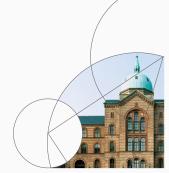


Adv. Macro: Heterogenous Agent Models

Jeppe Druedahl & Patrick Moran 2023







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 - 1. What explains the level and dynamics of heterogeneity/inequality?
 - 2. What role does heterogeneity play for understanding consumption-saving dynamics in partial equilibrium?
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- Central technical method: Programming in Python

Prerequisite: Intro. to Programming and Numerical Analysis

Complicated: Close to the research frontier

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- Plan for today:
 - 1. More about the course
 - 2. Consumption-saving models
 - 3. Numerical dynamic programming

Model components:

- 1. Optimizing individual agents (households + firms)
- 2. Idiosyncratic and aggregate risk
- 3. Information flows (who knows what when \Rightarrow often everything)
- 4. Market clearing (Walras vs. search-and-match)

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Ex post after realization of idiosyncratic shocks

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- HANC: Heterogeneous Agent Neo-Classical model (Aiyagari-Bewley-Hugget-Imrohoroglu or Standard Incomplete Market model)
- HANK: Heterogeneous Agent New Keynesian model (i.e. include price and wage setting frictions)

- **Lectures:** Thursday 10-13
 - ~2 hours of »normal« lecture
 - \sim 1 hour of active problem solving (no exercise classes)

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Material:

Web: sites.google.com/view/numeconcph-advmacrohet/ Git: github.com/numeconcopenhagen/adv-macro-het

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Code:

- 1. We provide code you will build upon
- 2. Based on the **GEModelTools** package

Individual assignments (hand-in on Absalon)

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- Exam:
 - 1. Hand-in 3×assignments
 - 2. 48 hour take-home: Programming of new extension
 - + analysis of model + interpretation of results

Python

- Assumed knowledge: From Introduction to Programming and Numerical Analysis you are assumed to know the basics of
 - 1.1 Python
 - 1.2 VSCode
 - 1.3 git
- 2. Updated Python: Install (or re-install) newest Anaconda
- 3. Packages: pip install quantecon, EconModel, consav
- 4. GEMoodel tools:
 - 4.1 Clone the GEModelTools repository
 - 4.2 Locate repository in command prompt
 - $4.3 \ {\rm Run \ pip \ install \ -e}$.

Course plan

See CoursePlan.pdf in repository

Knowledge

- 1. Account for, formulate and interpret precautionary saving models
- 2. Account for stochastic and non-stochastic simulation methods
- Account for, formulate and interpret general equilibrium models with ex ante and ex post heterogeneity, idiosyncratic and aggregate risk, and with and without pricing frictions
- 4. Discuss the difference between the stationary equilibrium, the transition path and the dynamic equilibrium
- Discuss the relationship between various equilibrium concepts and their solution methods
- Identify and account for methods for analyzing the dynamic distributional effects of long-run policy (e.g. taxation and social security) and short-run policy (e.g. monetary and fiscal policy)

Skills

- 1. Solve precautionary saving problems with dynamic programming and simulate behavior with stochastic and non-stochastic techniques
- 2. Solve general equilibrium models with ex ante and ex post heterogeneity, idiosyncratic and aggregate risk, and with and without pricing frictions (stationary equilibrium, transition path, dynamic equilibrium)
- 3. Analyze dynamics of income and wealth inequality
- 4. Analyze transitional and permanent structural changes (e.g. inequality trends and the long-run decline in the interest rate)
- Analyze the dynamic distributional effects of long-run policy (e.g. taxation and social security) and short-run policy (e.g. monetary and fiscal policy)

Competencies

- Independently formulate, discuss and assess research on both the causes and effects of heterogeneity and risk for both long-run and short-run outcomes
- 2. Discuss and assess the importance of how heterogeneity and risk is modeled for questions about both long-run and short-run dynamics

Consumption-Saving

Generations of models

- 1. Permanent income hypothesis (Friedman, 1957) or life-cycle model (Modigliani and Brumburg, 1954)
- Buffer-stock consumption model (Deaton, 1991, 1992; Carroll, 1992, 1997)
- Multiple-asset buffer-stock consumption models (e.g. Kaplan and Violante (2014))

