Structural Estimation of Dynamic Stochastic Optimizing Models of Intertemporal Choice For Dummies!

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http://www.econ2.jhu.edu/people/ccarroll/SolvingMicroDSOPs-Slides.pdf

- Efficient Solution Methods for Canonical C problem
  - CRRA utility
  - Plausible (microeconomically calibrated) uncertainty
  - Life cycle or infinite horizon
- How To Add a Second Choice Variable
- Method of Simulated Moments Estimation of Parameters

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The Basic Problem at Date t

$$\max \ \mathbb{E}_t \left[\sum_{n_\theta=0}^{T-t} \beth^{n_\theta} \mathrm{u}(\mathrm{c}_{t+n}) \right], \tag{1}$$

$$y_t = \boldsymbol{p}_t \boldsymbol{\theta}_t \tag{2}$$

$\mathrm{R}_t = \mathrm{R} \ \forall \ t$ - constant interest factor $= 1 + \mathrm{r}$

$\mathrm{p}_{t+1} = \boldsymbol{\Phi}_{t+1} \mathrm{p}_t$ - permanent labor income dynamics

$\log \ \boldsymbol{\theta}_{t+n} \sim \mathcal{N}(-\sigma_{\boldsymbol{\theta}}^2/2, \sigma_{\boldsymbol{\theta}}^2)$ - lognormal transitory shocks $\forall \ n > 0$.

Bellman Equation

$$\mathbf{v}_t(\mathrm{m}_t, \mathrm{p}_t) = \max_{\mathrm{c}_t} \; \mathrm{u}(\mathrm{c}_t) + \mathbb{E}_t[\beth \mathbf{v}_{t+1}(\mathrm{m}_{t+1}, \mathrm{p}_{t+1})] \tag{3}$$

$m-$ 'market resources' (net worth plus current income)

$\boldsymbol{p}-$ permanent labor income

Trick: Normalize the Problem

$$
\begin{aligned}
\mathrm{v}_t(m_t) &= \max_{c_t} \quad \mathrm{u}(c_t) + \mathbb{E}_t[\beta \boldsymbol{\Phi}_{t+1}^{1-\rho} \mathrm{v}_{t+1}(m_{t+1})] \\
&\text{s.t.} \\
a_t &= m_t - c_t \\
m_{t+1} &= \underbrace{(\mathsf{R}/\boldsymbol{\Phi}_{t+1})}_{\equiv \mathcal{R}_{t+1}} a_t + \boldsymbol{\theta}_{t+1}
\end{aligned}
$$

where nonbold variables are bold ones normalized by $\boldsymbol{p}$:

$$m_t = \boldsymbol{m}_t / \boldsymbol{p}_t \tag{4}$$

Yields $\mathrm{c}_t(m)$ from which we can obtain

$$\boldsymbol{c}_t(\boldsymbol{m}_t, \boldsymbol{p}_t) = \mathrm{c}_t(\boldsymbol{m}_t / \boldsymbol{p}_t)\boldsymbol{p}_t \tag{5}$$

When Doesn't Normalization Work?

- Non-CRRA utility
- Non-Friedman (transitory/permanent) income process
  - e.g., AR(1)
  - But micro evidence is consistent with Friedman

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Trick: View Everything from End of Period

Define

$$\mathfrak{v}_t(a_t) = \mathbb{E}_t[\beta \boldsymbol{\Phi}_{t+1}^{1-\rho} \mathrm{v}_{t+1}(\mathcal{R}_{t+1} a_t + \boldsymbol{\theta}_{t+1})] \tag{6}$$

so

$$\mathrm{v}_t(m_t) = \max_{c_t} \quad u(c_t) + \mathfrak{v}_t(m_t - c_t) \tag{7}$$

