \text{WMn}'] \]

Determines the weighting matrix used at each estimation stage. The number of elements will define the number of stages, i.e. weighting\_matrix = ['DIAGONAL', 'OPTIMAL', 'IDENTITY\_MATRIX'] performs a three-stage estimation. Possible values for WM are:

IDENTITY\_MATRIX

Sets the weighting matrix equal to the identity matrix.

OPTIMAL

Uses the optimal weighting matrix computed by a Newey-West-type estimate with a Bartlett kernel. At the first stage, the data-moments are used as initial estimate of the model moments, whereas at subsequent stages the previous estimate of model moments will be used when computing the optimal weighting matrix.

DIAGONAL

Uses the diagonal of the OPTIMAL weighting matrix. This choice puts weights on the specified moments instead of on their linear combinations.

FILENAME

The name of the MAT-file (extension .mat) containing a user-specified weighting matrix. The file must include a positive definite square matrix called weighting\_matrix with both dimensions equal to the number of orthogonality conditions.

Default value is ['DIAGONAL', 'OPTIMAL'].

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weighting_matrix_scaling_factor = DOUBLE
Scaling of weighting matrix in objective function. This value should be chosen to obtain values of
the objective function in a reasonable numerical range to prevent over- and underflows. Default: 1.

bartlett_kernel_lag = INTEGER

se_tolx = DOUBLE
Step size for numerical differentiation when computing standard errors with a two-sided finite
difference method. Default: 1e-5.

4.16.2.3 SMM specific options

burnin = INTEGER
Number of periods dropped at the beginning of simulation. Default: 500.

bounded_shock_support
Trim shocks in simulations to ±2 standard deviations. Default: not set.

seed = INTEGER
Common seed used in simulations. Default: 24051986.

simulation_multiple = INTEGER
Multiple of data length used for simulation. Default: 7.

4.16.2.4 GMM specific options

analytic_standard_errors
Compute standard errors using analytical derivatives of moments with respect to estimated pa-
rameters. Default: not set, i.e. standard errors are computed using a two-sided finite difference
method, see se_tolx.

4.16.2.5 IRF matching specific options

simulation_method = METHOD
Method to compute IRFs. Possible values for METHOD are:

STOCH SIMUL
Simulate the model with stochastic simulations and compute IRFs as the difference
between the simulated and steady state values. See stoch_simul for more details.

irf_matching_file = FILENAME
A MATLAB file containing additional transformations on the model IRFs. This enables more
flexibility in matching the model IRFs to the empirical IRFs, e.g. by adding constants to
model IRFs, multiplying them with factors, taking the cumulative sum, creating ratios etc. See NK_irf_matching_file.m in the examples directory for an example. Default: empty, i.e. model IRFs exactly match empirical IRFs.

add_tiny_number_to_cholesky = DOUBLE
In case of a non-positive definite covariance matrix, a tiny number is added to the Cholesky factor
to avoid numerical problems when computing IRFs. Default: 1e-14.

drop = INTEGER
Truncation when computing IRFs with perturbation at orders greater than 1. Default: 100.
relative_irf
Requests the computation of normalized IRFs. See relative_irf for more details. Default: false.

replic = INTEGER
Number of simulated series used to compute the IRFs. Default: 1 if order=1, and 50 otherwise.

4.16.2.6 General options

dirname = FILENAME

graph_format = FORMAT
Specify the file format(s) for graphs saved to disk. See graph_format for more details. Default: eps.

nodisplay
See nodisplay. Default: not set.
nograph
See nograph. Default: not set.
noprint
See noprint. Default: not set.

plot_priors = INTEGER
Control the plotting of priors. See plot_priors for more details. Default: 1, i.e. plot priors.

prior_trunc = DOUBLE
See prior_trunc for more details. Default: 1e-10.
tex
See tex. Default: not set.

4.16.2.7 Data options

prefilter = INTEGER
A value of 1 means that the estimation procedure will demean each data series by its empirical mean and each model moment by its theoretical mean. See prefilter for more details. Default: 0, i.e. no prefiltering.

first_obs = INTEGER
See first_obs. Default: 1.

nobs = INTEGER
See nobs. Default: all observations are considered.

logdata
See logdata. Default: not set.

xls_sheet = QUOTED_STRING

xls_range = RANGE
See xls_range. Default: empty.
4.16.2.8 Optimization options

**mode_file = FILENAME**
Name of the file containing previous value for the mode. See `mode_file`. Default: empty.

**mode_compute = INTEGER | FUNCTION_NAME**
See `mode_compute`. Default: 13 for GMM and SMM and 5 for IRF matching.

**additional_optimizer_steps = [INTEGER]  
additional_optimizer_steps = [INTEGER1:INTEGER2]  
additional_optimizer_steps = [INTEGER1 INTEGER2]**
Vector of additional minimization algorithms run after `mode_compute`. If `verbose` option is set, then the additional estimation results are saved into the `oo_.mom` structure prefixed with `verbose_`. Default: empty, i.e. no additional optimization iterations.

**optim = (NAME, VALUE, ...)**
See `optim`. Default: empty.

**analytic_jacobian**
Use analytic Jacobian in optimization, only available for GMM and gradient-based optimizers. Default: not set.

**huge_number = DOUBLE**
See `huge_number`. Default: 1e7.

**silent_optimizer**
See `silent_optimizer`. Default: not set.

**use_penalized_objective_for_hessian**
See `use_penalized_objective_for_hessian`. Default: not set.

4.16.2.9 Bayesian estimation options

General options

**posterior_sampling_method = NAME**
See `posterior_sampling_method`. Default: random_walk_metropolis_hastings.

**posterior_sampler_options = (NAME, VALUE, ...)**
See `posterior_sampler_options`. Default: not set.

**mh_posterior_mode_estimation**
See `mh_posterior_mode_estimation`. Default: not set.

**cova_compute = INTEGER**
See `cova_compute`. Default: 1.

**mcmc_jumping_covariance = OPTION**
See `mcmc_jumping_covariance`. Default: hessian.

**mh_replic = INTEGER**
See `mh_replic`. Default: 0.

**mh_nbblocks = INTEGER**
See `mh_nbblocks`. Default: 2.

**mh_jscale = DOUBLE**
See `mh_jscale`. Default: 2.38 divided by the square root of the number of estimated parameters.
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\texttt{mh\_tune\_jscale} \[= \text{DOUBLE}\]

See \texttt{mh\_tune\_jscale}. Default: 0.33.

\texttt{mh\_tune\_guess} = DOUBLE

See \texttt{mh\_tune\_guess}. Default: 2.38 divided by the square root of the number of estimated parameters.

\texttt{mh\_conf\_sig} = DOUBLE

See \texttt{mh\_conf\_sig}. Default: 0.9.

\texttt{mh\_drop} = DOUBLE

See \texttt{mh\_drop}. Default: 0.5.

\texttt{mh\_init\_scale\_factor} = DOUBLE

See \texttt{mh\_init\_scale\_factor}. Default: 2.

\texttt{no\_posterior\_kernel\_density}

See \texttt{no\_posterior\_kernel\_density}. Default: not set.

\texttt{posterior\_max\_subsample\_draws} = INTEGER

See \texttt{posterior\_max\_subsample\_draws}. Default: 1200.

\texttt{sub\_draws} = INTEGER

See \texttt{sub\_draws}. Default: \text{min}(\text{posterior\_max\_subsample\_draws}, (\text{Total number of draws})*\text{(number of chains)})

**MCMC initialization and recovery**

\texttt{load\_mh\_file}

See \texttt{load\_mh\_file}. Default: not set.

\texttt{load\_results\_after\_load\_mh}

See \texttt{load\_results\_after\_load\_mh}. Default: not set.

\texttt{mh\_initialize\_from\_previous\_mcmc}

See \texttt{mh\_initialize\_from\_previous\_mcmc}. Default: not set.

\texttt{mh\_initialize\_from\_previous\_mcmc\_directory} = FILENAME

See \texttt{mh\_initialize\_from\_previous\_mcmc\_directory}. Default: empty.

\texttt{mh\_initialize\_from\_previous\_mcmc\_prior} = FILENAME

See \texttt{mh\_initialize\_from\_previous\_mcmc\_prior}. Default: empty.

\texttt{mh\_initialize\_from\_previous\_mcmc\_record} = FILENAME

See \texttt{mh\_initialize\_from\_previous\_mcmc\_record}. Default: empty.

\texttt{mh\_recover}

See \texttt{mh\_recover}. Default: not set.

**Convergence diagnostics**

\texttt{nodiagnostic}

See \texttt{nodiagnostic}. Default: not set.

\texttt{brooks\_gelman\_plotrows} = INTEGER

See \texttt{brooks\_gelman\_plotrows}. Default: 3.

\texttt{geweke\_interval} = [DOUBLE DOUBLE]

See \texttt{geweke\_interval}. Default: [0.2 0.5].

\texttt{taper\_steps} = [INTEGER1 INTEGER2 ...]

See \texttt{taper\_steps}. Default: [4 8 15].
raftery_lewis_diagnostics
See raftery_lewis_diagnostics. Default: not set.

raftery_lewis_qrs = [DOUBLE DOUBLE DOUBLE]
See raftery_lewis_qrs. Default: [0.025 0.005 0.95].

4.16.2.10 Numerical algorithms options

aim_solver
See aim_solver. Default: not set.

k_order_solver
See k_order_solver. Default: disabled for order 1 and 2, enabled for order 3 and above.

dr = OPTION
See dr. Default: default, i.e. generalized Schur decomposition.

dr_cycle_reduction_tol = DOUBLE

dr_logarithmic_reduction_tol = DOUBLE
See dr_logarithmic_reduction_tol. Default: 1e-12.

dr_logarithmic_reduction_maxiter = INTEGER
See dr_logarithmic_reduction_maxiter. Default: 100.

lyapunov = OPTION
See lyapunov. Default: default, i.e. based on Bartletts-Stewart algorithm.

lyapunov_complex_threshold = DOUBLE

lyapunov_fixed_point_tol = DOUBLE
See lyapunov_fixed_point_tol. Default: 1e-10.

lyapunov_doubling_tol = DOUBLE
See lyapunov_doubling_tol. Default: 1e-16.

qz_criterium = DOUBLE
See qz_criterium. For unit roots (only possible at order=1) set e.g. to 1.000001. Default: 0.999999 as it is assumed that the observables are weakly stationary.

qz_zero_threshold = DOUBLE

schur_vec_tol = DOUBLE
Tolerance level used to find nonstationary variables in Schur decomposition of the transition matrix. Default: 1e-11.

mode_check
Plots univariate slices through the moments distance objective function around the computed minimum for each estimated parameter. This is helpful to diagnose problems with the optimizer. Default: not set.

mode_check_neighbourhood_size = DOUBLE
See mode_check_neighbourhood_size. Default: 0.5.

mode_check_symmetric_plots = INTEGER
See mode_check_symmetric_plots. Default: 1.

mode_check_number_of_points = INTEGER
4.16.3 Method of moments specific outputs

`method_of_moments` stores user options in a structure called `options_mom_` in the global workspace. After running the estimation, the parameters `M_.params` and the covariance matrices of the shocks `M_.Sigma_e` and of the measurement errors `M_.H` are set to the parameters that either minimize the quadratic moments distance objective function or at the posterior mean in case of Bayesian MCMC estimation. The estimation results are stored in a subfolder of `dirname` called `method_of_moments`. Moreover, output is stored in the `oo_.mom` structure with the following fields:

Common outputs

**MATLAB/Octave variable: `oo_.mom.data_moments`**
Variable set by the `method_of_moments` command. Stores the mean of the selected empirical moments/IRFs of data. NaN values due to leads/lags or missing data are omitted when computing the mean for moments. Vector of dimension equal to the number of orthogonality conditions or IRFs.

**MATLAB/Octave variable: `oo_.mom.model_moments`**
Variable set by the `method_of_moments` command. Stores the implied selected model moments or IRFs given the current parameter guess. Model moments are computed in closed-form from the pruned state-space system for GMM, whereas for SMM these are based on averages of simulated data. Model IRFs are computed from the specified `simulation_method`. Vector of dimension equal to the number of orthogonality conditions.

**MATLAB/Octave variable: `oo_.mom.model_moments_params_derivs`**
Variable set by the `method_of_moments` command. Stores the analytically computed Jacobian matrix of the derivatives of the model moments with respect to the estimated parameters. Only for GMM with `analytic_standard_errors`. Matrix with dimension equal to the number of orthogonality conditions times number of estimated parameters.

**MATLAB/Octave variable: `oo_.mom.weighting_info`**
Variable set by the `method_of_moments` command. Stores the currently used weighting matrix (`W`), its Cholesky factor (`Sw`), and an indicator whether the weighting matrix is the optimal one (`Woptflag`). The inverse (`Winv`) and its log determinant (`Winv_logdet`) are also stored.

**MATLAB/Octave variable: `oo_.mom.Q`**
Variable set by the `method_of_moments` command. Stores the scalar value of the quadratic moment’s distance objective function.

**MATLAB/Octave variable: `oo_.mom.verbose`**
Structure that contains intermediate estimation results if `verbose` is used.

SMM and GMM specific outputs

**MATLAB/Octave variable: `oo_.mom.m_data`**
Variable set by the `method_of_moments` command. Stores the selected empirical moments at each point in time. NaN values due to leads/lags or missing data are replaced by the corresponding mean of the moment. Matrix of dimension time periods times number of orthogonality conditions.

**MATLAB/Octave variable: `oo_.mom.gmm_mode`**
**MATLAB/Octave variable: `oo_.mom.smm_mode`**
Variables set by the `method_of_moments` command when estimating with GMM or SMM. Stores the estimated values of the final stage. The structures contain the following fields:

- `measurement_errors_corr`: estimated correlation between two measurement errors
- `measurement_errors_std`: estimated standard deviation of measurement errors
- `parameters`: estimated model parameters
- `shocks_corr`: estimated correlation between two structural shocks.
• shocks_std: estimated standard deviation of structural shocks.

MATLAB/Octave variable: oo_.mom.gmm_std_at_mode

MATLAB/Octave variable: oo_.mom.smm_std_at_mode

Variables set by the \texttt{method_of_moments} command when estimating with GMM or SMM. Stores the estimated standard errors of the final stage. The structures contain the following fields:

• measurement_errors_corr: standard error of estimated correlation between two measurement errors

• measurement_errors_std: standard error of estimated standard deviation of measurement errors

• parameters: standard error of estimated model parameters

• shocks_corr: standard error of estimated correlation between two structural shocks.

• shocks_std: standard error of estimated standard deviation of structural shocks.

MATLAB/Octave variable: oo_.mom.J_test

Variable set by the \texttt{method_of_moments} command. Structure where the value of the test statistic is saved into a field called \texttt{j_stat}, the degrees of freedom into a field called \texttt{degrees_freedom} and the p-value of the test statistic into a field called \texttt{p_val}.

IRF matching specific outputs

MATLAB/Octave variable: oo_.mom.irf_model_varobs

Variable set by the \texttt{method_of_moments} command. Stores all the implied model impulse response functions (not only the matched ones) and is used for the comparison plot. Array of dimension equal to number of observables by number of shocks by maximum horizon.

Bayesian specific outputs

MATLAB/Octave variable: oo_.mom.prior

Variable set by the \texttt{method_of_moments} command if Bayesian estimation is used. Stores information of the joint prior. Fields are of the form:

\begin{verbatim}
  oo_.mom.prior.OBJECT
\end{verbatim}

where \texttt{OBJECT} is one of the following:

\begin{verbatim}
  mean
      Prior mean parameter vector.

  mode
      Prior mode parameter vector.

  variance
      Covariance matrix of joint prior.

  hyperparameters
      Vectors of hyperparameters of the prior distributions stored in fields \texttt{first} and \texttt{second}.
\end{verbatim}

MATLAB/Octave variable: oo_.mom.posterior.optimization

Variable set by the \texttt{method_of_moments} command if mode-finding is used. Stores the results at the mode. Fields are of the form:

\begin{verbatim}
  oo_.mom.posterior.optimization.OBJECT
\end{verbatim}

where \texttt{OBJECT} is one of the following:

\begin{verbatim}
  mode
\end{verbatim}
Parameter vector at the mode.

Variance

Inverse Hessian matrix at the mode or MCMC jumping covariance matrix when used with the `MCMC_jumping_covariance` option.

log_density

Log likelihood (ML)/log posterior density (Bayesian) at the mode when used with `mode_compute>0`.

MATLAB/Octave variable: `oo_.mom.posterior.metropolis`

Variable set by the `method_of_moments` command if `mh_replic>0` is used. Fields are of the form:

`oo_.mom.posterior.metropolis.OBJECT`

where `OBJECT` is one of the following:

- mean
  
  Mean parameter vector from the MCMC.

Variance

Covariance matrix of the parameter draws in the MCMC.

MATLAB/Octave variable: `oo_.mom.prior_density`

Variable set by the `method_of_moments` command, if it is used with `mh_replic > 0` or `load_mh_file` option. Fields are of the form:

`oo_.mom.prior_density.PARAMETER_NAME`

MATLAB/Octave variable: `oo_.mom.posterior_density`

Variable set by the `method_of_moments` command, if it is used with `mh_replic > 0` or `load_mh_file` option. Fields are of the form:

`oo_.mom.posterior_density.PARAMETER_NAME`

MATLAB/Octave variable: `oo_.mom.posterior_hpdinf`

Variable set by the `method_of_moments` command, if it is used with `mh_replic > 0` or `load_mh_file` option. Fields are of the form:

`oo_.mom.posterior_hpdinf.ESTIMATED_OBJECT.PARAMETER_NAME`

MATLAB/Octave variable: `oo_.mom.posterior_hpdsup`

Variable set by the `method_of_moments` command, if it is used with `mh_replic > 0` or `load_mh_file` option. Fields are of the form:

`oo_.mom.posterior_hpdsup.ESTIMATED_OBJECT.PARAMETER_NAME`

MATLAB/Octave variable: `oo_.mom.posterior_mean`

Variable set by the `method_of_moments` command, if it is used with `mh_replic > 0` or `load_mh_file` option. Fields are of the form:

`oo_.mom.posterior_mean.ESTIMATED_OBJECT.PARAMETER_NAME`

MATLAB/Octave variable: `oo_.mom.posterior_mode`

Variable set by the `method_of_moments` command during mode-finding. Fields are of the form:

`oo_.mom.posterior_mode.ESTIMATED_OBJECT.PARAMETER_NAME`
MATLAB/Octave variable: oo_.mom.posterior_std_at_mode
Variable set by the method_of_moments command during mode-finding. It is based on the inverse Hessian at oo_.mom.posterior_mode. Fields are of the form:

```
oo_.mom.posterior_std_at_mode.ESTIMATED_OBJECT.VARIABLE_NAME
```

MATLAB/Octave variable: oo_.mom.posterior_std
Variable set by the method_of_moments command, if it is used with mh_replic > 0 or load_mh_file option. Fields are of the form:

```
oo_.mom.posterior_std.ESTIMATED_OBJECT.VARIABLE_NAME
```

MATLAB/Octave variable: oo_.mom.posterior_variance
Variable set by the method_of_moments command, if it is used with mh_replic > 0 or load_mh_file option. Fields are of the form:

```
oo_.mom.posterior_variance.ESTIMATED_OBJECT.VARIABLE_NAME
```

MATLAB/Octave variable: oo_.mom.posterior_median
Variable set by the method_of_moments command, if it is used with mh_replic > 0 or load_mh_file option. Fields are of the form:

```
oo_.mom.posterior_median.ESTIMATED_OBJECT.VARIABLE_NAME
```

MATLAB/Octave variable: oo_.mom.posterior_deciles
Variable set by the method_of_moments command, if it is used with mh_replic > 0 or load_mh_file option. Fields are of the form:

```
oo_.mom.posterior_deciles.ESTIMATED_OBJECT.VARIABLE_NAME
```

MATLAB/Octave variable: oo_.mom.MarginalDensity.LaplaceApproximation
Variable set by the method_of_moments command. Stores the marginal data density based on the Laplace Approximation.

MATLAB/Octave variable: oo_.mom.MarginalDensity.ModifiedHarmonicMean
Variable set by the method_of_moments command, if it is used with mh_replic > 0 or load_mh_file option. Stores the marginal data density based on Geweke (1999) Modified Harmonic Mean estimator.

### 4.17 Model Comparison

**Command:** model_comparison FILENAME[(DOUBLE)]...

**Command:** model_comparison(marginal_density = ESTIMATOR) FILENAME[(DOUBLE)]...

This command computes odds ratios and estimate a posterior density over a collection of models (see e.g. Koop (2003), Ch. 1). The priors over models can be specified as the DOUBLE values, otherwise a uniform prior over all models is assumed. In contrast to frequentist econometrics, the models to be compared do not need to be nested. However, as the computation of posterior odds ratios is a Bayesian technique, the comparison of models estimated with maximum likelihood is not supported.

It is important to keep in mind that model comparison of this type is only valid with proper priors. If the prior does not integrate to one for all compared models, the comparison is not valid. This may be the case if part of the prior mass is implicitly truncated because Blanchard and Kahn conditions (instability or indeterminacy of the model) are not fulfilled, or because for some regions of the parameters space the deterministic steady state is undefined (or Dynare is unable to find it). The compared marginal densities should be renormalized by the effective prior mass, but this not done by Dynare: it is the user’s responsibility to make sure that model...
comparison is based on proper priors. Note that, for obvious reasons, this is not an issue if the compared marginal densities are based on Laplace approximations.

**Options**

**marginal_density = ESTIMATOR**

Specifies the estimator for computing the marginal data density. *ESTIMATOR* can take one of the following two values: laplace for the Laplace estimator or modifiedharmonicmean for the Geweke (1999) Modified Harmonic Mean estimator. Default value: laplace

**Output**

The results are stored in `oo_.Model_Comparison`, which is described below.

**Example**

```matlab
model_comparison my_model(0.7) alt_model(0.3);
```

This example attributes a 70% prior over `my_model` and 30% prior over `alt_model`.

**MATLAB/Octave variable: oo_.Model_Comparison**

Variable set by the `model_comparison` command. Fields are of the form:

`oo_.Model_Comparison.FILENAME.VARIABLE_NAME`

where `FILENAME` is the file name of the model and `VARIABLE_NAME` is one of the following:

- **Prior**
  - (Normalized) prior density over the model.
- **Log_Marginal_Density**
  - Logarithm of the marginal data density.
- **Bayes_Ratio**
  - Ratio of the marginal data density of the model relative to the one of the first declared model
- **Posterior_Model_Probability**
  - Posterior probability of the respective model.

### 4.18 Shock Decomposition

**Command:** `shock_decomposition [VARIABLE_NAME]...;`

**Command:** `shock_decomposition(OPTIONS...) [VARIABLE_NAME]...;`

This command computes the historical shock decomposition for a given sample based on the Kalman smoother, i.e. it decomposes the historical deviations of the endogenous variables from their respective steady state values into the contribution coming from the various shocks. The `variable_names` provided govern for which variables the decomposition is plotted.

Note that this command must come after either `estimation` (in case of an estimated model) or `stoch_simul` (in case of a calibrated model).

**Options**

**parameter_set = OPTION**

Specify the parameter set to use for running the smoother. Possible values for OPTION are:

- `calibration`
- `prior_mode`
- `prior_mean`
• `posterior_mode`
• `posterior_mean`
• `posterior_median`
• `mle_mode`

Note that the parameter set used in subsequent commands like `stoch_simul` will be set to the specified `parameter_set`. Default value: `posterior_mean` if Metropolis has been run, `mle_mode` if MLE has been run.

datafile = FILENAME

See `datafile`. Useful when computing the shock decomposition on a calibrated model.

first_obs = INTEGER

See `first_obs`.

nobs = INTEGER

See `nobs`.

prefilter = INTEGER

See `prefilter`.

loglinear

See `loglinear`.

diffuse_kalman_tol = DOUBLE

See `diffuse_kalman_tol`.

diffuse_filter

See `diffuse_filter`.

xls_sheet = QUOTED_STRING

See `xls_sheet`.

xls_range = RANGE

See `xls_range`.

use_shock_groups [= NAME]

Uses shock grouping defined by the string instead of individual shocks in the decomposition. The groups of shocks are defined in the `shock_groups` block. If no group name is given, default is assumed.

colormap = VARIABLE_NAME

Controls the colormap used for the shocks decomposition graphs. VARIABLE_NAME must be the name of a MATLAB/Octave variable that has been declared beforehand and whose value will be passed to the MATLAB/Octave colormap function (see the MATLAB/Octave manual for the list of acceptable values).

nograph

See `nograph`. Suppresses the display and creation only within the `shock_decomposition` command, but does not affect other commands. See `plot_shock_decomposition` for plotting graphs.

init_state = BOOLEAN

If equal to 0, the shock decomposition is computed conditional on the smoothed state variables in period 0, i.e. the smoothed shocks starting in period 1 are used. If equal to 1, the shock decomposition is computed conditional on the smoothed state variables in period 1. Default: 0.

with_epilogue

If set, then also compute the decomposition for variables declared in the `epilogue` block (see `Epilogue Variables`).
MATLAB/Octave variable: oo_.shock_decomposition

The results are stored in the field oo_.shock_decomposition, which is a three dimensional array. The first dimension contains the _M_.endo_nbr endogenous variables. The second dimension stores in the first _M_.exo_nbr columns the contribution of the respective shocks. Column _M_.exo_nbr+1 stores the contribution of the initial conditions, while column _M_.exo_nbr+2 stores the smoothed value of the respective endogenous variable in deviations from their steady state, i.e. the mean and trends are subtracted. The third dimension stores the time periods. Both the variables and shocks are stored in the order of declaration, i.e. _M_.endo_names and _M_.exo_names, respectively.

Block: shock_groups;
Block: shock_groups(OPTIONS...);

Shocks can be regrouped for the purpose of shock decomposition. The composition of the shock groups is written in a block delimited by shock_groups and end.

Each line defines a group of shocks as a list of exogenous variables:

```
SHOCK_GROUP_NAME = VARIABLE_1 [ , ] VARIABLE_2 [ , ]...;
'SHOCK GROUP NAME' = VARIABLE_1 [ , ] VARIABLE_2 [ , ]...;
```

Options

name = NAME

Specifies a name for the following definition of shock groups. It is possible to use several shock_groups blocks in a model file, each grouping being identified by a different name. This name must in turn be used in the shock_decomposition command. If no name is given, default is used.

Example

```
varexo e_a, e_b, e_c, e_d;
...
shock_groups(name=group1);
supply = e_a, e_b;
'aggregate demand' = e_c, e_d;
end;
shock_decomposition(use_shock_groups=group1);
```

This example defines a shock grouping with the name group1, containing a set of supply and demand shocks and conducts the shock decomposition for these two groups.

Command: realtime_shock_decomposition [VARIABLE_NAME]...;
Command: realtime_shock_decomposition(OPTIONS...) [VARIABLE_NAME]...;

This command computes the real-time historical shock decomposition for a given sample based on the Kalman smoother. For each period \( T = [\text{presample}, \ldots, \text{nobs}] \), it recursively computes three objects:

- Real-time historical shock decomposition \( Y(t|T) \) for \( t = [1, \ldots, T] \), i.e. without observing data in \( [T+1, \ldots, \text{nobs}] \). This results in a standard shock decomposition being computed for each additional datapoint becoming available after presample.

- Forecast shock decomposition \( Y(T+k|T) \) for \( k = [1, \ldots, \text{forecast}] \), i.e. the \( k \)-step ahead forecast made for every \( T \) is decomposed in its shock contributions.

- Real-time conditional shock decomposition of the difference between the real-time historical shock decomposition and the forecast shock decomposition. If vintage is equal to \( 0 \), it computes the effect of shocks realizing in period \( T \), i.e. decomposes \( Y(T|T) - Y(T|T-1) \). Put differently, it conducts a 1-period ahead shock decomposition from \( T-1 \) to \( T \), by decomposing the update step of the Kalman filter. If \( \text{vintage} > 0 \) and smaller than \( \text{nobs} \), the decomposition is conducted of the forecast revision \( Y(T+k|T+k) - Y(T+k|T) \).
Like `shock_decomposition` it decomposes the historical deviations of the endogenous variables from their respective steady state values into the contribution coming from the various shocks. The variable_names provided govern for which variables the decomposition is plotted.

Note that this command must come after either `estimation` (in case of an estimated model) or `stoch_simul` (in case of a calibrated model).

**Options**

```plaintext
parameter_set = OPTION
  See parameter_set for possible values.
datafile = FILENAME
  See datafile.
first_obs = INTEGER
  See first_obs.
nobs = INTEGER
  See nobs.
use_shock_groups [= NAME]
  See use_shock_groups.
colormap = VARIABLE_NAME
  See colormap.
```

**nograph**

See nograph. Only shock decompositions are computed and stored in `oo_.realtime_shock_decomposition`, `oo_.conditional_shock_decomposition` and `oo_.realtime_forecast_shock_decomposition` but no plot is made (See `plot_shock_decomposition`).

**presample = INTEGER**

Data point above which recursive realtime shock decompositions are computed, i.e. for \( T = \) \[\text{presample}+1, \ldots, \text{nobs}\].

**forecast = INTEGER**

Compute shock decompositions up to \( T + k \) periods, i.e. get shock contributions to k-step ahead forecasts.

**save_realtime = INTEGER_VECTOR**

Choose for which vintages to save the full realtime shock decomposition. Default: \( \emptyset \).

**fast_realtime = INTEGER**

**fast_realtime = [INTEGER1:INTEGER2]**

**fast_realtime = [INTEGER1 INTEGER2 ...]**

Runs the smoother only for the data vintages provided by the specified integer (vector).

**with_epilogue**

See with_epilogue.

**Output**

**MATLAB/Octave variable: oo_.realtime_shock_decomposition**

Structure storing the results of realtime historical decompositions. Fields are three-dimensional arrays with the first two dimension equal to the ones of `oo_.shock_decomposition`. The third dimension stores the time periods and is therefore of size \( T + \text{forecast} \). Fields are of the form:

```plaintext
oo_.realtime_shock_decomposition.OBJECT
```

where OBJECT is one of the following:
pool
Stores the pooled decomposition, i.e. for every real-time shock decomposition terminal period $T = [\text{presample}, \ldots, \text{nobs}]$ it collects the last period’s decomposition $Y(T|T)$ (see also `plot_shock_decomposition`). The third dimension of the array will have size nobs+forecast.

time_*
Stores the vintages of real-time historical shock decompositions if `save_realtime` is used. For example, if `save_realtime=[5]` and `forecast=8`, the third dimension will be of size 13.

MATLAB/Octave variable: `oo_.realtime_conditional_shock_decomposition`
Structure storing the results of real-time conditional decompositions. Fields are of the form:

```
oo_.realtime_conditional_shock_decomposition.OBJECT
```

where OBJECT is one of the following:

pool
Stores the pooled real-time conditional shock decomposition, i.e. collects the decompositions of $Y(T|T) - Y(T|T-1)$ for the terminal periods $T = [\text{presample}, \ldots, \text{nobs}]$. The third dimension is of size nobs.

time_*
Stores the vintages of $k$-step conditional forecast shock decompositions $Y(t|T+k)$, for $t = [T \ldots T+k]$. See `vintage`. The third dimension is of size 1+forecast.

MATLAB/Octave variable: `oo_.realtime_forecast_shock_decomposition`
Structure storing the results of real-time forecast decompositions. Fields are of the form:

```
oo_.realtime_forecast_shock_decomposition.OBJECT
```

where OBJECT is one of the following:

pool
Stores the pooled real-time forecast decomposition of the $1$-step ahead effect of shocks on the $1$-step ahead prediction, i.e. $Y(T|T-1)$.

time_*
Stores the vintages of $k$-step out-of-sample forecast shock decompositions, i.e. $Y(t|T)$, for $t = [T \ldots T+k]$. See `vintage`.

Command: `plot_shock_decomposition` [VARIABLE_NAME]...;
Command: `plot_shock_decomposition` (OPTIONS...) [VARIABLE_NAME]...;

This command plots the historical shock decomposition already computed by `shock_decomposition` or `realtime_shock_decomposition`. For that reason, it must come after one of these commands. The variable_names provided govern which variables the decomposition is plotted for.

Further note that, unlike the majority of Dynare commands, the options specified below are overwritten with their defaults before every call to `plot_shock_decomposition`. Hence, if you want to reuse an option in a subsequent call to `plot_shock_decomposition`, you must pass it to the command again.

**Options**

- `use_shock_groups` [= NAME]
  See `use_shock_groups`.
- `colormap` = VARIABLE_NAME
  See `colormap`.
nodisplay
See nodisplay.
nograph
See nograph.

\[\text{graph\_format} = \text{FORMAT}\]

\[\text{graph\_format} = (\text{FORMAT, FORMAT}... )\]
See graph_format.
detail_plot
Plots shock contributions using subplots, one per shock (or group of shocks). Default: not activated

\text{interactive}
Under MATLAB, add uimenus for detailed group plots. Default: not activated

\text{screen\_shocks}
For large models (i.e. for models with more than 16 shocks), plots only the shocks that have the largest historical contribution for chosen selected \text{variable\_names}. Historical contribution is ranked by the mean absolute value of all historical contributions.

\text{steadystate}
If passed, the the \(y\)-axis value of the zero line in the shock decomposition plot is translated to the steady state level. Default: not activated

type = qoq | yoy | aoa
For quarterly data, valid arguments are: qoq for quarter-on-quarter plots, yoy for year-on-year plots of growth rates, aoa for annualized variables, i.e. the value in the last quarter for each year is plotted. Default value: empty, i.e. standard period-on-period plots (qoq for quarterly data).

\text{fig\_name} = \text{STRING}
Specifies a user-defined keyword to be appended to the default figure name set by plot\_shock\_decomposition. This can avoid to overwrite plots in case of sequential calls to plot\_shock\_decomposition.

\text{write\_xls}
Saves shock decompositions to Excel file in the main directory, named FILENAME\_shock\_decomposition\_TYPE\_FIG\_NAME.xls. This option requires your system to be configured to be able to write Excel files.\(^8\)

\text{realtime} = \text{INTEGER}
Which kind of shock decomposition to plot. INTEGER can take the following values:
\begin{itemize}
  \item 0: standard historical shock decomposition. See shock\_decomposition.
  \item 1: realtime historical shock decomposition. See realtime\_shock\_decomposition.
  \item 2: conditional realtime shock decomposition. See realtime\_shock\_decomposition.
  \item 3: realtime forecast shock decomposition. See realtime\_shock\_decomposition.
\end{itemize}
If no vintage is requested, i.e. vintage=0 then the pooled objects from realtime\_shock\_decomposition will be plotted and the respective vintage otherwise. Default: 0.

\text{vintage} = \text{INTEGER}
Selects a particular data vintage in [\text{presample},...,\text{nobs}] for which to plot the results from realtime\_shock\_decomposition selected via the realtime option. If the standard historical shock decomposition is selected (realtime=0), vintage will have no effect. If vintage=0 the pooled objects from realtime\_shock\_decomposition will be plotted. If vintage>0, it plots the shock decompositions for vintage \(T = \text{vintage}\) under the following scenarios:

• realtime=1: the full vintage shock decomposition $Y(t|T)$ for $t = [1, \ldots, T]$
• realtime=2: the conditional forecast shock decomposition from $T$, i.e. plots $Y(T + j|T + j)$ and the shock contributions needed to get to the data $Y(T + j)$ conditional on $T = \text{vintage}$, with $j = [0, \ldots, \text{forecast}]$.
• realtime=3: plots unconditional forecast shock decomposition from $T$, i.e. $Y(T + j|T)$, where $T = \text{vintage}$ and $j = [0, \ldots, \text{forecast}]$.

Default: 0.

*plot_init_date = DATE*
If passed, plots decomposition using plot_init_date as initial period. Default: first observation in estimation

*plot_end_date = DATE*
If passed, plots decomposition using plot_end_date as last period. Default: last observation in estimation

*diff*
If passed, plot the decomposition of the first difference of the list of variables. If used in combination with *flip*, the *diff* operator is first applied. Default: not activated

*flip*
If passed, plot the decomposition of the opposite of the list of variables. If used in combination with *diff*, the *diff* operator is first applied. Default: not activated

*max_nrows*
Maximum number of rows in the subplot layout of detailed shock decomposition graphs. Note that columns are always 3. Default: 6

*with_epilogue*
See *with_epilogue*.

*init2shocks*

*init2shocks = NAME*
Use the information contained in an *init2shocks* block, in order to attribute initial conditions to shocks. The name of the block can be explicitly given, otherwise it defaults to the default block.

*Block: init2shocks ;*

*Block: init2shocks(OPTIONS...) ;*
This block gives the possibility of attributing the initial condition of endogenous variables to the contribution of exogenous variables in the shock decomposition.

For example, in an AR(1) process, the contribution of the initial condition on the process variable can naturally be assigned to the innovation of the process.

Each line of the block should have the syntax:

```
VARIABLE_1 [,] VARIABLE_2;
```

Where VARIABLE_1 is an endogenous variable whose initial condition will be attributed to the exogenous VARIABLE_2.

The information contained in this block is used by the *plot_shock_decomposition* command when given the init2shocks option.

*Options*

*name = NAME*
Specifies a name for the block, that can be referenced from *plot_shock_decomposition*, so that several such blocks can coexist in a single model file. If the name is unspecified, it defaults to default.

*Example*
In this example, the initial conditions of $dq$ and $A$ will be respectively attributed to $e_q$ and $e_A$.

**Command**:

```
initial_condition_decomposition [VARIABLE_NAME]...;
```

**Command**:

```
initial_condition_decomposition(OPTIONS...) [VARIABLE_NAME]...;
```

This command computes and plots the decomposition of the effect of smoothed initial conditions of state variables. The `variable_names` provided govern which variables the decomposition is plotted for.

Further note that, unlike the majority of Dynare commands, the options specified below are overwritten with their defaults before every call to `initial_condition_decomposition`. Hence, if you want to reuse an option in a subsequent call to `initial_condition_decomposition`, you must pass it to the command again.

**Options**

- `colormap = VARIABLE_NAME`
  
  See `colormap`.

- `nodisplay`
  
  See `nodisplay`.

- `graph_format = FORMAT`
  
  See `graph_format`.

- `graph_format = ( FORMAT, FORMAT... )`
  
  For quarterly data, valid arguments are: `qoq` for quarter-on-quarter plots, `yoy` for year-on-year plots of growth rates, `aoa` for annualized variables, i.e. the value in the last quarter for each year is plotted.

- `type = qoq | yoy | aoa`
  
  Default value: empty, i.e. standard period-on-period plots (qoq for quarterly data).