Consumption-saving

$$v_0(a_{-1}) = \max_{\{c_t\}_{t=0}^{\infty}} \sum_{t=0}^{T-1} \beta^t u(c_t)$$

s.t.
 $a_t = (1+r)a_{t-1} + wz_t - c_t$
 $a_{T-1} \ge 0$

Variables:

Consumption: ct

Productivity: z_t

End-of-period savings: a_t (no debt at death)

Parameters:

Discount factor: β

Wage: w

Interest rate: r (define $R \equiv 1 + r$ as interest factor)

It is a static problem

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s.t.
 $a_t = (1+r)a_{t-1} + wz_t - c_t$
 $a_{T-1} \ge 0$

- It is a static problem:
 - 1. **Information:** z_t is known for all t at t = 0
 - 2. **Target:** Discounted utility, $\sum_{t=0}^{T-1} \beta^t u(c_t)$
 - 3. **Behavior:** Choose $c_0, c_1, \ldots, c_{T-1}$ simultaneously
 - 4. **Solution:** Sequence of consumption *choices* $c_0^*, c_1^*, \ldots, c_{T-1}^*$

IBC

Substitution implies Intertemporal Budget Constraint (IBC)

$$a_{T-1} = Ra_{T-2} + wz_{T-1} - c_{T-1}$$

$$= R^2 a_{T-3} + Rwz_{T-2} - Rc_{T-2} + wz_{T-1} - c_{T-1}$$

$$= R^T a_{-1} + \sum_{t=0}^{T-1} R^{T-1-t} (wz_t - c_t)$$

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$$= R^T a_{-1} + \sum_{t=0}^{T-1} R^{T-1-t} (wz_t - c_t)$$

• Use **terminal condition** $a_{T-1} = 0$ (equality due utility max.)

$$R^{-(T-1)}a_{T-1} = 0 \Leftrightarrow s_0 + h_0 - \sum_{t=0}^{T-1} R^{-t}c_t = 0$$

where $s_0 \equiv Ra_{-1}$ (after-interest assets) and $h_0 \equiv \sum_{t=0}^{T-1} R^{-t} w z_t$ (human capital)

FOC and **Euler-equation**

$$\mathcal{L} = \sum_{t=0}^{T-1} \beta^t u(c_t) + \lambda \left[\sum_{t=0}^{T-1} R^{-t} c_t - s_0 - h_0 \right]$$

First order conditions:

$$\forall t: 0 = \beta^t u'(c_t) - \lambda (1+r)^{-t} \Leftrightarrow u'(c_t) = -\lambda (\beta R)^{-t}$$

• **Euler-equation** for $k \in \{1, 2, \dots\}$:

$$\frac{u'(c_t)}{u'(c_{t+k})} = \frac{-\lambda (\beta R)^{-t}}{-\lambda (\beta R)^{-(t+k)}} = (\beta R)^k$$

Consumption choice

• CRRA: $u(c_t) = \frac{c_t^{1-\sigma}}{1-\sigma}$ imply Euler-equation

$$\frac{c_0^{-\sigma}}{c_t^{-\sigma}} = (\beta R)^t \Leftrightarrow c_t = (\beta R)^{\frac{t}{\sigma}} c_0$$

Insert Euler into IBC to get consumption choice

$$\sum_{t=0}^{T-1} R^{-t} (\beta R)^{t/\sigma} c_0 = s_0 + h_0 \Leftrightarrow$$

$$c_0^* = \frac{1 - \frac{(\beta R)^{1/\sigma}}{R}}{1 - \left(\frac{(\beta R)^{1/\sigma}}{R}\right)^T} (s_0 + h_0)$$

Infinite horizon

Infinite horizon for $\beta R < 1$: Let $T \to \infty$ to get

$$c_0^* = \left(1 - \frac{(\beta R)^{1/\sigma}}{R}\right)(s_0 + h_0)$$

- Interesting properties are e.g.:
 - 1. Interest rate sensitivity: $\frac{\partial c_0}{\partial r}$
 - 2. MPC of permanent income change: $\frac{\partial c_0}{\partial w}$
 - MPC of future income: ^{∂c₀}/_{∂z₁}
 MPC of windfall income: ^{∂c₀}/_{∂s₀}
- No borrowing constraints or uncertainty
- Other simplifications: No age life-cycle, bequests etc.

