

ECON 609/610

1.9

Book: Christian Gollier, Economics of Time and Risk  
 Read Chapters 1-6 by 1 week from Wednesday (1.18)

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## I. One and two-period models

A. Diffidence Theorem

B. Method of Polars

## II. Multi-period models (Basic)

A. Backwards Recursion (Programming)  
(Induction)

a lot of work characterizing the value function

$V(K_t)$  = function giving lifetime utility as a function of the current vector  
 of state variables (anything that can only change gradually over time)

B. Symmetry Theorem

## III. Multi-period models (Advanced)

A. Horizontal and Vertical Aggregation (Conjugate functions)

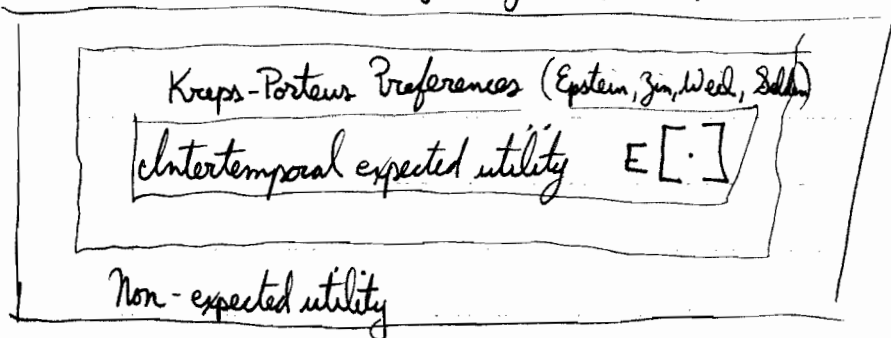
B. Prerer-Max Theorem

## IV. Computation

Paradox of Choice

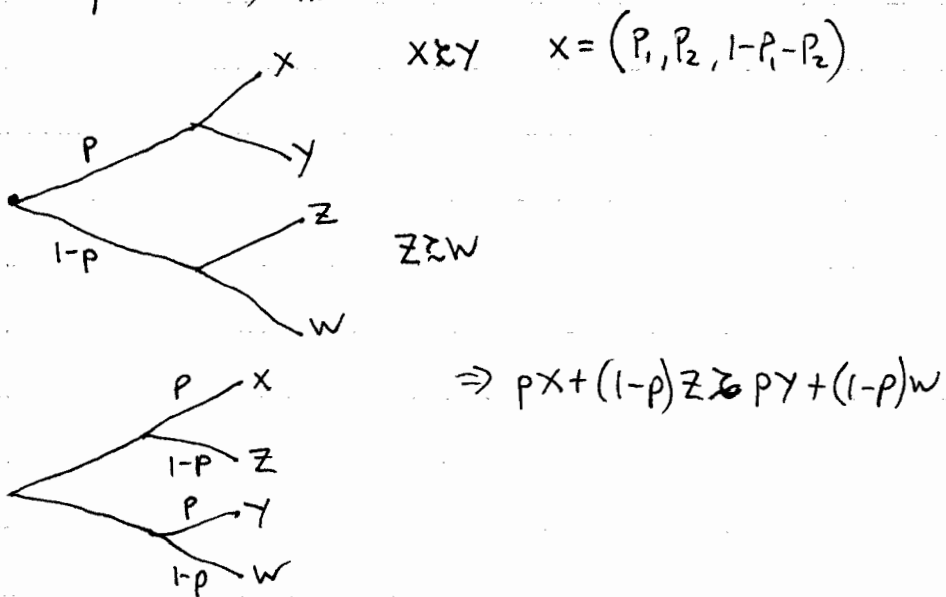
When people do wiered things

- (1) Look for deep wisdom
- (2) Look at bounded cognition (people aren't infinitely smart)
- (3) → (1) Think about how hard to think about something (infinite regress prob.)
- (2) Approximate  $IQ < \infty$  by information transmission limitations
- (3) Agent-based modelling → Scott Page
- (3) Look at other psychological principles such as evolved emotions



- Key Principles to get expected utility (these are normative; people may violate them)
- (1) Fungibility (consequentialism) (labelling doesn't matter)
  - (2) Transitivity
  - (3) Sunk cost principle

Independence Axiom



Proof of expected utility theorem

W = worst

B = best

$U(W) = 0$

$U(B) = 1$

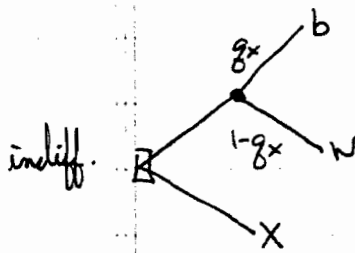
By continuity,  $\exists g_x, g_y, X \sim g_x B + (1-g_x)W$   
 $Y \sim g_y B + (1-g_y)W$

Claim: We can take  $U(X) = g_x$  and  $U(Y) = g_y$   
 (Utility is a probability metric here)

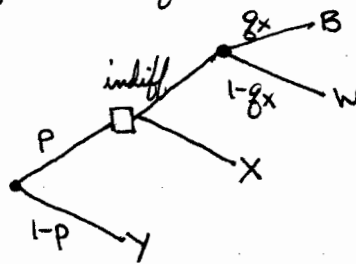
To show:

$$pX + (1-p)Y \sim pg_x + (1-p)g_y = pU(X) + (1-p)U(Y)$$

Step 1:  $pX + (1-p)Y \sim pg_x b + p(1-g_x)W + (1-p)Y$

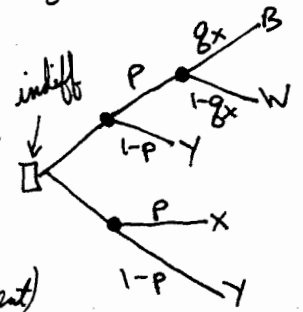


Version of  
sunk cost  
principle



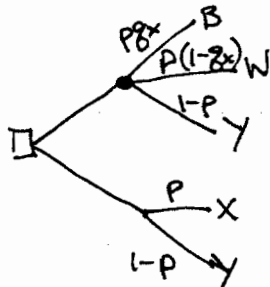
Equivalence  
of dif. representations  
 $\Leftrightarrow$   
(same choice if  
given as written  
instructions to agent)

fungibility



Compound  
Probability  
equivalence

(Consequentialism)



$$(pg_x + (1-p)g_y)B + (p(1-g_x) + (1-p)(1-g_y))W$$



$$E = (e_1, e_2, \dots, e_N)'$$

$Y$  is a random variable with prob.  $\underline{P}_Y = (P_{Y,1}; P_{Y,2}; \dots; P_{Y,N})'$   
 $Z$   $\underline{P}_Z = (P_{Z,1}; P_{Z,2}; \dots; P_{Z,N})'$

$$\underline{Q} = \underline{P}_Y - \underline{P}_Z = (P_{Y,1} - P_{Z,1}; P_{Y,2} - P_{Z,2}; \dots; P_{Y,N} - P_{Z,N})'$$

$$\underline{1} = (1, 1, \dots, 1)'$$

$$\underline{1} \cdot \underline{P}_Y = 1 \Leftrightarrow \sum_{i=1}^N P_{Y,i} = 1$$

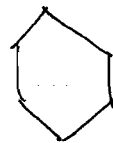
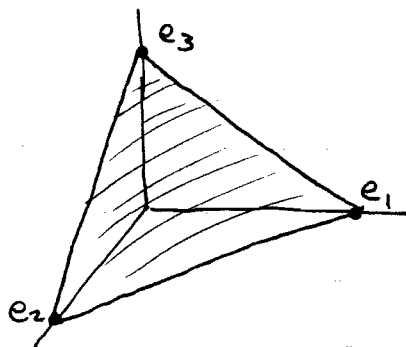
$$\underline{1} \cdot \underline{P}_Z = 1$$

$$\underline{1} \cdot \underline{Q} = 0$$

$Q$  lives on a hexagon

$$(-1, 1, 0) \quad (1, -1, 0) \quad (1, 0, -1) \quad (-1, 0, 1)$$

$$(0, 1, -1) \quad (0, -1, 1) \text{ vertices}$$



$$U = (U_1, U_2, \dots, U_N) \quad U_i = u(e_i)$$

$$\underline{U} \cdot \underline{Q} = \underline{U} \cdot (\underline{P}_Y - \underline{P}_Z) \geq 0 \Rightarrow \text{choose } Y \quad \underline{U} \cdot \underline{Q} \leq 0 \Rightarrow \text{choose } Z$$

$$U_1 P_{Y,1} + U_2 P_{Y,2} + \dots + U_N P_{Y,N} - U_1 P_{Z,1} - U_2 P_{Z,2} - \dots - U_N P_{Z,N}$$

From Convex Analysis,

$\mathcal{Q}$  = set of  $Q$ 's

$\mathcal{U}$  = set of  $U$ 's

$$\mathcal{U} = \mathcal{Q}^\circ \text{ (Polar of } \mathcal{Q}, \mathcal{Q} \text{ polar)} = \{U \mid U \cdot \underline{Q} \geq 0 \quad \forall Q \in \mathcal{Q}\}$$

set of all utility functions for which you would choose  $Y$  over  $Z$  when  $P_Y - P_Z \in \mathcal{Q}$ .

Alternatively,  $\mathcal{Z} = \mathcal{U}^0 = \{Q \mid U \cdot Q \geq 0 \forall U \in \mathcal{U}\}$   
 set of random variable pairs for which  $\gamma$  is chosen over  $Z$  for all utilities functions  
 is set  $\mathcal{U}$ .

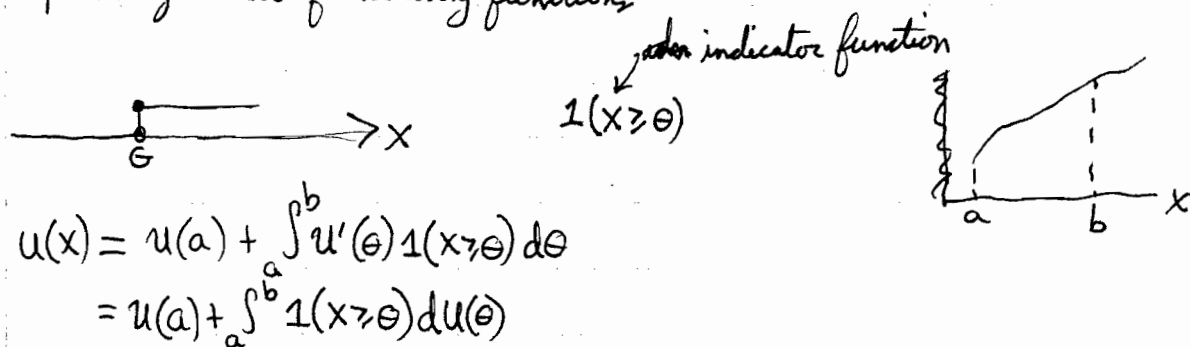
I. Find  $\mathcal{U}^0$  if  $\mathcal{U} =$  increasing functions  
 = increasing concave functions  
 expectation operator

II Find  $\mathcal{Z}^0$  if  $\mathcal{Z} = \{P_Y - P_Z \mid P_Y = \delta(\omega), E \cdot (P_Y - P_Z) = 0\}$

$$\delta = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 1 \\ 0 \\ 0 \end{bmatrix} \leftarrow \omega \quad Z = \gamma + \tilde{\epsilon}, \quad E[\tilde{\epsilon}] = 0$$

$\mathcal{Z} = \{P_Y - P_Z \mid P_Y = \delta(\omega), u \cdot (P_Y - P_Z) \geq 0\}$  set of rv  $Z$  worse than constant  $\omega$ .

Representing the set of increasing functions



$$u(x) = u(a) + \int_a^b u'(\theta) 1(x \geq \theta) d\theta$$

$$= u(a) + \int_a^b 1(x \geq \theta) dU(\theta)$$

Scaling this, we can get  $u(x) = E_\theta[1(x \geq \theta)]$

$\mathcal{U} =$  non-negative linear combinations of the extremal or basis functions

If  $\mathcal{U}$  = set of increasing functions,  $\mathcal{U}^0 = \{1(x \geq \theta)\}$

if  $u \cdot Q \geq 0 \quad \forall$  inc. functions  
 $\Rightarrow u \cdot 1(x \geq \theta) \geq 0 \quad \forall \theta$

If all increasing functions prefer  $Y$  to  $Z$ , step functions must prefer  $Y$  to  $Z$   
 $\Rightarrow$  necessary condition for first-order stochastic dominance.

