

# Advanced Tools in Macroeconomics

## Continuous time models (and methods)

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August 25, 2017

# Plan for today

1. Speeding things up while making them more robust
  - 1.1 Use the “implicit method” to somewhat bring back the contraction property
  - 1.2 Make use of sparsity
2. Set up a continuous time heterogenous agents model and show how to solve it
3. Kolmogorov Forward equation
4. Equilibrium

# Why is the contraction property lost?

- ▶ Consider the deterministic Ramsey growth model again

$$v(k) = \max_c \{u(c) + (1 - \rho)v(f(k) + (1 - \delta)k - c)\}.$$

- ▶ In discrete time we iterate as

$$v_{n+1}(k) = \max_c \{u(c) + (1 - \rho)v_n(f(k) + (1 - \delta)k - c)\},$$

- ▶ This is a contraction mapping and we know that  $v_n \rightarrow v$ .

# Why is the contraction property lost?

- ▶ Let's, heuristically, convert this into continuous time

$$v_{n+1}(k) = \max_c \{ \Delta u(c) + (1 - \Delta\rho)v_n(k + \Delta(f(k) - \delta k - c)) \}.$$

$$0 = \max_c \left\{ u(c) + \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_{n+1}(k)}{\Delta} - \rho v_n(k + \Delta(f(k) - \delta k - c)) \right\}.$$

Taking limits and rearranging

$$\rho v_n(k) = \max_c \left\{ u(c) + \lim_{\Delta \rightarrow 0} \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_{n+1}(k)}{\Delta} \right\}.$$

# Why is the contraction property lost?

- ▶ Problem

$$\lim_{\Delta \rightarrow 0} \frac{v_n(k + \Delta(f(k) - \delta k - c)) - v_{n+1}(k)}{\Delta} \neq v_n'(k)(f(k) - \delta - c)$$

- ▶ The right hand side of the HJB equation contains  $v_{n+1}$  and that's a major issue

# How to get it back

- ▶ Back to discrete time

$$v_{n+1}(k) = \max_c \{u(c) + (1 - \rho)v_n(f(k) + (1 - \delta)k - c)\},$$

- ▶ Call the optimal choice  $c_n$  (it's really a function of  $k$  but I'm saving some space)
- ▶ Howard's Improvement Algorithm says that we can then iterate on

$$v_{n+1}^{h+1}(k) = u(c_n) + (1 - \rho)v_{n+1}^h(f(k) + (1 - \delta)k - c_n)\},$$

with  $v_{n+1}^0 = v_n$ .

- ▶ Until  $v_{n+1}^{h+1} \approx v_{n+1}^h$ . This can speed things up considerably, and preserves the contraction property

# How to get it back

- ▶ Suppose that it holds exactly  $v_{n+1}^{h+1} = v_{n+1}^h$ , and let's just call this function  $v_{n+1}$ . Then it must satisfy

$$v_{n+1}(k) = \max_c \{u(c_n) + (1 - \rho)v_{n+1}(f(k) + (1 - \delta)k - c_n)\},$$

- ▶ In  $\Delta$  units of time

$$v_{n+1}(k) = \Delta u(c_n) + (1 - \Delta\rho)v_{n+1}(k + \Delta(f(k) - \delta k - c_n)).$$

# How to get it back

Rearrange

$$0 = u(c_n) + \frac{v_{n+1}(k + \Delta(f(k) - \delta k - c_n)) - v_{n+1}(k)}{\Delta} - \rho v_{n+1}(k + \Delta(f(k) - \delta k - c_n)).$$

and take limits

$$\rho v_{n+1}(k) = u(c_n) + v'_{n+1}(k)(f(k) - \delta k - c_n),$$



# How to get it back

$$\rho v_{n+1}(k) = u(c_n) + v'_{n+1}(k)(f(k) - \delta k - c_n),$$

- ▶ Now the awkward discrepancy between  $v_{n+1}$  and  $v_n$  is gone!
- ▶ But the problem looks a bit hard to solve!
- ▶ Turns out it is not!
- ▶ This is where the “implicit method” comes in.