Liquidity/borrowing constraints

Implied period 0 savings are:

$$a_0 = Ra_{-1} + wz_0 - c_0$$

- Borrowing constraint: $a_0 \ge -w \cdot b$
- Maximum consumption: $\overline{c}_0 = Ra_{-1} + wz_0 + wb$
- Optimal consumption: Constrained or unconstrained.

$$c_0^* = \min \left\{ \overline{c}_0, \left(1 - rac{(eta R)^{1/\sigma}}{R}
ight) (s_0 + h_0)
ight\}$$

- **Empirical realism.** Incl. high MPC of constrained.
- Technical issue: Borrowing constraints further in the future complicated the analytical solution considerably.

Uncertainty

$$egin{aligned} v_0(a_{-1}) &= \max_{\{c_t\}_{t=0}^\infty} \mathbb{E}_0\left[\sum_{t=0}^\infty eta^t u(c_t)
ight] \end{aligned}$$
 s.t. $a_t &= (1+r)a_{t-1} + wz_t - c_t$ $z_t \sim \mathcal{Z}(z_{t-1})$ $a_t \geq -wb$ $\lim_{t o \infty} (1+r)^{-t} a_t \geq 0 \quad ext{[No-Ponzi game]}$

- Stochastic income from 1st order Markov-process, $\mathcal Z$
- A true dynamic problem:
 - 1. **Information:** z_t is revealed period-by-period
 - 2. **Target:** Expected discounted utility, $\mathbb{E}_0\left[\sum_{t=0}^{\infty} \beta^t u(c_t)\right]$
 - 3. Behavior: Choose c_t sequentially as information is revealed
 - 4. **Solution:** Sequence of consumption functions, $c_t^*(z_t, a_{t-1})$

IBC

Substitution still implies:

$$R^{-(T-1)}a_{T-1} = 0 \Leftrightarrow b_0 + h_0 - \sum_{t=0}^{T-1} R^{-t}c_t = 0$$

- What if $T \to \infty$? We must have $\lim_{T \to \infty} R^{-(T-1)} a_{T-1} = 0$
 - 1. $\lim_{T\to\infty} R^{-(T-1)}a_{T-1} > 0$: Consumption can be increased
 - 2. $\lim_{T\to\infty} R^{-(T-1)}a_{T-1} < 0$: Violates No-Ponzi game condition
- For $T \to \infty$ we have the **IBC**:

$$\sum_{t=0}^{\infty} R^{-t} c_t = Ra_{-1} + \sum_{t=0}^{\infty} R^{-t} w z_t$$

Euler-equation from variation argument

- Case I: If $u'(c_t) > \beta R \mathbb{E}_t [u'(c_{t+1})]$: Increase c_t by marginal $\Delta > 0$, and lower c_{t+1} by $R\Delta$
 - 1. **Feasible:** Yes, if $a_t > -\underline{a}$
 - 2. Utility change: $u'(c_t) + \beta(-R)\mathbb{E}_t[u'(c_{t+1})] > 0$

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- Case II: If $u'(c_t) < \beta(1+r)\mathbb{E}_t \left[u'(c_{t+1})\right]$: Lower c_t by marginal $\Delta > 0$, and increase c_{t+1} by $R\Delta$
 - 1. Feasible: Yes (always)
 - 2. Utility change: $u'(c_t) + \beta R \mathbb{E}_t \left[u'(c_{t+1}) \right] > 0$

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 - 1. Feasible: Yes (always)
 - 2. Utility change: $u'(c_t) + \beta R \mathbb{E}_t \left[u'(c_{t+1}) \right] > 0$
- Conclusion: By contradiction
 - 1. Constrained: $a_t = -\underline{a}$ and $u'(c_t) \geq \beta R \mathbb{E}_t [u'(c_{t+1})]$, or
 - 2. Unconstrained: $a_t > -\underline{a}$ and $u'(c_t) = \beta R \mathbb{E}_t \left[u'(c_{t+1}) \right]$

Special case I: Quadratic utility

- Quadratic utility: $u(c_t) = -\frac{1}{2}(\overline{c} c)^2$ with $\beta R = 1$
- **Euler-equation:** Consumption = expected future consumption

$$(\overline{c} - c_t) = \mathbb{E}_t \left[(\overline{c} - c_{t+k}) \right] \Leftrightarrow c_t = \mathbb{E}_t \left[c_{t+k} \right]$$