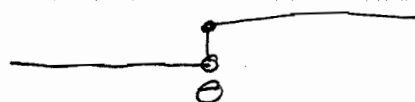
If all step functions  $1(x \geq \theta)$  prefer  $Y$  to  $Z$ , then all increasing functions prefer  $Y$  to  $Z$ .

$$\left[ U(a) + \int_a^b 1(x \geq \theta) dU(\theta) \right] \cdot P_Y - P_Z$$

$$*E \begin{bmatrix} Q_1 = x_1 \\ Q_2 = x_2 \\ \vdots \end{bmatrix}$$

$F(\theta)$

$$E_{\theta} [1(x \geq \theta)] = E_U [1(x \geq \theta)]$$



$$E_{F_Y} \left[ E_{\theta} [1(x \geq \theta)] \right] - E_{F_Z} \left[ E_U [1(x \geq \theta)] \right]$$

$$E_U \left[ E_{F_Y} [1(x \geq \theta)] \right] - E_{F_Z} [1(x \geq \theta)] = E_U \left[ [1 - F_Y(\theta)] - [1 - F_Z(\theta)] \right]$$

$$= E_U [F_Z(\theta) - F_Y(\theta)] \geq 0$$

need this to be  $\geq 0$

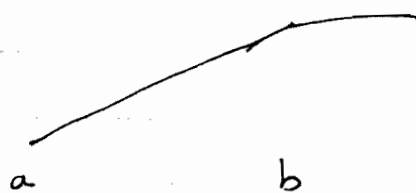
$\frac{1}{2}$

$b_1$  basis function  $Q \cdot b_1 \geq 0$

$b_2$  basis function  $Q \cdot b_2 \geq 0$

$\Rightarrow Q(\alpha b_1 + (1-\alpha)b_2) \geq 0$  for all  $\alpha \in [0,1]$

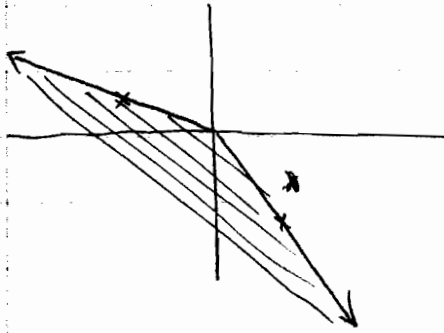
increasing concave functions



$\min(x - \theta, 0)$

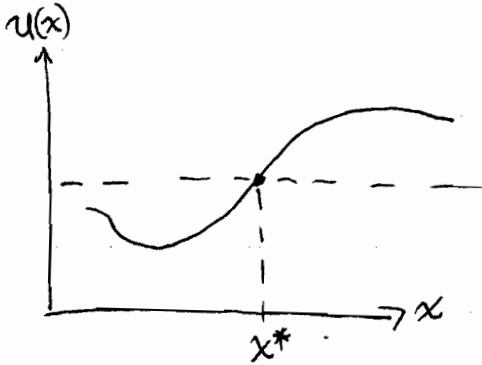
$$u(x) = u(b) - \int_a^b u''(\theta) \min(x-\theta, 0) d\theta$$

$(u^0)^0 = ccc(u)$  closed convex cone of  $u$

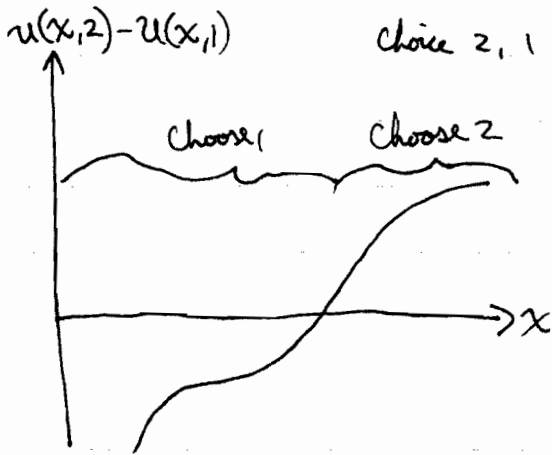


cone  $\rightarrow$  rays from origin

1.18



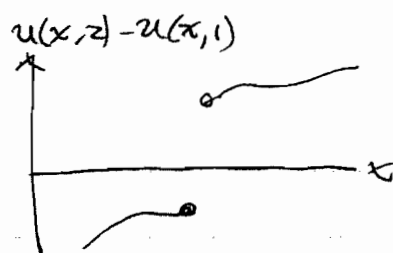
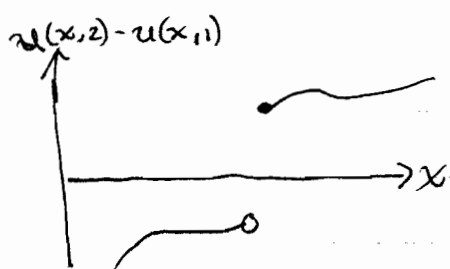
Choose  $\nearrow$   
up  $\nearrow$   
stay  $\rightarrow$



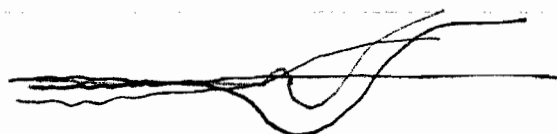
single crossing property

$\uparrow x$  doesn't reverse your choice after  $x^*$

SCP necessary to get monotone comparative statics results



Is the set of functions satisfying SCP convex? NO



If, however, we fix  $x^*$ , and take functions that have SCP at  $x^*$ , that set is convex.

$$\mathcal{Q} = \{Q \mid Q = P - 1(x=x^*), \exists P \in \Delta\} \quad \text{changing from being @ } x^* \text{ to some other dist.}$$

Interested in dist better.

$$\mathcal{U} = \{u \mid u(x) \geq u(x^*), \forall x > x^*; u(x) \leq u(x^*), \forall x < x^*\}$$

Basis functions? Constant function

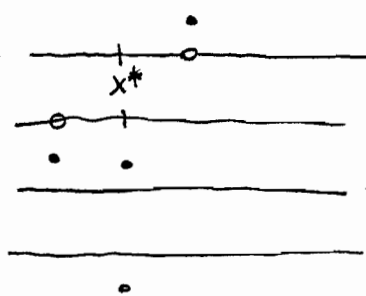
$$b_\theta = 1(x=\theta), \theta > x^*$$

$$b_\theta = -1(x=\theta), \theta < x^*$$

$$b_{x^*+} = 1(x=x^*)$$

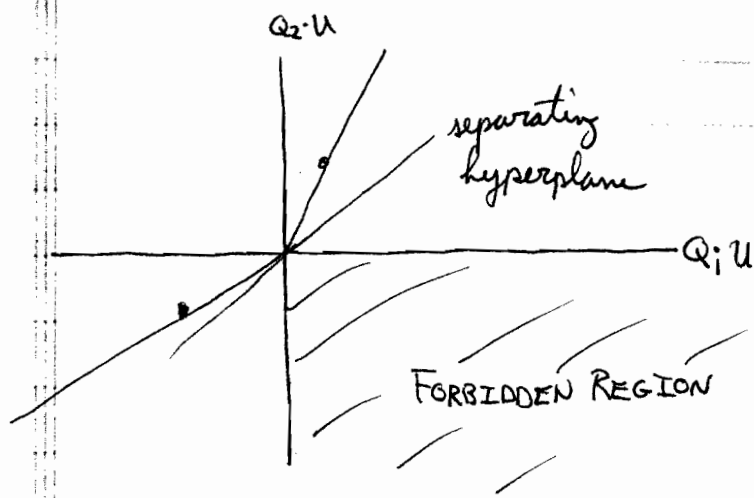
$$b_{x^*-} = -1(x=x^*)$$

$$b_{\text{const}} = 1$$



~~if~~ for all  $u \in \mathcal{U}$ , if  $Q_1 \cdot u > 0$ , then  $Q_2 \cdot u > 0$ .  
 $P_1 \succ x^* \Rightarrow P_2 \succ x^*$





combinations  $(Q_1 \cdot u, Q_2 \cdot u)$   
is convex set

if interiors of two sets disjoint,  $\exists$  a separating hyperplane.

$$\exists m, b_0 \quad Q_2 \cdot u \geq m Q_1 \cdot u \quad \Leftrightarrow \quad \exists m \geq 0 \text{ s.t. } Q_2 \cdot b_0 \geq m Q_1 \cdot b_0 \text{ for all } b_0 \in \text{whole set of basis found}$$

$$\begin{aligned} [P_2 - 1(x^*)] 1(x=\theta) &\geq m & [P_1 - 1(x^*)] 1(x=\theta) &\forall \theta > x^* \\ [P_2 - 1(x^*)] [-1(x=\theta)] &\geq m & [P_1 - 1(x^*)] [-1(x=\theta)] &\forall \theta < x^* \end{aligned}$$

$$f_2(\theta) \geq m f_1(\theta) \quad \forall \theta > x^*$$

$$-f_2(\theta) \geq -m f_1(\theta) \quad \forall \theta < x^*$$

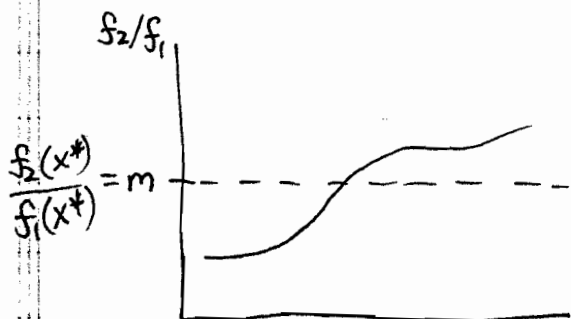
$$f_2(\theta) \leq m f_1(\theta) \quad \forall \theta < x^*$$

$$f_2(x)/f_1(x) \geq m \text{ as } x \geq x^*$$

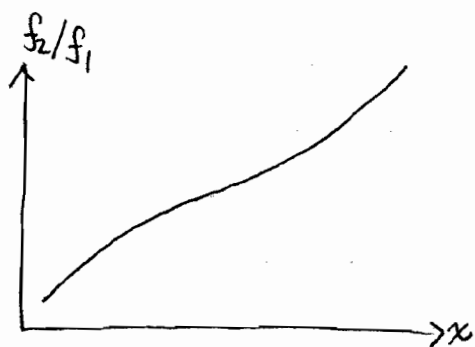
$$f_2(x^*) \geq m f_1(x^*) \text{ and } f_2(x^*) \leq m f_1(x^*) \Rightarrow f_2(x^*) = m f_1(x^*)$$

$$\Rightarrow m = f_2(x^*)/f_1(x^*)$$

$$f_2(x)/f_1(x) \geq \frac{f_2(x^*)}{f_1(x^*)} \text{ as } x \geq x^*$$



what conditions will make this hold for <sup>any</sup>  $x^*$ ? Monotonicity



We're increasing set of utility functions  
but decreasing set of pairs of priors  $(P, P_2)$ .

log-supermodularity

$$\log(f_2(x)/f_1(x)) = \log(f_2(x)) - \log(f_1(x))$$

if  $\geq 0 \Rightarrow$  log supermodularity

~~$u(x)$~~   
 ~~$u'(x)$~~

$x$   
 $V(w+x)$   
 $V'(w+x)$   
 $xV''(w+x)$

$$E[X] = 0$$

$$E[V(w+\tilde{x})] - V(w) < 0 \quad \text{You don't like } \tilde{x}$$

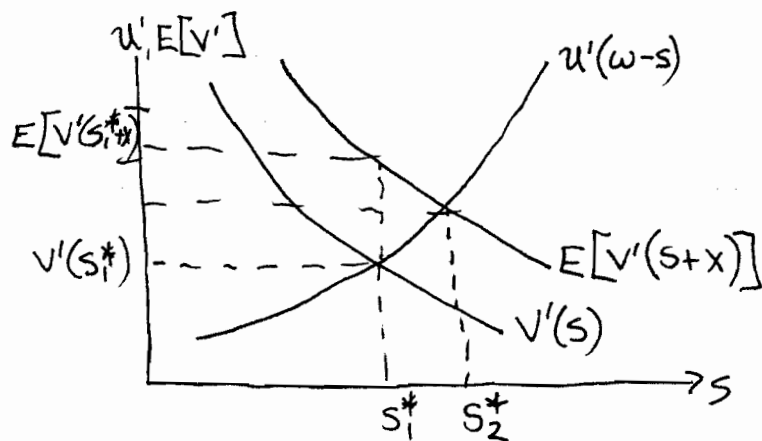
$$E[V'(w+\tilde{x})] - V'(w) > 0$$

$$\textcircled{2} \quad \text{MAX}_S \quad u(w-s) + E[V(s+x)]$$

$$\textcircled{1} \quad \text{MAX}_S \quad u(w-s) + v(s)$$

$$u'(w-s) = E[V'(s+x)]$$

$$u'(w-s) = v'(s)$$



what does value function have to look like to get this

$$E[\tilde{x} V'(\omega + \tilde{x})] \stackrel{!}{=} 0 \quad \text{Portfolio allocation}$$

$$\text{MAX}_{\alpha} E[u(\omega + \alpha \tilde{x})]$$

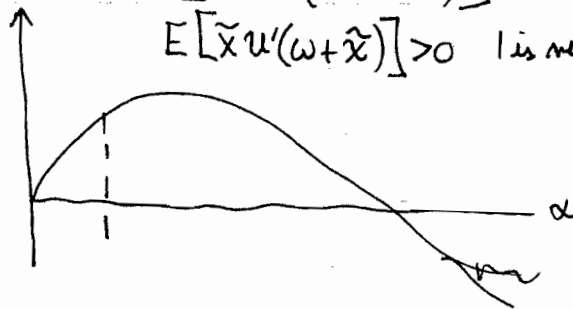
$$\text{FONC} \quad E\left[\frac{\partial}{\partial \alpha} u(\omega + \alpha \tilde{x})\right] = 0$$

$$\Leftrightarrow E[\tilde{x} u'(\omega + \alpha \tilde{x})] = 0$$

Unit of  $\tilde{x}$  is  $\alpha^*$  is right amount of  $\tilde{x}$ .

$$\text{if } u(\cdot) \text{ concave } E[\tilde{x}^2 u''(\omega + \alpha \tilde{x})] \leq 0$$

$$E[\tilde{x} u'(\omega + \tilde{x})] > 0 \quad | \text{ is not enough}$$



$x$

$V(\omega + \tilde{x})$

$V'(\omega + \tilde{x})$

$\tilde{x} V'(\omega + \tilde{x})$

$x$

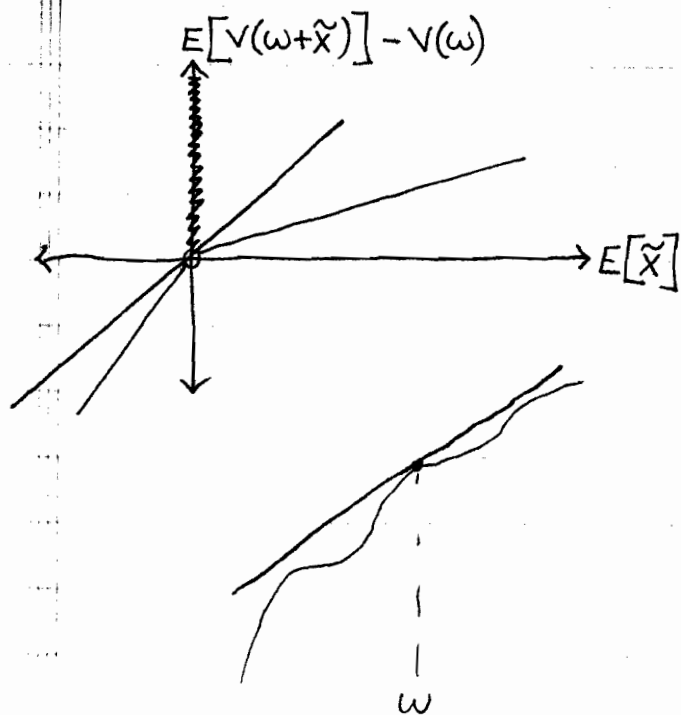
$V(\omega + \tilde{x})$

$V'(\omega + \tilde{x})$

$\tilde{x} V'(\omega + \tilde{x})$

if  $E[\tilde{x}] = 0$ ,  $E[V(\omega + \tilde{x})] - V(\omega) \leq 0$  disliking mean zero r.v.'s.

