Advanced Tools in Macroeconomics

The endogenous cross-sectional distribution

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2023

- Once you have found the policy functions of a problem, you often need to calculate the long run distribution
 - We did that quite easily for the continuous time model yesterday
- ▶ It is need for market clearing in incomplete markets models
- ▶ But it can also be quite useful for representative agent models.
- ► This note will explain how you can do that in a discrete time setting.

- ▶ These problems typically give rise to a policy function of the type g(b, s).
 - where b is wealth or capital, and s is either employment status or TFP.
- This cannot be represented as a transition matrix.
- So how can we find the long run distribution of bonds (and employment status) in this case?

- ▶ In general, suppose that $\psi_0(b, s)$ is a probability density function in period zero
- ► Then

$$\psi_1(b',s') = \sum_{s \in \mathcal{S}} \sum_{\{b:b'=g(b,s)\}} \psi_0(b,s) p(s',s)$$

► And in general

$$\psi_{t+1}(b',s') = \sum_{s \in \mathcal{S}} \sum_{\{b:b'=g(b,s)\}} \psi_t(b,s) p(s',s)$$

Complications

ightharpoonup A stationary cross-sectional distribution, ψ , is such that

$$\psi(b',s') = \sum_{s \in \mathcal{S}} \sum_{\{b:b'=g(b,s)\}} \psi(b,s) p(s',s)$$

▶ This is very tricky to compute. The best practice I am aware of is to convert g(b, s) into a transition matrix!

Consider the following policy function

$$egin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{pmatrix}
ightarrow egin{pmatrix} 1.8 \\ 2.4 \\ 3 \\ 3.6 \\ 4.2 \end{pmatrix}$$

Nearest neighbor interpolation

$$\begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{pmatrix} \rightarrow \begin{pmatrix} 2 \\ 2 \\ 3 \\ 4 \\ 4 \end{pmatrix}$$

Can be written as transition matrix

$$\begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

But we can be a bit smarter. Policy function

$$\begin{array}{c}
1 \\
2 \\
3 \\
4 \\
5
\end{array}
\rightarrow
\begin{pmatrix}
1.8 \\
2.4 \\
3 \\
3.6 \\
4.2
\end{pmatrix}$$

Can be written as

$$\begin{pmatrix} 0.2 & 0.8 & 0 & 0 & 0 \\ 0 & 0.6 & 0.4 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0.4 & 0.6 & 0 \\ 0 & 0 & 0 & 0.8 & 0.2 \end{pmatrix}$$

But in the income fluctuation problem (and many others) we normally have two (or many) policy functions

$$\begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{pmatrix} \xrightarrow{\text{if good state}} \begin{pmatrix} 2.2 \\ 2.8 \\ 3.4 \\ 4 \\ 4.6 \end{pmatrix}, \text{ and } \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{pmatrix} \xrightarrow{\text{if bad state}} \begin{pmatrix} 1.4 \\ 2 \\ 2.6 \\ 3.2 \\ 3.8 \end{pmatrix}$$

With some transition matrix for good and bad states

$$T = \begin{pmatrix} 0.8 & 0.2 \\ 0.3 & 0.7 \end{pmatrix}$$

Nearest neighbor interpolation

$$\begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{pmatrix} \xrightarrow{\text{if good state}} \begin{pmatrix} 2 \\ 3 \\ 3 \\ 4 \\ 5 \end{pmatrix}, \quad \text{and} \quad \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{pmatrix} \xrightarrow{\text{if bad state}} \begin{pmatrix} 1 \\ 2 \\ 3 \\ 3 \\ 4 \end{pmatrix}$$

With some transition matrix for good and bad states

$$T = \begin{pmatrix} 0.8 & 0.2 \\ 0.3 & 0.7 \end{pmatrix}$$

Two transition matrices

$$M_{g} = egin{pmatrix} 0 & 1 & 0 & 0 & 0 \ 0 & 0 & 1 & 0 & 0 \ 0 & 0 & 1 & 0 & 0 \ 0 & 0 & 0 & 1 & 0 \ 0 & 0 & 0 & 0 & 1 \end{pmatrix}, \quad ext{and} \quad M_{b} = egin{pmatrix} 1 & 0 & 0 & 0 & 0 \ 0 & 1 & 0 & 0 & 0 \ 0 & 0 & 1 & 0 & 0 \ 0 & 0 & 1 & 0 & 0 \ 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

