Lecture 5 Approximating Distribution

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Approaches

- Continuum of households makes the wealth distribution an infinite dimensional object in the state space
- Need approximation
- Several approaches beyond Monte-Carlo simulation
 - 1. Discretization of the density function
 - 2. Eigenvector method
 - 3. Parametrizing in exponential family

Discretization of the Invariant Density Function

- The grid should be finer than the one we used to compute the optimal savings rule
- Choose some initial density function λ^0 (a_k, y_i)
- For every (a_k, y_i) on the grid:

$$\lambda^{1}(a_{k}, y_{j}) = \sum_{y_{i} \in Y} \pi_{ij} \sum_{m \in M_{i}} \frac{a_{k+1} - g(a_{m}, y_{i})}{a_{k+1} - a_{k}} \lambda^{0}(a_{m}, y_{i})$$

$$\lambda^{1}(a_{k+1}, y_{j}) = \sum_{y_{i} \in Y} \pi_{ij} \sum_{m \in M_{i}} \frac{g(a_{m}, y_{i}) - a_{k}}{a_{k+1} - a_{k}} \lambda^{0}(a_{m}, y_{i})$$

where
$$M_i = \{m = 1, ..., N | a_k \leq g(a_m, y_i) \leq a_{k+1} \}$$

Lottery Rule

- We can think of this way of handling the discrete approximation to the density function as forcing the agents in the economy to play a lottery.
- If the optimal policy is to save $a' \in [a_k, a_{k+1}]$, then with probability $\frac{a_{k+1} a'}{a_{k+1} a_k}$ you go to a_k , and with probability $\frac{a' a_k}{a_{k+1} a_k}$ you go to a_{k+1} .

Eigenvector Method

- The invariant pdf for a Markov transition matrix Q is λ^* that satisfies $\lambda^*Q = \lambda^*$
- Perron-Frobenius Theorem: Q has a unique dominant eigenvalue $\epsilon=1$ such that
 - its associated eigenvector has all positive entries
 - all other eigenvalues are smaller than ϵ in absolute value
 - Q has no other eigenvector with all non-negative entries
- This eigenvector (renormalized so that it sums to one) is the unique invariant distribution

- For smooth and unimodal distributions we can approximate with parameterized functions in the exponential families
- Central moments are sufficient statistics of the distribution

- To approximate a one-dimensional distribution on k, assume the density function form

$$P(k,\rho) = \rho_0 \exp \begin{pmatrix} \rho_1 (k - m_1) \\ + \rho_2 \left[(k - m_1)^2 - m_2 \right] \\ + \rho_3 \left[(k - m_1)^3 - m_3 \right] \\ & \cdots \\ + \rho_N \left[(k - m_1)^N - m_N \right] \end{pmatrix}$$

 $-\rho$ – parameters to pin down, m – central moments

- We choose ρ such that moment condition holds

$$\int (k - m_1) P(k, \rho) dk = 0$$

$$\int \left[(k - m_1)^2 - m_2 \right] P(k, \rho) dk = 0$$

$$\dots$$

$$\int \left[(k - m_1)^N - m_N \right] P(k, \rho) dk = 0$$

These condition happen to be the optimal condition of

$$\min_{\rho_1,\dots,\rho_N} \int P(k,\rho) \, \mathrm{d}k$$

And the distribution has to be normalized to unity

$$\frac{1}{\rho_0} = \int P(k, \rho) \, \mathrm{d}k$$

Steps to compute invariant distribution:

- 1. Choose capital grid k_i and guess initial central moments $m_{i,0}$
- 2. Solve the minimization problem for ρ with $m_{j,0}$

$$\frac{1}{\rho_0} = \min_{\rho_1, \dots, \rho_N} \int P(k, \rho) \, \mathrm{d}k$$

3. With current distribution $P(k, \rho)$, compute moments using policy function g(k)

$$m_{1,1} = \int g(k) P(k,\rho) dk$$

 $m_{2,1} = \int (g(k) - m_{1,1})^2 P(k,\rho) dk$
...

$$m_{N,1} = \int (g(k) - m_{1,1})^N P(k, \rho) dk$$

4. Check convergence of *m*