Lecture 10: Discrete-Continuous Choice Models

Dynamic Programming

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Introduction

- A lot of choices are inherently discrete
 - Full-time / half-time
 - 2 Retirement
 - 3 Industry
 - 4 Sector
 - **6** Durable purchases

etc.

- Today: Method for efficiently solving discrete-continuous choice models
- Example: Consumption-saving model with a discrete retirement choice



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Bellman equation

• Value function (Is retirement absorbing?, timing?)

$$V_t(m_t, z_t, \varepsilon_t^0, \varepsilon_t^1) = \max_{z_{t+1} \in \mathcal{Z}(z_t)} \left\{ v_t(m_t | z_{t+1}) + \sigma_{\varepsilon} \varepsilon_t^{z_{t+1}} \right\}$$

$$\mathcal{Z}(z_t) = \begin{cases} \{0, 1\} & \text{if } z_t = 0 \\ \{1\} & \text{if } z_t = 1 \end{cases}$$

Choice-specific value functions

$$\begin{array}{lcl} v_{t}(m_{t}|z_{t+1}) & = & \max_{c_{t}} \frac{c_{t}^{1-\rho}}{1-\rho} - \alpha \mathbf{1}_{\{z_{t+1}=0\}} + \beta \mathbb{E}_{t} \left[V_{t+1}(\bullet_{t+1}) \right] \\ & \text{s.t.} \\ \\ m_{t+1} & = & R(m_{t}-c_{t}) + W\xi_{t+1} \mathbf{1}_{\{z_{t+1}=0\}} \\ & c_{t} & \leq & m_{t} \\ \log \xi_{t+1} & \sim & \mathcal{N}(-0.5\sigma_{\xi}^{2}, \sigma_{\xi}^{2}) \\ \varepsilon_{t+1}^{0}, \varepsilon_{t+1}^{1} & \sim & \text{Extreme Value Type 1} \end{array}$$



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Logsum and choice probabilities

Retired: Simple perfect foresight problem - Why?

• For working households

$$v_{t}(m_{t}|z_{t+1}) = \max_{c_{t}} \frac{c_{t}^{1-\rho}}{1-\rho} - \alpha z_{t+1} + \beta \mathbb{E}_{t} \left[\mathcal{W}_{t+1}(m_{t+1}) \right]$$

where

$$W_t(m_t) = \begin{cases} \sigma_{\varepsilon} \log \left(\sum_{j \in \{0,1\}} \exp \left(\frac{v_t(m_t|j)}{\sigma_{\varepsilon}} \right) \right) & \text{if } \sigma_{\varepsilon} > 0 \\ \max_{j \in \{0,1\}} v_t(m_t|j) & \text{if } \sigma_{\varepsilon} = 0 \end{cases}$$

• Choice probilities for working households

$$\Pr(z_{t+1} = z | m_t) = \begin{cases} \frac{\exp(v_t(m_t | z) / \sigma_{\varepsilon})}{\sum_{j \in \{0,1\}} \exp(v_t(m_t | j) / \sigma_{\varepsilon})} & \text{if } \sigma_{\varepsilon} > 0\\ \mathbf{1}_{v_t(m_t | z) > v_t(m_t | j), \forall j \neq z} & \text{if } \sigma_{\varepsilon} = 0 \end{cases}$$



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Closed form solution?

 For a particular parametrization, John Rust showed in Iskhakov, Jørgensen, Rust and Schjerning (2017):

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Quantitative Economics 8 (2017)

and instantaneous utility is given by $u(c) = \log(c)$. Then for $\tau \in \{1, ..., T\}$ the optimal consumption rule in the worker's problem (2)–(4) is given by

