

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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$$\mathbf{v}_t(m_t, \mathbf{p}_t) = \max_{c_t} u(c_t) + \mathbb{E}_t[\mathbf{v}_{t+1}(m_{t+1}, \mathbf{p}_{t+1})] \quad (4)$$

m = 'market resources' (net worth plus current income)

p — permanent labor income

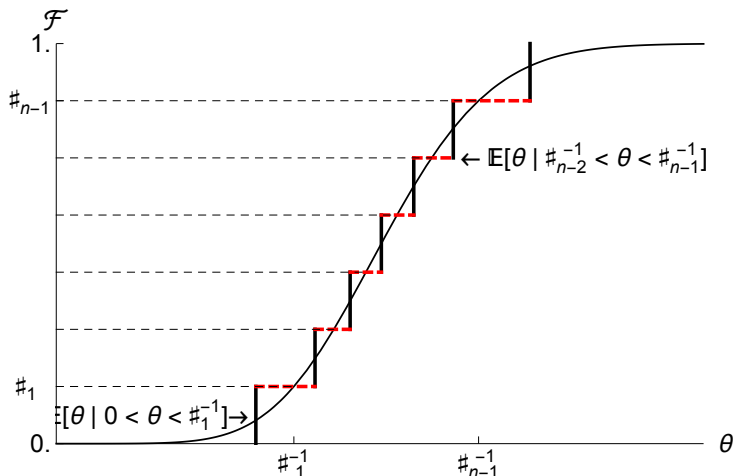
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- Non-Friedman (transitory/permanent) income process
 - e.g., AR(1)
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When Doesn't Normalization Work?

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

Trick: Discretize the Risks

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



$$\mathbf{v}'_t(a_t) = \beta \mathbf{R} \Gamma_{t+1}^{-\rho} \left(\frac{1}{n} \right) \sum_{i=1}^n u'(\mathbf{c}_{t+1}(\mathcal{R}_{t+1} a_t + \theta_i)) \quad (12)$$

Trick: Discretize the Risks

$$v'_t(a_t) = \beta R \Gamma_{t+1}^{-\rho} \left(\frac{1}{n} \right) \sum_{i=1}^n u'(c_{t+1}(\mathcal{R}_{t+1} a_t + \theta_i)) \quad (12)$$

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

$$u'(c_t) = v'_t(m_t - c_t). \quad (13)$$

Trick: Interpolate a Consumption Rule

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

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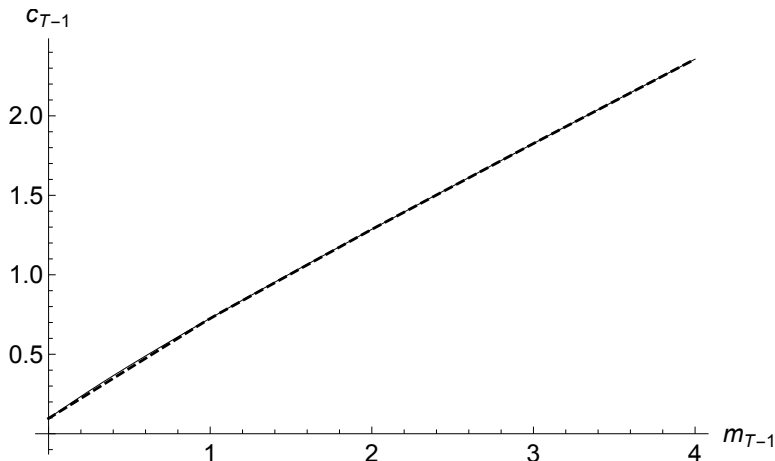
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Trick: Interpolate a Consumption Rule

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

$$v'_{T-1}(\overbrace{m_{T-1} - c_{T-1}}^{a_{T-1}}) = \beta_T \Gamma_T^{1-\rho} \left(\frac{1}{n} \right) \sum_{i=1}^n \frac{(\mathcal{R}_T a_{T-1} + \theta_i)^{1-\rho}}{1-\rho}$$

Solution: The Method of Endogenous Gridpoints

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

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

$$c[j]^{-\rho} = v'_t(a[j]) \quad (14)$$

$$c[j] = (v'_t(a[j]))^{-1/\rho} \quad (15)$$

But the DBC says

$$a_t = m_t - c_t \quad (16)$$

$$m[j] = a[j] + c[j] \quad (17)$$

So computing 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 $\hat{c}_t(m)$.

