

Discussion of
“Behavioral Macroeconomics Via Sparse
Dynamic Programming”
by Xavier Gabaix

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Sparse Dynamic Programming

- Agent builds a “sparse” simplified model of the world
 - pays attention only to the most important variables
 - pays zero attention to less important variables
- This Paper: Application to Dynamic Programming and Macro

This Discussion

- General Sparsity Framework: Static Example
- Dynamic Two-Period Application
- Infinite Horizon, Dynamic Programming Problem
- My Comments

Sparsity General Framework: Simple Static Example

Single Agent Static Maximization Problem

$$\max_a v(a, \mathbf{x})$$

- suppose a is a single action
- $\mathbf{x} = (x_1, x_2, \dots, x_n)$ is a vector of state variables

$$x_i \sim \mathcal{N}(0, \sigma_i^2)$$

- but perhaps the set of x_i is really, really, really big!

Alternative: Sparsity (Gabaix 2014 QJE)

- agent instead chooses a *sparse* representation of x_i

$$x_i^s = m_i x_i$$

with attention vector

$$\mathbf{m} = (m_1, m_2, \dots, m_n) \quad \text{where} \quad m_i \in [0, 1]$$

- if $m_i < 1$ then agent pays only partial attention to x_i
 - if $m_i = 0$ then agent pays no attention to x_i
- agent maximizes new, sparse objective

$$v(\mathbf{a}, \mathbf{x}) \rightarrow v(\mathbf{a}, m_1 x_1, \dots, m_n x_n)$$

Step 1: Choose attention vector

- minimize utility loss due to inattentiveness

$$\min_{m_i} \frac{1}{2} \Lambda_i (1 - m_i)^2 + \kappa m_i$$

- Λ_i denotes expected utility loss
(and here I assume x_i are uncorrelated)
- κ constant cost of attention

Utility Loss evaluated at Default Model

- How do you calculate Λ_j ?

$$\Lambda_j \equiv -v_{aa} \left(\frac{\partial a}{\partial x_j} \right)^2 \sigma_j^2$$

- derivatives evaluated around a “Default Model”

$$v_{aa} = \left. \frac{\partial^2 v}{\partial a^2} \right|_{a=a^d} \quad \text{and} \quad \left. \frac{\partial a}{\partial x_j} \right|_{a=a^d}$$

- Default Model: can choose, but for most applications, $m_j^d = 0$

Optimal Attention Choice

$$\min_{m_i} \frac{1}{2} \Lambda_i (1 - m_i)^2 + \kappa m_i$$

- FOC

$$\kappa = \Lambda_i (1 - m_i)$$

- solve for m to obtain optimal attention coefficient

$$m_i^* = \max \left\{ 1 - \frac{\kappa}{\Lambda_i}, 0 \right\}$$

Optimal Attention is Sparse

$$m_i^* = \begin{cases} 0 & \text{if } \kappa > |v_{aa}| \left(\frac{\partial a}{\partial x_i} \right)^2 \sigma_i^2 \\ 1 - \frac{\kappa}{|v_{aa}| \left(\frac{\partial a}{\partial x_i} \right)^2 \sigma_i^2} & \text{otherwise} \end{cases}$$

“Eliminate attention if the marginal cost of attention is too high relative to the marginal benefit”

Step 2: Solve problem with sparse representation

$$\max_a v(a, m_1^* x_1, \dots, m_n^* x_n)$$

Sparsity in a Two-Period Model

Single Agent Consumption-Savings Problem

$$\max_{c_0, c_1} u(c_0) + \mathbb{E}\beta u(c_1)$$

subject to

$$\begin{aligned}c_0 + a_1 &\leq y_0 \\c_1 &\leq (1+r)a_1 + y_1\end{aligned}$$

where

$$\begin{aligned}r &= \bar{r} + \varepsilon_r & \varepsilon_r &\sim \mathcal{N}(0, \sigma_r^2) \\y_1 &= \bar{y}_1 + \varepsilon_y & \varepsilon_y &\sim \mathcal{N}(0, \sigma_y^2)\end{aligned}$$

