4. Transition Path

Adv. Macro: Heterogenous Agent Models

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Introduction

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    2. Example from GEModelToolsNotebooks/HANC

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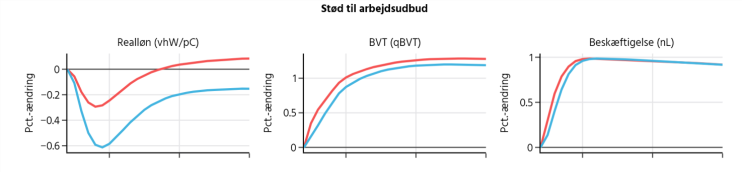
- **Model:** Heterogeneous Agent Neo-Classical (HANC) model
- **Code:**
  1. Based on the GEModelTools package
  2. Example from GEModelToolsNotebooks/HANC
- **Literature:**
  1. Auclert et. al. (2021), »Using the Sequence-Space Jacobian to Solve and Estimate Heterogeneous-Agent Models«
  2. Documentation for GEModelTools
  3. Kirkby (2017)

Outline

1. Introduction to transitions with the Ramsey model
2. Transition path in HA in partial equilibrium
3. Transition path in HA in general equilibrium: using sequence-space Jacobians
4. Fake news algorithm: computing SSJ fast
5. Exercises
6. First-order approximations of transition paths

Example I

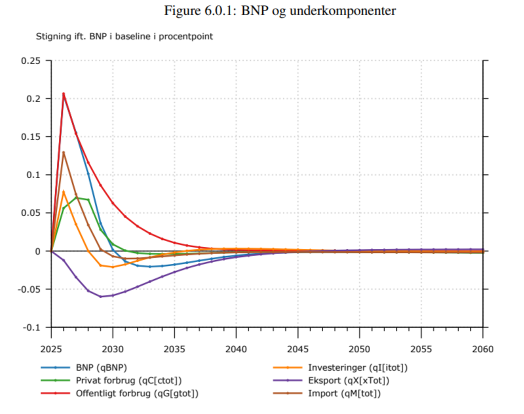
- What do we mean by transition path?
- Permanent shock to labor supply (think increase in retirement age) in the macroeconomic model of the Ministry of Finance:



- Note: Permanent shock, so transition path *between* two different steady states

Example II

- Temporary shock to public spending (i.e. fiscal stimulus during recessions)



- Note: Temporary shock, so model returns to the *same steady state*

Ramsey model

Ramsey: Summary

- **Simplified form:**

$$u'(C_t^{hh}) = \beta(1 + F_K(K_t, 1) - \delta)u'(C_{t+1}^{hh})$$
$$K_t = (1-\delta)K_{t-1} + F(K_{t-1}, 1) - C_t^{hh}$$

- **Production function:** $\Gamma_t K_t^\alpha L_t^{1-\alpha}$
- **Utility function:** $\frac{\left(C_t^{hh}\right)^{1-\sigma}}{1-\sigma}$
- **Steady state:**

$$K_{ss} = \left(\frac{\left(\frac{1}{\beta} - 1 + \delta\right)}{\Gamma_{ss}\alpha}\right)^{\frac{1}{\alpha-1}}$$
$$C_{ss}^{hh} = (1-\delta)K_{ss} + \Gamma_{ss}K_{ss}^\alpha - K_{ss}$$

Ramsey: As an equation system

$$\begin{bmatrix} r_t^K - \alpha \Gamma_t K_{t-1}^{\alpha-1} L_t^{1-\alpha} \\ w_t - (1-\alpha)\Gamma_t K_{t-1}^{\alpha} L_t^{-\alpha} \\ r_t - (r_t^K - \delta) \\ A_t - K_t \\ A_t^{hh} - \left((1+r_t)A_{t-1}^{hh} + w_t L_t^{hh} - C_t^{hh}\right) \\ C_t^{hh,-\sigma} - \beta(1+r_{t+1}) C_{t+1}^{hh,-\sigma} \\ A_t - A_t^{hh} \\ L_t - L_t^{hh} \\ \forall t \in \{0,1,\dots\}, \text{given } K_{-1} \end{bmatrix} = \mathbf{0}$$

Remember: Perfect foresight w.r.t aggregate variables

Unknowns: $\{r_t^K, w_t, L_t, K_t, r_t, A_t, C_t^{hh}, A_t^{hh}\}$ for $\forall t \in \{0,1,\dots\}$

Recap: Newton's method I

- Before solving the dynamic Ramsey model, consider a simpler example

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$$f(x) \approx f\left(x^i\right) + f'\left(x^i\right)\left(x - x^i\right)$$

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- Set $f(x) = 0$ and solve for x to get:

$$x = x^i - \frac{f\left(x^i\right)}{f'\left(x^i\right)}$$

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- Newton's method: Given initial guess x_0 update guess for x from i to $i+1$ as:

$$x^{i+1} = x^i - \frac{f\left(x^i\right)}{f'\left(x^i\right)}$$

  - until $\left|f\left(x^i\right)\right| < \epsilon$

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$$f'\left(x^i\right) \approx \frac{f\left(x^i + h\right) - f\left(x^i\right)}{h}$$