with FOC

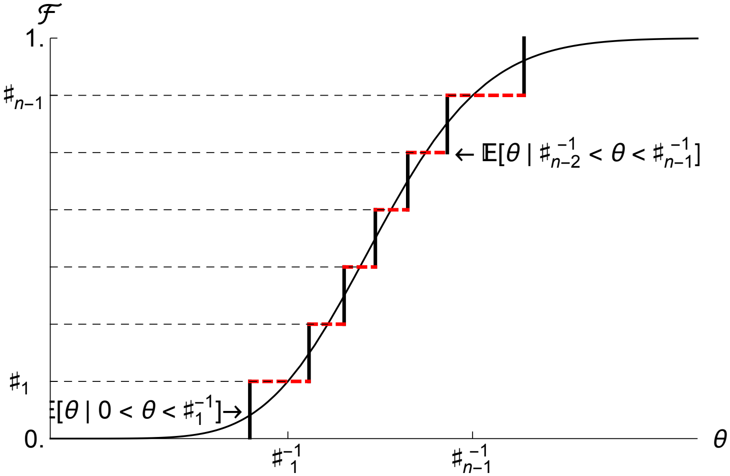
$$\mathrm{u}'(c_t) = \mathfrak{v}_t'(m_t - c_t). \tag{8}$$

and Envelope relation

$$\mathrm{u}'(c_t) = \mathrm{v}_t'(m_t) \tag{9}$$

Trick: Discretize the Risks

E.g. use an equiprobable 7-point distribution:



Trick: Discretize the Risks

$$\mathfrak{v}_t'(a_t) = \beta \mathrm{R} \mathbf{\Phi}_{t+1}^{-\rho} \left(\frac{1}{n}\right) \sum_{i=1}^{n} u' \left(\mathrm{c}_{t+1}(\mathcal{R}_{t+1} a_t + \boldsymbol{\theta}_i)\right) \tag{10}$$

So for any particular m_{T-1} the corresponding c_{T-1} can be found using the FOC:

$$\mathrm{u}'(c_t) = \mathfrak{v}_t'(m_t - c_t). \tag{11}$$

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Trick: Interpolate a Consumption Rule

1. Define a grid of points $\vec{m}$ (indexed $m[i]$)
2. Use numerical rootfinder to solve $u'(c) = \mathfrak{v}'_t(m[i] - c)$
   - The c that solves this becomes $c[i]$
3. Construct interpolating function $\grave{c}$ by linear interpolation
   - 'Connect-the-dots'

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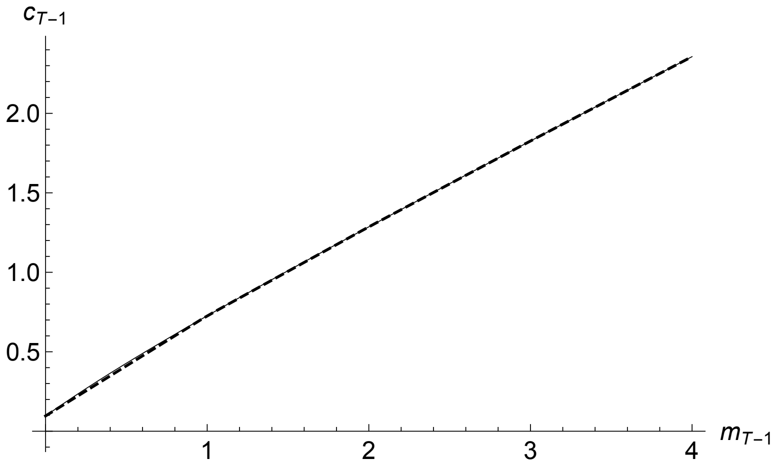
Example: $\vec{m}_{T-1} = \{0., 1., 2., 3., 4.\}$ (solid is 'correct' soln)



Problem: Numerical Rootfinding is *Slow*

Numerical search for values of c_{T-1} satisfying $u'(c) = \mathfrak{v}'_t(m[i] - c)$ at, say, 6 gridpoints of $\vec{m}_{T-1}$ may require hundreds or even thousands of evaluations of

$$\mathfrak{v}'_{T-1}(\overbrace{m_{T-1} - c_{T-1}}^{a_{T-1}}) = \beta_T \mathbf{\Phi}_T^{1-\rho} \left(\frac{1}{n}\right) \sum_{i=1}^{n} (\mathcal{R}_T a_{T-1} + \boldsymbol{\theta}_i)^{-\rho}$$