Sparse Model

$$v(a_1, m_r \varepsilon_r, m_y \varepsilon_y) = u(y_0 - a_1) + \beta u((1 + r) a_1 + y_1)$$

where

$$r = \bar{r} + m_r \varepsilon_r$$

$$y_1 = \bar{y}_1 + m_y \varepsilon_y$$

Default Model

- default model:

$$m_r = 0, \quad m_y = 0$$

so that agent completely ignores the stochastic components

$$r = \bar{r} \quad \text{and} \quad y_1 = \bar{y}_1$$

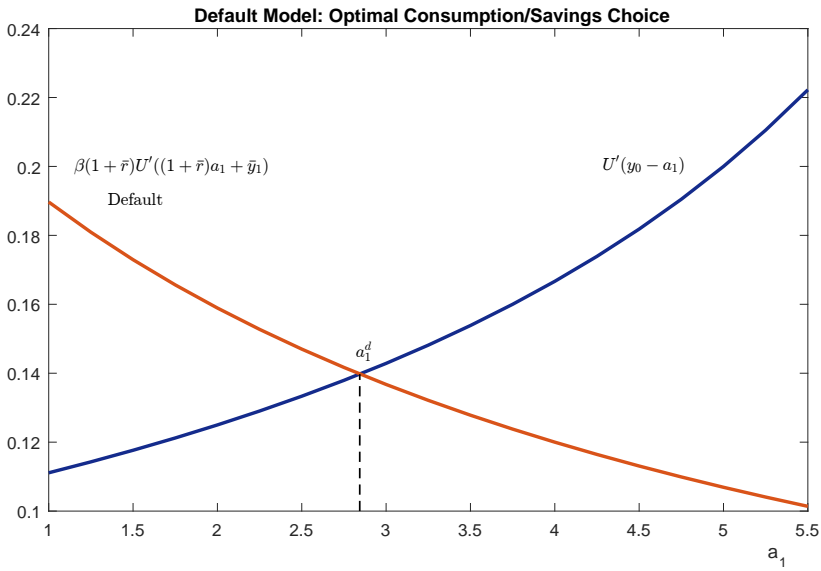
- optimality condition: Euler Equation

$$u'(c_0) = \beta(1 + \bar{r}) u'(c_1)$$

- one line solution

$$u'(y_0 - a_1) = \beta(1 + \bar{r}) u'((1 + \bar{r}) a_1 + \bar{y}_1)$$

Default Model Solution



Rational Agent

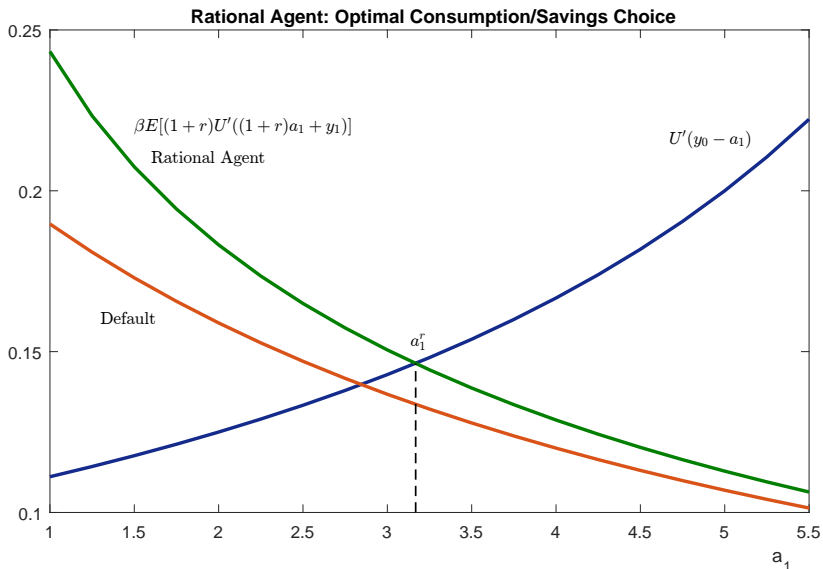
- Euler equation