Use IBC in expectation to get consumption function:

$$\sum_{t=0}^{\infty} R^{-t} \mathbb{E}_{0} [c_{t}] = Ra_{-1} + \sum_{t=0}^{\infty} R^{-t} w \mathbb{E}_{0} [z_{t}] \Rightarrow$$

$$c_{0} = ra_{-1} + \frac{r}{R} \sum_{t=0}^{T} R^{-t} w \mathbb{E}_{0} [z_{t}] \Rightarrow$$

$$c^{*}(a_{t-1}, z_{t}) = ra_{t-1} + \frac{r}{R} \sum_{k=0}^{\infty} R^{-k} w \mathbb{E}_{t} [z_{t+k}]$$

Certainty equivalence: Only expected income matter.

Special case II: CARA utility

- CARA utility: $u(c_t) = -\frac{1}{\alpha}e^{-\alpha c}$
- Productivity is absolute random walk:

$$z_t = z_{it-1} + \psi_{it}$$
$$\psi_{it} \sim \mathcal{N}(0, \sigma_{\psi}^2)$$

Consumption function (see proof):

$$c_t^*(a_{it-1}, z_{it}) = ra_{it-1} + wz_{it} - \frac{\log\left(\beta R\right)^{\frac{1}{\alpha}} + \alpha \frac{\sigma_{\psi}^2}{2}}{r^2}$$

■ Precautionary saving: $\sigma_{\psi}^2 \uparrow$ implies $c_t^* \downarrow$ for given a_{t-1} and z_t \Rightarrow accumulation of buffer-stock

Further resources

- 1. Lecture notes by Christopher Carroll
- 2. Lecture notes by Pierre-Olivier Gourinchas
- 3. The Economics of Consumption, Jappelli and Pistaferri (2017)
- »Liquidity constraints and precautionary saving« Carroll, Holm, Kimball (JET, 2021)
- Theoretical Foundations of Buffer Stock Saving« Carroll (QE, forthcomming)

• In words: An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision. (See Bellman, 1957, Chap. III.3.)

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 - 1. Value function, v_t : Defined recursively from

$$v_t(z_t,a_{t-1})=\max_{c_t} u(c_t)+eta \mathbb{E}_t[v_{t+1}(z_{t+1},a_t)]$$
 s.t. $a_t=(1+r)a_{t-1}+wz_t-c_t\geq wb$ with $v_T(ullet)=0$.

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with
$$v_T(\bullet) = 0$$
.

2. **Policy function,** c_t^* : Is the same as

$$c_t^*(z_t, a_{t-1}) = \arg\max_{c_t} u(c_t) + \beta \mathbb{E}_t[v_{t+1}(z_{t+1}, a_t)]$$

s.t. $a_t = (1+r)a_{t-1} + wz_t - c_t \ge wb$

Vocabulary

$$v_t(z_t, a_{t-1}) = \max_{c_t} u(c_t) + \beta \mathbb{E}_t[v_{t+1}(z_{t+1}, a_t)]$$

s.t. $a_t = (1+r)a_{t-1} + wz_t - c_t \ge wb$

- 1. State variables: z_t and a_{t-1}
- 2. Control variable: c_t
- 3. Continuation value: $\beta \mathbb{E}_t[v_{t+1}(z_{t+1}, a_t)]$
- 4. **Parameters:** r, w, and stuff in $u(\bullet)$

Note: Conceptually straightforward to extend to more goods, more assets or other states, more complex uncentainty, bounded rationality etc.

Infinite horizon: $T \to \infty$?

$$v_t(z_t, a_{t-1}) = \max_{c_t} u(c_t) + \beta \mathbb{E}_t[v_{t+1}(z_{t+1}, a_t)]$$

s.t. $a_t = (1+r)a_{t-1} + wz_t - c_t \ge wb$

- Contraction mapping result: If β is low enough (strong enough impatience) then the value and policy function converge to $v(z_t, a_{t-1})$ and $c^*(z_t, a_{t-1})$ for large enough T
- Maximum upper limit for β : $\frac{1}{1+r}$
- In practice: Solve backwards until value and policy functions does not change anymore (given some tolerance)

• Minimum income: $\underline{z} = \min_{z \in \mathcal{G}_z} z$

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- Thought experiment: Assumptions
 - 1. $a_{t-1} = -\frac{wz}{r} + \Delta$
 - 2. $z_t = \underline{z}$, $\forall t$
 - 3. $c_t = 0$, $\forall t$

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$$a_{t-1} = -\frac{wz}{r} + \Delta$$

- 2. $z_t = \underline{z}$, $\forall t$
- 3. $c_t = 0$, $\forall t$
- **Implication:** For $\Delta < 0$ assets will be decreasing without bound!

$$a_t = (1+r)\left(-rac{w\underline{z}}{r} + \Delta\right) + w\underline{z} = -rac{w\underline{z}}{r} + (1+r)\Delta$$
 $a_{t+1} = -rac{w\underline{z}}{r} + (1+r)^2\Delta$
...