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- How well does it work?
    - If $f\left(x\right)$ is linear this update solves $f\left(x\right) = 0$ in **1 iteration**
    - If $f\left(x\right)$ is non-linear we typically need more iterations, but works well if initial guess is within basis of attraction

Recap: Multivariate Newton's method

- Generalize to vector-valued, multivariate functions $\left[f_1\left(x_{1,}x_2\right), f_2\left(x_{1,}x_2\right)\right]' = \boldsymbol{f}\left(\boldsymbol{x}\right)$ with $\boldsymbol{x} = \left(x_{1,}x_2\right)'$:

$$\boldsymbol{x}^{i+1} = \boldsymbol{x}^i - \boldsymbol{J}\left(\boldsymbol{x}^i\right)^{-1}\boldsymbol{f}\left(\boldsymbol{x}^i\right)$$

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- Where $\boldsymbol{J}\left(\boldsymbol{x}^i\right)$ is the *Jacobian* of $f(\boldsymbol{x})$ w.r.t $\boldsymbol{x}^i$:

$$\boldsymbol{J}(\boldsymbol{x}_i) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1^i} & \frac{\partial f_1}{\partial x_2^i} \\ \frac{\partial f_2}{\partial x_1^i} & \frac{\partial f_2}{\partial x_2^i} \end{bmatrix}$$

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- Newton's method updates Jacobian $\boldsymbol{J}$ in **every iteration**
- If $\boldsymbol{J}$ is expensive to calculate, this is a serious bottleneck
- Broyden's method solves this issue by only calculating J around some initial point.
- Then apply following (linear) update of $f'\left(x^{i+1}\right)$ at every iteration i:

$$f'\left(x^{i+1}\right) = f'\left(x^{i}\right) + \frac{\left[f\left(x^{i+1}\right) - f\left(x^{i}\right)\right] - f'\left(x^{i}\right)\left(x^{i+1} - x^{i}\right)}{x^{i+1} - x^{i}}$$

Recap: Broyden's method II

1. Guess $\boldsymbol{x}^0$ and set $i = 0$
2. Calculate the Jacobian around initial point $\boldsymbol{J_0}$
3. Calculate $\boldsymbol{f}^i = \boldsymbol{f}(\boldsymbol{x}^i)$.
4. Stop if $\left|\boldsymbol{f}^i\right|$ below tolerance ϵ
5. Calculate Jacobian by
$$\boldsymbol{J}^i = \begin{cases} \boldsymbol{J_0} & \text{if } i = 0 \\ \boldsymbol{J}^{i-1} + \frac{(\boldsymbol{f}^i - \boldsymbol{f}^{i-1}) - \boldsymbol{J}^{i-1}(\boldsymbol{x}^i - \boldsymbol{x}^{i-1})}{|\boldsymbol{x}^i - \boldsymbol{x}^{i-1}|_2} \left(\boldsymbol{x}^i - \boldsymbol{x}^{i-1}\right)' & \text{if } i > 0 \end{cases}$$
6. Update guess by $\boldsymbol{x}^{i+1} = \boldsymbol{x}^i - \left(\boldsymbol{J}^i\right)^{-1} \boldsymbol{f}^i$
7. Increment i and return to step 3

- **Go through code**

Back to Ramsey

$$
\begin{bmatrix}
r_t^K - \alpha \Gamma_t K_{t-1}^{\alpha-1} L_t^{1-\alpha} \\
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r_t - (r_t^K - \delta) \\
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- 2 issues:
  - Many unknowns (8 eqs per period)
  - In fact, infinitely many since time is infinite, $T \to \infty$

Truncated Ramsey, reduced vector form

$$\boldsymbol{H}(\boldsymbol{K}, \boldsymbol{L}, \boldsymbol{\Gamma}, K_{-1}) = \begin{bmatrix} A_t - A_t^{hh} \\ L_t - L_t^{hh} \\ \forall t \in \{0, 1, \dots, T-1\} \end{bmatrix} = \mathbf{0}$$

where $\boldsymbol{X} = (X_0, X_1, \dots, X_{T-1})$, $A_{-1}^{hh} = K_{-1}$ and

$$\begin{aligned} r_t^K &= \alpha \Gamma_t (K_{t-1}/L_t)^{\alpha-1} \\ w_t &= (1-\alpha)\Gamma_t (K_{t-1}/L_t)^{\alpha} \\ A_t &= K_t \\ r_t &= r_t^K - \delta \\ C_t^{hh} &= (\beta(1+r_{t+1}))^{-\sigma} C_{t+1}^{hh} \text{ (backwards)} \\ L_t^{hh} &= 1 \\ A_t^{hh} &= (1+r_t)A_{t-1}^{hh} + w_t L_t^{hh} - C_t^{hh} \text{ (forwards)} \end{aligned}$$