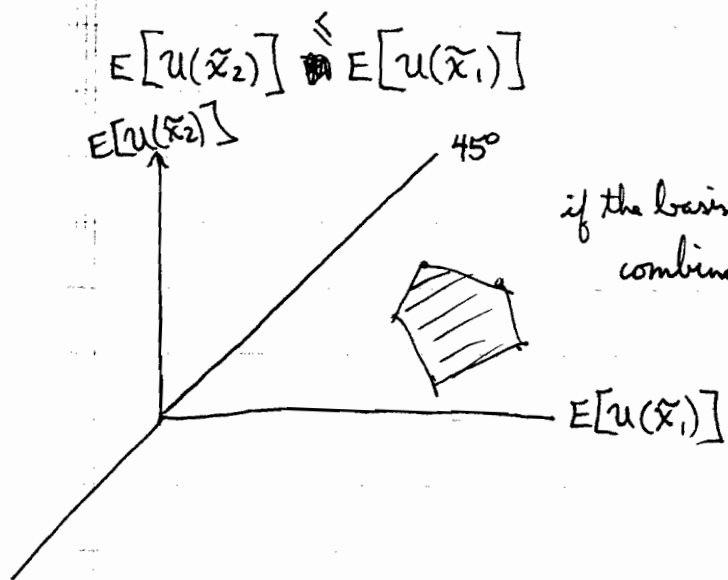
$V(\cdot)$  is different at  $\omega$  (dislikes mean zero r.v.'s at particular  $\omega$ )



$$\exists m \quad E[V(w+\tilde{x})] - V(w) \leq m E[\tilde{x}]$$

$$\exists m \quad \begin{matrix} \updownarrow \\ E[V(w+x)] - V(w) \leq mx \end{matrix}$$

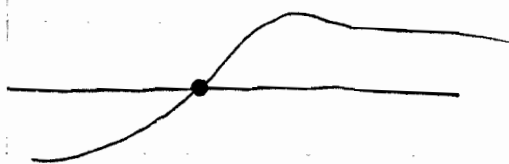
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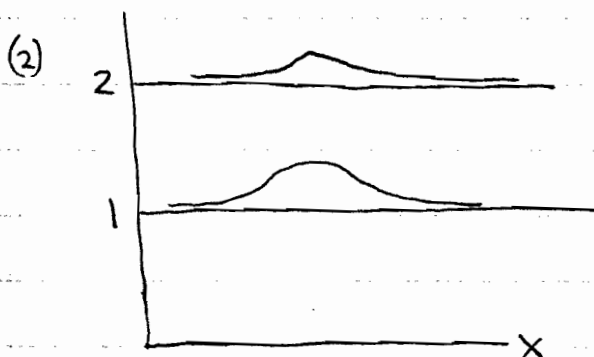
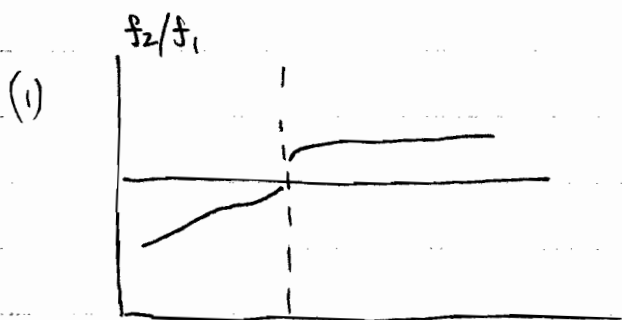
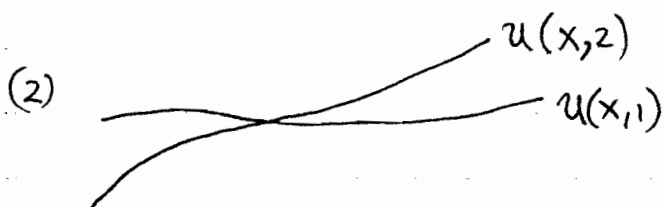
check 2004 notes

if the basis functions are all below, the convex combination of them is too.

(1)



comparing @ crossing  $w$ /certainty vs around it with density  $f(\cdot)$



$\forall \tilde{x}$  if  $E[\tilde{x}] \leq 0$ , then  $E[V(\omega + \tilde{x})] - V(\omega) \leq 0$

For what  $V$ 's will this be true

$$E[V(\omega + \tilde{x})] - V(\omega)$$

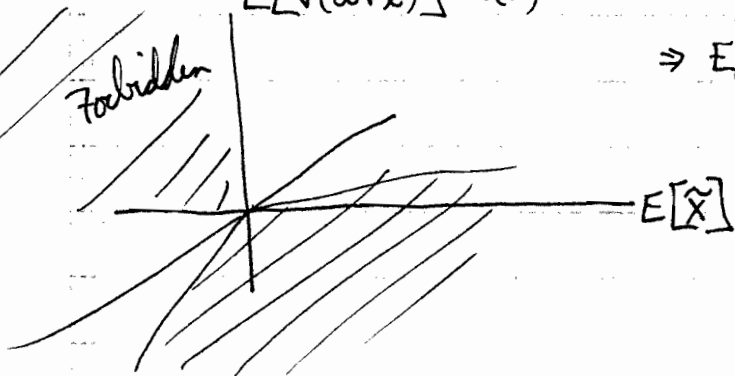
$$\Rightarrow E[V(\omega + \tilde{x})] - V(\omega) \leq m E[\tilde{x}]$$

$$\Downarrow$$

$$V(\omega + x) - V(\omega) \leq mx$$

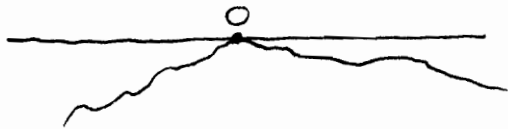
by extremal  
degenerate  
pdf = 1 @ x

Forbidden



$$\phi(x) = V(\omega+x) - V(\omega) - mx \leq 0$$

$$\phi(x) \leq 0, \phi(0) = 0 \Rightarrow \phi'(0) = 0 \text{ if } \phi(\cdot) \text{ is differentiable}$$



$$\Rightarrow V'(\omega+x) - m \Big|_{x=0} = V'(\omega) - m = 0$$

$$\Rightarrow \phi(x) = V(\omega+x) - V(\omega) - V'(\omega)x \leq 0 \quad \text{necessary \& sufficient condition}$$

$$\text{sufficiency: } V(\omega+x) - V(\omega) \leq V'(\omega)x$$

$$\Rightarrow E[V(\omega+\tilde{x}) - V(\omega)] \leq E[V'(\omega)\tilde{x}] \\ = E[\tilde{x}]V'(\omega) \leq 0 \text{ for } E[\tilde{x}] \leq 0$$

$$\forall \omega, \tilde{x} \text{ if } E[\tilde{x}] \leq 0, \text{ then } E[V(\omega+\tilde{x})] - V(\omega) \leq 0$$



$$\forall \omega \Rightarrow \phi(x) = V(\omega+x) - V(\omega) - V'(\omega)x \leq 0$$

$$\Rightarrow \phi''(0) \leq 0$$

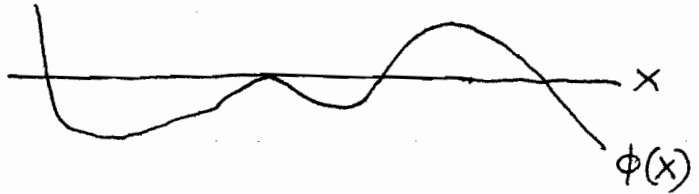
$$V''(\omega+x) \Big|_{x=0} = V''(\omega) \leq 0$$

<sup>nsc</sup>  
central condition  
holding globally  
  
this is necessary  
(local condition)  
holding globally

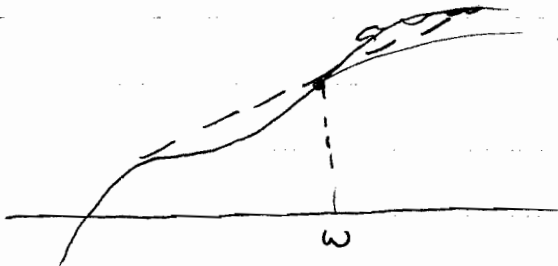
$$V'(\omega) = m \quad V'(\omega+x) \Big|_{x=0} = m \Big|_{x=0} \\ V''(\omega+x) \Big|_{x=0} \leq 0 \Big|_{x=0}$$

Question: if the local necessary condition holds globally, ~~is it equivalent to~~  
does it imply the central necessary & sufficient condition holds  
globally ( $\forall \omega$ )? sometimes

We need to rule out



Knowing  $\phi(\cdot)$  concave, is there way to rule out  $\phi(x) = V(w+x) - V(w) - V'(w)x \leq 0$

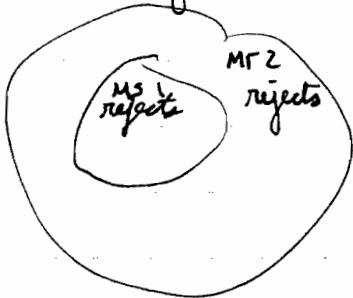


$V(w+x) \leq V(w) + V'(w)x$  ← tangent line  
Concavity is enough to show this

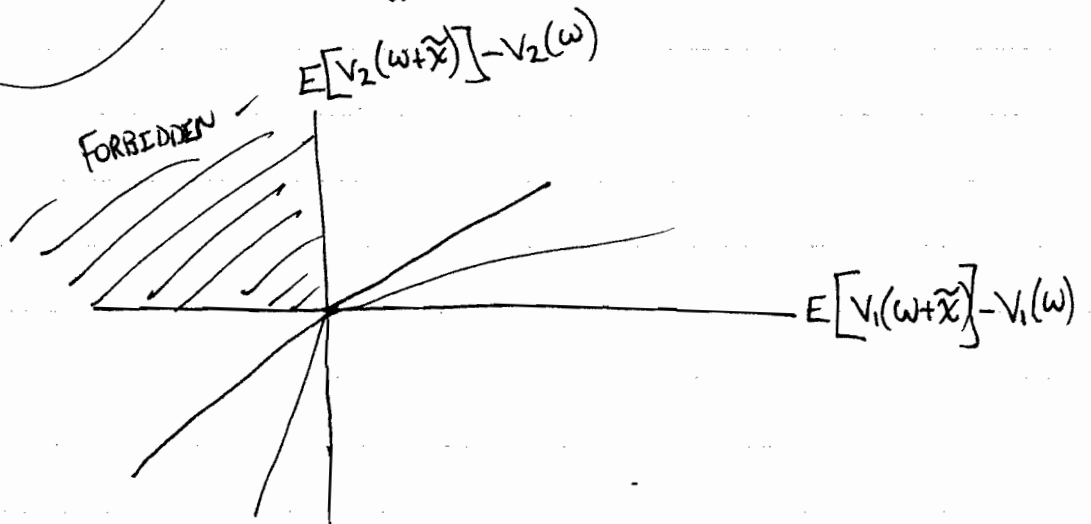
$$\begin{aligned} V(w+x) - V(w) - V'(w)x &= \int_0^x \int_0^{\xi} V''(w+\zeta) d\zeta d\xi \\ &= \int_0^x [V'(w+\xi) - V'(w)] d\xi \end{aligned}$$

Comparative Risk Aversion

$\forall \tilde{x}$  if  $E[V_1(w+\tilde{x})] - V_1(w) \leq 0$ , then  $E[V_2(w+\tilde{x})] - V_2(w) \leq 0$



- different around  $w$
- more different around  $x$



$$\forall \tilde{x} \quad E[V_2(\omega + \tilde{x}) - V_2(\omega)] \leq m E[V_1(\omega + \tilde{x}) - V_1(\omega)]$$

$$\Leftrightarrow V_2(\omega + x) - V_2(\omega) \leq m [V_1(\omega + \tilde{x}) - V_1(\omega)]$$

$$V_2'(\omega + x)|_{x=0} = m V_1'(\omega + x)|_{x=0} \quad m = V_2'(\omega) / V_1'(\omega)$$

$$V_2''(\omega + x)|_{x=0} \leq m V_1''(\omega + x)|_{x=0} \quad \text{local necessary condition}$$

$$\uparrow V_2'(\omega) / V_1'(\omega)$$

$$V_2''(\omega) \leq \frac{V_2'(\omega)}{V_1'(\omega)} V_1''(\omega)$$

Central NSC

$$\Rightarrow V_2(\omega + x) - V_2(\omega) \leq \frac{V_2'(\omega)}{V_1'(\omega)} [V_1(\omega + x) - V_1(\omega)]$$

$$\frac{V_2(\omega + x) - V_2(\omega)}{V_2'(\omega)} \leq \frac{V_1(\omega + x) - V_1(\omega)}{V_1'(\omega)} \Rightarrow \text{local nc}$$

$$\text{Does } V_2''(\omega) \leq \frac{V_2'(\omega)}{V_1'(\omega)} V_1''(\omega) \quad \forall \omega \Rightarrow \frac{V_2(\omega + x) - V_2(\omega)}{V_2'(\omega)} \leq \frac{V_1(\omega + x) - V_1(\omega)}{V_1'(\omega)}$$

$\forall \omega, x$ ?

$$\frac{V_2''(\omega)}{V_2'(\omega)} \leq \frac{V_1''(\omega)}{V_1'(\omega)}$$

$$\text{log} \frac{d}{d\omega} \log(V_2'(\omega)) \leq \frac{d}{d\omega} \log(V_1'(\omega))$$

$$\Rightarrow \text{log} \left( \frac{V_2'(\omega)}{V_1'(\omega)} \right) \text{ is decreasing} \Leftrightarrow \frac{V_2'(\omega)}{V_1'(\omega)} \text{ is decreasing}$$



We know  $v_2'/v_1'$  is decreasing

To prove:

$$\int_0^x \frac{v_2'(\omega+z)}{v_2'(\omega)} dz \leq \int_0^x \frac{v_1'(\omega+z)}{v_1'(\omega)} dz$$