 $a_{t+k} = -\frac{w\underline{z}}{r} + (1+r)^k \Delta \to -\infty$

- Minimum income: $\underline{z} = \min_{z \in \mathcal{G}_z} z$
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 $a_{t+1} = -\frac{w\underline{z}}{r} + (1+r)^2\Delta$
 \dots
 $a_{t+k} = -\frac{w\underline{z}}{r} + (1+r)^k\Delta \to -\infty$

r

• Natural borrowing constraint: $a_t > w \max \left\{-b, -\frac{z}{r}\right\}$

Numerical solution

Timing of shocks

• **Realization of shocks:** First in the period before choices are made

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- Beginning-of-period value function (before realization):

$$\underline{v}_t(z_{t-1}, a_{t-1}) = \mathbb{E}_{t-1}[v_t(z_t, a_{t-1})]$$

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$$\underline{v}_t(z_{t-1}, a_{t-1}) = \mathbb{E}_{t-1}[v_t(z_t, a_{t-1})]$$

End-of-period value function (after realization):

$$\begin{aligned} v_t(z_t, a_{t-1}) &= \max_{c_t} u(c_t) + \beta \underline{v}_{t+1}(z_t, a_t) \\ \text{s.t. } a_t &= (1+r)a_{t-1} + wz_t - c_t \geq wb \end{aligned}$$

Discretization and linear interpolation

Discretization: All state variables belong to discrete sets ≡ grids,

$$z_t \in \mathcal{G}_z = \{z^0, z^1, \dots, z^{\#z-1}\}$$

 $a_t \in \mathcal{G}_a = \{a^0, a^1, \dots, a^{\#_a-1}\}$
 $a^0 = w \max \left\{-b, -\frac{z}{r}\right\}$

Discretization and linear interpolation

• **Discretization:** All state variables belong to discrete sets \equiv *grids*,

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■ Transition probabilities: $\pi_{i_z,i_z} = \Pr[z_t = z^{i_z} \mid z_{t-1} = z^{i_{z-1}}]$

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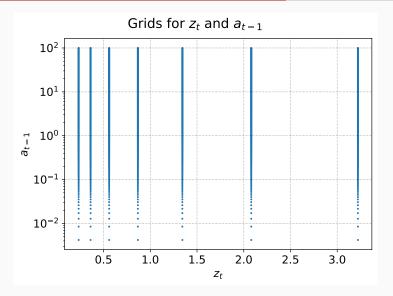
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- Transition probabilities: $\pi_{i_z,i_z} = \Pr[z_t = z^{i_z} \mid z_{t-1} = z^{i_{z-1}}]$
- Linear interpolation (function approximation):
 - 1. Assume \underline{v}_{t+1} is known on $\mathcal{G}_z \times \mathcal{G}_a$ (tensor product)
 - 2. Evaluate $\underline{v}_{t+1}(z^{i_z}, a)$ for arbitrary a by

$$\begin{split} \underline{\breve{\mathbf{v}}}_{t+1}(\mathbf{z}^{i_{\mathbf{z}}},\mathbf{a}) &= \underline{\mathbf{v}}_{t+1}(\mathbf{z}^{i_{\mathbf{z}}},\mathbf{a}^{\iota}) + \omega_{i}(\mathbf{a} - \mathbf{a}^{\iota}) \\ \omega_{i} &\equiv \frac{\mathbf{v}_{t+1}(\mathbf{z}^{i_{\mathbf{z}}},\mathbf{a}^{\iota+1}) - \mathbf{v}_{t+1}(\mathbf{z}^{\iota_{\mathbf{z}}},\mathbf{a}^{\iota})}{\mathbf{a}^{\iota+1} - \mathbf{a}^{\iota}} \\ \iota &\equiv \mathsf{largest}\ i_{\mathbf{a}} \in \{0,1,\ldots,\#_{\mathbf{a}} - 2\}\ \mathsf{such\ that}\ \mathbf{a}^{i_{\mathbf{a}}} \leq \mathbf{a} \end{split}$$