$$u'(c_0) = \beta \mathbb{E} (1 + r) u'(c_1)$$

- one line solution

$$u'(y_0 - a_1) = \beta \mathbb{E} [(1 + r) u'((1 + r) a_1 + y_1)]$$

Rational Agent Solution



Sparse Agent. Step 1: Optimal Attention

- calculate Λ_i expected utility loss

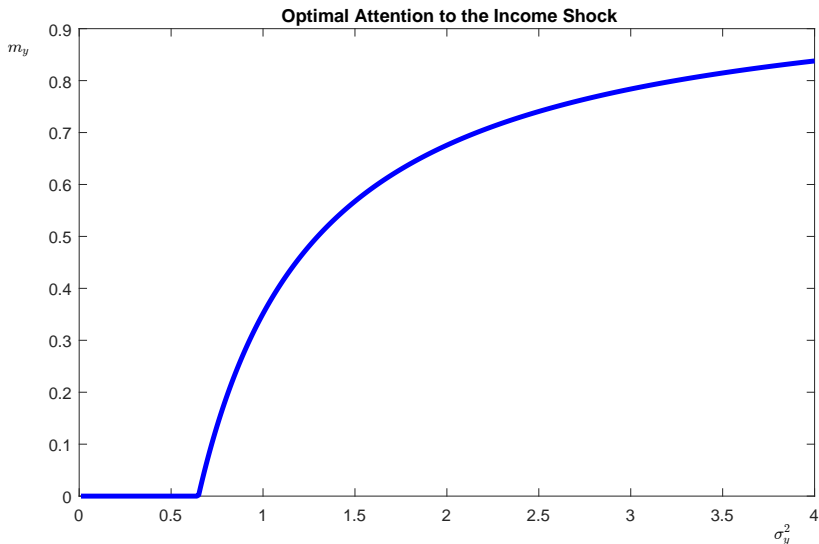
$$\Lambda_i = -v_{aa} \left(\frac{\partial a}{\partial x_i} \right)^2 \sigma_i^2$$

with derivatives evaluated around the Default Model

- obtain optimal attention coefficient

$$m_i^* = \max \left\{ 1 - \frac{\kappa}{\Lambda_i}, 0 \right\}$$

Optimal Attention as a function of Variance



Optimal Attention as a function of Cost

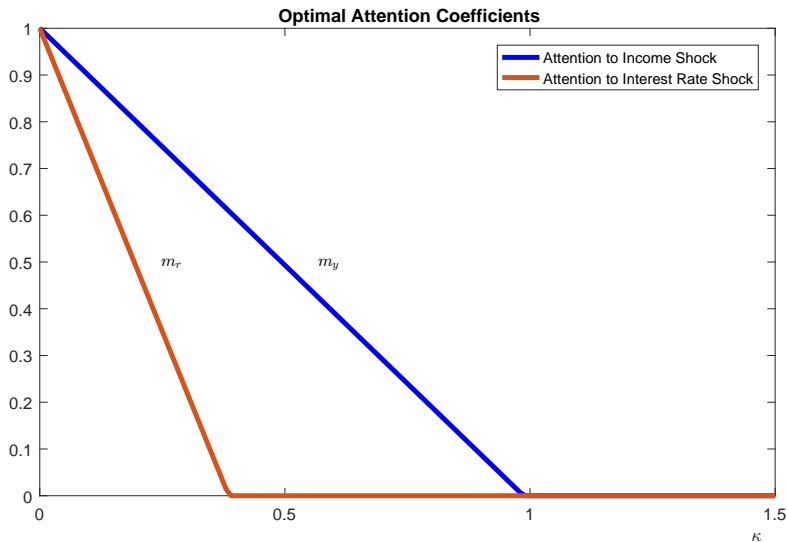


Figure:

Sparse Agent. Step 2: Consumption-Savings Choice.