Truncation: $T < \infty$ fine when $\Gamma_t = \Gamma_{ss}$ for all $t > \underline{t}$ with $\underline{t} \ll T$

Further reduced

$$\boldsymbol{H}(\boldsymbol{K}, \boldsymbol{\Gamma}, K_{-1}) = \left[\boldsymbol{A} - \boldsymbol{A}^{hh}\right] = \boldsymbol{0}$$

where $\boldsymbol{X} = (X_0, X_1, \ldots, X_{T-1})$, $A_{-1}^{hh} = K_{-1}$ and

$$\begin{aligned}
L_t = L_t^{hh} = 1 & \\
r_t^K &= \alpha \Gamma_t (K_{t-1}/L_t)^{\alpha-1} \\
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\end{aligned}$$

for $\forall t \in \{0, 1, \ldots, T-1\}$

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  - Representing an entire timepath/*sequence* of variables as a function of timepath/*sequence* of other variables

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$$\begin{bmatrix} C_0 & C_1 & C_2 & \dots \end{bmatrix}' = a + b \begin{bmatrix} Y_0 & Y_1 & Y_2 & \dots \end{bmatrix}'$$
$$\Leftrightarrow \boldsymbol{C} = a + b\boldsymbol{Y}$$
$$\Leftrightarrow \boldsymbol{C} = f\left(\boldsymbol{Y}\right)$$

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- Powerfull since it also applies *non-linear*, forward-looking and backwards-looking eqs:

$$\begin{aligned} C_t &= a + b_0 Y_t + b_1 \log Y_{t-4} + b_2 Y_{t+4}^2 \\ \Leftrightarrow \boldsymbol{C} &= g(\boldsymbol{Y}) \end{aligned}$$

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- As long as we have the sequence $\boldsymbol{Y}$ we can calculate $\boldsymbol{C}$
  - Will leverage this later when working with the HA model

Solution in sequence space

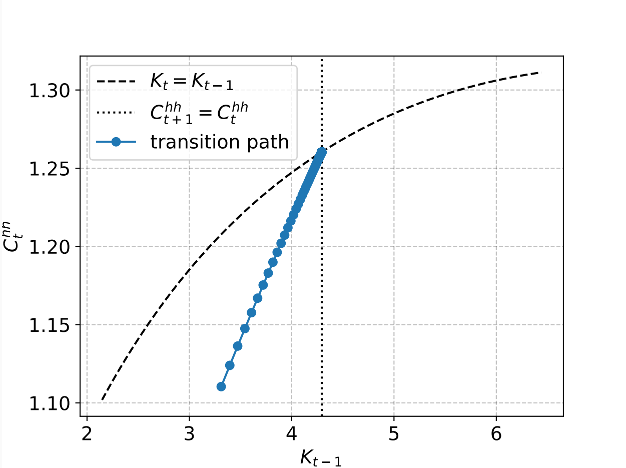
- **Truncation:** $T = 200$ (transition path should have converged to ss by then)
- **Jacobian:** Find $\boldsymbol{H_K}$ by *numerical differentiation*

$$\boldsymbol{H_K} = \begin{bmatrix} \frac{\partial(A_0 - A_0^{hh})}{\partial K_0} & \frac{\partial(A_0 - A_0^{hh})}{\partial K_1} & \cdots \\ \frac{\partial(A_1 - A_1^{hh})}{\partial K_0} & \ddots & \ddots \\ \vdots & \ddots & \ddots \end{bmatrix}$$

- **Transition path:** Given $\boldsymbol{\Gamma}$ and K_{-1} solve $\boldsymbol{H}(\boldsymbol{K}, \boldsymbol{\Gamma}, K_{-1})$ with non-linear equation system solver (e.g. broyden)
- **Two types of perfect foresight transitions:**
  1. *Transitory:* both the initial and terminal conditions are the steady-state values
  2. *Permanent:* the economy moves from one state to another state (the terminal state must be a stationary one)
- **Notebook:** *Ramsey.ipynb*

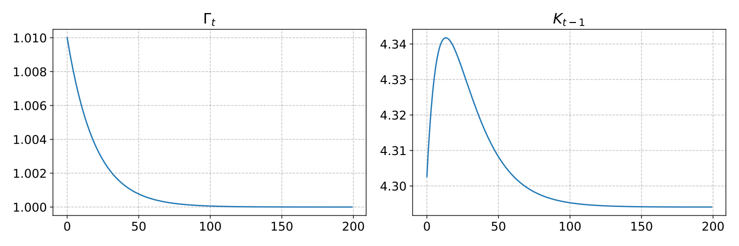
Example 1: permanent from low capital

Initially away from steady state: $K_{-1} = 0.75K_{ss}$



Example 2: transitory following technology shock

Technology shock: $\Gamma_t = 0.01 \times \Gamma_{ss} \times 0.95^t$ (i.e AR(1) with $\rho = 0.95$) (exogenous, deterministic)



Terminology: MIT-shock

Transition path in PE

Household model in a transition

Recall the household block in the HANC model

$$v_0(z_{it}, a_{it-1}) = \max_{\{c_{it}\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_{it})$$

s.t.

$$\begin{aligned}
\ell_{it} &= z_{it} \\
a_{it} &= (1 + r_t) a_{it-1} + w_t \ell_{it} - c_{it} \\
\log z_{it+1} &= \rho_z \log z_{it} + \psi_{it+1}, \;\; \psi_{it} \sim \mathcal{N}(\mu_\psi, \sigma_\psi), \;\; \mathbb{E}[z_{it}] = 1 \\
a_{it} &\geq 0
\end{aligned}$$

Until now, we assume that $r_t = r_{ss}$ and $w_t = w_{ss}$ for all t.