$$\begin{cases} M & \text{if } M \leq y/R\beta, \\ |M+y/R|/(1+\beta) & \text{if } y/R\beta \leq M \leq \overline{M}_{T-\tau}^{+}, \\ |M+y(1/R+R^{2})|/(1+\beta+\beta^{2})| & \text{if } y/R\beta \leq M \leq \overline{M}_{T-\tau}^{+}, \\ |M+y(1/R+|R^{2})|/(1+\beta+\beta^{2}) & \text{if } \overline{M}_{T-\tau}^{+} \leq M \leq \overline{M}_{T-\tau}^{+}, \\ |M+y\left(\sum_{i=1}^{-1}R^{-i}\right)|\left(\sum_{i=0}^{-1}\beta^{i}\right)^{-1} & \text{if } \overline{M}_{T-\tau}^{+} \leq M \leq \overline{M}_{T-\tau}^{+-1}, \\ |M+y\left(\sum_{i=1}^{-1}R^{-i}\right)|\left(\sum_{i=0}^{-1}\beta^{i}\right)^{-1} & \text{if } \overline{M}_{T-\tau}^{+} \leq M < \overline{M}_{T-\tau}^{+-1}, \\ |M+y\left(\sum_{i=1}^{-1}R^{-i}\right)|\left(\sum_{i=0}^{-1}\beta^{i}\right)^{-1} & \text{if } \overline{M}_{T-\tau}^{+} \leq M < \overline{M}_{T-\tau}^{+-2}, \\ |M+y(1/R+1/R^{2})|\left(\sum_{i=0}^{-1}\beta^{i}\right)^{-1} & \text{if } \overline{M}_{T-\tau}^{2} \leq M < \overline{M}_{T-\tau}^{2}, \\ |M+y/R|\left(\sum_{j=0}^{-1}\beta^{i}\right)^{-1} & \text{if } \overline{M}_{T-\tau}^{2} \leq M < \overline{M}_{T-\tau}^{2}, \\ |M-y/R|\left(\sum_{j=0}^{-1}\beta^{i}\right)^{-1} & \text{if } \overline{M}_{T-\tau}^{2} \leq M < \overline{M}_{T-\tau}, \\ |M\left(\sum_{j=0}^{-1}\beta^{i}\right)^{-1} & \text{if } M \geq \overline{M}_{T-\tau}. \end{cases}$$

The segment boundaries are totally ordered with

$$V/RB < \overline{M}_{T}^{l_1} < \cdots < \overline{M}_{T}^{l_{T-1}} < \overline{M}_{T}^{l_{T-1}} < \cdots < \overline{M}_{T}^{l_1} < \overline{M}_{T-\sigma}$$
, (8)

and the rightmost threshold $\overline{M}_{T=\tau}$, given by

$$\overline{M}_{T-\tau} = \frac{(y/R)e^{-K}}{1 - e^{-K}}, \quad \text{where } K = \delta \left(\sum_{i=1}^{\tau} \beta^{i}\right)^{-1},$$
 (9)

defines the smallest level of wealth sufficient to induce the consumer to retire at age $t = T - \tau$.



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Euler-equation

• Euler-equation for interior choices

$$c_t^{-\rho} = \beta R \mathbb{E}_t \left[c_{t+1}^{-\rho} \right]$$

- Necessary? Yes, e.g. by variational argument
- **Sufficient?** Only if the value function is strictly concave
 - **1 Retired:** Yes, no discrete choices ⇒ can be solved by *standard* EGM
 - ② Working: Possibly no, due to discrete choices ⇒ we need an extended EGM
- Consumption functions: $c_t(m_t|z_{t+1})$ $c_t(m_t|0)$ optimal consumption if *working* $c_t(m_t|1)$ optimal consumption if *retiring/retired*



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Recap: EGM

- Prerequisites
 - **1** Inverted Euler-equation: $c_t = \left\lceil \beta R \mathbb{E}_t \left\lceil c_{t+1}^{-\rho} \right\rceil \right\rceil^{-\frac{1}{\rho}}$
 - **2** Next-period consumption functions: $c_{t+1}(m_{t+1}|z_{t+2})$
 - **3** Asset grid: $G_a = \{a_1, a_2, \dots, a_\#\}$ with $a_1 = 10^{-6}$
- **Algorithm:** For each $a_i \in \mathcal{G}_a$
 - Find consumption (using $Pr(z_{t+2} = z | m_{t+1})$)

$$c_i = \left(\beta R \mathbb{E}_t \left[c_{t+1} (Ra_i + W \xi_{t+1} \mathbf{1}_{z_{t+1}=0} | z_{t+2})^{-\rho} \right] \right)^{-\frac{1}{\rho}}$$