Grids



Deriving transition probabilities

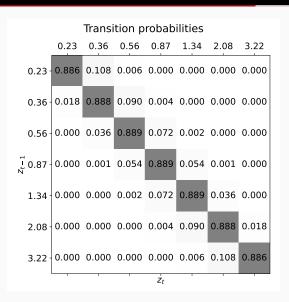
Specification: Assume

$$\begin{split} z_t &= \tilde{z}_t \xi_t, \ \log \xi_t \sim \mathcal{N}(\mu_\xi, \sigma_\xi) \\ \log \tilde{z}_{t+1} &= \rho_z \log \tilde{z}_t + \psi_{t+1}, \ \psi_{t+1} \sim \mathcal{N}(\mu_\psi, \sigma_\psi) \end{split}$$

where μ_{ξ} and μ_{ψ} ensures $\mathbb{E}[\xi_t]=1$, $\mathbb{E}[ilde{z}_t]=1$ and $\mathbb{E}[z_t]=1$

- **Discretization of** \tilde{z}_t : Derive $\mathcal{G}_{\tilde{z}}$ and $\pi_{i_{\tilde{z}_-},i_{\tilde{z}}}$ given ρ_z and σ_ψ (using a method such as Tauchen (1986) or Rouwenhorst (1995))
- **Discretization of** ξ_t : Derive \mathcal{G}_{ξ} and $\pi_{i_{\xi-},i_{\xi}}$ given σ_{ξ} (using Gauss-Hermite quadrature, see next slides)
- Combined: Derive $\mathcal{G}_z = \mathcal{G}_{\tilde{\mathbf{z}}} \times \mathcal{G}_{\xi}$ (tensor product) and use independence of $\tilde{\mathbf{z}}_t$ and ξ_t to get transition probabilities π_{i_z,i_z} (kronecker product)

Transition probability matrix



Extra: Gauss-Hermite I

General problem: How can we calculate

$$\mathbb{E}(f(x)) = \int f(x)g(x)dx$$

- $f: \mathbb{R} \to \mathbb{R}$ some function
- g(x) is the probability distribution function (PDF) for x
- General solution: Turn it into a discrete sum

$$\mathbb{E}(f(x)) \approx \sum_{i=1}^{S} \omega_i f(x_i)$$

• How to choose S and the *nodes* (x_i) and *weights* (ω_i) ? Answer: Guassian quadrature

Extra: Gauss-Hermite II

Gauss-Hermite quadrature uses that

$$\int_{-\infty}^{\infty} f(x)e^{-x^2}dx = \sum_{i=1}^{S} \omega_i f(x_i) + \frac{S!\sqrt{\pi}}{s^S(2S)!}f^{(2S)}(\epsilon)$$

for some ϵ and where the (x_i, ω_i) 's can be easily found

• Well behaved function: For $S \to \infty$ we have

$$\int_{-\infty}^{\infty} f(x)e^{-x^2}dx \approx \sum_{i=1}^{S} \omega_i f(x_i)$$

■ Example: Random normal variable: $Y \sim \mathcal{N}(\mu, \sigma^2)$ so that

$$\mathbb{E}[f(Y)] = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} f(y) e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy$$
$$\approx \frac{1}{\sqrt{\pi}} \sum_{i=1}^{S} \omega_i f(\sqrt{2}\sigma x_i + \mu)$$

Value function iteration

Beginning-of-period value function:

$$\underline{v}_{t}(z^{i_{z-}}, a^{i_{a-}}) = \sum_{i_{z}=0}^{\#_{z}-1} \pi_{i_{z-}, i_{z}} v_{t}(z^{i_{z}}, a^{i_{a-}})$$