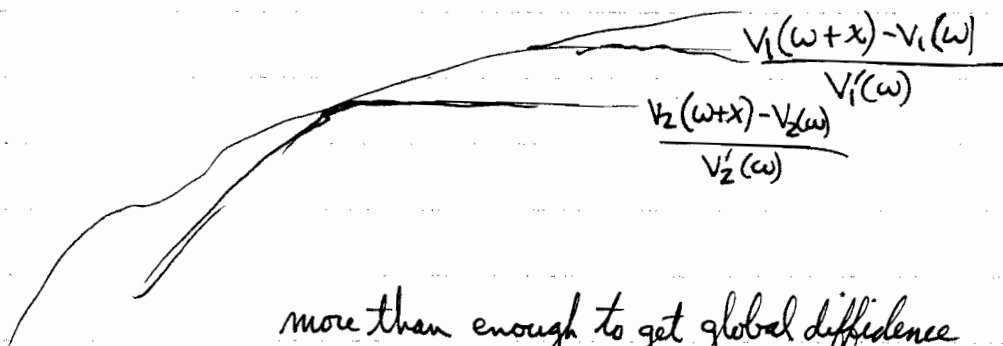
$$\int_0^x \left[ \frac{v_2'(\omega+z)}{v_2'(\omega)} - \frac{v_1'(\omega+z)}{v_1'(\omega)} \right] dz \leq 0$$

$$\Leftrightarrow \frac{v_2'(\omega+z)}{v_2'(\omega)} - \frac{v_1'(\omega+z)}{v_1'(\omega)} \leq 0 \text{ if } z \geq 0$$

$$\geq 0 \text{ if } z \leq 0$$

$$\frac{v_2'(\omega+z)}{v_2'(\omega)} \leq \frac{v_1'(\omega+z)}{v_1'(\omega)} \Leftrightarrow \frac{v_2'(\omega+z)}{v_1'(\omega+z)} \leq \frac{v_2'(\omega)}{v_1'(\omega)} \text{ if } z \geq 0$$

$$\geq \text{ if } z \leq 0$$

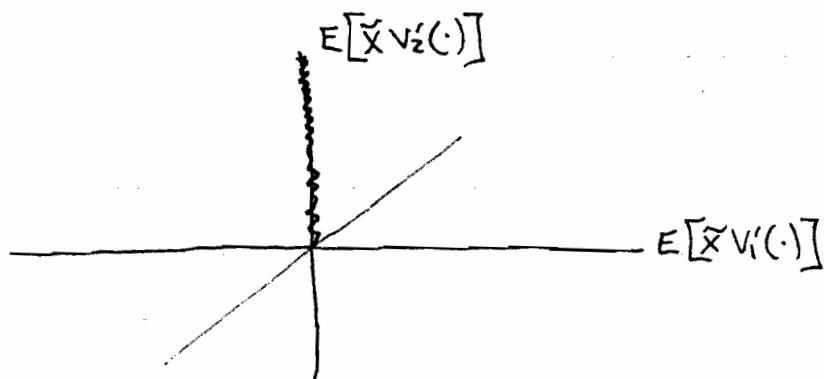


more than enough to get global difference

- 1 person wanting less of a risky asset than another person if  $E[\tilde{x} v_1'(\omega+\tilde{x})] \leq 0$ , then  $E[\tilde{x} v_2'(\omega+\tilde{x})] \leq 0$   
Centrally greater risk aversion ( $\Rightarrow$  centrally greater difference)
- (1) Do procedure we've been doing
- (2) Show it implies centrally greater difference
- (3) Show centrally greater difference  $\nRightarrow$  centrally greater risk aversion

1.25

Check out Journal of answers to Kimball

if  $E[\tilde{x} V_1'(\omega + \tilde{x})] = 0$ , then  $E[\tilde{x} V_2'(\omega + \tilde{x})] \leq 0$  $\exists m$ 

$$x V_2'(\omega + x) \leq m x V_1'(\omega + x)$$

$$V_2'(\omega + x) + x V_2''(\omega + x)$$

$$m(V_1'(\omega + x) + x V_1''(\omega + x))$$

$$2V_2''(\frac{\omega}{2}) + x V_2'''(\omega + x)$$

$$m(2V_1''(\omega + x) + x V_1'''(\omega + x))$$

$$\text{let } x=0 \Rightarrow V_2'(\omega) = m V_1'(\omega) \Rightarrow m = V_2'(\omega) / V_1'(\omega)$$

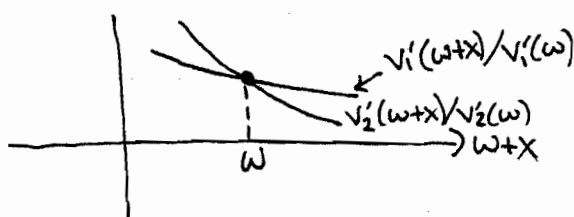
$$2V_2''(\omega) \leq m 2V_1''(\omega)$$

$$V_2''(\omega) \leq \left( \frac{V_2'(\omega)}{V_1'(\omega)} \right) V_1''(\omega) \quad \text{local NC}$$

 $\Downarrow ?$ 

$$x V_2'(\omega + x) \leq \left( \frac{V_2'(\omega)}{V_1'(\omega)} \right) x V_1'(\omega + x) \quad \text{Central NSC}$$

$$x \frac{V_2'(\omega + x)}{V_2'(\omega)} \leq x \frac{V_1'(\omega + x)}{V_1'(\omega)}$$



$$\frac{V_2''(\omega)}{V_2'(\omega)} \leq \frac{V_1''(\omega)}{V_1'(\omega)} \Leftrightarrow \frac{\partial}{\partial \omega} \log(V_2'(\omega)) \leq \frac{\partial}{\partial \omega} \log(V_1'(\omega))$$

~~Prop~~

Notation  $E[u(x)] = P \cdot u$

Def

$$\int_a^b u(x) dF(x) = [u(x)F(x)]_a^b - \int_a^b u'(x)F(x) dx$$

$$= u(b) - u(a) - \int_a^b u'(x)F(x) dx$$

$$= u(b) - [u(x)G(x)]_a^b + \int_a^b u''(x)G(x) dx$$

$$= u(b) - u'(b) + \int_a^b u''(x)G(x) dx$$

$$G(x) = \int_a^x F(\xi) d\xi$$

$$F = F_2 - F_1$$

$$G = G_2 - G_1$$

difference  
in two  
random  
variables

$$-\int_a^b u'(x) F(x) dx = -u'(b)G(b) + \int_a^b u''(x)G(x) dx$$

$$G(b) = -(E[X_2] - E[X_1])$$

Polar: Def.  $A^\circ = \{B \mid BA \geq 0, \forall A \in A\} = B$  B is polar of A.

Suppose  $P_2 \neq P_1 \Rightarrow$  EU theory says  $P_2 \in gP_2 + (1-g)P_1$

Theorem 1: If A and B are both closed convex cone, then  $A \cap B$  is a closed convex cone (ccc)

$$\text{Theorem 2: } ccc(A \cup B) = ccc(A) + ccc(B)$$

Theorem 3:  $A^\circ$  is a ccc.

$$\text{Theorem 4: } (A^\circ)^\circ = ccc(A)$$

$$\text{Theorem 5: } A^\circ = (ccc A)^\circ$$

$$\text{Theorem 6: } (A \cup B)^\circ = A^\circ \cap B^\circ$$

$$\text{Theorem 7: } (A \cap B)^\circ = A^\circ + B^\circ \quad (\text{positive linear combination})$$

Say you have value functions  $V_1, V_2$

$\mathcal{V} = \{V \text{ s.t. } V \text{ more risk averse than } V_1, V \text{ less risk averse than } V_2\}$

$\mathcal{A} = \{V \mid V \text{ m.r.a. } V_1\}$

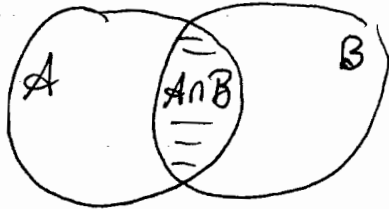
$\mathcal{B} = \{V \mid V \text{ l.r.a. } V_2\}$

Then random variables such that these are true:  $(\mathcal{A} \cap \mathcal{B})^\circ = \mathcal{A}^\circ + \mathcal{B}^\circ$

~~Theorem 8.1~~

Proof of 1:  $\sum_i \alpha_i A_i \in \mathcal{A}$   $\sum_i \beta_i B_i \in \mathcal{B}$   $\xrightarrow{\text{convex cones}}$   $\sum_i \gamma_i C_i \in \mathcal{A} \cap \mathcal{B}$   $\xrightarrow{\text{closed}}$   $\lim_{i \rightarrow \infty} C_i \in \mathcal{A} \cap \mathcal{B}$   
 $\forall \alpha_i \geq 0$   $\forall \beta_i \geq 0$   $A_i \in \mathcal{A} \forall i \Rightarrow \lim_{i \rightarrow \infty} A_i \in \mathcal{A}$   
 $B_i \in \mathcal{B} \forall i \Rightarrow \lim_{i \rightarrow \infty} B_i \in \mathcal{B}$

Let  $C_i \in \mathcal{A} \cap \mathcal{B} \Rightarrow \sum_i \gamma_i C_i \in \mathcal{A}$  and  $\sum_i \gamma_i C_i \in \mathcal{B} \Rightarrow \sum_i \gamma_i C_i \in \mathcal{A} \cap \mathcal{B}$   
 $\lim_{i \rightarrow \infty} C_i \in \mathcal{A}, \lim_{i \rightarrow \infty} C_i \in \mathcal{B} \Rightarrow \lim_{i \rightarrow \infty} C_i \in \mathcal{A} \cap \mathcal{B}$



Proof of 2:  $\sum_i \alpha_i A_i \in \text{ccc}(\mathcal{A}), \sum_i \beta_i B_i \in \text{ccc}(\mathcal{B})$   $\alpha_i \geq 0, \beta_i \geq 0$   
 $\lim_{i \rightarrow \infty} A_i \in \text{ccc}(\mathcal{A}), \lim_{i \rightarrow \infty} B_i \in \text{ccc}(\mathcal{B})$

$C_i \in \mathcal{A} \cup \mathcal{B}$

$\sum_i \gamma_i C_i = \sum_i \alpha_i A_i + \sum_i \beta_i B_i$   $\gamma_i \geq 0$   
 $\text{ccc}(\mathcal{A}) \quad \text{ccc}(\mathcal{B})$

Proof of 3:  $\mathcal{B} = \mathcal{A}^\circ = \{B \mid B \cdot A \geq 0, \forall A \in \mathcal{A}\}$

if  $B_i \in \mathcal{A}^\circ$ , then  $\sum_i \beta_i B_i \in \mathcal{A}^\circ$  (want to show)

$B_i \cdot A \geq 0 \forall A \in \mathcal{A} \forall i$

$\sum_i \beta_i B_i \cdot A = \sum_i \beta_i (B_i \cdot A) \geq 0 \forall A \in \mathcal{A}$  convex cone part

$$B_i \cdot A \geq 0 \quad \forall A \in \mathcal{A} \quad \forall i$$

$$\left( \lim_{i \rightarrow \infty} B_i \right) \cdot A = \lim_{i \rightarrow \infty} (B_i \cdot A) \geq 0 \quad \forall A \in \mathcal{A} \quad \text{closed}$$

~~Proof of 4:~~

$$Q: \text{ what is the set } \forall \omega \text{ if } E[\tilde{x}] = 0 \Rightarrow E[V(\omega + \tilde{x})] \leq V(\omega)$$

$$\text{then } \forall V''(\omega) \leq 0$$

Polar of  $(V''(x) \leq 0)$  is the set of mean-preserving spreads

\* Making a ~~set~~ the set larger  $\Rightarrow$  make the polar smaller

1.30

The polar of increasing functions is ... 1st order stochastic dominant risk

$$(4) \text{ For any } \mathcal{A} \subset \mathbb{R}^n, \quad (\mathcal{A}^\circ)^\circ = \text{ccc}(\mathcal{A})$$

$$(a) x \in \text{ccc}(\mathcal{A}) \Rightarrow x \in (\mathcal{A}^\circ)^\circ$$

$$\text{ccc}(\mathcal{A}) \subset (\mathcal{A}^\circ)^\circ$$

$$\mathcal{B} = \mathcal{A}^\circ = \{ B \mid B \cdot A \geq 0, \forall A \in \mathcal{A} \}$$

$$\forall B \in \mathcal{B}, B \cdot \sum_i \alpha_i A_i = \sum_i \alpha_i (B \cdot A_i) \geq 0$$

$$\text{if } B \cdot A_i \geq 0 \quad \forall A_i \in \mathcal{A}, \text{ then } \lim_{i \rightarrow \infty} B \cdot A_i \geq 0$$

$$\Rightarrow \text{ccc}(\mathcal{A}) \subset \mathcal{B}^\circ$$

$$\text{ccc}(\mathcal{A}) \subset (\mathcal{A}^\circ)^\circ$$

$$(b) x \notin \text{ccc}(\mathcal{A}) \Rightarrow x \notin (\mathcal{A}^\circ)^\circ$$

(i) First, if  $\mathcal{A}$  is in a subspace  $S$  of  $\mathbb{R}^n$ , then so is  $(\mathcal{A}^\circ)^\circ$

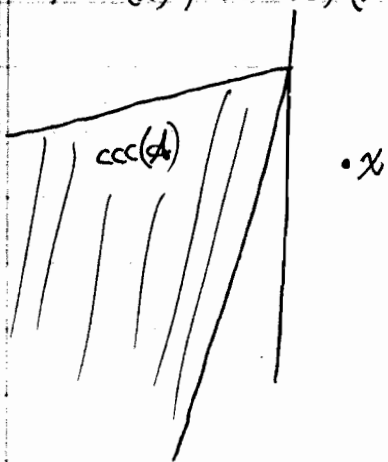
Proof:  $\forall y \in \perp S, y \cdot A = 0$  for all  $A \in \mathcal{A}$ .

So,  $\perp S \subset \mathcal{A}^\circ$ .

If  $x \notin S$ , then  $x \cdot y \neq 0$  for some  $y \in \perp S$ .

Also,  $x \cdot (-y) \neq 0$ . Therefore,  $x \notin (\mathcal{A}^\circ)^\circ$

(b) (ii) if  $x \in S$ , where  $S$  is the minimal subspace including  $A$ , but  $x \notin \text{ccc}(A)$ , then  $x \notin (A^\circ)^\circ$ .