# The implicit method

1. Start with a grid for capital  $\mathbf{k} = [k_1, k_2, \dots, k_N]$ .
2. For each grid point for capital you have a guess for  $v_0(k_i)$ ,  
 $\forall k_i \in \mathbf{k}$
3. So you have a vector of  $N$  values of  $v_0$ . Call this  $\mathbf{v}_0$
4. You should also have a difference operator (an  $N \times N$  matrix)  $\mathbf{D}$  such that

$$\mathbf{D}\mathbf{v} \approx \mathbf{v}'(k), \quad \forall k_i \in \mathbf{K}$$

# The implicit method

5. Optimal consumption choice given by FOC

$$u'(\mathbf{c}_0) = \mathbf{D}\mathbf{v}_0$$

reasonable to call this  $c(\mathbf{v}_0)$  – an  $N \times 1$  vector

6. This implies another  $N \times 1$  vector of savings

$$\mathbf{s}_0 = (f(\mathbf{k}) - \delta\mathbf{k} - c(\mathbf{v}_0))$$

(This vector can be used to improve on  $\mathbf{D}$  – more on that in a second).

7. Create the  $N \times N$  matrix  $\mathbf{S}_0 = \text{diag}(\mathbf{s}_0)$

# The implicit method

That is

$$\mathbf{S} = \begin{pmatrix} s_1 & 0 & \dots & 0 \\ 0 & s_2 & \dots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & s_N \end{pmatrix},$$

# The implicit method

8. Then our HJB equation can now be written as

$$\rho \mathbf{v}_1 = u(c(\mathbf{v}_0)) + \mathbf{S}_0 \mathbf{D} \mathbf{v}_1$$

9. Manipulate

$$(\rho \mathbf{I} - \mathbf{S}_0 \mathbf{D}) \mathbf{v}_1 = u(c(\mathbf{v}_0))$$

10. Lastly

$$\mathbf{v}_1 = (\rho \mathbf{I} - \mathbf{S}_0 \mathbf{D})^{-1} u(c(\mathbf{v}_0))$$

11. Generally

$$\mathbf{v}_{n+1} = (\rho \mathbf{I} - \mathbf{S}_n \mathbf{D})^{-1} u(c(\mathbf{v}_n))$$

# The implicit method

Or even more generally

$$\mathbf{v}_{n+1} = ((\rho + 1/\Gamma)\mathbf{I} - \mathbf{S}_n\mathbf{D})^{-1}[u(c(\mathbf{v}_n)) + \mathbf{v}_n/\Gamma]$$

for  $\Gamma$  very large (my experience:  $\Gamma = \infty$  is fastest, but set lower if convergence issues arise)

- ▶ In matlab always use backslash operator to calculate  $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$ . I.e.  $\mathbf{x} = \mathbf{A}\backslash\mathbf{b}$

We are talking very substantial speed/robustness gains here. Perhaps by a factor of 1,000.

# The implicit method: Improvement trick I

- ▶ Yesterday we created the matrix  $\mathbf{D}$  as central differences
- ▶ We can do better. In particular,  $\mathbf{s}_n$  tells us where the economy is drifting for each  $k_i \in \mathbf{k}$
- ▶ So trick one is to use forward differences for all

$$\{k_i \in \mathbf{k} : s_i > 0\}$$

- ▶ and backward differences for all

$$\{k_i \in \mathbf{k} : s_i < 0\}$$

- ▶ This leads to

$$\mathbf{v}_{n+1} = ((\rho + 1/\Gamma)\mathbf{I} - \mathbf{S}_n\mathbf{D}_n)^{-1}[u(c(\mathbf{v}_n)) + \mathbf{v}_n/\Gamma]$$

# The implicit method: Improvement trick II

- ▶ Inspect the matrix

$$((\rho + 1/\Gamma)\mathbf{I} - \mathbf{S}_n\mathbf{D}_n),$$

and notice that all matrices are super sparse!