Solution: The Method of Endogenous Gridpoints

- Define vector of *end-of-period* asset values $\vec{a}$
- For each $a[j]$ compute $\mathfrak{v}'_t(a[j])$

Each of these $\mathfrak{v}'_t[j]$ corresponds to a unique $c[j]$ via FOC:

$$\begin{aligned} c[j]^{-\rho} &= \mathfrak{v}'_t(a[j]) \\ c[j] &= \left(\mathfrak{v}'_t(a[j])\right)^{-1/\rho} \end{aligned} \tag{12}$$

But the DBC says

$$\begin{aligned} a_t &= m_t - c_t \\ m[j] &= a[j] + c[j] \end{aligned} \tag{13}$$

So computing $\mathfrak{v}'_t$ at a vector of $\vec{a}$ values has produced for us the corresponding $\vec{c}$ and $\vec{m}$ values at virtually no cost!

From these we can interpolate as before to construct $\grave{\mathrm{c}}_t(m)$.

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- Define vector of *end-of-period* asset values $\vec{a}$
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Why Directly Approximating v_t is a Bad Idea

Principles of Approximation

- Hard to approximate things that approach ∞ for relevant m
  - Not a prob for Rep Agent models: 'relevant' m's are $\approx$ SS
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Approximate Something That Would Be Linear in PF Case

Perfect Foresight Theory:

$$\mathrm{c}_t(m) = (m + \mathfrak{h}_t)\underline{\kappa}_t \tag{14}$$

for market resources m and end-of-period human wealth $\mathfrak{h}$.

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Bonus: Easy to debug programs by setting $\sigma^2 = 0$ and testing whether numerical solution matches analytical!

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But What if You *Need* the Value Function?

Perfect foresight value function:

$$\begin{aligned}\bar{\mathrm{v}}_t(m_t) &= \mathrm{u}(\bar{c}_t)\mathbb{C}_t^T \\ &= \mathrm{u}(\bar{c}_t)\underline{\kappa}_t^{-1} \\ &= \mathrm{u}((\blacktriangle m_t + \blacktriangle \mathfrak{h}_t)\underline{\kappa}_t)\underline{\kappa}_t^{-1} \\ &= \mathrm{u}(\blacktriangle m_t + \blacktriangle \mathfrak{h}_t)\underline{\kappa}_t^{1-\rho}\underline{\kappa}_t^{-1} \\ &= \mathrm{u}(\blacktriangle m_t + \blacktriangle \mathfrak{h}_t)\underline{\kappa}_t^{-\rho}\end{aligned} \tag{15}$$

where the second line uses the fact demonstrated in Carroll (2022) that $\mathbb{C}_t = \kappa_t^{-1}$.
This can be transformed as

$$\begin{aligned}\bar{\Lambda}_t &\equiv ((1-\rho)\bar{\mathrm{v}}_t)^{1/(1-\rho)} \\ &= c_t(\mathbb{C}_t^T)^{1/(1-\rho)} \\ &= (\blacktriangle m_t + \blacktriangle \mathfrak{h}_t)\underline{\kappa}_t^{-\rho/(1-\rho)}\end{aligned}$$

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Approximate Slope Too

Carroll (2022) shows that c_t^m exists everywhere.

Define *consumed* function and its derivative as

$$\begin{aligned} \mathfrak{c}_t(a) &= \left(\mathfrak{v}_t'(a)\right)^{-1/\rho} \\ \mathfrak{c}_t^a(a) &= -(1/\rho)\left(\mathfrak{v}_t'(a)\right)^{-1-1/\rho}\mathfrak{v}_t''(a) \end{aligned} \tag{17}$$

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To Implement: Modify Prior Procedures in Two Ways

1. Construct $\vec{c}_t^m$ along with $\vec{c}_t$ in EGM algorithm
2. Approximate $c_t(m)$ using piecewise Hermite polynomial
   - Exact match to both level and derivative at set of points