- given m_r^* and m_y^* , now solve

$$\max_{a_1} v(a_1, m_r^* \varepsilon_r, m_y^* \varepsilon_y)$$

- that is,

$$\max_{a_1} u(y_0 - a_1) + \beta \mathbb{E} u((1+r)a_1 + y_1)$$

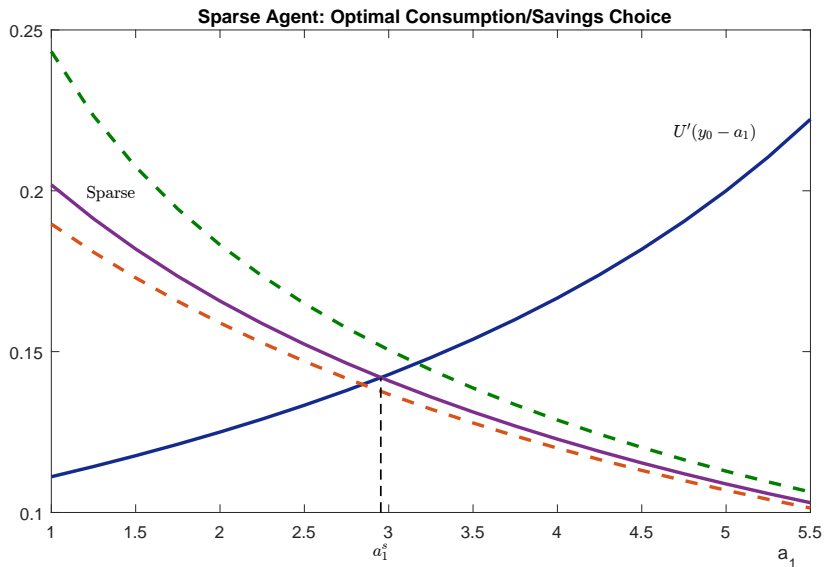
where

$$\begin{aligned} r &= \bar{r} + m_r^* \varepsilon_r \\ y_1 &= \bar{y}_1 + m_y^* \varepsilon_y \end{aligned}$$

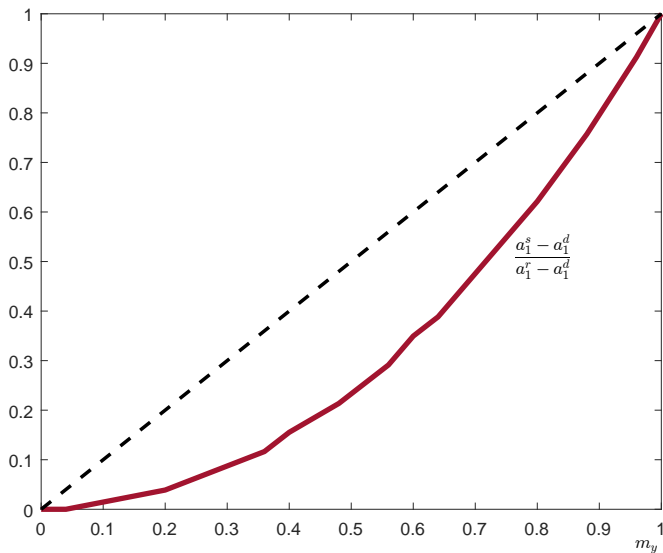
- one line solution

$$u'(y_0 - a_1) = \beta \mathbb{E} [(1+r) u'((1+r)a_1 + y_1)]$$

Sparse Agent Solution



Action isn't linear in attention



Implications

- for intermediate values of attention cost,
 - agent pays no attention to interest rate shock
 - pays less than full attention to income shock
- optimal action, savings, is attenuated relative to fully rational model
 - agent builds less precautionary savings
- affects estimation/measurement of IES

Infinite-Horizon Model with Sparse Dynamic Programming

Infinite Horizon Model

$$\max_{\{c_t\}} \mathbb{E} \sum_{t=0}^{\infty} \beta^t u(c_t)$$

subject to

$$w_{t+1} \leq (1 + \bar{r} + \hat{r}_{t+1})(w_t - c_t) + \bar{y} + \hat{y}_{t+1}$$

where

$$\begin{aligned} \hat{r}_{t+1} &= \rho_r \hat{r}_t + \varepsilon_{t+1}^r, & \varepsilon_{t+1}^r &\sim \mathcal{N}(0, \sigma_r^2) \\ \hat{y}_{t+1} &= \rho_y \hat{y}_t + \varepsilon_{t+1}^y, & \varepsilon_{t+1}^y &\sim \mathcal{N}(0, \sigma_y^2) \end{aligned}$$

Rational Model

- state space

$$(w_t, \hat{r}_t, \hat{y}_t)$$

- bellman equation

$$V(w, \hat{r}, \hat{y}) = \max_a \{u(a, w, \hat{r}, \hat{y}) + \beta EV(w', \hat{r}', \hat{y}')\}$$