- ▶ So declaring them as sparse will free up a lot of memory and give you enormous speed gains too (this is particularly true for problems with  $N > 200$  or so. Below that it doesn't really matter).
- ▶ **Never** declare any of these matrices as anything else than sparse! Use commands as `speye` and `spdiags`
- ▶ **Don't** be too concerned about loops. That doesn't seem to be what can clog these systems.



# The Aiyagari Model in Continuous Time

- ▶ The rest of today's lecture will be to apply our knowledge thus far to the Aiyagari model in continuous time.
  - ▶ This will also be today's exercise
1. Households' problem
  2. Firms problem
  3. Equilibrium

# Households

- ▶ Households can be employed or unemployed
- ▶ When employed they receive income  $w_t(1 - \tau_t)$
- ▶ When unemployed they receive unemployment benefits equal to  $\mu w_t$
- ▶ An employed individual becomes unemployed with probability  $\lambda_e$ .
- ▶ An unemployed individual becomes employed with probability  $\lambda_u$
- ▶ In an Aiyagari model prices are constant:  $r_t = r$  and  $w_t = w \forall t$

# Households

- ▶ Dynamics of aggregate unemployment

$$e_{t+1} = (1 - \lambda_e)e_t + \lambda_u u_t$$

$$u_{t+1} = \lambda_e e_t + (1 - \lambda_u)u_t$$

- ▶  $\Delta$  units of time

$$e_{t+\Delta} = (1 - \Delta\lambda_e)e_t + \Delta\lambda_u u_t$$

$$u_{t+\Delta} = \Delta\lambda_e e_t + (1 - \Delta\lambda_u)u_t$$

- ▶ Rearrange and take limits

$$\dot{e}_t = -\lambda_e e_t + \lambda_u u_t$$

$$\dot{u}_t = \lambda_e e_t - \lambda_u u_t$$

# Households

- ▶ System

$$\dot{\mathbf{s}}_t = \mathbf{T}\mathbf{s}_t$$

with

$$\mathbf{T} = \begin{pmatrix} -\lambda_e & \lambda_u \\ \lambda_e & -\lambda_u \end{pmatrix}$$

- ▶ Stationary equilibrium

$$\mathbf{0} = \mathbf{T}\mathbf{s}$$

- ▶ Thus  $\mathbf{s}$  is an eigenvector associated with a zero eigenvalue, with the eigenvector normalised to sum to one.

# Households

- ▶ Can be solved as a regular eigenvalue problem
- ▶ But since the eigenvector is only defined up to a scalar we can use the following trick
  1. Create vector

$$\mathbf{b} = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad \text{and matrix} \quad \hat{\mathbf{T}} = \begin{pmatrix} 1 & 0 \\ \lambda_e & -\lambda_u \end{pmatrix}$$

2. Find  $\hat{\mathbf{s}}$  as  $\hat{\mathbf{s}} = \hat{\mathbf{T}}^{-1}\mathbf{b}$ .
  3. Normalise  $\hat{\mathbf{s}}$  to sum to one to find  $\mathbf{s}$ .
- ▶ The first element of  $\mathbf{s}$  is then the stationary employment rate, and the second the stationary unemployment rate.

# Households

- ▶ Government runs a balanced budget, so not deficits
- ▶ The tax rate then solves  $u\mu w = e\tau w$
- ▶ Or just  $\tau = \frac{u}{e}\mu$

# Households

- ▶ Bellman equation for an employed agent

$$v(a_t, e) = \max_{c_t} \{ u(c_t) + (1 - \rho) \times \\ [(1 - \lambda_e)v(w_t(1 - \tau_t) + (1 + r_t)a_t - c_t, e) \\ + \lambda_e v(w_t(1 - \tau_t) + (1 + r_t)a_t - c_t, u)] \}$$

subject to  $a_t \geq \phi \forall t$ .