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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
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Approximate Something That Would Be Linear in PF Case

Perfect Foresight Theory:

$$c_t(m) = (m + h_t)\underline{\kappa}_t \quad (18)$$

for market resources m and end-of-period human wealth h .

This is why it's a good idea to approximate c_t

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:

$$\bar{v}_t(m_t) = u(\bar{c}_t)\mathbb{C}_t^T \quad (19)$$

$$= u(\bar{c}_t)\underline{\kappa}_t^{-1} \quad (20)$$

$$= u((\blacktriangle m_t + \blacktriangle h_t)\underline{\kappa}_t)\underline{\kappa}_t^{-1} \quad (21)$$

$$= u(\blacktriangle m_t + \blacktriangle h_t)\underline{\kappa}_t^{1-\rho}\underline{\kappa}_t^{-1} \quad (22)$$

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where the second line uses the fact demonstrated in Carroll (2020) that $\mathbb{C}_t = \kappa_t^{-1}$.

This can be transformed as

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

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Approximate Slope Too

Carroll (2020) shows that c_t^m exists everywhere.

Define *consumed* function and its derivative as

$$c_t(a) = (v'_t(a))^{-1/\rho} \quad (25)$$

$$c_t^a(a) = -(1/\rho) (v'_t(a))^{-1-1/\rho} v''_t(a) \quad (26)$$

and using chain rule it is easy to show that

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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: \hat{c} Below Bottom m Gridpoint and Extrapolation

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

$$\begin{aligned} \lim_{a \downarrow \underline{a}_{T-1}} v'_{T-1}(a) &= \lim_{a \downarrow \underline{a}_{T-1}} \beta R \Gamma_T^{-\rho} \left(\frac{1}{n} \right) \sum_{i=1}^n (a \mathcal{R}_T + \theta_i)^{-\rho} \\ &= \infty \end{aligned}$$

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

Suppose we construct \hat{c} by linear interpolation:

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

True c is strictly concave $\Rightarrow \exists m^- > \underline{m}_{T-1}$ for which

$$m^- - \hat{c}_{T-1}(m^-) < \underline{a}_{T-1}$$

Solution: Hard-Code the Bottom Point

Theory says that

$$\lim_{m \downarrow \underline{m}_{T-1}} c_{T-1}(m) = 0 \quad (28)$$

$$\lim_{m \downarrow \underline{m}_{T-1}} c_{T-1}^m(m) = \bar{\kappa}_{T-1} \quad (29)$$

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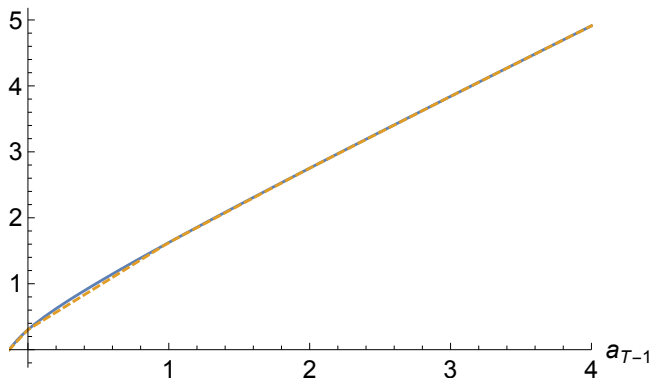
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Trick: Improving the a Grid

Grid Spacing: Uniform

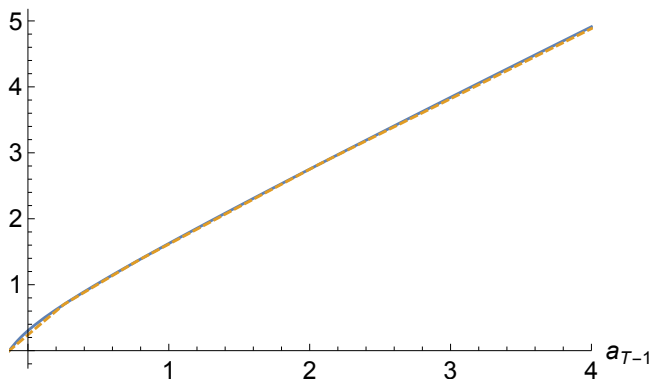
$$(u'_{T-1}(a_{T-1}))^{-1/\rho}, \dot{c}_{T-1}(a_{T-1})$$



