

Dynamic Programming and Structural Estimation

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2024

Outline

- 1 Introduction
- 2 Stochastic DP
- 3 Structural Estimation

Stochastic Dynamic Programming

- **Last time:** Dynamic Programming
 - Backwards induction
 - Grids
 - Interpolation

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 - + “Normalization” of one state variable.

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Simulated Method of Moments (SMM/SMD)

Relate to “reduced-form”

Can we combine approaches?

See Eisenhauer, Heckman and Mosso (2015) Todd and Wolpin (2023)

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 - Simulated Method of Moments (SMM/SMD)
 - Relate to “reduced-form”
 - Can we combine approaches?
 - See Eisenhauer, Heckman and Mosso (2015) Todd and Wolpin (2023)
- **Example:** Buffer Stock model of Deaton (1991); Carroll (1992)
 - Estimated in Gourinchas and Parker (2002)

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 1. **Estimate model** with 2+ motives:
 - Buffer-stock motive: Income risk while working.
 - Life cycle motive: Consumption in retirement.

Gourinchas and Parker (2002)

- **Research question:** “Which savings motives dominate across life?”
- **Approach:**
 1. **Estimate model** with 2+ motives:
Buffer-stock motive: Income risk while working.
Life cycle motive: Consumption in retirement.
 2. **Quantify importance** of these motives over life
Counterfactual simulations

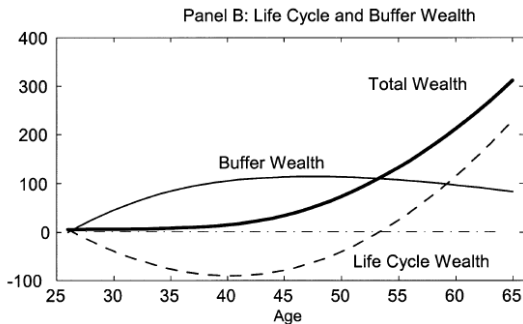


FIGURE 7.—The role of risk in saving and wealth accumulation.

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Buffer-stock model (Deaton-Carroll) Bellman equation

- **Simplest version** of the buffer-stock model is

$$V_t(M_t, P_t) = \max_{C_t} \frac{C_t^{1-\rho}}{1-\rho} + \beta \mathbb{E}_t [V_{t+1}(M_{t+1}, P_{t+1})]$$

s.t.

$$A_t = M_t - C_t \quad (\text{assets})$$

$$M_{t+1} = RA_t + Y_{t+1} \quad (\text{resources/cash-on-hand})$$

$$Y_{t+1} = P_{t+1}\tilde{\zeta}_{t+1} \quad (\text{income})$$

$$P_{t+1} = GP_t\psi_{t+1} \quad (\text{perm. income})$$

$$A_t \geq 0, \forall t \quad (\text{no borrowing})$$

where $\mathbb{E}_t[V_{t+1}(M_{t+1}, P_{t+1})] = \mathbb{E}[V_{t+1}(M_{t+1}, P_{t+1}) | M_t, P_t, C_t]$
are expectations over perm. and trans. income shocks,

$$\log \tilde{\zeta}_{t+1} \sim \mathcal{N}(\mu_{\tilde{\zeta}}, \sigma_{\tilde{\zeta}}^2), \log \psi_{t+1} \sim \mathcal{N}(\mu_{\psi}, \sigma_{\psi}^2)$$

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- Gourinchas and Parker (2002): “natural” borrowing constraint.
mass-point at zero in trans. income shock distribution, $\tilde{\zeta}_{t+1}$

Buffer-stock model (Deaton-Carroll) Bellman equation

- **Last period:** Everything is consumed,

$$C_T^*(M_T, P_T) = M_T$$

$$V_T(M_T, P_T) = \frac{M_T^{1-\rho}}{1-\rho}$$

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- **Gourinchas and Parker (2002):** Retirement-periods
Assumes a linear post-retirement value (w. $P_{T+1} = P_T$)

$$V_{T+1}(M_{T+1}, P_{T+1}) = \kappa \cdot (M_{T+1} + h \cdot P_{T+1})$$

Motivated by a deterministic perfect credit market solution (estimate κ and h , through γ_0 and γ_1 – see e.g. Jørgensen and Tô, 2020)

- They also allow for time-varying taste-shifters, $v_t(Z_t)$.