- ▶  $\Delta$  units of time

$$v(a_t, e) = \max_{c_t} \{ \Delta u(c_t) + (1 - \Delta\rho) \times \\ [(1 - \Delta\lambda_e)v(\Delta(w_t(1 - \tau_t) + r_t a_t - c_t) + a_t, e) \\ + \Delta\lambda_e v(\Delta(w_t(1 - \tau_t) + r_t a_t - c_t) + a_t, u)] \}$$

# Households

- ▶ Rearrange and divide by  $\Delta$

$$\begin{aligned} 0 = & \max_{c_t} \{ u(c_t) \\ & + \frac{v(\Delta(w_t(1 - \tau_t) + r_t a_t - c_t) + a_t, e) - v(a_t, e)}{\Delta} \\ & - (\rho + \lambda_e + \Delta \rho \lambda_e) v(\Delta(w_t(1 - \tau_t) + r_t a_t - c_t) + a_t, e) \\ & + \lambda_e v(\Delta(w_t(1 - \tau_t) + r_t a_t - c_t) + a_t, u) \} \end{aligned}$$

- ▶ Take limits and rearrange

$$\begin{aligned} \rho v(a, e) = & \max_c \{ u(c) + v_a(a, e)(w(1 - \tau) + ra - c) \\ & - \lambda_e(v(a, e) - v(a, u)) \} \end{aligned}$$



# Households

So households' problem is given by the two HJB equations

$$\rho v(a, e) = \max_c \{ u(c) + v_a(a, e)(w(1 - \tau) + ra - c) - \lambda_e(v(a, e) - v(a, u)) \}$$

$$\rho v(a, u) = \max_c \{ u(c) + v_a(a, u)(w\mu + ra - c) - \lambda_u(v(a, u) - v(a, e)) \}$$

Let's be smart in solving them!

# Households

1. Start with a linearly spaced grid for assets  
 $\mathbf{a} = [a_1, a_2, \dots, a_N]$ . Let  $da = a(n+1) - a(n)$ .
2. For each grid for assets guess a for  $v_0(a_i, j)$ ,  $\forall a_i \in \mathbf{a}$ , and  $j \in \{e, u\}$ . This gives us  $\mathbf{v}_{0,e}$  and  $\mathbf{v}_{0,u}$
3. Call the stacked  $2N \times 1$  vector  $(\mathbf{v}_{0,e}, \mathbf{v}_{0,u})'$  for  $\mathbf{v}_0$ .

# Households

4. Create two  $N \times N$  difference operators as

$$\mathbf{D}_f = \begin{pmatrix} -1/da & 1/da & 0 & \dots & 0 \\ 0 & -1/da & 1/da & 0 & \\ \vdots & 0 & \ddots & \ddots & \vdots \\ \vdots & \dots & & -1/da & 1/da \\ 0 & \dots & & 0 & -1 \end{pmatrix}$$

$$\mathbf{D}_b = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ -1/da & 1/da & 0 & & \\ \vdots & -1/da & 1/da & \ddots & \vdots \\ \vdots & 0 & \ddots & \ddots & \vdots \\ \vdots & \dots & & -1/da & 1/da \end{pmatrix}$$

# Households

5. Create one  $2N \times 2N$  matrix as

$$\mathbf{B} = \begin{pmatrix} -\lambda_e & 0 & \dots & 0 & \lambda_e & 0 & \dots & 0 \\ 0 & -\lambda_e & 0 & \dots & 0 & \lambda_e & \dots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots & \dots & \ddots & \vdots \\ 0 & 0 & 0 & -\lambda_e & 0 & \dots & \dots & \lambda_e \\ \lambda_u & 0 & \dots & 0 & -\lambda_u & 0 & \dots & 0 \\ 0 & \lambda_u & 0 & \dots & 0 & -\lambda_u & \dots & 0 \\ \vdots & 0 & \ddots & \ddots & \vdots & \dots & \ddots & \vdots \\ 0 & 0 & 0 & \lambda_u & 0 & 0 & \dots & -\lambda_u \end{pmatrix}$$