With some transition matrix for good and bad states

$$T = \begin{pmatrix} 0.8 & 0.2 \\ 0.3 & 0.7 \end{pmatrix}$$

Full transition matrix is given by

$$\begin{pmatrix} T(1,1) \cdot M_g & T(1,2) \cdot M_g \\ T(2,1) \cdot M_b & T(2,2) \cdot M_b \end{pmatrix}$$

Full transition matrix is given by

$$\begin{pmatrix} 0 & 0.8 & 0 & 0 & 0 & 0 & 0.2 & 0 & 0 & 0 \\ 0 & 0 & 0.8 & 0 & 0 & 0 & 0 & 0.2 & 0 & 0 \\ 0 & 0 & 0.8 & 0 & 0 & 0 & 0 & 0.2 & 0 & 0 \\ 0 & 0 & 0.8 & 0 & 0 & 0 & 0.2 & 0 & 0 \\ 0 & 0 & 0 & 0.8 & 0 & 0 & 0 & 0.2 & 0 \\ 0.3 & 0 & 0 & 0 & 0.7 & 0 & 0 & 0 & 0 \\ 0 & 0.3 & 0 & 0 & 0 & 0.7 & 0 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0 & 0 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0.7 & 0 \\ 0$$

Doing the same thing with the smarter method gives

(0	0.64	0.16	0	0	0	0.16	0.04	0	0 \
0	0.16	0.64	0	0	0	0.04	0.16	0	0
0	0	0.48	0.32	0	0	0	0.12	0.08	0
0	0	0	8.0	0	0	0	0	0.2	0
0	0	0	0.32	0.48	0	0	0	0.08	0.12
0.18	0.12	0		0	0.42	0.28	0	0	0
0	0.3	0	0	0	0	0.7	0	0	0
0	0.12	0.18	0	0	0	0.28	0.42	0	0
	•	0.10	•	-	-	00	· · · -	•	•
0	0	0.24		0	-	0	0.56		0

- lacktriangle Once you have the transition matrix it is quite easy to find the long run distribution, ψ
- As a linear system the law of motion is

$$oldsymbol{\psi_{t+1}} = \mathsf{T} \psi_\mathsf{t}$$

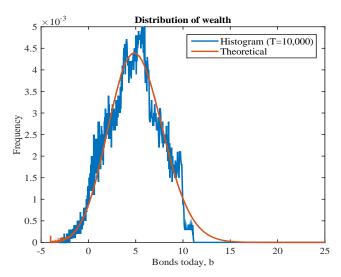
where \mathbf{T} is the transition matrix.

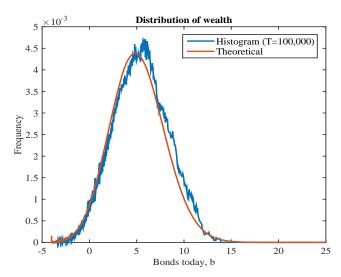
lacktriangle Then ψ can be found as the solution to

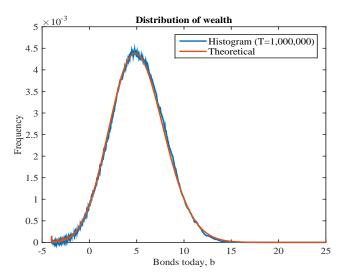
$$(\mathsf{T}-\mathsf{I})\psi=\mathsf{0}$$

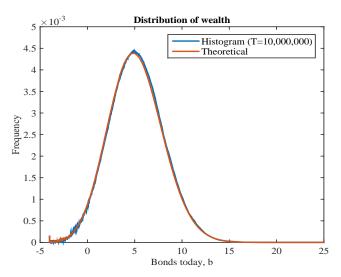
► That is, the long run distribution is the eigenvector of T associated with a *unit* eigenvalue, and normalized to sum to one.

- The next graphs will show this distribution for a heterogenous agent model
- ► I will illustrate it in two ways: The red line is the "theoretical" distribution calculated as in the previous slides
- The blue line is instead a histogram over a simulated path for one agent
- ► In the limit, when the simulated path is infinitely long, they will coincide
- ▶ But the theoretical distribution is much much faster to compute.









- ► The next graph shows the theoretical distribution for the model with irreversible investment
- Often it's not as important in rep agent models as in het agent models
- But I just want to show that you can do it.

Irreversible investment