Normalization I

- Defining $c_t \equiv C_t/P_t$, $m_t \equiv M_t/P_t$ etc. implies

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and state transition

$$M_{t+1} = RA_t + Y_{t+1}$$

$$M_{t+1}/P_{t+1} = RA_t/P_{t+1} + Y_{t+1}/P_{t+1}$$

$$m_{t+1} = R a_t P_t / P_{t+1} + \tilde{\zeta}_{t+1}$$

$$m_{t+1} = \frac{R}{G\psi_{t+1}} a_t + \tilde{\zeta}_{t+1}$$

The **adjustment factor** $\frac{1}{G\psi_{t+1}}$ is due to changes in permanent income

Normalization II

- Defining $v_t(m_t) = V_t(M_t, P_t) / P_t^{1-\rho}$ implies

$$\begin{aligned} V_t(M_t, P_t) &= \max_{c_t} \frac{C_t^{1-\rho}}{1-\rho} + \beta \mathbb{E}_t [V_{t+1}(M_{t+1}, P_{t+1})] \\ &= \max_{c_t} \frac{(c_t P_t)^{1-\rho}}{1-\rho} + \beta \mathbb{E}_t [V_{t+1}(M_{t+1}, P_{t+1})] \Leftrightarrow \end{aligned}$$

$$V_t(M_t, P_t) / P_t^{1-\rho} = \max_{c_t} \frac{(c_t P_t)^{1-\rho} / P_t^{1-\rho}}{1-\rho} + \beta \mathbb{E}_t \left[V_{t+1}(M_{t+1}, P_{t+1}) / P_t^{1-\rho} \right] \Leftrightarrow$$

$$v_t(m_t) = \max_{c_t} \frac{c_t^{1-\rho}}{1-\rho} + \beta \mathbb{E}_t \left[\underbrace{V_{t+1}(M_{t+1}, P_{t+1}) / P_{t+1}^{1-\rho}}_{=v_{t+1}(m_{t+1})} \cdot \underbrace{P_{t+1}^{1-\rho} / P_t^{1-\rho}}_{=(G\psi_{t+1})^{1-\rho}} \right]$$

$$= \max_{c_t} \frac{c_t^{1-\rho}}{1-\rho} + \beta \mathbb{E}_t \left[(G\psi_{t+1})^{1-\rho} v_{t+1}(m_{t+1}) \right]$$

Bellman equation in ratio form

$$\begin{aligned}v_t(m_t) &= \max_{c_t} \frac{c_t^{1-\rho}}{1-\rho} + \beta \mathbb{E}_t [(G\psi_{t+1})^{1-\rho} v_{t+1}(m_{t+1})] \\&\text{s.t.} \\a_t &= m_t - c_t \\m_{t+1} &= \frac{1}{G\psi_{t+1}} Ra_t + \xi_{t+1} \\a_t &\geq 0\end{aligned}$$

- **Benefit:** Dimensionality of state space reduced, $2 \rightarrow 1$.
Can this always be done?

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Can this always be done?
- No... Uses that utility is homothetic (budget constraint also important)

$$V_T(M_T, P_T) = \frac{M_T^{1-\rho}}{1-\rho} = \frac{(\textcolor{blue}{m}_T P_T)^{1-\rho}}{1-\rho} = \frac{\textcolor{blue}{m}_T^{1-\rho}}{1-\rho} P_T^{1-\rho}$$

such that $v_T(m_T) = V_T(M_T, P_T) / P_T^{1-\rho}$ holds!

Solving the model: Numerical Integration

- Solved by **backwards induction**

Terminal period:

$$v_T(m_T) = \frac{m_T^{1-\rho}}{1-\rho}$$

For $t < T$:

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- **How to evaluate expectations?**

$$\mathbb{E}_t[\bullet] = \int_{\psi_{t+1}} \int_{\tilde{\xi}_{t+1}} \left[(G\psi_{t+1})^{1-\rho} v_{t+1}(m_{t+1}) \right] f(d\psi_{t+1}, d\tilde{\xi}_{t+1})$$

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- Numerical Integration:** Discretize into sum (Gauss-Hermite)

$$\mathbb{E}_t[\bullet] \approx \sum_{j=1}^J \sum_{k=1}^K [(G\psi^{(j)})^{1-\rho} v_{t+1}(m^{(j,k)})] \omega_j \omega_k$$

and interpolate $v_{t+1}(\bullet)$ for values $m^{(j,k)} = \frac{1}{G\psi^{(j)}} Ra_t + \tilde{\xi}^{(k)}$ of \vec{m} grid.