will be used later

# Households

6. Calculate the derivative of the value functions using both forward and backward differences

$$\begin{aligned}\mathbf{v}'_f(a, e) &= \mathbf{D}_f \mathbf{v}_{0,e}, & \mathbf{v}'_b(a, e) &= \mathbf{D}_b \mathbf{v}_{0,e}, \\ \mathbf{v}'_f(a, u) &= \mathbf{D}_f \mathbf{v}_{0,u}, & \mathbf{v}'_b(a, u) &= \mathbf{D}_b \mathbf{v}_{0,u},\end{aligned}$$

7. Set the **first** elements of  $\mathbf{v}'_b(a, e) = u'(w(1 - \tau) + r\phi)$  and  $\mathbf{v}'_b(a, u) = u'(w\mu + r\phi)$ , and the **last** elements of  $\mathbf{v}'_f(a, e) = u'(w(1 - \tau) + ra_N)$  and  $\mathbf{v}'_f(a, u) = u'(w\mu + ra_N)$
8. Find optimal consumption through

$$\begin{aligned}u'(\mathbf{c}_{e,f}) &= \mathbf{D}_f \mathbf{v}_{0,e}, & u'(\mathbf{c}_{e,b}) &= \mathbf{D}_b \mathbf{v}_{0,e}, \\ u'(\mathbf{c}_{u,f}) &= \mathbf{D}_f \mathbf{v}_{0,u}, & u'(\mathbf{c}_{u,b}) &= \mathbf{D}_b \mathbf{v}_{0,u},\end{aligned}$$

# Households

9. Find optimal savings as

$$\mathbf{s}_{e,f} = w(1 - \tau) + r\mathbf{a} - \mathbf{c}_{e,f}, \quad \mathbf{s}_{e,b} = w(1 - \tau) + r\mathbf{a} - \mathbf{c}_{e,b},$$
$$\mathbf{s}_{u,f} = w\mu + r\mathbf{a} - \mathbf{c}_{u,f}, \quad \mathbf{s}_{u,b} = w\mu + r\mathbf{a} - \mathbf{c}_{u,b}$$

10. Create indicator vectors

$$\mathbf{l}_{e,f} = (l_{1,e,f}, l_{2,e,f}, \dots, l_{N,e,f})', \quad \mathbf{l}_{e,b} = (l_{1,e,b}, l_{2,e,b}, \dots, l_{N,e,b})',$$
$$\mathbf{l}_{u,f} = (l_{1,u,f}, l_{2,u,f}, \dots, l_{N,u,f})', \quad \mathbf{l}_{u,b} = (l_{1,u,b}, l_{2,u,b}, \dots, l_{N,u,b})',$$

where  $l_{i,j,f} = 1$  if  $s_{i,j,f} > 0$  and  $l_{i,j,b} = 1$  if  $s_{i,j,b} < 0$ , for  $i = 1, \dots, N$  and  $j \in \{e, u\}$ .

# Households

11. Find consumption as

$$\mathbf{c}_e = \mathbf{l}_{e,f} \cdot \mathbf{c}_{e,f} + \mathbf{l}_{e,b} \cdot \mathbf{c}_{e,b}$$

$$\mathbf{c}_u = \mathbf{l}_{u,f} \cdot \mathbf{c}_{u,f} + \mathbf{l}_{u,b} \cdot \mathbf{c}_{u,b}$$

12. Find savings as

$$\mathbf{s}_e = \mathbf{l}_{e,f} \cdot \mathbf{s}_{e,f} + \mathbf{l}_{e,b} \cdot \mathbf{s}_{e,b}$$

$$\mathbf{s}_u = \mathbf{l}_{u,f} \cdot \mathbf{s}_{u,f} + \mathbf{l}_{u,b} \cdot \mathbf{s}_{u,b}$$