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Problem: $\grave{\mathrm{c}}$ Below Bottom m Gridpoint and Extrapolation

Consider what happens as a_{T-1} approaches $\underline{a}_{T-1} \equiv -\underline{\boldsymbol{\theta}}\mathcal{R}_T^{-1}$,

$$\lim_{a \downarrow \underline{a}_{T-1}} \mathfrak{v}'_{T-1}(a) = \lim_{a \downarrow \underline{a}_{T-1}} \beta \mathsf{R} \boldsymbol{\Phi}_T^{-\rho} \left(\frac{1}{n}\right) \sum_{i=1}^{n} (a\mathcal{R}_T + \boldsymbol{\theta}_i)^{-\rho}$$
$$= \infty$$

This means our lowest value in $\vec{a}_{T-1}$ should be $> \underline{a}_{T-1}$.

Suppose we construct $\grave{\mathrm{c}}$ by linear interpolation:

$$\grave{\mathrm{c}}_{T-1}(m) = \grave{\mathrm{c}}_{T-1}(\vec{m}_{T-1}[1]) + \grave{\mathrm{c}}'_{T-1}(\vec{m}_{T-1}[1])(m - \vec{m}_{T-1}[1])$$

True c is strictly concave $\Rightarrow \exists m^{-} > \underline{m}_{T-1}$ for which
$m^{-} - \grave{\mathrm{c}}_{T-1}(m^{-}) < \underline{a}_{T-1}$

Solution: Hard-Code the Bottom Point

Theory says that

$$\begin{aligned} \lim_{m \downarrow \underline{m}_{T-1}} \mathrm{c}_{T-1}(m) &= 0 \\ \lim_{m \downarrow \underline{m}_{T-1}} \mathrm{c}^{m}_{T-1}(m) &= \bar{\kappa}_{T-1} \end{aligned} \tag{19}$$

1. Redefine $\vec{a}$ *relative* to $\underline{a}_{T-1}$
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then proceed as before.

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5. Prepend $\bar{\kappa}_{T-1}$ to $\vec{\kappa}_{T-1}$

then proceed as before.

Solution: Hard-Code the Bottom Point

Theory says that

$$\begin{aligned} \lim_{m \downarrow \underline{m}_{T-1}} \mathrm{c}_{T-1}(m) &= 0 \\ \lim_{m \downarrow \underline{m}_{T-1}} \mathrm{c}^{m}_{T-1}(m) &= \bar{\kappa}_{T-1} \end{aligned} \tag{19}$$

1. Redefine $\vec{a}$ *relative* to $\underline{a}_{T-1}$
2. Construct corresponding $\vec{m}_{T-1}$ and $\vec{c}_{T-1}$
3. Prepend $\underline{m}_{T-1}$ to $\vec{m}_{T-1}$
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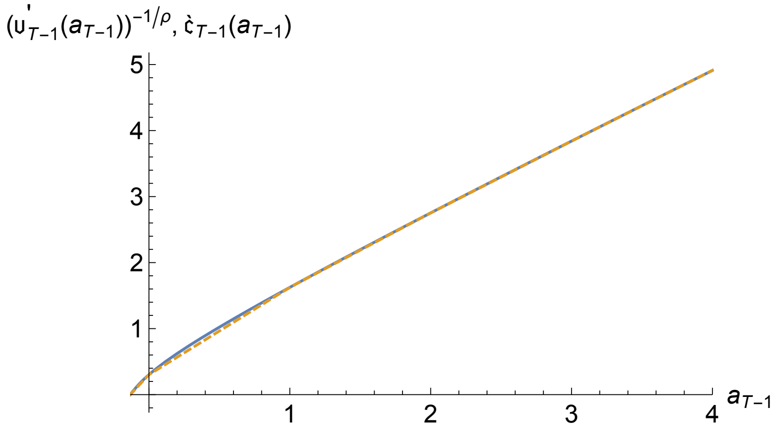
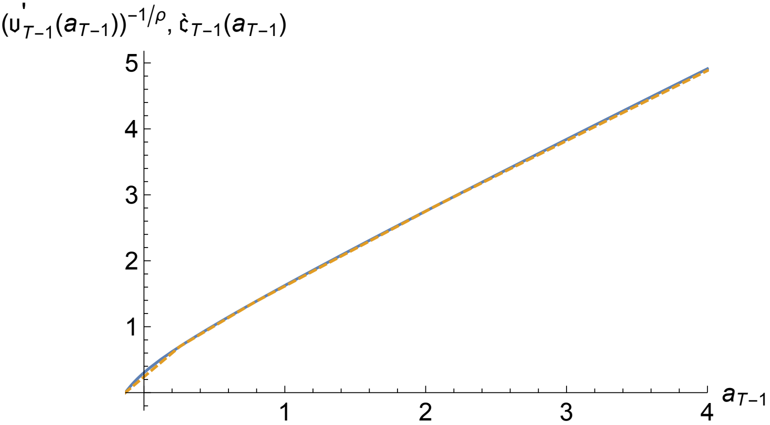
Trick: Improving the a Grid