2 Find endogenous state

$$m_i = a_i + c_i$$

• The **consumption function**, $c_t(m_t|z_{t+1})$, is given by

$$G_c = \{0, c_1, c_2, \dots, c_\#\} \text{ for } G_m = \{0, m_1, m_2, \dots, m_\#\}$$



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Parameters

- **Demograhics:** T = 20
- **Preferences:** $\beta = 0.96$, $\rho = 2$, $\alpha = 0.75$
- Taste shocks: $\sigma_{\varepsilon} = 0$
- **Income:** W = 1, $\sigma_{\xi} = 0$
- **Assets:** R = 1.04



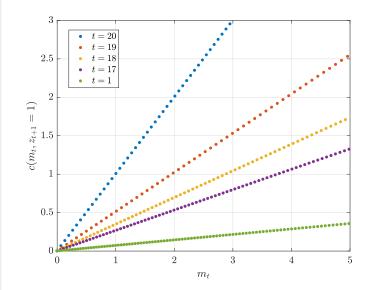
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Retired: Consumption function





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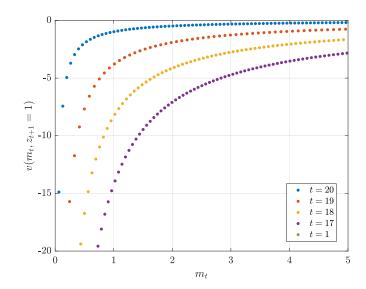
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Retired: Value function





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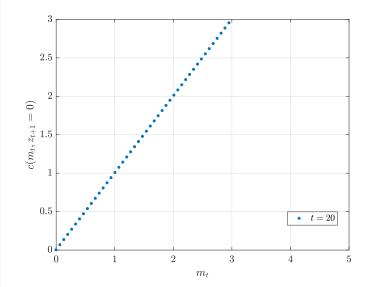
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Working: Consumption, t = T





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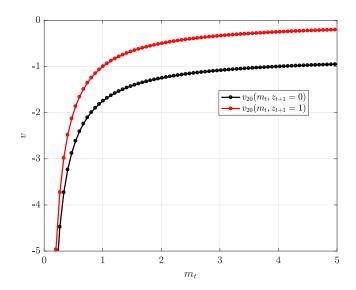
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Choice-specific value functions, t = T





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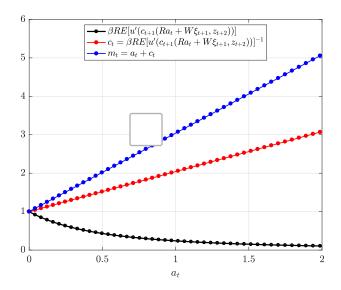
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Working: EGM, t = T - 1 (a_t -space)





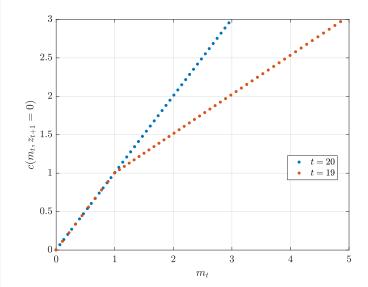
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Working: Consumption, t = T - 1





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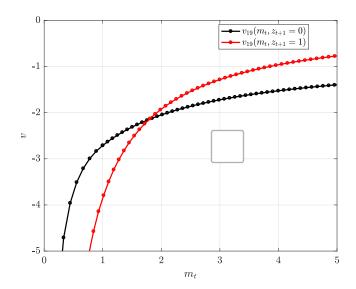
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Choice-specific value functions, t = T - 1





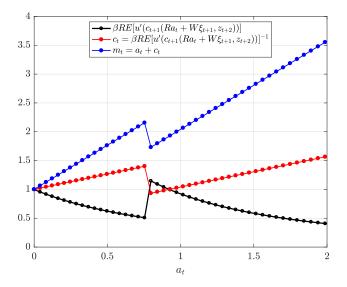
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Working: EGM, t = T - 2 (a_t -space)





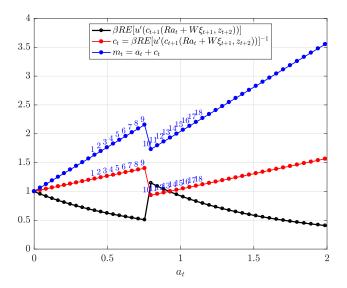
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Working: EGM, t = T - 2 (a_t -space)





