

ECON 210: Section 7

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Plan for today

- ▶ Recap on consumption-savings with uncertainty
 - ▶ finite and markovian states
- ▶ Tauchen method to approximate $AR(1)$
- ▶ Consumption-savings with uncertainty (?)
- ▶ Coding
- ▶ Simulation of time-series:
 - ▶ $AR(1)$
 - ▶ Markov Chains

Consumption-Savings with Uncertainty

Recap

- Sequential problem with uncertainty

$$\max_{\{c_t(S^t), b_t(S^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \sum_{S^t} \beta^t P(S^t) u(c_t(S^t)) \quad (1)$$

$$c_t(S^t) + R^{-1} b_t(S^t) = b_{t-1}(S^{t-1}) + y_t(S^t) \quad (2)$$

$$c_t(S^t) \geq 0, b_t(S^t) \geq \underline{b} \quad (3)$$

- Assume income depends only on today's state + S_t is markovian
- Bellman equation is:

$$V(b, s) = \max_{c, b'} u(c) + \beta \sum_{s'} P(s'|s) V(b', s') \quad (4)$$

$$c + R^{-1} b' = b + y(s), c \geq 0, b' \geq \underline{b} \quad (5)$$

- New object: $P(s'|s)$

Tauchen Method

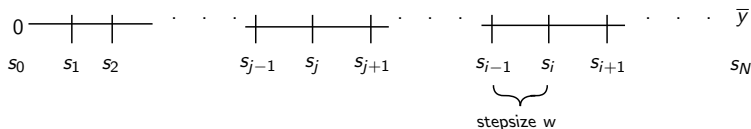
- ▶ The framework we introduced allows us to model uncertainty represented by finite states
- ▶ But in reality, the state space of uncertainty can actually be continuous
- ▶ Example: income can be \$203.43, \$12.41,...
- ▶ i.e. data from income is not discretized as in the model
- ▶ One possible model for income process is AR(1):

$$y_t = \lambda y_{t-1} + \sigma_\epsilon \epsilon_t, \epsilon_t \sim N(0, 1) \text{ iid} \quad (6)$$

- ▶ How to translate this to a finite state Markov chain?
 - ▶ → Tauchen Method

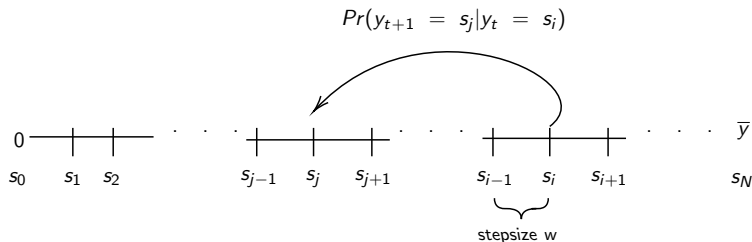
Tauchen Method

- Broad picture: discretize state space and say that the realized state is one the closest to continuous-variable



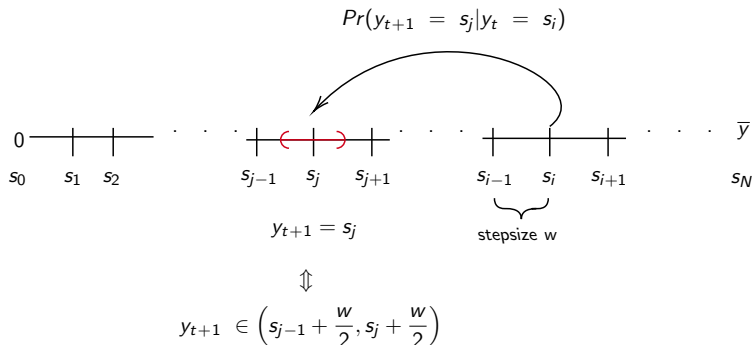
Tauchen Method

- Broad picture: discretize state space and say that the realized state is one the closest to continuous-variable



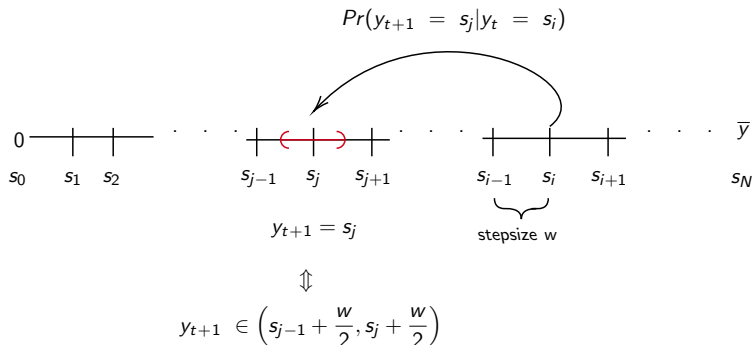
Tauchen Method

- Broad picture: discretize state space and say that the realized state is one the closest to continuous-variable



Tauchen Method

- Broad picture: discretize state space and say that the realized state is one the closest to continuous-variable