Grid Spacing: Uniform



Trick: Improving the a Grid

Grid Spacing: Same $\{\underline{a}, \bar{a}\}$ But Triple Exponential $e^{e^{e^{\cdots}}}$ Growth



The Method of Moderation

- Further improves speed and accuracy of solution
- See my talk at the conference!

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Imposing 'Artificial' Borrowing Constraints

$$
\begin{aligned}
\mathrm{v}_{T-1}(m_{T-1}) &= \max_{c_{T-1}} \; u(c_{T-1}) + \mathbb{E}_{T-1}[\beta \boldsymbol{\Phi}_T^{1-\rho} \mathrm{v}_T(m_T)] \\
&\text{s.t.} \\
a_{T-1} &= m_{T-1} - c_{T-1} \\
m_T &= \mathcal{R}_T a_{T-1} + \boldsymbol{\theta}_T \\
a_{T-1} &\geq 0.
\end{aligned}
$$

Define $\grave{\mathrm{c}}_t^*$ as soln to unconstrained problem. Then

$$
\grave{\mathrm{c}}_{T-1}(m_{T-1}) = \min[m_{T-1}, \grave{\mathrm{c}}^*_{T-1}(m_{T-1})]. \tag{20}
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Imposing 'Artificial' Borrowing Constraints

Point where constraint makes transition from binding to not is

$$u'(m^{\#}_{T-1}) = \mathfrak{v}'_{T-1}(0.)$$
$$m^{\#}_{T-1} = \left(\mathfrak{v}'_{T-1}(0.)\right)^{-1/\rho}$$

Procedure is very easy:

- Add 0. as first point in $\vec{a}$
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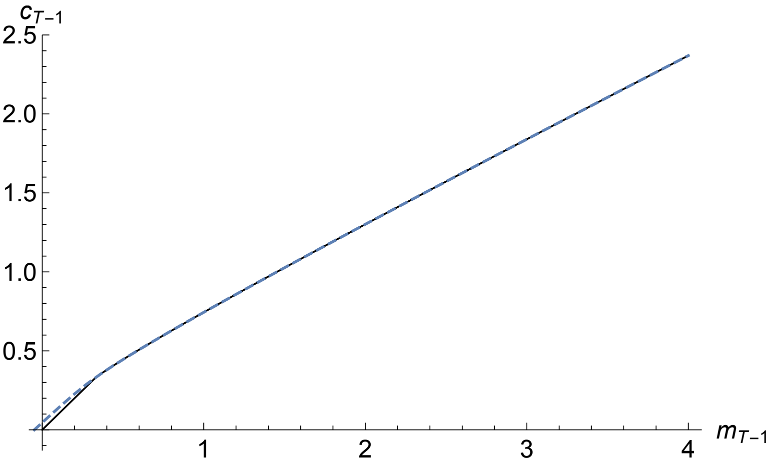

