

# Solving DSGE models

Macro II - Fluctuations - ENSAE, 2023-2024

Pablo Winant

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## Introduction

What is the main specificity of economic modeling?

In (macro)economics, we *model* the behaviour of economic agents by specifying:

- ▶ their objective

$$\max_{c_t} E_t \sum_{s \geq t} \beta^s U(c_s)$$

$$\max \pi_t$$

...

- ▶ their constraints (budget constraint, econ. environment...)



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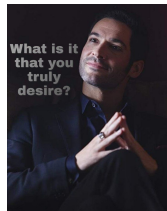
...

- ▶ their constraints (budget constraint, econ. environment...)

This has important implications:

- ▶ macro models are *forward looking*
- ▶ macro models need to be **solved**

In many cases, there is not closed form for the solution -> we need numerical techniques



# Dynare

- ▶ 1996: Michel Juillard created an opensource software to solve DSGE models
- ▶ It has been widely adopted:
  - ▶ early version in Gauss
  - ▶ then Matlab/Octave/Scilab
  - ▶ latest version in Julia



Figure 1: Michel Juillard

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## DSGE Models in institutions

Nowadays most DSGE models built in institutions have a Dynare version (IMF/GIMF, EC/Quest, ECB/, NYFed/FRBNY)

- ▶ they are usually based on the *midsize model* from Smets & Wouters (10 equations)
- ▶ but have grown up a lot (»100 equations)

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Institutions (led by researchers) are (slowly) diversifying their model

- ▶ Computational General Equilibrium Models
- ▶ Agent-based
- ▶ Semi-structural models
- ▶ Heterogenous Agents Models

Solving a model

# Model

A very concise representation of a model

$$\mathbb{E}_t [f(y_{t+1}, y_t, y_{t-1}, \epsilon_t)] = 0$$

The **problem**:

- ▶  $y_t \in \mathbb{R}^n$ : the vector of endogenous variables
- ▶  $\epsilon_t \in \mathbb{R}^{n_e}$ : the vector of exogenous variables
  - ▶ we assume that  $\epsilon_t$  is a zero-mean gaussian process
- ▶  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ : the model equations

The **solution**:

- ▶  $g$  such that

$$\forall t, y_t = g(y_{t-1}, \epsilon_t)$$

# The timing of the equations



Tip

In dynare the model equations are coded in the `model; ...`  
`; end; block`.

New information arrives with the innovations  $\epsilon_t$ .

At date  $t$ , the information set is spanned by

$$\mathcal{F}_t = \mathcal{F}(\dots, \epsilon_{t-3}, \epsilon_{t-2}, \epsilon_{t-1}, \epsilon_t)$$

By convention *an endogenous variable has a subscript  $t$  if it is known first at date  $t$ .*

# Example

## The timing of equations

Using Dynare's timing conventions:

- ▶ Write the production function in the RBC
- ▶ Write the law of motion for capital  $k$ , with a depreciation rate  $\delta$  and investment  $i$ 
  - ▶ when is capital known?
  - ▶ when is investment known?
- ▶ Add a multiplicative investment efficiency shock  $\chi_t$ . Assume it is an  $AR1$  driven by innovation  $\eta_t$  and autocorrelation  $\rho_\chi$

# Steady-state

The deterministic steady-state satisfies:

$$f(\bar{y}, \bar{y}, \bar{y}, 0) = 0$$

Often, there is a closed-form solution.

Otherwise, one must resort to a numerical solver to solve

$$\bar{y} \rightarrow f(\bar{y}, \bar{y}, \bar{y}, 0)$$



In dynare the steady-state values are provided in the `steadystate_model; ... ; end; block`. One can check they are correct using the `check; statement`.