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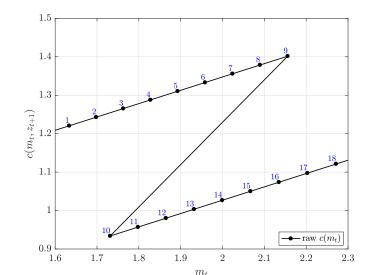
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Raw consumption, t = T - 2 (m_t -space, working)





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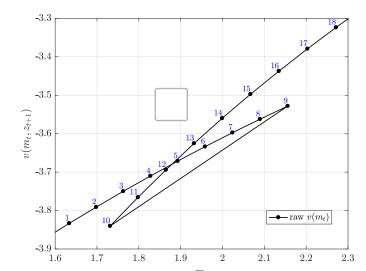
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Raw values-of-choice, t = T - 2 (m_t -space, working)





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Summary

- **1** For high m_{T-1} retirement is optimal
 - con retirement: lower consumption due to no income
 - pro retirement: *no disutility of labor*
- **2** Implies **kink in the value function** in period T-1
- **(3)** Implies *downward* **jump in optimal level of consumption** in T-1 at the kink
- **4** From T-2 implies *upward* jump in the **marginal utility of consumption** at some a_{T-2}
- **6** In the EGM c_{T-2} is then **not a montonic function** of a_{T-2}
- **6** For given m_t there are multiple solutions to the Euler-equation
 - the EGM finds all of them! (potentially in closed form)
 - **Q:** How do we find the optimum!? (what is the difficulty?)



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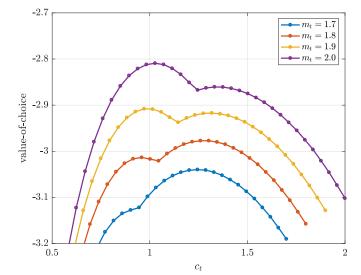
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VFI in trouble: multi-start, grid search (even more expensive)

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G^2EGM 1D algorithm for $z_{t+1} = 0$

- **1 Apply EGM** to get $\mathcal{G}_m = \{m_i\}_1^\#$ and $\mathcal{G}_c = \{c_i\}_1^\#$
- **2** Find the **values-of-choice** $\mathcal{G}_v = \{v_i\}_1^{\#}$ with elements

$$v_i = u(c_i) + \beta \mathbb{E}_t \left[\mathcal{W}_{t+1} (R(m_i - c_i) + W \xi_{t+1}) \right]$$

3 Let \mathcal{I} denote a **reordering** making \mathcal{G}_m **strictly increasing**

$$\overline{\mathcal{G}}_m \equiv \mathcal{G}_m(\mathcal{I}) = \{\overline{m}_i\}_1^{\#}, \ \overline{\mathcal{G}}_c \equiv \mathcal{G}_c(\mathcal{I}) = \{\overline{c}_i\}_1^{\#}, \ \overline{\mathcal{G}}_v = \mathcal{G}_v(\mathcal{I}) = \{\overline{v}_i\}_1^{\#}$$

1 Loop through $i \in \{1, 2, ..., \#-1\}$ Loop through $j \in \{1, 2, ..., \#\}$ If $m_i < \overline{m}_j < m_{i+1}$ then **interpolate**

$$\begin{array}{lcl} c_{ij} & = & \frac{c_{i+1} - c_i}{m_{i+1} - m_i} (\overline{m}_j - m_i) \\ v_{ij} & = & u(c_{ij}) + \beta \mathbb{E}_t \left[\mathcal{W}_{t+1} (R(\overline{m}_j - c_{ij}) + W \xi_{t+1}) \right] \end{array}$$

and if
$$v_{ij} > \overline{v}_j$$
 then **update** $\overline{v}_j = v_{ij}$ and $\overline{c}_j = c_{ij}$

6 Extend $\overline{\mathcal{G}}_m$, $\overline{\mathcal{G}}_c$ and $\overline{\mathcal{G}}_v$ with points on the borrowing constraint where m is between 0 and \overline{m}_1 and c = m