Figure: Constrained (solid) and Unconstrained (dashed) Consumption

Recursion: Period t Solution Given Period $t+1$

1. Construct

$$\begin{aligned}\mathfrak{c}_{t,i} &= \left(\mathfrak{v}_t'(a_{t,i})\right)^{-1/\rho}, \\ &= \left(\beta \mathbb{E}_t\left[\mathsf{R}\mathbf{\Phi}_{t+1}^{-\rho}(\grave{\mathrm{c}}_{t+1}(\mathcal{R}_{t+1}a_{t,i}+\boldsymbol{\theta}_{t+1}))^{-\rho}\right]\right)^{-1/\rho},\end{aligned} \tag{21}$$

2. Call the result $\vec{c}_t$ and generate the corresponding $\vec{m}_t = \vec{c}_t + \vec{a}_t$
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Consumption Rules $\grave{c}_{T-n}$ Converge

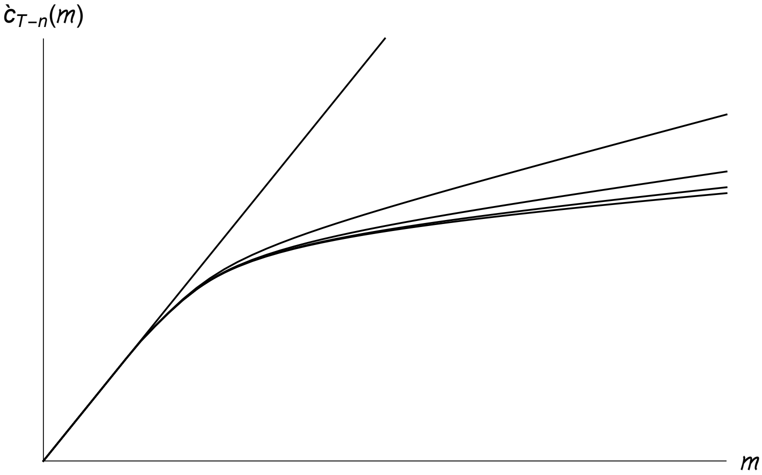

Figure: Converging $\grave{c}_{T-n}(m)$ Functions for $n = \{1, 5, 10, 15, 20\}$

Portfolio Choice

Now the consumer has a choice between a risky and a safe asset.
The portfolio return is

$$\begin{aligned} \mathbb{R}_{t+1} &= \mathsf{R}(1-\varsigma_t) + \mathbf{R}_{t+1}\varsigma_t \\ &= \mathsf{R} + (\mathbf{R}_{t+1} - \mathsf{R})\varsigma_t \end{aligned} \tag{22}$$

so (setting $\mathbf{\Phi} = 1$) the maximization problem is

$$\mathrm{v}_t(m_t) = \max_{\{c_t, \varsigma_t\}} \quad \mathrm{u}(c_t) + \beta \mathbb{E}_t[\mathrm{v}_{t+1}(m_{t+1})]$$

s.t.

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The FOC with respect to c_t now yields an Euler equation

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while the FOC with respect to the portfolio share yields

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When the problem satisfies certain conditions (Carroll (2022)), it defines a 'converged' consumption rule with a 'target' ratio $\check{m}$ that satisfies:

$$\mathbb{E}_t[m_{t+1}/m_t] = 1 \text{ if } m_t = \check{m} \tag{24}$$

Define the target m implied by the consumption rule c_t as $\check{m}_t$.

Then a plausible metric for convergence is to define some value ϵ and to declare the solution to have converged when

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Trick: Coarse then Fine $\boldsymbol{\theta}$

1. Start with coarse grid for $\boldsymbol{\theta}$ (say, 3 points)
2. Solve to convergence; call period of convergence n
3. Construct finer grid for $\boldsymbol{\theta}$ (say, 7 points)
4. Solve for period $T - n - 1$ assuming $\grave{c}_{T-n}$
5. Continue to convergence