- `fig_name = STRING`
  
  Specifies a user-defined keyword to be appended to the default figure name set by `plot_shock_decomposition`. This can avoid to overwrite plots in case of sequential calls to `plot_shock_decomposition`.

```
write_xls
Saves shock decompositions to Excel file in the main directory, named FILENAME_shock_decomposition_TYPE_FIG_NAME_initval.xls. This option requires your system to be configured to be able to write Excel files.

plot_init_date = DATE
If passed, plots decomposition using plot_init_date as initial period. Default: first observation in estimation

plot_end_date = DATE
If passed, plots decomposition using plot_end_date as last period. Default: last observation in estimation

diff
If passed, plot the decomposition of the first difference of the list of variables. If used in combination with flip, the diff operator is first applied. Default: not activated

flip
If passed, plot the decomposition of the opposite of the list of variables. If used in combination with diff, the diff operator is first applied. Default: not activated

Command: squeeze_shock_decomposition [VARIABLE_NAME]...;

For large models, the size of the information stored by shock decompositions (especially various settings of realtime decompositions) may become huge. This command allows to squeeze this information in two possible ways:

- Automatic (default): only the variables for which plotting has been explicitly required with plot_shock_decomposition will have their decomposition left in oo_ after this command is run;
- If a list of variables is passed to the command, then only those variables will have their decomposition left in oo_ after this command is run.

4.19 Calibrated Smoother

Dynare can also run the smoother on a calibrated model:

Command: calib_smoother [VARIABLE_NAME]...;
Command: calib_smoother(OPTIONS...) [VARIABLE_NAME]...;

This command computes the smoothed variables (and possible the filtered variables) on a calibrated model.

A datafile must be provided, and the observable variables declared with varobs. The smoother is based on a first-order approximation of the model.

By default, the command computes the smoothed variables and shocks and stores the results in oo_. SmoothedVariables and oo_.SmoothedShocks. It also fills oo_.UpdatedVariables.

Options

datafile = FILENAME
See datafile.

filtered_vars
Triggers the computation of filtered variables. See filtered_vars, for more details.

filter_step_ahead = [INTEGER1:INTEGER2]
See filter_step_ahead.

prefilter = INTEGER
See prefilter.
**4.20 Forecasting**

On a calibrated model, forecasting is done using the `forecast` command. On an estimated model, use the `forecast` option of `estimation` command.

It is also possible to compute forecasts on a calibrated or estimated model for a given constrained path of the future endogenous variables. This is done, from the reduced form representation of the DSGE model, by finding the structural shocks that are needed to match the restricted paths. Use `conditional_forecast`, `conditional_forecast_paths` and `plot_conditional_forecast` for that purpose.

Finally, it is possible to do forecasting with a Bayesian VAR using the `bvar_forecast` command.

**Command:** `forecast [VARIABLE_NAME...]`;

**Command:** `forecast(OPTIONS...) [VARIABLE_NAME...]`;

This command computes a simulation of a stochastic model from an arbitrary initial point.

When the model also contains deterministic exogenous shocks, the simulation is computed conditionally to the agents knowing the future values of the deterministic exogenous variables.

`forecast` must be called after `stoch_simul`. 

```plaintext
parameter_set = OPTION
    See parameter_set for possible values. Default: calibration.

loglinear
    See loglinear.

first_obs = INTEGER
    See first_obs.

filter_decomposition
    See filter_decomposition.

filter_covariance
    See filter_covariance.

smoother_redux
    See smoother_redux.

kalman_algo = INTEGER
    See kalman_algo.

diffuse_filter = INTEGER
    See diffuse_filter.

diffuse_kalman_tol = DOUBLE
    See diffuse_kalman_tol.

gxls_sheet = QUOTED_STRING
    See xls_sheet.

xls_range = RANGE
    See xls_range.

heteroskedastic_filter
    See heteroskedastic_filter.

nobs = INTEGER
nobs = [INTEGER1:INTEGER2]
    See nobs.
```
forecast plots the trajectory of endogenous variables. When a list of variable names follows the command, only those variables are plotted. A 90% confidence interval is plotted around the mean trajectory. Use option conf_sig to change the level of the confidence interval.

**Options**

**periods = INTEGER**
Number of periods of the forecast. Default: 5.

**conf_sig = DOUBLE**
Level of significance for confidence interval. Default: 0.90.

**nograph**
See nograph.

**nodisplay**
See nodisplay.

**graph_format = FORMAT**
graph_format = ( FORMAT, FORMAT... )
See graph_format = FORMAT.

**Initial Values**

forecast computes the forecast taking as initial values the values specified in histval (see histval). When no histval block is present, the initial values are the one stated in initval. When initval is followed by command steady, the initial values are the steady state (see steady).

**Output**

The results are stored in oo_.forecast, which is described below.

**Example**

```plaintext
varexo_det tau;

varexo e;
...
shocks;
var e; stderr 0.01;
var tau;
periods 1:9;
values -0.15;
end;

stoch_simul(irf=0);

forecast;
```

**MATLAB/Octave variable: oo_.forecast**

Variable set by the forecast command, or by the estimation command if used with the forecast option and ML or if no Metropolis-Hastings has been computed (in that case, the forecast is computed for the posterior mode). Fields are of the form:

```plaintext
oo_.forecast.FORECAST_MOMENT.VARIABLE_NAME
```

where FORECAST_MOMENT is one of the following:

- **HPDinf**
  Lower bound of a 90% HPD interval\(^9\) of forecast due to parameter uncertainty, but ignoring the effect of measurement error on observed variables. In case of ML, it stores the lower bound of the confidence interval.

\(^9\) See option conf_sig to change the size of the HPD interval.
HPDsup

Upper bound of a 90% HPD forecast interval due to parameter uncertainty, but ignoring the effect of measurement error on observed variables. In case of ML, it stores the upper bound of the confidence interval.

HPDinf_ME

Lower bound of a 90% HPD interval\(^{10}\) of forecast for observed variables due to parameter uncertainty and measurement error. In case of ML, it stores the lower bound of the confidence interval.

HPDsup_ME

Upper bound of a 90% HPD interval of forecast for observed variables due to parameter uncertainty and measurement error. In case of ML, it stores the upper bound of the confidence interval.

Mean

Mean of the posterior distribution of forecasts.

**MATLAB/Octave variable: oo_.PointForecast**

Set by the estimation command, if it is used with the forecast option and if either mh_replic > 0 or the load_mh_file option are used.

Contains the distribution of forecasts taking into account the uncertainty about both parameters and shocks.

Fields are of the form:

\[
\text{oo_.PointForecast.MOMENT_NAME.VARIABLE_NAME}
\]

**MATLAB/Octave variable: oo_.MeanForecast**

Set by the estimation command, if it is used with the forecast option and if either mh_replic > 0 or load_mh_file option are used.

Contains the distribution of forecasts where the uncertainty about shocks is averaged out. The distribution of forecasts therefore only represents the uncertainty about parameters.

Fields are of the form:

\[
\text{oo_.MeanForecast.MOMENT_NAME.VARIABLE_NAME}
\]

**Command: conditional_forecast(OPTIONS...)**;

This command computes forecasts on an estimated or calibrated model for a given constrained path of some future endogenous variables. This is done using the reduced form first order state-space representation of the DSGE model by finding the structural shocks that are needed to match the restricted paths. Consider the augmented state space representation that stacks both predetermined and non-predetermined variables into a vector \(y_t\):

\[
y_t = T y_{t-1} + R \varepsilon_t
\]

Both \(y_t\) and \(\varepsilon_t\) are split up into controlled and uncontrolled ones, and we assume without loss of generality that the constrained endogenous variables and the controlled shocks come first:

\[
\begin{pmatrix}
y_{c,t} \\
y_{u,t}
\end{pmatrix} =
\begin{pmatrix}
T_{c,c} & T_{c,u} \\
T_{u,c} & T_{u,u}
\end{pmatrix}
\begin{pmatrix}
y_{c,t-1} \\
y_{u,t-1}
\end{pmatrix} +
\begin{pmatrix}
R_{c,c} & R_{c,u} \\
R_{u,c} & R_{u,u}
\end{pmatrix}
\begin{pmatrix}
\varepsilon_{c,t} \\
\varepsilon_{u,t}
\end{pmatrix}
\]

\(^{10}\) See option conf_sig to change the size of the HPD interval.
where matrices $T$ and $R$ are partitioned consistently with the vectors of endogenous variables and innovations. Provided that matrix $R_{c,c}$ is square and full rank (a necessary condition is that the number of free endogenous variables matches the number of free innovations), given $y_{c,t}$, $\varepsilon_{u,t}$ and $y_{t-1}$ the first block of equations can be solved for $\varepsilon_{c,t}$:

$$
\varepsilon_{c,t} = R_{c,c}^{-1} (y_{c,t} - T_{c,c} y_{c,t} - T_{c,u} y_{u,t} - R_{c,u} \varepsilon_{u,t})
$$

and $y_{u,t}$ can be updated by evaluating the second block of equations:

$$
y_{u,t} = T_{u,c} y_{c,t-1} + T_{u,u} y_{u,t-1} + R_{u,c} \varepsilon_{c,t} + R_{u,u} \varepsilon_{u,t}
$$

By iterating over these two blocks of equations, we can build a forecast for all the endogenous variables in the system conditional on paths for a subset of the endogenous variables. If the distribution of the free innovations $\varepsilon_{u,t}$ is provided (i.e. some of them have positive variances) this exercise is replicated (the number of replication is controlled by the option replic described below) by drawing different sequences of the option free innovations. The result is a predictive distribution for the uncontrolled endogenous variables, $y_{u,t}$, that Dynare will use to report confidence bands around the point conditional forecast.

A few things need to be noted. First, the controlled exogenous variables are set to zero for the uncontrolled periods. This implies that there is no forecast uncertainty arising from these exogenous variables in uncontrolled periods. Second, by making use of the first order state space solution, even if a higher-order approximation was performed, the conditional forecasts will be based on a first order approximation. Since the controlled exogenous variables are identified on the basis of the reduced form model (i.e. after solving for the expectations), they are unforeseen shocks from the perspective of the agents in the model. That is, agents expect the endogenous variables to return to their respective steady state levels but are surprised in each period by the realisation of shocks keeping the endogenous variables along a predefined (unexpected) path. Fourth, if the structural innovations are correlated, because the calibrated or estimated covariance matrix has non zero off diagonal elements, the results of the conditional forecasts will depend on the ordering of the innovations (as declared after varexo). As in VAR models, a Cholesky decomposition is used to factorise the covariance matrix and identify orthogonal impulses. It is preferable to declare the correlations in the model block (explicitly imposing the identification restrictions), unless you are satisfied with the implicit identification restrictions implied by the Cholesky decomposition.

This command has to be called after estimation or stoch_simul.

Use conditional_forecast_paths block to give the list of constrained endogenous, and their constrained future path. Option controlled_varexo is used to specify the structural shocks which will be matched to generate the constrained path.

Use plot_conditional_forecast to graph the results.

Options

- **parameter_set = OPTION**
  
  See parameter_set for possible values. No default value, mandatory option.

- **controlled_varexo = (VARIABLE_NAME...)**
  
  Specify the exogenous variables to use as control variables. No default value, mandatory option.

- **periods = INTEGER**
  
  Number of periods of the forecast. Default: 40. periods cannot be smaller than the number of constrained periods.

- **replic = INTEGER**
  
  Number of simulations used to compute the conditional forecast uncertainty. Default: 5000.
conf_sig = DOUBLE
Level of significance for confidence interval. Default: 0.80.

Output
The results are stored in oo_.conditional_forecast, which is described below.

Example

```plaintext
var y a;
varexo e u;
...
estimation(...);

conditional_forecast_paths;
var y;
periods 1:3, 4:5;
values 2, 5;
var a;
periods 1:5;
values 3;
end;

conditional_forecast(parameter_set = calibration, controlled_varexo = (e, u), replic = 3000);
plot_conditional_forecast(periods = 10) a y;
```

MATLAB/Octave variable: oo_.conditional_forecast.cond
Variable set by the conditional_forecast command. It stores the conditional forecasts. Fields are periodic by 1 vectors storing the steady state (time 0) and the subsequent forecasts. Fields are of the form:

```plaintext
oo_.conditional_forecast.cond.FORECAST_MOMENT.VARIABLE_NAME
```

where FORECAST_MOMENT is one of the following:

- **Mean**
  - Mean of the conditional forecast distribution.
- **ci**
  - Confidence interval of the conditional forecast distribution. The size corresponds to conf_sig.

MATLAB/Octave variable: oo_.conditional_forecast.uncond
Variable set by the conditional_forecast command. It stores the unconditional forecasts. Fields are of the form:

```plaintext
oo_.conditional_forecast.uncond.FORECAST_MOMENT.VARIABLE_NAME
```

MATLAB/Octave variable: forecasts.instruments
Variable set by the conditional_forecast command. Stores the names of the exogenous instruments.

MATLAB/Octave variable: oo_.conditional_forecast.controlled_variables
Variable set by the conditional_forecast command. Stores the position of the constrained endogenous variables in declaration order.
**MATLAB/Octave variable: oo_.conditional_forecast.controlled_exo_variables**

Variable set by the `conditional_forecast` command. Stores the values of the controlled exogenous variables underlying the conditional forecasts to achieve the constrained endogenous variables. Fields are [number of constrained periods] by 1 vectors and are of the form:

`oo_.conditional_forecast.controlled_exo_variables.FORECAST_MOMENT.SHOCK_NAME`

**MATLAB/Octave variable: oo_.conditional_forecast.graphs**

Variable set by the `conditional_forecast` command. Stores the information for generating the conditional forecast plots.

**Block: conditional_forecast_paths**

Describes the path of constrained endogenous, before calling `conditional_forecast`. The syntax is similar to deterministic shocks in `shocks`, see `conditional_forecast` for an example.

The syntax of the block is the same as for the deterministic shocks in the `shocks` blocks (see `Shocks on exogenous variables`). Note that you need to specify the full path for all constrained endogenous variables between the first and last specified period. If an intermediate period is not specified, a value of 0 is assumed. That is, if you specify only values for periods 1 and 3, the values for period 2 will be 0. Currently, it is not possible to have uncontrolled intermediate periods.

It is however possible to have different number of controlled periods for different variables. In that case, the order of declaration of endogenous controlled variables and of `controlled_varexo` matters: if the second endogenous variable is controlled for less periods than the first one, the second `controlled_varexo` isn’t set for the last periods.

In case of the presence of `observation_trends`, the specified controlled path for these variables needs to include the trend component. When using the `loglinear` option, it is necessary to specify the logarithm of the controlled variables.

**Block: filter_initial_state**

This block specifies the initial values of the endogenous states at the beginning of the Kalman filter recursions. That is, if the Kalman filter recursion starts with time $t=1$ being the first observation, this block provides the state estimate at time 0 given information at time 0, $E_0(x_0)$. If nothing is specified, the initial condition is assumed to be at the steady state (which is the unconditional mean for a stationary model).

This block is terminated by `end;`.

Each line inside of the block should be of the form:

```
VARIABLE_NAME(INTEGER)=EXPRESSION;
```

`EXPRESSION` is any valid expression returning a numerical value and can contain parameter values. This allows specifying relationships that will be honored during estimation. `INTEGER` refers to the lag with which a variable appears. By convention in Dynare, period 1 is the first period. Going backwards in time, the first period before the start of the simulation is period 0, then period -1, and so on. Note that the `filter_initial_state` block does not take non-state variables.

**Example**

```
filter_initial_state;
  k(0)= ((1/bet-(1-del))/alp)^((1/(alp-1)))*l_ss;
P(0)=2.5258;
m(0)= mst;
end
```

**Command: plot_conditional_forecast [VARIABLE_NAME...];**

**Command: plot_conditional_forecast(periods = INTEGER) [VARIABLE_NAME...];**

Plots the conditional (plain lines) and unconditional (dashed lines) forecasts.

To be used after `conditional_forecast`.

**Options**
**periods** = INTEGER

Number of periods to be plotted. Default: equal to periods in conditional_forecast. The number of periods declared in plot_conditional_forecast cannot be greater than the one declared in conditional_forecast.

**Command:** bvar_forecast;

This command computes (out-of-sample) forecasts for an estimated BVAR model, using Minnesota priors.

See bvar-a-la-sims.pdf, which comes with Dynare distribution, for more information on this command.

If the model contains strong non-linearities or if some perfectly expected shocks are considered, the forecasts and the conditional forecasts can be computed using an extended path method. The forecast scenario describing the shocks and/or the constrained paths on some endogenous variables should be build. The first step is the forecast scenario initialization using the function init_plan:

**MATLAB/Octave command:** HANDLE = init_plan(DATES);

Creates a new forecast scenario for a forecast period (indicated as a dates class, see dates class members). This function return a handle on the new forecast scenario.

The forecast scenario can contain some simple shocks on the exogenous variables. This shocks are described using the function basic_plan:

**MATLAB/Octave command:**

HANDLE = basic_plan(HANDLE, 'VAR_NAME','SHOCK_TYPE',DATES, MATLAB VECTOR OF DOUBLE);

Adds to the forecast scenario a shock on the exogenous variable indicated between quotes in the second argument. The shock type has to be specified in the third argument between quotes: 'surprise' in case of an unexpected shock or 'perfect_foresight' for a perfectly anticipated shock. The fourth argument indicates the period of the shock using a dates class (see dates class members). The last argument is the shock path indicated as a MATLAB vector of double. This function return the handle of the updated forecast scenario.

The forecast scenario can also contain a constrained path on an endogenous variable. The values of the related exogenous variable compatible with the constrained path are in this case computed. In other words, a conditional forecast is performed. This kind of shock is described with the function flip_plan:

**MATLAB/Octave command:**

HANDLE = flip_plan(HANDLE, 'VAR_NAME', 'VAR_NAME', 'SHOCK_TYPE', DATES, MATLAB VECTOR OF DOUBLE);

Adds to the forecast scenario a constrained path on the endogenous variable specified between quotes in the second argument. The associated exogenous variable provided in the third argument between quotes, is considered as an endogenous variable and its values compatible with the constrained path on the endogenous variable will be computed. The nature of the expectation on the constrained path has to be specified in the fourth argument between quotes: 'surprise' in case of an unexpected path or 'perfect_foresight' for a perfectly anticipated path. The fifth argument indicates the period where the path of the endogenous variable is constrained using a dates class (see dates class members). The last argument contains the constrained path as a MATLAB vector of double. This function return the handle of the updated forecast scenario.

Once the forecast scenario if fully described, the forecast is computed with the command det_cond_forecast:

**MATLAB/Octave command:**

DSERIES = det_cond_forecast(HANDLE[, DSERIES [, DATES]]);

Computes the forecast or the conditional forecast using an extended path method for the given forecast scenario (first argument). The past values of the endogenous and exogenous variables provided with a dseries class (see dseries class members) can be indicated in the second argument. By default, the past values of the variables are equal to their steady-state values. The initial date of the forecast can be provided in the third argument. By default, the forecast will start at the first date indicated in the init_plan command. This function returns a dataset containing the historical and forecast values for the endogenous and exogenous variables.

**Example**

```
% conditional forecast using extended path method
% with perfect foresight on r path
```

(continues on next page)
var y r;
varx o e u;

smoothed = dseries('smoothed_variables.csv');

fplan = init_plan(2013Q4:2029Q4);
fplan = flip_plan(fplan, 'y', 'u', 'surprise', 2013Q4:2014Q4, [1 1.1 1.2 1.
˓→1 1.1 1.2 1.
˓→1 1.1 1.2 1.
˓→1.9 1.9 1.9 ]);
fplan = flip_plan(fplan, 'r', 'e', 'perfect_foresight', 2013Q4:2014Q4, [2 ˓→1.9 1.9 1.9 ]);

dset_forecast = det_cond_forecast(fplan, smoothed);

plot(dset_forecast.{'y','u'});
plot(dset_forecast.{'r','e'});

Command: smoother2histval;
Command: smoother2histval(OPTIONS...);

The purpose of this command is to construct initial conditions (for a subsequent simulation) that are the
smoothed values of a previous estimation.

More precisely, after an estimation run with the smoother option, smoother2histval will extract the
smoothed values (from oo_.SmoothedVariables, and possibly from oo_.SmoothedShocks if there are
lagged exogenous), and will use these values to construct initial conditions (as if they had been manually
entered through histval).

Options

period = INTEGER
Period number to use as the starting point for the subsequent simulation. It should be between 1 and
the number of observations that were used to produce the smoothed values. Default: the last observation.

infile = FILENAME
Load the smoothed values from a _results.mat file created by a previous Dynare run. Default: use
the smoothed values currently in the global workspace.

invars = ( VARIABLE_NAME [VARIABLE_NAME ...] )
A list of variables to read from the smoothed values. It can contain state endogenous variables, and also
exogenous variables having a lag. Default: all the state endogenous variables, and all the exogenous
variables with a lag.

outfile = FILENAME
Write the initial conditions to a file. Default: write the initial conditions in the current workspace, so
that a simulation can be performed.

outvars = ( VARIABLE_NAME [VARIABLE_NAME ...] )
A list of variables which will be given the initial conditions. This list must have the same length than
the list given to invars, and there will be a one-to-one mapping between the two list. Default: same
value as option invars.

Use cases

There are three possible ways of using this command:

• Everything in a single file: run an estimation with a smoother, then run smoother2histval (without
the infile and outfile options), then run a stochastic simulation.

• In two files: in the first file, run the smoother and then run smoother2histval with the outfile
option; in the second file, run histval_file to load the initial conditions, and run a (deterministic or
stochastic) simulation.

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In two files: in the first file, run the smoother; in the second file, run smoother2histval with the infile option equal to the _results.mat file created by the first file, and then run a (deterministic or stochastic) simulation.

4.21 Optimal policy

Dynare has tools to compute optimal policies for various types of objectives. You can either solve for optimal policy under commitment with ramsey_model, for optimal policy under discretion with discretionary_policy or for optimal simple rules with osr (also implying commitment).

Command: planner_objective MODEL_EXPRESSION ;
This command declares the policy maker objective, for use with ramsey_model or discretionary_policy.

You need to give the one-period objective, not the discounted lifetime objective. The discount factor is given by the planner_discount option of ramsey_model and discretionary_policy. The objective function can only contain current endogenous variables and no exogenous ones. This limitation is easily circumvented by defining an appropriate auxiliary variable in the model.

With ramsey_model, you are not limited to quadratic objectives: you can give any arbitrary nonlinear expression.

With discretionary_policy, the objective function must be quadratic.

Command: evaluate_planner_objective ;
Command: evaluate_planner_objective(OPTIONS...);
This command computes, displays, and stores the value of the planner objective function under Ramsey policy or discretion in oo_.planner_objective_value. It will provide both unconditional welfare and welfare conditional on the initial (i.e. period 0) values of the endogenous and exogenous state variables inherited by the planner. In a deterministic context, the respective initial values are set using initval or histval (depending on the exact context).

In a stochastic context, if no initial state values have been specified with histval, their values are taken to be the steady state values. Because conditional welfare is computed conditional on optimal policy by the planner in the first endogenous period (period 1), it is conditional on the information set in the period 1. This information set includes both the predetermined states inherited from period 0 (specified via histval for both endogenous and lagged exogenous states) as well as the period 1 values of the exogenous shocks. The latter are specified using the perfect foresight syntax of the shocks block.

At the current stage, the stochastic context does not support the pruning option. At order>3, only the computation of conditional welfare with steady state Lagrange multipliers is supported. Note that at order=2, the output is based on the second-order accurate approximation of the variance stored in oo_.var.

Options

periods = INTEGER
The value of the option specifies the number of periods to use in the simulations in the computation of unconditional welfare at higher order.

Default: 10000.

drop = INTEGER
The number of burn-in draws out of periods discarded before computing the unconditional welfare at higher order. Default: 1000.

Example (stochastic context)

```plaintext
var a ...;
varexo u;
model;
```
(continued from previous page)

\[
a = \rho \cdot a(-1) + u + u(-1);
\]

\[
\ldots
\]

\[
\text{end};
\]

\[
\text{histval};
\]

\[
u(0)=1;
\]

\[
a(0)=-1;
\]

\[
\text{end};
\]

\[
\text{shocks};
\]

\[
\text{var u; stderr 0.008;}
\]

\[
\text{var u;}
\]

\[
\text{periods 1;}
\]

\[
\text{values 1;}
\]

\[
\text{end;}
\]

\[
\text{evaluate_planner_objective;}
\]

**MATLAB/Octave variable:** `oo_.planner_objective_value.unconditional`

Scalar storing the value of unconditional welfare. In a perfect foresight context, it corresponds to welfare in the long-run, approximated as welfare in the terminal simulation period.

**MATLAB/Octave variable:** `oo_.planner_objective_value.conditional`

In a perfect foresight context, this field will be a scalar storing the value of welfare conditional on the specified initial condition and zero initial Lagrange multipliers.

In a stochastic context, it will have two subfields:

**MATLAB/Octave variable:**

`oo_.planner_objective_value.conditional.steady_initial_multiplier`

Stores the value of the planner objective when the initial Lagrange multipliers associated with the planner’s problem are set to their steady state values (see `ramsey_policy`).

**MATLAB/Octave variable:**

`oo_.planner_objective_value.conditional.zero_initial_multiplier`

Stores the value of the planner objective when the initial Lagrange multipliers associated with the planner’s problem are set to 0, i.e. it is assumed that the planner exploits its ability to surprise private agents in the first period of implementing Ramsey policy. This value corresponds to the planner implementing optimal policy for the first time and committing not to re-optimize in the future.

### 4.21.1 Optimal policy under commitment (Ramsey)

Dynare allows to automatically compute optimal policy choices of a Ramsey planner who takes the specified private sector equilibrium conditions into account and commits to future policy choices. Doing so requires specifying the private sector equilibrium conditions in the `model` block and a `planner_objective` as well as potentially some `instruments` to facilitate computations.

**Warning:** Be careful when employing forward-looking auxiliary variables in the context of timeless perspective Ramsey computations. They may alter the problem the Ramsey planner will solve for the first period, although they seemingly leave the private sector equilibrium unaffected. The reason is the planner optimizes with respect to variables dated t and takes the value of time 0 variables as given, because they are predetermined. This set of initially predetermined variables will change with forward-looking definitions. Thus, users are strongly advised to use model-local variables instead.
Example

Consider a perfect foresight example where the Euler equation for the return to capital is given by

\[ \frac{1}{C} = \beta \frac{1}{C(+1)} (R(+1) + (1 - \delta)) \]

The job of the Ramsey planner in period 1 is to choose \( C_1 \) and \( R_1 \), taking as given \( C_0 \). The above equation may seemingly equivalently be written as

\[ \frac{1}{C} = \beta \frac{1}{C(+1)} (R_{cap}); \]
\[ R_{cap} = R(+1) + (1 - \delta); \]

due to perfect foresight. However, this changes the problem of the Ramsey planner in the first period to choosing \( C_1 \) and \( R_1 \), taking as given both \( C_0 \) and \( R_{cap}^0 \). Thus, the relevant return to capital in the Euler equation of the first period is not a choice of the planner anymore due to the forward-looking nature of the definition in the second line!

A correct specification would be to instead define \( R_{cap} \) as a model-local variable:

\[ \frac{1}{C} = \beta \frac{1}{C(+1)} (R_{cap}); \]
\[ #R_{cap} = R(+1) + (1 - \delta); \]

Command: \texttt{ramsey\_model(OPTIONS...)};

This command computes the First Order Conditions for maximizing the policy maker objective function subject to the constraints provided by the equilibrium path of the private economy.

The planner objective must be declared with the \texttt{planner\_objective} command.

This command only creates the expanded model, it doesn’t perform any computations. It needs to be followed by other instructions to actually perform desired computations. Examples are calls to \texttt{steady} to compute the steady state of the Ramsey economy, to \texttt{stoch\_simul} with various approximation orders to conduct stochastic simulations based on perturbation solutions, to \texttt{estimation} in order to estimate models under optimal policy with commitment, and to perfect foresight simulation routines.

See Auxiliary variables, for an explanation of how Lagrange multipliers are automatically created.

Options

This command accepts the following options:

- \texttt{planner\_discount = EXPRESSION}
  
  Declares or reassigns the discount factor of the central planner optimal\_policy\_discount\_factor.
  
  Default: 1.0.

- \texttt{planner\_discount\_latex\_name = LATEX\_NAME}
  
  Sets the LaTeX name of the optimal\_policy\_discount\_factor parameter.

- \texttt{instruments = (VARIABLE\_NAME,...)}
  
  Declares instrument variables for the computation of the steady state under optimal policy. Requires a steady\_state\_model block or a _steadystate.m file. See below.

Steady state

Dynare takes advantage of the fact that the Lagrange multipliers appear linearly in the equations of the steady state of the model under optimal policy. Nevertheless, it is in general very difficult to compute the steady state with simply a numerical guess in \texttt{initval} for the endogenous variables.

It greatly facilitates the computation, if the user provides an analytical solution for the steady state (in steady\_state\_model block or in a _steadystate.m file). In this case, it is necessary to provide a steady state solution CONDITIONAL on the value of the instruments in the optimal policy problem and declared with the option \texttt{instruments}. The initial value of the instrument for steady state finding in this case is set with \texttt{initval}. Note that computing and displaying steady state values using the \texttt{steady} command or calls to \texttt{resid} must come after the \texttt{ramsey\_model} statement and the \texttt{initval} block.
Note that choosing the instruments is partly a matter of interpretation and you can choose instruments that are handy from a mathematical point of view but different from the instruments you would refer to in the analysis of the paper. A typical example is choosing inflation or nominal interest rate as an instrument.

**Block:** `ramsey_constraints`;

This block lets you define constraints on the variables in the Ramsey problem. The constraints take the form of a variable, an inequality operator (\(>\) or \(<\)) and a constant.

**Example**

```plaintext
ramsey_constraints;
i > 0;
end;
```

**Command:** `ramsey_policy` [VARIABLE_NAME...];

**Command:** `ramsey_policy` (OPTIONS...) [VARIABLE_NAME...];

This command is deprecated and formally equivalent to the calling sequence

```plaintext
ramsey_model;
stoch_simul;
evaluate_planner_objective;
```

It computes an approximation of the policy that maximizes the policy maker’s objective function subject to the constraints provided by the equilibrium path of the private economy and under commitment to this optimal policy. The Ramsey policy is computed by approximating the equilibrium system around the perturbation point where the Lagrange multipliers are at their steady state, i.e. where the Ramsey planner acts as if the initial multipliers had been set to 0 in the distant past, giving them time to converge to their steady state value. Consequently, the optimal decision rules are computed around this steady state of the endogenous variables and the Lagrange multipliers.

Note that the variables in the list after the `ramsey_policy` or `stoch_simul` command can also contain multiplier names, but in a case-sensitive way (e.g. `MULT_1`). In that case, Dynare will for example display the IRFs of the respective multipliers when `irf>0`.

The planner objective must be declared with the `planner_objective` command.

**Options**

This command accepts all options of `stoch_simul`, plus:

- `planner_discount = EXPRESSION`
  
  See `planner_discount`.

- `instruments = (VARIABLE_NAME,...)`
  
  Declares instrument variables for the computation of the steady state under optimal policy. Requires a `steady_state_model` block or a `_steadystate.m` file. See below.

**Output**

This command generates all the output variables of `stoch_simul`. For specifying the initial values for the endogenous state variables (except for the Lagrange multipliers), see above.

**Steady state**

See *Ramsey steady state.*
4.21.2 Optimal policy under discretion

**Command:** discretionary_policy [VARIABLE_NAME...];

This command computes an approximation of the optimal policy under discretion. The algorithm implemented is essentially an LQ solver, and is described by Dennis (2007).

You must ensure that your objective is quadratic. Regarding the model, it must either be linear or solved at first order with an analytical steady state provided. In the first case, you should set the linear option of the model block.

It is possible to use the estimation command after the discretionary_policy command, in order to estimate the model with optimal policy under discretion and evaluate_planner_objective to compute welfare.

**Options**

This command accepts the same options as ramsey_policy, plus:

**discretionary_tol = NON-NEGATIVE DOUBLE**

Sets the tolerance level used to assess convergence of the solution algorithm. Default: 1e-7.

**maxit = INTEGER**

Maximum number of iterations. Default: 3000.

4.21.3 Optimal Simple Rules (OSR)

**Command:** osr [VARIABLE_NAME...];

This command computes optimal simple policy rules for linear-quadratic problems of the form:

$$\min \gamma E(y_t'W y_t)$$

such that:

$$A_1E_1y_{t+1} + A_2y_t + A_3y_{t-1} + C e_t = 0$$

where:

- $E$ denotes the unconditional expectations operator;
- $\gamma$ are parameters to be optimized. They must be elements of the matrices $A_1, A_2, A_3$, i.e. be specified as parameters in the params command and be entered in the model block;
- $y$ are the endogenous variables, specified in the var command, whose (co)-variance enters the loss function;
- $e$ are the exogenous stochastic shocks, specified in the varexo-command;
- $W$ is the weighting matrix;

The linear quadratic problem consists of choosing a subset of model parameters to minimize the weighted (co)-variance of a specified subset of endogenous variables, subject to a linear law of motion implied by the first order conditions of the model. A few things are worth mentioning. First, $y$ denotes the selected endogenous variables’ deviations from their steady state, i.e. in case they are not already mean 0 the variables entering the loss function are automatically demeaned so that the centered second moments are minimized. Second, osr only solves linear quadratic problems of the type resulting from combining the specified quadratic loss function with a first order approximation to the model’s equilibrium conditions. The reason
is that the first order state-space representation is used to compute the unconditional (co-)variances. Hence, osr will automatically select order=1. Third, because the objective involves minimizing a weighted sum of unconditional second moments, those second moments must be finite. In particular, unit roots in $y$ are not allowed.

The subset of the model parameters over which the optimal simple rule is to be optimized, $\gamma$, must be listed with osr_params.

The weighting matrix $W$ used for the quadratic objective function is specified in the optim_weights block.

By attaching weights to endogenous variables, the subset of endogenous variables entering the objective function, $y$, is implicitly specified.

The linear quadratic problem is solved using the numerical optimizer specified with opt_algo.

**Options**

The osr command will subsequently run stoch_simul and accepts the same options, including restricting the endogenous variables by listing them after the command, as stoch_simul (see Stochastic solution and simulation) plus

- **opt_algo = INTEGER**
  Specifies the optimizer for minimizing the objective function. The same solvers as for mode_compute (see mode_compute) are available, except for 5, 6, and 10.

- **optim = (NAME, VALUE, ...)**
  A list of NAME`` and VALUE pairs. Can be used to set options for the optimization routines. The set of available options depends on the selected optimization routine (i.e. on the value of option opt_algo). See optim.

- **maxit = INTEGER**
  Determines the maximum number of iterations used in opt_algo=4. This option is now deprecated and will be removed in a future release of Dynare. Use optim instead to set optimizer-specific values. Default: 1000.

- **tolf = DOUBLE**
  Convergence criterion for termination based on the function value used in opt_algo=4. Iteration will cease when it proves impossible to improve the function value by more than tolf. This option is now deprecated and will be removed in a future release of Dynare. Use optim instead to set optimizer-specific values. Default: 1e-7.

- **analytic_derivation**
  Triggers estimation with analytic gradient of the objective function.

- **analytic_derivation_mode = INTEGER**
  See :opt:analytic_derivation_mode.

- **silent_optimizer**
  See silent_optimizer.

- **huge_number = DOUBLE**
  Value for replacing the infinite bounds on parameters by finite numbers. Used by some optimizers for numerical reasons (see huge_number). Users need to make sure that the optimal parameters are not larger than this value. Default: 1e7.

The value of the objective is stored in the variable oo_.osr.objective_function and the value of parameters at the optimum is stored in oo_.osr.optim_params. See below for more details.

After running osr the parameters entering the simple rule will be set to their optimal value so that subsequent runs of stoch_simul will be conducted at these values.

**Command:** osr_params PARAMETER_NAME...;

This command declares parameters to be optimized by osr.
Block: **optim_weights** ;

This block specifies quadratic objectives for optimal policy problems.

More precisely, this block specifies the nonzero elements of the weight matrix $W$ used in the quadratic form of the objective function in `osr`.

An element of the diagonal of the weight matrix is given by a line of the form:

```
VARIABLE_NAME EXPRESSION;
```

An off-the-diagonal element of the weight matrix is given by a line of the form:

```
VARIABLE_NAME, VARIABLE_NAME EXPRESSION;
```

**Example**

```latex
var y inflation r;
varexo y_ inf_; 
parameters delta sigma alpha kappa gammarr gammac0 gamma_y_ gamma_ inf_; 
delta = 0.44;
kappa = 0.18;
alpha = 0.48;
sigma = -0.06;
gammarr = 0;
gammac0 = 0.2;
gamma_y_ = 8;
gamma_inf_ = 3;
model(linear);
y = delta * y(-1) + (1-delta)*y(+1)+sigma *(r - inflation(+1)) + y_;
inflation = alpha * inflation(-1) + (1-alpha) * inflation(+1) + kappa*y_+ inf_;
r = gammac0*y(-1)+gammac0*inflation(-1)+gamma_y_*y_+gamma_inf_*inf_; 
end;
shocks;
var y_; stderr 0.63;
var inf_; stderr 0.4;
end;
optim_weights;
inflation 1;
y 1;
y, inflation 0.5;
end;
```

Block: **osr_params_bounds** ;

This block declares lower and upper bounds for parameters in the optimal simple rule. If not specified the optimization is unconstrained.

Each line has the following syntax:
PARAMETER_NAME, LOWER_BOUND, UPPER_BOUND;

Note that the use of this block requires the use of a constrained optimizer, i.e. setting opt_algo to 1, 2, 5 or 9.

Example