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- **Benefit of models:**
 1. Ensure *consistent* world view
 2. Assumptions are clear: Better models are well defined.
 3. Hopefully “deep” policy-invariant parameters (Lucas critique).

Structural vs. Reduced-Form Estimation

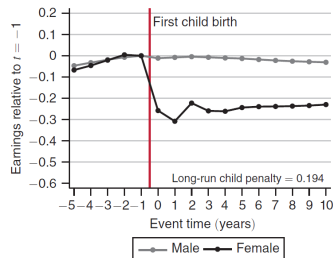
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- **Frontier:** Use exogenous variation to estimate structural model.

Structural vs. Reduced-Form Estimation

- **Example:** Event-studies (child-birth, Kleven, Landais and Sørensen, 2019)

- **Reduced-form** to be *causal*:
“statistical” assumptions
 - No self-selection (timing)
 - No anticipation effects.
 - Parallel trends.

Panel A. Earnings



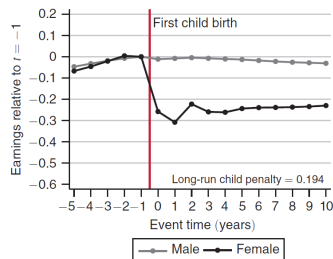
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Panel A. Earnings



- **A model can allow** for these assumptions to be violated
But only through the chosen functional forms and mechanisms
 - “Economic” assumptions
 - Easier to debate and improve upon (?)

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- **Example model:** Life-cycle buffer-stock model
 - States: M_{it}, P_{it}
 - Choice: C_{it}
- **Parameters** to estimate: $\theta = \{\beta, \rho\}$
 - Calibration: $G, \sigma_\psi, \sigma_{\tilde{\xi}}, R$, and λ ("known")

Simulated Method of Moments (SMM/SMD)

- $\Lambda^d = \frac{1}{N} \sum_{i=1}^N \Lambda_i^d$ are some **moments in the data**
Could be avg., var, cov, regression-coefs, etc.

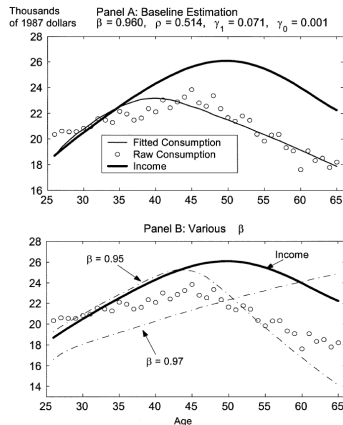


FIGURE 5.—The fitted consumption profile.

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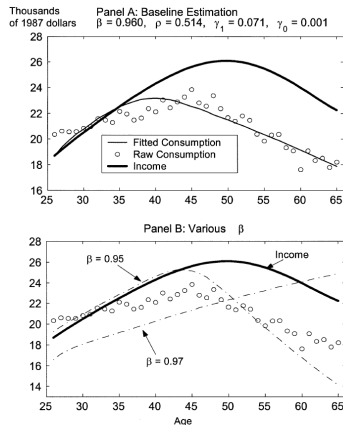


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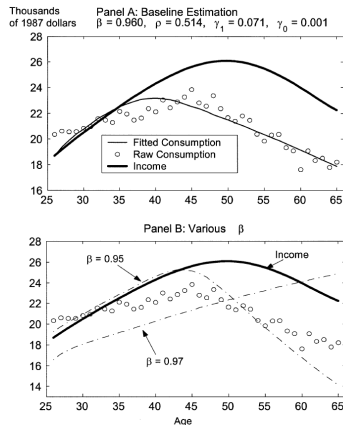


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- **SMM** then is

$$\hat{\theta} = \arg \min_{\theta} g(\theta)' W g(\theta)$$

where W is **weighting matrix**.