Separating hyperplane.

$$(A^\circ)^\circ \subset \text{ccc}(A)$$

(5)  $A^\circ = (\text{ccc}(A))^\circ$

Proof:  $((A^\circ)^\circ)^\circ = (\text{ccc}(A))^\circ = \text{ccc}(A^\circ) = A^\circ$

(6)  $(A \cup B)^\circ = A^\circ \cap B^\circ$

$$\{x \mid x \cdot A \geq 0 \forall A \in A \text{ and } x \cdot B \geq 0 \forall B \in B\} = (A \cup B)^\circ$$

$$\stackrel{?}{=} \{x \mid x \cdot A \geq 0 \forall A \in A\} \cap \{x \mid x \cdot B \geq 0 \forall B \in B\} = A^\circ \cap B^\circ$$

(7)  $(A \cap B)^\circ = A^\circ + B^\circ$  if  $A$  and  $B$  are ccc

(a)  $A^\circ + B^\circ \subset (A \cap B)^\circ$

$x \in A^\circ, y \in B^\circ$

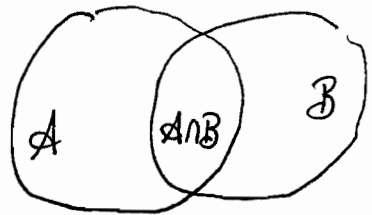
$x \cdot A \geq 0 \forall A \in A$

$y \cdot B \geq 0 \forall B \in B$

$x \cdot C \geq 0 \forall C \in (A \cap B)$

$y \cdot C \geq 0 \forall C \in (A \cap B)$

$\Rightarrow (x+y) \cdot C \geq 0$



(b)  $(A \cap B)^{\circ} \subset A^{\circ} + B^{\circ}$

← since  $A$  &  $B$  are ccc

$$(A \cap B)^{\circ} = [(A^{\circ}) \cap (B^{\circ})]^{\circ} = [(A^{\circ} \cup B^{\circ})^{\circ}]^{\circ} = \text{ccc}(A^{\circ} \cup B^{\circ}) = A^{\circ} + B^{\circ}$$

interesting sets

(Polar:  $V' \geq 0$ )  
basis

- (1) change in r.v.'s from  $\omega$  to  $\omega + \tilde{x}$  (basis:  $\omega \rightarrow \omega + \tilde{x}$ )
- (2) first order stochastic dominance change (basis:  $\omega \rightarrow \omega - \theta, \theta \geq 0$ )
- (3) second mean preserving spreads (basis:  $\omega \rightarrow \begin{cases} \omega - (1-p)\theta & \text{w/prob } p \\ \omega + p\theta & \text{1-p} \end{cases}$ )

(Polar:  $V'' \leq 0$ ) basis

if  $E[\tilde{x}] = 0$ , then  $E[V(\omega + \tilde{x})] - V(\omega) \leq 0$

- (4) SSD changes (basis:  $\omega \rightarrow \begin{cases} \omega - \theta \\ \omega - (1-p)\theta & \text{w/prob } p \\ \omega + p\theta & \text{1-p} \end{cases}$ )
7. Polar  $V' \geq 0, V'' \leq 0$   
basis

(5)  $V'$   
Polar

8.  $V$  mra than  $\bar{V}$

v.s.t.  $V(x) = \phi(\bar{V}(x))$  for some increasing concave  $\phi$   
 $= \alpha_0 + \sum_i \alpha_i \min\{0, V(x) - \bar{V}(\theta)\}$

9.  $V$  lra than  $\bar{V}$

v.s.t.  $V(x) = \phi(\bar{V}(x))$  for some increasing convex  $\phi$   
 $= \alpha_0 + \sum_i \alpha_i \max\{0, V(x) - \bar{V}(\theta)\}$

intersection is not a nice set. The polar ~~stuff~~ will help here.

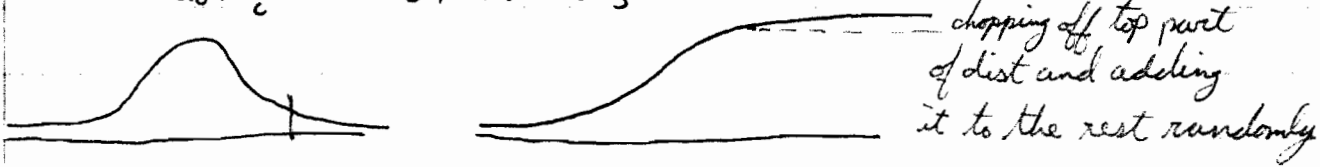
10.  $F$  is worse by MLR order than  $\bar{F}$ .

$F'(x)/\bar{F}'(x)$  is decreasing

(a lot like  $u_2/u_1$  is decreasing)

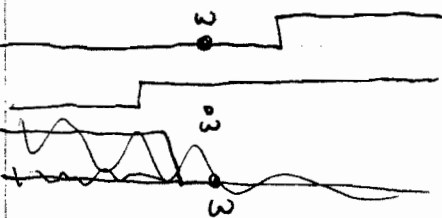
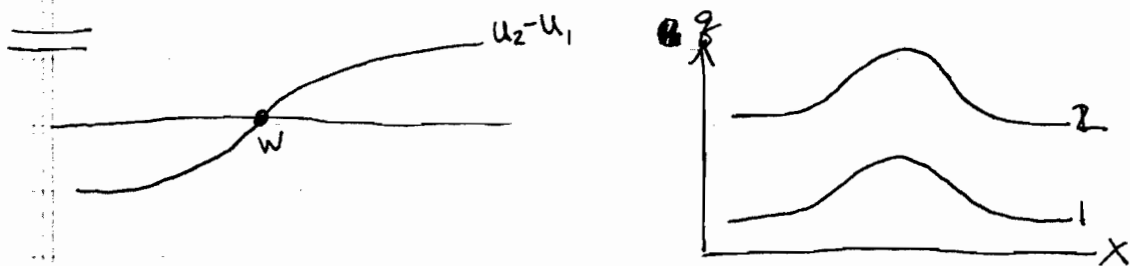
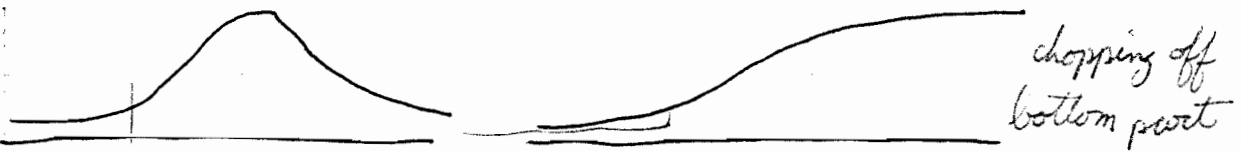
$F = \phi(\bar{F})$ ,  $\phi$  concave

$$= \alpha_0 + \sum_i \alpha_i \min\{0, F(x) - \bar{F}(\theta)\}$$

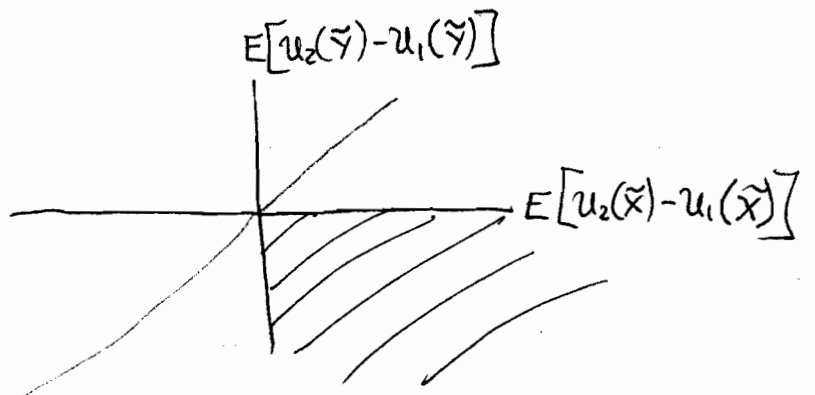


11.  $F$  is better by MLR order than  $\bar{F}$

$$F = \alpha_0 + \sum_i \alpha_i \max\{0, F(x) - \bar{F}(\theta)\}$$



Have  $u_2(w) = u_1(w)$



$$E[u_2(\bar{y}) - u_1(\bar{y})] \geq m(E[u_2(\bar{x}) - u_1(\bar{x})])$$

$$\exists m \text{ s.t. } 1 - F_y(\theta) \geq m(1 - F_x(\theta)) \quad \forall \theta \geq w$$

$$-F_y(\theta) \geq m(-F_x(\theta)) \quad \forall \theta < w \Leftrightarrow F_y(\theta) \leq m F_x(\theta) \quad \forall \theta < w$$



2.1

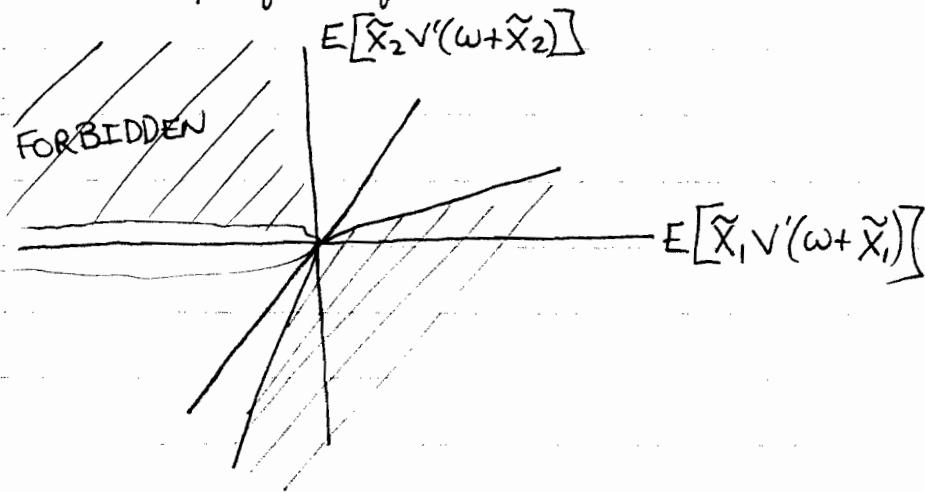
Example relevant to #6 on exam

$$\forall \tilde{X}_2 \stackrel{FSD}{\preceq} \tilde{X}_1$$

Assume  $V' \geq 0$ , if  $E[\tilde{X}_1 V'(\omega + \tilde{X}_1)] \leq 0$

(\*) then  $E[\tilde{X}_2 V'(\omega + \tilde{X}_2)] \leq 0$

Find shapes of value functions where this is true.



$$\tilde{X}_2 \stackrel{FSD}{\preceq} \tilde{X}_1, \tilde{Y}_2 \stackrel{FSD}{\preceq} \tilde{Y}_1 \Rightarrow \alpha \tilde{X}_2 + (1-\alpha) \tilde{X}_2 \stackrel{FSD}{\preceq} \alpha \tilde{X}_1 + (1-\alpha) \tilde{Y}_1$$

F for X, G for Y

$$F_2(x) \geq F_1(x) \quad G_2(x) \geq G_1(x)$$

$$F_2(x) - F_1(x) \geq 0 \quad G_2(x) - G_1(x) \geq 0$$

$$\alpha(F_2 - F_1) + (1-\alpha)(G_2 - G_1) \geq 0$$

for all x and  $\alpha$ .

$$\exists m : E[\tilde{X}_2 V'(\omega + \tilde{X}_2)] \leq m E[\tilde{X}_1 V'(\omega + \tilde{X}_1)] \quad \forall (\tilde{X}_1, \tilde{X}_2) \text{ s.t. } \tilde{X}_2 \stackrel{FSD}{\preceq} \tilde{X}_1$$

Taking prob. mass from lower point to higher  $(\tilde{X} \rightarrow x + \theta \quad \theta \geq 0)$   
basis for  $\tilde{X}_2 \rightarrow \tilde{X}_1$

$$x V'(\omega + x) \leq m(x + \theta) V'(\omega + x + \theta) \quad \forall x, \forall \theta \geq 0$$

$$x V'(\omega + x) - m(x + \theta) V'(\omega + x + \theta) \leq 0$$

$$\text{In particular, } \theta = 0 \Rightarrow (1-m)x V'(\omega + x) \leq 0$$

For  $V' > 0$ ,  $m = 1$ . If  $V'(\omega) = 0$ , ?

$$V'(\omega + x) \in (V'(\omega) - \epsilon, V'(\omega) + \epsilon)$$

$$xV'(\omega+x) \leq (x+\theta)V'(\omega+x+\theta)$$

$$f(\omega, x) = xV'(\omega+x)$$

$$f(\omega, x+\theta) \geq f(\omega, x) \quad V \text{ increasing in } x$$

$$\frac{\partial}{\partial x} xV'(\omega+x) \geq 0 \quad \forall x$$

$$V'(\omega+x) + xV''(\omega+x) \geq 0$$

$$1 + \frac{xV''(\omega+x)}{V'(\omega+x)} \geq 0$$

$$1 \geq -\frac{xV''(\omega+x)}{V'(\omega+x)}$$

$$\text{if } x > 0, \text{ then } \frac{-V''(\omega+x)}{V'(\omega+x)} \leq \frac{1}{x}$$

$$\leq 0, \text{ then } \frac{-V''(\omega+x)}{V'(\omega+x)} \geq \frac{1}{x}$$

↑  
neg. #

Suppose this is true  $\forall \omega$ .

$\forall \omega, \forall x > 0,$

$$\frac{-V''(\omega+x)(\omega+x)}{V'(\omega+x)} \leq \frac{\omega}{x} + 1$$

limit  $\omega+x \geq 0$

FSD isn't enough for people to want less of risky asset. Need implausibly low coefficient of risk aversion.