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Perfect foresight, initial and terminal conditions,

Important assumptions:

1. **Perfect foresight:** from $t = 0$, households know the future path of $\{r_t, w_t\}_{t=0}^{\infty}$
2. **Truncation:** the model converges to a stationary state after $t \geq T$, T large
3. **Initial conditions:** we compute the transition from a given distribution D_0 that we already know
4. **Terminal condition:** we compute a transition towards some stationary state where we know the value function (or its derivative)

Impulse reponses: backward and forward step

Our goal is to compute a sequence of impulse responses

$$A_t^{hh}(\{r_\tau, w_\tau\}_{\tau=0}^{T} = \int a_t(a,z) dD_t(a,z) \quad \forall t \in (0, T)$$

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We will proceed in two steps:

1. **Backward step**: using the terminal condition on the value function, and going back in time, obtain the policy functions $a_t(a,z)$ and $c_t(a,z)$

Impulse reponses: backward and forward step

Our goal is to compute a sequence of impulse responses

$$A_t^{hh}(\{r_\tau, w_\tau\}_{\tau=0}^{T} = \int a_t(a,z)dD_t(a,z) \quad \forall t \in (0,T)$$

We thus need to obtain a sequence of policy functions $a_t(a,z)$ and distributions D_t. *(note the t subscript!)*

We will proceed in two steps:

1. **Backward step**: using the terminal condition on the value function, and going back in time, obtain the policy functions $a_t(a,z)$ and $c_t(a,z)$
2. **Forward step**: using the initial condition on the distribution, and going forward in time, simulate the distribution over time $D_t(a,z)$

Summing up the transition in PE

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We can then obtain the aggregate values of the household as usual by computing $A_t = \int a_t(a, z) dD_t(a, z)$. This is the **impulse response**!

Let's code!

Transition path in GE

Equation system

The model can be written as an **equation system**

$$\begin{bmatrix} r_t^K - F_K(K_{t-1}, L_t) \\ w_t - F_L(K_{t-1}, L_t) \\ r_t - (r_t^K - \delta) \\ A_t - K_t \\ \boldsymbol{D}_t - \Pi_z \underline{\boldsymbol{D}}_t \\ \underline{\boldsymbol{D}}_{t+1} - \Lambda_t \boldsymbol{D}_t \\ A_t^{hh} - A_t \\ L_t^{hh} - L_t \\ \forall t \in \{0, 1, \dots\}, \text{given } \underline{\boldsymbol{D}}_0 \end{bmatrix} = \mathbf{0}$$

where $\{\Gamma_t\}_{t \geq 0}$ is a given technology path and $K_{-1} = \int a_{t-1} d\underline{\boldsymbol{D}}_0$

Remember: Policies and choice transitions depend on prices

1. Policy function: $x_t^* = x^* \left(\{r_\tau, w_\tau\}_{\tau \geq t} \right)$ and $X_t^{hh} = \sum_i x_{it}^* D_{it} = \boldsymbol{x}_t^{*\prime} \boldsymbol{D}_t$
2. Choice transition: $\Lambda_t = \Lambda \left(\{r_\tau, w_\tau\}_{\tau \geq t} \right)$

Transition path - close to verbal definition

For a given $\underline{\boldsymbol{D}}_0$ and a path $\{\Gamma_t\}$

1. Quantities $\{K_t\}$ and $\{L_t\}$,
2. prices $\{r_t\}$ and $\{w_t\}$,
3. the distributions $\{\boldsymbol{D}_t\}$ over β_i, z_t and a_{t-1}
4. and the policy functions $\{a_t^*\}$, $\{\ell_t^*\}$ and $\{c_t^*\}$

are such that in all periods

1. Firms maximize profits (prices)
2. Household maximize expected utility (policy functions)
3. $\boldsymbol{D}_t$ is implied by simulating the household problem forwards from $\underline{\boldsymbol{D}}_0$
4. Mutual fund balance sheet is satisfied
5. The capital market clears
6. The labor market clears
7. The goods market clears

Reduce size of equation system

- In the equation system above we have many **unknowns** and many **equations**
- Makes finding the solution with Broyden's method since **Jacobian is large**
  - With truncation T and N equations/unknowns $\boldsymbol{J}$ has size $(T \times N, T \times N,)$
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    - $\Rightarrow$ Expensive to calculate
- We can typically **exploit model structure** to reduce size of system
    - Did this earlier for Ramsey
    - Now more formally