To find numerically the steady-state: `steady; .`

# The implicit system

Replacing the solution

$$y_t = g(y_{t-1}, \epsilon_t)$$

in the system

$$\mathbb{E}_t [f(y_{t+1}, y_t, y_{t-1}, \epsilon_t)] = 0$$

we obtain:

$$\mathbb{E}_t [f(g(g(y_{t-1}, \epsilon_t), \epsilon_{t+1}), g(y_{t-1}, \epsilon_t), y_{t-1}, \epsilon_t)] = 0$$

It is an equation defining implicitly the function  $g()$



## The state-space

$$\mathbb{E}_t [f(g(g(y_{t-1}, \epsilon_t), \epsilon_{t+1}), g(y_{t-1}, \epsilon_t), y_{t-1}, \epsilon_t))] = 0$$

In this expression,  $y_{t-1}, \epsilon_t$  is the state-space.

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Dropping the time subscripts, the equation must be satisfied for any realization of  $(y, \epsilon)$

$$\forall (y, \epsilon) \quad \Phi(g)(y, \epsilon) = \mathbb{E}_{\epsilon'} [f(g(g(y, \epsilon), \epsilon'), g(y, \epsilon), y, \epsilon)] = 0$$

It is a functional equation  $\Phi(g) = 0$

## Expected shocks

First order approximation:

► Assume  $|y_t - \bar{y}| \ll 1, |\epsilon| \ll 1, |\epsilon'| \ll 1$

Perform a Taylor expansion with respect to future shock:

$$\mathbb{E}_{\epsilon'} [f(g(g(y, \epsilon), \epsilon'), g(y, \epsilon), y, \epsilon)] \quad (1)$$

$$= \mathbb{E}_{\epsilon'} [f(g(g(y, \epsilon), 0), g(y, \epsilon), y, \epsilon)] \quad (2)$$

$$+ \mathbb{E}_{\epsilon'} [f'_{y_{t+1}}(g(g(y, \epsilon), 0), g(y, \epsilon), y, \epsilon) g'_\epsilon \epsilon'] + o(\epsilon') \quad (3)$$

$$\approx f(g(g(y, \epsilon), 0), g(y, \epsilon), y, \epsilon) \quad (4)$$

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This uses the fact that  $\mathbb{E}[\epsilon'] = 0$ .

At first order, expected shocks play no role.

To capture precautionary behaviour (like risk premia), we would need to increase the approximation order.

## First order perturbation

We are left with the system:

$$F(y, \epsilon) = f(g(g(y, \epsilon), 0), g(y, \epsilon), y, \epsilon) = 0$$

We can now use a variant of the *implicit function theorem* to recover a first approximation of  $g$  as:

$$g(y, \epsilon) = \bar{y} + g'_y(y - \bar{y}) + g'_e \epsilon_t$$

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We can obtain the unknown quantities  $g'_y$ , and  $g'_\epsilon$  using the *method of undeterminate coefficients*:

Plug the first approximation into the system and write the conditions

$$F'_y(\bar{y}, 0) = 0$$

$$F'_\epsilon(\bar{y}, 0) = 0$$

## Computing $g'_y$

Recall the system:

$$F(y, \epsilon) = f(g(g(y, 0), \epsilon), g(y, \epsilon), y, \epsilon) = 0$$

We have

$$F'_y(\bar{y}, 0) = f'_{y_{t+1}} g'_y g'_y + f'_{y_t} g'_y + f'_{y_{t-1}} = 0$$

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This is a specific Riccatti equation

$$AX^2 + BX + C$$

where  $A, B, C$  and  $X = g'_y$  are square matrices  $\in \mathbb{R}^n \times \mathbb{R}^n$



# First Order Deterministic Model

Let's pause a minute to observe the first order deterministic model:

$$AX^2 + BX + C$$

From our intuition in dimension 1, we know there must be multiple solutions

- ▶ how do we find them?
- ▶ how do we select the right ones?

In the absence of shocks the dynamics of the model are given by

$$y_t = Xy_{t-1}$$

What is the condition for the model to be stationary?

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What is the condition for the model to be stationary?