Trick: Improving the a Grid

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

$$(u'_{T-1}(a_{T-1}))^{-1/\rho}, \dot{c}_{T-1}(a_{T-1})$$



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

$$\begin{aligned}
 v_{T-1}(m_{T-1}) &= \max_{c_{T-1}} u(c_{T-1}) + \mathbb{E}_{T-1}[\beta \Gamma_T^{1-\rho} v_T(m_T)] \\
 &\text{s.t.} \\
 a_{T-1} &= m_{T-1} - c_{T-1} \\
 m_T &= \mathcal{R}_T a_{T-1} + \theta_T \\
 a_{T-1} &\geq 0.
 \end{aligned}$$

Define \hat{c}_t^* as soln to unconstrained problem. Then

$$\hat{c}_{T-1}(m_{T-1}) = \min[m_{T-1}, \hat{c}_{T-1}^*(m_{T-1})]. \quad (30)$$

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$$\begin{aligned} u'(m_{T-1}^{\#}) &= v'_{T-1}(0.) \\ m_{T-1}^{\#} &= (v'_{T-1}(0.))^{-1/\rho} \end{aligned}$$

Procedure is very easy:

- Add 0. as first point in \vec{a}
- $\Rightarrow \vec{m}[1] = m_{T-1}^{\#}$
- Above $m_{T-1}^{\#}$, $\hat{c}_{T-1}(m)$ obtained as before
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Imposing 'Artificial' Borrowing Constraints

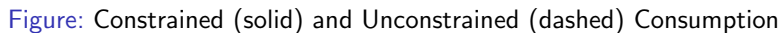
Point where constraint makes transition from binding to not is

$$u'(m_{T-1}^{\#}) = v'_{T-1}(0.)$$

$$m_{T-1}^{\#} = (v'_{T-1}(0.))^{-1/\rho}$$

Procedure is very easy:

- Add 0. as first point in \vec{a}
- $\Rightarrow \vec{m}[1] = m_{T-1}^{\#}$
- Above $m_{T-1}^{\#}$, $\hat{c}_{T-1}(m)$ obtained as before
- Below $m_{T-1}^{\#}$, $\hat{c}_{T-1}(m) = m$



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1 Construct

$$\mathbf{c}_{t,i} = (\mathbf{v}'_t(\mathbf{a}_{t,i}))^{-1/\rho}, \quad (31)$$

$$= \left(\beta \mathbb{E}_t \left[\mathbf{R} \Gamma_{t+1}^{-\rho} (\dot{\mathbf{c}}_{t+1} (\mathcal{R}_{t+1} \mathbf{a}_{t,i} + \theta_{t+1}))^{-\rho} \right] \right)^{-1/\rho} (32)$$

- 2 Call the result \vec{c}_t and generate the corresponding $\vec{m}_t = \vec{c}_t + \vec{a}_t$
- 3 Interpolate to create $\hat{c}_t(m)$

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- ③ Interpolate to create $\hat{c}_t(m)$

Consumption Rules \dot{c}_{T-n} Converge

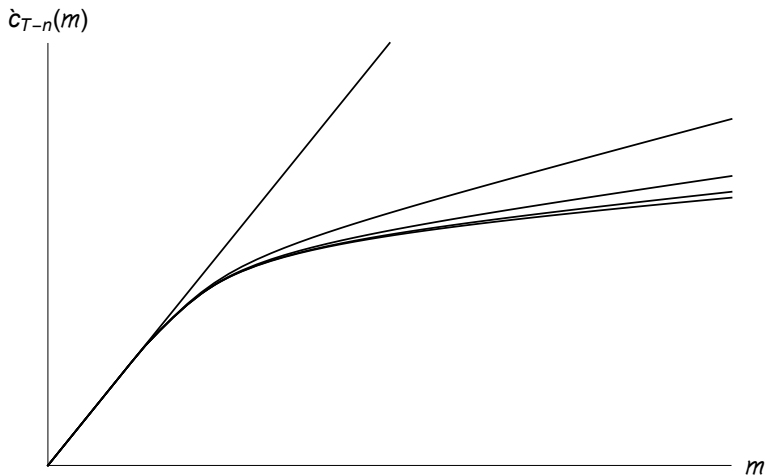


Figure: Converging $\dot{c}_{T-n}(m)$ Functions for $n = \{1, 5, 10, 15, 20\}$

Portfolio Choice

Now the consumer has a choice between a risky and a safe asset.