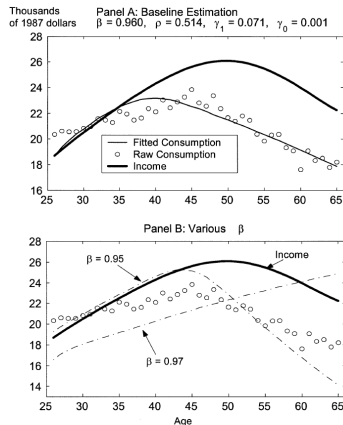


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Weighting Matrix, W

- Common weighting matrices, W , are (should be positive-definite)
 1. **Theoretically optimal**
Inverse of covariance matrix of empirical moments
Can cause problems in finite samples
 2. **Identity, I**
Equal weighting.
Does not take level-differences out of moments
 3. **Diagonal matrix** with *inverse* of empirical moment *variances*
Removes “level” differences.
Scales with uncertainty about empirical moments
Popular
 4. **Freely chosen**
Focus on fitting some specific dimensions of the data

Estimation experiment

1. **Solve** the buffer-stock model and **simulate** a full panel
2. Construct a **data set** from the simulated data
3. Try to **estimate** $\theta = \{\beta, \rho\}$
using as moments the **average wealth for each age between 40 and 55**
 $\Lambda^d = (A_{40}, A_{41}, \dots, A_{55})$

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- I will now describe how to calculate the objective function

$$Q(\theta) = \left(\Lambda^d - \Lambda^m(\theta) \right)' W \left(\Lambda^d - \Lambda^m(\theta) \right)$$

for a given value of θ .

- This function should then be minimized to get

$$\hat{\theta} = \arg \min_{\theta} Q(\theta)$$

Implementation, $\hat{\theta}_{MSM} = \arg \min_{\theta} Q(\theta)$

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2. For $s = 1, \dots, S$:

2.1 Simulate N agents for T periods to get

$$C_{it}^{(s)}(\theta) = P_{it}^{(s)} \cdot \check{c}_t^*(M_{it}^{(s)}(\theta) / P_{it}^{(s)}; \theta)$$

$$M_{it}^{(s)}(\theta) = RA_{it-1}^{(s)}(\theta) + Y_{it}^{(s)}$$

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3. Calculate the objective function with $\Lambda^m(\theta) = \frac{1}{S} \sum_{s=1}^S \Lambda_s(\theta)$

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2. Simulate $\tilde{S} = SN$ agents for T periods to get

$$C_t^{(s)}(\theta) = P_t^{(s)} \cdot \check{c}_t^*(M_i^{(s)}(\theta) / P_t^{(s)}; \theta)$$

$$M_t^{(s)}(\theta) = RA_{t-1}^{(s)}(\theta) + Y_t^{(s)}$$

$$A_{t-1}^{(s)}(\theta) = M_{t-1}^{(s)}(\theta) - C_{t-1}^{(s)}(\theta)$$

$$Y_t^{(s)} = P_t^{(s)} \tilde{\zeta}_t^{(s)}$$

$$P_t^{(s)} = GP_{t-1}^{(s)} \psi_t^{(s)}$$

for some initial A_0 and P_0 and draws of $\tilde{\zeta}_t^{(s)}$ and $\psi_t^{(s)}$.

Alt. Implementation, $\hat{\theta}_{MSM} = \arg \min_{\theta} Q(\theta)$

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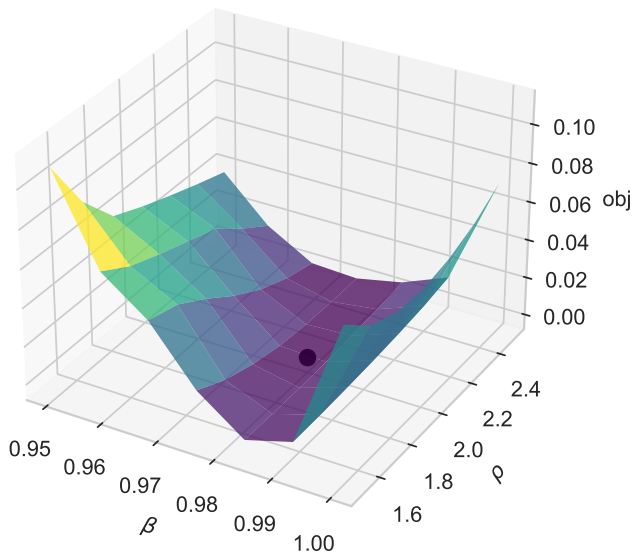
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4. Calculate the objective function

$$Q(\theta) = \left(\Lambda^d - \Lambda^m(\theta) \right)' W \left(\Lambda^d - \Lambda^m(\theta) \right)$$