13. And matrices  $\mathbf{S}_e \mathbf{D}_e$  and  $\mathbf{S}_u \mathbf{D}_u$  as

$$\mathbf{S}_e \mathbf{D}_e = \text{diag}(\mathbf{l}_{e,f} \cdot \mathbf{s}_{e,f}) \mathbf{D}_f + \text{diag}(\mathbf{l}_{e,b} \cdot \mathbf{s}_{e,b}) \mathbf{D}_b$$

$$\mathbf{S}_u \mathbf{D}_u = \text{diag}(\mathbf{l}_{u,f} \cdot \mathbf{s}_{u,f}) \mathbf{D}_f + \text{diag}(\mathbf{l}_{u,b} \cdot \mathbf{s}_{u,b}) \mathbf{D}_b$$

# Households

14. Lastly find the  $2N \times 2N$  matrix  $\mathbf{S}_0\mathbf{D}_0$  as

$$\mathbf{S}_0\mathbf{D}_0 = \begin{pmatrix} \mathbf{S}_e\mathbf{D}_e & \mathbf{0} \\ \mathbf{0} & \mathbf{S}_u\mathbf{D}_u \end{pmatrix}$$

15. And the matrix  $\mathbf{P}_0$  as

$$\mathbf{P}_0 = \mathbf{S}_0\mathbf{D}_0 + \mathbf{B}$$



# Households

Using the implicit method the households' problem is given by the two HJB equations

$$\begin{aligned}\rho v_{n+1}(a, e) = & u(c_n) + v_{a,n+1}(a, e)(w(1 - \tau) + ra - c_n) \\ & - \lambda_e(v_{n+1}(a, e) - v_{n+1}(a, u))\end{aligned}$$

$$\begin{aligned}\rho v_{n+1}(a, u) = & u(c_n) + v_{a,n+1}(a, u)(w\mu + ra - c) \\ & - \lambda_u(v_{n+1}(a, u) - v_{n+1}(a, e))\end{aligned}$$

# Households

- ▶ These can now be written as

$$\rho \mathbf{v}_{n+1} = u(\mathbf{c}_n) + \mathbf{P}_n \mathbf{v}_{n+1}$$

with  $\mathbf{c}_n = (\mathbf{c}_{n,e}, \mathbf{c}_{n,u})$ .

- ▶ So we iterate on

$$\mathbf{v}_{n+1} = [(\rho + 1/\Gamma)\mathbf{I} - \mathbf{P}_n]^{-1}[u(\mathbf{c}_n) + \mathbf{v}_n/\Gamma]$$

until convergence

# Firms

- ▶ Firms face the standard static optimisations problem

$$\Pi_t = \max\{K_t^\alpha N_t^{1-\alpha} - w_t N_t - (r_t + \delta)K_t\}$$

- ▶ With first order conditions

$$r_t = \alpha \left(\frac{K_t}{N_t}\right)^{\alpha-1} - \delta, \quad w_t = (1 - \alpha) \left(\frac{K_t}{N_t}\right)^\alpha$$

- ▶ In a stationary equilibrium this implies

$$r = \alpha \left(\frac{K}{(1-u)N}\right)^{\alpha-1} - \delta, \quad w = (1 - \alpha) \left(\frac{r + \delta}{\alpha}\right)^{\frac{\alpha}{\alpha-1}}$$

# Stationary distribution

- ▶ What is the evolution of the endogenous stationary distribution of wealth and employment status?
- ▶ Denote the CDF as  $G_{t+1}(a, e)$ . This must satisfy

$$G_{t+1}(a, e) = (1 - \lambda_e)G_t(a_{-1}^e, e) + \lambda_u G_t(a_{-1}^u, u),$$

where  $a_{-1}^j$  denotes “where you came from” from optimally setting  $a_{t+1} = a$  in employment status  $j \in \{e, u\}$ .