Truncated, reduced vector form

$$\boldsymbol{H}\left(\boldsymbol{K},\boldsymbol{L},\boldsymbol{\Gamma},\underline{\boldsymbol{D}}_0\right)=\left[\begin{array}{c} A_t^{hh}-A_t \\ L_t^{hh}-L_t \\ \forall t\in\{0,1,\dots,T-1\} \end{array}\right]=\mathbf{0}$$

where $\boldsymbol{X}=(X_0,X_1,\dots,X_{T-1})$, $K_{-1}=\int a_{t-1}d\underline{\boldsymbol{D}}_0$ and

$$\begin{aligned} r_t^K &= \alpha\Gamma_t(K_{t-1}/L_t)^{\alpha-1} \\ w_t &= (1-\alpha)\Gamma_t(K_{t-1}/L_t)^{\alpha} \\ r_t &= r_t^K-\delta \\ A_t &= K_t \\ \boldsymbol{D}_t &= \Pi_z'\underline{\boldsymbol{D}}_t \\ \underline{\boldsymbol{D}}_{t+1} &= \Lambda_t'\boldsymbol{D}_t \\ A_t^{hh} &= \boldsymbol{a}_t^{*\prime}\boldsymbol{D}_t \\ L_t^{hh} &= \ell_t^{*\prime}\boldsymbol{D}_t \\ &\forall t\in\{0,1,\dots,T-1\} \end{aligned}$$

Truncation: $T<\infty$ fine when $\Gamma_t=\Gamma_{ss}$ for all $t>\underline{t}$ with $\underline{t}\ll T$

DAG - Directed Acyclic Graph

- **Orange square:** Shocks (exogenous)
- **Blue square:** Unknowns (endogenous)
- **Green circles:** Blocks (with variables and targets inside)

- This DAG implies: Exo. input + guess ⇒ Firm block ⇒ Mutual fund ⇒HHs ⇒ Residuals

Further reduction

$$\boldsymbol{H}(\boldsymbol{K}, \boldsymbol{\Gamma}, \underline{\boldsymbol{D}}_0) = \left[\begin{array}{c} A_t^{hh}(\boldsymbol{w}(\boldsymbol{K}), \boldsymbol{r}(\boldsymbol{K})) - K_t \\ \forall t \in \{0, 1, \ldots, T-1\} \end{array} \right] = \mathbf{0}$$

where $\boldsymbol{X} = (X_0, X_1, \ldots, X_{T-1})$, $K_{-1} = \int a_{t-1} d\underline{\boldsymbol{D}}_0$ and

$$\begin{aligned}
L_t &= 1 \\
r_t^K &= \alpha \Gamma_t (K_{t-1}/L_t)^{\alpha-1} \\
w_t &= (1-\alpha)\Gamma_t (K_{t-1}/L_t)^{\alpha} \\
A_t &= K_t \\
r_t &= r_t^K - \delta \\
\boldsymbol{D}_t &= \Pi_z' \underline{\boldsymbol{D}}_t \\
\underline{\boldsymbol{D}}_{t+1} &= \Lambda_t' \boldsymbol{D}_t \\
A_t^{hh} &= \boldsymbol{a}_t^{*\prime} \boldsymbol{D}_t \\
&\forall t \in \{0, 1, \ldots, T-1\}
\end{aligned}$$

Truncation: $T < \infty$ fine when $\Gamma_t = \Gamma_{ss}$ for all $t > \underline{t}$ with $\underline{t} \ll T$

Solve with Broyden

- As with standard Ramsey model from before we have:
  - Equation system with T equations ($\boldsymbol{H}$)
  - And T unknowns ($\boldsymbol{K}$)
- If we can calculate the jacobian of $\boldsymbol{H}$ w.r.t $\boldsymbol{K}$ we can solve with Broyden's method as before

How to compute Jacobian?

- How do we compute the Jacobian of the residuals $\boldsymbol{H}$ w.r.t unknowns $\boldsymbol{K}$?
  - Before: Compute Jacobian of entire model using num. diff
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- *Example*. Represent model in block form:

$$\boldsymbol{w}, \boldsymbol{r}^K = Firm\left(\boldsymbol{K}\right), \quad \boldsymbol{A}, \boldsymbol{r} = MutFund\left(\boldsymbol{K}, \boldsymbol{r}^K\right)$$

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- Collapsing the previous equations, we write the asset-market clearing condition as

$$\boldsymbol{H} = \boldsymbol{A}^{hh}(\boldsymbol{w}(\boldsymbol{K}), \boldsymbol{r}(\boldsymbol{K})) - \boldsymbol{K}$$

What is a Jacobian

Let $\mathcal{J}^{y,x}$ be Jacobian of y w.r.t x. Then:

$$\boldsymbol{H_K} = \mathcal{J}^{A^{hh},r}\mathcal{J}^{r,K} + \mathcal{J}^{A^{hh},w}\mathcal{J}^{w,K} - \boldsymbol{I}$$

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Interpretation: row t of column s gives us the savings change at t in response to a shock on r at s. Not just a computational tool, also a lot of economic intuition behind it!