-> the biggest eigenvalue of  $X$  should be smaller than 1

## Multiplicity of solution

It is possible to show that the system is associated with  $2n$  generalized eigenvalues:

$$|\lambda_1| \leq \dots \leq |\lambda_{2n}|$$

For each choice  $C$  of  $n$  eigenvalues ( $|C| = n$ ), a specific recursive solution  $X_C$  can be *constructed*. It has eigenvalues  $C$ .

This yields at least  $\binom{2n}{n}$  different combinations.

## Well defined model

A model is well defined when there is **exactly one solution that is non divergent**.

This implies:

$$|\lambda_1| \leq \dots \leq |\lambda_n| \leq 1 < |\lambda_{n+1}| \leq \dots \leq |\lambda_{2n}|$$

## Example 1

Forward looking inflation:

$$\pi_t = \alpha \pi_{t+1}$$

with  $\alpha > 1$ .

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We can rewrite the system as:

$$\alpha \pi_{t+1} - \pi_t + 0 \pi_{t-1} = \pi_{t+1} - \left(\frac{1}{\alpha} + 0\right) \pi_t + \left(\frac{1}{\alpha} 0\right) \pi_{t-1}$$

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The generalized eigenvalues are  $0 \leq 1 < \frac{1}{\alpha}$ .

The unique solution is  $\pi_t = 0 \pi_{t-1}$



## Example 2

Debt accumulation equation by a rational agent:

$$b_{t+1} - (1 + \frac{1}{\beta})b_t + \frac{1}{\beta}b_{t-1} = 0$$

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Two generalized eigenvalues  $\lambda_1 = 1 < \lambda_2 = \frac{1}{\beta}$

The unique non-diverging solution is  $b_t = b_{t-1}$ .

- ▶ it is a *unit-root*: any initial deviation in  $b_{t-1}$  has persistent effects

## Example 3

Productivity process:

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In that case there is a hidden infinite eigenvalue  $\infty$  associated to  $z_{t+1}$ .

The generalized eigenvalues are  $\lambda_1 = \rho \leq 1 < \lambda_2 = \infty$

More generally, any variable that does not appear in  $t + 1$  creates one infinite generalized eigenvalue.

## A criterium for well-definedness

Looking again at the list of eigenvalues we set aside the infinite ones.

The model is well specified iff we can sort the eigenvalues as:

$$|\lambda_1| \leq \dots \leq |\lambda_n| \leq 1 < |\lambda_{n+1}| \leq \dots |\lambda_{n+k}| \leq \underbrace{|\lambda_{n+k+1}| \dots \leq |\lambda_{2n}|}_{\text{infinite eigenvalues}}$$

### **i** Blanchard-Kahn criterium

The model satisfies the Blanchard-Kahn criterium if the number of eigenvalues greater than one, is exactly equal to the number of variables *appearing* in  $t + 1$ .

In that case the model is well-defined.

# Computing the solution

There are several classical methods to compute the solution to the algebraic Riccati equation:

$$AX^2 + BX + C = 0$$

- ▶ qz decomposition
  - ▶ traditionnally used in the DSGE literature since Chris Sims
  - ▶ a little bit unintuitive
- ▶ cyclic reduction
  - ▶ new default in dynare, more adequate for big models
- ▶ linear time iteration
  - ▶ conceptually very simple

## Computing $g'_e$

Now we have  $g'_y$ , how do we get  $g'_e$ ?

Recall:

$$F(y, \epsilon) = f(g(g(y, \epsilon), 0), g(y, \epsilon), y, \epsilon) = 0$$

We have

$$F'_e(\bar{y}, 0) = f'_{y_{t+1}} g'_y g'_e + f'_{y_t} g'_e + f'_{\epsilon_t} = 0$$

Now this is easy:

$$g'_e = -(f'_{y_{t+1}} g'_y + f'_{y_t})^{-1} f'_{\epsilon_t} = 0$$



## The model solution

The result of the model solution:

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Then to compare the model to the data we compute