Buffer-stock: MSM



Indirect inference / minimum distance

- Many different names for very similar approaches
 - McFadden (1989): Method of Simulated Moments (MSM)
 - Duffie and Singleton (1993): Simulated Minimum Distance (SMD)
 - Gouriéroux, Monfort and Renault (1993) + Smith (1993): Indirect Inference (II)

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- SMD/II rely on an **auxillary statistical model**
 - Let Λ^d be the parameters of the auxillary model when estimated on the *actual* data
 - Let $\Lambda_s(\theta)$ be the parameters of the auxillary model when estimated on *simulated* data
- **Note:** The auxillary statistical model is *misspecified* and its parameters are thus typically *not interpretable*

Simulation Pitfalls

- **FIX the seed (or draws!)**
- **Flat** objective function!
 - Discrete choices: Taking a mean of an **indicator function**
- **Gradient** based numerical optimization will likely FAIL!
 - Use, e.g., `scipy.optimize.minimize(fun , method='Nelder-Mead')` (Nelder-Mead)
 - Or some smoothing device (e.g. Logit)
- As $N, S \rightarrow \infty$ this problem vanishes
- The problem is also less severe around θ_0
- Continuous outcomes do not have this problem

Asymptotics

- **MSM** is **consistent** and **asymptotically normal** under standard assumptions

$$\sqrt{N}(\hat{\theta} - \theta_0) \rightarrow \mathcal{N}(0, (1 + S^{-1})V)$$

where θ_0 is vector of true parameters

- **Standard formulas for V:**

$$V = (G'WG)^{-1}G'W\Omega W'G(G'WG)^{-1}$$

where $G = -\frac{\partial \Lambda^m(\theta)}{\partial \theta}$ is the Jacobian of the objective function.

$\Omega = \text{Var}(\Lambda_i^d)$ is the variance of the (individual) moments in the data.

Remember: Standard errors are large if large changes in θ imply small changes in the objective function

Identification

- **Is there enough variation in the data to identify θ ?**

Very hard to *prove* anything because the model is typically strongly non-linear

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- **Problems:**

1. The objective function might have multiple minima (*no global solver exists*)
2. The objective function could be very flat in some directions (*increasing S might help*)

Robustness/Sensitivity

- **Curse of dimensionality and lack of identification**
 - ⇒ we cannot estimate all the parameters of the model
 - ⇒ *first step estimation/calibration is often necessary*
 1. Calculations on own data (e.g. exogenous processes)
 2. References to previous estimates
 3. Standard choices

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- **Robustness:** Can we vary the calibration choices without changing the result substantially?

“Sensitivity to Calibration”: (Jørgensen, 2023)

“*How much does estimates of θ change when 1. step calibrations change?*”

Calibration vs. Estimation

- **Estimation** or **calibration**: What is the difference?
(my take)

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Calibration vs. Estimation

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(my take)
- **Estimation:** “systematic”
Use a solver to minimize a criteria function wrt. θ
Report standard errors on $\hat{\theta}$
Time-consuming!
- **Calibration:** “hand-held”
Use a (small) grid of values for θ
to minimize some moment(s). Sometimes eyeballing, sequentially for each parameter.
Do not report standard errors
Less time-consuming!
“Illustrate proposed mechanism”

Next Time

- **Next time:**

Static and dynamic labor supply

Recap for some + new stuff for most.

- **Literature:**

Keane (2011, sections 1–5): “Labor Supply and Taxes: A Survey”

- **Read** before lecture

- **Reading guide:**

Section 1: short Introduction

Section 2: Optimal Taxation, Motivation. Skim fast.

Section 3: Basic model. *Key, focus here.*

Section 4: Econometric issues. Skim.

Section 5: Roadmap of empirical literature. *Short, read.*

(Remaining: empirical literature.)

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