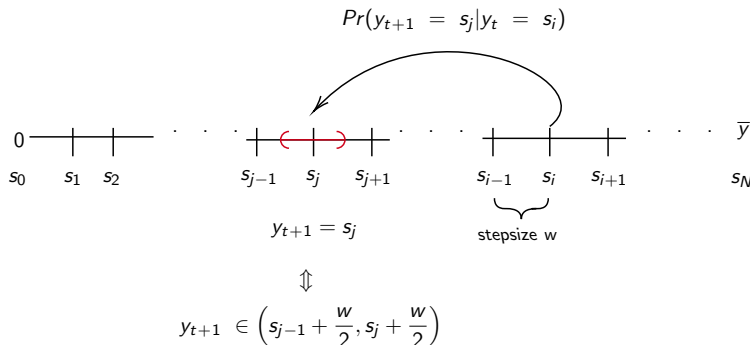


- Use the fact that y_t is $AR(1)$ to calculate

$$Pr \left(y_{t+1} \in \left(s_{j-1} + \frac{w}{2}, s_j + \frac{w}{2} \right) \right)$$

Tauchen Method

- Broad picture: discretize state space and say that the realized state is one the closest to continuous-variable



- Use the fact that y_t is $AR(1)$ to calculate

$$Pr\left(y_{t+1} \in \left(s_{j-1} + \frac{w}{2}, s_j + \frac{w}{2}\right)\right)$$

- What to do at the boundaries? Use only half the interval.

Tauchen Method

- ▶ Let $[\Pi_{ij}]$ be the transition matrix
- ▶ We set:

$$\Pi_{ij} = Pr \left[y_{t+1} \in \left(s_{j-1} + \frac{w}{2}, s_j + \frac{w}{2} \right) \right] \quad (7)$$

$$= Pr \left[s_{j-1} + \frac{w}{2} < \phi y_t + \sigma \varepsilon_{t+1} < s_j + \frac{w}{2} \right] \quad (8)$$

$$= Pr \left[\frac{s_{j-1} + \frac{w}{2} - \phi y_t}{\sigma} < \varepsilon_{t+1} < \frac{s_j + \frac{w}{2} - \phi y_t}{\sigma} \right] \quad (9)$$

$$= \Phi \left(\frac{s_j + \frac{w}{2} - \phi y_t}{\sigma} \right) - \Phi \left(\frac{s_{j-1} + \frac{w}{2} - \phi y_t}{\sigma} \right) \quad (10)$$

$$= \Phi \left(\frac{s_j + \frac{w}{2} - \phi s_i}{\sigma} \right) - \Phi \left(\frac{s_{j-1} + \frac{w}{2} - \phi s_i}{\sigma} \right) \quad (11)$$

where Φ is the cumulative distribution function of the standard normal

Tauchen Method

- At the boundaries:

$$\Pi_{i1} = \Phi \left(\frac{s_0 + \frac{w}{2} - \phi s_i}{\sigma} \right) \quad (12)$$

$$\Pi_{iN} = 1 - \Phi \left(\frac{s_N - \frac{w}{2} - \phi s_i}{\sigma} \right) \quad (13)$$

- How to set s_0 and s_N ?
 - Support of y_t is $(-\infty, \infty)$.
 - Typically truncate at 3 standard deviations.
 - Hence,

$$s_0 = -m \times \sqrt{\frac{\sigma^2}{1 - \phi^2}} \quad (14)$$

$$s_N = m \times \sqrt{\frac{\sigma^2}{1 - \phi^2}} \quad (15)$$

$$m = 3 \quad (16)$$

Files

- ▶ `markovappr_section.m`: Tauchen for Matlab
- ▶ `markovsimul_section.m`: simulates markov chain for Matlab
- ▶ `tauchen.py`: Tauchen for Python
- ▶ `simulate_mc.py`: simulates markov chain for Python

Consumption-Savings with Uncertainty

Recap

- Sequential problem with uncertainty

$$\max_{\{c_t(S^t), b_t(S^t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \sum_{S^t} \beta^t P(S^t) u(c_t(S^t)) \quad (17)$$

$$c_t(S^t) + R^{-1} b_t(S^t) = b_{t-1}(S^{t-1}) + y_t(S^t) \quad (18)$$

$$c_t(S^t) \geq 0, b_t(S^t) \geq \underline{b} \quad (19)$$

- Assume income depends only on today's state + S_t is markovian
- Bellman equation is:

$$V(b, s) = \max_{c, b'} u(c) + \beta E_{s'} [V(b', s') | s] \quad (20)$$

$$c + R^{-1} b' = b + y(s), c \geq 0, b' \geq \underline{b} \quad (21)$$

Consumption-Savings with Uncertainty

- Once we discretize, we have

$$V(b, s) = \max_{c, b'} u(c) + \beta \sum_{s'} P(s'|s) V(b', s') \quad (22)$$

$$c + R^{-1}b' = b + y(s), c \geq 0, b' \geq \underline{b} \quad (23)$$

- Writing with cash-in-hand $w_t := b_t + y_t$

$$V(w, s) = \max_{b'} u\left(w - \frac{b'}{R}\right) + \beta \sum_{s'} P(s'|s) V(w', s') \quad (24)$$

$$w' = b' + y(s'), c = w - \frac{b'}{R} \geq 0, b' \geq \underline{b} \quad (25)$$