## Multiperiod models

### Recursive approach

- Recursive definition of utility

$v_t$  ← lifetime utility unmaximized counterpart to value function  $V$

$$v_t = \Psi(K_t, X_t, E_t[v_{t+h}]; h) \quad h = \Delta t$$

$K_t$  = vector of state variables (parameters, <sup>endogenous</sup> state variables, time)

$X_t$  = vector of control variables

terminal condition  ~~$v_{T+h} = 0$~~   $v_{T+h} \equiv 0$

Examples:

$$(1) v_t = h u^t(K_t, X_t) + e^{-\rho h} E_t[v_{t+h}]$$

$$\Downarrow \int_t^T \\ v_t = h \sum_{n=0}^{T-t} e^{-\rho n h} u^{t+n h}(K_{t+n h}, X_{t+n h})$$

$$(2) v_t = h u^t(K_t, X_t) + e^{-\rho h} (E_t[v_{t+h}] - E_t[v_t])$$

$$(3) \frac{v_t - e^{-\rho h} v_{t+h}}{h} = u^t(K_t, X_t)$$

$$\frac{v_{t-h} - e^{-\rho h} v_t}{h} = u^{t-h}(K_{t-h}, X_{t-h})$$

$$- \dot{v}_{t-h} - e^{-\rho h} (\rho v_t - E_{t-h}[v_t]) = u^{t-h}(K_{t-h}, X_{t-h})$$

$$h \rightarrow 0 \quad - \dot{v}_t - e^{-\rho h} E_{t-h}[v_t] = u^t(K_t, X_t)$$

look at old notes (#30-30<sup>b</sup>, stochastic calculus)

### 3. Kreps-Porteus Preferences separate intertemporal substitution and risk aversion

$$v_t = h u^t(K_t, X_t) + \exp(-eh) \Phi^{-1}(E_t[\Phi(v_{t+h})])$$

$$\Leftrightarrow \Phi(v_t) = \Phi(h u^t(K_t, X_t) + \exp(-eh) \Phi^{-1}(E_t[\Phi(v_{t+h})]))$$

$$v_t = \Phi(h u^t(K_t, X_t) + \exp(-eh) \Phi^{-1}(E_t[v_{t+h}]))$$

2.6

General formulation of lifetime utility

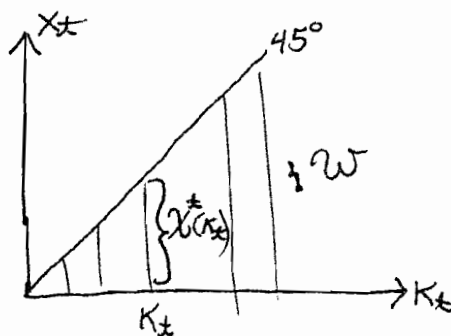
$$v_t = \psi^t(K_t, X_t, E_t[v_{t+h}]; h)$$

$$v_{t+T+h} = 0 \text{ for } h > 0$$

Constraints

• contemporaneous constraints:  $X_t \in \mathcal{X}^t(K_t) \Leftrightarrow (K_t, X_t) \in \mathcal{W}$

e.g.  $0 \leq X_t \leq K_t$



• intertemporal transition equation

$K_{t+h} = \Gamma^t(K_t, X_t, \omega_{t+h})$ ,  $\omega_{t+h}$  = vector of uniform  $[0, 1]$  random variables

e.g. (1)  $K_{t+h} = K_t + h A^t(K_t, X_t) \Rightarrow \dot{K}_t = A(K_t, X_t)$

(2)  $K_{t+h} = \begin{cases} K_t + h A^t(K_t, X_t) + \sqrt{h \Omega^t(K_t, X_t)} \omega_{t+h} & \omega / p = 1/2 \\ K_t + h A^t(K_t, X_t) - \sqrt{h \Omega^t(K_t, X_t)} \omega_{t+h} & \omega / p = 1/2 \end{cases}$

(3) same continuous time limit as (2)

$$K_{t+h} = K_t + h A^t(K_t, X_t) + \sqrt{h \Omega^t(K_t, X_t)} \tilde{\epsilon}_{t+h}, \quad E[\tilde{\epsilon}_{t+h}] = 0, \quad V[\tilde{\epsilon}_{t+h}] = 1$$

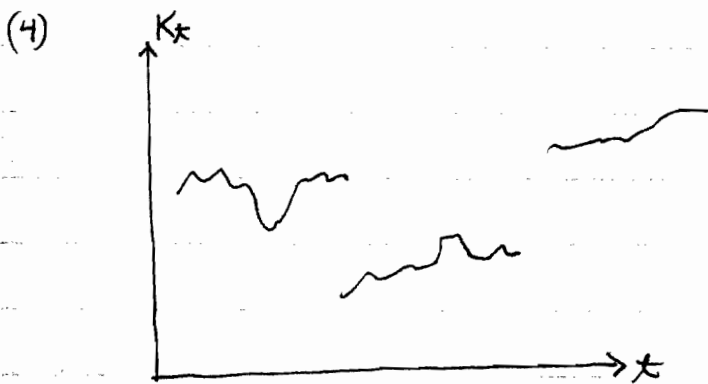
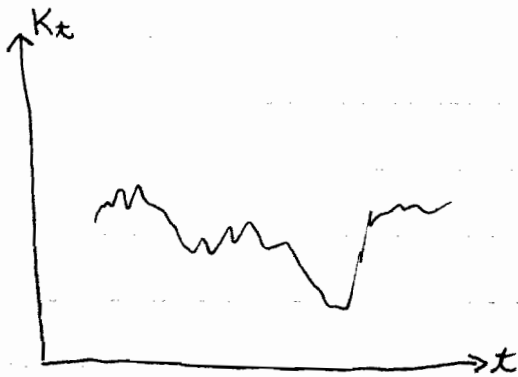
$\tilde{\epsilon}_{t+h}$  has finite support,  $\tilde{\epsilon}_{t+h}$  is iid

$$K_{t+h} = K_t + hA^*(K_t, X_t) + \sqrt{h} \Omega^*(K_t, X_t) \tilde{\epsilon}_{t+h} \quad \text{w/ PROB } 1-hp$$

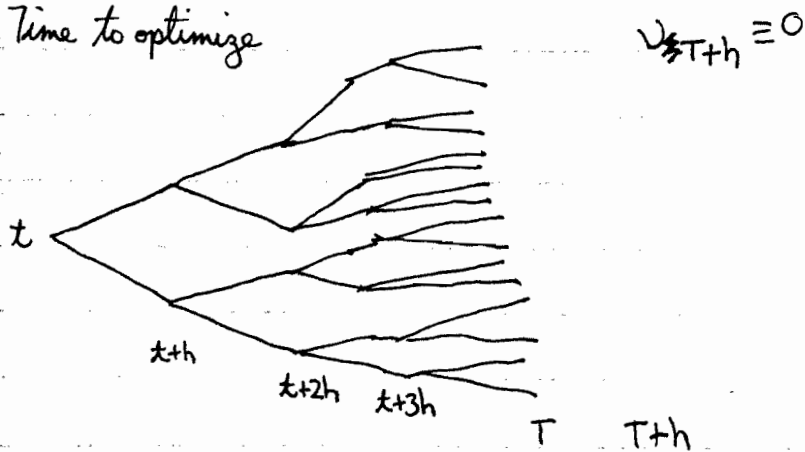
$$\left( \mathbb{E}(K_t, X_t, \tilde{\epsilon}_{t+h}) \right) \quad \text{w/ PROB } hp$$

small prob of ~~something~~ something big happening

Start w/ (2) or (3)



Time to optimize



Backwards recursion

Mathematical induction: prove for  $n=1$ , prove true  $n \Rightarrow$  true for  ~~$n+1$~~   $\Rightarrow$  true  $\forall n$

Recursion: mathematical induction for  $V_{T+h-nh}$ . Prove for  $n=0$ . Prove true for  $n \Rightarrow$  true for  $n+1 \Rightarrow$  true for all  $n=0, 1, 2, \dots$

$V^t$  . Prove for  $t=T+h$

. Prove that if true for  $t+h$ , then true for  $t \Rightarrow$  true for all  $t$ .

$V^t$  value function  $V^t(K_t) = \max_{X_t \in \mathcal{X}(K_t)} \psi^t(K_t, X_t, E_t[V^{t+h}(K_{t+h})])$

This is the Bellman equation

dynamic consistency says time  $t$ 's self  $V^t(K_{t+h}) = V^{t+h}$  (time  $t+h$ 's self  $V^{t+h}(K_{t+h})$ ).

Step 0: Prove  ~~$V^{T+h}$~~   $V^{T+h} \in P$  (has property P)

Step 1: Show that  $V_{(K_{t+h})}^{t+h} \in P \Rightarrow \underset{(F^t, W^t) \in Q}{\text{max}} F^t(K_t, X_t) = \psi^t(K_t, X_t, E_t[V_{(K_{t+h})}^{t+h}(K_{t+h})])$ , where  $F^t(K_t, X_t) = \psi^t(K_t, X_t, E_t[V_{(K_{t+h})}^{t+h}(K_{t+h})])$

remember,  $X_t \in \mathcal{X}(K_t) \Leftrightarrow (K_t, X_t) \in W^t$

= Bellman maximand

Step 2: Show that  $(F^t, W^t) \in Q \Rightarrow V^t \in P$

Step 3: By mathematical induction (recursion),  $V^t \in P \forall t = T+h-nh$ .

Easy optional steps (can do in either order; can done none, one, or both)

Step 4:  $T \rightarrow \infty$  <sup>show</sup>  $V^t(K_t; T, h) \in P \forall T \Rightarrow \lim_{T \rightarrow \infty} V^t(K_t; T, h) \in P$ .

Typically,  $V^t(K_t; T, h) \in P \Leftrightarrow \Phi(V^t) \geq 0$   $\xrightarrow{\dots} T$

example:  $V^t$  increasing in  $K_t$ .  $\mathbb{Q}(V) = V^t(K_{t+\delta}) - V^t(K_t) \geq 0 \quad \forall K_t$   
 functional is a function of a function (root of)

Step 5: Show that  $V^t(K_t; T, h) \in P \quad \forall h \Rightarrow \lim_{h \rightarrow 0} V^t(K_t; T, h) \in P$

Example  $\forall K'_t \geq K_t, V^t(K'_t) \geq V^t(K_t) \Leftrightarrow V^t(K'_t) - V^t(K_t) \geq 0$

$\Leftrightarrow \forall \delta > 0, V^t(K_t + \delta) - V^t(K_t) \geq 0, \forall K_t$

want to show this ( $V(\cdot)$  increasing in  $K_t$ )

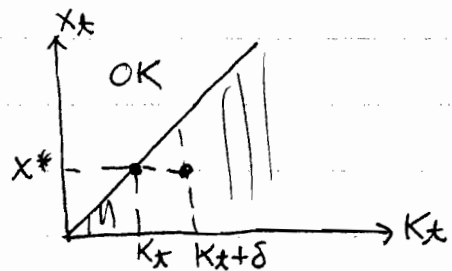
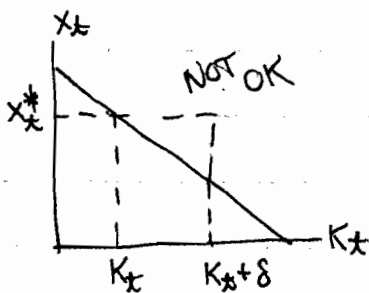
$$V^t(K_t + \delta) - V^t(K_t) = \left( \max_{(K_t + \delta, X_t) \in \mathcal{W}^t} \psi^t(K_t + \delta, X_t, E_t[V^{t+h}(\pi^t(K_t + \delta, X_t; \omega_{t+h}))]] \right) - \left( \max_{(K_t, X_t) \in \mathcal{W}^t} \psi^t(K_t, X_t, E_t[V^{t+h}(\pi^t(K_t, X_t; \omega_{t+h}))]] \right)$$

let  $X^* = \text{argmax}_{X_t} \psi^t(K_t, X_t, E_t[V^{t+h}(\pi^t(K_t, X_t; \omega_{t+h}))]]$

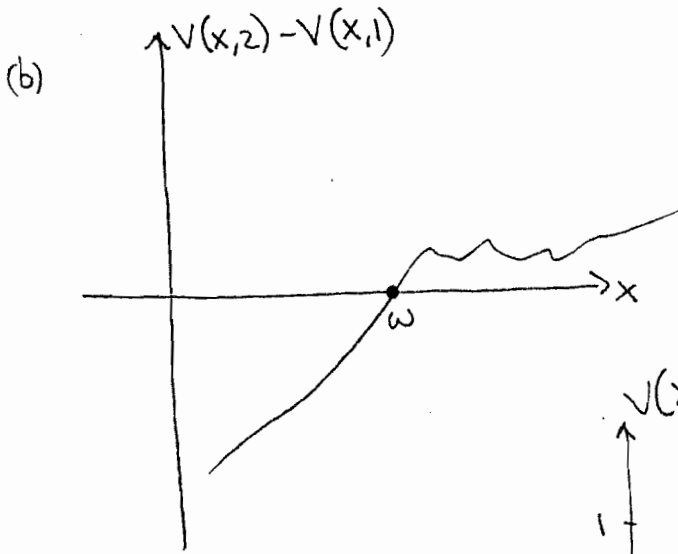
$\rightarrow ? \psi^t(K_t + \delta, X_t^*, E_t[V^{t+h}(\pi^t(K_t + \delta, X_t^*; \omega_{t+h}))]] - \psi^t(K_t, X_t^*, E_t[V^{t+h}(\pi^t(K_t, X_t^*; \omega_{t+h}))]]$

$F^t(K_t + \delta, X_t^*) - F^t(K_t, X_t^*)$  want to show  $\geq 0$  (need  $F$  increasing in  $K$ )

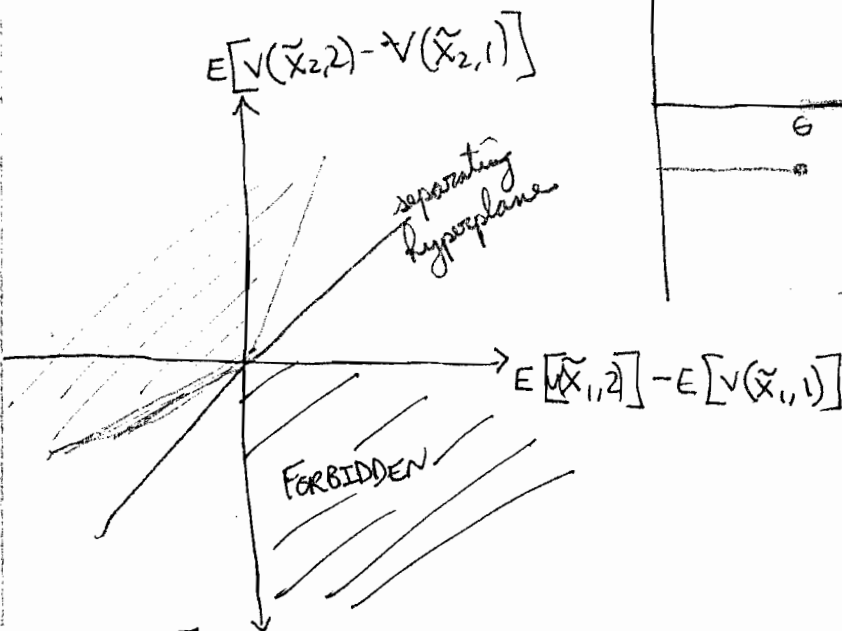
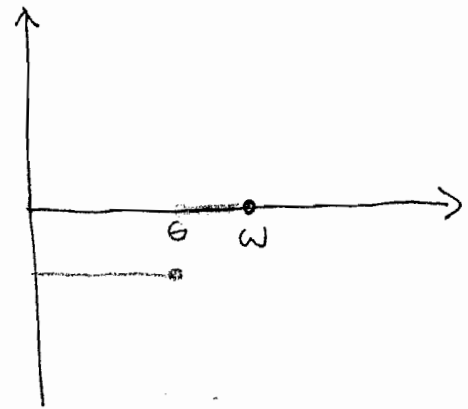
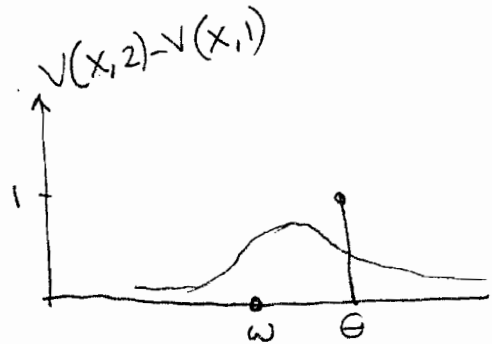
if  $(K_t, X_t) \in \mathcal{W}^t \Rightarrow (K_t + \delta, X_t) \in \mathcal{W}^t$