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    - Cheap, and can often be vectorized
  - What about HH Jacobians $\mathcal{J}^{A_{hh},r}, \mathcal{J}^{A_{hh},w}$?
    - Need to compute T impulse reponse!

Bottleneck: How do we find the Jacobian?

- **Naive approach:** For each input i into HH block $i \in \{r, w\}$
  - For each $s \in \{0, 1, ..., T-1\}$
    1. Shock input i in period s by small amount Δ
    2. Solve household problem backwards along transition path
    3. Simulate households forward along transition path
    4. Calculate column s, row t of jacobian as $\frac{\partial \mathcal{J}_t^{A_{hh},i}}{\partial i_s} = \frac{A_t^{hh} - A_{ss}^{hh}}{\Delta}$ for all t

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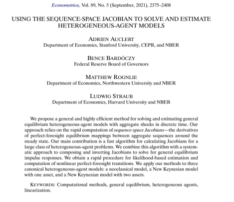
- Solution: **Fake news algorithm** - only need T steps! (later today)



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USING THE SEQUENCE-SPACE JACOBIAN TO SOLVE AND ESTIMATE HETEROGENEOUS-AGENT MODELS

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We propose a general and highly efficient method for solving and estimating general equilibrium heterogeneous-agent models with aggregate shocks in discrete time. Our approach relies on the rapid computation of *sequence-space Jacobians*—the derivatives of perfect-foresight equilibrium mappings between aggregate sequences around the steady state. Our main contribution is a fast algorithm for calculating Jacobians for a large class of heterogeneous-agent problems. We combine this algorithm with a systematic approach to composing and inverting Jacobians to solve for general equilibrium impulse responses. We obtain a rapid procedure for likelihood-based estimation and computation of nonlinear perfect-foresight transitions. We apply our methods to three canonical heterogeneous-agent models: a neoclassical model, a New Keynesian model with one asset, and a New Keynesian model with two assets.

KEYWORDS: Computational methods, general equilibrium, heterogeneous agents, linearization.

Summary

- Conditional on being able to compute HH jacobian efficiently we can compute **transition path** through following steps:
  1. Compute stationary state of model
  2. Formulate transition path as DAG
     - Reduce number of unknowns and residual equations
     - Not essential, but often good idea
  3. Compute Jacobian of residuals $\boldsymbol{H}$ w.r.t unknowns $\boldsymbol{K}$
  4. Formulate shock (i.e. TFP increases by 1% for 4 years)
  5. Use Broyden's method to solve for transition path

Let's code!

Assumptons and interpretation

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  - Unexpected before occuring at time 0
  - From time 0 and onwards agents have perfect foresight w.r.t transition dynamics
- **Transition path, $\boldsymbol{K}$:** Non-linear perfect foresight response to
  1. Initial distribution, $\underline{\boldsymbol{D}}_0 \neq \boldsymbol{D}_{ss}$or $K_0 \neq K_{ss}$ (convergence to steady state)
  2. Shock, $\Gamma_t \neq \Gamma_{ss}$ for some t (i.e. impulse-response)

Fake News Algorithm

Fake news algorithm

- **Household block:**

$$\boldsymbol{Y}^{hh} = hh(\boldsymbol{X}^{hh})$$

    - i.e. $\boldsymbol{Y}^{hh} = C^{hh}, A^{hh}$ and $\boldsymbol{X}^{hh} = w, r$

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- **Next slides:** *Sketch of much faster approach*

Initial step

- Note that aggregate is (matrix) product of individual policy function $\boldsymbol{y}_t$ and distribution $\boldsymbol{D}_t$.
- Linearize (first-order Taylor) around ss:

$$\boldsymbol{Y}^{hh} = (\boldsymbol{y}_t')\,\boldsymbol{D}_t$$
$$\Rightarrow \frac{d\boldsymbol{Y}^{hh}}{d\boldsymbol{X}^{hh}} = \left(\frac{d\boldsymbol{y}_t}{d\boldsymbol{X}^{hh}}'\right)\boldsymbol{D}_{ss} + (\boldsymbol{y}_{ss}')\,\frac{d\boldsymbol{D}_t}{d\boldsymbol{X}^{hh}}$$

- What can we say about policy function term $d\boldsymbol{y}_t$?

Pertubation of policy function

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- Let $\boldsymbol{y}_t^s$ be policy function at time t following a shock in period s. Then:

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- Verbally: The response of the policy function $\boldsymbol{y}$ at time t to a shock at s is the as the response at time $t+j$ to a shock at $s+j$
  - Policy function **does not depend on the absolut time of shock** only the relative distance between »today« and the shock, $s-t$.