Consumption-Savings with Uncertainty

Solution Algorithm

1. Discretize income grid and construct Markov matrix to approximate $AR(1)$ process for income.
2. Define grids for cash-on-hand and bond holdings.
3. Guess a value function $V^{(0)}(w, s)$.
4. Updating the value function:
 - i) Fix a point in the state space (say (w_i, s_j)).
 - ii) For each possible savings b_k , compute the right-hand side of the Bellman equation

$$T_{kij} = u\left(w_i - \frac{b'_k}{R}\right) + \beta \sum_{s'} \left[V^{(0)}(w', s') \times P(s' | s_j) \right] \quad (26)$$

$$w' = b'_k + y(s') \quad (27)$$

5. Set $V^{(1)}(w_i, s_j) = \max_k T_{kij}$.
6. Having done this for all i, j , compute distance between new and guessed value functions $d = ||V^{(1)} - V^{(0)}||$.
7. If d is smaller than some pre specified threshold, claim convergence. If not, iterate with $V^{(1)}$ replacing $V^{(0)}$.

Consumption-Savings with Uncertainty

Solution Algorithm

Some reminders and points to take care:

- ▶ Note $w' = b'_k + y'$ might not be in original grid $\rightarrow$ find closest point
- ▶ Impose non-negativity constraint of consumption as usual
- ▶ Careful with bounds on the grids, check results are insensitive to these
- ▶ Remember to also save policy functions
- ▶ This problem can take longer to run on a finer grid, so try to make the implementation efficient (Numba and parallel code!)

Consumption-Savings with Uncertainty

Simulation

1. Simulate the markov income for T periods, yielding a sequence $\{s_0, \dots, s_{T-1}\}$.
2. Set initial bond holdings b_{-1} and compute initial cash-on-hand $w_0 = s_0 + b_{-1}$.
3. Compute optimal consumption and bond holdings from policy functions

$$c_0 = c^{pol}(w_0, s_0), b_0 = b^{pol}(w_0, s_0) \quad (28)$$

4. Compute next period cash-on-hand $w_1 = s_1 + b_0$.
5. Iterate until time T .

Simulation of time-series

AR(1)

- ▶ We define the autoregressive of order 1 ($AR(1)$) process as

$$y_{t+1} = \phi y_t + \sigma \varepsilon_{t+1} \quad (29)$$

$$\varepsilon_t \sim N(0, 1) \quad (30)$$

- ▶ Simulation:
 - i) Set an initial value $y_0 = y$
 - ii) Simulate ϵ from $N(0, 1)$
 - iii) Calculate y_1 from (??)
 - iv) Iterate until the desired horizon (say T)
- ▶ Software will typically have pre-built functions to perform the simulation of normal random variables, but we can always implement our own random-number generator if we can generate uniform random numbers

Moving Average Processes

- ▶ We can generalize autoregressive processes to an autoregressive moving-average process, which allows unobservables/shocks to affect the variable of interest with lags

$$y_t = \phi y_{t-1} + \theta_0 u_t + \theta_1 u_{t-1} \quad (31)$$

- ▶ This is an ARMA(1,1) process, since u_{t-1} has a predictive effect on y_t
- ▶ Subject to some conditions, we can map moving-average processes to “pure” AR(p) processes (and vice-versa)
- ▶ More about this in the problem set and also in time-series econometrics

Simulation of time-series

Markov Chain

- ▶ Reference: ?, Chapter 11
- ▶ Suppose $\{s_t\}$ is a Markov chain with states $\{s_1, \dots, s_N\}$ and transition matrix $\Pi = [\Pi_{ij}]$
- ▶ Start with some value s_i at date 0. We want to assign values s_t for $t = 1, 2, \dots, T$
 1. compute cumulative distribution of the Markov chain Π^c

$$\Pi_{ij}^c = \sum_{k=1}^j \Pi_{ik} = \Pr(s_t \leq s_k | s_{t-1} = s_i)$$

2. set initial state and simulate T random numbers from a uniform distribution over $[0, 1]$: $\{p_t\}_{t=1}^T$
3. assume Markov chain was in state $i = 1$, find the index j such that

$$\Pi_{i(j-1)}^c < p_t \leq \Pi_{ij}^c \text{ for } j \geq 2$$

then s_j is the state in period t . If $p_t \leq \Pi_{i1}^c$ then s_1 is the state in period t .

Simulation

Fixing the seed

- ▶ Sometimes we may want to generate the same historical realization many times, to compare different procedures over the same series
- ▶ For example: want to compare consumption paths when the agent is more or less patient
- ▶ To do so, we have to fix the seed of the random number generator (rng) in our programs
- ▶ In Matlab use `rng`, in Python use `np.random.default_rng`

Deaton, Angus, "Saving and Liquidity Constraints,"
Econometrica, 1991, 59 (5), 1221–1248.

Miao, Jianjun, *Economic dynamics in discrete time*, MIT press,
2020.