Sparse Model

- Gabaix proposes the following law of motion for states

$$w_{t+1} = (1 + \bar{r} + m_r \hat{r}) (w_t - c_t) + \bar{y} + m_y \hat{y}_t$$

and

$$\begin{aligned} \hat{r}_{t+1} &= \rho_r(m) \hat{r}_t + m_{\sigma r} \varepsilon_{t+1}^r, \quad \text{where } \rho_r(m) = m_{\rho r} \rho_r + (1 - m_{\rho r}) \rho_r^d \\ \hat{y}_{t+1} &= \rho_y(m) \hat{y}_t + m_{\sigma y} \varepsilon_{t+1}^y, \quad \text{where } \rho_y(m) = m_{\rho y} \rho_y + (1 - m_{\rho y}) \rho_y^d \end{aligned}$$

where $\rho_r^d, \rho_y^d \in [0, 1]$ are some default persistence parameters

- six attention coefficients

$$\mathbf{m} = (m_r, m_{\rho r}, m_{\sigma r}; m_y, m_{\rho y}, m_{\sigma y})$$

Comments

Comment 1: Disciplining Sparse Dynamic Programming

- Given static sparsity framework, in dynamic model:
 - what is the default model?
 - where can you place m ?
- Natural to choose default model = true non-stochastic steady state

$$\rho_r^d = \rho_r, \quad \hat{r}_{t+1} = \rho_r \hat{r}_t + m_{\sigma r} \varepsilon_{t+1}^r$$

- two attention coefficients:

$$m_{\sigma r} \quad \text{and} \quad m_{\sigma y}$$

Disciplining Sparse Dynamic Programming

- With proposed formulation,

$$\mathbf{m} = (m_r, m_{\rho_r}, m_{\sigma_r}; m_y, m_{\rho_y}, m_{\sigma_y})$$

if $\rho_r^d = 0$ then

$$\rho_r(m) = m_{\rho_r} \rho_r$$

- this introduces cognitive discounting of future variables

$$E[\hat{r}_{t+\tau}] = m_{\rho_r}^\tau \rho_r^\tau \hat{r}_{t+\tau} < \rho_r^\tau \hat{r}_{t+j}$$

- departure from “information processing” interpretation
- Even if model is completely deterministic, agents have the wrong perception of future variables

Departure from Rational Life-Cycle Model

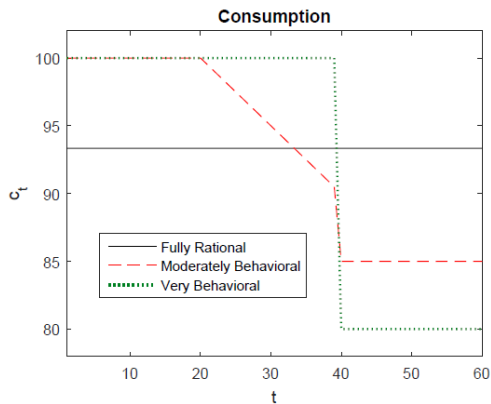


Figure: Sparsity in Life-Cycle

Sparse Bellman Equation

- how do you formulate the value function?
- in rational model, invariance of value function

$$V(w, \hat{r}, \hat{y}) = V(w, \hat{r}, \hat{y}, \text{anything else})$$

- in sparsity model with default=true non-stochastic model,
same invariance of value function, just different measure for shocks

Sparse Bellman Equation

- how do you formulate the value function?
- in rational model, invariance of value function

$$V(w, \hat{r}, \hat{y}) = V(w, \hat{r}, \hat{y}, \mathbb{E}\hat{r}_{t+\tau}, \mathbb{E}\hat{y}_{t+\tau}, \dots)$$

- in sparsity model with default=true non-stochastic model,
same invariance of value function, just different measure for shocks

Sparse Bellman Equation

- in proposed sparsity model, with

$$\mathbf{m} = (m_r, m_{pr}, m_{\sigma r}; m_y, m_{py}, m_{\sigma y})$$

suppose instead

$$V(w, \hat{r}, \hat{y}) = V(w, \hat{r}, \hat{y}, \mathbb{E}\hat{r}_{t+\tau}, \mathbb{E}\hat{y}_{t+\tau}, \dots)$$

where $\mathbb{E}\hat{r}_{t+\tau}$, $\mathbb{E}\hat{y}_{t+\tau}$ are the true future means of these processes

- if agent then chooses m 's, he could pay attention to these
- what stops agents from paying attention to certain sufficient statistics?