Trick: Coarse then Fine θ

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Life Cycle Maximization Problem

$$\mathrm{v}_t(m_t) = \max_{c_t} \left\{ \mathrm{u}(c_t) + \beth\mathcal{L}_{t+1}\hat{\beta}_{t+1}\mathbb{E}_t[(\Psi_{t+1}\boldsymbol{\Phi}_{t+1})^{1-\rho}\mathrm{v}_{t+1}(m_{t+1})] \right\}$$

s.t.

$$a_t = m_t - c_t$$

$$m_{t+1} = a_t \underbrace{\left(\frac{\mathsf{R}}{\Psi_{t+1}\boldsymbol{\Phi}_{t+1}}\right)}_{\equiv\mathcal{R}_{t+1}} + \boldsymbol{\theta}_{t+1}$$

$\mathcal{L}_s$: probability alive (not dead) until age s given alive at age $s-1$

$\hat{\beta}_s$: time-varying discount factor between age $s-1$ and s

Ψ_s : mean-one shock to permanent income

$\beth$: time-invariant discount factor

Details follow Cagetti (2003)

- Parameterization of Uncertainty
- Probability of Death
- Demographic Adjustments to β

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Empirical Wealth Profiles

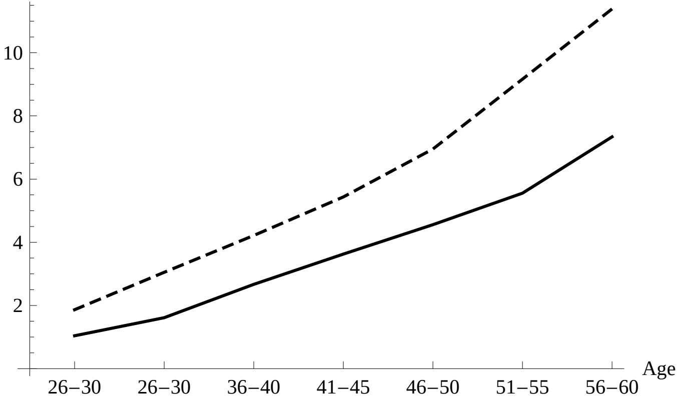

Figure: m from SCF (means (dashed) and medians (solid))

Simulated Moments

Given a set of parameter values $\{\rho, \beth\}$:

- Start at age 25 with empirical *m* data
- Draw shocks using calibrated σ^2_{Ψ},$\sigma^2_{\boldsymbol{\theta}}$
- Consume according to solved c_t

$\Rightarrow$ *m* distribution by age

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Choose What to Simulate

$\texttt{GapEmpiricalSimulatedMedians}[\rho, \beth] := $

$[\qquad \texttt{ConstructcFuncLife}[\rho, \beth];$

$\texttt{Simulate};$

$$\sum_i^N \omega_i \left| \varsigma_i^\tau - \mathrm{s}^\tau(\xi) \right|$$

$];$

Calculate Match Between Theory and Data

$$\xi = \{\rho, \beth\} \tag{26}$$

solve

$$\min_{\xi} \sum_{i}^{N} \omega_i \left|\varsigma_i^{\mathcal{T}} - \mathrm{s}^{\mathcal{T}}(\xi)\right| \tag{27}$$

Bootstrap Standard Errors (Horowitz (2001))

Yields estimates of

Table: Estimation Results

ρ	$\beth$
4.68	1.00
(0.13)	(0.00)

Contour Plot

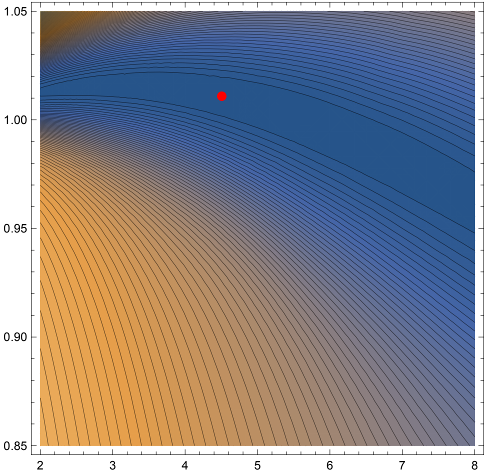

Figure: Point Estimate and Height of Minimized Function

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