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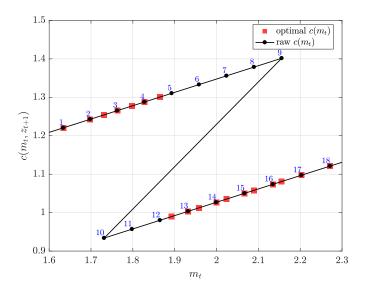
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Upperenvelope, c_t , t = T - 2





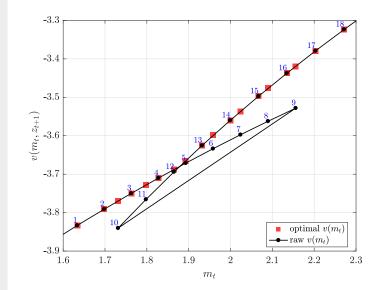
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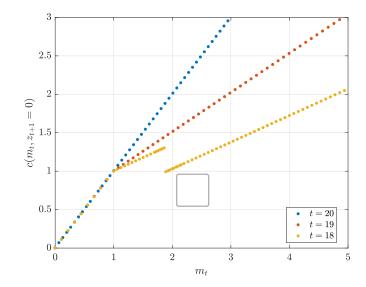
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Working: Consumption, $t \ge 18$





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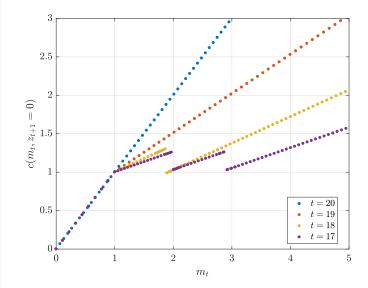
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Working: Consumption, $t \ge 17$





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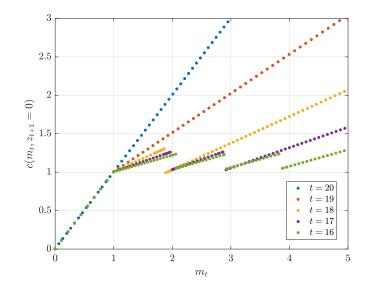
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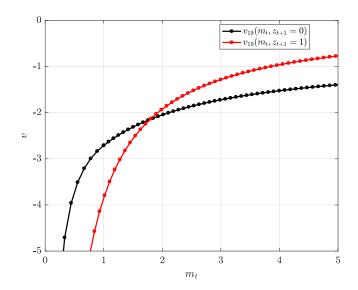
Working: Consumption, $t \ge 16$





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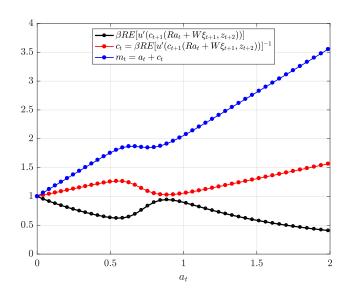
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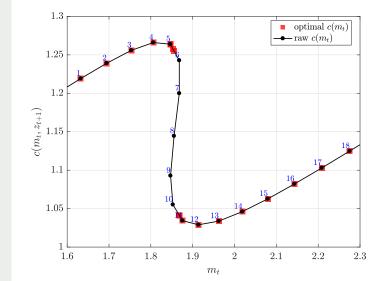
 $\sigma_{\varepsilon} = 0.05$: EGM





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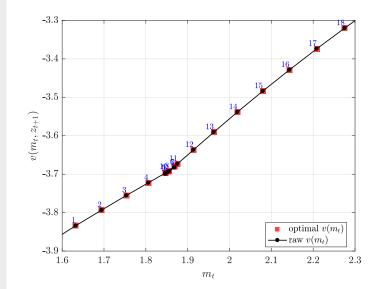
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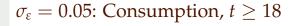
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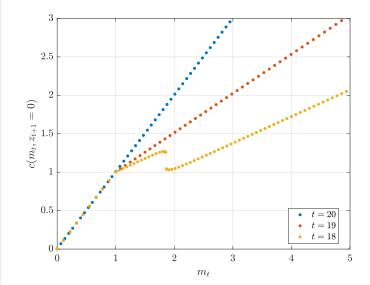
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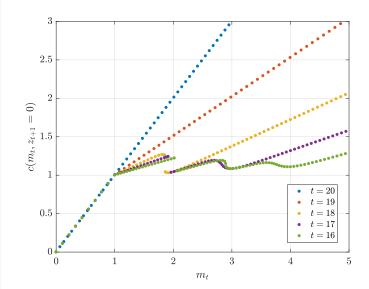