```matlab
osr_params_bounds;
gamma_inf_, 0, 2.5;
end;
osr(opt_algo=9) y;
```

MATLAB/Octave variable: oo_.osr.objective_function

After an execution of the osr command, this variable contains the value of the objective under optimal policy.

MATLAB/Octave variable: oo_.osr.optim_params

After an execution of the osr command, this variable contains the value of parameters at the optimum, stored in fields of the form oo_.osr.optim_params.PARAMETER_NAME.

MATLAB/Octave variable: M_.osr.param_names

After an execution of the osr command, this cell contains the names of the parameters.

MATLAB/Octave variable: M_.osr.param_indices

After an execution of the osr command, this vector contains the indices of the OSR parameters in M_.params.

MATLAB/Octave variable: M_.osr.param_bounds

After an execution of the osr command, this two by number of OSR parameters matrix contains the lower and upper bounds of the parameters in the first and second column, respectively.

MATLAB/Octave variable: M_.osr.variable_weights

After an execution of the osr command, this sparse matrix contains the weighting matrix associated with the variables in the objective function.

MATLAB/Octave variable: M_.osr.variable_indices

After an execution of the osr command, this vector contains the indices of the variables entering the objective function in M_.endo_names.

4.22 Sensitivity and identification analysis

Dynare provides an interface to the global sensitivity analysis (GSA) toolbox (developed by the Joint Research Center (JRC) of the European Commission), which is now part of the official Dynare distribution. The GSA toolbox can be used to answer the following questions:

1. What is the domain of structural coefficients assuring the stability and determinacy of a DSGE model?
2. 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?
3. 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).

With respect to the previous version of the toolbox, in order to work properly, the GSA toolbox no longer requires that the Dynare estimation environment is set up.
4.22.1 Performing sensitivity analysis

**Command:** sensitivity ;

**Command:** sensitivity(OPTIONS...);

This command triggers sensitivity analysis on a DSGE model.

**Sampling Options**

Nsam = INTEGER

Size of the Monte-Carlo sample. Default: 2048.

ilptau = INTEGER

If equal to 1, use $L_P$ quasi-Monte-Carlo. If equal to 0, use LHS Monte-Carlo. Default: 1.

pprior = INTEGER

If equal to 1, sample from the prior distributions. If equal to 0, sample from the multivariate normal $N(\theta, \Sigma)$, where $\theta$ is the posterior mode and $\Sigma = H^{-1}$, $H$ is the Hessian at the mode. Default: 1.

prior_range = INTEGER

If equal to 1, sample uniformly from prior ranges. If equal to 0, sample from prior distributions. Default: 1.

morris = INTEGER

If equal to 0, ANOVA mapping (Type I error) If equal to 1, Screening analysis (Type II error). If equal to 2, Analytic derivatives (similar to Type II error, only valid when identification=1). Default: 1 when identification=1, 0 otherwise.

morris_nliv = INTEGER

Number of levels in Morris design. Default: 6.

morris_ntra = INTEGER

Number trajectories in Morris design. Default: 20.

ppost = INTEGER

If equal to 1, use Metropolis posterior sample. If equal to 0, do not use Metropolis posterior sample. Default: 0.

NB: This overrides any other sampling option.

neighborhood_width = DOUBLE

When pprior=0 and ppost=0, allows for the sampling of parameters around the value specified in the mode_file, in the range $x_{param1} \pm |x_{param1} \times \text{neighborhood_width}|$. Default: 0.

**Stability Mapping Options**

stab = INTEGER

If equal to 1, perform stability mapping. If equal to 0, do not perform stability mapping. Default: 1.

load_stab = INTEGER

If equal to 1, load a previously created sample. If equal to 0, generate a new sample. Default: 0.

alpha2_stab = DOUBLE

Critical value for correlations $\rho$ in filtered samples: plot couples of paramters with $|\rho| > \alpha_2$ stab. Default: 0.

pvalue_ks = DOUBLE

The threshold $pvalue$ for significant Kolmogorov-Smirnov test (i.e. plot parameters with $pvalue < pvalue_ks$). Default: 0.001.

pvalue_corr = DOUBLE

The threshold $pvalue$ for significant correlation in filtered samples (i.e. plot bivariate samples when $pvalue < pvalue_corr$). Default: 1e-5.
Reduced Form Mapping Options

\texttt{redform = INTEGER}

If equal to 1, prepare Monte-Carlo sample of reduced form matrices. If equal to 0, do not prepare
Monte-Carlo sample of reduced form matrices. Default: 0.

\texttt{load_redform = INTEGER}

If equal to 1, load previously estimated mapping. If equal to 0, estimate the mapping of the reduced
form model. Default: 0.

\texttt{logtrans_redform = INTEGER}

If equal to 1, use log-transformed entries. If equal to 0, use raw entries. Default: 0.

\texttt{threshold_redform = [DOUBLE DOUBLE]}

The range over which the filtered Monte-Carlo entries of the reduced form coefficients should be an-
alysed. The first number is the lower bound and the second is the upper bound. An empty vector
indicates that these entries will not be filtered. Default: empty.

\texttt{ksstat_redform = DOUBLE}

Critical value for Smirnov statistics \(d\) when reduced form entries are filtered. Default: 0.001.

\texttt{alpha2_redform = DOUBLE}

Critical value for correlations \(\rho\) when reduced form entries are filtered. Default: 1e-5.

\texttt{namendo = (VARIABLE_NAME...)}

List of endogenous variables. ‘:’ indicates all endogenous variables. Default: empty.

\texttt{namlagendo = (VARIABLE_NAME...)}

List of lagged endogenous variables. ‘:’ indicates all lagged endogenous variables. Analyze entries

\texttt{namexo = (VARIABLE_NAME...)}

List of exogenous variables. ‘:’ indicates all exogenous variables. Analyze entries [namendo ×
namexo]. Default: empty.

RMSE Options

\texttt{rmse = INTEGER}

If equal to 1, perform RMSE analysis. If equal to 0, do not perform RMSE analysis. Default: 0.

\texttt{load_rmse = INTEGER}

If equal to 1, load previous RMSE analysis. If equal to 0, make a new RMSE analysis. Default: 0.

\texttt{lik_only = INTEGER}

If equal to 1, compute only likelihood and posterior. If equal to 0, compute RMSE’s for all observed
series. Default: 0.

\texttt{var_rmse = (VARIABLE_NAME...)}

List of observed series to be considered. ‘:’ indicates all observed variables. Default: varobs.

\texttt{pfilt_rmse = DOUBLE}

Filtering threshold for RMSE’s. Default: 0.1.

\texttt{istart_rmse = INTEGER}

Value at which to start computing RMSE’s (use 2 to avoid big intitial error). Default: presample+1.

\texttt{alpha_rmse = DOUBLE}

Critical value for Smirnov statistics \(d\): plot parameters with \(d > \alpha_{\text{rmse}}\). Default: 0.001.

\texttt{alpha2_rmse = DOUBLE}

Critical value for correlation \(\rho\): plot couples of parameters with \(|\rho| = \alpha_{2\text{rmse}}\). Default: 1e-5.
datafile = FILENAME
    See datafile.

nobs = INTEGER
nobs = [INTEGER1:INTEGER2]
    See nobs.

first_obs = INTEGER
    See first_obs.

prefilter = INTEGER
    See prefilter.

presample = INTEGER
    See presample.

nograph
    See nograph.

nodisplay
    See nodisplay.

graph_format = FORMAT
    graph_format = ( FORMAT, FORMAT... )
    See graph_format.

conf_sig = DOUBLE
    See conf_sig.

loglinear
    See loglinear.

mode_file = FILENAME
    See mode_file.

kalman_algo = INTEGER
    See kalman_algo.

Identification Analysis Options

identification = INTEGER
    If equal to 1, performs identification analysis (forcing redform=0 and morris=1) If equal to 0, no
    identification analysis. Default: 0.

morris = INTEGER
    See morris.

morris_nliv = INTEGER
    See morris_nliv.

morris_ntra = INTEGER
    See morris_ntra.

load_ident_files = INTEGER
    Loads previously performed identification analysis. Default: 0.

useautocorr = INTEGER
    Use autocorrelation matrices in place of autocovariance matrices in moments for identification analysis.
    Default: 0.

ar = INTEGER
    Maximum number of lags for moments in identification analysis. Default: 1.
diffuse_filter = INTEGER
   See diffuse_filter.

Command: dynare_sensitivity ;
Command: dynare_sensitivity(OPTIONS...);
   This is a deprecated alias for the sensitivity command.

4.22.2 IRF/Moment calibration

The irf_calibration and moment_calibration blocks allow imposing implicit “endogenous” priors about IRFs and moments on the model. The way it works internally is that any parameter draw that is inconsistent with the “calibration” provided in these blocks is discarded, i.e. assigned a prior density of 0. In the context of dynare_sensitivity, these restrictions allow tracing out which parameters are driving the model to satisfy or violate the given restrictions.

IRF and moment calibration can be defined in irf_calibration and moment_calibration blocks:

Block: irf_calibration ;
Block: irf_calibration(OPTIONS...);
   This block allows defining IRF calibration criteria and is terminated by end;. To set IRF sign restrictions, the following syntax is used:

VARIABLE_NAME(INTEGER), EXOGENOUS_NAME, -;
VARIABLE_NAME(INTEGER:INTEGER), EXOGENOUS_NAME, +;

To set IRF restrictions with specific intervals, the following syntax is used:

VARIABLE_NAME(INTEGER), EXOGENOUS_NAME, [EXPRESSION, EXPRESSION];
VARIABLE_NAME(INTEGER:INTEGER), EXOGENOUS_NAME, [EXPRESSION, EXPRESSION];

When (INTEGER:INTEGER) is used, the restriction is considered to be fulfilled by a logical OR. A list of restrictions must always be fulfilled with logical AND.

Options

relative_irf
   See relative_irf.

Example

    irf_calibration;
    y(1:4), e_ys, [-50, 50]; //first year response with logical OR
    @#for ilag in 21:40
    R_obs(@(ilag)), e_ys, [0, 6]; //response from 5th to 10th years with...
    endfor
    end;

Block: moment_calibration ;
Block: moment_calibration(OPTIONS...);
   This block allows defining moment calibration criteria. This block is terminated by end;, and contains lines of the form:

VARIABLE_NAME1, VARIABLE_NAME2(+/-INTEGER), [EXPRESSION, EXPRESSION];
VARIABLE_NAME1, VARIABLE_NAME2(+/-INTEGER), +/-;
VARIABLE_NAME1, VARIABLE_NAME2(+/-INTEGER:INTEGER), [EXPRESSION, EXPRESSION];
VARIABLE_NAME1, VARIABLE_NAME2((+INTEGER:+INTEGER), [EXPRESSION, EXPRESSION];
When \((\text{INTEGER} : \text{INTEGER})\) is used, the restriction is considered to be fulfilled by a logical OR. A list of restrictions must always be fulfilled with logical AND. The moment restrictions generally apply to auto- and cross-correlations between variables. The only exception is a restriction on the unconditional variance of an endogenous variable, specified as shown in the example below.

**Example**

```plaintext
moment_calibration;
  y_obs, y_obs, [0.5, 1.5]; // [unconditional variance]
  y_obs, y_obs(-(1:4)), +; // [sign restriction for first year, autocorrelation with logical OR]
  @#for ilag in -2:2
    y_obs, R_obs(@{ilag}), -; // [-2:2 cross correlation with logical AND]
  @#endfor
  @#for ilag in -4:4
    y_obs, pie_obs(@{ilag}), -; // [-4:4 cross correlation with logical AND]
  @#endfor
end;
```

### 4.22.3 Performing identification analysis

**Command:** `identification`;

**Command:** `identification(OPTIONS...)`;

This command triggers:

1. Theoretical identification analysis based on
   - moments as in Iskrev (2010)
   - spectral density as in Qu and Tkachenko (2012)
   - minimal system as in Komunjer and Ng (2011)
   - reduced-form solution and linear rational expectation model as in Ratto and Iskrev (2011)

   Note that for orders 2 and 3, all identification checks are based on the pruned state space system as in Mutschler (2015). That is, theoretical moments and spectrum are computed from the pruned ABCD-system, whereas the minimal system criteria is based on the first-order system, but augmented by the theoretical (pruned) mean at order 2 or 3.

2. Identification strength analysis based on (theoretical or simulated) curvature of moment information matrix as in Ratto and Iskrev (2011)

3. Parameter checks based on nullspace and multicorrelation coefficients to determine which (combinations of) parameters are involved

**General Options**

- **order = 1|2|3**
  
  Order of approximation. At orders 2 and 3 identification is based on the pruned state space system. Note that the order set in other functions does not overwrite the default. Default: 1.

- **parameter_set = OPTION**
  
  See `parameter_set` for possible values. Default: `prior_mean`.

- **prior_mc = INTEGER**
  

- **prior_range = INTEGER**
  
  Triggers uniform sample within the range implied by the prior specifications (when `prior_mc>1`). Default: 0.
advanced = INTEGER
If set to 1, shows a more detailed analysis, comprised of an analysis for the linearized rational expectation model as well as the associated reduced form solution. Further performs a brute force search of the groups of parameters best reproducing the behavior of each single parameter. The maximum dimension of the group searched is triggered by max_dim_cova_group. Default: 0.

max_dim_cova_group = INTEGER
In the brute force search (performed when advanced=1) this option sets the maximum dimension of groups of parameters that best reproduce the behavior of each single model parameter. Default: 2.

gsa_sample_file = INTEGER|FILENAME
If equal to 0, do not use sample file. If equal to 1, triggers gsa prior sample. If equal to 2, triggers gsa Monte-Carlo sample (i.e. loads a sample corresponding to pprior=0 and ppost=0 in the dynare_sensitivity options). If equal to FILENAME uses the provided path to a specific user defined sample file. Default: 0.

diffuse_filter
Deals with non-stationary cases. See diffuse_filter.

Numerical Options

analytic_derivation_mode = INTEGER
Different ways to compute derivatives either analytically or numerically. Possible values are:

• 0: efficient Sylvester equation method to compute analytical derivatives
• 1: Kronecker products method to compute analytical derivatives (only at order=1)
• -1: numerical two-sided finite difference method to compute all identification Jacobians (numerical tolerance level is equal to options_.dynatol.x)
• -2: numerical two-sided finite difference method to compute derivatives of steady state and dynamic model numerically, the identification Jacobians are then computed analytically (numerical tolerance level is equal to options_.dynatol.x)

Default: 0.

normalize_jacobians = INTEGER
If set to 1: Normalize Jacobian matrices by rescaling each row by its largest element in absolute value. Normalize Gram (or Hessian-type) matrices by transforming into correlation-type matrices. Default: 1

tol_rank = DOUBLE
Tolerance level used for rank computations. Default: 1.e-10.

tol_deriv = DOUBLE

tol_sv = DOUBLE

schur_vec_tol = DOUBLE
See schur_vec_tol.

Identification Strength Options

no_identification_strength
Disables computations of identification strength analysis based on sample information matrix.

periods = INTEGER
When the analytic Hessian is not available (i.e. with missing values or diffuse Kalman filter or univariate Kalman filter), this triggers the length of stochastic simulation to compute Simulated Moments Uncertainty. Default: 300.
replic = INTEGER
When the analytic Hessian is not available, this triggers the number of replicas to compute Sim-
ulated Moments Uncertainty. Default: 100.

Moments Options

no_identification_moments
Disables computations of identification check based on Iskrev (2010)’s J, i.e. derivative of first
two moments.

ar = INTEGER
Number of lags of computed autocovariances-autocorrelations (theoretical moments) in Iskrev

useautocorr = INTEGER
If equal to 1, compute derivatives of autocorrelation. If equal to 0, compute derivatives of auto-
covariances. Default: 0.

Spectrum Options

no_identification_spectrum
Disables computations of identification check based on Qu and Tkachenko (2012)’s G, i.e. Gram
matrix of derivatives of first moment plus outer product of derivatives of spectral density.

grid_nbr = INTEGER
Number of grid points in [-pi;pi] to approximate the integral to compute Qu and Tkachenko

Minimal State Space System Options

no_identification_minimal
Disables computations of identification check based on Komunjer and Ng (2011)’s D, i.e. mini-
mal state space system and observational equivalent spectral density transformations.

Misc Options

nograph
See nograph.

nodisplay
See nodisplay.

graph_format = FORMAT
See graph_format.

Misc Options

tex
See tex.

Debug Options

load_ident_files = INTEGER
If equal to 1, allow Dynare to load previously computed analyzes. Default: 0.

lik_init = INTEGER
See lik_init.

kalman_algo = INTEGER
See kalman_algo.

no_identification_reducedform
Disables computations of identification check based on steady state and reduced-form solution.
checks_via_subsets = INTEGER
If equal to 1: finds problematic parameters in a brute force fashion: It computes the rank of the
Jacobians for all possible parameter combinations. If the rank condition is not fullfilled, these
parameter sets are flagged as non-identifiable. The maximum dimension of the group searched
is triggered by max_dim_subsets_groups. Default: 0.

max_dim_subsets_groups = INTEGER
Sets the maximum dimension of groups of parameters for which the above brute force search is
performed. Default: 4.

4.22.4 Types of analysis and output files

The sensitivity analysis toolbox includes several types of analyses. Sensitivity analysis results are saved locally in
<mod_file>/gsa, where <mod_file>.mod is the name of the Dynare model file.

4.22.4.1 Sampling

The following binary files are produced:
- <mod_file>_prior.mat: this file stores information about the analyses performed sampling from the prior,
i.e. pprior=1 and ppost=0;
- <mod_file>_mc.mat: this file stores information about the analyses performed sampling from multivariate
normal, i.e. pprior=0 and ppost=0;
- <mod_file>_post.mat: this file stores information about analyses performed using the Metropolis poste-
rior sample, i.e. ppost=1.

4.22.4.2 Stability Mapping

Figure files produced are of the form <mod_file>_prior_*.fig and store results for stability mapping from
prior Monte-Carlo samples:
- <mod_file>_prior_stable.fig: plots of the Smirnov test and the correlation analyses confronting the
cdf of the sample fulfilling Blanchard-Kahn conditions (blue color) with the cdf of the rest of the sample
(red color), 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);
- <mod_file>_prior_indeterm.fig: plots of the Smirnov test and the correlation analyses confronting
the cdf of the sample producing indeterminacy (red color) with the cdf of the rest of the sample (blue color);
- <mod_file>_prior_unstable.fig: plots of the Smirnov test and the correlation analyses confronting
the cdf of the sample producing explosive roots (red color) with the cdf of the rest of the sample (blue color);
- <mod_file>_prior_wrong.fig: plots of the Smirnov test and the correlation analyses confronting the cdf
of the sample where the solution could not be found (e.g. the steady state solution could not be found by the
solver - red color) with the cdf of the rest of the sample (blue color);
- <mod_file>_prior_calib.fig: plots of the Smirnov test and the correlation analyses splitting the sample
fulfilling Blanchard-Kahn conditions, by confronting the cdf of the sample where IRF/moment restrictions
are matched (blue color) with the cdf where IRF/moment restrictions are NOT matched (red color);

Similar conventions apply for <mod_file>_mc_*.fig files, obtained when samples from multivariate normal are
used.
4.22.4.3 IRF/Moment restrictions

The following binary files are produced:

- `<mod_file>_prior_restrictions.mat`: this file stores information about the IRF/moment restriction analysis performed sampling from the prior ranges, i.e. `pprior=1` and `ppost=0`;
- `<mod_file>_mc_restrictions.mat`: this file stores information about the IRF/moment restriction analysis performed sampling from multivariate normal, i.e. `pprior=0` and `ppost=0`;
- `<mod_file>_post_restrictions.mat`: this file stores information about IRF/moment restriction analysis performed using the Metropolis posterior sample, i.e. `ppost=1`.

Figure files produced are of the form `<mod_file>_prior_irf_calib_*_.fig` and `<mod_file>_prior_moment_calib_*_.fig` and store results for mapping restrictions from prior Monte-Carlo samples:

- `<mod_file>_prior_irf_calib_<ENDO_NAME>_vs_<EXO_NAME>_vs_<PERIOD>.fig`: plots of the Smirnov test and the correlation analyses splitting the sample fulfilling Blanchard-Kahn conditions, by confronting the cdf of the sample where the individual IRF restriction `<ENDO_NAME>` vs. `<EXO_NAME>` at period(s) `<PERIOD>` is matched (blue color) with the cdf where the IRF restriction is NOT matched (red color);
- `<mod_file>_prior_irf_calib_<ENDO_NAME>_*<EXO_NAME>_ALL.fig`: plots of the Smirnov test and the correlation analyses splitting the sample fulfilling Blanchard-Kahn conditions, by confronting the cdf of the sample where ALL the individual IRF restrictions for the same couple `<ENDO_NAME>` vs. `<EXO_NAME>` are matched (blue color) with the cdf where the IRF restriction is NOT matched (red color);
- `<mod_file>_prior_irf_restrictions.fig`: plots visual information on the IRF restrictions compared to the actual Monte Carlo realization from prior sample.
- `<mod_file>_prior_moment_calib_<ENDO_NAME1>_vs_<ENDO_NAME2>_vs_<LAG>.fig`: plots of the Smirnov test and the correlation analyses splitting the sample fulfilling Blanchard-Kahn conditions, by confronting the cdf of the sample where the individual acf/ccf moment restriction `<ENDO_NAME1>` vs. `<ENDO_NAME2>` at lag(s) `<LAG>` is matched (blue color) with the cdf where the IRF restriction is NOT matched (red color);
- `<mod_file>_prior_moment_calib_<ENDO_NAME>_vs_<EXO_NAME>_ALL.fig`: plots of the Smirnov test and the correlation analyses splitting the sample fulfilling Blanchard-Kahn conditions, by confronting the cdf of the sample where ALL the individual acf/ccf moment restrictions for the same couple `<ENDO_NAME1>` vs. `<ENDO_NAME2>` are matched (blue color) with the cdf where the IRF restriction is NOT matched (red color);
- `<mod_file>_prior_moment_restrictions.fig`: plots visual information on the moment restrictions compared to the actual Monte Carlo realization from prior sample.

Similar conventions apply for `<mod_file>_mc_*.fig` and `<mod_file>_post_*.fig` files, obtained when samples from multivariate normal or from posterior are used.

4.22.4.4 Reduced Form Mapping

When the option `threshold_redform` is not set, or it is empty (the default), this analysis estimates a multivariate smoothing spline ANOVA model (the ‘mapping’) for the selected entries in the transition matrix of the shock matrix of the reduce form first order solution of the model. This mapping is done either with prior samples or with MC samples with `neighborhood_width`. Unless `neighborhood_width` is set with MC samples, the mapping of the reduced form solution forces the use of samples from prior ranges or prior distributions, i.e.: `pprior=1` and `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. One can also load a previously estimated mapping with a new Monte-Carlo sample, to look at the forecast for the new Monte-Carlo sample.

The following synthetic figures are produced:

- `<mod_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 vari-
ables (namendo) versus lagged endogenous variables (namlagendo); suffix log indicates the results for log-transformed entries;
• <mod_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;
• <mod_file>_redform_gsa(_log).fig: shows bar chart of all sensitivity indices for each parameter: this allows one 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 <mod_file>/gsa/redform_prior for prior samples and in <mod_file>/gsa/redform_mc for MC samples with option neighborhood_width, where the detailed results of the estimation of the single functional relationships between parameters \( \theta \) and reduced form coefficient (denoted as \( y \) hereafter) 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.

The following files are stored in each directory (we stick with prior sample but similar conventions are used for MC samples):
• <mod_file>_prior_<namendo>_vs_<namexo>.fig: histogram and CDF plot of the MC sample of the individual entry of the shock matrix, in sample and out of sample fit of the ANOVA model;
• <mod_file>_prior_<namendo>_vs_<namexo>_map_SE.fig: for entries of the shock matrix it shows graphs of the estimated first order ANOVA terms \( y = f(\theta_i) \) for each deep parameter \( \theta_i \);
• <mod_file>_prior_<namendo>_vs_<namlagendo>.fig: histogram and CDF plot of the MC sample of the individual entry of the transition matrix, in sample and out of sample fit of the ANOVA model;
• <mod_file>_prior_<namendo>_vs_<namlagendo>_map_SE.fig: for entries of the transition matrix it shows graphs of the estimated first order ANOVA terms \( y = f(\theta_i) \) for each deep parameter \( \theta_i \);
• <mod_file>_prior_<namendo>_vs_<namexo>_map.mat, <mod_file>_<namendo>_vs_<namlagendo>_map.mat: these files store info in the estimation;

When option logtrans_redform is set, the ANOVA estimation is performed using a log-transformation of each \( y \). The ANOVA mapping is then transformed back onto the original scale, to allow comparability with the baseline estimation. Graphs for this log-transformed case, are stored in the same folder in files denoted with the _log suffix.

When the option threshold_redform is set, the analysis is performed via Monte Carlo filtering, by displaying parameters that drive the individual entry \( y \) inside the range specified in threshold_redform. If no entry is found (or all entries are in the range), the MCF algorithm ignores the range specified in threshold_redform and performs the analysis splitting the MC sample of \( y \) into deciles. Setting threshold_redform=[-inf inf] triggers this approach for all \( y \)'s.

Results are stored in subdirectories of <mod_file>/gsa/redform_prior named
• <mod_file>_prior_<namendo>_vs_<namlagendo>_threshold, for the entries of the transition matrix;
• <mod_file>_prior_<namendo>_vs_<namexo>_threshold, for entries of the matrix of the shocks.

The files saved are named:
• <mod_file>_prior_<namendo>_vs_<namexo>_threshold.fig, <mod_file>_<namendo>_vs_<namlagendo>_threshold.fig: graphical outputs;
• <mod_file>_prior_<namendo>_vs_<namexo>_threshold.mat, <mod_file>_<namendo>_vs_<namlagendo>_threshold.mat: info on the analysis;
4.22.4.5 RMSE

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

1. When $pprior=1$ and $ppost=0$, the toolbox analyzes the RMSEs for the Monte-Carlo 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 analyzes the RMSEs for a multivariate normal Monte-Carlo sample, with covariance matrix based on the inverse Hessian at the optimum: this analysis is useful when maximum likelihood estimation is done (i.e. no Bayesian estimation);

3. When $ppost=1$ the toolbox analyzes the RMSEs 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 you to indicate some options of the `estimation` command. These are:

- `datafile`
- `nobs`
- `first_obs`
- `prefilter`
- `presample`
- `nograph`
- `nodisplay`
- `graph_format`
- `conf_sig`
- `loglinear`
- `mode_file`

Binary files produced by my RMSE analysis are:

- `<mod_file>_prior_*.mat`: these files store the filtered and smoothed variables for the prior Monte-Carlo sample, generated when doing RMSE analysis ($pprior=1$ and $ppost=0$);
- `<mod_file>_mc_*.mat`: these files store the filtered and smoothed variables for the multivariate normal Monte-Carlo sample, generated when doing RMSE analysis ($pprior=0$ and $ppost=0$).

Figure files `<mod_file>_rmse_*.fig` store results for the RMSE analysis:

- `<mod_file>_rmse_prior*.fig`: save results for the analysis using prior Monte-Carlo samples;
- `<mod_file>_rmse_mc*.fig`: save results for the analysis using multivariate normal Monte-Carlo samples;
- `<mod_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):

- `<mod_file>_rmse_prior_params_*.fig`: for each parameter, plots the cdfs corresponding to the best 10% RMSEs of each observed series (only those cdfs below the significance threshold $\alpha_{\text{rmse}}$);
- `<mod_file>_rmse_prior_<var_obs>_*.fig`: if a parameter significantly affects the fit of $\text{var\_obs}$, all possible trade-off’s with other observables for same parameter are plotted;
- `<mod_file>_rmse_prior_<var_obs>_map.fig`: plots the MCF analysis of parameters significantly driving the fit the observed series $\text{var\_obs}$;
- `<mod_file>_rmse_prior_Lnlik*.fig`: for each observed series, plots in BLUE the cdf of the log-likelihood corresponding to the best 10% RMSEs, in RED the cdf of the rest of the sample and in BLACK the cdf of the full sample; this allows one to see the presence of some idiosyncratic behavior;
• `<mod_file>_rmse_prior_lnprior*.fig`: for each observed series, plots in BLUE the cdf of the log-prior corresponding to the best 10% RMSEs, in RED the cdf of the rest of the sample and in BLACK the cdf of the full sample; this allows one to see idiosyncratic behavior;

• `<mod_file>_rmse_prior_lnprior*.fig`: for each observed series, plots in BLUE the cdf of the log-prior corresponding to the best 10% RMSEs, in RED the cdf of the rest of the sample and in BLACK the cdf of the full sample; this allows one to see idiosyncratic behavior;

• `<mod_file>_rmse_prior_lnprior*.fig`: for each observed series, plots in BLUE the cdf of the log-prior corresponding to the best 10% RMSEs, in RED the cdf of the rest of the sample and in BLACK the cdf of the full sample; this allows one to see idiosyncratic behavior;

• `<mod_file>_rmse_prior_lik.fig`: when lik_only=1, this shows the MCF tests for the filtering of the best 10% log-likelihood values;

• `<mod_file>_rmse_prior_post.fig`: when lik_only=1, this shows the MCF tests for the filtering of the best 10% log-posterior values.

4.22.4.6 Screening Analysis

Screening analysis does not require any additional options with respect to those listed in Sampling Options. The toolbox performs all the analyses required and displays results.

The results of the screening analysis with Morris sampling design are stored in the subfolder `<mod_file>/gsa/screen`. The data file `<mod_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 Monte-Carlo samples are saved:

• `<mod_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);

• `<mod_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);

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

4.22.4.7 Identification Analysis

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 option morris=2, which implements Iskrev (2010) identification analysis.

For example, the placing:

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

in the Dynare model file triggers identification analysis using analytic derivatives as in Iskrev (2010), jointly with the mapping of the acceptable region.

The identification analysis with derivatives can also be triggered by the single command:

```
identification;
```

This does not do the mapping of acceptable regions for the model and uses the standard random sampler of Dynare. Additionally, using only identification; adds two additional identification checks: namely, of Qu and Tkachenko (2012) based on the spectral density and of Komunjer and Ng (2011) based on the minimal state space system. It completely offsets any use of the sensitivity analysis toolbox.

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4.23 Markov-switching SBVAR

Given a list of variables, observed variables and a data file, Dynare can be used to solve a Markov-switching SBVAR model according to Sims, Waggoner and Zha (2008). Having done this, you can create forecasts and compute the marginal data density, regime probabilities, IRFs, and variance decomposition of the model.

The commands have been modularized, allowing for multiple calls to the same command within a `<mod_file>`. The default is to use `<mod_file>` to tag the input (output) files used (produced) by the program. Thus, to call any command more than once within a `<mod_file>`, you must use the `_tag` options described below.

**Command:** `markov_switching(OPTIONS...)`

Declares the Markov state variable information of a Markov-switching SBVAR model.

**Options**

- **chain = INTEGER**

- **number_of_regimes = INTEGER**
  - Specifies the total number of regimes in the Markov Chain. This is a required option.

- **duration = DOUBLE | [ROW VECTOR OF DOUBLES]**
  - The duration of the regimes or regimes. This is a required option. When passed a scalar real number, it specifies the average duration for all regimes in this chain. When passed a vector of size equal `number_of_regimes`, it specifies the average duration of the associated regimes (1:`number_of_regimes`) in this chain. An absorbing state can be specified through the `restrictions` option.

- **restrictions = [[[ROW VECTOR OF 3 DOUBLES]], [ROW VECTOR OF 3 DOUBLES], ...]**
  - Provides restrictions on this chain’s regime transition matrix. Its vector argument takes three inputs of the form: `[current_period_regime, next_period_regime, transition_probability]`.
    - The first two entries are positive integers, and the third is a non-negative real in the set [0,1]. If restrictions are specified for every transition for a regime, the sum of the probabilities must be 1. Otherwise, if restrictions are not provided for every transition for a given regime the sum of the provided transition probabilities must be <1. Regardless of the number of lags, the restrictions are specified for parameters at time t since the transition probability for a parameter at t is equal to that of the parameter at t-1.

In case of estimating a MS-DSGE model, in addition the following options are allowed:

- **parameters = [LIST OF PARAMETERS]**
  - This option specifies which parameters are controlled by this Markov Chain.

- **number_of_lags = DOUBLE**
  - Provides the number of lags that each parameter can take within each regime in this chain.

**Example**

```markov_switching(chain=1, duration=2.5, restrictions=[[1,3,0],[3,1,0]]);
```

Specifies a Markov-switching BVAR with a first chain with 3 regimes that all have a duration of 2.5 periods. The probability of directly going from regime 1 to regime 3 and vice versa is 0.

**Example**

```markov_switching(chain=2, number_of_regimes=3, duration=[0.5, 2.5, 2.5], parameter=[alpha, rho], number_of_lags=2, restrictions=[[1,3,0],[3,3, →1]]);
```

---

11. If you want to align the paper with the description herein, please note that $A$ is $A^0$ and $F$ is $A^+$.  
12. An example can be found at https://git.dynare.org/Dynare/dynare/blob/master/tests/ms-dsge/test_ms_dsge.mod.
Specifications a Markov-switching DSGE model with a second chain with 3 regimes that have durations of 0.5, 2.5, and 2.5 periods, respectively. The switching parameters are \( \alpha \) and \( \rho \). The probability of directly going from regime 1 to regime 3 is 0, while regime 3 is an absorbing state.

**Command:** svar(OPTIONS...);

Each Markov chain can control the switching of a set of parameters. We allow the parameters to be divided equation by equation and by variance or slope and intercept.

**Options**

**coefficients**

Specifies that only the slope and intercept in the given equations are controlled by the given chain. One, but not both, of coefficients or variances must appear. Default: none.

**variances**

Specifies that only variances in the given equations are controlled by the given chain. One, but not both, of coefficients or variances must appear. Default: none.

**equations**

Defines the equation controlled by the given chain. If not specified, then all equations are controlled by chain. Default: none.

**chain = INTEGER**

Specifies a Markov chain defined by \texttt{markov_switching}. Default: none.

**Command:** sbvar(OPTIONS...);

To be documented. For now, see the wiki: https://archives.dynare.org/DynareWiki/SbvarOptions

**Options**

datafile, freq, initial_year, initial_subperiod, final_year, final_subperiod, data, vlist, vlistlog, vlistper, restriction_fname, nlags, cross_restrictions, contemp_reduced_form, real_pseudo_forecast, no_bayesian_prior, dummy_obs, nstates, indxscalesstates, alpha, beta, gsig2_lmdm, q_diag, flat_prior, ncsk, nstd, ninv, indexparr, indxovr, aband, indxap, apband, indximf, indxfore, foreband, indxgforhat, indxgmufhat, indexestima, indxgdls, eq_ms, cms, ncms, eq_cms, tlindx, tlnumber, cnum, forecast, coefficients_prior_hyperparameters

**Block:** svar_identification ;

This block is terminated by \texttt{end}; and contains lines of the form:

```plaintext
UPPER_CHOLESKY;
LOWER_CHOLESKY;
EXCLUSION CONSTANTS;
EXCLUSION LAG INTEGER; EQUATION INTEGER, VARIABLE_NAME [\[,\] VARIABLE_NAME...];
RESTRICTION EQUATION INTEGER, EXPRESSION = EXPRESSION;
```

To be documented. For now, see the wiki: https://archives.dynare.org/DynareWiki/MarkovSwitchingInterface

**Command:** ms_estimation(OPTIONS...);

Triggers the creation of an initialization file for, and the estimation of, a Markov-switching SBVAR model. At the end of the run, the \( A^0, A^+, Q \) and \( \zeta \) matrices are contained in the \texttt{oo_.ms} structure.

**General Options**

**file_tag = FILENAME**

The portion of the filename associated with this run. This will create the model initialization file, \texttt{init_<file_tag>.dat}. Default: \texttt{<mod_file>}.  

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output_file_tag = FILENAME

The portion of the output filename that will be assigned to this run. This will create, among other files, est_final_<output_file_tag>.out, est_intermediate_<output_file_tag>.out. Default: <file_tag>.

no_create_init

Do not create an initialization file for the model. Passing this option will cause the Initialization Options to be ignored. Further, the model will be generated from the output files associated with the previous estimation run (i.e. est_final_<file_tag>.out, est_intermediate_<file_tag>.out or init_<file_tag>.dat, searched for in sequential order). This functionality can be useful for continuing a previous estimation run to ensure convergence was reached or for reusing an initialization file. NB: If this option is not passed, the files from the previous estimation run will be overwritten. Default: off (i.e. create initialization file)

Initialization Options

coefficients_prior_hyperparameters = [DOUBLE1 DOUBLE2 ... DOUBLE6]

Sets the hyper parameters for the model. The six elements of the argument vector have the following interpretations:

1

Overall tightness for $A^0$ and $A^+$. 

2

Relative tightness for $A^+$. 

3

Relative tightness for the constant term. 

4

Tightness on lag decay (range: 1.2 - 1.5); a faster decay produces better inflation process. 

5

Weight on nvar sums of coeffs dummy observations (unit roots). 

6

Weight on single dummy initial observation including constant. 

Default: [1.0 1.0 0.1 1.2 1.0 1.0]

freq = INTEGER | monthly | quarterly | yearly

Frequency of the data (e.g. monthly, 12). Default: 4.

initial_year = INTEGER

The first year of data. Default: none.

initial_subperiod = INTEGER

The first period of data (i.e. for quarterly data, an integer in [1,4]). Default: 1.

final_year = INTEGER

The last year of data. Default: Set to encompass entire dataset.

final_subperiod = INTEGER

The final period of data (i.e. for monthly data, an integer in [1,12]). Default: When final_year is also missing, set to encompass entire dataset; when final_year is indicated, set to the maximum number of subperiods given the frequency (i.e. 4 for quarterly data, 12 for monthly,...).

datafile = FILENAME

See datafile.
**nlags = INTEGER**

The number of lags in the model. Default: 1.

**cross_restrictions**

Use cross $A^0$ and $A^+$ restrictions. Default: **off**.

**contemp_reduced_form**

Use contemporaneous recursive reduced form. Default: **off**.

**no_bayesian_prior**

Do not use Bayesian prior. Default: **off** (i.e. use Bayesian prior).

**alpha = INTEGER**

Alpha value for squared time-varying structural shock lambda. Default: 1.

**beta = INTEGER**


**gsig2_lmdm = INTEGER**

The variance for each independent $\lambda$ parameter under SimsZha restrictions. Default: $50^2$.

**specification = sims_zha | none**

This controls how restrictions are imposed to reduce the number of parameters. Default: Random Walk.

### Estimation Options

**convergence_starting_value = DOUBLE**

This is the tolerance criterion for convergence and refers to changes in the objective function value. It should be rather loose since it will gradually be tightened during estimation. Default: $1e^{-3}$.

**convergence_ending_value = DOUBLE**

The convergence criterion ending value. Values much smaller than square root machine epsilon are probably overkill. Default: $1e^{-6}$.

**convergence_increment_value = DOUBLE**

Determines how quickly the convergence criterion moves from the starting value to the ending value. Default: 0.1.

**max_iterations_starting_value = INTEGER**

This is the maximum number of iterations allowed in the hill-climbing optimization routine and should be rather small since it will gradually be increased during estimation. Default: 50.

**max_iterations_increment_value = DOUBLE**

Determines how quickly the maximum number of iterations is increased. Default: 2.

**max_block_iterations = INTEGER**

The parameters are divided into blocks and optimization proceeds over each block. After a set of blockwise optimizations are performed, the convergence criterion is checked and the blockwise optimizations are repeated if the criterion is violated. This controls the maximum number of times the blockwise optimization can be performed. Note that after the blockwise optimizations have converged, a single optimization over all the parameters is performed before updating the convergence value and maximum number of iterations. Default: 100.
**max_repeated_optimization_runs** = INTEGER
The entire process described by **max_block_iterations** is repeated until improvement has stopped. This is the maximum number of times the process is allowed to repeat. Set this to 0 to not allow repetitions. Default: 10.

**function_convergence_criterion** = DOUBLE
The convergence criterion for the objective function when **max_repeated_optimization_runs** is positive. Default: 0.1.

**parameter_convergence_criterion** = DOUBLE
The convergence criterion for parameter values when **max_repeated_optimization_runs** is positive. Default: 0.1.

**number_of_large_perturbations** = INTEGER
The entire process described by **max_block_iterations** is repeated with random starting values drawn from the posterior. This specifies the number of random starting values used. Set this to 0 to not use random starting values. A larger number should be specified to ensure that the entire parameter space has been covered. Default: 5.

**number_of_small_perturbations** = INTEGER
The number of small perturbations to make after the large perturbations have stopped improving. Setting this number much above 10 is probably overkill. Default: 5.

**number_of_posterior_draws_after_perturbation** = INTEGER
The number of consecutive posterior draws to make when producing a small perturbation. Because the posterior draws are serially correlated, a small number will result in a small perturbation. Default: 1.

**max_number_of_stages** = INTEGER
The small and large perturbation are repeated until improvement has stopped. This specifies the maximum number of stages allowed. Default: 20.

**random_function_convergence_criterion** = DOUBLE
The convergence criterion for the objective function when **number_of_large_perturbations** is positive. Default: 0.1.

**random_parameter_convergence_criterion** = DOUBLE
The convergence criterion for parameter values when **number_of_large_perturbations** is positive. Default: 0.1.

**Example**