Parsimony with Dynamic Programing

1. Either impose more discipline from original Sparsity Theory
2. Or, change original theory in a way that allows for these departures

Comment 2: When Sparsity gains Traction

- When would *Sparsity* be the most useful?
- complex network models of interactions between many agents
- large production input-output models
 - actions are linear or log-linear
 - implies linear sufficient statistics → sparsity not needed
- but network models of interconnected banks, households
 - contracts are not linear (debt contracts)
 - set of all individual states cannot be reduced
 - sparsity seems almost generically necessary!

Network of CDS Contracts (Boyarchenko, Costello, La'O, Shachar)

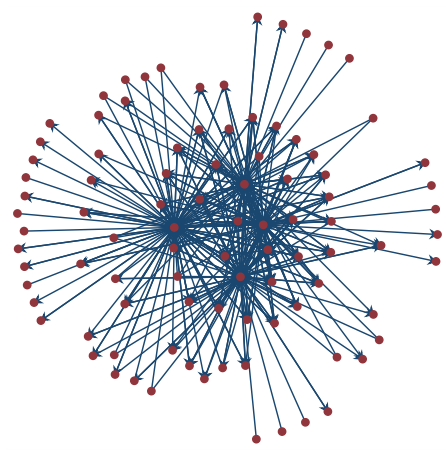


Figure: Inter-Dealer CDS Network (unweighted), January 2015

Last Comment: Technicalities with Feynman-Kac Method

Proof The proof yields the general method of calculation. We shut down uncertainty and differentiate the rational Bellman equation (68), first with respect to the new variable x (using the envelope theorem):

$$V_x(w, x) = u_x + \beta V'_w F'_w + \beta V'_c F'_c$$

which yields the announced expression for V_x . Then we take the total derivative w.r.t. w :

$$V_{w,x}(w, x) = D_w u_x + \beta D_w [V'_w F'_w(w, x, a)] + \beta F''_w V'_{w,c} D_w w' + \beta V'_{w,c} D_w F'_c$$

so

$$V_{w,x}(w, 0) = \frac{D_w u_x + \beta D_w [F'_w(w, 0, a) V'_w(w', 0)] + \beta V'_{w,c} D_w F'_c}{1 - \beta F''_w D_w w'}$$

□

Lemma 10.2 Assume the local autonomy condition (32), $F''_w = 0$, and consider some value function $V(w, x)$. Then, the impact of a change x on the optimal action is (around $x = 0$):

$$a_x = -\Psi_x^{-1} \Phi_x \quad (72)$$

with $\Psi(a, x) = u_x + \beta V'_w F'_w$, and

$$\Phi_x = u_{xx} + \beta F''_w V'_{w,c} F'_w + \beta V'_{w,c} F''_c, \quad \Psi_x = u_{xx} + \beta F''_w V'_{w,c} F'_w + \beta F''_w V'_{w,c} F'_w + \beta V'_{w,c} F''_c \quad (73)$$

evaluated at $(a, x) = (a^*(w), 0)$. They depend only on the transition functions and the derivatives of the simpler baseline value function $V^a(w)$.

Proof The FOC for a is $\Psi(a, x) = 0$ with

$$\Psi(a, x) = u_x + \beta V'_w F'_w + \beta V'_{w,c} F'_c$$

The rest follows by the implicit function theorem: terms in $V_{w,x}$ drop out because $F''_w = 0$ around the default action. □

When the local autonomy condition (32) doesn't hold, a term $V_{w,x}$ appears. Then, the situation is more complex, and requires solving for a fixed point, in the form of a matrix Riccati equation.