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 $\sigma_{\varepsilon} = 0.05$: Consumption, $t \geq 16$





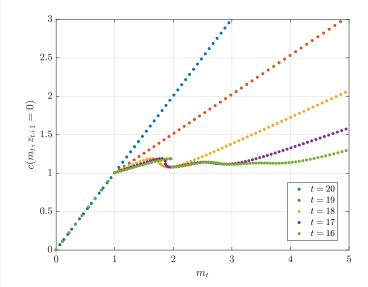
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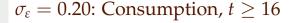
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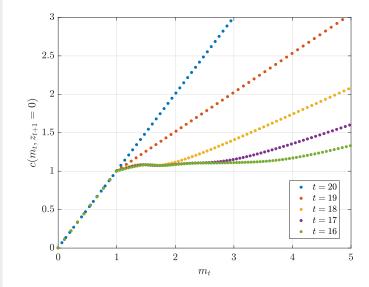
 $\sigma_{\varepsilon} = 0.10$: Consumption, $t \geq 16$





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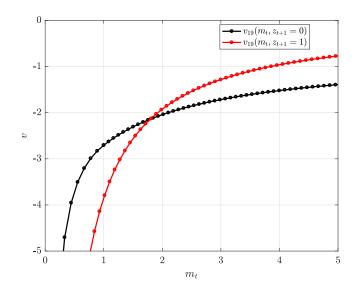
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 $\sigma_{\varepsilon} = 0.20$: Choice-specific value function





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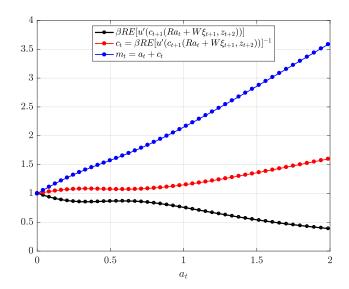
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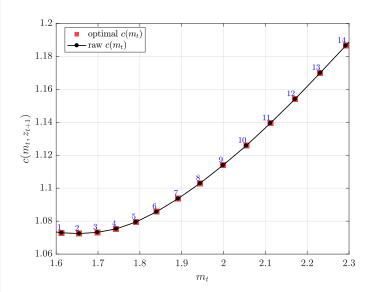
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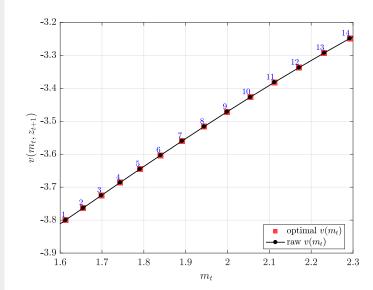






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Other extended EGMs

- This version based on: Druedahl and Jørgensen (2017)
- Similar, but in my view more complicated
 - **1** Fella (2014)
 - 2 Iskhakov, Jørgensen, Rust and Schjerning (2017)
- **Common:** Use EGM to find all candidate solutions Note: Any interior solution is a solution to the Euler-equation
- **Differences:** Different upper envelope algorithms used to disgard non-optimal points



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Multi-dimensional EGM

- Think of models with
 - Multiple continuous states and choices
 - Multiple discrete states and choices
 - 3 Multiple potentially binding constraints
- Problems for an EGM
 - 1 Euler-equations only necessary (like in 1D)
 - 2 Endogenous grids are irregular very costly to interpolate
 - **3** We do not know where the constraints are binding
- Solution from Druedahl and Jørgensen (2017): Procede as we have done here but
 - **1** Choose the $\overline{\mathcal{G}}_m$ grid exogenously (*common grid*)
 - Add a discrete choice determining which choices are respectively constrained and interior
- No other EGM can handle multi-dimensional models with constraints and non-convexities such as discrete choices!



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- Ensure that you understand:
 - That non-convexities can create multiple local optima
 - The problems non-convexities cause for EGM

 How to apply C2ECM for a one dimensional problem
 - **3** How to apply G²EGM for a one-dimensional problem
- **Prepare for next time:** Look at the model section from a paper of your choice listed at Absalon