```ms_estimation```
(datafile=data, initial_year=1959, final_year=2005, nlags=4, max_repeated_optimization_runs=1, max_number_of_stages=0);
```
```ms_estimation```
(file_tag=second_run, datafile=data, initial_year=1959, final_year=2005, nlags=4, max_repeated_optimization_runs=1, max_number_of_stages=0);
```
```ms_estimation```
(file_tag=second_run, output_file_tag=third_run, no_create_init, max_repeated_optimization_runs=5, number_of_large_perturbations=10);
```

**Command:** `ms_simulation` ;

**Command:** `ms_simulation(OPTIONS...)`;

Simulates a Markov-switching SBVAR model.

**Options**

**file_tag** = FILENAME
The portion of the filename associated with the `ms_estimation` run. Default: `<mod_file>`.

---

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output_file_tag = FILENAME
The portion of the output filename that will be assigned to this run. Default: <file_tag>.

mh_replic = INTEGER
The number of draws to save. Default: 10,000.

drop = INTEGER
The number of burn-in draws. Default: 0.1*mh_replic*thinning_factor.

thinning_factor = INTEGER
The total number of draws is equal to thinning_factor*mh_replic+drop. Default: 1.

adaptive_mh_draws = INTEGER
Tuning period for Metropolis-Hastings draws. Default: 30,000.

save_draws
Save all elements of $A^0$, $A^+$, $Q$, and $\zeta$, to a file named draws_<<file_tag>>.out with each
draw on a separate line. A file that describes how these matrices are laid out is contained in
draws_header_<<file_tag>>.out. A file called load_flat_file.m is provided to simplify loading
the saved files into the corresponding variables $A0$, Aplus, $Q$, and $\zeta$ in your MATLAB/Octave
workspace. Default: off.

Example

ms_simulation(file_tag=second_run);
ms_simulation(file_tag=third_run, mh_replic=5000, thinning_factor=3);

Command: ms_compute_mdd ;
Command: ms_compute_mdd(OPTIONS...);

Computes the marginal data density of a Markov-switching SBVAR model from the posterior draws. At the
end of the run, the Muller and Bridge log marginal densities are contained in the oo_.ms structure.

Options

file_tag = FILENAME
See file_tag.

output_file_tag = FILENAME
See output_file_tag.

simulation_file_tag = FILENAME
The portion of the filename associated with the simulation run. Default: <file_tag>.

proposal_type = INTEGER
The proposal type:
1
Gaussian.
2
Power.
3
Truncated Power.
4
Step.
5
Truncated Gaussian.
Default: 3
**proposal_lower_bound = DOUBLE**
The lower cutoff in terms of probability. Not used for proposal_type in [1,2]. Required for all other proposal types. Default: 0.1.

**proposal_upper_bound = DOUBLE**
The upper cutoff in terms of probability. Not used for proposal_type equal to 1. Required for all other proposal types. Default: 0.9.

**mdd_proposal_draws = INTEGER**
The number of proposal draws. Default: 100,000.

**mdd_use_mean_center**
Use the posterior mean as center. Default: off.

**Command:** `ms_compute_probabilities` ;
**Command:** `ms_compute_probabilities(OPTIONS...)`;
Computes smoothed regime probabilities of a Markov-switching SBVAR model. Output .eps files are contained in `<output_file_tag/Output/Probabilities>`.

**Options**

**file_tag = FILENAME**
See `file_tag`.

**output_file_tag = FILENAME**
See `output_file_tag`.

**filtered_probabilities**
Filtered probabilities are computed instead of smoothed. Default: off.

**real_time_smoothed**
Smoothed probabilities are computed based on time t information for 0 ≤ t ≤ nobs. Default: off.

**Command:** `ms_irf` ;
**Command:** `ms_irf(OPTIONS...)`;
Computes impulse response functions for a Markov-switching SBVAR model. Output .eps files are contained in `<output_file_tag/Output/IRF>`, while data files are contained in `<output_file_tag/IRF>`.

**Options**

**file_tag = FILENAME**
See `file_tag`.

**output_file_tag = FILENAME**
See `output_file_tag`.

**simulation_file_tag = FILENAME**
See `simulation_file_tag`.

**horizon = INTEGER**
The forecast horizon. Default: 12.

**filtered_probabilities**
Uses filtered probabilities at the end of the sample as initial conditions for regime probabilities. Only one of filtered_probabilities, regime and regimes may be passed. Default: off.

**error_band_percentiles = [DOUBLE1 ...]**
The percentiles to compute. Default: [0.16 0.50 0.84]. If median is passed, the default is [0.5].

**shock_draws = INTEGER**
The number of regime paths to draw. Default: 10,000.
**shocks_per_parameter** = INTEGER

The number of regime paths to draw under parameter uncertainty. Default: 10.

**thinning_factor** = INTEGER

Only 1/thinning_factor of the draws in posterior draws file are used. Default: 1.

**free_parameters** = NUMERICAL_VECTOR

A vector of free parameters to initialize theta of the model. Default: use estimated parameters

**parameter_uncertainty**

Calculate IRFs under parameter uncertainty. Requires that ms_simulation has been run. Default: off.

**regime** = INTEGER

Given the data and model parameters, what is the ergodic probability of being in the specified regime. Only one of filtered_probabilities, regime and regimes may be passed. Default: off.

**regimes**

Describes the evolution of regimes. Only one of filtered_probabilities, regime and regimes may be passed. Default: off.

**median**

A shortcut to setting error_band_percentiles=[0.5]. Default: off.

**Command**: ms_forecast ;

**Command**: ms_forecast(OPTIONS...);

Generates forecasts for a Markov-switching SBVAR model. Output .eps files are contained in <output_file_tag/Output/Forecast>, while data files are contained in <output_file_tag/Forecast>.

**Options**

**file_tag** = FILENAME

See file_tag.

**output_file_tag** = FILENAME

See output_file_tag.

**simulation_file_tag** = FILENAME

See simulation_file_tag.

**data_obs_nbr** = INTEGER

The number of data points included in the output. Default: 0.

**error_band_percentiles** = [DOUBLE1 ...]

See error_band_percentiles.

**shock_draws** = INTEGER

See shock_draws.

**shocks_per_parameter** = INTEGER

See shocks_per_parameter.

**thinning_factor** = INTEGER

See thinning_factor.

**free_parameters** = NUMERICAL_VECTOR

See free_parameters.

**parameter_uncertainty**

See parameter_uncertainty.
regime = INTEGER
   See regime.
regimes
   See regimes.
median
   See median.
horizon = INTEGER
   See horizon.

Command: ms_variance_decomposition ;
Command: ms_variance_decomposition(OPTIONS...);

Computes the variance decomposition for a Markov-switching SBVAR model. Output .eps files are contained in <output_file_tag/Output/Variance_Decomposition>, while data files are contained in <output_file_tag/Variance_Decomposition>.

Options

file_tag = FILENAME
   See file_tag.
output_file_tag = FILENAME
   See output_file_tag.
simulation_file_tag = FILENAME
   See simulation_file_tag.
horizon = INTEGER
   See horizon.
filtered_probabilities
   See filtered_probabilities.
no_error_bands
   Do not output percentile error bands (i.e. compute mean). Default: off (i.e. output error bands)
error_band_percentiles = [DOUBLE1 ...]
   See error_band_percentiles.
shock_draws = INTEGER
   See shock_draws.
shocks_per_parameter = INTEGER
   See shocks_per_parameter.
thinning_factor = INTEGER
   See thinning_factor.
free_parameters = NUMERICAL_VECTOR
   See free_parameters.
parameter_uncertainty
   See parameter_uncertainty.
regime = INTEGER
   See regime.
regimes
   See regimes.
4.24 Epilogue Variables

Block: epilogue;

The epilogue block is useful for computing output variables of interest that may not be necessarily defined in the model (e.g. various kinds of real/nominal shares or relative prices, or annualized variables out of a quarterly model).

It can also provide several advantages in terms of computational efficiency and flexibility:

- You can calculate variables in the epilogue block after smoothers/simulations have already been run without adding the new definitions and equations and rerunning smoothers/simulations. Even posterior smoother subdraws can be recycled for computing epilogue variables without rerunning subdraws with the new definitions and equations.
- You can also reduce the state space dimension in data filtering/smoothing. Assume, for example, you want annualized variables as outputs. If you define an annual growth rate in a quarterly model, you need lags up to order 7 of the associated quarterly variable; in a medium/large scale model this would just blow up the state dimension and increase by a huge amount the computing time of a smoother.

The epilogue block is terminated by end; and contains lines of the form:

NAME = EXPRESSION;

Example

```
epilogue;
// annualized level of y
ya = exp(y)+exp(y(-1))+exp(y(-2))+exp(y(-3));
// annualized growth rate of y
gya = ya/ya(-4)-1;
end;
```

4.25 Semi-structural models

Dynare provides tools for semi-structural models, in the vain of the FRB/US model (see Brayton and Tinsley (1996)), where expectations are not necessarily model consistent but based on a VAR auxiliary model. In the following, it is assumed that each equation is written as VARIABLE = EXPRESSION or T(VARIABLE) = EXPRESSION where T(VARIABLE) stands for a transformation of an endogenous variable (log or diff). This representation, where each equation determines the endogenous variable on the LHS, can be exploited when simulating the model (see algorithms 12 and 14 in solve_algo) and is mandatory to define auxiliary models used for computing expectations (see below).

4.25.1 Auxiliary models

The two auxiliary models defined in this section are linear backward-looking models used to form expectations. Both models can be recast as VAR(1)-processes and therefore offer isomorphic ways of specifying the expectations process, but differ in their convenience of specifying features like cointegration and error correction. var_model directly specifies a VAR, while trend_component_model allows to define a trend target to which the endogenous variables may be attracted in the long-run (i.e. an error correction model).

Command: var_model(OPTIONS...);

Picks equations in the model block to form a VAR model. This model can be used as an auxiliary model in var_expectation_model or pac_model. It must be of the following form:

\[ Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t \]
or

\[ A_0 Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + \epsilon_t \]

if the VAR is structural (see below), where \( Y_t \) and \( \epsilon_t \) are \( n \times 1 \) vectors, \( c \) is a \( n \times 1 \) vector of parameters, \( A_i \) (\( i = 0, \ldots, p \)) are \( n \times n \) matrices of parameters, and \( A_0 \) is non singular square matrix. Vector \( c \) and matrices \( A_i \) (\( i = 0, \ldots, p \)) are set by parsing the equations in the model block. Then, Dynare builds a VAR(1)-companion form model for \( Y_t = (1, Y_t, \ldots, Y_{t-p+1})' \) as:

\[
\begin{pmatrix}
1 & 0' \\
Y_t & A_1 & A_2 & \ldots & A_p \\
& c & A_1 & A_2 & \ldots & A_p \\
& & 0_n & I_n & O_n & \ldots & O_n \\
& & 0_n & O_n & I_n & O_n & \ldots & O_n \\
& & & \vdots & \ddots & \ddots & \ddots & \vdots \\
& & & 0_n & O_n & \ldots & O_n & I_n & O_n \end{pmatrix}
\begin{pmatrix}
1 \\
0_n' \\
Y_{t-1} \\
Y_{t-2} \\
\vdots \\
Y_{t-p} \end{pmatrix}
+ \begin{pmatrix}
0 \\
0_n' \\
\epsilon_t \\
\vdots \\
\epsilon_t \end{pmatrix}
\]

assuming that we are dealing with a reduced form VAR (otherwise, the right-hand side would additionally be premultiplied by \( A_0^{-1} \) to obtain the reduced for representation). If the VAR does not have a constant, we remove the first line of the system and the first column of the companion matrix \( C \). Dynare only saves the companion matrix, since that is the only information required to compute the expectations.

**MATLAB/Octave variable:** oo_.var.MODEL_NAME.CompanionMatrix

Reduced form companion matrix of the var_model.

**Options**

- **model_name = STRING**
  
  Name of the VAR model, which will be referenced in var_expectation_model or pac_model as an auxiliary_model. Needs to be a valid MATLAB field name.

- **eqtags = [QUOTED_STRING[, QUOTED_STRING[, ...]]]**
  
  List of equations in the model block (referenced using the equation tag name) used to build the VAR model.

- **structural**

  By default the VAR model is not structural, *i.e.* each equation must contain exactly one contemporaneous variable (on the LHS). If the structural option is provided then any variable defined in the system can appear at time \( t \) in each equation. Internally Dynare will rewrite this model as a reduced form VAR (by inverting the implied matrix \( A_0 \)).

**Example**

```matlab
var_model(model_name = toto, eqtags = [ 'X', 'Y', 'Z' ]);` model;` [ name = 'X' ]` x = a'x(-1) + b'x(-2) + c'z(-2) + e_x;` [ name = 'Z' ]` z = f'z(-1) + e_z;`
```

(continues on next page)
Command: trend_component_model(OPTIONS...);

Picks equations in the model block to form a trend component model. This model can be used as an auxiliary model in var_expectation_model or pac_model. It must be of the following form:

\[
\begin{align*}
\Delta X_t &= A_0(X_{t-1} - C_0 Z_{t-1}) + \sum_{i=1}^{p} A_i \Delta X_{t-i} + \varepsilon_t \\
Z_t &= Z_{t-1} + \eta_t
\end{align*}
\]

where \(X_t\) and \(Z_t\) are \(n \times 1\) and \(m \times 1\) vectors of endogenous variables. \(Z_t\) defines the trend target to whose linear combination \(C_0 Z_t\) the endogenous variables \(X_t\) will be attracted, provided the implied error correction matrix \(A_0\) is negative definite. \(\varepsilon_t\) and \(\eta_t\) are \(n \times 1\) and \(m \times 1\) vectors of exogenous variables, \(A_i\) \((i = 0, \ldots, p)\) are \(n \times n\) matrices of parameters, and \(C_0\) is a \(n \times m\) matrix. This model can also be cast into a VAR(1) model by first rewriting it in levels. Let \(Y_t = (X_t', Z_t')'\) and \(\zeta_t = (\varepsilon_t', \eta_t')'\). Then we have:

\[
Y_t = \sum_{i=1}^{p+1} B_i Y_{t-i} + \zeta_t
\]

with

\[
B_1 = \begin{pmatrix}
I_n + A_0 + A_1 & -A \\
0_{m,n} & I_m
\end{pmatrix}
\]

where \(A = A_0 C_0\).

\[
B_i = \begin{pmatrix}
A_i - A_{i-1} & 0_{n,m} \\
0_{m,n} & O_m
\end{pmatrix}
\]

for \(i = 2, \ldots, p\), and

\[
B_{p+1} = \begin{pmatrix}
-A_p & 0_{n,m} \\
0_{m,n} & O_m
\end{pmatrix}
\]

This VAR(p+1) in levels can again be rewritten as a VAR(1)-companion model form.

MATLAB/Octave variable: oo_.trend_component.MODEL_NAME.CompanionMatrix

Reduced form companion matrix of the trend_component_model.

Options

\[
\text{model_name} = \text{STRING}
\]

Name of the trend component model, will be referenced in var_expectation_model or pac_model as an auxiliary_model. Needs to be a valid MATLAB field name.

\[
eq t a g s = [\text{QUOTED_STRING}, \text{QUOTED_STRING}, \ldots]
\]

List of equations in the model block (referenced using the equation tag name) used to build the trend component model.

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targets = [QUOTED_STRING[, QUOTED_STRING[, ...]]]

List of targets, corresponding to the variables in vector \( Z_t \), referenced using the equation tag name) of the associated equation in the model block. target must be a subset of eqtags.

Example

trend_component_model(model_name=toto, eqtags=['eq:x1', 'eq:x2',
  →'eq:x1bar', 'eq:x2bar'], targets=['eq:x1bar', 'eq:x2bar']);

model;

[name='eq:x1']
diff(x1) = a_x1_0*(x1(-1)-x1bar(-1))+a_x1_0_*(x2(-1)-x2bar(-1)) + a_x1_
  →_1*diff(x1(-1)) + a_x1_2*diff(x1(-2)) + + a_x1_x2_1*diff(x2(-1)) + a_x1_
  →_x2_2*diff(x2(-2)) + ex1;

[name='eq:x2']
diff(x2) = a_x2_0*(x2(-1)-x2bar(-1)) + a_x2_1*diff(x1(-1)) + a_x2_
  →_2*diff(x1(-2)) + a_x2_x1_1*diff(x2(-1)) + a_x2_x1_2*diff(x2(-2)) + ex2;

[name='eq:x1bar']
x1bar = x1bar(-1) + ex1bar;

[name='eq:x2bar']
x2bar = x2bar(-1) + ex2bar;

division

4.25.2 VAR expectations

Suppose we wish to forecast a variable \( y_t \) and that \( y_t \) is an element of vector of variables \( \mathbf{y}_t \) whose law of motion is described by a VAR(1) model \( \mathbf{y}_t = C \mathbf{y}_{t-1} + \mathbf{\epsilon}_t \). More generally, \( y_t \) may be a linear combination of the scalar variables \( \mathbf{y}_t \). Let the vector \( \alpha \) be such that \( y_t = \alpha' \mathbf{y}_t \) (\( \alpha \) is a selection vector if \( y_t \) is a variable in \( \mathbf{y}_t \), i.e. a column of an identity matrix, or an arbitrary vector defining the weights of a linear combination). Then the best prediction, in the sense of the minimisation of the RMSE, for \( y_{t+h} \) given the information set at \( t - \tau \) (which we assume to include all observables up to time \( t - \tau \), \( \mathbf{y}_{t-\tau} \) is:

\[
y_{t+h|t-\tau} = \mathbb{E}[y_{t+h}|\mathbf{y}_{t-\tau}] = \alpha \mathbf{C}^{h} \mathbf{y}_{t-\tau}
\]

In a semi-structural model, variables appearing in \( t + h \) (e.g. the expected output gap in a dynamic IS curve or expected inflation in a New Keynesian Phillips curve) will be replaced by the expectation implied by an auxiliary VAR model. Another use case is for the computation of permanent incomes. Typically, consumption will depend on something like:

\[
\sum_{h=0}^{\infty} \beta^h y_{t+h|t-\tau}
\]

Assuming that \( 0 < \beta < 1 \) and knowing the limit of geometric series, the conditional expectation of this variable can be evaluated based on the same auxiliary model:

\[
\mathbb{E} \left[ \sum_{h=0}^{\infty} \beta^h y_{t+h} \bigg| \mathbf{y}_{t-\tau} \right] = \alpha \mathbf{C}^{\tau} (I - \beta \mathbf{C})^{-1} \mathbf{y}_{t-\tau}
\]
Finite discounted sums can also be considered.

**Command:**  \texttt{var\_expectation\_model(OPTIONS...)};

Declares a model used to forecast an endogenous variable or linear combination of variables in \( t + h \). More generally, the same model can be used to forecast the discounted flow of a variable or a linear expression of variables:

\[
\sum_{h=a}^{b} \beta^{h-\tau} E[y_{t+h}|Y_{t-\tau}]
\]

where \((a, b) \in \mathbb{N}^2\) with \( a < b \) and \( a < \infty \), \( \beta \in (0, 1) \) is a discount factor, and \( \tau \) is a finite positive integer.

**Options**

- \texttt{model\_name = STRING}
  
  Name of the VAR based expectation model, which will be referenced in the \texttt{model} block.

- \texttt{auxiliary\_model = STRING}
  
  Name of the associated auxiliary model, defined with \texttt{var\_model} or \texttt{trend\_component\_model}.

- \texttt{expression = VARIABLE\_NAME | EXPRESSION}
  
  Name of the variable or expression (linear combination of variables) to be expected.

- \texttt{discount = PARAMETER\_NAME | DOUBLE}
  
  Discount factor (\( \beta \)).

- \texttt{horizon = INTEGER | [INTEGER:INTEGER]}
  
  If the value of \texttt{horizon} is a finite integer scalar, the following expectation is computed:

  \[
  \beta^{h-\tau} E[y_{t+h}|Y_{t-\tau}]
  \]
  
  otherwise the value is a range of periods \( a : b \) over which the expected discounted sum is computed (the upper bound can be \texttt{Inf}).

- \texttt{time\_shift = INTEGER}
  
  Shift of the information set (\( \tau \)), default value is 0.

**Operator:**  \texttt{var\_expectation (NAME\_OF\_VAR\_EXPECTATION\_MODEL)};

This operator is used instead of a leaded variable, e.g. \( X(1) \), in the \texttt{model} block to substitute a model-consistent forecast with a forecast based on a VAR model.

**Example**

\begin{verbatim}
var_model(model_name=toto, eqtags=['X', 'Y', 'Z']);
var_expectation_model(model_name=varexp, expression=x, auxiliary_model_name=toto, horizon=1, discount=beta);
model;
[name='X']
  x = a*x(-1) + b*x(-2) + c*z(-2) + e_x;
[name='Z']
\end{verbatim}

(continues on next page)
z = f^z(-1) + e_z;

[name='Y']
y = d^y(-2) + e^z(-1) + e_y;

foo = .5*foo(-1) + \texttt{var\_expectation}(varexp);

\textbf{MATLAB/Octave command: \texttt{var\_expectation.initialize}(NAME\_OF\_VAR\_EXPECTATION\_MODEL);} 
Initiate the \texttt{var\_expectation\_model} by building the companion matrix of the associated auxiliary \texttt{var\_model}. Needs to be executed before attempts to simulate or estimate the model.

\textbf{MATLAB/Octave command: \texttt{var\_expectation.update}(NAME\_OF\_VAR\_EXPECTATION\_MODEL);} 
Update/compute the reduced form parameters of \texttt{var\_expectation\_model}. Needs to be executed before attempts to simulate or estimate the model and requires the auxiliary \texttt{var\_model} to have previously been initialized.

\textbf{Example (continued)}

\texttt{var\_expectation.initialize('varexp');}
\texttt{var\_expectation.update('varexp');}

\textbf{Warning:} Changes to the parameters of the underlying auxiliary \texttt{var\_model} require calls to \texttt{var\_expectation.initialize} and \texttt{var\_expectation.update} to become effective. Changes to the \texttt{var\_expectation\_model} or its associated parameters require a call to \texttt{var\_expectation.update}.

\subsection*{4.25.3 PAC equation}

In its simplest form, a PAC equation breaks down changes in a variable of interest $y$ into three contributions: (i) the lagged deviation from a target $y^\star$, (ii) the lagged changes in the variable $y$, and (iii) the expected changes in the target $y^\star$:

$$
\Delta y_t = a_0(y^\star_{t-1} - y_{t-1}) + \sum_{i=1}^{m-1} a_i \Delta y_{t-i} + \sum_{i=0}^{\infty} d_i \Delta y^\star_{t+i} + \varepsilon_t
$$

\textit{Brayton et alii} (2000) shows how such an equation can be derived from the minimisation of a quadratic cost function penalising expected deviations from the target and non-smoothness of $y$, where future costs are discounted (with discount factor $\beta$). They also show that the parameters $(d_i)_{i\in\mathbb{N}}$ are non-linear functions of the $m$ parameters $a_i$ and the discount factor $\beta$. To simulate or estimate this equation we need to figure out how to determine the expected changes of the target. This can be done as in the previous section using VAR based expectations, or considering model consistent expectations (MCE).

To ensure that the endogenous variable $y$ is equal to its target $y^\star$ in the (deterministic) long run, i.e. that the error correction term is zero in the long run, we can optionally add a growth neutrality correction to this equation. Suppose that $g$ is the long run growth rate, for $y$ and $y^\star$, then in the long run (assuming that the data are in logs) we must have:
\[ g = a_0(y^*_\infty - y_\infty) + g \sum_{i=1}^{m-1} a_i + g \sum_{i=0}^{\infty} d_i \]
\[ \iff a_0(y^*_\infty - y_\infty) = \left(1 - \sum_{i=1}^{m-1} a_i - \sum_{i=0}^{\infty} d_i\right) g \]

Unless additional restrictions are placed on the coefficients \((a_i)_{i=0}^{m-1}\), i.e., on the form of the minimised cost function, there is no reason for the right-hand side to be zero. Instead, we can optionally add the right hand side to the PAC equation, to ensure that the error correction term is asymptotically zero.

The PAC equations can be generalised by adding exogenous variables. This can be done in two, non exclusive, manners. We can replace the PAC equation by a convex combination of the original PAC equation (derived from an optimisation program) and a linear expression involving exogenous variables (referred as the rule of thumb part as opposed to the part derived from the minimisation of a cost function; not to be confused with exogenous shocks):

\[ \Delta y_t = \lambda \left(a_0(y^*_{t-1} - y_{t-1}) + \sum_{i=1}^{m-1} a_i \Delta y_{t-1} + \sum_{i=0}^{\infty} d_i \Delta y^*_{t+i}\right) + (1 - \lambda) \gamma' X_t + \epsilon_t \]

where \(\lambda \in [0, 1]\) is the weight of the pure PAC equation, \(\gamma\) is a \(k \times 1\) vector of parameters, and \(X_t\) a \(k \times 1\) vector of variables in the rule of thumb part. Or we can simply add the exogenous variables to the PAC equation (without the weight \(\lambda\)):

\[ \Delta y_t = a_0(y^*_{t-1} - y_{t-1}) + \sum_{i=1}^{m-1} a_i \Delta y_{t-1} + \sum_{i=0}^{\infty} d_i \Delta y^*_{t+i} + \gamma' X_t + \epsilon_t \]

**Command:** `pac_model(OPTIONS...)`;
Declares a PAC model. A `.mod` file can have more than one PAC model or PAC equation, but each PAC equation must be associated to a different PAC model.

**Options**

`model_name = STRING`
Name of the PAC model, will be referenced in the `model` block.

`auxiliary_model = STRING`
Name of the associated auxiliary model, defined with `var_model` or `trend_component_model`, to compute the VAR based expectations for the expected changes in the target, i.e., to evaluate \(\sum_{i=0}^{\infty} d_i \Delta y^*_{t+i}\). The infinite sum will then be replaced by a linear combination, defined by a vector \(h_i\), of the variables involved in the companion representation of the auxiliary model. The weights defining the linear combination are nonlinear functions of the \((a_i)_{i=0}^{m-1}\) coefficients in the PAC equation. This option is not mandatory, if absent Dynare understands that the expected changes of the target have to be computed under the MCE assumption. This is done by rewriting recursively the infinite sum as shown in equation 10 of Brayton et alii (2000).

`discount = PARAMETER_NAME | DOUBLE`
Discount factor (\(\beta\)) for future expected costs appearing in the definition of the cost function.

`growth = PARAMETER_NAME | VARIABLE_NAME | EXPRESSION | DOUBLE`
If present a growth neutrality correction is added to the PAC equation. The user must ensure that the provided value (or long term level if a variable or expression is given) is consistent with the asymptotic growth rate of the endogenous variable.

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kind = dd | dl

Instructs Dynare how to compute the vector $h$, the weights defining the linear combination of the companion VAR variables. The default value `dd` must be used if the target appears in first difference in the auxiliary model, see equation (A.79) in Brayton et alii (2000), while value `dl` must be used if the target shows up in level in the auxiliary model, equation (A.74) in Brayton et alii (2000).

auxname = STRING

Name the auxiliary variable, created by the preprocessor, that will define the expectation term in the PAC equation.

**Operator:** `pac_expectation (NAME_OF_PAC_MODEL);`

This operator is used instead of the infinite sum, $\sum_{t=0}^{\infty} d_i \Delta y_{t+i}$, in a PAC equation defined in the model block. Depending on the assumption regarding the formation of expectations, it will be replaced by a linear combination of the variables involved in the companion representation of the auxiliary model or by a recursive forward equation.

The PAC equation target can be composite and defined as a weighted sum of stationary and non-stationary components. Such a target requires an additional equation in the model block, with the target variable on the left hand-side and the components in the right-hand-side. Each component must be an endogenous variable in the auxiliary model. The characteristics of each component must be described in the `pac_target_info` block, see below, and the `pac_target_nonstationary` operator must be used in the error correction term of the PAC equation to link the target to the provided description. Note that composite targets make only sense if the auxiliary model is not a trend component model (where all the variables are non-stationary).

**Block:** `pac_target_info(NAME_OF_PAC_MODEL);`

This block enables the user to provide the properties of each component of a target in PAC models with a composite target. The `NAME_OF_PAC_MODEL` argument refers to a PAC model (must match the value of option `model_name` in the declaration of a PAC model).

On the first line of the block, the name of the composite target variable must be provided using the following syntax:

```
target VARIABLE_NAME ;
```

where `VARIABLE_NAME` is a declared endogenous variable, its associated equation is not part of the auxiliary model but all the components (the variables on the right hand-side) must be defined in the auxiliary model. Next, the following line declares the name of the auxiliary variable that will appear in the error correction term, this variable contains only the non-stationary components of the target:

```
auxname_target_nonstationary NAME ;
```

The block should contain the following group of lines for each stationary component:

```
component STATIONARY_VARIABLE_NAME ;
kind ll ;
auxname AUX_VAR_NAME ;
```

where `STATIONARY_VARIABLE_NAME` is the name of a stationary variable appearing in the right hand-side of the equation defining the target `VARIABLE_NAME`. The second line instructs Dynare that the component appears in levels in the auxiliary model and in the PAC expectations. The third line specifies the name of the auxiliary variable created by Dynare for the component of the PAC expectation related to `STATIONARY_VARIABLE_NAME`.

The block should contain the following group of lines for each non-stationary component:

```
component NONSTATIONARY_VARIABLE_NAME ;
kind dd | dl ;
auxname AUX_VAR_NAME ;
growth PARAMETER_NAME | VARIABLE_NAME | EXPRESSION | DOUBLE ;
```
where NONSTATIONARY_VARIABLE_NAME is the name of a nonstationary variable appearing in the right hand-side of the equation defining the target VARIABLE_NAME. The second line instructs Dynare on how to calculate the weights that define the linear combination of the companion VAR variables. Use value dd if the target appears in first difference in the auxiliary model, or dl if the target shows up in level in the auxiliary model. The third line sets the name of the auxiliary variable created by Dynare for the component of the PAC expectation related to NONSTATIONARY_VARIABLE_NAME. The fourth line is mandatory if a growth neutrality correction is required. The provided value for this option must be consistent with the asymptotic growth rate of the PAC endogenous variable.

**Operator:** pac_target_nonstationary (NAME_OF_PAC_MODEL);

This operator is only required in presence of a composite target in the PAC equation. The operator, used in the error correction term of the PAC equation, selects the non stationary components of the target.

**MATLAB/Octave command:** pac.initialize(NAME_OF_PAC_MODEL);

**MATLAB/Octave command:** pac.update(NAME_OF_PAC_MODEL);

Same as in the previous section for the VAR expectations, initialise the PAC model, by building the companion matrix of the auxiliary model, and computes the reduced form parameters of the PAC equation (the weights in the linear combination of the variables involved in the companion representation of the auxiliary model, or the parameters of the recursive representation of the infinite sum in the MCE case).

**Example (trend component auxiliary model)**

```plaintext
trend_component_model(model_name=toto, eqtags=['eq:x1', 'eq:x2', 'eq:x1bar', 'eq:x2bar'], targets=['eq:x1bar', 'eq:x2bar']);
pac_model(auxiliary_model_name=toto, discount=beta, model_name=pacman);
model;
[name='eq:y']
y = (1-rho_1-rho_2)*diff(x2(-1)) + rho_1*y(-1) + rho_2*y(-2) + ey;
[name='eq:x1']
diff(x1) = a_x1_0*(x1(-1)-x1bar(-1)) + a_x1_1*diff(x1(-1)) + a_x1_2*diff(x1(-2)) + a_x1_x2_1*diff(x2(-1)) + a_x1_x2_2*diff(x2(-2)) + ex1;
[name='eq:x2']
diff(x2) = a_x2_0*(x2(-1)-x2bar(-1)) + a_x2_1*diff(x1(-1)) + a_x2_2*diff(x1(-2)) + a_x2_x1_1*diff(x2(-1)) + a_x2_x1_2*diff(x2(-2)) + ex2;
[name='eq:x1bar']
x1bar = x1bar(-1) + ex1bar;
[name='eq:x2bar']
x2bar = x2bar(-1) + ex2bar;
[name='zpac']
diff(z) = e_c_m*(x1(-1)-z(-1)) + c_z_1*diff(z(-1)) + c_z_2*diff(z(-2)) + pac_expectation(pacman) + ez;
end;
pac.initialize('pacman');
pac.update.expectation('pacman');
```

**Example (VAR auxiliary model and composite target)**
var_model(model_name=toto, eqtags=['eq:x', 'eq:y']);

pac_model(auxiliary_model_name=toto, discount=beta, model_name=pacman);

pac_target_info(pacman);

target v;
auxname_target_nonstationary vns;

component y;
auxname pv_y_;
kind ll;

component x;
growth diff(x(-1));
auxname pv_dx_;
kind dd;

end;

model;

[name='eq:y']
y = a_y_1*y(-1) + a_y_2*diff(x(-1)) + b_y_1*y(-2) + b_y_2*diff(x(-2)) + ey;

[name='eq:x']
diff(x) = b_x_1*y(-2) + b_x_2*diff(x(-1)) + ex;

[name='eq:v']
v = x + d_y*y; // Composite PAC target, no residuals here only
variables defined in the auxiliary model.

[name='zp']
diff(z) = e_c_m*(pac_target_nonstationary(pacman)-z(-1)) + c_z_1*diff(z(-1)) + c_z_2*diff(z(-2)) + pac_expectation(pacman) + ez;

end;
pac.initialize('pacman');
pac.update.expectation('pacman');

4.25.4 Estimation of a PAC equation

The PAC equation, introduced in the previous section, can be estimated. This equation is nonlinear with respect to the estimated parameters \((a_i)_{i=0}^{m-1}\), since the reduced form parameters (in the computation of the infinite sum) are nonlinear functions of the autoregressive parameters and the error correction parameter. Brayton et alii (2000) shows how to estimate the PAC equation by iterative OLS. Although this approach is implemented in Dynare, mainly for comparison purposes, we also propose NLS estimation, which is much preferable (asymptotic properties of NLS being more solidly grounded).

Note that it is currently not feasible to estimate the PAC equation jointly with the remaining parameters of the model using e.g. Bayesian techniques. Thus, estimation of the PAC equation can only be conducted conditional on the values of the parameters of the auxiliary model.
Warning: The estimation routines described below require the option json=compute be passed to the preprocessor (via the command line or at the top of the .mod file, see Dynare invocation).

MATLAB/Octave command: \texttt{pac.estimate.nls(EQNAME, GUESS, DATA, RANGE[, ALGO]);}

MATLAB/Octave command: \texttt{pac.estimate.iterative_ols(EQNAME, GUESS, DATA, RANGE);}

Trigger the NLS or iterative OLS estimation of a PAC equation. \texttt{EQNAME} is a row char array designating the PAC equation to be estimated (the PAC equation must have a name specified with an equation tag). \texttt{DATA} is a dseries object containing the data required for the estimation (i.e. data for all the endogenous and exogenous variables in the equation). The residual values of the PAC equation (which correspond to a defined \texttt{varexo}) must also be a member of \texttt{DATA}, but filled with \texttt{NaN} values. \texttt{RANGE} is a dates object defining the time span of the sample. \texttt{ALGO} is a row char array used to select the method (or minimisation algorithm) for NLS. Possible values are: \texttt{'fmincon'}, \texttt{'fminunc'}, \texttt{'fminsearch'}, \texttt{'lsqnonlin'}, \texttt{'particleswarm'}, \texttt{'csminwel'}, \texttt{'simplex'}, \texttt{'annealing'}, and \texttt{'GaussNewton'}. The first four algorithms require the Mathworks Optimisation toolbox. The fifth algorithm requires the Mathworks Global Optimisation toolbox. When the optimisation algorithm allows it, we impose constraints on the error correction parameter, which must be positive and smaller than 1 (it the case for \texttt{'fmincon'}, \texttt{'lsqnonlin'}, \texttt{'particleswarm'}, and \texttt{'annealing'}). The default optimisation algorithm is \texttt{'csminwel'}. \texttt{GUESS} is a structure containing the initial guess values for the estimated parameters. Each field is the name of a parameter in the PAC equation and holds the initial guess for this parameter. If some parameters are calibrated, then they should not be members of the \texttt{GUESS} structure (and values have to be provided in the .mod file before the call to the estimation routine).

For the NLS routine the estimation results are displayed in a table after the estimation. For both the NLS and iterative OLS routines, the results are saved in \texttt{oo_.} (under the fields \texttt{nls} or \texttt{iterative_ols}). Also, the values of the parameters are updated in \texttt{M_.params}.

Example (continued)

```matlab
// Set the initial guess for the estimated parameters
eparams.e_c_m = .9;
eparams.c_z_1 = .5;
eparams.c_z_2 = .2;