- ▶ In  $\Delta$  units of time approximate this as  $a_{-1}^e = a - \Delta s_e$  and  $a - \Delta s_u$ . Thus

$$G_{t+\Delta}(a, e) = (1 - \Delta\lambda_e)G_t(a - \Delta s_e, e) + \Delta\lambda_u G_t(a - \Delta s_u, u),$$

# Stationary distribution

$$G_{t+\Delta}(a, e) = (1 - \Delta\lambda_e)G_t(a - \Delta s_e, e) + \Delta\lambda_u G_t(a - \Delta s_u, u),$$

- ▶ Subtract  $G_t(a, e)$  from both sides and divide by  $\Delta$

$$\frac{G_{t+\Delta}(a, e) - G_t(a, e)}{\Delta} = \frac{G_t(a - \Delta s_e, e) - G_t(a, e)}{\Delta} - \lambda_e G_t(a - \Delta s_e, e) + \lambda_u G_t(a - \Delta s_u, u),$$

- ▶ Take limits

$$\dot{G}_t(a, e) = -g_t(a, e)s_e(a) - \lambda_e G_t(a, e) + \lambda_u G_t(a, u),$$

# Stationary distribution/Kolmogorov Forward Equation

$$\dot{G}_t(a, e) = -g_t(a, e)s_e(a) - \lambda_e G_t(a, e) + \lambda_u G_t(a, u),$$

- ▶ Differentiate with respect to  $a$

$$\dot{g}_t(a, e) = -\frac{\partial[g_t(a, e)s_e(a)]}{\partial a} - \lambda_e g_t(a, e) + \lambda_u g_t(a, u),$$

- ▶ Thus the law of motion for the endogenous distribution is

$$\dot{g}_t(a, e) = -\frac{\partial[g_t(a, e)s_e(a)]}{\partial a} - \lambda_e g_t(a, e) + \lambda_u g_t(a, u),$$

$$\dot{g}_t(a, u) = -\frac{\partial[g_t(a, u)s_u(a)]}{\partial a} - \lambda_u g_t(a, u) + \lambda_e g_t(a, e)$$

# Stationary distribution/Kolmogorov Forward Equation

- ▶ Remember the matrix

$$\mathbf{P}_n = \mathbf{S}_n \mathbf{D}_n + \mathbf{B}.$$

- ▶ When converged

$$\mathbf{P} = \mathbf{S} \mathbf{D} + \mathbf{B}$$

- ▶ Turns out that

$$\dot{\mathbf{g}}_t = \mathbf{P}' \mathbf{g}_t$$

- ▶ Where  $\mathbf{g}_t$  is the stacked vector  $(\mathbf{g}_t(a, e), \mathbf{g}_t(a, u))'$

# Solving the Aiyagari model

1. Guess for an interest rate  $r_n$ . Find  $w_n$  as

$$w_n = (1 - \alpha) \left( \frac{r_n + \delta}{\alpha} \right)^{\frac{\alpha}{\alpha-1}}$$

2. Find  $\mathbf{v}$  such that

$$\mathbf{v} = [(\rho + 1/\Gamma)\mathbf{I} - \mathbf{P}]^{-1}[u(c(\mathbf{v})) + \mathbf{v}/\Gamma]$$

3. Find  $\mathbf{g}$  by solving

$$\mathbf{0} = \mathbf{P}'\mathbf{g}$$

and normalise to sum to one (remember how we found  $\mathbf{s}$  above)



# Solving the Aiyagari model

4. Find  $K_n$  as

$$K_n = \mathbf{g}' \begin{pmatrix} \mathbf{a} \\ \mathbf{a} \end{pmatrix}$$

5. Find  $\hat{r}$  as

$$\hat{r} = \alpha \left( \frac{K_n}{(1-u)} \right)^{\alpha-1} - \delta$$

6. If  $\hat{r} > r$  set  $r_{n+1} > r_n$ , else set  $r_{n+1} < r_n$ .  
7. Repeat until  $\hat{r} \approx r_n$ .