Feynman-Kac method In some cases, it is useful to do the same via a Feynman-Kac type of approach.⁴⁷ Here we view x_t as exogenous, i.e. assume $x_{t+1} = F^x(x_t)$. Calling w the initial

⁴⁷I call it "Feynman-Kac" because this approach deals particularly well with stochastic problems.

condition for wealth, the Lagrangian is:

$$L = \sum_{t=0}^{\infty} \beta^t u(w_t, x_t, a_t) + \sum_{t=1}^{\infty} \beta^t q_t^w (-w_t + F^w(w_{t-1}, x_{t-1}, a_{t-1})) + q_0^w (-w_0 + w)$$

where $q_t^w = V_w(w_t)$ are the Lagrange multipliers. At the optimum, the agent solves $V(w) = \max_{(a_t, w_t)_{t \geq 1}} L$. This implies that $L_{a_t} = L_{w_t} = 0$. The envelope theorem gives:

$$V_{c_t} = L_{a_t} = \beta^t [u_x(w_t, x_t, a_t) + \beta q_{t+1}^w F''_w(w_t, x_t, a_t)]$$

so that, using the total derivative notation (69),

$$V_{a_t, w_t} = \beta^t \frac{D u_x}{D w_t} D_{w_t} [u_x(w_t, x_t, a_t^*(w_t))]_{t=0} + \beta V_w(w_{t+1}) F''_w(w_{t+1}, x_{t+1}, a_t^*(w_t))_{t=0}$$

or in short

$$V_{a_t, w_t} = \sum_{t=0}^{\infty} \beta^t \frac{D u_x}{D w_t} D_{w_t} [u_x^* + \beta V_{w_{t+1}} F''_w(w_{t+1})] \quad (74)$$

Application. In the consumption problem with $\beta R = 1$, let us derive again at the impact of a one-time change of interest rate \bar{r} , from Lemma 4.2. Under the default model $c_t = c_0$ and $w_t = w_0$. So $\frac{D u_x}{D w_t} = 1$, $u_{w_t} = 0$, $V_w^a(w_t) = V'(c_t) = (\frac{u''(c_t)}{u'(c_t)})^{-1}$, and given $F^{w_{t+1}} = (1 + r_t)(w_t - c_t) + \bar{y}$,

$$F''_w(w_{t+1}) = w_t - c_t = w_t - r w_t + \bar{y} = \frac{w_t - \bar{y}}{R}$$

using the notation $w_t^- := w_t - \bar{y}$ for the beginning of period wealth. Using (74) gives:

$$\begin{aligned} V_{a_t, w_t} &= \beta^t D_{w_t} \left[\beta \left(\frac{u''(w_{t+1}) + u''}{R} \right)^{-1} \frac{w_t^-}{R} \right] = \frac{1}{R^{t+1}} D_{w_t} \left[\left(\frac{u''(w_{t+1}) + u''}{R} \right)^{-1} w_t^- \right] \\ &= \frac{1}{R^{t+1}} \left(-\frac{F''_w c_t^{-1}}{R} \frac{D u''(w_{t+1})}{D w_t} w_t^- + c_t^{-2} \right) = \frac{1}{R^{t+1}} c_t^{-1} (-\gamma \frac{F''_w}{R} w_t^- + c_t) \end{aligned}$$

as under the default model $c_t = c_0$. As time-0 consumption satisfies $u_{c_0} = V_{w_0}$, we have $u_{c_0} \partial_{c_0} c_0 = \partial_{c_0} V_{w_0}$, and

$$\partial_{c_0} c_0 = \frac{\partial_{c_0} V_{w_0}}{u_{c_0}} = \frac{\frac{1}{R^{t+1}} c_0^{-1} (-\gamma \frac{F''_w}{R} w_0^- + c_0)}{-\gamma c_0^{-2}} = \frac{1}{R^{t+1}} \left(\frac{F''_w}{R} w_0^- - \psi c_0 \right) = \frac{1}{R^{t+1}} \left(\frac{F''_w}{R} (w_0 - \bar{y}) - \psi c_0 \right).$$

which gives again Lemma 4.2 (the income part being easy as always).

all of you, previous slide:

$$m_{\text{this discussion}}^* = 0$$

Conclusion

Conclusion

- Perfectly Rational Agents (in the strict sense) seems ridiculous
- Sparsity Framework and Agenda: ambitious, creative, also realistic
- Dynamic programming application
 - discipline from General Sparsity Theory
- Most useful in complex network models that are not linear