// Define the dataset used for estimation
data = TrueData;
data.ez = dseries(NaN); // Set to NaN the residual of the equation.
pac.estimate.nls('zpac', eparams, data, 2005Q1:2005Q1+200, 'annealing');
```

Warning: The specification of \texttt{GUESS} and \texttt{DATA} involves the use of structures. As such, their subfields will not be cleared across Dynare runs as the structures stay in the workspace. Be careful to clear these structures from the memory (e.g. within the .mod file) when e.g. changing which parameters are calibrated.

4.26 Displaying and saving results

Dynare has commands to plot the results of a simulation and to save the results.

Command: \texttt{rplot VARIABLE_NAME...;}

Plots the simulated path of one or several variables, as stored in \texttt{oo_.endo_simul} by either \texttt{perfect_foresight_solver}, \texttt{simul} (see Deterministic simulation) or \texttt{stoch_simul} with option periods (see Stochastic solution and simulation). The variables are plotted in levels.
Command: dynatype(FILENAME) [VARIABLE_NAME...];
This command prints the listed endogenous or exogenous variables in a text file named FILENAME. If no VARIABLE_NAME is listed, all endogenous variables are printed.

Command: dynasave(FILENAME) [VARIABLE_NAME...];
This command saves the listed endogenous or exogenous variables in a binary file named FILENAME. If no VARIABLE_NAME is listed, all endogenous variables are saved.

In MATLAB or Octave, variables saved with the dynasave command can be retrieved by the command:

\texttt{load(FILENAME,'-mat')}\

\section*{4.27 Macro processing language}

It is possible to use “macro” commands in the \texttt{.mod} file for performing tasks such as: including modular source files, replicating blocks of equations through loops, conditionally executing some code, writing indexed sums or products inside equations...

The Dynare macro-language provides a new set of \textit{macro-commands} which can be used in \texttt{.mod} files. It features:

\begin{itemize}
  \item File inclusion
  \item Loops (\texttt{for} structure)
  \item Conditional inclusion (\texttt{if/then/else} structures)
  \item Expression substitution
\end{itemize}

This macro-language is totally independent of the basic Dynare language, and is processed by a separate component of the Dynare pre-processor. The macro processor transforms a \texttt{.mod} file with macros into a \texttt{.mod} file without macros (doing expansions/inclusions), and then feeds it to the Dynare parser. The key point to understand is that the macro processor only does text substitution (like the C preprocessor or the PHP language). Note that it is possible to see the output of the macro processor by using the \texttt{savemacro} option of the \texttt{dynare} command (see \textit{Dynare invocation}).

The macro processor is invoked by placing \textit{macro directives} in the \texttt{.mod} file. Directives begin with an at-sign followed by a pound sign (\texttt{@#}). They produce no output, but give instructions to the macro processor. In most cases, directives occupy exactly one line of text. If needed, two backslashes (\texttt{\\}) at the end of the line indicate that the directive is continued on the next line. Macro directives following // are not interpreted by the macro processor. For historical reasons, directives in commented blocks, \texttt{ie} surrounded by /* and */, are interpreted by the macro processor. The user should not rely on this behavior. The main directives are:

\begin{itemize}
  \item \texttt{@#includepath}, paths to search for files that are to be included,
  \item \texttt{@#include}, for file inclusion,
  \item \texttt{@#define}, for defining a macro processor variable,
  \item \texttt{@#if}, \texttt{@#ifdef}, \texttt{@#ifndef}, \texttt{@#elseif}, \texttt{@#else}, \texttt{@#endif} for conditional statements,
  \item \texttt{@#for}, \texttt{@#endfor} for constructing loops.
\end{itemize}

The macro processor maintains its own list of variables (distinct from model variables and MATLAB/Octave variables). These macro-variables are assigned using the \texttt{@#define} directive and can be of the following basic types: boolean, real, string, tuple, function, and array (of any of the previous types).
4.27.1 Macro expressions

Macro-expressions can be used in two places:

- Inside macro directives, directly;
- In the body of the .mod file, between an @-sign and curly braces (like @{expr}): the macro processor will substitute the expression with its value.

It is possible to construct macro-expressions that can be assigned to macro-variables or used within a macro-directive. The expressions are constructed using literals (i.e. fixed values) of the basic types (boolean, real, string, tuple, array), comprehensions, macro-variables, macro-functions, and standard operators.

Note: Elsewhere in the manual, MACRO_EXPRESSION designates an expression constructed as explained in this section.

Boolean

The following operators can be used on booleans:

- Comparison operators: ==, !=
- Logical operators: &&, ||, !

Real

The following operators can be used on reals:

- Arithmetic operators: +, -, *, /, ^
- Comparison operators: <, >, <=, >=, ==, !=
- Logical operators: &&, ||, !
- Ranges with an increment of 1: REAL1:REAL2 (for example, 1:4 is equivalent to real array [1, 2, 3, 4]). Changed in version 4.6: Previously, putting brackets around the arguments to the colon operator (e.g. [1:4]) had no effect. Now, [1:4] will create an array containing an array (i.e. [[1, 2, 3, 4]]).
- Ranges with user-defined increment: REAL1:REAL2:REAL3 (for example, 6:-2.1:-1 is equivalent to real array [6, 3.9, 1.8, -0.3]).
- Functions: max, min, mod, exp, log, log10, sin, cos, tan, asin, acos, atan, sqrt, cbrt, sign, floor, ceil, trunc, erf, erfc, gamma, lgamma, round, normpdf, normcdf. NB ln can be used instead of log

String

String literals have to be enclosed by double quotes (like "name").

The following operators can be used on strings:

- Comparison operators: <, >, <=, >=, ==, !=
- Concatenation of two strings: +
- Extraction of substrings: if s is a string, then s[3] is a string containing only the third character of s, and s[4:6] contains the characters from 4th to 6th
- Function: length
Tuple

Tuples are enclosed by parentheses and elements are separated by commas (like \((a, b, c)\) or \((1, 2, 3)\)).

The following operators can be used on tuples:

- Comparison operators: \(==, !=\)
- Functions: \(\text{empty}, \text{length}\)

Array

Arrays are enclosed by brackets, and their elements are separated by commas (like \([1, [2, 3], 4]\) or \("US", "FR"\)).

The following operators can be used on arrays:

- Comparison operators: \(==, !=\)
- Dereferencing: if \(v\) is an array, then \(v[2]\) is its 2nd element
- Concatenation of two arrays: \(+\)
- Set union of two arrays: \(|\)
- Set intersection of two arrays: \&
- Difference -: returns the first operand from which the elements of the second operand have been removed.
- Cartesian product of two arrays: \(*\)
- Cartesian product of one array \(N\) times: \(^N\)
- Extraction of sub-arrays: e.g. \(v[4:6]\)
- Testing membership of an array: \(\text{in}\) operator (for example: \"b\" in \[\"a\", \"b\", \"c\"\] returns 1)
- Functions: \(\text{empty}, \text{sum}, \text{length}\)

Comprehension

Comprehension syntax is a shorthand way to make arrays from other arrays. There are three different ways the comprehension syntax can be employed: filtering, mapping, and filtering and mapping.

Filtering

Filtering allows one to choose those elements from an array for which a certain condition hold.

**Example**

Create a new array, choosing the even numbers from the array 1:5:

\[
[ \ i \ \text{in} \ 1:5 \ \text{when} \ \mod(i,2) == 0 \ ]
\]

would result in:

\[\[2, 4\]\]

Mapping

Mapping allows you to apply a transformation to every element of an array.

**Example**

Create a new array, squaring all elements of the array 1:5:

\[
[ i^2 \ \text{for} \ i \ \text{in} \ 1:5 ]
\]
would result in:

\[1, 4, 9, 16, 25]\]

Filtering and Mapping

Combining the two preceding ideas would allow one to apply a transformation to every selected element of an array.

Example

Create a new array, squaring all even elements of the array 1:5:

\[[ i^2 \text{ for } i \text{ in } 1:5 \text{ when } \text{mod}(i,2) == 0]\]

would result in:

\[4, 16]\]

Further Examples

\[[ \langle j, i+1 \rangle \text{ for } (i,j) \text{ in } (1:2)^2]\]
\[[ \langle j, i+1 \rangle \text{ for } (i,j) \text{ in } (1:2)^*(1:2) \text{ when } i < j]\]

would result in:

\[
\begin{array}{l}
[\langle 1, 2 \rangle, \langle 2, 2 \rangle, \langle 1, 3 \rangle, \langle 2, 3 \rangle] \\
[\langle 2, 2 \rangle]
\end{array}
\]

Function

Functions can be defined in the macro processor using the `@define` directive (see below). A function is evaluated at the time it is invoked during the macroprocessing stage, not at define time. Functions can be included in expressions and the operators that can be combined with them depend on their return type.

Checking variable type

Given a variable name or literal, you can check the type it evaluates to using the following functions: `isboolean`, `isreal`, `isstring`, `istuple`, and `isarray`.

Examples

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>isboolean(0)</code></td>
<td>false</td>
</tr>
<tr>
<td><code>isboolean(true)</code></td>
<td>true</td>
</tr>
<tr>
<td><code>isreal(&quot;str&quot;)</code></td>
<td>false</td>
</tr>
</tbody>
</table>

Casting between types

Variables and literals of one type can be cast into another type. Some type changes are straightforward (e.g. changing a `real` to a `string`) whereas others have certain requirements (e.g. to cast an `array` to a `real` it must be a one element array containing a type that can be cast to `real`).

Examples
Casts can be used in expressions:

**Examples**

<table>
<thead>
<tr>
<th>Code</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>(bool) -1.1</td>
<td>true</td>
</tr>
<tr>
<td>(bool) @</td>
<td>false</td>
</tr>
<tr>
<td>(real) &quot;2.2&quot;</td>
<td>2.2</td>
</tr>
<tr>
<td>(tuple) [3.3]</td>
<td>(3.3)</td>
</tr>
<tr>
<td>(array) 4.4</td>
<td>[4.4]</td>
</tr>
<tr>
<td>(real) [5.5]</td>
<td>5.5</td>
</tr>
<tr>
<td>(real) [6.6, 7.7]</td>
<td>error</td>
</tr>
<tr>
<td>(real) &quot;8.8 in a string&quot;</td>
<td>error</td>
</tr>
</tbody>
</table>

### 4.27.2 Macro directives

**Macro directive: @@includepath "PATH"**

**Macro directive: @@includepath MACRO_EXPRESSION**

This directive adds the path contained in PATH to the list of those to search when looking for a .mod file specified by @@include. If provided with a MACRO_EXPRESSION argument, the argument must evaluate to a string. Note that these paths are added after any paths passed using -I.

**Example**

```bash
@@includepath "/path/to/folder/containing/modfiles"
@@includepath folders_containing_mod_files
```

**Macro directive: @@include "FILENAME"**

**Macro directive: @@include MACRO_EXPRESSION**

This directive simply includes the content of another file in its place; it is exactly equivalent to a copy/paste of the content of the included file. If provided with a MACRO_EXPRESSION argument, the argument must evaluate to a string. Note that it is possible to nest includes (i.e. to include a file from an included file). The file will be searched for in the current directory. If it is not found, the file will be searched for in the folders provided by -I and @@includepath.

**Example**

```bash
@@include "modelcomponent.mod"
@@include location_of_modfile
```

**Macro directive: @@define MACRO_VARIABLE**

**Macro directive: @@define MACRO_VARIABLE = MACRO_EXPRESSION**

**Macro directive: @@define MACRO_FUNCTION = MACRO_EXPRESSION**

Defines a macro-variable or macro function.

**Example**

```bash
@@define var // Equals true
@@define x = 5 // Real
```

(continues on next page)
Example

```
@#define x = 1
@#define y = [ "B", "C" ]
@#define i = 2
@#define f(x) = x + " + " + y[i]
@#define i = 1

model:
    A = @(y[i] + f("D"));
end;
```

The latter is strictly equivalent to:

```
model:
    A = BD + B;
end;
```

**Macro directive:** `@#ifdef` `MACRO_VARIABLE`

Conditional inclusion of some part of the `.mod` file. The lines between `@#if`, `@#ifdef`, or `@#ifndef` and the next `@#elseif`, `@#else` or `@#endif` is executed only if the condition evaluates to `true`. Following the `@#if` body, zero or more `@#elseif` branches are allowed. An `@#elseif` condition is only evaluated if the preceding `@#if` or `@#elseif` condition(s) evaluated to `false`. The `@#else` branch is optional and only evaluated if all `@#if` and `@#elseif` statements evaluate to `false`.

Note that when using `@#ifdef`, the condition will evaluate to `true` if the `MACRO_VARIABLE` has been previously defined, regardless of its value. Conversely, `@#ifndef` will evaluate to `true` if the `MACRO_VARIABLE` has not yet been defined.

Note that when using `@#elseif` you can check whether or not a variable has been defined by using the `defined` operator. Hence, to enter the body of an `@#elseif` branch if the variable `X` has not been defined, you would write: `@#elseif !defined(X)`.

Note that if a real appears as the result of the `MACRO_EXPRESSION`, it will be interpreted as a boolean; a value of 0 is interpreted as `false`, otherwise it is interpreted as `true`. Further note that because of the imprecision of reals, extra care must be taken when testing them in the `MACRO_EXPRESSION`. For example, `exp(log(5)) == 5` will evaluate to `false`. Hence, when comparing real values, you should generally use a non-zero tolerance around the value desired, e.g. `exp(log(5)) > 5-1e-14 && exp(log(5)) < 5+1e-14`.

**Example**

Choose between two alternative monetary policy rules using a macro-variable:
@@define linear_mon_pol = false // 0 would be treated the same
...
model;
@if linear_mon_pol
  i = w*i(-1) + (1-w)*i_ss + w2*(pie-piestar);
@else
  i = i(-1)^w * i_ss^(1-w) * (pie/piestar)^w2;
@endif
...
end;

This would result in:

...
model;
  i = i(-1)^w * i_ss^(1-w) * (pie/piestar)^w2;
...
end;

**Example**

Choose between two alternative monetary policy rules using a macro-variable. The only difference between this example and the previous one is the use of @@ifdef instead of @@if:

@@define linear_mon_pol = false // 0 would be treated the same
...
model;
@if linear_mon_pol
  i = w*i(-1) + (1-w)*i_ss + w2*(pie-piestar);
@else
  i = i(-1)^w * i_ss^(1-w) * (pie/piestar)^w2;
@endif
...
end;

Although linear_mon_pol contains the value false because @@ifdef only checks that the variable has been defined, the linear monetary policy is output:

This would result in:

...
model;
  i = w*i(-1) + (1-w)*i_ss + w2*(pie-piestar);
...
end;

**Macro directive:** @@for MACRO_VARIABLE in MACRO_EXPRESSION

**Macro directive:** @@for MACRO_VARIABLE in MACRO_EXPRESSION when MACRO_EXPRESSION

**Macro directive:** @@for MACRO_TUPLE in MACRO_EXPRESSION

**Macro directive:** @@for MACRO_TUPLE in MACRO_EXPRESSION when MACRO_EXPRESSION

**Macro directive:** @@endfor

Loop construction for replicating portions of the .mod file. Note that this construct can enclose variable/parameter declarations, computational tasks, but not a model declaration.

**Example**

```plaintext
model;
@@for country in ["home", "foreign"]
  GDP_@{country} = A * K_@{country}^a * L_@{country}^(1-a);
```

(continues on next page)
The latter is equivalent to:

```plaintext
model;
    GDP_home = A * K_home^a * L_home^(1-a);
    GDP_foreign = A * K_foreign^a * L_foreign^(1-a);
end;
```

**Example**

```plaintext
model;
    @#define countries = ["US", "FR", "JA"]
    @#define nth_co = "US"
    @#for co in countries when co != nth_co
        (1+i_@{co}) = (1+i_@{nth_co}) * E_@{co}(+1) / E_@{co};
    @#endfor
    E_@{nth_co} = 1;
end;
```

The latter is equivalent to:

```plaintext
model;
    (1+i_FR) = (1+i_US) * E_FR(+1) / E_FR;
    (1+i_JA) = (1+i_US) * E_JA(+1) / E_JA;
    E_US = 1;
end;
```

**Macro directive:** `@#echo MACRO_EXPRESSION`

Asks the preprocessor to display some message on standard output. The argument must evaluate to a string.

**Macro directive:** `@#error MACRO_EXPRESSION`

Asks the preprocessor to display some error message on standard output and to abort. The argument must evaluate to a string.

**Macro directive:** `@#echomacrovars`

**Macro directive:** `@#echomacrovars MACRO_VARIABLE_LIST`

**Macro directive:** `@#echomacrovars(save) MACRO_VARIABLE_LIST`

Asks the preprocessor to display the value of all macro variables up until this point. If the save option is passed, then values of the macro variables are saved to `options_.macrovars_line_<<line_numbers>>`. If `NAME_LIST` is passed, only display/save variables and functions with that name.

**Example**
@define A = 1
@define B = 2
@define C(x) = x^2
@echomacrovars A C D

The output of the command above is:

Macro Variables:
A = 1
Macro Functions:
C(x) = (x * 2)

4.27.3 Typical usages

4.27.3.1 Modularization

The `@include` directive can be used to split `.mod` files into several modular components. Example setup:

modeldesc.mod
Contains variable declarations, model equations, and shocks declarations.

simul.mod
Includes modeldesc.mod, calibrates parameters and runs stochastic simulations.

estim.mod
Includes modeldesc.mod, declares priors on parameters, and runs Bayesian estimation.

Dynare can be called on simul.mod and estim.mod, but it makes no sense to run it on modeldesc.mod.

The main advantage is that you don’t have to copy/paste the whole model (during initial development) or changes to the model (during development).

4.27.3.2 Indexed sums of products

The following example shows how to construct a moving average:

@define window = 2

var x MA_x;
...
model;
...
MA_x = @1/(2*window+1)*(  
@for i in -window:window  
x[@{i}]  
@endfor  
);
...
end;

After macro processing, this is equivalent to:

var x MA_x;
...
model;

(continues on next page)
...\n\nMA_x = 0.2*(
  +x(-2)
  +x(-1)
  +x(0)
  +x(1)
  +x(2)
);
...
end;

4.27.3.3 Multi-country models

Here is a bare bones example for a multi-country model:

@#define nth_co = "US"

@#for co in countries
var Y_@{co} K_@{co} L_@{co} i_@{co} E_@{co} ...;
parameters a_@{co} ...;
varexo ...;
@#endfor

model;
@#for co in countries
Y_@{co} = K_@{co}^a_@{co} * L_@{co}^(1-a_@{co});
...
@#if co != nth_co
(1+i_@{co}) = (1+i_@{nth_co}) * E_@{co}(+1) / E_@{co}; // UIP relation
@#else
E_@{co} = 1;
@#endif
@#endfor
end;

4.27.3.4 Endogeneizing parameters

When calibrating the model, it may be useful to pin down parameters by targeting endogenous objects.

For example, suppose production is defined by a CES function:

\[
y_t = \left(\alpha^{1/\xi} \ell_t^{1-1/\xi} + (1 - \alpha)^{1/\xi} k_t^{1-1/\xi}\right)^{\xi/(\xi - 1)}
\]

and the labor share in GDP is defined as:

\[
\text{lab}_r at_t = (w_t \ell_t) / (p_t y_t)
\]

In the model, \(\alpha\) is a (share) parameter and \(\text{lab}_rat_t\) is an endogenous variable.

It is clear that setting a value for \(\alpha\) is not straightforward. But we have real world data for \(\text{lab}_rat_t\) and it is clear that these two objects are economically linked.
The solution is to use a method called *variable flipping*, which consists in changing the way of computing the steady state. During this computation, $\alpha$ will be made an endogenous variable and the steady state value $\text{lab\_rat}$ of the dynamic variable $\text{lab\_rat}_t$ will be made a parameter. An economically sensible value will be calibrated for $\text{lab\_rat}$, and the solution algorithm will deduce the implied value for $\alpha$.

An implementation could consist of the following files:

**modeqs.mod**

This file contains variable declarations and model equations. The code for the declaration of $\alpha$ and $\text{lab\_rat}$ would look like:

```matlab
@if steady
  var alpha;
  parameter lab_rat;
@else
  parameter alpha;
  var lab_rat;
@endif
```

**steadystate.mod**

This file computes the steady state. It begins with:

```matlab
@#define steady = 1
@include "modeqs.mod"
```

Then it initializes parameters (including $\text{lab\_rat}$, excluding $\alpha$), computes the steady state (using guess values for endogenous, including $\alpha$), then saves values of parameters and variables at steady state in a file, using the `save_params_and_steady_state` command.

**simulate.mod**

This file computes the simulation. It begins with:

```matlab
@#define steady = 0
@include "modeqs.mod"
```

Then it loads values of parameters and variables at steady state from file, using the `load_params_and_steady_state` command, and computes the simulations.

### 4.27.4 MATLAB/Octave loops versus macro processor loops

Suppose you have a model with a parameter $\rho$ and you want to run simulations for three values: $\rho = 0.8, 0.9, 1$. There are several ways of doing this:

**With a MATLAB/Octave loop**

```matlab
rhos = [0.8, 0.9, 1];
for i = 1:length(rhos)
  set_param_value('rho',rhos(i));
  stoch_simul(order=1);
  if info(1)==0
    error('Simulation failed for parameter draw')
  end
end
```

Here the loop is not unrolled, MATLAB/Octave manages the iterations. This is interesting when there are a lot of iterations. It is strongly advised to always check whether the error flag `info(1)==0` to prevent erroneously relying on stale results from previous iterations.

**With a macro processor loop (case 1)**

```matlab
```
rhos = [ 0.8, 0.9, 1];
@for i in 1:3
    set_param_value('rho',rhos(@{i}));
    stoch_simul(order=1);
    if info(1)==0
        error('Simulation failed for parameter draw')
    end
@endfor

This is very similar to the previous example, except that the loop is unrolled. The macro processor manages the loop index but not the data array (rhos).

With a macro processor loop (case 2)

@for rho_val in [ 0.8, 0.9, 1]
    rho = @{rho_val};
    stoch_simul(order=1);
    if info(1)==0
        error('Simulation failed for parameter draw')
    end
@endfor

The advantage of this method is that it uses a shorter syntax, since the list of values is directly given in the loop construct. The inconvenience is that you can not reuse the macro array in MATLAB/Octave.

### 4.28 Verbatim inclusion

Pass everything contained within the verbatim block to the <mod_file>.m file.

**Block: verbatim**

By default, whenever Dynare encounters code that is not understood by the parser, it is directly passed to the preprocessor output.

In order to force this behavior you can use the `verbatim` block. This is useful when the code you want passed to the driver file contains tokens recognized by the Dynare preprocessor.

**Example**

verbatim;
% Anything contained in this block will be passed
% directly to the driver file, including comments
var = 1;
end;

### 4.29 Misc commands

- **Command:** `set_dynare_seed(INTEGER)`
- **Command:** `set_dynare_seed('default')`
- **Command:** `set_dynare_seed('clock')`
- **Command:** `set_dynare_seed('reset')`
- **Command:** `set_dynare_seed('ALGORITHM', INTEGER)`

Sets the seed used for random number generation. It is possible to set a given integer value, to use a default value, or to use the clock (by using the latter, one will therefore get different results across different Dynare runs). The `reset` option serves to reset the seed to the value set by the last `set_dynare_seed` command.
On MATLAB 7.8 or above, it is also possible to choose a specific algorithm for random number generation; accepted values are `mcg16807`, `mlfg6331_64`, `mrg32k3a`, `mt19937ar` (the default), `shr3cong` and `swb2712`.

**Command:** `save_params_and_steady_state(Filename);`

For all parameters, endogenous and exogenous variables, stores their value in a text file, using a simple name/value associative table.

- for parameters, the value is taken from the last parameter initialization.
- for exogenous, the value is taken from the last `initval` block.
- for endogenous, the value is taken from the last steady state computation (or, if no steady state has been computed, from the last `initval` block).

Note that no variable type is stored in the file, so that the values can be reloaded with `load_params_and_steady_state` in a setup where the variable types are different.

The typical usage of this function is to compute the steady-state of a model by calibrating the steady-state value of some endogenous variables (which implies that some parameters must be endogeneized during the steady-state computation).

You would then write a first `.mod` file which computes the steady state and saves the result of the computation at the end of the file, using `save_params_and_steady_state`.

In a second file designed to perform the actual simulations, you would use `load_params_and_steady_state` just after your variable declarations, in order to load the steady state previously computed (including the parameters which had been endogeneized during the steady state computation).

The need for two separate `.mod` files arises from the fact that the variable declarations differ between the files for steady state calibration and for simulation (the set of endogenous and parameters differ between the two); this leads to different `var` and `parameters` statements.

Also note that you can take advantage of the `@include` directive to share the model equations between the two files (see *Macro processing language*).

**Command:** `load_params_and_steady_state(Filename);`

For all parameters, endogenous and exogenous variables, loads their value from a file created with `save_params_and_steady_state`.

- for parameters, their value will be initialized as if they had been calibrated in the `.mod` file.
- for endogenous and exogenous variables, their value will be initialized as they would have been from an `initval` block.

This function is used in conjunction with `save_params_and_steady_state`; see the documentation of that function for more information.

**Command:** `compilation_setup(OPTIONS);`

When the `use_dll` option is present, Dynare uses the GCC compiler that was distributed with it to compile the static and dynamic C files produced by the preprocessor. You can use this option to change the compiler, flags, and libraries used.

**Options**

- `compiler = FILENAME`
  The path to the compiler.

- `substitute_flags = QUOTED_STRING`
  The flags to use instead of the default flags.

- `add_flags = QUOTED_STRING`
  The flags to use in addition to the default flags. If `substitute_flags` is passed, these flags are added to the flags specified there.
substitute_libs = QUOTED_STRING
The libraries to link against instead of the default libraries.

add_libs = QUOTED_STRING
The libraries to link against in addition to the default libraries. If substitute_libs is passed, these libraries are added to the libraries specified there.

MATLAB/Octave command: dynare_version;
Output the version of Dynare that is currently being used (i.e. the one that is highest on the MATLAB/Octave path).

MATLAB/Octave command: write_latex_definitions;
Writes the names, LaTeX names and long names of model variables to tables in a file named <<M_.fname>>_latex_definitions.tex. Requires the following LaTeX packages: longtable.

MATLAB/Octave command: write_latex_parameter_table;
Writes the LaTeX names, parameter names, and long names of model parameters to a table in a file named <<M_.fname>>_latex_parameters.tex. The command writes the values of the parameters currently stored. Thus, if parameters are set or changed in the steady state computation, the command should be called after a steady command to make sure the parameters were correctly updated. The long names can be used to add parameter descriptions. Requires the following LaTeX packages: longtable, booktabs.

MATLAB/Octave command: write_latex_prior_table;
Writes descriptive statistics about the prior distribution to a LaTeX table in a file named <<M_.fname>>_latex_priors_table.tex. The command writes the prior definitions currently stored. Thus, this command must be invoked after the estimated_params block. If priors are defined over the measurement errors, the command must also be preceded by the declaration of the observed variables (with varobs). The command displays a warning if no prior densities are defined (ML estimation) or if the declaration of the observed variables is missing. Requires the following LaTeX packages: longtable, booktabs.

MATLAB/Octave command: collect_latex_files;
Writes a LaTeX file named <<M_.fname>>_TeX_binder.tex that collects all TeX output generated by Dynare into a file. This file can be compiled using pdflatex and automatically tries to load all required packages. Requires the following LaTeX packages: breqn, psfrag, graphicx, epstopdf, longtable, booktabs, caption, float, amsmath, amsfonts, and morefloats.
THE CONFIGURATION FILE

The configuration file is used to provide Dynare with information not related to the model (and hence not placed in the model file). At the moment, it is only used when using Dynare to run parallel computations.

On Linux and macOS, the configuration file is searched by default under `dynare/dynare.ini` in the configuration directories defined by the XDG specification (typically `$HOME/.config/dynare/dynare.ini` for the user-specific configuration and `/etc/xdg/dynare/dynare.ini` for the system-wide configuration, the former having precedence over the latter). Under Windows, the configuration file is searched by default in `%APPDATA%\dynare\dynare.ini` (typically `c:\Users\USERNAME\AppData\Roaming\dynare\dynare.ini`). You can specify a non standard location using the `conffile` option of the `dynare` command (see `Dynare invocation`).

The parsing of the configuration file is case-sensitive and it should take the following form, with each option/choice pair placed on a newline:

```
[command0]
option0 = choice0
option1 = choice1

[command1]
option0 = choice0
option1 = choice1
```

The configuration file follows a few conventions (self-explanatory conventions such as `USER_NAME` have been excluded for concision):

**COMPUTER_NAME**

Indicates the valid name of a server (e.g. `localhost`, `server.cepremap.org`) or an IP address.

**DRIVE_NAME**

Indicates a valid drive name in Windows, without the trailing colon (e.g. `C`).

**PATH**

Indicates a valid path in the underlying operating system (e.g. `/home/user/dynare/matlab/`).

**PATH_AND_FILE**

Indicates a valid path to a file in the underlying operating system (e.g. `/usr/local/MATLAB/R2023b/bin/matlab`).

**BOOLEAN**

Is `true` or `false`. 
5.1 Dynare Configuration

This section explains how to configure Dynare for general processing. Currently, there is only one option available.

Configuration block: [hooks]

This block can be used to specify configuration options that will be used when running Dynare.

Options

GlobalInitFile = PATH_AND_FILE

The location of a global initialization file that can be used to customize some Dynare internals (typically default option values). This is a MATLAB/Octave script.

If this option is not specified, Dynare will look for a `global_init.m` file in its configuration directory (typically `$HOME/.config/dynare/global_init.m` under Linux and macOS, and `c:\Users\USERNAME\AppData\Roaming\dynare\global_init.m` under Windows).

Example

```
[hooks]
GlobalInitFile = /home/user/dynare/myInitFile.m
```

Configuration block: [paths]

This block can be used to specify paths that will be used when running dynare.

Options

Include = PATH

A colon-separated path to use when searching for files to include via `@#include`. Paths specified via `-I` take priority over paths specified here, while these paths take priority over those specified by `@#includepath`.

Example

```
[paths]
Include = /path/to/folder/containing/modfiles:/path/to/another/folder
```

5.2 Parallel Configuration

This section explains how to configure Dynare for parallelizing some tasks which require very little inter-process communication.

The parallelization is done by running several MATLAB or Octave processes, either on local or on remote machines. Communication between leader and follower processes are done through SMB on Windows and SSH on UNIX. Input and output data, and also some short status messages, are exchanged through network filesystems. Currently the system works only with homogenous grids: only Windows or only Unix machines.

The following routines are currently parallelized:

- the posterior sampling algorithms when using multiple chains;
- the Metropolis-Hastings diagnostics;
- the posterior IRFs;
- the prior and posterior statistics;
- some plotting routines.

Note that creating the configuration file is not enough in order to trigger parallelization of the computations: you also need to specify the `parallel` option to the `dynare` command. For more details, and for other options related to the parallelization engine, see Dynare invocation.
You also need to verify that the following requirements are met by your cluster (which is composed of a leader and one or more followers):

For a Windows grid:

- a standard Windows network (SMB) must be in place;
- the PsTools suite must be installed in the path of the leader Windows machine;
- the Windows user on the leader machine has to be user of any other follower machine in the cluster, and that user will be used for the remote computations.
- detailed step-by-step setup instructions can be found in *Windows Step-by-Step Guide*.

For a UNIX grid:

- SSH must be installed on the leader and on the follower machines;
- SSH keys must be installed so that the SSH connection from the leader to the follower can be done without passwords, or using an SSH agent.

**Warning:** Compatibility considerations between leader and follower

It is highly recommended to use the same version of Dynare on both the leader and all followers. Different versions regularly cause problems like zero acceptance rates during estimation. When upgrading to a newer Dynare version do not forget to adjust the DynarePath.

We now turn to the description of the configuration directives. Note that comments in the configuration file can be provided by separate lines starting with a hashtag (#).

**Configuration block: [cluster]**

When working in parallel, [cluster] is required to specify the group of computers that will be used. It is required even if you are only invoking multiple processes on one computer.

*Options*

Name = CLUSTER_NAME

The reference name of this cluster.

Members = NODE_NAME[(WEIGHT)] NODE_NAME[(WEIGHT)] ...

A list of nodes that comprise the cluster with an optional computing weight specified for that node. The computing weight indicates how much more powerful one node is with respect to the others (e.g. n1(2) n2(1) n3(3) means that n1 is two times more powerful than n2 whereas n3 is three times more powerful than n2). Each node is separated by at least one space and the weights are in parenthesis with no spaces separating them from their node.

*Example*

```
[cluster]
Name = c1
Members = n1 n2 n3

[cluster]
Name = c2
Members = n1(4) n2 n3
```

**Configuration block: [node]**

When working in parallel, [node] is required for every computer that will be used. The options that are required differ, depending on the underlying operating system and whether you are working locally or remotely.

*Options*
**Name = NODE_NAME**

The reference name of this node.

**CPUnbr = INTEGER | [INTEGER:INTEGER]**

If just one integer is passed, the number of processors to use. If a range of integers is passed, the specific processors to use (processor counting is defined to begin at one as opposed to zero). Note that using specific processors is only possible under Windows; under Linux and macOS, if a range is passed the same number of processors will be used but the range will be adjusted to begin at one.

**ComputerName = COMPUTER_NAME**

The name or IP address of the node. If you want to run locally, use localhost (case-sensitive).

**Port = INTEGER**

The port number to connect to on the node. The default is empty, meaning that the connection will be made to the default SSH port (22).

**UserName = USER_NAME**

The username used to log into a remote system. Required for remote runs on all platforms.

**Password = PASSWORD**

The password used to log into the remote system. Required for remote runs originating from Windows.

**RemoteDrive = DRIVE_NAME**

The drive to be used for remote computation. Required for remote runs originating from Windows.

**RemoteDirectory = PATH**

The directory to be used for remote computation. Required for remote runs on all platforms.

**DynarePath = PATH**

The path to the matlab subdirectory within the Dynare installation directory. The default is the empty string.

**MatlabOctavePath = PATH_AND_FILE**

The path to the MATLAB or Octave executable. The default value is matlab as MATLAB’s executable is typically in the %PATH% environment variable. When using full paths on Windows, you may need to enclose the path in quoted strings, e.g. MatlabOctavePath="C:\Program Files\MATLAB\R2023b\bin\matlab.exe"

**NumberOfThreadsPerJob = INTEGER**

This option controls the distribution of jobs (e.g. MCMC chains) across additional MATLAB instances that are run in parallel. Needs to be an exact divisor of the number of cores. The formula $\frac{CPUnbr}{NumberOfThreadsPerJob}$ divided by $NumberOfThreadsPerJob$ calculates the number of MATLAB/Octave instances that will be launched in parallel, where each instance will then execute a certain number of jobs sequentially. For example, if you run a MCMC estimation with 24 chains on a 12 core machine, setting $CPUnbr = 12$ and $NumberOfThreadsPerJob = 4$ will launch 3 MATLAB instances in parallel, each of which will compute 8 chains sequentially. Note that this option does not dictate the number of maximum threads utilized by each MATLAB/Octave instance, see related option SingleCompThread for this. Particularly for very large models, setting this option to 2 might distribute the workload in a more efficient manner, depending on your hardware and task specifics. It’s advisable to experiment with different values to achieve optimal performance. The default value is 1.

**SingleCompThread = BOOLEAN**

This option allows you to enable or disable MATLAB’s native multithreading capability. When set to true, the additional MATLAB instances are initiated in single thread mode utilizing the -singleCompThread startup option, thereby disabling MATLAB’s native multithreading. When set to false, MATLAB’s native multithreading is enabled, e.g. the actual number of threads utilized by each MATLAB instance is usually determined by the number of CPU cores (you can check this by running maxNumCompThreads in MATLAB’s command window). Note: While MATLAB aims to accelerate calculations by distributing them across your computer’s threads, certain tasks, like MCMC estimations, may exhibit slowdowns with MATLAB’s multitasking especially when Dynare’s parallel computing is turned on as we do not use MATLAB’s parallel toolbox. So in many cases it is advisable
to set this setting to \texttt{true}. If you want to have more control, you can manually add the MATLAB command \texttt{maxNumCompThreads(N)} at the beginning of \texttt{fParallel.m}. The default value is \texttt{false}. This option is ineffective under Octave.

\textbf{OperatingSystem = OPERATING\_SYSTEM}

The operating system associated with a node. Only necessary when creating a cluster with nodes from different operating systems. Possible values are \texttt{unix} or \texttt{windows}. There is no default value.

\textbf{Example}

\begin{verbatim}
[node]
Name = n1
ComputerName = localhost
CPUnbr = 1

[node]
Name = n2
ComputerName = dynserv.cepremap.org
CPUnbr = 5
UserName = usern
RemoteDirectory = /home/usern/Remote
DynarePath = /home/usern/dynare/matlab
MatlabOctavePath = matlab

[node]
Name = n3
ComputerName = dynserv.dynare.org
Port = 3333
CPUnbr = [2:4]
UserName = usern
RemoteDirectory = /home/usern/Remote
DynarePath = /home/usern/dynare/matlab
MatlabOctavePath = matlab
\end{verbatim}

\section*{5.3 Windows Step-by-Step Guide}

This section outlines the steps necessary on most Windows systems to set up Dynare for parallel execution. Note that the steps 3 to 6 are required unless parallel execution is confined to a local pool with the \texttt{parallel\_use\_psexec=false} option.

1. Write a configuration file containing the options you want. A minimum working example setting up a cluster consisting of two local CPU cores that allows for e.g. running two Monte Carlo Markov Chains in parallel is shown below.

2. Save the configuration file somewhere. The name and file ending do not matter if you are providing it with the \texttt{conffile} command line option. The only restrictions are that the path must be a valid filename, not contain non-alpha-numeric characters, and not contain any whitespaces. For the configuration file to be accessible without providing an explicit path at the command line, you must save it under the name \texttt{dynare.ini} into your user account's Application Data folder.

3. Install PSTools to your system, e.g. into \texttt{C:\PSTools}.

4. Set the Windows System Path to the PSTools folder (e.g. using something along the line of pressing Windows Key+Pause to open the System Configuration, then go to Advanced -> Environment Variables -> Path).

5. Restart your computer to make the path change effective.

6. Open MATLAB and type into the command window:
This executes the `psexec.exe` from PSTools on your system and shows whether Dynare will be able to locate it. If MATLAB complains at this stage, you did not correctly set your Windows system path for the PSTools folder.

7. If `psexec.exe` was located in the previous step, a popup will show up, asking for confirmation of the license agreement. Confirm this copyright notice of `psexec` (this needs to be done only once). After this, Dynare should be ready for parallel execution.

8. Call Dynare on your mod-file invoking the parallel option and providing the path to your configuration file with the conffile option (if you did not save it as `%APPDATA%\dynare.ini` in step 2 where it should be detected automatically):

```
dynare ls2003 parallel conffile='C:\Users\Dynare~1\parallel\conf_file.ini'
```

Please keep in mind that no white spaces or names longer than 8 characters are allowed in the conffile path. The 8-character restriction can be circumvented by using the tilde Windows path notation as in the above example.

**Example:**

```
#cluster needs to always be defined first
[cluster]
#Provide a name for the cluster
Name=Local
#declare the nodes being member of the cluster
Members=n1

#declare nodes (they need not all be part of a cluster)
[node]
#name of the node
Name=n1
#name of the computer (localhost for the current machine)
ComputerName=localhost
#cores to be included from this node
CPUnbr=[1:2]
#path to matlab.exe; on Windows, the MATLAB bin folder is in the system path
#so we only need to provide the name of the exe file
MatlabOctavePath=matlab
#Dynare path you are using
DynarePath=C:\dynare/4.7.0/matlab
```
Dynare provides a MATLAB/Octave class for handling time series data, which is based on a class for handling dates. Dynare also provides a new type for dates, so that the user does not have to worry about class and methods for dates. Below, you will first find the class and methods used for creating and dealing with dates and then the class used for using time series. Dynare also provides an interface to the X-13 ARIMA-SEATS seasonal adjustment program produced, distributed, and maintained by the U.S. Census Bureau (2020).

### 6.1 Dates

#### 6.1.1 Dates in a mod file

Dynare understands dates in a mod file. Users can declare annual, bi-annual, quarterly, or monthly dates using the following syntax:

- `1990Y`
- `1990S2`
- `1990Q4`
- `1990M11`

Behind the scene, Dynare’s preprocessor translates these expressions into instantiations of the MATLAB/Octave’s class `dates` described below. Basic operations can be performed on dates:

**plus binary operator (+)**

An integer scalar, interpreted as a number of periods, can be added to a date. For instance, if `a = 1950Q1` then `b = 1951Q2` and `b = a + 5` are identical.

**plus unary operator (+)**

Increments a date by one period. `+1950Q1` is identical to `1950Q2`, `++++1950Q1` is identical to `1951Q1`.

**minus binary operator (-)**

Has two functions: difference and subtraction. If the second argument is a date, calculates the difference between the first date and the second date (e.g. `1951Q2-1950Q1` is equal to `5`). If the second argument is an integer `X`, subtracts `X` periods from the date (e.g. `1951Q2-2` is equal to `1950Q4`).

**minus unary operator (-)**

Subtracts one period to a date. `-1950Q1` is identical to `1949Q4`. The unary minus operator is the reciprocal of the unary plus operator, `+-1950Q1` is identical to `1950Q1`.

**colon operator (:)**

Can be used to create a range of dates. For instance, `r = 1950Q1:1951Q1` creates a `dates` object with five elements: `1950Q1`, `1950Q2`, `1950Q3`, `1950Q4` and `1951Q1`. By default the increment between each element is one period. This default can be changed using, for instance, the following instruction: `1950Q1:2:1951Q1` which will instantiate a `dates` object with three elements: `1950Q1`, `1950Q3` and `1951Q1`. 
horzcat operator ([,])

Concatenates dates objects without removing repetitions. For instance \([1950Q1, 1950Q2]\) is a dates object with two elements (1950Q1 and 1950Q2).

vertcat operator ([;])

Same as horzcat operator.

eq operator (equal, ==)

Tests if two dates objects are equal. +1950Q1==1950Q2 returns true, 1950Q1==1950Q2 returns false. If the compared objects have both \(n>1\) elements, the eq operator returns a column vector, \(n\) by 1, of logicals.

ne operator (not equal, ~=)

Tests if two dates objects are not equal. +1950Q1~=1950Q2 returns false while 1950Q1~=1950Q2 returns true. If the compared objects both have \(n>1\) elements, the ne operator returns an \(n\) by 1 column vector of logicals.

lt operator (less than, <)

Tests if a dates object preceeds another dates object. For instance, 1950Q1<1950Q3 returns true. If the compared objects have both \(n>1\) elements, the lt operator returns a column vector, \(n\) by 1, of logicals.

gt operator (greater than, >)

Tests if a dates object follows another dates object. For instance, 1950Q1>1950Q3 returns false. If the compared objects have both \(n>1\) elements, the gt operator returns a column vector, \(n\) by 1, of logicals.

le operator (less or equal, <=)

Tests if a dates object preceeds another dates object or is equal to this object. For instance, 1950Q1<=1950Q3 returns true. If the compared objects have both \(n>1\) elements, the le operator returns a column vector, \(n\) by 1, of logicals.

ge operator (greater or equal, >=)

Tests if a dates object follows another dates object or is equal to this object. For instance, 1950Q1>=1950Q3 returns false. If the compared objects have both \(n>1\) elements, the ge operator returns a column vector, \(n\) by 1, of logicals.

One can select an element, or some elements, in a dates object as he would extract some elements from a vector in MATLAB/Octave. Let \(a = 1950Q1:1951Q1\) be a dates object, then \(a(1)==1950Q1\) returns true, \(a(end)==1951Q1\) returns true and \(a(end-1:end)\) selects the two last elements of \(a\) (by instantiating the dates object \([1950Q4, 1951Q1]\)).

Remark: Dynare substitutes any occurrence of dates in the .mod file into an instantiation of the dates class regardless of the context. For instance, \(d = 1950Q1\) will be translated as \(d = \text{dates}('1950Q1')\);. This automatic substitution can lead to a crash if a date is defined in a string. Typically, if the user wants to display a date:

\[
\text{disp('Initial period is 1950Q1');}
\]

Dynare will translate this as:

\[
\text{disp('Initial period is dates('1950Q1'));}
\]

which will lead to a crash because this expression is illegal in MATLAB. For this situation, Dynare provides the $ escape parameter. The following expression:

\[
\text{disp('Initial period is $1950Q1');}
\]

will be translated as:
disp('Initial period is 1950Q1');

in the generated MATLAB script.

### 6.1.2 The dates class

**Dynare class:** dates

**Members**

- `freq` – equal to 1, 2, 4, 12 or 365 (resp. for annual, bi-annual, quarterly, monthly, or daily dates).
- `time` – a n x 1 array of integers, the number of periods since year 0 (0).

Each member is private, one can display the content of a member but cannot change its value directly. Note also that it is not possible to mix frequencies in a `dates` object: all the elements must have common frequency.

The `dates` class has the following constructors:

**Constructor:** dates()

**Constructor:** dates(FREQ)

Returns an empty `dates` object with a given frequency (if the constructor is called with one input argument). FREQ is a character equal to 'Y' or 'A' for annual dates, 'S' or 'H' for bi-annual dates, 'Q' for quarterly dates, 'M' for monthly dates, or 'D' for daily dates. Note that FREQ is not case sensitive, so that, for instance, 'q' is also allowed for quarterly dates. The frequency can also be set with an integer scalar equal to 1 (annual), 2 (bi-annual), 4 (quarterly), 12 (monthly), or 365 (daily). The instantiation of empty objects can be used to rename the `dates` class. For instance, if one only works with quarterly dates, object `qq` can be created as:

```matlab
qq = dates('Q')
```

and a `dates` object holding the date 2009Q2:

```matlab
d0 = qq(2009,2);
```

which is much simpler if `dates` objects have to be defined programmatically. For daily dates, we would instantiate an empty daily dates object as:

```matlab
dd = dates('D')
```

and a `dates` object holding the date 2020-12-31:

```matlab
d1 = dd(2020,12,31);
```

**Constructor:** dates(STRING)

**Constructor:** dates(STRING, STRING, ...)

Returns a `dates` object that represents a date as given by the string STRING. This string has to be interpretable as a date (only strings of the following forms are admitted: '1990Y', '1990A', 1990S1, 1990H1, '1990Q1', '1990M2', or '2020-12-31'), the routine `isdate` can be used to test if a string is interpretable as a date. If more than one argument is provided, they should all be dates represented as strings, the resulting `dates` object contains as many elements as arguments to the constructor. For the daily dates, the string must be of the form yyyy-mm-dd with two digits for the months (mm) and days (dd), even if the number of days or months is smaller than ten (in this case a leading 0 is required).

**Constructor:** dates(DATES)
**Constructor: dates (DATES, DATES, ...)**

Returns a copy of the dates object DATES passed as input arguments. If more than one argument is provided, they should all be dates objects. The number of elements in the instantiated dates object is equal to the sum of the elements in the dates passed as arguments to the constructor.

**Constructor: dates (FREQ, YEAR, SUBPERIOD[, S])**

where FREQ is a single character ('Y', 'A', 'S', 'H', 'Q', 'M', 'D') or integer (1, 2, 4, 12, or 365) specifying the frequency, YEAR and SUBPERIOD and S are n*1 vectors of integers. Returns a dates object with n elements. The last argument, S, is only to be used for daily frequency. If FREQ is equal to 'Y', 'A' or 1, the third argument is not needed (because SUBPERIOD is necessarily a vector of ones in this case).

**Example**

```
do1 = dates('1950Q1');
do2 = dates('1950Q2','1950Q3');
do3 = dates(do1,do2);
do4 = dates('Q',1950, 1);
do5 = dates('D',1973, 1, 25);
```

A list of the available methods, by alphabetical order, is given below. Note that by default the methods do not allow in place modifications: when a method is applied to an object a new object is instantiated. For instance, to apply the method multiplybytwo to an object X we write:

```
>> X = 2;
>> Y = X.multiplybytwo();
>> X
2
>> Y
4
```

or equivalently:

```
>> Y = multiplybytwo(X);
```

the object X is left unchanged, and the object Y is a modified copy of X (multiplied by two). This behaviour is altered if the name of the method is postfixed with an underscore. In this case the creation of a copy is avoided. For instance, following the previous example, we would have:

```
>> X = 2;
>> X.multiplybytwo_();
>> X
4
```

Modifying the objects in place, with underscore methods, is particularly useful if the methods are called in loops, since this saves the object instantiation overhead.

**Method: C = append(A, B)**

**Method: C = append_(A, B)**

Appends dates object B, or a string that can be interpreted as a date, to the dates object A. If B is a dates object it is assumed that it has no more than one element.

**Example**
>> D = dates('1950Q1','1950Q2');
>> d = dates('1950Q3');
>> E = D.append(d);
>> F = D.append('1950Q3');
>> isequal(E,F)

ans =
   1

>> F

F = <dates: 1950Q1, 1950Q2, 1950Q3>

>> D

D = <dates: 1950Q1, 1950Q2>

>> D.append_('1950Q3')

ans = <dates: 1950Q1, 1950Q2, 1950Q3>

Method: B = char(A)

Overloads the MATLAB/Octave char function. Converts a dates object into a character array.

Example

>> A = dates('1950Q1');
> A.char()

ans =
   '1950Q1'

Method: C = colon(A, B)

Method: C = colon(A, i, B)

Overloads the MATLAB/Octave colon (:) operator. A and B are dates objects. The optional increment i is a scalar integer (default value is i=1). This method returns a dates object and can be used to create ranges of dates.

Example

>> A = dates('1950Q1');
>> B = dates('1951Q2');
>> C = A:B

C = <dates: 1950Q1, 1950Q2, 1950Q3, 1950Q4, 1951Q1>

>> D = A:2:B

D = <dates: 1950Q1, 1950Q3, 1951Q1>

Method: B = copy(A)

Returns a copy of a dates object.

Method: disp(A)

Overloads the MATLAB/Octave disp function for dates object.

Method: display(A)

Overloads the MATLAB/Octave display function for dates object.
Example

>> disp(B)
B = <dates: 1950Q1, 1950Q2, 1950Q3, 1950Q4, 1951Q1, 1951Q2, 1951Q3, ...
    1951Q4, 1952Q1, 1952Q2, 1952Q3>

>> display(B)
B = <dates: 1950Q1, 1950Q2, ..., 1952Q2, 1952Q3>

Method: B = double(A)
Overloads the MATLAB/Octave double function. A is a dates object. The method returns a floating point representation of a dates object, the integer and fractional parts respectively corresponding to the year and the subperiod. The fractional part is the subperiod number minus one divided by the frequency (1, 4, or 12).

Example:

>> a = dates('1950Q1'):dates('1950Q4');
>> a.double()
ans =
    1950.00
    1950.25
    1950.50
    1950.75

Method: C = eq(A, B)
Overloads the MATLAB/Octave eq (equal, ==) operator. dates objects A and B must have the same number of elements (say, n). The returned argument is a n by 1 vector of logicals. The i-th element of C is equal to true if and only if the dates A(i) and B(i) are the same.

Example

>> A = dates('1950Q1','1951Q2');
>> B = dates('1950Q1','1950Q2');
>> A==B
ans =
    2x1 logical array
    1
    0

Method: C = ge(A, B)
Overloads the MATLAB/Octave ge (greater or equal, >=) operator. dates objects A and B must have the same number of elements (say, n). The returned argument is a n by 1 vector of logicals. The i-th element of C is equal to true if and only if the date A(i) is posterior or equal to the date B(i).

Example

>> A = dates('1950Q1','1951Q2');
>> B = dates('1950Q1','1950Q2');
>> A>=B
(continues on next page)
ans =

2x1 logical array

1
1

**Method:** C = gt(A, B)

Overloads the MATLAB/Octave `gt` (greater than, >) operator. `dates` objects A and B must have the same number of elements (say, n). The returned argument is a n by 1 vector of logits. The i-th element of C is equal to 1 if and only if the date A(i) is posterior to the date B(i).

Example

```matlab
>> A = dates('1950Q1','1951Q2');
>> B = dates('1950Q1','1950Q2');
>> A>B
ans =

2x1 logical array

0
1
```

**Method:** D = horzcat(A, B, C, ...)

Overloads the MATLAB/Octave `horzcat` operator. All the input arguments must be `dates` objects. The returned argument is a `dates` object gathering all the dates given in the input arguments (repetitions are not removed).

Example

```matlab
>> A = dates('1950Q1');
>> B = dates('1950Q2');
>> C = [A, B];
>> C
C = <dates: 1950Q1, 1950Q2>
```

**Method:** C = intersect(A, B)

Overloads the MATLAB/Octave `intersect` function. All the input arguments must be `dates` objects. The returned argument is a `dates` object gathering all the common dates given in the input arguments. If A and B are disjoint `dates` objects, the function returns an empty `dates` object. Returned dates in `dates` object C are sorted by increasing order.

Example

```matlab
>> A = dates('1950Q1'):dates('1951Q4');
>> B = dates('1951Q1'):dates('1951Q4');
>> C = intersect(A, B);
>> C
C = <dates: 1951Q1, 1951Q2, 1951Q3, 1951Q4>
```

**Method:** B = isempty(A)

Overloads the MATLAB/Octave `isempty` function.

Example
```matlab
>> A = dates('1950Q1');
>> A isempty()
ans =
    logical
    0

>> B = dates();
>> B isempty()
ans =
    logical
    1

Method: C = isequal(A, B)
Overloads the MATLAB/Octave isequal function.

Example
```matlab
>> A = dates('1950Q1');
>> B = dates('1950Q2');
>> isequal(A, B)
ans =
    logical
    0
```

Method: C = le(A, B)
Overloads the MATLAB/Octave le (less or equal, <=) operator. dates objects A and B must have the same number of elements (say, n). The returned argument is a n by 1 vector of logicals. The i-th element of C is equal to true if and only if the date A(i) is anterior or equal to the date B(i).

Example
```matlab
>> A = dates('1950Q1','1951Q2');
>> B = dates('1950Q1','1950Q2');
>> A <= B
ans =
    2x1 logical array
    1
    0
```

Method: B = length(A)
Overloads the MATLAB/Octave length function. Returns the number of elements in a dates object.

Example
```matlab
>> A = dates('1950Q1'):dates(2000Q3);
>> A.length()
```

Method: C = lt(A, B)

Overloads the MATLAB/Octave lt (less than, <) operator. dates objects A and B must have the same number of elements (say, n). The returned argument is a n by 1 vector of logicals. The i-th element of C is equal to true if and only if the date A(i) is anterior or equal to the date B(i).

Example

```
>> A = dates('1950Q1','1951Q2');
>> B = dates('1950Q1','1950Q2');
>> A<B
ans =
2x1 logical array
 0
 0
```

Method: D = max(A, B, C, ...)

Overloads the MATLAB/Octave max function. All input arguments must be dates objects. The function returns a single element dates object containing the greatest date.

Example

```
>> A = {dates('1950Q2'), dates('1953Q4','1876Q2'), dates('1794Q3')};
>> max(A{:})
ans = <dates: 1953Q4>
```

Method: D = min(A, B, C, ...)

Overloads the MATLAB/Octave min function. All input arguments must be dates objects. The function returns a single element dates object containing the smallest date.

Example

```
>> A = {dates('1950Q2'), dates('1953Q4','1876Q2'), dates('1794Q3')};
>> min(A{:})
ans = <dates: 1794Q3>
```

Method: C = minus(A, B)

Overloads the MATLAB/Octave minus operator (-). If both input arguments are dates objects, then number of periods between A and B is returned (so that A+C=B). If B is a vector of integers, the minus operator shifts the dates object by B periods backward.

Example

```
>> d1 = dates('1950Q1','1950Q2','1960Q1');
>> d2 = dates('1950Q3','1950Q4','1960Q1');
>> ee = d2 - d1
ee =
```

(continues on next page)
Method: \( C = \text{mtimes}(A, B) \)

Overloads the MATLAB/Octave \texttt{mtimes} operator (*). \( A \) and \( B \) are respectively expected to be a \texttt{dates} object and a scalar integer. Returns \texttt{dates} object \( A \) replicated \( B \) times.

Example

\begin{verbatim}
>> d = dates('1950Q1');
>> d*2
ans = <dates: 1950Q1, 1950Q1>
\end{verbatim}

Method: \( C = \text{ne}(A, B) \)

Overloads the MATLAB/Octave \texttt{ne} (not equal, \texttt{~=}) operator. \texttt{dates} objects \( A \) and \( B \) must have the same number of elements (say, \( n \)) or one of the inputs must be a single element \texttt{dates} object. The returned argument is a \( n \) by 1 vector of logicals. The \( i \)-th element of \( C \) is equal to \texttt{true} if and only if the \texttt{dates} \( A(i) \) and \( B(i) \) are different.

Example

\begin{verbatim}
>> A = dates('1950Q1','1951Q2');
>> B = dates('1950Q1','1950Q2');
>> A==B
ans =
     2x1 logical array
              0
              1
\end{verbatim}

Method: \( C = \text{plus}(A, B) \)

Overloads the MATLAB/Octave \texttt{plus} operator (+). If both input arguments are \texttt{dates} objects, then the method combines \( A \) and \( B \) without removing repetitions. If \( B \) is a vector of integers, the \texttt{plus} operator shifts the \texttt{dates} object by \( B \) periods forward.

Example

\begin{verbatim}
>> d1 = dates('1950Q1','1950Q2')+dates('1960Q1');
>> d2 = (dates('1950Q1','1950Q2')+2)+dates('1960Q1');
>> ee = d2-d1;
>> d1+ee
ans = <dates: 1950Q3, 1950Q4, 1960Q1>
\end{verbatim}
Method: C = pop(A)
Method: C = pop(A, B)
Method: C = pop_(A)
Method: C = pop_(_, A, B)

Pop method for dates class. If only one input is provided, the method removes the last element of a dates object. If a second input argument is provided, a scalar integer between 1 and A.length(), the method removes element number B from dates object A.

Example

```matlab
>> d = dates('1950Q1','1950Q2');
>> d.pop()
ans = <dates: 1950Q1>
>> d.pop_(1)
ans = <dates: 1950Q2>
```

Method: C = remove(A, B)
Method: C = remove_(_, A, B)

Remove method for dates class. Both inputs have to be dates objects, removes dates in B from A.

Example

```matlab
>> d = dates('1950Q1','1950Q2');
>> d.remove(dates('1950Q2'))
ans = <dates: 1950Q1>
```

Method: C = setdiff(A, B)

Overloads the MATLAB/Octave setdiff function. All the input arguments must be dates objects. The returned argument is a dates object all dates present in A but not in B. If A and B are disjoint dates objects, the function returns A. Returned dates in dates object C are sorted by increasing order.

Example

```matlab
>> A = dates('1950Q1'):dates('1969Q4');
>> B = dates('1960Q1'):dates('1969Q4');
>> C = dates('1970Q1'):dates('1979Q4');
>> setdiff(A, B)
ans = <dates: 1950Q1, 1950Q2, ..., 1959Q3, 1959Q4>
>> setdiff(A, C)
ans = <dates: 1950Q1, 1950Q2, ..., 1969Q3, 1969Q4>
```

Method: B = sort(A)
Method: B = sort_(_, A)

Sort method for dates objects. Returns a dates object with elements sorted by increasing order.

Example

```matlab
>> dd = dates('1945Q3','1938Q4','1789Q3');
>> dd.sort()
ans = <dates: 1789Q3, 1938Q4, 1945Q3>
```
Method: \( B = \text{strings}(A) \)

Converts a \texttt{dates} object into a cell of char arrays.

\textit{Example}

\begin{verbatim}
>> A = dates('1950Q1');
>> A = A:A+1;
>> A.strings()

ans =
1x2 cell array
    {'1950Q1'}    {'1950Q2'}
\end{verbatim}

Method: \( B = \text{subperiod}(A) \)

Returns the subperiod of a date (an integer scalar between 1 and \( A.f\text{req} \)). This method is not implemented for daily dates.

\textit{Example}

\begin{verbatim}
>> A = dates('1950Q2');
>> A.subperiod()

ans =
    2
\end{verbatim}

Method: \( B = \text{uminus}(A) \)

Overloads the MATLAB/Octave unary minus operator. Returns a \texttt{dates} object with elements shifted one period backward.

\textit{Example}

\begin{verbatim}
>> dd = dates('1945Q3','1938Q4','1973Q1');
>> -dd

ans =<dates: 1945Q2, 1938Q3, 1972Q4>
\end{verbatim}

Method: \( D = \text{union}(A, B, C, \ldots) \)

Overloads the MATLAB/Octave union function. Returns a \texttt{dates} object with elements sorted by increasing order (repetitions are removed, to keep the repetitions use the \texttt{horzcat} or \texttt{plus} operators).

\textit{Example}

\begin{verbatim}
>> d1 = dates('1945Q3','1973Q1','1938Q4');
>> d2 = dates('1973Q1','1976Q1');
>> union(d1,d2)

ans =<dates: 1938Q4, 1945Q3, 1973Q1, 1976Q1>
\end{verbatim}

Method: \( B = \text{unique}(A) \)

Overloads the MATLAB/Octave unique function. Returns a \texttt{dates} object with repetitions removed (only the last occurrence of a date is kept).

\textit{Example}
>> d1 = dates('1945Q3','1973Q1','1945Q3');
>> d1.unique()
ans = <dates: 1973Q1, 1945Q3>

Method: \( B = \text{uplus}(A) \)
Overloads the MATLAB/Octave unary plus operator. Returns a dates object with elements shifted one period ahead.

Example

>> dd = dates('1945Q3','1938Q4','1973Q1');
>> +dd
ans = <dates: 1945Q4, 1939Q1, 1973Q2>

Method: \( D = \text{vertcat}(A, B, C, \ldots) \)
Overloads the MATLAB/Octave \text{horzcat} operator. All the input arguments must be dates objects. The returned argument is a dates object gathering all the dates given in the input arguments (repetitions are not removed).

Method: \( B = \text{year}(A) \)
Returns the year of a date (an integer scalar between 1 and \( A.\text{freq} \)).

Example

>> A = dates('1950Q2');
>> A.subperiod()
ans =
    1950

### 6.2 The \texttt{dseries} class

\textbf{Dynare class:} \texttt{dseries}

The MATLAB/Octave \texttt{dseries} class handles time series data. As any MATLAB/Octave statements, this class can be used in a Dynare’s mod file. A \texttt{dseries} object has six members:

\textbf{Members}

- \texttt{name} – A \texttt{vobs}\(^*\)1 cell of strings or a \texttt{vobs}\(^*\)p character array, the names of the variables.
- \texttt{tex} – A \texttt{vobs}\(^*\)1 cell of strings or a \texttt{vobs}\(^*\)p character array, the tex names of the variables.
- \texttt{dates} (\texttt{dates}) – An object with \texttt{nobs} elements, the dates of the sample.
- \texttt{data} (\texttt{double}) – A \texttt{nobs} by \texttt{vobs} array, the data.
- \texttt{ops} – The history of operations on the variables.
- \texttt{tags} – The user-defined tags on the variables.

data, name, tex, and ops are private members. The following constructors are available:

\textbf{Constructor:} \texttt{dseries()}

\textbf{Constructor:} \texttt{dseries(INITIAL_DATE)}
Instantiates an empty \texttt{dseries} object with, if defined, an initial date given by the single element \texttt{dates} object \texttt{INITIAL_DATE}. 

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Constructor: dseries(FILENAME[, INITIAL_DATE])

Instantiates and populates a dseries object with a data file specified by FILENAME, a string passed as input. Valid file types are .m, .mat, .csv and .xls/.xlsx (Octave only supports .xlsx files and the io package from Octave-Forge must be installed). The extension of the file should be explicitly provided.

A typical .m file will have the following form:

```matlab
FREQ__ = 4;
INIT__ = '1994Q3';
NAMES__ = {'azert';'yuiop'};
TEX__ = {'azert';'yuiop'};
azert = randn(100,1);
yuiop = randn(100,1);
```

If a .mat file is used instead, it should provide the same informations, except that the data should not be given as a set of vectors, but as a single matrix of doubles named DATA__. This array should have as many columns as elements in NAMES__ (the number of variables). Note that the INIT__ variable can be either a dates object or a string which could be used to instantiate the same dates object. If INIT__ is not provided in the .mat or .m file, the initial is by default set equal to dates('1Y'). If a second input argument is passed to the constructor, dates object INITIAL_DATE, the initial date defined in FILENAME is reset to INITIAL_DATE. This is typically useful if INIT__ is not provided in the data file.

If an .xlsx file is used, the first row should be a header containing the variable names. The first column may contain date information that must correspond to a valid date format recognized by Dynare. If such date information is specified in the first column, its header name must be left empty.

Constructor: dseries(DATA_MATRIX[,INITIAL_DATE[,LIST_OF_NAMES[,TEX_NAMES]]]])

Constructor: dseries(DATA_MATRIX[,RANGE_OF_DATES[,LIST_OF_NAMES[,TEX_NAMES]]]])

If the data is not read from a file, it can be provided via a T × N matrix as the first argument to dseries, with T representing the number of observations on N variables. The optional second argument, INITIAL_DATE, can be either a dates object or a string which could be used to instantiate the dates object. Its default value is dates('1Y'). The optional third argument, LIST_OF_NAMES, is a N × 1 cell of strings with one entry for each variable name. The default name associated with column i of DATA_MATRIX is Variable_i. The final argument, TEX_NAMES, is a N × 1 cell of strings composed of the LaTeX names associated with the variables. The default LaTeX name associated with column i of DATA_MATRIX is Variable_i. If the optional second input argument is a range of dates, dates object RANGE_OF_DATES, the number of rows in the first argument must match the number of elements RANGE_OF_DATES or be equal to one (in which case the single observation is replicated).

Constructor: dseries(TABLE)

Creates a dseries object given the MATLAB Table provided as the sole argument. It is assumed that the first column of the table contains the dates of the dseries and the first row contains the names. This feature is not available under Octave or MATLAB R2013a or earlier.

Example

Various ways to create a dseries object:

```matlab
d01 = dseries(1999Q3);
d02 = dseries('filename.csv');
d03 = dseries([1; 2; 3], 1999Q3, {'var123'}, {'var_{123}'});

>> d01 = dseries(dates('1999Q3'));
>> d02 = dseries('filename.csv');
>> d03 = dseries([1; 2; 3], dates('1999Q3'), {'var123'}, {'var_{123}'});
```

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One can easily create subsamples from a \texttt{dseries} object using the overloaded parenthesis operator. If \texttt{ds} is a \texttt{dseries} object with \( T \) observations and \texttt{d} is a \texttt{dates} object with \( S < T \) elements, such that \( \min(d) \) is not smaller than the date associated to the first observation in \texttt{ds} and \( \max(d) \) is not greater than the date associated to the last observation, then \texttt{ds \( (d) \)} instantiates a new \texttt{dseries} object containing the subsample defined by \texttt{d}.

A list of the available methods, by alphabetical order, is given below. As in the previous section the in place modifications versions of the methods are postfixed with an underscore.

\textbf{Method: } \texttt{A = abs(B)}

\textbf{Method: } \texttt{abs\_}(B)

Overloads the \texttt{abs()} function for \texttt{dseries} objects. Returns the absolute value of the variables in \texttt{dseries} object \texttt{B}.

\textit{Example}

\begin{verbatim}
>> ts0 = dseries(randn(3,2),'1973Q1',{''A1''; ''A2''},{''A_1''; ''A_2''});
>> ts1 = ts0.abs();
>> ts0

\end{verbatim}

\texttt{ts0} is a \texttt{dseries} object:

\begin{verbatim}
| A1     | A2     |
1973Q1 | -0.67284 | 1.4367  \
1973Q2 | -0.51222 | -0.4948 \
1973Q3 | 0.99791  | 0.22677 |
\end{verbatim}

\begin{verbatim}
>> ts1

\end{verbatim}

\texttt{ts1} is a \texttt{dseries} object:

\begin{verbatim}
| abs(A1) | abs(A2) |
1973Q1 | 0.67284  | 1.4367  \
1973Q2 | 0.51222  | 0.4948  \
1973Q3 | 0.99791  | 0.22677 |
\end{verbatim}

\textbf{Method: } \texttt{[A, B] = align(A, B)}

\textbf{Method: } \texttt{align\_}(A, B)

If \texttt{dseries} objects \texttt{A} and \texttt{B} are defined on different time ranges, this function extends \texttt{A} and/or \texttt{B} with NaNs so that they are defined on the same time range. Note that both \texttt{dseries} objects must have the same frequency.

\textit{Example}

\begin{verbatim}
>> ts0 = dseries(rand(5,1),dates('2000Q1'));
% 2000Q1 -> 2001Q1
>> ts1 = dseries(rand(3,1),dates('2000Q4'));
% 2000Q4 -> 2001Q2
>> [ts0, ts1] = align(ts0, ts1);
% 2000Q1 -> 2001Q2
>> ts0

\end{verbatim}

\texttt{ts0} is a \texttt{dseries} object:

\begin{verbatim}
| Variable_1 |
2000Q1 | 0.81472  \
2000Q2 | 0.90579  \
2000Q3 | 0.12699  \
2000Q4 | 0.92336  \
2001Q1 | NaN      \
2001Q2 | NaN      |
\end{verbatim}
>> ts1

**ts1** is a dseries object:

| Variable_1 |
|----------------
| 2000Q1 | NaN |
| 2000Q2 | NaN |
| 2000Q3 | NaN |
| 2000Q4 | 0.66653 |
| 2001Q1 | 0.17813 |
| 2001Q2 | 0.12801 |

>> ts0 = dseries(rand(5,1),dates('2000Q1')); % 2000Q1 -> 2001Q1
>> ts1 = dseries(rand(3,1),dates('2000Q4')); % 2000Q4 -> 2001Q2
>> align_(ts0, ts1); % 2000Q1 -> 2001Q2
>> ts1

**ts1** is a dseries object:

| Variable_1 |
|----------------
| 2000Q1 | NaN |
| 2000Q2 | NaN |
| 2000Q3 | NaN |
| 2000Q4 | 0.66653 |
| 2001Q1 | 0.17813 |
| 2001Q2 | 0.12801 |

**Method:** C = backcast(A, B[, diff])

**Method:** backcast_(A, B[, diff])

Backcasts dseries object A with dseries object B’s growth rates (except if the last optional argument, diff, is true in which case first differences are used). Both dseries objects must have the same frequency.

**Method:** B = baxter_king_filter(A, hf, lf, K)

**Method:** baxter_king_filter_(A, hf, lf, K)

Implementation of the Baxter and King (1999) band pass filter for dseries objects. This filter isolates business cycle fluctuations with a period of length ranging between hf (high frequency) to lf (low frequency) using a symmetric moving average smoother with 2K + 1 points, so that K observations at the beginning and at the end of the sample are lost in the computation of the filter. The default value for hf is 6, for lf is 32, and for K is 12.

**Example**

```matlab
% Simulate a component model (stochastic trend, deterministic trend, and a stationary autoregressive process).
e = 0.2*randn(200,1);
u = randn(200,1);
stochastic_trend = cumsum(e);
deterministic_trend = .1*transpose(1:200);
x = zeros(200,1);
for i=2:200
    x(i) = .75*x(i-1) + u(i);
end
y = x + stochastic_trend + deterministic_trend;
```

% Instantiates time series objects.
ts0 = dseries(y,'1950Q1');
ts1 = dseries(x,'1950Q1'); % stationary component.

% Apply the Baxter-King filter.
ts2 = ts0.baxter_king_filter();

% Plot the filtered time series.
plot(ts1(ts2.dates).data,'-k'); % Plot of the stationary component.
hold on
plot(ts2.data,'--r'); % Plot of the filtered y.
hold off
axis tight
id = get(gca,'XTick');
set(gca,'XTickLabel',strings(ts1.dates(id)));

Method: B = center(A[, geometric])
Method: center_(A[, geometric])

Centers variables in dseries object A around their arithmetic means, except if the optional argument geometric is set equal to true in which case all the variables are divided by their geometric means.

Method: C = chain(A, B)
Method: chain_(A, B)

Merge two dseries objects along the time dimension. The two objects must have the same number of observed variables, and the initial date in B must not be posterior to the last date in A. The returned dseries object, C, is built by extending A with the cumulated growth factors of B.

Example

>> ts = dseries([1; 2; 3; 4],dates('1950Q1'))

ts is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>1950Q2</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>1950Q3</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>1950Q4</td>
</tr>
<tr>
<td>4</td>
</tr>
</tbody>
</table>

>> us = dseries([3; 4; 5; 6],dates('1950Q3'))

us is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q3</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>1950Q4</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>1951Q1</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>1951Q2</td>
</tr>
<tr>
<td>6</td>
</tr>
</tbody>
</table>

>> chain(ts, us)

ans is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>1950Q2</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>1950Q3</td>
</tr>
<tr>
<td>3</td>
</tr>
</tbody>
</table>

(continues on next page)
Method: \([\text{error\_flag}, \text{message}] = \text{check}(A)\)
Sanity check of `dseries` object \(A\). Returns 1 if there is an error, 0 otherwise. The second output argument is a string giving brief informations about the error.

Method: \(B = \text{copy}(A)\)
Returns a copy of \(A\). If an inplace modification method is applied to \(A\), object \(B\) will not be affected. Note that if \(A\) is assigned to \(C, C = A\), then any in place modification method applied to \(A\) will change \(C\).

Example

```matlab
>> a = dseries(randn(5,1))
a is a dseries object:
    | Variable_1
1Y | -0.16936
2Y | -1.1451
3Y | -0.034331
4Y | -0.089042
5Y | -0.66997

>> b = copy(a);
>> c = a;
>> a.abs();
>> a.abs_();
>> a

a is a dseries object:
    | Variable_1
1Y | 0.16936
2Y | 1.1451
3Y | 0.034331
4Y | 0.089042
5Y | 0.66997

>> b

b is a dseries object:
    | Variable_1
1Y | -0.16936
2Y | -1.1451
3Y | -0.034331
4Y | -0.089042
5Y | -0.66997

>> c

c is a dseries object:
    | Variable_1
```
Method: \( B = \text{cumprod}(A[, \ d[, \ v]]) \)

Method: \( \text{cumprod}_{-}(A[, \ d[, \ v]]) \)

Overloads the MATLAB/Octave \texttt{cumprod} function for \texttt{dseries} objects. The cumulated product cannot be computed if the variables in \texttt{dseries} object \( A \) have NaNs. If a \texttt{dates} object \( d \) is provided as a second argument, then the method computes the cumulated product with the additional constraint that the variables in the \texttt{dseries} object \( B \) are equal to one in period \( d \). If a single-observation \texttt{dseries} object \( v \) is provided as a third argument, the cumulated product in \( B \) is normalized such that \( B(d) \) matches \( v \) (\texttt{dseries} objects \( A \) and \( v \) must have the same number of variables).

Example

```matlab
>> ts1 = dseries(2*ones(7,1));
>> ts2 = ts1.cumprod();
>> ts2

\texttt{ts2} \textit{is a dseries object:}

\begin{verbatim}
| cumprod(Variable_1) |
1Y | 2
2Y | 4
3Y | 8
4Y | 16
5Y | 32
6Y | 64
7Y | 128
\end{verbatim}

>> ts3 = ts1.cumprod(dates('3Y'));
>> ts3

\texttt{ts3} \textit{is a dseries object:}

\begin{verbatim}
| cumprod(Variable_1) |
1Y | 0.25
2Y | 0.5
3Y | 1
4Y | 2
5Y | 4
6Y | 8
7Y | 16
\end{verbatim}

>> ts4 = ts1.cumprod(dates('3Y'),dseries(pi));
>> ts4

\texttt{ts4} \textit{is a dseries object:}

\begin{verbatim}
| cumprod(Variable_1) |
1Y | 0.7854
2Y | 1.5708
3Y | 3.1416
4Y | 6.2832
\end{verbatim}

(continues on next page)
Method: \( B = \text{cumsum}(A[,\ d[,\ v]]) \)

Overloads the MATLAB/Octave \texttt{cumsum} function for \texttt{dseries} objects. The cumulated sum cannot be computed if the variables in \texttt{dseries} object \( A \) have NaNs. If a \texttt{dates} object \( d \) is provided as a second argument, then the method computes the cumulated sum with the additional constraint that the variables in the \texttt{dseries} object \( B \) are zero in period \( d \). If a single observation \texttt{dseries} object \( v \) is provided as a third argument, the cumulated sum in \( B \) is such that \( B(d) \) matches \( v \) (\texttt{dseries} objects \( A \) and \( v \) must have the same number of variables).

Example

```
>> ts1 = dseries(ones(10,1));
>> ts2 = ts1.cumsum();
>> ts2

  ts2 is a dseries object:
      | cumsum(Variable_1)
  1Y | 1
  2Y | 2
  3Y | 3
  4Y | 4
  5Y | 5
  6Y | 6
  7Y | 7
  8Y | 8
  9Y | 9
 10Y | 10
```

```
>> ts3 = ts1.cumsum(dates('3Y'));
>> ts3

  ts3 is a dseries object:
      | cumsum(Variable_1)
  1Y | -2
  2Y | -1
  3Y | 0
  4Y | 1
  5Y | 2
  6Y | 3
  7Y | 4
  8Y | 5
  9Y | 6
 10Y | 7
```

```
>> ts4 = ts1.cumsum(dates('3Y'),dseries(pi));
>> ts4

  ts4 is a dseries object:
      | cumsum(Variable_1)
  1Y | 0.125664
  2Y | 0.251327
  3Y | 0.502655
```

(continues on next page)
Method: B = detrend(A, m)
Method: detrend_(A, m)

Detrends dseries object A with a fitted polynomial of order m. Note that each variable is detrended with a different polynomial.

Method: B = dgrowth(A)
Method: dgrowth_(A)

Computes daily growth rates.

Method: B = diff(A)
Method: diff_(A)

Returns the first difference of dseries object A.

Method: disp(A)

Overloads the MATLAB/Octave disp function for dseries object.

Method: display(A)

Overloads the MATLAB/Octave display function for dseries object. display is the function called by MATLAB to print the content of an object if a semicolon is missing at the end of a MATLAB statement. If the dseries object is defined over a too large time span, only the first and last periods will be printed. If the dseries object contains too many variables, only the first and last variables will be printed. If all the periods and variables are required, the disp method should be used instead.

Method: C = eq(A, B)

Overloads the MATLAB/Octave eq (equal, ==) operator. dseries objects A and B must have the same number of observations (say, T) and variables (N). The returned argument is a $T \times N$ matrix of logicals. Element $(i, j)$ of C is equal to true if and only if observation $i$ for variable $j$ in A and B are the same.

Example

```matlab
>> ts0 = dseries(2*ones(3,1));
>> ts1 = dseries([2; 0; 2]);
>> ts0==ts1

ans =

3x1 logical array
1
0
1
```

Method: l = exist(A, varname)

Tests if variable varname exists in dseries object A. Returns true iff variable exists in A.

Example
\begin{verbatim}
>> ts = dseries(randn(100,1));
>> ts.exist('Variable_1')
ans =
    logical
    1
>> ts.exist('Variable_2')
ans =
    logical
    0
\end{verbatim}

**Method:** \( B = \text{exp}(A) \)

**Method:** \( \text{exp}(A) \)

Overloads the MATLAB/Octave \texttt{exp} function for \texttt{dseries} objects.

**Example**

\begin{verbatim}
>> ts0 = dseries(rand(10,1));
>> ts1 = ts0.exp();
\end{verbatim}

**Method:** \( C = \text{extract}(A, B[, ...]) \)

Extracts some variables from a \texttt{dseries} object \( A \) and returns a \texttt{dseries} object \( C \). The input arguments following \( A \) are strings representing the variables to be selected in the new \texttt{dseries} object \( C \). To simplify the creation of sub-objects, the \texttt{dseries} class overloads the curly braces (\( D = \text{extract}(A, B, C) \)) and allows implicit loops (defined between a pair of @ symbol, see examples below) or MATLAB/Octave’s regular expressions (introduced by square brackets).

**Example**

The following selections are equivalent:

\begin{verbatim}
>> ts0 = dseries(ones(100,10));
>> ts1 = ts0.exp();
    >> ts2 = ts0{'Variable_1','Variable_2','Variable_3'};
    >> ts3 = ts0{'Variable_@1,2,3@'};
    >> ts4 = ts0{'Variable_[1-3]$'};
    >> isequal(ts1,ts2) && isequal(ts1,ts3)
ans =
    logical
    1
\end{verbatim}

It is possible to use up to two implicit loops to select variables:

\begin{verbatim}
names = {'GDP_1';'GDP_2';'GDP_3'; 'GDP_4'; 'GDP_5'; 'GDP_6'; 'GDP_7';
    'GDP_8' ...;
    'GDP_9'; 'GDP_10'; 'GDP_11'; 'GDP_12'; ...;
    'HICP_1';'HICP_2';'HICP_3'; 'HICP_4'; 'HICP_5'; 'HICP_6'; 'HICP_7
    '@;
    'HICP_8' ...;
    'HICP_9'; 'HICP_10'; 'HICP_11'; 'HICP_12'};
\end{verbatim}

(continues on next page)
ts0 = dseries(randn(4,24),dates('1973Q1'),names);

ans is a dseries object:

<table>
<thead>
<tr>
<th>GDP_1</th>
<th>GDP_3</th>
<th>GDP_5</th>
<th>HICP_1</th>
<th>HICP_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1973Q1</td>
<td>1.7906</td>
<td>-1.6606</td>
<td>-0.57716</td>
<td>0.60963</td>
</tr>
<tr>
<td></td>
<td>26172</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1973Q2</td>
<td>2.1624</td>
<td>3.0125</td>
<td>0.52563</td>
<td>0.70912</td>
</tr>
<tr>
<td></td>
<td>7792</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1973Q3</td>
<td>-0.81928</td>
<td>1.5008</td>
<td>1.152</td>
<td>0.2798</td>
</tr>
<tr>
<td></td>
<td>8927</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1973Q4</td>
<td>-0.03705</td>
<td>-0.35899</td>
<td>0.85838</td>
<td>-1.4675</td>
</tr>
<tr>
<td></td>
<td>62032</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Method: \( f = \) firstdate\( (A) \)

Returns the first period in dseries object \( A \).

Method: \( f = \) firstobservedperiod\( (A) \)

Returns the first period where all the variables in dseries object \( A \) are observed (non NaN).

Method: \( B = \) flip\( (A) \)

Method: \( \) flip_\( (A) \)

Flips the rows in the data member (without changing the periods order).

Method: \( f = \) frequency\( (B) \)

Returns the frequency of the variables in dseries object \( B \).

Example

\[
\begin{align*}
\text{>> } ts &= \text{dseries(randn(3,2),'1973Q1');} \\
\text{>> } ts.\text{frequency} \\
\text{ans} &= \\
\end{align*}
\]

4

Method: \( D = \) horzcat\( (A, B[, ...]) \)

Overloads the horzcat MATLAB/Octave’s method for dseries objects. Returns a dseries object \( D \) containing the variables in dseries objects passed as inputs: \( A, B, ... \). If the inputs are not defined on the same time ranges, the method adds NaNs to the variables so that the variables are redefined on the smallest common time range. Note that the names in the dseries objects passed as inputs must be different and these objects must have common frequency.

Example

\[
\begin{align*}
\text{>> } ts0 &= \text{dseries(rand(5,2),'1950Q1',\{'nifnif';'noufnouf'\});} \\
\text{>> } ts1 &= \text{dseries(rand(7,1),'1950Q3',\{'nafnaf'\});} \\
\text{>> } ts2 &= [ts0, ts1]; \\
\text{>> } ts2 \\
\end{align*}
\]

ts2 is a dseries object:

<table>
<thead>
<tr>
<th>nifnif</th>
<th>noufnouf</th>
<th>nafnaf</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
<td>0.17404</td>
<td>0.71431</td>
</tr>
<tr>
<td>1950Q2</td>
<td>0.62741</td>
<td>0.90704</td>
</tr>
<tr>
<td>1950Q3</td>
<td>0.84189</td>
<td>0.21854</td>
</tr>
</tbody>
</table>
Method: \( B = \text{hpcycle}(A[, \lambda]) \)

Extracts the cycle component from a `dseries` \( A \) object using the *Hodrick and Prescott (1997)* filter and returns a `dseries` object, \( B \). The default value for \( \lambda \), the smoothing parameter, is 1600.

**Example**