(1) (a) Choose  $\alpha=2$  if face  $\tilde{X}_1 \Rightarrow$  choose  $\alpha=2$  if face  $\tilde{X}_2$ .  
 single crossing property



Find basis:



$\exists m > 0$

$$E[V(\tilde{X}_2,2) - V(\tilde{X}_2,1)] \geq m E[V(\tilde{X}_1,2) - V(\tilde{X}_1,1)]$$



if this is true for any value function in the set  $(*)$ , it must be true for the basis functions.

$$\theta > \omega : E_{\theta} [b_{\theta}(X_2)] \geq m E_{\theta} [b_{\theta}(X_1)]$$

$$\int_a^b f(x) b_{\theta}(x) dx = f(\theta)$$

$\exists m \geq 0$

$$(1) f_2(\theta) \geq m f_1(\theta)$$

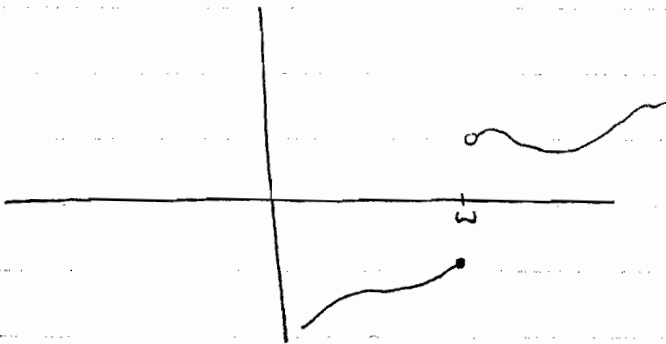
$$(2) -F_2(\theta) \geq -m F_1(\theta)$$

$\int_a^b$

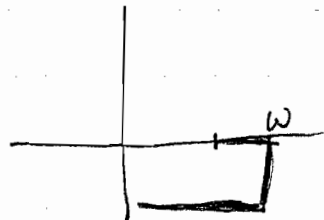
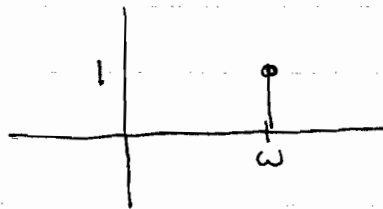
$$\theta < \omega \quad \int_a^b f(x) b_{\theta}(x) dx = \int_a^{\theta} (-f(x)) dx = -F(\theta)$$

$\int_a^b$

(c)



add to set of basis functions



$$(1) f_2(\theta) \geq m f_1(\theta), \theta \geq \omega$$

$$(2) -F_2(\theta) \geq -m F_1(\theta), \theta \leq \omega$$

$$(2) (\mathbb{R}^2)^{\circ} = \{0\}$$

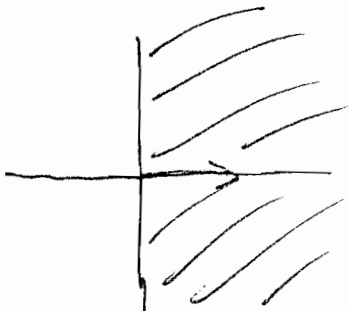
only point w/  
non-negative dot product with any vector



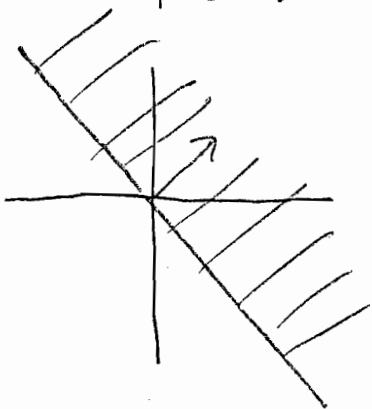
~~ccs~~

$$\{(0,0)\}^{\circ} = \mathbb{R}^2$$

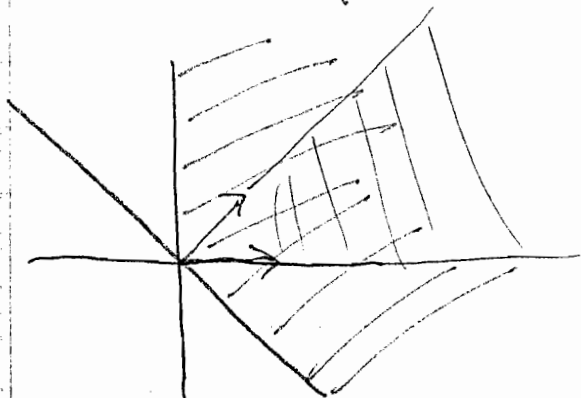
$(0,0)$  is acc, as is  $\mathbb{R}^2$



$$\{(1,0)\}^{\circ} = \{(x,y) \mid x \geq 0, \forall y\}$$



say this is risk aversion  $\leq 6 \Rightarrow$  changes in RV  
on purple line



Purple/Green <sup>polars</sup> acc of each other

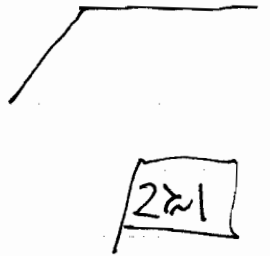
$(A \cap B)^{\circ} = A^{\circ} + B^{\circ}$   
any changes in <sup>RV</sup> in purple cone

$$A = \int V'(x) / V(x)$$

$$\int_a^b V(x) [f_2(x) dx - f_1(x)] dx = V(x) [F_2(x) - F_1(x)] \Big|_a^b - \int_a^b V'(x) (F_2(x) - F_1(x)) dx$$

$\phi\left(\frac{-1}{x}\right)$  where  $\phi' \geq 0, \phi'' \leq 0$  (risk aversion = 2 for  $\frac{-1}{x}$ )

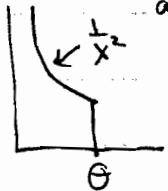
$\min \{0, V(x) - V(\theta)\}$  basis  $b_\theta(x)$   
 marginal value  $b_\theta(x) = b'_\theta(x) = \begin{cases} 0 & \text{if } x \geq \theta \\ V'(x) & \text{if } x < \theta \end{cases}$



$2 \geq 1$

$$\int_a^b V(x) (f_2(x) - f_1(x)) dx = - \int_a^b b'_\theta(x) [F_2(x) - F_1(x)] dx$$

$$= - \int_a^\theta V(x) (F_2(x) - F_1(x)) dx \stackrel{?}{\geq} 0 \quad \forall \theta \in [a, b]$$



$V(x) = \frac{-1}{x}$   
 $V'(x) = \frac{1}{x^2}$

$\Rightarrow \int_a^b \left(\frac{1}{x^2}\right) (F_2(x) - F_1(x)) dx \geq 0 \quad \forall \theta \in [a, b]$   
 NSC for all value functions with  $rra \geq 2$  to prefer  $\tilde{X}_2$  to  $\tilde{X}_1$ .  $A^0$

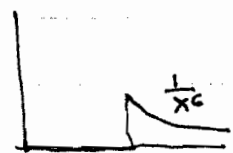
$B = V$  w/ rel risk aversion  $\leq 6$



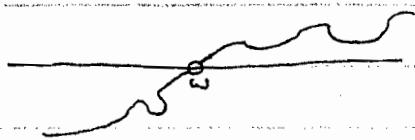
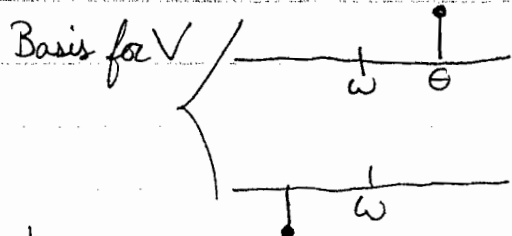
Basis of utility function

marginal utility basis  $b_\theta(x) = \begin{cases} 0 & x < \theta \\ \frac{1}{x^6} & x > \theta \end{cases}$

$\int_a^b \frac{1}{x^6} (F_1(x) - F_2(x)) \geq 0 \quad \forall \theta \in [a, b]$   
 criterion for polar of B



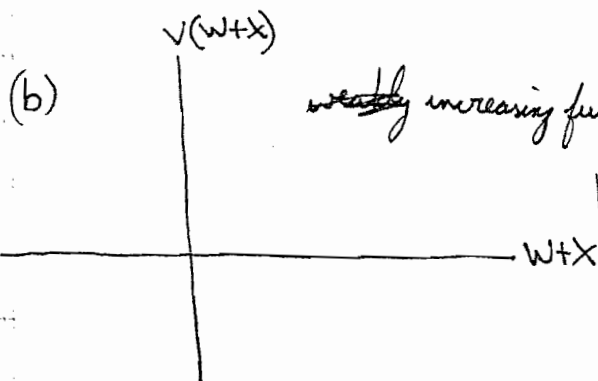
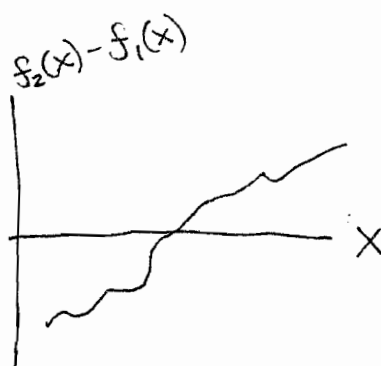
(a)  $\Theta [V(\omega+\Theta) - V(\omega)] \geq 0$



$\sum_a^b [f_2(x) - f_1(x)] b_\Theta(x) \geq 0 \quad \forall b_\Theta(x)$

$f_2(\Theta) - f_1(\Theta) \geq 0 \quad \forall \Theta \geq \omega$   
 $-(f_2(\Theta) - f_1(\Theta)) \geq 0 \quad \forall \Theta \leq \omega$

$\Rightarrow$  single crossing of densities



~~strictly~~ increasing functions  $V(x)$

polars of this is first order stochastic dominance

FSD is ccc of densities that cross at different values.

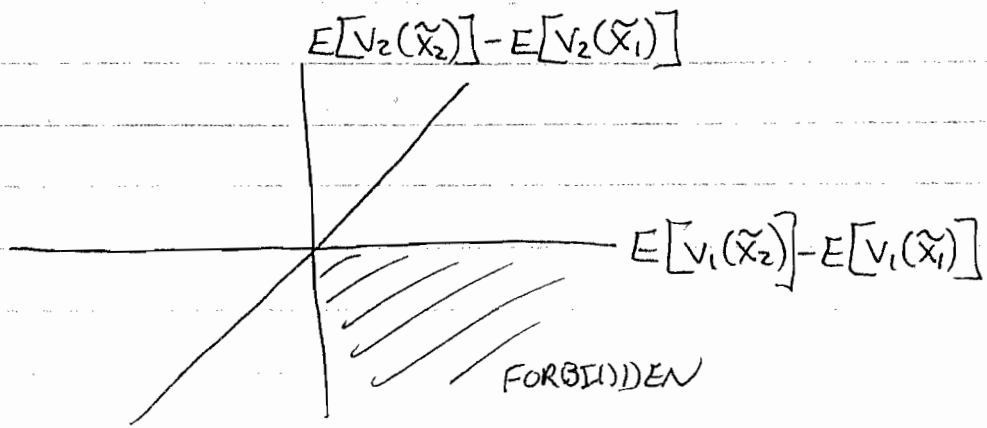
$\exists m \geq 0$   
 (5)  $E[X^2 V_2'''(\omega+x)] \leq m E[X^2 V_1'''(\omega+x)]$

$X^2 V_2'''(\omega+x) \leq m X^2 V_1'''(\omega+x)$

$V_2'''(\omega+x) \leq m V_1'''(\omega+x)$

Draw picture of these

(6)



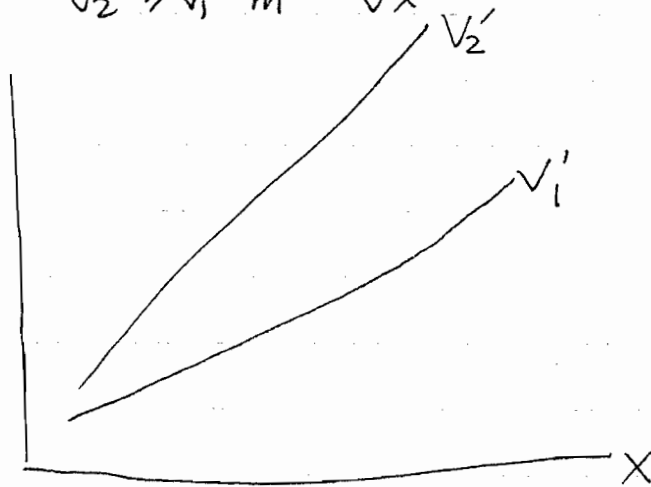
$$E[V_2(x_2)] - E[V_2(x_1)] \geq m(E[V_1(x_2)] - E[V_1(x_1)])$$

$\Updownarrow$

$$V_2(x+\theta) - V_2(x) \geq m[V_1(x+\theta) - V_1(x)]$$

$$\lim_{\theta \rightarrow 0^+} \frac{V_2(x+\theta) - V_2(x)}{\theta} \geq \lim_{\theta \rightarrow 0^+} \frac{V_1(x+\theta) - V_1(x)}{\theta} \cdot m$$

$$V_2' \geq V_1' \cdot m \quad \forall x$$



2.13

$$V^t(K_t) = \max_{0 \leq c_t \leq K_t} U(c_t) + \beta E_t [V^{t+1}(\tilde{R}_{t+1}(K_{t+1} - c_t) + \tilde{Y}_{t+1})]$$

$$X(K_t) = [0, K_t]$$

$$V^t(K_t + \theta) - V^t(K_t) \stackrel{\theta > 0}{\geq} \max_{c_t \in [0, K_t + \theta]} U(c_t) + \beta E_t [V^{t+1}(\tilde{R}_{t+1}(K_t + \theta - c_t) + \tilde{Y}_{t+1})] - \max_{c_t \in [0, K_t]} U(c_t) + \beta E_t [V^{t+1}(\tilde{R}_{t+1}(K_t - c_t) + \tilde{Y}_{t+1})]$$