The portfolio return is

s.t.

$$\mathbb{R}_{t+1} = R + (\mathbf{R}_{t+1} - R)\zeta_t$$

$$m_{t+1} = (m_t - c_t)\mathbb{R}_{t+1} + \theta_{t+1}$$

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$$0 \leq \zeta_t \leq 1,$$

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$$u'(c_t) = \mathbb{E}_t[\beta R_{t+1} u'(c_{t+1})]. \quad (35)$$

$$\begin{aligned} 0 &= \mathbb{E}_t[v'_{t+1}(m_{t+1})(\mathbf{R}_{t+1} - \mathbf{R})a_t] \\ &= a_t \mathbb{E}_t[u'(c_{t+1}(m_{t+1}))(\mathbf{R}_{t+1} - \mathbf{R})]. \end{aligned} \quad (36)$$

Convergence

When the problem satisfies certain conditions (Carroll (2020)), it defines a ‘converged’ consumption rule with a ‘target’ ratio \check{m} that satisfies:

$$\mathbb{E}_t[m_{t+1}/m_t] = 1 \text{ if } m_t = \check{m} \quad (37)$$

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

$$|\check{m}_{t+1} - \check{m}_t| < \epsilon \quad (38)$$

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Trick: Coarse then Fine θ

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

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Details follow Cagetti (2003)

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

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Empirical Wealth Profiles

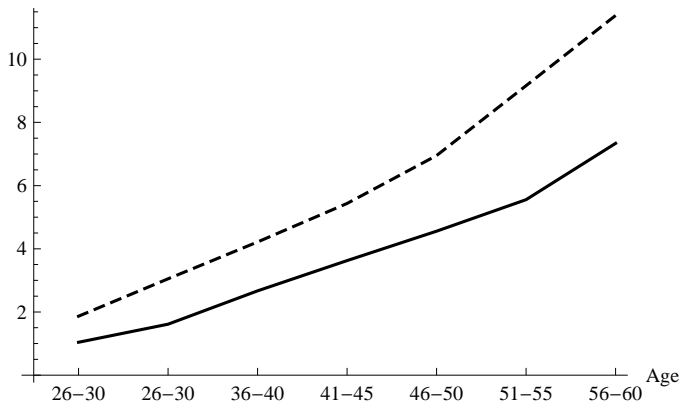


Figure: m from SCF (means (dashed) and medians (solid))

Simulated Moments

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

- Start at age 25 with empirical m data
- Draw shocks using calibrated $\sigma_\psi^2, \sigma_\theta^2$
- Consume according to solved c_t

$\Rightarrow m$ distribution by age

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```

GapEmpiricalSimulatedMedians[ $\rho, \mathfrak{N}$ ]:=
[ ConstructcFuncLife[ $\rho, \mathfrak{N}$ ];
  Simulate;
  
$$\sum_i^N \omega_i |\varsigma_i^\tau - \mathbf{s}^\tau(\xi)|$$

];

```

$$\xi = \{\rho, \mathbb{I}\} \quad (39)$$

solve

$$\min_{\xi} \sum_i^N \omega_i |\varsigma_i^T - \mathbf{s}^T(\xi)| \quad (40)$$

Bootstrap Standard Errors (Horowitz (2001))

Yields estimates of

Table: Estimation Results

ρ	β
4.68	1.00
(0.13)	(0.00)

Contour Plot

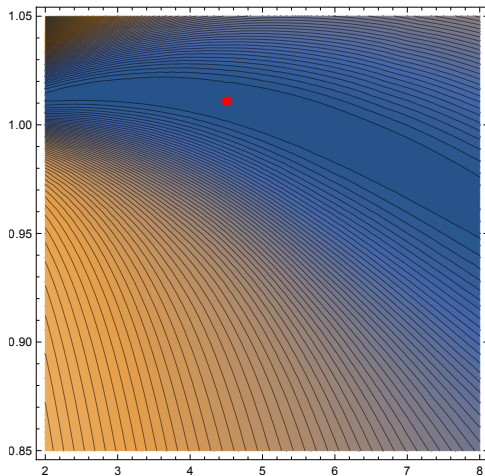


Figure: Point Estimate and Height of Minimized Function

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