```matlab
% Simulate a component model (stochastic trend, deterministic trend, and a stationary autoregressive process).
e = 0.2*randn(200,1);
u = randn(200,1);
stochastic_trend = cumsum(e);
deterministic_trend = .1*transpose(1:200);
x = zeros(200,1);
for i=2:200
    x(i) = .75*x(i-1) + u(i);
end
y = x + stochastic_trend + deterministic_trend;

% Instantiate time series objects.
%ts0 = dseries(y,'1950Q1');
%ts1 = dseries(x,'1950Q1'); % stationary component.
% Apply the HP filter.
ts2 = ts0.hpcycle();

% Plot the filtered time series.
plot(ts1(ts2.dates).data,'-k'); % Plot of the stationary component.
hold on
plot(ts2.data,'--r'); % Plot of the filtered y.
hold off
axis tight
id = get(gca,'XTick');
set(gca,'XTickLabel',strings(ts.dates(id)));
```

Method: \( B = \text{hptrend}(A[, \lambda]) \)

Extracts the trend component from a `dseries` \( A \) object using the *Hodrick and Prescott (1997)* filter and returns a `dseries` object, \( B \). Default value for \( \lambda \), the smoothing parameter, is 1600.

**Example**

```matlab
% Using the same generating data process
% as in the previous example:

ts1 = dseries(stochastic_trend + deterministic_trend,'1950Q1');
% Apply the HP filter.
ts2 = ts0.hptrend();

% Plot the filtered time series.
```
plot(ts1.data,'-k'); % Plot of the nonstationary components.
hold on
plot(ts2.data,'--r'); % Plot of the estimated trend.
hold off
axis tight
id = get(gca,'XTick');
set(gca,'XTickLabel',strings(ts0.dates(id)));

Method: C = insert(A, B, I)

Inserts variables contained in dseries object B in dseries object A at positions specified by integer scalars in vector I, returns augmented dseries object C. The integer scalars in I must take values between 1 and A.length()+1 and refers to A’s column numbers. The dseries objects A and B need not be defined over the same time ranges, but it is assumed that they have common frequency.

Example

```matlab
>> ts0 = dseries(ones(2,4),’1950Q1’,{"Sly’; ’Gobbo’; ’Sneaky’;
→ ’Stealthy’});
>> ts1 = dseries(pi*ones(2,1),’1950Q1’,{"Noddy’});
>> ts2 = ts0.insert(ts1,3)

ts2 is a dseries object:

<table>
<thead>
<tr>
<th>Sly</th>
<th>Gobbo</th>
<th>Noddy</th>
<th>Sneaky</th>
<th>Stealthy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>3.1416</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>3.1416</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

>> ts3 = dseries([pi*ones(2,1) sqrt(pi)*ones(2,1)],’1950Q1’,{"Noddy’;
→ ’Tessie Bear’});
>> ts4 = ts0.insert(ts1,[3, 4])

ts4 is a dseries object:

<table>
<thead>
<tr>
<th>Sly</th>
<th>Gobbo</th>
<th>Noddy</th>
<th>Sneaky</th>
<th>Tessie Bear</th>
<th>Stealthy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>3.1416</td>
<td>1</td>
<td>1.7725</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>3.1416</td>
<td>1</td>
<td>1.7725</td>
<td>1</td>
</tr>
</tbody>
</table>
```

Method: B = isempty(A)

Overloads the MATLAB/octave’s isempty function. Returns true if dseries object A is empty.

Method: C = isequal(A, B)

Overloads the MATLAB/octave’s isequal function. Returns true if dseries objects A and B are identical.

Method: C = isnan(A)

Overloads the MATLAB/octave’s isnan function. Returns a logical array, with element (i,j) equal to true if and only if variable j isn’t NaN in period A.dates(i).

Method: C = isreal(A)

Overloads the MATLAB/octave’s isreal function. Returns a logical array, with element (i,j) equal to true if and only if variable j is real in period A.dates(i).

Method: B = lag(A[, p])
**Method:** \texttt{lag(A[, p])}

Returns lagged time series. Default value of integer scalar \texttt{p}, the number of lags, is 1.

**Example**

\begin{verbatim}
>> ts0 = dseries(transpose(1:4), '1950Q1')

\texttt{ts0} is a dseries object:
\begin{center}
\begin{tabular}{ll}
| Variable_1 | \hline
1950Q1 & 1 \\
1950Q2 & 2 \\
1950Q3 & 3 \\
1950Q4 & 4 \\
\end{tabular}
\end{center}

>> ts1 = ts0.lag()

\texttt{ts1} is a dseries object:
\begin{center}
\begin{tabular}{ll}
| Variable_1 | \hline
1950Q1 & NaN \\
1950Q2 & 1 \\
1950Q3 & 2 \\
1950Q4 & 3 \\
\end{tabular}
\end{center}

>> ts2 = ts0.lag(2)

\texttt{ts2} is a dseries object:
\begin{center}
\begin{tabular}{ll}
| Variable_1 | \hline
1950Q1 & NaN \\
1950Q2 & NaN \\
1950Q3 & 1 \\
1950Q4 & 2 \\
\end{tabular}
\end{center}

% dseries class overloads the parenthesis
% so that ts.lag(p) can be written more
% compactly as ts(-p). For instance:

>> ts0.lag(1)

\texttt{ans} is a dseries object:
\begin{center}
\begin{tabular}{ll}
| Variable_1 | \hline
1950Q1 & NaN \\
1950Q2 & 1 \\
1950Q3 & 2 \\
1950Q4 & 3 \\
\end{tabular}
\end{center}

or alternatively:

>> ts0(-1)

\texttt{ans} is a dseries object:
\begin{center}
\begin{tabular}{ll}
| Variable_1 | \hline
1950Q1 & NaN \\
1950Q2 & 1 \\
\end{tabular}
\end{center}
\end{verbatim}
Method: \( l = \text{lastdate}(B) \)

Returns the last period in \( \text{dseries} \) object \( B \).

Example

\begin{verbatim}
>> ts = \text{dseries(randn(3,2),}'1973Q1');
>> ts.lastdate()
ans = \text{dates: 1973Q3}
\end{verbatim}

Method: \( f = \text{lastobservedperiod}(A) \)

Returns the last period where all the variables in \( \text{dseries} \) object \( A \) are observed (non NaN).

Method: \( f = \text{lastobservedperiods}(A) \)

Returns for each variable the last period without missing observations in \( \text{dseries} \) object \( A \). Output argument \( f \) is a structure, each field name is the name of a variable in \( A \), each field content is a singleton date object.

Method: \( B = \text{lead}(A[, p]) \)

Returns lead time series. Default value of integer scalar \( p \), the number of leads, is 1. As in the \text{lag} method, the \( \text{dseries} \) class overloads the parenthesis so that \( \text{ts.lead}(p) \) is equivalent to \( \text{ts}(p) \).

Example

\begin{verbatim}
>> ts0 = \text{dseries(transpose(1:4),}'1950Q1');
>> ts1 = ts0.lead()

\text{ts1} is a \text{dseries} object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
</tr>
<tr>
<td>1950Q2</td>
</tr>
<tr>
<td>1950Q3</td>
</tr>
<tr>
<td>1950Q4</td>
</tr>
</tbody>
</table>

>> ts2 = ts0(2)

\text{ts2} is a \text{dseries} object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
</tr>
<tr>
<td>1950Q2</td>
</tr>
<tr>
<td>1950Q3</td>
</tr>
<tr>
<td>1950Q4</td>
</tr>
</tbody>
</table>
\end{verbatim}

Remark

The overloading of the parenthesis for \( \text{dseries} \) objects, allows to easily create new \( \text{dseries} \) objects by copying/pasting equations declared in the \text{model} block. For instance, if an Euler equation is defined in the \text{model} block:

\begin{verbatim}
model;
...
1/C - beta/C(1)*(exp(A(1))*K^(alpha-1)+1-delta) ;
\end{verbatim}
and if variables $A$ and $K$ are defined as dseries objects, then by writing:

$$\text{Residuals} = \frac{1}{C} - \beta/C(1) \cdot (\exp(A(1)) \cdot K^{\alpha-1} + 1 - \delta) ;$$

outside of the model block, we create a new dseries object, called Residuals, for the residuals of the Euler equation (the conditional expectation of the equation defined in the model block is zero, but the residuals are non zero).

**Method**: $B = \text{lineartrend}(A)$

Returns a linear trend centered on 0, the length of the trend is given by the size of dseries object $A$ (the number of periods).

**Example**

```matlab
>> ts = dseries(ones(3,1));
>> ts.lineartrend()
ans =
   -1
    0
    1
```

**Method**: $B = \log(A)$

**Method**: $\log_(A)$

Overloads the MATLAB/Octave \log function for dseries objects.

**Example**

```matlab
>> ts0 = dseries(rand(10,1));
>> ts1 = ts0.log();
```

**Method**: $B = \text{mdiff}(A)$

**Method**: $\text{mdiff}_{(A)}$

**Method**: $B = \text{mgrowth}(A)$

**Method**: $\text{mgrowth}_{(A)}$

 Computes monthly differences or growth rates of variables in dseries object $A$.

**Method**: $B = \text{mean}(A[, \text{geometric}])$

Overloads the MATLAB/Octave mean function for dseries objects. Returns the mean of each variable in dseries object $A$. If the second argument is true the geometric mean is computed, otherwise (default) the arithmetic mean is reported.

**Method**: $C = \text{merge}(A, B[, \text{legacy}])$

Merges two dseries objects $A$ and $B$ in dseries object $C$. Objects $A$ and $B$ need to have common frequency but can be defined on different time ranges. If a variable, say $x$, is defined both in dseries objects $A$ and $B$, then the merge will select the variable $x$ as defined in the second input argument, $B$, except for the NaN elements in $B$ if corresponding elements in $A$ (ie same periods) are well defined numbers. This behaviour can be changed by setting the optional argument legacy equal to true, in which case the second variable overwrites the first one even if the second variable has NaNs.

**Example**
>> ts0 = dseries(rand(3,2),'1950Q1',{"A1';'A2'})

ts0 is a dseries object:

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
<th>A2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
<td>0.96284</td>
<td>0.5363</td>
</tr>
<tr>
<td>1950Q2</td>
<td>0.25145</td>
<td>0.31866</td>
</tr>
<tr>
<td>1950Q3</td>
<td>0.34447</td>
<td>0.4355</td>
</tr>
</tbody>
</table>

>> ts1 = dseries(rand(3,1),'1950Q2',{"A1'})

ts1 is a dseries object:

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q2</td>
<td>0.40161</td>
</tr>
<tr>
<td>1950Q3</td>
<td>0.81763</td>
</tr>
<tr>
<td>1950Q4</td>
<td>0.97769</td>
</tr>
</tbody>
</table>

>> merge(ts0,ts1)

ans is a dseries object:

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
<th>A2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
<td>0.96284</td>
<td>0.5363</td>
</tr>
<tr>
<td>1950Q2</td>
<td>0.25145</td>
<td>0.31866</td>
</tr>
<tr>
<td>1950Q3</td>
<td>0.34447</td>
<td>0.4355</td>
</tr>
<tr>
<td>1950Q4</td>
<td>0.97769</td>
<td>NaN</td>
</tr>
</tbody>
</table>

>> merge(ts1,ts0)

ans is a dseries object:

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
<th>A2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
<td>0.96284</td>
<td>0.5363</td>
</tr>
<tr>
<td>1950Q2</td>
<td>0.25145</td>
<td>0.31866</td>
</tr>
<tr>
<td>1950Q3</td>
<td>0.34447</td>
<td>0.4355</td>
</tr>
<tr>
<td>1950Q4</td>
<td>0.97769</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Method: C = minus(A, B)

Overloads the MATLAB/Octave `minus` operator for `dseries` objects, element by element subtraction. If both A and B are `dseries` objects, they do not need to be defined over the same time ranges. If A and B are `dseries` objects with $T_A$ and $T_B$ observations and $N_A$ and $N_B$ variables, then $N_A$ must be equal to $N_B$ or 1 and $N_B$ must be equal to $N_A$ or 1. If $T_A = T_B$, `isequal(A.init,B.init)` returns 1 and $N_A = N_B$, then the `minus` operator will compute for each couple $(t, n)$, with $1 \leq t \leq T_A$ and $1 \leq n \leq N_A$, $C.data(t,n)$=$A.data(t,n)$-$B.data(t,n)$. If $N_B$ is equal to 1 and $N_A > 1$, the smaller `dseries` object (B) is “broadcast” across the larger `dseries` (A) so that they have compatible shapes, the `minus` operator will subtract the variable defined in B from each variable in A. If B is a double scalar, then the method `minus` will subtract B from all the observations/variables in A. If B is a row vector of length $N_A$, then the `minus` method will subtract B(1) from all the observations of variable $i$, for $i = 1, \ldots, N_A$. If B is a column vector of length $T_A$, then the `minus` method will subtract B from all the variables.

Example

```matlab
>> ts0 = dseries(rand(3,2));
>> ts1 = ts0('Variable_2');
>> ts0-ts1
```

(continues on next page)
ans is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
<th>Variable_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
<td>-0.48853</td>
</tr>
<tr>
<td>2Y</td>
<td>-0.50535</td>
</tr>
<tr>
<td>3Y</td>
<td>-0.32063</td>
</tr>
</tbody>
</table>

>> ts1

ts1 is a dseries object:

<table>
<thead>
<tr>
<th>Variable_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
</tr>
<tr>
<td>2Y</td>
</tr>
<tr>
<td>3Y</td>
</tr>
</tbody>
</table>

>> ts1-ts1.data(1)

ans is a dseries object:

<table>
<thead>
<tr>
<th>Variable_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
</tr>
<tr>
<td>2Y</td>
</tr>
<tr>
<td>3Y</td>
</tr>
</tbody>
</table>

>> ts1.data(1)-ts1

ans is a dseries object:

<table>
<thead>
<tr>
<th>Variable_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
</tr>
<tr>
<td>2Y</td>
</tr>
<tr>
<td>3Y</td>
</tr>
</tbody>
</table>

Method: \( C = \text{mpower}(A, B) \)

Overloads the MATLAB/Octave \text{mpower}(\)^ operator for dseries objects and computes element-by-element power. \( A \) is a dseries object with \( N \) variables and \( T \) observations. If \( B \) is a real scalar, then \text{mpower}(A, B) returns a dseries object \( C \) with \( C.data(t,n)=A.data(t,n)^C \). If \( B \) is a dseries object with \( N \) variables and \( T \) observations then \text{mpower}(A,B) returns a dseries object \( C \) with \( C.data(t,n)=A.data(t,n)^C.data(t,n) \).

Example

```matlab
>> ts0 = dseries(transpose(1:3));
>> ts1 = ts0^2

ts1 is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
</tr>
<tr>
<td>2Y</td>
</tr>
<tr>
<td>3Y</td>
</tr>
</tbody>
</table>

>> ts2 = ts0^ts0

ts2 is a dseries object:
```

(continues on next page)
<table>
<thead>
<tr>
<th>Variable_1</th>
<th>1Y</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2Y</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>3Y</td>
<td>27</td>
</tr>
</tbody>
</table>

Method: \texttt{C = mrdivide(A, B)}

Overloads the MATLAB/Octave \texttt{mrdivide (\textcolor{red}{/})} operator for \texttt{dseries} objects, element by element division (like the \texttt{./} MATLAB/Octave operator). If both \texttt{A} and \texttt{B} are \texttt{dseries} objects, they do not need to be defined over the same time ranges. If \texttt{A} and \texttt{B} are \texttt{dseries} objects with \( T_A \) and \( T_B \) observations and \( N_A \) and \( N_B \) variables, then \( N_A \) must be equal to \( N_B \) or 1 and \( N_B \) must be equal to \( N_A \) or 1. If \( T_A = T_B, isequal(A.init,B.init) \) returns 1 and \( N_A = N_B \), then the \texttt{mrdivide} operator will compute for each couple \((t,n)\), with \( 1 \leq t \leq T_A \) and \( 1 \leq n \leq N_A \), \( C.data(t,n) = A.data(t,n)/B.data(t,n) \). If \( N_B \) is equal to 1 and \( N_A > 1 \), the smaller \texttt{dseries} object \( B \) is “broadcast” across the larger \texttt{dseries} \( A \) so that they have compatible shapes. In this case the \texttt{mrdivide} operator will divide each variable defined in \( A \) by the variable in \( B \), observation per observation. If \( B \) is a double scalar, then the method \texttt{mrdivide} will divide all the observations/variables in \( A \) by \( B \). If \( B \) is a row vector of length \( N_A \), then \texttt{mrdivide} will divide all the observations of variable \( i \) by \( B(i) \), for \( i = 1, \ldots, N_A \). If \( B \) is a column vector of length \( T_A \), then \texttt{mrdivide} will perform a division of all the variables by \( B \), element by element.

Example

\begin{verbatim}
>> ts0 = dseries(rand(3,2))

\texttt{ts0 is a dseries object:}

<table>
<thead>
<tr>
<th>Variable_1</th>
<th>Variable_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
<td>0.72918</td>
</tr>
<tr>
<td>2Y</td>
<td>0.93756</td>
</tr>
<tr>
<td>3Y</td>
<td>0.51725</td>
</tr>
</tbody>
</table>

>> ts1 = ts0{'Variable_2'};

>> ts0/ts1

\texttt{ans is a dseries object:}

<table>
<thead>
<tr>
<th>Variable_1</th>
<th>Variable_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
<td>0.80745</td>
</tr>
<tr>
<td>2Y</td>
<td>4.2969</td>
</tr>
<tr>
<td>3Y</td>
<td>0.59235</td>
</tr>
</tbody>
</table>
\end{verbatim}

Method: \texttt{C = mtimes(A, B)}

Overloads the MATLAB/Octave \texttt{mtimes (*)} operator for \texttt{dseries} objects and the Hadamard product (the \texttt{.*} MATLAB/Octave operator). If both \texttt{A} and \texttt{B} are \texttt{dseries} objects, they do not need to be defined over the same time ranges. If \texttt{A} and \texttt{B} are \texttt{dseries} objects with \( T_A \) and \( T_B \) observations and \( N_A \) and \( N_B \) variables, then \( N_A \) must be equal to \( N_B \) or 1 and \( N_B \) must be equal to \( N_A \) or 1. If \( T_A = T_B, isequal(A.init,B.init) \) returns 1 and \( N_A = N_B \), then the \texttt{mtimes} operator will compute for each couple \((t,n)\), with \( 1 \leq t \leq T_A \) and \( 1 \leq n \leq N_A \), \( C.data(t,n) = A.data(t,n) * B.data(t,n) \). If \( N_B \) is equal to 1 and \( N_A > 1 \), the smaller \texttt{dseries} object \( B \) is “broadcast” across the larger \texttt{dseries} \( A \) so that they have compatible shapes, \texttt{mtimes} operator will multiply each variable defined in \( A \) by the variable in \( B \), observation per observation. If \( B \) is a double scalar, then the method \texttt{mtimes} will multiply all the observations/variables in \( A \) by \( B \). If \( B \) is a row vector of length \( N_A \), then the \texttt{mtimes} method will multiply all the observations of variable \( i \) by \( B(i) \), for \( i = 1, \ldots, N_A \). If \( B \) is a column vector of length \( T_A \), then the \texttt{mtimes} method will perform a multiplication of all the variables by \( B \), element by element.
Method: \[ B = \text{nanmean}(A[,\ \text{geometric}]) \]
Overloads the MATLAB/Octave \texttt{nanmean} function for \texttt{dseries} objects. Returns the mean of each variable in \texttt{dseries} object \( A \) ignoring the NaN values. If the second argument is \texttt{true} the geometric mean is computed, otherwise (default) the arithmetic mean is reported.

Method: \[ B = \text{nanstd}(A[,\ \text{geometric}]) \]
Overloads the MATLAB/Octave \texttt{nanstd} function for \texttt{dseries} objects. Returns the standard deviation of each variable in \texttt{dseries} object \( A \) ignoring the NaN values. If the second argument is \texttt{true} the geometric std is computed, default value of the second argument is \texttt{false}.

Method: \[ C = \text{ne}(A, B) \]
Overloads the MATLAB/Octave \texttt{ne} (not equal, \texttt{~=}) operator. \texttt{dseries} objects \( A \) and \( B \) must have the same number of observations (say, \( T \)) and variables (\( N \)). The returned argument is a \( T \) by \( N \) matrix of zeros and ones. Element \((i, j)\) of \( C \) is equal to 1 if and only if observation \( i \) for variable \( j \) in \( A \) and \( B \) are not equal.

Example

\begin{verbatim}
>> ts0 = dseries(2*ones(3,1));
>> ts1 = dseries([2; 0; 2]);
>> ts0~=ts1
ans =
    3x1 logical array
   0
   1
   0
\end{verbatim}

Method: \[ B = \text{nobs}(A) \]
Returns the number of observations in \texttt{dseries} object \( A \).

Example

\begin{verbatim}
>> ts0 = dseries(randn(10));
>> ts0.nobs
ans =
    10
\end{verbatim}

Method: \[ B = \text{onesidedhpcycle}(A[,\ \text{lambda},[,\ \text{init}]]]) \]
Method: \[ \text{onesidedhpcycle}_*)(A[,\ \text{lambda},[,\ \text{init}]]]) \]
Extracts the cycle component from a \texttt{dseries} \( A \) object using a one sided HP filter (with a Kalman filter) and returns a \texttt{dseries} object, \( B \). The default value for \texttt{lambda}, the smoothing parameter, is 1600. By default, if \texttt{init} is not provided, the initial value is based on the first two observations.

Method: \[ B = \text{onesidedhptrend}(A[,\ \text{lambda},[,\ \text{init}]])) \]
Method: \[ \text{onesidedhptrend}_*)(A[,\ \text{lambda},[,\ \text{init}]])) \]
Extracts the trend component from a \texttt{dseries} \( A \) object using a one sided HP filter (with a Kalman filter) and returns a \texttt{dseries} object, \( B \). The default value for \texttt{lambda}, the smoothing parameter, is 1600. By default, if \texttt{init} is not provided, the initial value is based on the first two observations.

Method: \( h = \text{plot}(A) \)
Method: \( h = \text{plot}(A, B) \)
Method: \( h = \text{plot}(A[,\ ...]) \)
Method: \( h = \text{plot}(A, B[, ...]) \)

Overloads MATLAB/Octave’s `plot` function for `dseries` objects. Returns a MATLAB/Octave plot handle, that can be used to modify the properties of the plotted time series. If only one `dseries` object, \( A \), is passed as argument, then the plot function will put the associated dates on the x-absissa. If this `dseries` object contains only one variable, additional arguments can be passed to modify the properties of the plot (as one would do with the MATLAB/Octave’s version of the plot function). If `dseries` object \( A \) contains more than one variable, it is not possible to pass these additional arguments and the properties of the plotted time series must be modified using the returned plot handle and the MATLAB/Octave `set` function (see example below). If two `dseries` objects, \( A \) and \( B \), are passed as input arguments, the plot function will plot the variables in \( A \) against the variables in \( B \) (the number of variables in each object must be the same otherwise an error is issued). Again, if each object contains only one variable, additional arguments can be passed to modify the properties of the plotted time series, otherwise the MATLAB/Octave `set` command has to be used.

Example

Define a `dseries` object with two variables (named by default `Variable_1` and `Variable_2`):

```matlab
>> ts = dseries(randn(100,2), '1950Q1');
```

The following command will plot the first variable in `ts`:

```matlab
>> plot(ts{'Variable_1'}, '-k', 'linewidth', 2);
```

The next command will draw all the variables in `ts` on the same figure:

```matlab
>> h = plot(ts);
```

If one wants to modify the properties of the plotted time series (line style, colours, ...), the `set` function can be used (see MATLAB’s documentation):

```matlab
>> set(h(1), '-k', 'linewidth', 2);
>> set(h(2), '--r');
```

The following command will plot `Variable_1` against \( \exp(\text{Variable}_1) \):

```matlab
>> plot(ts{'Variable_1'}, ts{'Variable_1'}.exp(), 'ok');
```

Again, the properties can also be modified using the returned plot handle and the `set` function:

```matlab
>> h = plot(ts, ts.exp());
>> set(h(1), 'ok');
>> set(h(2), '+r');
```

Method: \( C = \text{plus}(A, B) \)

Overloads the MATLAB/Octave `plus` (+) operator for `dseries` objects, element by element addition. If both \( A \) and \( B \) are `dseries` objects, they do not need to be defined over the same time ranges. If \( A \) and \( B \) are `dseries` objects with \( T_A \) and \( T_B \) observations and \( N_A \) and \( N_B \) variables, then \( N_A \) must be equal to \( N_B \) or 1 and \( N_B \) must be equal to \( N_A \) or 1. If \( T_A = T_B \), `isequal(A.init,B.init)` returns 1 and \( N_A = N_B \), then the `plus` operator will compute for each couple \((t, n)\), with \( 1 \leq t \leq T_A \) and \( 1 \leq n \leq N_A \), \( C.data(t,n)=A.data(t,n)+B.data(t,n) \). If \( N_B \) is equal to 1 and \( N_A > 1 \), the smaller `dseries` object \( B \) is “broadcast” across the larger `dseries` \( A \) so that they have compatible shapes, the `plus` operator will add the variable defined in \( B \) to each variable in \( A \). If \( B \) is a double scalar, then the method `plus` will add \( B \) to all the observations/variables in \( A \). If \( B \) is a row vector of length \( N_A \), then the `plus` method will add \( B(i) \) to all the observations of variable \( i \), for \( i = 1, ..., N_A \). If \( B \) is a column vector of length \( T_A \), then the `plus` method will add \( B \) to all the variables.

Method: \( C = \text{pop}(A[, B]) \)
Method: pop(A[, B])
Removes variable B from dseries object A. By default, if the second argument is not provided, the last variable is removed.

Example

```matlab
>> ts0 = dseries(ones(3,3));
>> ts1 = ts0.pop('Variable_2');

is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
<th>Variable_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
<td>1</td>
</tr>
<tr>
<td>2Y</td>
<td>1</td>
</tr>
<tr>
<td>3Y</td>
<td>1</td>
</tr>
</tbody>
</table>
```

Method: A = projection(A, info, periods)
Projects variables in dseries object A. info is a $n \times 3$ cell array. Each row provides information necessary to project a variable. The first column contains the name of variable (row char array), the second column contains the name of the method used to project the associated variable (row char array), possible values are 'Trend', 'Constant', and 'AR'. Last column provides quantitative information about the projection. If the second column value is 'Trend', the third column value is the growth factor of the (exponential) trend. If the second column value is 'Constant', the third column value is the level of the variable. If the second column value is 'AR', the third column value is the autoregressive parameter. The variables can be projected with an AR(p) model, if the third column contains a 1xp vector of doubles. The stationarity of the AR(p) model is not tested. The case of the constant projection, using the last value of the variable, is covered with 'Trend' and a growth factor equal to 1, or 'AR' with an autoregressive parameter equal to one (random walk). This projection routine only deals with exponential trends.

Example

```matlab
>> data = ones(10,4);
>> ts = dseries(data, '1990Q1', {'A1', 'A2', 'A3', 'A4'});
>> info = {'A1', 'Trend', 1.2; 'A2', 'Constant', 0.0; 'A3', 'AR', .5; 'A4', 'AR', [.4, -.2]);
>> ts.projection(info, 10);
```

Method: B = qdiff(A)
Method: B = qgrowth(A)
Method: qdiff_(A)
Method: qgrowth_(A)
Computes quarterly differences or growth rates.

Example

```matlab
>> ts0 = dseries(transpose(1:4), '1950Q1');
>> ts1 = ts0.qdiff()
```

```matlab
ts1 is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950Q1</td>
</tr>
<tr>
<td>1950Q2</td>
</tr>
<tr>
<td>1950Q3</td>
</tr>
<tr>
<td>1950Q4</td>
</tr>
</tbody>
</table>
```


```
>> ts1 = ts0.qdiff()

ts1 is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950M1</td>
</tr>
<tr>
<td>1950M2</td>
</tr>
<tr>
<td>1950M3</td>
</tr>
<tr>
<td>1950M4</td>
</tr>
<tr>
<td>1950M5</td>
</tr>
<tr>
<td>1950M6</td>
</tr>
</tbody>
</table>
```

**Method:** `C = remove(A, B)`  
**Method:** `remove_(A, B)`

If B is a row char array, the name of a variable, these methods are aliases for pop and pop_ methods with two arguments. They remove variable B from dseries object A. To remove more than one variable, one can pass a cell of row char arrays for B.

**Example**
```
>> ts0 = dseries(ones(3,3));
>> ts1 = ts0.remove('Variable_2');

ts1 is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
<th>Variable_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
<td>1</td>
</tr>
<tr>
<td>2Y</td>
<td>1</td>
</tr>
<tr>
<td>3Y</td>
<td>1</td>
</tr>
</tbody>
</table>
```

A shorter syntax is available: `remove(ts,'Variable_2')` is equivalent to `ts('Variable_2') = []` ([ ] can be replaced by any empty object). This alternative syntax is useful if more than one variable has to be removed. For instance:
```
ts('Variable_@2,3,4@') = [];
```

will remove `Variable_2`, `Variable_3` and `Variable_4` from dseries object ts (if these variables exist). Regular expressions cannot be used but implicit loops can.

**Method:** `B = rename(A, oldname, newname)`  
**Method:** `rename_(A, oldname, newname)`

Rename variable oldname to newname in dseries object A. Returns a dseries object. If more than one variable needs to be renamed, it is possible to pass cells of char arrays as second and third arguments.

**Example**
```
>> ts0 = dseries(ones(2,2));
>> ts1 = ts0.rename('Variable_1','Stinkly')

ts1 is a dseries object:

<table>
<thead>
<tr>
<th>Stinkly</th>
<th>Variable_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
<td>1</td>
</tr>
<tr>
<td>2Y</td>
<td>1</td>
</tr>
</tbody>
</table>
```

**Method:** `C = rename(A, newname)`

```
**Method:** rename\( (A, \text{newname}) \)
Replace the names in \( A \) with those passed in the cell string array \text{newname}. \text{newname} must have the same number of elements as \text{dseries} object \( A \) has variables. Returns a \text{dseries} object.

*Example*

\[
\begin{align*}
\text{ts0} & = \text{dseries(ones(2, 3))};
\text{ts1} & = \text{ts0.rename(['TinkyWinky', 'Dipsy', 'LaaLaa'])}
\end{align*}
\]

\( \text{ts1 is a dseries object:} \)

<table>
<thead>
<tr>
<th>TinkyWinky</th>
<th>Dipsy</th>
<th>LaaLaa</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Y</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2Y</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

**Method:** \( A = \text{resetops}(A, \text{ops}) \)
Redefine \text{ops} member.

**Method:** \( A = \text{resetags}(A, \text{ops}) \)
Redefine \text{tags} member.

**Method:** \( B = \text{round}(A[, \text{n}]) \)
**Method:** \( \text{round}_1(A[, \text{n}]) \)
Rounds to the nearest decimal or integer. \( \text{n} \) is the precision parameter (number of decimals), default value is 0 meaning that that by default the method rounds to the nearest integer.

*Example*

\[
\begin{align*}
\text{ts} & = \text{dseries(pi)}
\text{ts.round()};
\text{ts}
\end{align*}
\]

**Method:** \( \text{save}(A, \text{basename}[,, \text{format}]) \)
Overloads the MATLAB/Octave \text{save} function and saves \text{dseries} object \( A \) to disk. Possible formats are \text{mat} (this is the default), \text{m} (MATLAB/Octave script), and \text{csv} (MATLAB binary data file). The name of the file without extension is specified by \text{basename}.

*Example*

\[
\begin{align*}
\text{ts0} & = \text{dseries(ones(2, 2))};
\text{ts0.save('ts0', 'csv')};
\end{align*}
\]

The last command will create a file ts0.csv with the following content:

,Variable_1,Variable_2
1Y, 1, 1
2Y, 1, 1

To create a MATLAB/Octave script, the following command:
```matlab
>> ts0.save('ts0','m');
```

will produce a file `ts0.m` with the following content:

```matlab
% File created on 14-Nov-2013 12:08:52.
FREQ__ = 1;
INIT__ = ' 1Y';

NAMES__ = {'Variable_1'; 'Variable_2'};
TEX__ = {'Variable_1'; 'Variable_2'};
OPS__ = {};
TAGS__ = struct();

Variable_1 = [ 1 1 ];
Variable_2 = [ 1 1 ];
```

The generated (csv, m, or mat) files can be loaded when instantiating a `dseries` object as explained above.

**Method:** 

```matlab
B = set_names(A, s1, s2, ...)
```

Renames variables in `dseries` object `A` and returns a `dseries` object `B` with new names `s1, s2, ...`

The number of input arguments after the first one (`dseries` object `A`) must be equal to `A.vobs` (the number of variables in `A`). `s1` will be the name of the first variable in `B`, `s2` the name of the second variable in `B`, and so on.

**Example**

```matlab
>> ts0 = dseries(ones(1,3));
>> ts1 = ts0.set_names('Barbibul',[],'Barbouille')
```

`ts1` is a `dseries` object:

<table>
<thead>
<tr>
<th>Barbibul</th>
<th>Variable_2</th>
<th>Barbouille</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

**Method:** 

```matlab
[T, N ] = size(A[, dim])
```

Overloads the MATLAB/Octave's `size` function. Returns the number of observations in `dseries` object `A` (i.e. `A.nobs`) and the number of variables (i.e. `A.vobs`). If a second input argument is passed, the `size` function returns the number of observations if `dim=1` or the number of variables if `dim=2` (for all other values of `dim` an error is issued).

**Example**

```matlab
>> ts0 = dseries(ones(1,3));
>> ts0.size()
```

```matlab
ans =
    1  3
```

**Method:** 

```matlab
B = std(A[, geometric])
```

Overloads the MATLAB/Octave `std` function for `dseries` objects. Returns the standard deviation of
each variable in dseries object A. If the second argument is true the geometric standard deviation is computed (default value of the second argument is false).

**Method: B = subsample(A, d1, d2)**

Returns a subsample, for periods between dates d1 and d2. The same can be achieved by indexing a dseries object with a dates object, but the subsample method is easier to use programmatically.

**Example**

```matlab
>> o = dseries(transpose(1:5));
>> o.subsample(dates('2y'),dates('4y'))
```

```
ans is a dseries object:
    | Variable_1
  2Y | 2
  3Y | 3
  4Y | 4
```

**Method: A = tag(A, a[, b, c])**

Add a tag to a variable in dseries object A.

**Example**

```matlab
>> ts = dseries(randn(10, 3));
>> tag(ts, 'type');                 % Define a tag name.
>> tag(ts, 'type', 'Variable_1', 'Stock');
>> tag(ts, 'type', 'Variable_2', 'Flow');
>> tag(ts, 'type', 'Variable_3', 'Stock');
```

**Method: B = tex_rename(A, name, newtexname)**

Redefines the tex name of variable name to newtexname in dseries object A. Returns a dseries object.

With only two arguments A and newtexname, it redefines the tex names of the A to those contained in newtexname. Here, newtexname is a cell string array with the same number of entries as variables in A.

**Method: B = uminus(A)**

Overloads uminus (-, unary minus) for dseries object.

**Example**

```matlab
>> ts0 = dseries(1)
ts0 is a dseries object:
    | Variable_1
  1Y | 1
>> ts1 = -ts0
ts1 is a dseries object:
    | Variable_1
  1Y | -1
```
Method: \[ D = \text{vertcat}(A, B[,\,\ldots]) \]

Overloads the \text{vertcat} MATLAB/Octave method for \text{dseries} objects. This method is used to append more observations to a \text{dseries} object. Returns a \text{dseries} object \( D \) containing the variables in \text{dseries} objects passed as inputs. All the input arguments must be \text{dseries} objects with the same variables defined on different time ranges.

Example

\begin{verbatim}
>> ts0 = dseries(rand(2,2),'1950Q1',{nifnif;'noufnouf'});
>> ts1 = dseries(rand(2,2),'1950Q3',{nifnif;'noufnouf'});
>> ts2 = [ts0; ts1]

\text{ts2} is a \text{dseries} object:
\hspace{1cm}
\begin{center}
| nifnif | noufnouf |
| 1950Q1 | 0.82558 | 0.31852 |
| 1950Q2 | 0.78996 | 0.53406 |
| 1950Q3 | 0.089951 | 0.13629 |
| 1950Q4 | 0.11171 | 0.67865 |
\end{center}
\end{verbatim}

Method: \[ B = \text{vobs}(A) \]

Returns the number of variables in \text{dseries} object \( A \).

Example

\begin{verbatim}
>> ts0 = dseries(randn(10,2));
>> ts0.vobs

ans =
    2
\end{verbatim}

Method: \[ B = \text{ydiff}(A) \]

Computes yearly differences or growth rates.

6.3 X-13 ARIMA-SEATS interface

Dynare class: \text{x13}

The \text{x13} class provides a method for each X-13 command as documented in the X-13 ARIMA-SEATS reference manual (\text{x11}, \text{automdl}, \text{estimate}, \ldots). The respective options (see Chapter 7 of U.S. Census Bureau (2020)) can then be passed by key/value pairs. The \text{x13} class has 22 members:

Members

\begin{itemize}
\item \text{y} – \text{dseries} object with a single variable.
\item \text{x} – \text{dseries} object with an arbitrary number of variables (to be used in the \text{REGRESSION} block).
\item \text{arima} – structure containing the options of the ARIMA model command.
\item \text{automdl} – structure containing the options of the ARIMA model selection command.
\item \text{regression} – structure containing the options of the Regression command.
\item \text{estimate} – structure containing the options of the estimation command.
\end{itemize}
• **transform** – structure containing the options of the transform command.
• **outlier** – structure containing the options of the outlier command.
• **forecast** – structure containing the options of the forecast command.
• **check** – structure containing the options of the check command.
• **x11** – structure containing the options of the X11 command.
• **force** – structure containing the options of the force command.
• **history** – structure containing the options of the history command.
• **metadata** – structure containing the options of the metadata command.
• **identify** – structure containing the options of the identify command.
• **pickmdl** – structure containing the options of the pickmdl command.
• **seats** – structure containing the options of the seats command.
• **slidingspans** – structure containing the options of the slidingspans command.
• **spectrum** – structure containing the options of the spectrum command.
• **x11regression** – structure containing the options of the x11Regression command.
• **results** – structure containing the results returned by x13.
• **commands** – cell array containing the list of commands.

All these members are private. The following constructors are available:

**Constructor:** `x13(y)`

Instantiates an `x13` object with `dseries` object `y`. The `dseries` object passed as an argument must contain only one variable, the one we need to pass to X-13.

**Constructor:** `x13(y, x)`

Instantiates an `x13` object with `dseries` objects `y` and `x`. The first `dseries` object passed as an argument must contain only one variable, the second `dseries` object contains the exogenous variables used by some of the X-13 commands. Both objects must be defined on the same time span.