- ▶ implied moments
- ▶ likelihood

Optimizing the fit to the data is called *model* estimation

# Linear Time Iteration

Recall the system to solve:

$$F(y, \epsilon) = f(g(g(y, \epsilon), 0), g(y, \epsilon), y, \epsilon) = 0$$

but now assume the decision rules today and tomorrow are different:

- ▶ today:  $y_t = g(y_{t-1}, \epsilon_t) = \bar{y} + Xy_{t-1} + g_y\epsilon_t$
- ▶ tomorrow:  $y_{t+1} = \tilde{g}(y_t, \epsilon_{t+1}) = \bar{y} + \tilde{X}y_{t-1} + \tilde{g}_y\epsilon_t$

Then the Ricatti equation is written:

$$A\tilde{X}X + BX + C = 0$$

## Linear Time Iteration (2)

The linear time iteration algorithm consists in solving the decision rule  $X$  today as a function of decision rule tomorrow  $\tilde{X}$ .

This corresponds to the simple formula:

$$X = -(A\tilde{X} + B)^{-1}C$$

And the full algorithm can be described as:

- ▶ choose  $X_0$
- ▶ for any  $X_n$ , compute  $X_{n+1} = T(X_n) = -(AX_n + B)^{-1}C$ 
  - ▶ repeat until convergence

## Linear Time Iteration (3)

It can be shown that, starting from a random initial guess, the linear time-iteration algorithm converges to the solution  $X$  with the smallest modulus:

$$\underbrace{|\lambda_1| \leq \dots \leq |\lambda_n|}_{\text{Selected eigenvalues}} \leq |\lambda_{n+1}| \dots \leq |\lambda_{2n}|$$

In other words, it finds the right solution when the model is well specified.

How do you check it is well specified?

- ▶  $\lambda_n$  is the biggest eigenvalue of solution  $X$
- ▶ what about  $\lambda_{n+1}$ ?
  - ▶  $\frac{1}{\lambda_{n+1}}$  is the biggest eigenvalue of  $(AX + B)^{-1}A$
  - ▶ jump to Section ??

## Linear Time Iteration (4)

Define

$$M(\lambda) = A\lambda^2 + B\lambda + C$$

For any solution  $X$ ,  $M(\lambda)$  can be factorized as: <sup>1</sup>

$$M(\lambda) = (\lambda A + AX + B)(\lambda I - X)$$

and

$$\det(M(\lambda)) = \underbrace{\det(\lambda A + AX + B)}_{Q(\lambda)} \det(\lambda I - X)$$

By construction  $Q(\lambda)$  is a polynomial whose roots are those that are not selected by the solution i.e.  $\Lambda \setminus Sp(X)$ .

---

<sup>1</sup>Special case of Bezout theorem. Easy to check in that case

## Linear Time Iteration (5)

For  $\lambda \neq 0$  we have:

$$\begin{aligned}\lambda &\in Sp((AX + B)^{-1}A) \\ \Leftrightarrow \det((AX + B)^{-1}A - I\lambda) &= 0 \\ \Leftrightarrow \det\left(\frac{1}{\lambda}A - I(AX + B)\right) &= 0 \\ \Leftrightarrow Q\left(\frac{1}{\lambda}\right) &= 0 \\ \Leftrightarrow \frac{1}{\lambda} \in G \cap Sp(X)\end{aligned}$$

In words,  $(AX + B)^{-1}$  contains all the eigenvalues that have been rejected by the selection of  $X$ .

In particular,  $\rho((AX + B)^{-1}A) = 1/\min(G \cap Sp(X))$



## Conclusion

# What can you do with the solution

The solution of a model found by Dynare has an especially simple form: an AR1

- ▶  $y_t = Xy_{t-1} + Y\epsilon_t$
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- ▶ perform stochastic simulations, impulse response function

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# Going Further

Taking the model to the data with Dynare

- ▶ “estimate” the model: compute the likelihood of a solution and maximize it by choosing the right parameters
- ▶ “identify” shocks in the data

Other functions

- ▶ higher order approximation
- ▶ ramsey plan
- ▶ discretionary policy
- ▶ ...

Coming Next



Many models