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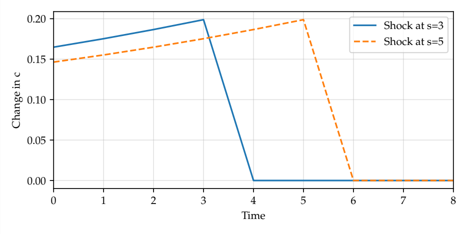
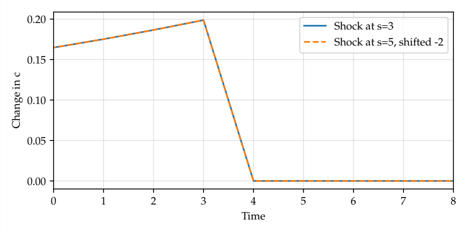
  - Policy function **does not depend on the absolut time of shock** only the relative distance between »today« and the shock, $s-t$.
- **Implication**: We need to only do a single backwards iteration to a shock at $s = T-1$.
  - Can then construct change in policy function $d\boldsymbol{y}_t^s/d\boldsymbol{X}^{hh}$ for different s by shifting policy function around

Numerical illustration

Graphically. Response of c_t to income shock at $s = 3, 5$





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- Can we use same logic for aggreregate Jacobian, $\mathcal{J}_{t,s} = \mathcal{J}_{t-1,s-1}$?
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- Can write aggregate Jacobian as:

$$\mathcal{J}_{t,s} = \begin{cases} \mathcal{F}_{t,s} & \text{for } t = 0, s = 0 \\ \mathcal{J}_{t-1,s-1} + \mathcal{F}_{t,s} & \text{for } t, s > 0 \end{cases}$$

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$$\mathcal{J}_{t,s} = \begin{cases} \mathcal{F}_{t,s} & \text{for } t = 0, s = 0 \\ \mathcal{J}_{t-1,s-1} + \mathcal{F}_{t,s} & \text{for } t, s > 0 \end{cases}$$

- where $\mathcal{F}_{t,s}$ is the **fake news** matrix.

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- Why »fake news«? $\mathcal{F}_{t,s}$ captures effect of announcing a date$-s$ shock at time 0, and retracting the annountment at date 1
  - Policy variables revert to steady state after period 1, but distribution changes since $d\boldsymbol{y}_0 \neq 0$

Fake News Matrix

- Can show that the fake news matrix can be computed as:

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- $t > 0$ elements: Only involves basic matrix multiplication once we have $d\boldsymbol{D}_1^s/d\boldsymbol{X}^{hh}$
  - Since we have derivatves of policy function for all t, s $d\boldsymbol{y}_t^s/d\boldsymbol{X}^{hh}$ can get $d\boldsymbol{D}_1^s/d\boldsymbol{X}^{hh}$ easily
  - Note: Not too expensive since histogram method for distribution is fast and efficient

Fake news algorithm - summary

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  - Can then use Quasi-Newton methods to solve dynamic GE model!
- GEModeltools does all of this »under the hood« when you compute HH Jacobians
  - You just tell GEModeltools the inputs and outputs of the household block
  - Entire algorithm is automated

Exercises

Exercises: HANCGovModel

Same model. Your choice of τ_{ss}. New questions:

1. **Define the transition path.**
2. **Plot the DAG**
3. **What do the Jacobians look like?**
4. **Find the transition path for** $G_t = G_{ss} + 0.01 G_{ss} 0.95^t$
5. **What explains household savings behavior?**
6. **What happens to consumption inequality?**

Summary

Summary and next week

- **Today:**
  1. The concept of a transition path
  2. Details of the GEModelTools package
- **Homework:** Work on completing the model extension exercise
- **Next week:** Linear transitions + begin working on Assignment 1

Linear transitions and aggregate uncertainty

Reminder of model class

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- In deterministic, perfect foresigh model (MIT shocks), solve $H(\boldsymbol{U}, \boldsymbol{Z}) = 0$ by
  1. Calculating the Jacobian of H w.r.t $\boldsymbol{U}$ around s.s.
  2. Use Newton's method to find non-linear transition given $\boldsymbol{Z}$

  $\Rightarrow$ But we have abstracted from real aggregate uncertainty

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  - Implies that aggregate shocks are not random process, but rather *MIT shocks*
  - Interpretation of MIT shocks generally hard to reconcile with business cycles

Stochastic vs deterministic models

- To see how the **stochastic** model and deterministic model are related consider the Euler with random x:

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- Same result! Aggregate uncertainty **does not matter to first-order** when linearizing w.r.t aggregate shock

When does aggregate uncertainty matter?

- **Insight:** *The IRF from an MIT shock is* <u>*equivalent*</u> *to the IRF in a model with aggregate risk, which is linearized in the aggregate variables* (Boppart et. al., 2018)

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- In deterministic model $\sigma^2_{x,t} = 0$ - not true in stochastic model!
  - Models deviate once we go beyond 1st order approximation (linearization)
- Still extremely usefull though - we may solve deterministic models to first-order and interpret as models with aggregate uncertainty
  - How do we linearize models numerically?