The following methods allow to set sequence of X-13 commands, write an `.spc` file, and run the X-13 binary:

**Method:** `A = arima(A, key, value[, , key, value[, [...]]])`

Interface to the `arima` command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

**Method:** `A = automdl(A, key, value[, , key, value[, [...]]])`

Interface to the `automdl` command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

**Method:** `A = regression(A, key, value[, , key, value[, [...]]])`

Interface to the `regression` command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

**Method:** `A = estimate(A, key, value[, , key, value[, [...]]])`

Interface to the `estimate` command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

**Method:** `A = transform(A, key, value[, , key, value[, [...]]])`

Interface to the `transform` command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs. For example, the key/value pair `function,log` instructs the use of a multiplicative instead of an additive seasonal pattern, while `function,auto` triggers an automatic selection between the two based on their fit.
Method: $A = \text{outlier}(A, \text{key}, \text{value}, [\ldots])$

Interface to the outlier command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{forecast}(A, \text{key}, \text{value}, [\ldots])$

Interface to the forecast command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{check}(A, \text{key}, \text{value}, [\ldots])$

Interface to the check command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{x11}(A, \text{key}, \text{value}, [\ldots])$

Interface to the x11 command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{force}(A, \text{key}, \text{value}, [\ldots])$

Interface to the force command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{history}(A, \text{key}, \text{value}, [\ldots])$

Interface to the history command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{metadata}(A, \text{key}, \text{value}, [\ldots])$

Interface to the metadata command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{identify}(A, \text{key}, \text{value}, [\ldots])$

Interface to the identify command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{pickmdl}(A, \text{key}, \text{value}, [\ldots])$

Interface to the pickmdl command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{seats}(A, \text{key}, \text{value}, [\ldots])$

Interface to the seats command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{slidingspans}(A, \text{key}, \text{value}, [\ldots])$

Interface to the slidingspans command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{spectrum}(A, \text{key}, \text{value}, [\ldots])$

Interface to the spectrum command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{x11regression}(A, \text{key}, \text{value}, [\ldots])$

Interface to the x11regression command, see the X-13 ARIMA-SEATS reference manual. All the options must be passed by key/value pairs.

Method: $A = \text{print}(A[, \text{basefilename}])$

Prints an .spc file with all the X-13 commands. The optional second argument is a row char array specifying the name (without extension) of the file.

Method: $A = \text{run}(A)$

Calls the X-13 binary and run the previously defined commands. All the results are stored in the structure $A.result$. When it makes sense these results are saved in dseries objects (e.g. for forecasts or filtered variables).

6.3. X-13 ARIMA-SEATS interface
**Method:** clean(A)

Removes the temporary files created by an x13 run that store the intermediate results. This method allows keeping the main folder clean but will also delete potentially important debugging information.

**Example**

```matlab
>> ts = dseries(rand(100,1), '1999M1');
>> o = x13(ts);

>> o.x11('save','(d11)');
>> o.automdl('savelog','amd','mixed','no');
>> o.outlier('types','all','save','(fts)');
>> o.check('maxlag',24,'save','(acf pcf)');
>> o.estimate('save','(mdl est)');
>> o.forecast('maxlead',18,'probability',0.95,'save','(fct fvr)');

>> o.run();
```

The above example shows a run of X13 with various commands and options specified.

**Example**

```plaintext
y = [112 115 145 196 204 242 284 315 340 360 417 ..
     118 126 150 180 196 188 233 277 301 318 342 391 ..
     132 141 178 236 235 267 317 356 362 406 419 ..
     129 135 163 235 227 269 313 348 348 396 461 ..
     121 125 172 183 229 234 270 318 355 363 420 472 ..
     135 149 178 218 243 264 315 374 422 435 472 535 ..
     148 170 199 230 264 302 364 413 465 491 548 622 ..
     148 170 199 242 272 293 347 405 467 505 559 606 ..
     136 158 184 209 237 259 312 355 404 404 463 508 ..
     119 133 162 191 211 229 274 306 347 359 407 461 ..
     164 114 146 172 180 203 237 271 305 310 362 390 ..
     118 140 166 194 201 229 278 306 336 337 405 432 ]
```

```matlab
ts = dseries(y,'1949M1');
o = x13(ts);
o.transform('function','auto','savelog','atr');
o.automdl('savelog','all');
o.x11('save','(d11 d10)');
o.run();
o.clean();
y_SA=o.results.d11;
y_seasonal_pattern=o.results.d10;
```

(continues on next page)
The above example shows how to remove a seasonal pattern from a time series. `o.transform('function','auto','savelog','atr')` instructs the subsequent `o.automdl()` command to check whether an additional or a multiplicative pattern fits the data better and to save the result. The result is saved in `o.results.autotransform`, which in the present example indicates that a log transformation, i.e. a multiplicative model was preferred. The `o.automdl('savelog','all')` automatically selects a fitting ARIMA model and saves all relevant output to the `.log`-file. The `o.x11('save', '(d11, d10)')` instructs `x11` to save both the final seasonally adjusted series `d11` and the final seasonal factor `d10` into `dseries` with the respective names in the output structure `o.results`. `o.clean()` removes the temporary files created by `o.run()`. Among these are the `.log`-file storing summary information, the `.err`-file storing information on problems encountered, the `.out`-file storing the raw output, and the `.spc`-file storing the specification for the `x11` run. There may be further files depending on the output requested. The last part of the example reads out the results and plots a comparison of the logged raw data and its log-additive decomposition into a seasonal pattern and the seasonally adjusted series.

### 6.4 Miscellaneous

#### 6.4.1 Time aggregation

A set of functions allows to convert time series to lower frequencies:

- `dseries2M` converts daily time series object to monthly time series object.
- `dseries2Q` converts daily or monthly time series object to quarterly time series object.
- `dseries2S` converts daily, monthly, or quarterly time series object to bi-annual time series object.
- `dseries2Y` converts daily, monthly, quarterly, or bi-annual time series object to annual time series object.

All these routines have two mandatory input arguments: the first one is a `dseries` object, the second one the name (row char array) of the aggregation method. Possible values for the second argument are:

- arithmetic-average (for growth rates),
- geometric-average (for growth factors),
- sum (for flow variables), and
- end-of-period (for stock variables).

**Example**

```matlab
>> ts = dseries(rand(12,1), '2000M1')
```

*ts* is a `dseries` object:

```
<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000M1</td>
</tr>
<tr>
<td>2000M2</td>
</tr>
<tr>
<td>2000M3</td>
</tr>
<tr>
<td>2000M4</td>
</tr>
</tbody>
</table>
```
2000M5 |   0.57674
2000M6 |   0.019402
2000M7 |   0.57758
2000M8 |   0.9322
2000M9 |   0.10687
2000M10 |   0.73215
2000M11 |   0.97052
2000M12 |   0.60889

>> ds = dseries2Y(ts, 'end-of-period')

ds is a dseries object:

<table>
<thead>
<tr>
<th>Variable_1</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000Y</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>0.60889</td>
</tr>
</tbody>
</table>

### 6.4.2 Create time series with a univariate model

It is possible to expand a dseries object recursively with the `from` command. For instance to create a dseries object containing the simulation of an ARMA(1,1) model:

```matlab
>> e = dseries(randn(100, 1), '2000Q1', 'e', '\varepsilon');
>> y = dseries(zeros(100, 1), '2000Q1', 'y');
>> from 2000Q2 to 2024Q4 do y(t) = .9*y(t-1) + e(t) - .4*e(t-1);
>> y
```

```
y is a dseries object:

<table>
<thead>
<tr>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000Q1</td>
</tr>
<tr>
<td>2000Q2</td>
</tr>
<tr>
<td>2000Q3</td>
</tr>
<tr>
<td>2000Q4</td>
</tr>
<tr>
<td>2001Q1</td>
</tr>
<tr>
<td>2001Q2</td>
</tr>
<tr>
<td>2001Q3</td>
</tr>
<tr>
<td>2001Q4</td>
</tr>
<tr>
<td>2002Q1</td>
</tr>
<tr>
<td>2002Q2</td>
</tr>
<tr>
<td>2002Q3</td>
</tr>
<tr>
<td>2002Q4</td>
</tr>
<tr>
<td>2003Q1</td>
</tr>
<tr>
<td>2003Q2</td>
</tr>
<tr>
<td>2003Q3</td>
</tr>
<tr>
<td>2003Q4</td>
</tr>
<tr>
<td>2004Q1</td>
</tr>
<tr>
<td>2004Q2</td>
</tr>
<tr>
<td>2004Q3</td>
</tr>
<tr>
<td>2004Q4</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
```

The expression following the `do` keyword can be any univariate equation, the only constraint is that the model cannot have leads. It can be a static equation, or a very nonlinear backward equation with an arbitrary number of lags. The `from` command must be followed by a range, which is separated from the (recursive) expression to be evaluated by the `do` command.
Dynare provides a simple interface for creating \LaTeX reports, comprised of \LaTeX tables and PGFPlots/TikZ graphs. You can use the report as created through Dynare or pick out the pieces (tables and graphs) you want for inclusion in your own paper. Though Dynare provides a subset of options available through PGFPlots/TikZ, you can easily modify the graphs created by Dynare using the options available in the PGFPlots/TikZ manual. You can either do this manually or by passing the options to \texttt{miscTikzAxisOptions} or \texttt{graphMiscTikzAddPlotOptions}.

Reports are created and modified by calling methods on class objects. The objects are hierarchical, with the following order (from highest to lowest): \texttt{Report}, \texttt{Page}, \texttt{Section}, \texttt{Graph/Table/Vspace}, \texttt{Series}. For simplicity of syntax, we abstract away from these classes, allowing you to operate directly on a \texttt{Report} object, while maintaining the names of these classes in the \texttt{Report} class methods you will use.

The report is created sequentially, command by command, hence the order of the commands matters. When an object of a certain hierarchy is inserted, all methods will function on that object until an object of equal or greater hierarchy is added. Hence, once you add a \texttt{Page} to the report, every time you add a \texttt{Section} object, it will be added to this \texttt{Page} until another \texttt{Page} is added to the report (via \texttt{addPage}). This will become more clear with the example at the end of the section.

Options to methods are passed differently than those to Dynare commands. They take the form of named options to MATLAB functions where the arguments come in pairs (e.g. \texttt{function_name('option_1_name', 'option_1_value', 'option_2_name', 'option_2_value', ...)}, where \texttt{option_X_name} is the name of the option while \texttt{option_X_value} is the value assigned to that option). The ordering of the option pairs matters only in the unusual case when an option is provided twice (probably erroneously). In this case, the last value passed is the one that is used.

Below, you will see a list of methods available for the \texttt{Report} class and a clarifying example.

\textbf{Constructor: } \texttt{report}

- Instantiates a \texttt{Report} object.

\textit{Options}

\texttt{compiler, FILENAME}

- The full path to the \LaTeX compiler on your system. If this option is not provided, Dynare will try to find the appropriate program to compile \LaTeX on your system. Default is system dependent:

  - Windows: the result of \texttt{findtexmf --file-type=exe pdflatex}.
  - macOS and Linux: the result of \texttt{which pdflatex}.

\texttt{directory, FILENAME}

- The path to the directory you want the report created in. Default: current directory.

\texttt{showDate, BOOLEAN}

- Display the date and time when the report was compiled. Default: \texttt{true}.

\texttt{fileName, FILENAME}

- The file name to use when saving this report. Default: \texttt{report.tex}.

\texttt{header, STRING}

- The valid \LaTeX code to be included in the report before \texttt{\begin{document}}. Default: \texttt{empty}.
maketoc, BOOLEAN
Whether or not to make the table of contents. One entry is made per page containing a title. Default: false.

margin, DOUBLE
The margin size. Default: 2.5.

marginUnit, `cm' | `in'
Units associated with the margin. Default: `cm'.

orientation, `landscape' | `portrait'
Paper orientation: Default: `portrait'.

paper, `a4' | `letter'
Paper size. Default: `a4'.

reportDirName, FILENAME
The name of the folder in which to store the component parts of the report (preamble, document, end). Default: tmpRepDir.

showDate, BOOLEAN
Display the date and time when the report was compiled. Default: true.

showOutput, BOOLEAN
Print report creation progress to screen. Shows you the page number as it is created and as it is written. This is useful to see where a potential error occurs in report creation. Default: true.

title, STRING

Method: addPage
Adds a Page to the Report.

Options

footnote, STRING
A footnote to be included at the bottom of this page. Default: none.

latex, STRING
The valid \LaTeX{} code to be used for this page. Allows the user to create a page to be included in the report by passing \LaTeX{} code directly. If this option is passed, the page itself will be saved in the pageDirName directory in the form page_X.tex where X refers to the page number. Default: empty.

orientation, `landscape' | `portrait'
See orientation.

pageDirName, FILENAME
The name of the folder in which to store this page. Directory given is relative to the directory option of the report class. Only used when the latex command is passed. Default: tmpRepDir.

paper, `a4' | `letter'
See paper.

title, STRING | CELL_ARRAY_STRINGS
With one entry (a STRING), the title of the page. With more than one entry (a CELL_ARRAY_STRINGS), the title and subtitle(s) of the page. Values passed must be valid \LaTeX{} code (e.g., \% must be \%). Default: none.

titleFormat, STRING | CELL_ARRAY_STRINGS
A string representing the valid \LaTeX{} markup to use on title. The number of cell array entries must be equal to that of the title option if you do not want to use the default value for the title (and subtitles). Default: \large\bfseries.
**titleTruncate**, INTEGER

Useful when automatically generating page titles that may become too long, **titleTruncate** can be used to truncate a title (and subsequent subtitles) when they pass the specified number of characters. Default: `.off`.

**Method: addSection**

Adds a Section to a Page.

**Options**

- **cols**, INTEGER
  The number of columns in the section. Default: 1.

- **height**, STRING
  A string to be used with the `\sectionheight` \LaTeX{} command. Default: `'!'`

**Method: addGraph**

Adds a Graph to a Section.

**Options**

- **data**, dseries
  The dseries that provides the data for the graph. Default: `none`.

- **axisShape**, `box' | `L`
  The shape the axis should have. `box' means that there is an axis line to the left, right, bottom, and top of the graphed line(s). `L' means that there is an axis to the left and bottom of the graphed line(s). Default: `box'.

- **graphDirName**, FILENAME
  The name of the folder in which to store this figure. Directory given is relative to the `directory` option of the report class. Default: `tmpRepDir`.

- **graphName**, STRING
  The name to use when saving this figure. Default: something of the form `graph_pg1_sec2_row1_col3.tex`.

- **height**, DOUBLE
  The height of the graph, in inches. Default: 4.5.

- **showGrid**, BOOLEAN
  Whether or not to display the major grid on the graph. Default: `true`.

- **showLegend**, BOOLEAN
  Whether or not to display the legend.

  Unless you use the `graphLegendName` option, the name displayed in the legend is the tex name associated with the dseries. You can modify this tex name by using `tex_rename`. Default: `false`.

- **legendAt**, NUMERICAL VECTOR
  The coordinates for the legend location. If this option is passed, it overrides the `legendLocation` option. Must be of size 2. Default: `empty`.

- **showLegendBox**, BOOLEAN
  Whether or not to display a box around the legend. Default: `false`.

- **legendLocation**, OPTION
  Where to place the legend in the graph. Possible values for OPTION are:

  - `south west' | `south east' | `north west' | `north east' | `outer north east`

  Default: `south east'.
**legendOrientation**: `vertical` | `horizontal`

Orientation of the legend. Default: `horizontal`.

**legendFontSize**: `OPTION`

The font size for legend entries. Possible values for `OPTION` are:

- `tiny`
- `scriptsize`
- `footnotesize`
- `small`
- `normalsize`
- `large`
- `Large`
- `LARGE`
- `huge`
- `Huge`

Default: tiny.

**miscTikzAxisOptions**: STRING

If you are comfortable with PGFPLOTS/TikZ, you can use this option to pass arguments directly to the PGFPLOTS/TikZ axis environment command. Specifically to be used for desired PGFPLOTS/TikZ options that have not been incorporated into Dynare Reporting. Default: empty.

**miscTikzPictureOptions**: STRING

If you are comfortable with PGFPLOTS/TikZ, you can use this option to pass arguments directly to the PGFPLOTS/TikZ `tikzpicture` environment command. (e.g., to scale the graph in the x and y dimensions, you can pass following to this option: `xscale=2.5,yscale=0.5`). Specifically to be used for desired PGFPLOTS/TikZ options that have not been incorporated into Dynare Reporting. Default: empty.

**seriesToUse**: CELL ARRAY STRINGS

The names of the series contained in the `dseries` provided to the `data` option. If empty, use all series provided to data option. Default: empty.

**shade**: dates

The date range showing the portion of the graph that should be shaded. Default: none.

**shadeColor**: STRING

The color to use in the shaded portion of the graph. All valid color strings defined for use by PGFPLOTS/TikZ are valid. A list of defined colors is:

- `red`, `green`, `blue`, `cyan`, `magenta`, `yellow`, `black`, `gray`, `white`, `darkgray`, `lightgray`, `brown`, `lime`, `olive`, `orange`, `pink`, `purple`, `teal`, `violet`.

Furthermore, You can use combinations of these colors. For example, if you wanted a color that is 20% green and 80% purple, you could pass the string `green!20!purple`. You can also use RGB colors, following the syntax: `rgb,255:red,231;green,84;blue,121` which corresponds to the RGB color `(231;84;121)`. More examples are available in the section 4.7.5 of the PGFPLOTS/TikZ manual, revision 1.10. Default: `green`.

**shadeOpacity**: DOUBLE

The opacity of the shaded area, must be in `[0,100]`. Default: 20.

**tickFontSize**: `OPTION`

The font size for x- and y-axis tick labels. Possible values for `OPTION` are:

- `tiny`
- `scriptsize`
- `footnotesize`
- `small`
- `normalsize`
- `large`
- `Large`
- `LARGE`
- `huge`
- `Huge`

Default: normalsize.

**title**: STRING | CELL ARRAY STRINGS

Same as `title`, just for graphs.

**titleFontSize**: `OPTION`

The font size for title. Possible values for `OPTION` are:
`tiny` | `scriptsize` | `footnotesize` | `small` | `normalsize` | `large` | `Large` | `LARGE` | `huge` | `Huge`

Default: normalsize.

**titleFormat, STRING**

The format to use for the graph title. Unlike `titleFormat`, due to a constraint of TikZ, this format applies to the title and subtitles. Default: TikZ default.

**width, DOUBLE**

The width of the graph, in inches. Default: 6.0.

**writeCSV, BOOLEAN**

Whether or not to write a CSV file with only the plotted data. The file will be saved in the directory specified by `graphDirName` with the same base name as specified by `graphName` with the ending `.csv`. Default: false.

**xlabel, STRING**

The x-axis label. Default: none.

**ylabel, STRING**

The y-axis label. Default: none.

**xAxisTight, BOOLEAN**

Use a tight x axis. If false, uses PGFPLOTS/TikZ `enlarge x limits` to choose appropriate axis size. Default: true.

**xrange, dates**

The boundary on the x-axis to display in the graph. Default: all.

**xTicks, NUMERICAL_VECTOR**

Used only in conjunction with `xTickLabels`, this option denotes the numerical position of the label along the x-axis. The positions begin at 1. Default: the indices associated with the first and last dates of the dseries and, if passed, the index associated with the first date of the `shade` option.

**xTickLabels, CELL_ARRAY_STRINGS | 'ALL'**

The labels to be mapped to the ticks provided by `xTicks`. Default: the first and last dates of the dseries and, if passed, the date first date of the `shade` option.

**xTickLabelAnchor, STRING**

Where to anchor the x tick label. Default: `east`.

**xTickLabelRotation, DOUBLE**

The amount to rotate the x tick labels by. Default: 0.

**yAxisTight, BOOLEAN**

Use a tight y axis. If false, uses PGFPLOTS/TikZ `enlarge y limits` to choose appropriate axis size. Default: false.

**yrange, NUMERICAL_VECTOR**

The boundary on the y-axis to display in the graph, represented as a `NUMERICAL_VECTOR` of size 2, with the first entry less than the second entry. Default: all.

**yTickLabelFixed, BOOLEAN**

Round the y tick labels to a fixed number of decimal places, given by `yTickLabelPrecision`. Default: true.

**yTickLabelPrecision, INTEGER**

The precision with which to report the `yTickLabel`. Default: 0.
yTickLabelScaled, BOOLEAN
Determines whether or not there is a common scaling factor for the y axis. Default: true.

yTickLabelZeroFill, BOOLEAN
Whether or not to fill missing precision spots with zeros. Default: true.

showZeroLine, BOOLEAN
Display a solid black line at $y = 0$. Default: false.

zeroLineColor, STRING
The color to use for the zero line. Only used if showZeroLine is true. See the explanation in shadeColor for how to use colors with reports. Default: 'black'.

Method: addTable
Adds a Table to a Section.

Options
data, dseries
See data.

highlightRows, CELL_ARRAY_STRINGS
A cell array containing the colors to use for row highlighting. See shadeColor for how to use colors with reports. Highlighting for a specific row can be overridden by using the tableRowColor option to addSeries. Default: empty.

showHlines, BOOLEAN
Whether or not to show horizontal lines separating the rows. Default: false.

precision, INTEGER
The number of decimal places to report in the table data (rounding done via the round half away from zero method). Default: 1.

range, dates
The date range of the data to be displayed. Default: all.

seriesToUse, CELL_ARRAY_STRINGS
See seriesToUse.

tableDirName, FILENAME
The name of the folder in which to store this table. Directory given is relative to the directory option of the report class. Default: tmpRepDir.

tableName, STRING
The name to use when saving this table. Default: something of the form table_pg1_sec2_row1_col3.tex.

title, STRING
Same as title, just for tables.

titleFormat, STRING
Same as titleFormat, just for tables. Default: \large.

vlineAfter, dates | CELL_ARRAY_DATES
Show a vertical line after the specified date (or dates if a cell array of dates is passed). Default: empty.

vlineAfterEndOfPeriod, BOOLEAN
Show a vertical line after the end of every period (i.e. after every year, after the fourth quarter, etc.). Default: false.

showVlines, BOOLEAN
Whether or not to show vertical lines separating the columns. Default: false.
writeCSV, BOOLEAN

Whether or not to write a CSV file containing the data displayed in the table. The file will be saved in
the directory specified by `tableDirName` with the same base name as specified by `tableName` with
the ending `.csv`. Default: false.

Method: addSeries

Adds a Series to a Graph or a Table.

Options specific to graphs begin with `graph` while options specific to tables begin with `table`.

Options

data, dseries

See `data`.

graphBar, BOOLEAN

Whether or not to display this series as a bar graph as oppsed to the default of displaying it as a line
graph. Default: false.

graphFanShadeColor, STRING

The shading color to use between a series and the previously-added series in a graph. Useful for making
fan charts. Default: empty.

graphFanShadeOpacity, INTEGER

The opacity of the color passed in `graphFanShadeColor`. Default: 50.

graphBarColor, STRING

The outline color of each bar in the bar graph. Only active if `graphBar` is passed. Default: `black`.

graphBarFillColor, STRING

The fill color of each bar in the bar graph. Only active if `graphBar` is passed. Default: `black`.

graphBarWidth, DOUBLE

The width of each bar in the bar graph. Only active if `graphBar` is passed. Default: 2.

graphHline, DOUBLE

Use this option to draw a horizontal line at the given value. Default: empty.

graphLegendName, STRING

The name to display in the legend for this series, passed as valid LaTeX (e.g., GDP_{US}, $\alpha$,
\color{red}GDP\color{black}). Will be displayed only if the data and `showLegend` options have
been passed. Default: the tex name of the series.

graphLineColor, STRING

Color to use for the series in a graph. See the explanation in `shadeColor` for how to use colors with
reports. Default: `black`.

graphLineStyle, OPTION

Line style for this series in a graph. Possible values for OPTION are:

<table>
<thead>
<tr>
<th>'none'</th>
<th>'solid'</th>
<th>'dotted'</th>
<th>'densely dotted'</th>
<th>'loosely dotted'</th>
<th>'dashed'</th>
</tr>
</thead>
<tbody>
<tr>
<td>'densely dashed'</td>
<td>'loosely dashed'</td>
<td>'dashdotted'</td>
<td>'densely dashdotted'</td>
<td>'loosely dashdotted'</td>
<td>'dashdotdotted'</td>
</tr>
</tbody>
</table>

Default: `solid`.

graphLineWidth DOUBLE

Line width for this series in a graph. Default: 0.5.
**graphMarker, OPTION**

The Marker to use on this series in a graph. Possible values for OPTION are:

```
x' | '+' | '-' | '|' | 'o' | 'asterisk' | 'star' | '10-pointed star' |
oplus' | 'oplus' | 'otimes' | 'otimes*' | 'square' | 'square*' |
'triangle' | 'triangle*' | 'diamond' | 'diamond*' | 'halfdiamond*' |
'halfsquare*' | 'halfsquare right*' | 'halfsquare left*' | 'Mercedes star' |
'Mercedes star flipped' | 'halfcircle' | 'halfcircle*' | 'pentagon' |
'pentagon star' |
```

Default: none.

**graphMarkerEdgeColor, STRING**

The edge color of the graph marker. See the explanation in shadeColor for how to use colors with reports. Default: graphLineColor.

**graphMarkerFaceColor, STRING**

The face color of the graph marker. See the explanation in shadeColor for how to use colors with reports. Default: graphLineColor.

**graphMarkerSize, DOUBLE**

The size of the graph marker. Default: 1.

**graphMiscTikzAddPlotOptions, STRING**

If you are comfortable with PGFPLOTS/TikZ, you can use this option to pass arguments directly to the PGFPLOTS/TikZ addPlots command. (e.g., Instead of passing the marker options above, you can pass a string such as the following to this option: `mark=halfcircle*,mark options={rotate=90, scale=3}`). Specifically to be used for desired PGFPLOTS/TikZ options that have not been incorporated into Dynare Reporting. Default: empty.

**graphShowInLegend, BOOLEAN**

Whether or not to show this series in the legend, given that the showLegend option was passed to addGraph. Default: true.

**graphVline, dates**

Use this option to draw a vertical line at a given date. Default: empty.

**tableDataRhs, dseries**

A series to be added to the right of the current series. Usefull for displaying aggregate data for a series. e.g. if the series is quarterly tableDataRhs could point to the yearly averages of the quarterly series. This would cause quarterly data to be displayed followed by annual data. Default: empty.

**tableRowColor, STRING**

The color that you want the row to be. Predefined values include LightCyan and Gray. Default: white.

**tableRowIndent, INTEGER**

The number of times to indent the name of the series in the table. Used to create subgroups of series. Default: 0.

**tableShowMarkers, BOOLEAN**

In a Table, if true, surround each cell with brackets and color it according to tableNegColor and tablePosColor. No effect for graphs. Default: false.

**tableAlignRight, BOOLEAN**

Whether or not to align the series name to the right of the cell. Default: false.

**tableMarkerLimit, DOUBLE**

For values less than $\text{tableMarkerLimit}$, mark the cell with the color denoted by tableNegColor. For those greater than tableMarkerLimit, mark the cell with the color denoted by tablePosColor. Default: $1e^{-4}$. 
tableNaNsymb, STRING
Replace NaN values with the text in this option. Default: NaN.

tableNegColor, LATEX_COLOR
The color to use when marking Table data that is less than zero. Default: ’red’

tablePrecision, INTEGER
The number of decimal places to report in the table data. Default: the value set by precision.

tablePosColor, LATEX_COLOR
The color to use when marking Table data that is greater than zero. Default: ‘blue’

tableSubSectionHeader, STRING
A header for a subsection of the table. No data will be associated with it. It is equivalent to adding an empty series with a name. Default: ‘’

terotol, DOUBLE
The zero tolerance. Anything smaller than zeroTol and larger than -zeroTol will be set to zero before being graphed or written to the table. Default: 1e-6.

Method: addParagraph
Adds a Paragraph to a Section.
The Section can only be comprised of Paragraphs and must only have 1 column.

Options

balancedCols, BOOLEAN
Determines whether the text is spread out evenly across the columns when the Paragraph has more than one column. Default: true.

cols, INTEGER
The number of columns for the Paragraph. Default: 1.

heading, STRING
The heading for the Paragraph (like a section heading). The string must be valid \LaTeX code. Default: empty.

indent, BOOLEAN
Whether or not to indent the paragraph. Default: true.

text, STRING
The paragraph itself. The string must be valid \LaTeX code. Default: empty.

Method: addVspace
Adds a Vspace (vertical space) to a Section.

Options

hline, INTEGER
The number of horizontal lines to be inserted. Default: 0.

number, INTEGER
The number of new lines to be inserted. Default: 1.

Method: write
Writes the \LaTeX representation of this Report, saving it to the file specified by filename.

Method: compile
Compiles the report written by write into a pdf file. If the report has not already been written (determined by the existence of the file specified by filename, write is called.

Options
compiler, FILENAME
 Like compiler, except will not overwrite the value of compiler contained in the report object. Hence, passing the value here is useful for using different \LaTeX{} compilers or just for passing the value at the last minute.

showOutput, BOOLEAN
 Print the compiler output to the screen. Useful for debugging your code as the \LaTeX{} compiler hangs if there is a problem. Default: the value of showOutput.

showReport, BOOLEAN
 Open the compiled report (works on Windows and macOS on MATLAB). Default: true.

Example

The following code creates a one page report. The first part of the page contains two graphs displayed across two columns and one row. The bottom of the page displays a centered table:

```latex
\begin{verbatim}
%% Create dseries
dsq = dseries('quarterly.csv');
dsa = dseries('annual.csv');
dsca = dseries('annual_control.csv');

%% Report
rep = report();

%% Page 1
rep.addPage('title', {'My Page Title', 'My Page Subtitle'}, ...
'pageTitle', {'\large\bfseries', '\large'});

% Section 1
rep.addSection('cols', 2);
rep.addSection();
rep.addTable('title', 'Table 1', 'range', dates('2012Y'):dates('2014Y'));
shortNames = {'US', 'EU'};
longNames = {'United States', 'Euro Area'};
for i=1:length(shortNames)
    rep.addSeries('data', dsa{['GROWTH_' shortNames(i)]});
    delta = dsa{['GROWTH_' shortNames(i)]}-dsca{['GROWTH_' shortNames(i)]};
    delta.tex_rename_($\Delta$);
    rep.addSeries('data', delta, ...
```
(continues on next page)
Once compiled, the report looks like:
Table 1

<table>
<thead>
<tr>
<th></th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>GROWTH_US</td>
<td>1.7</td>
<td>2.7</td>
<td>3.3</td>
</tr>
<tr>
<td>Δ</td>
<td>[0.0]</td>
<td>[-0.1]</td>
<td>[0.0]</td>
</tr>
<tr>
<td>GROWTH.EU</td>
<td>-0.8</td>
<td>0.6</td>
<td>1.5</td>
</tr>
<tr>
<td>Δ</td>
<td>[-0.2]</td>
<td>[-0.2]</td>
<td>[-0.1]</td>
</tr>
</tbody>
</table>
Dynare comes with a database of example .mod files, which are designed to show a broad range of Dynare features, and are taken from academic papers for most of them. You should have these files in the examples subdirectory of your distribution.

Here is a short list of the examples included. For a more complete description, please refer to the comments inside the files themselves.

`ramst.mod`

An elementary real business cycle (RBC) model, simulated in a deterministic setup.

`example1.mod` `example2.mod`

Two examples of a small RBC model in a stochastic setup, presented in Collard (2001) (see the file guide.pdf which comes with Dynare).

`example3.mod`

A small RBC model in a stochastic setup, presented in Collard (2001). The steady state is solved analytically using the steady_state_model block (see steady_state_model).

`fs2000.mod`


`fs2000_nonstationary.mod`

The same model than fs2000.mod, but written in non-stationary form. Detrending of the equations is done by Dynare.

`bkk.mod`

Multi-country RBC model with time to build, presented in Backus, Kehoe and Kydland (1992). The file shows how to use Dynare’s macro processor.

`agtrend.mod`

Small open economy RBC model with shocks to the growth trend, presented in Aguiar and Gopinath (2004).

`Gali_2015.mod`

Basic New Keynesian model of Galí (2015), Chapter 3 showing how to i) use “system prior”-type prior restrictions as in Andrle and Plašil (2018) and ii) run prior/posterior-functions.

`NK_baseline.mod`

Baseline New Keynesian Model estimated in Fernández-Villaverde (2010). It demonstrates how to use an explicit steady state file to update parameters and call a numerical solver.

`Occbin_example.mod`

RBC model with two occasionally binding constraints. Demonstrates how to set up Ocbin.

`Ramsey_Example.mod`
File demonstrating how to conduct optimal policy experiments in a simple New Keynesian model either under commitment (Ramsey) or using optimal simple rules (OSR)

Ramsey_steady_file.mod

File demonstrating how to conduct optimal policy experiments in a simple New Keynesian model under commitment (Ramsey) with a user-defined conditional steady state file
MATLAB/Octave command: `send_endogenous_variables_to_workspace`;

Puts the simulation results for the endogenous variables stored in `oo_.endo_simul` into vectors with the same name as the respective variables into the base workspace.

MATLAB/Octave command: `send_exogenous_variables_to_workspace`;

Puts the simulation results for the exogenous variables stored in `oo_.exo_simul` into vectors with the same name as the respective variables into the base workspace.

MATLAB/Octave command: `send_irfs_to_workspace`;

Puts the IRFs stored in `oo_.irfs` into vectors with the same name into the base workspace.

Command: `prior_function(OPTIONS)`;

Executes a user-defined function on parameter draws from the prior distribution. Dynare returns the results of the computations for all draws in an `ndraws` by `n` cell array named `oo_.prior_function_results`.

Options

- `function = FUNCTION_NAME`
  The function must have the following header `output_cell = FILENAME(xparam1,M_,options_, oo_.estim_params_,bayestopt_,dataset_,dataset_info)`, providing read-only access to all Dynare structures. The only output argument allowed is a `1 × n` cell array, which allows for storing any type of output/computations. This option is required.

- `sampling_draws = INTEGER`
  Number of draws used for sampling. Default: 500.

Command: `posterior_function(OPTIONS)`;

Same as the `prior_function` command but for the posterior distribution. Results returned in `oo_.posterior_function_results`.

Options

- `function = FUNCTION_NAME`
  See `prior_function_function`.

- `sampling_draws = INTEGER`
  See `prior_function_sampling_draws`.

Command: `generate_trace_plots(CHAIN_NUMBER)`;

Generates trace plots of the MCMC draws for all estimated parameters and the posterior density for the specified Markov Chain(s) `CHAIN_NUMBER`. If `CHAIN_NUMBER` is a vector of integers, the trace plots will plot contains separate lines for each chain.
MATLAB/Octave command: internals FLAG ROUTINENAME[.m]|MODFILENAME

Depending on the value of FLAG, the internals command can be used to run unitary tests specific to a MATLAB/Octave routine (if available), to display documentation about a MATLAB/Octave routine, or to extract some informations about the state of Dynare.

Flags

--test

Performs the unitary test associated to ROUTINENAME (if this routine exists and if the matlab/octave .m file has unitary test sections).

Example

```
>> internals --test ROUTINENAME
```

if routine.m is not in the current directory, the full path has to be given:

```
>> internals --test ../matlab/fr/ROUTINENAME
```

--display-mh-history

Displays information about the previously saved MCMC draws generated by a .mod file named MODFILENAME. This file must be in the current directory.

Example

```
>> internals --display-mh-history MODFILENAME
```

--load-mh-history

Loads into the MATLAB/Octave’s workspace informations about the previously saved MCMC draws generated by a .mod file named MODFILENAME.

Example

```
>> internals --load-mh-history MODFILENAME
```

This will create a structure called mcmc_informations (in the workspace) with the following fields:

Nb1ck

The number of MCMC chains.

InitialParameters

A Nb1ck*n, where n is the number of estimated parameters, array of doubles. Initial state of the MCMC.

LastParameters

A Nb1ck*n, where n is the number of estimated parameters, array of doubles. Current state of the MCMC.

InitialLogPost

A Nb1ck*1 array of doubles. Initial value of the posterior kernel.

LastLogPost

A Nb1ck*1 array of doubles. Current value of the posterior kernel.

InitialSeeds

A 1*Nb1ck structure array. Initial state of the random number generator.

LastSeeds

A 1*Nb1ck structure array. Current state of the random number generator.
AcceptanceRatio

A 1xNb1ck array of doubles. Current acceptance ratios.

**MATLAB/Octave command:** prior [OPTIONS [...]];

Prints information about the prior distribution given the provided options. If no options are provided, the command returns the list of available options.

*Options*

**table**

Prints a table describing the marginal prior distributions (mean, mode, std., lower and upper bounds, HPD interval).

**moments**

Computes and displays first and second order moments of the endogenous variables at the prior mode (considering the linearized version of the model).

**moments(distribution)**

Computes and displays the prior mean and prior standard deviation of the first and second moments of the endogenous variables (considering the linearized version of the model) by randomly sampling from the prior. The results will also be stored in the prior subfolder in a _endogenous_variables_prior_draws.mat file.

**optimize**

Optimizes the prior density (starting from a random initial guess). The parameters such that the steady state does not exist or does not satisfy the Blanchard and Kahn conditions are penalized, as they would be when maximizing the posterior density. If a significant proportion of the prior mass is defined over such regions, the optimization algorithm may fail to converge to the true solution (the prior mode).

**simulate**

Computes the effective prior mass using a Monte-Carlo. Ideally the effective prior mass should be equal to 1, otherwise problems may arise when maximising the posterior density and model comparison based on marginal densities may be unfair. When comparing models, say A and B, the marginal densities, $m_A$ and $m_B$, should be corrected for the estimated effective prior mass $p_A 
eq p_B \leq 1$ so that the prior mass of the compared models are identical.

**plot**

Plots the marginal prior density.

**MATLAB/Octave command:** search VARIABLENAME [ OPTION]

Searches all occurrences of a variable in a model, and prints the equations where the variable appear in the command line window. If OPTION is set to withparamvalues, the values of the parameters (if available) are displayed instead of the name of the parameters. Requires the json command line option to be set.

*Example*

Assuming that we already ran a .mod file and that the workspace has not been cleaned after, we can search for all the equations containing variable X.

```matlab
>> search X
Y = alpha*X/(1-X)+e;
diff(X) = beta*(X(-1)-mX) + gamma1*Z + gamma2*R + u;
```

To replace the parameters with estimated or calibrated parameters:
MATLAB/Octave command: \texttt{dplot [OPTION VALUE[ ...]]}

Plot expressions extracting data from different \texttt{dseries} objects.

\textit{Options}

\texttt{--expression EXPRESSION}

\texttt{EXPRESSION} is a mathematical expression involving variables available in the \texttt{dseries} objects, \texttt{dseries} methods, numbers or parameters. All the referenced objects are supposed to be available in the calling workspace.

\texttt{--dseries NAME}

\texttt{NAME} is the name of a \texttt{dseries} object from which the variables involved in \texttt{EXPRESSION} will be extracted.

\texttt{--range DATE1:DATE2}

This option is not mandatory and allows to plot the expressions only over a sub-range. \texttt{DATE1} and \texttt{DATE2} must be dates as defined in \textit{Dates in a mod file}.

\texttt{--style MATLAB_SCRIPT_NAME}

Name of a Matlab script (without extension) containing Matlab commands to customize the produced figure.

\texttt{--title MATLAB_STRING}

Adds a title to the figure.

\texttt{--with-legend}

Prints a legend below the produced plot.

\textit{Remarks}

- More than one \texttt{--expression} argument is allowed, and they must come first.
- For each \texttt{dseries} object we plot all the expressions. We use two nested loops, the outer loop is over the \texttt{dseries} objects and the inner loop over the expressions. This determines the ordering of the plotted lines.
- All \texttt{dseries} objects must be defined in the calling workspace, if a \texttt{dseries} object is missing the routine throws a warning (we only build the plots for the available \texttt{dseries} objects), if all \texttt{dseries} objects are missing the routine throws an error.
- If the range is not provided, the expressions cannot involve leads or lags.

\textit{Example}

\texttt{>> dplot --expression 2/b*cumsum(x/y(-1)-1) --dseries toto --dseries noddy --range 2001Q1:2024Q1 --title 'This is my plot'}

will produce plots for \texttt{2/b*cumsum(x/y(-1)-1)}, where \texttt{x} and \texttt{y} are variables in \texttt{dseries} objects \texttt{toto} and \texttt{noddy}, in the same figure.


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• Koop, Gary (2003), *Bayesian Econometrics*, John Wiley & Sons.


• Kuntsevich, Alexei V. and Franz Kappel (1997): “SolvOpt - The solver for local nonlinear optimization problems (version 1.1, Matlab, C, FORTRAN)”, University of Graz, Graz, Austria.


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