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End-of-period value-of-choice:

$$v_t(z^{i_z}, a^{i_{s-}}|c_t) = u(c_t) + \beta \sum_{i_{z+}=0}^{\#_z-1} \pi_{i_z, i_{z+}} \check{v}_{t+1}(z^{i_{z+1}}, a_t)$$

$$a_t = (1+r)a^{i_{s-}} + wz^{i_z} - c_t$$

Value function iteration

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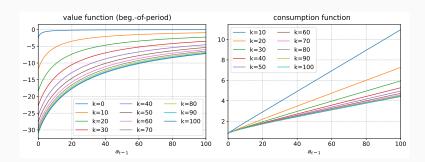
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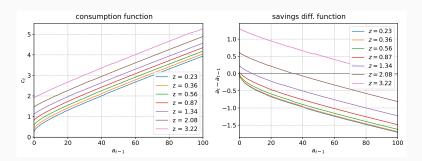
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 $a_t = (1+r)a^{i_{a-}} + wz^{i_z} - c_t$

- Nested loops:
 - 1. **Outer loop:** Backwards from t = T 1 (note $\underline{v}_T = 0$, or known)
 - 2. **Inner loop:** For each grid point in $\mathcal{G}_z \times \mathcal{G}_a$ find $c_t^*(z_t, a_{t-1})$ and therefore $v_t^*(z_t, a_{t-1})$ with a *numerical optimizer*

Convergence (t = T - 1 - k)



Converged policy functions



Numerical Monte Carlo simulation

■ Initial distribution: Draw $z_{i,-1}$ and $a_{i,-1}$ for $i \in \{0,1,\ldots,N-1\}$

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 - 1. Draw z_{it} given transition probabilities
 - 2. Use linear interpolation to evaluate

$$c_{it} = \breve{c}_t^*(z_{it}, a_{it-1})$$

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- Review:
 - Pro: Simple to implement
 - Con: Computationally costly and introduces randomness

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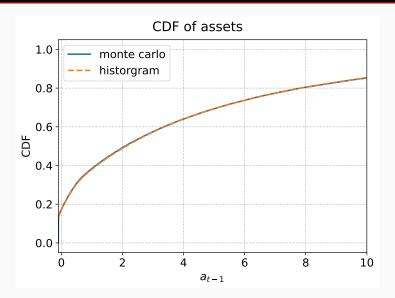
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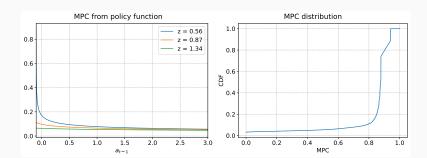
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- Review:
 - 1. Pro: Computationally efficient and no randomness
 - 2. Con: Introduces a non-continuous distribution

CDF of savings in final period



MPCs



Side-note: Matrix formulation

• The histogram method can be written in **matrix form**:

$$oldsymbol{D}_t = \Pi_z' \underline{oldsymbol{D}}_t \ \underline{oldsymbol{D}}_{t+1} = \Lambda_t' oldsymbol{D}_t$$

where

 $\underline{\boldsymbol{D}}_t$ is vector of length $\#_z \times \#_a$

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 Π_z' is derived from the π_{i_z,i_z} 's

 Λ'_t is derived from the ι 's and ω 's

- Note: Example shown in notebook
- Further details: Young (2010), Tan (2020), Ocampo and Robinson (2022)



Alternative to value function iteration:

1. Calculate post-decision marginal value of cash:

$$q(z^{i_z}, a^{i_s}) = \sum_{i_{r+}=0}^{\#_z-1} \pi_{i_z, i_{z+}} c_+ (z^{i_{z+}}, a^{i_s})^{-\sigma}$$

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4. Consumption function: Calculate $m=(1+r)a^{i_3-}+wz^{i_2}$ If $m \leq m(z^{i_2},a^0)$ con. binds: $c^*(z^{i_2},a^{i_3-})=m+w\max\left\{-b,-\frac{z}{r}\right\}$ Else: $c^*(z^{i_2},a^{i_3-})=$ interpolate $m(z^{i_2},:)$ to $c(z^{i_2},:)$ at m

Practice

In practice

- **EconModel:** Go through notebook 01. Using the EconModelClass (except part on C++)
- ConSav: Look at the 04. Tools folder.
- Todays notebook: Consumption-Saving Model show implementation of solution and simulation methods.

Summary

Summary and next week

Today:

- 1. Introduction to course
- 2. Consumption-saving models
- 3. Numerical dynamic programming
- Next week: Stationary equilibrium
- Homework:
 - 1. Work on: Familiarize your self with today's code
 - 2. Read: Aiyagari (1994),
 - »Uninsured Idiosyncratic Risk and Aggregate Saving«