Linearized IRFs

- Solve for IRfs for unknowns using first-order approximation

$$H(\boldsymbol{U}, \boldsymbol{Z}) = 0 \Rightarrow H_U d\boldsymbol{U} + H_{\boldsymbol{Z}} d\boldsymbol{Z} = 0 \Leftrightarrow d\boldsymbol{U} = \underbrace{-H_U^{-1} H_z}_{=G_U} d\boldsymbol{Z}$$

- We can find H_U and H_Z as before using fake-news
- Limitations:
  - Imprecise for large shocks
  - Imprecise in models with aggregate non-linearities
  - No real aggregate uncertainty (precautionary savings w.r.t. aggregate shocks, etc)

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     Note: $d\boldsymbol{Z}_s \tilde{\boldsymbol{\epsilon}}_{t-s} =$ effect of shock s periods ago today

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- **Intuition:** Sum of first order effects from all previous shocks

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- Same principle with more shocks

Calculating moments - covariance

- **Covariances:**

$$\text{cov}(dC_t, dY_{t+k}) = \sum_{i \in \mathcal{Z}} \sigma_i^2 \sum_{s=0}^{T-1-k} dC_s^i dY_{s+k}^i$$

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- **Covariance decomposition:**

$$\frac{\text{contribution from one shock}}{\text{contributions from all shocks}} = \frac{\sigma_j^2 \sum_{s=0}^{T-1-k} dC_s^j dY_{s+k}^j}{\sum_{i\in\mathcal{Z}} \sigma_i^2 \sum_{s=0}^{T-1-k} dC_s^i dY_{s+k}^i}$$

Solving HA model with aggregate risk (advanced)

- To solve models with aggregate risk we need to write them in *state-space* form instead of *sequence-space*
  - Think of HA household problem - that is always in state-space form
  - Endogenous variables c_t, a_t as function of current states a_{t-1}, z_t

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$$\begin{bmatrix} \boldsymbol{U}_t \\ \boldsymbol{Z}_t \end{bmatrix} = \mathcal{M}\left(\begin{bmatrix} \boldsymbol{U}_{t-1} \\ \boldsymbol{Z}_{t-1} \end{bmatrix}, \boldsymbol{\epsilon}_t \right)$$

$\neq$ perfect foresight wrt. future agg. variables in *sequence-space*

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  - Endogenous variables c_t, a_t as function of current states a_{t-1}, z_t
- **Aggregate stochastic variables:** $\boldsymbol{Z}$ follow some known process with innovations ϵ. *State space form*: RHS is what is known today

$$\begin{bmatrix} \boldsymbol{U}_t \\ \boldsymbol{Z}_t \end{bmatrix} = \mathcal{M}\left(\begin{bmatrix} \boldsymbol{U}_{t-1} \\ \boldsymbol{Z}_{t-1} \end{bmatrix}, \boldsymbol{\epsilon}_t\right)$$

  $\neq$ perfect foresight wrt. future agg. variables in *sequence-space*
- In standard NK model: no backward looking eqs. so number of state variables = Number of shocks

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- **Recursive formulation of household problem:**

$$v(\boldsymbol{D}_t, \Gamma_t, z_{it}, a_{it-1}) = \max_{a_{it}, c_{it}} u(c_{it}) + \beta \mathbb{E}_t \left[v(\boldsymbol{D}_{t+1}, \Gamma_{t+1}, z_{it+1}, a_{it}) \right]$$

s.t.

$$\begin{aligned}
K_{t-1} &= \int a_{it-1} d\boldsymbol{D}_t \\
r_t &= \alpha \Gamma_t K_{t-1}^{\alpha-1} - \delta \\
w_t &= (1-\alpha) \Gamma_t K_{t-1}^{\alpha} \\
a_{it} + c_{it} &= (1 + r_t) a_{it-1} + w_t z_{it} \\
\log z_{it+1} &= \rho_z \log z_{it} + \psi_{it+1}, \;\; \psi_{it} \sim \mathcal{N}(\mu_\psi, \sigma_\psi), \;\; \mathbb{E}[z_{it}] = 1 \\
a_{it} &\geq 0,
\end{aligned}$$

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- $\boldsymbol{D}_t$ is a state variable $\Rightarrow$ Massive state space

Comparisons

- **State-space approach with linearization**: Ahn et al. (2018); Bayer and Luetticke (2020); Bhandari et al. (2023); Bilal (2023)
  Con:
  1. Harder to implement
  2. Valuable to be able to interpret Jacobians

  Pro**:**
  1. Easier path to 2nd and higher order approximations
- **Global solution:** The distribution of households is a state variable for each household $\Rightarrow$ *explosion in complexity*
  1. Original: Krusell and Smith (1997, 1998); Algan et al. (2014);
  2. Deep learning: Fernández-Villaverde et al. (2021); Maliar et al. (2021); Han et al. (2021); Kase et al. (2022); Azinovic et al. (2022); Gu et al. (2023); Chen et al. (2023)
- **Discrete aggregate risk:** Lin and Peruffo (2023)