• want to show this is  $\geq 0$

(i)  $c_t^* \in \text{argmax } U(c_t) + \beta E_t [V^{t+1}(\tilde{R}_{t+1}(K_t - c_t) + \tilde{Y}_{t+1})]$

$$\Rightarrow V^t(K_t + \theta) - V^t(K_t) \geq \beta E_t [V^{t+1}(\tilde{R}_{t+1}(K_t + \theta - c_t^*) + \tilde{Y}_{t+1}) - V^{t+1}(\tilde{R}_{t+1}(K_t - c_t^*) + \tilde{Y}_{t+1})] \geq 0 \Leftrightarrow \text{need } V^{t+1}(\cdot) \text{ non-decreasing to prove } V^t \text{ is non-decreasing.}$$

$$V^{T+1}(K_{T+1}) \equiv 0$$

Now for concavity



always above secant line

$$V^t(\theta K_1 + (1-\theta)K_2) - \theta V^t(K_1) - (1-\theta)V^t(K_2) \geq 0, \forall K_1, K_2, \forall \theta \in [0, 1]$$

Preservermax Theorem

$$V^t(\theta K_1 + (1-\theta)K_2) - \theta V^t(K_1) - (1-\theta)V^t(K_2) = \max_{c_t \in X(\theta K_1 + (1-\theta)K_2)} U(c_t) + \beta E_t [V^{t+1}(\tilde{R}_{t+1}(\theta K_1 + (1-\theta)K_2 - c_t) + \tilde{Y}_{t+1})] - \left( \theta \max_{c_t \in X(K_1)} U(c_t) + \beta E_t [V^{t+1}(\tilde{R}_{t+1}(K_1 - c_t) + \tilde{Y}_{t+1})] + (1-\theta) \max_{c_t \in X(K_2)} U(c_t) + \beta E_t [V^{t+1}(\tilde{R}_{t+1}(K_2 - c_t) + \tilde{Y}_{t+1})] \right)$$

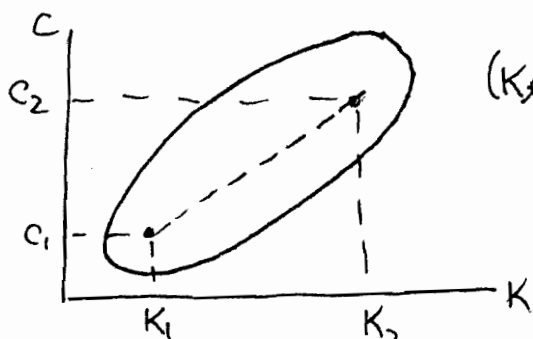
$c_1 \in \text{argmax} \Rightarrow$

$c_2 \in \text{argmax} \Rightarrow$

QED

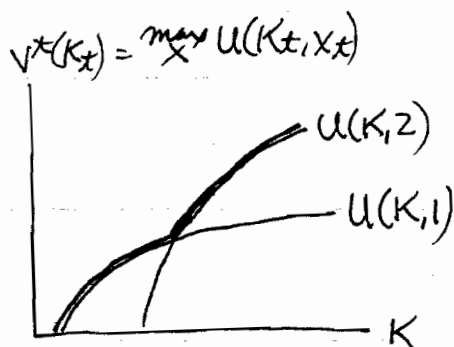
$$\begin{aligned} &\geq u(\theta K_1 + (1-\theta)K_2, \theta C_1 + (1-\theta)C_2) - \theta u(K_1, C_1) - (1-\theta)u(K_2, C_2) \\ &+ \beta E_t \left[ V^{t+1}(\tilde{R}_{t+1}(\theta(K_1 - C_1) + (1-\theta)(K_2 - C_2)) + \tilde{Y}_{t+1}) \right] - \theta V^{t+1}(\tilde{R}_{t+1}(K_1 - C_1) + \tilde{Y}_{t+1}) \\ &- (1-\theta) V^{t+1}(\tilde{R}_{t+1}(K_2 - C_2) + \tilde{Y}_{t+1}) \geq 0 \end{aligned}$$

we need  $\theta C_1 + (1-\theta)C_2 \in [C_1, C_2]$



$(K_t, C_t) \in W$ ,  $W$  is a convex set

Discrete choices make you look risk loving



$V^{t+1}(\cdot)$  concave assumed gives  $\beta E_t[\cdot] \geq 0$   
 $u(\cdot)$  jointly concave in  $(C, K)$ . (think baseball cap)

Bellman's equation for diffusion process in continuous time (p 37)

$$e V^t(K_t) - V_t^t = \max_{x_t \in X(K_t)} \left[ u^t(K_t, x_t) + V_K^t(K_t) A(K_t, x_t) + V_{KK}^t(K_t) \frac{\Omega(K_t, x_t)}{2} \right]$$

$$\lim_{\Delta t \rightarrow 0} V^t(K_{t+\Delta t}) = V^t(K_t) + \Delta t A(K_t, x_t) + \frac{\Delta t}{2} \Omega(K_t, x_t) + \epsilon_{t+\Delta t}$$

$\epsilon_{t+\Delta t} \sim$   
 $\uparrow$  mean 0, variance 1

in particular, it is often most convenient to take limit w/  $\epsilon_{t+\Delta t} = \begin{cases} +1 & \text{w prob. } 1/2 \\ -1 & \text{w prob. } 1/2 \end{cases}$

$$dK = A(K_t, x_t) dt + \sqrt{\Omega(K_t, x_t)} dz$$

$dz \sim$  mean 0, variance  $dt$  (Itô)

$$\max E_0 \left[ \int_0^T e^{-\rho t} u(K_t, X_t) dt \right]$$

$$\text{s.t. } dK = A(K_t, X_t) dt + \sqrt{\Omega(K_t, X_t)} dz$$

$$V^*(K_t) = \max$$

$$u(K_t, X_t) + e^{-\rho h} E[V^{*+h}(K_{t+h})] \approx V^*(K_t) + [V^{*+h}(K_t) - V^*(K_t)]$$

$$\approx V^*(K_t) + (e^{-\rho h} - 1)V^*(K_t) + e^{-\rho h} [V^{*+h}(K_t) - V^*(K_t)]$$

$$+ e^{-\rho h} [V^{*+h}(K_t + hA(K_t, X_t)) - V^{*+h}(K_t)]$$

$$+ e^{-\rho h} E_x [V^{*+h}(K_t + hA(K_t, X_t) + \sqrt{h\Omega(K_t, X_t)} \tilde{\epsilon}_{t+1}) - V^{*+h}(K_t + hA(K_t, X_t))]$$

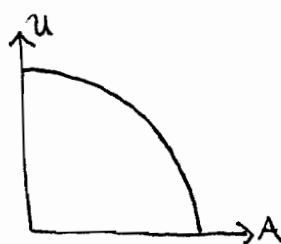
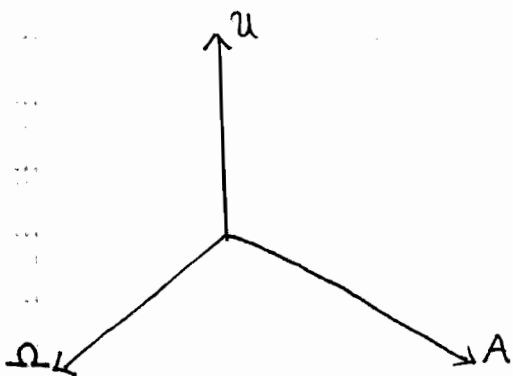
2.15

Hint: Prob. 1 : concavity : ~~convex~~ think of X as amount of labor  $\approx$  linear function of capital

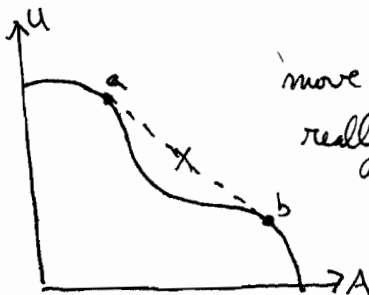
convexity : think of X as labor to capital ratio held constant

redefine X and use change of variables. Careful then about last question.

$$eV^*(K_t) - V^*(K_t) = \max_{X_t} u(K_t, X_t) + V_K^*(K_t) A^*(K_t, X_t) + V_{KK}^*(K_t) \frac{\Omega^*(K_t, X_t)}{2}$$

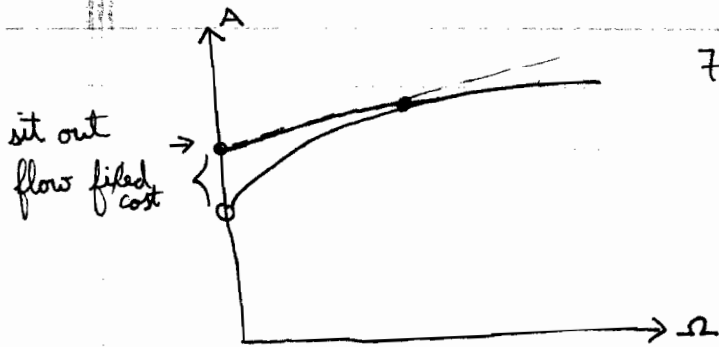


Chattering principle:



move back + forth between a & b  
really quickly in continuous time  
 $\Rightarrow$  gets you convexity





Flow fixed cost  
can get convex hull by chattering

### Symmetry Method

Theorem: one version is a Boyd Chapter

Symmetry of constraint set  $\Rightarrow$  Symmetry of the value function  
Symmetry of preferences

Symmetry of

$$V_t(K_t) = \max_{X \in X(K_t)} \psi(K_t, X_t, E[V_{t+h}(K_{t+h}, X_{t+h}, \tilde{\omega}_{t+h})])$$

$$V_t = \psi(K_t, X_t, E[V_{t+h}]) \quad V_{T+h} = 0$$

$X(\cdot)$  contemp constraint

$\Pi(\cdot)$  Transition eq.

A: Contemporaneous Constraints:  $(K_t, X_t) \in W \Leftrightarrow T(K_t, X_t) \in W$

$(\hat{K}_t, \hat{X}_t) = T(K_t, X_t)$   $T(\cdot)$  is a triangular transformation

$$\hat{K}_t = T^K(K_t) \quad \hat{X}_t = T^X(K_t, X_t)$$

B: Intertemporal Constraints:  $\{ K_{t+h} = \Pi(K_t, X_t, \tilde{\omega}_{t+h}) \Leftrightarrow T(K_{t+h}) = \Pi(T^K(K_t), T^X(K_t, X_t), \tilde{\omega}_{t+h})$

transformation must be invertible

## Symmetry of Preferences

Def.  $S$  is a preference symmetry corresponding to  $T$  if  $S$  is monotonically increasing

$$\text{iff } v_t = \Psi(K_t, X_t, E[v_{t+h}]) \Leftrightarrow S(K_t, v_t) = \Psi(T^K(K_t), T^X(K_t, X_t), E[S(\hat{T}(K_t, X_t, \omega_{t+h}), \hat{v}_{t+h})])$$

$S$  describes what  $T(\cdot)$  does to the utility function

If you have symmetry of constraint sets and symmetry of preferences, then  $v(T(K_t)) = S(v(K_t))$

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## Examples of symmetry method

Merton Model:  $\max_{C, \alpha} E_0 \left[ \int_0^T e^{-\rho t} \frac{C_t^{1-\gamma}}{1-\gamma} dt \right]$

s.t.  $dW = [rW + \alpha\mu - C_t]dt + \alpha\sigma dz$   $dZ = \sqrt{dt} \tilde{z}$   $\Delta Z = \pm \sqrt{h}$

$W(0) = W_0$

$\mu = E \text{ return stock}$   
 $- E \text{ return T Bill} = \frac{0.01}{YR}$   
 $\sigma^2 = 0.0225/YR$

$$E \frac{dV}{dt} - V_t(W, t) = \max_{C, \alpha} \frac{C^{1-\gamma}}{1-\gamma} + V_W(W, t) [rW + \alpha\mu - C] + V_{WW}(W, t) \frac{\alpha^2 \sigma^2}{2}$$

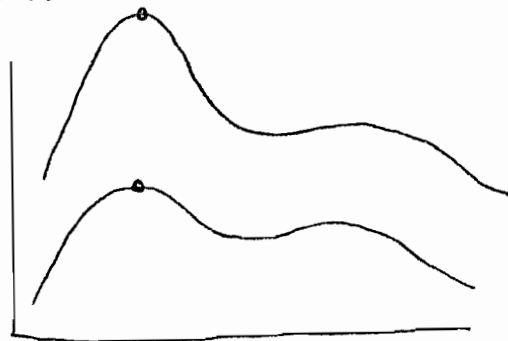
quadratic at a point in time

$$C \rightarrow \theta C \quad v \rightarrow \theta^{1-\gamma} v$$

what would allow us to consume  $\theta$  as much?

$$W \rightarrow \theta W, \quad \alpha \rightarrow \theta \alpha$$

$$\Rightarrow V(\theta W, t) = \theta^{1-\gamma} V(W, t)$$



In particular, let  $\theta = \frac{c}{w}$ ,  $V(1,t) = \left(\frac{c}{w}\right)^{1-\gamma} V(w,t)$

$$\Rightarrow V(w,t) = w^{1-\gamma} V(1,t)$$

$$V_w(w,t) = (1-\gamma) w^{-\gamma} V(1,t)$$

$$V_{ww} = -\gamma(1-\gamma) w^{-\gamma-1} V(1,t)$$

$$\Rightarrow e^{r-\delta} V(1,t) - E W^{1-\gamma} V_t(1,t) = \max_{c,\alpha} \frac{c^{1-\gamma}}{1-\gamma} + (1-\gamma) w^{-\gamma} V(1,t) [r w + \alpha \mu - c] - \gamma(1-\gamma) w^{-\gamma-1} V(1,t) \frac{\alpha^2 \sigma^2}{2}$$

$$\bar{c}^{-\gamma} = (1-\gamma) w^{-\gamma} V(1,t)$$

$$c = \left[ (1-\gamma) V(1,t) \right]^{-\frac{1}{\gamma}} w$$

$\frac{A(t)^{-\gamma}}{1-\gamma}$  *average propensity to consume*  $\frac{c}{w} = A(t)$

Divide by  $\frac{w^{1-\gamma}}{1-\gamma}$

$$\mu V_w + V_{ww} \alpha \sigma^2 = 0$$

$$\alpha = \frac{\mu}{-\frac{V_{ww}}{V_w} \sigma^2} = \frac{\mu/\sigma^2}{\text{absolute risk aversion of } V}$$

$$\Rightarrow e A^{-\gamma} + \gamma A^{-\gamma-1} = A^{-\gamma} + (1-\gamma) A^{-\gamma} \left[ r + \frac{\alpha}{w} \mu - A \right] - \gamma A^{-\gamma} \left( \frac{\mu}{\gamma \sigma^2} \right)^2 \frac{\sigma^2}{2}$$

ARA of  $V = \frac{\gamma}{w}$   
RRR of  $V = \gamma$

This is a differential equation in  $A$ .

Solve by writing  $B = \frac{1}{A}$ .

$$\max_{\alpha, c, t} E_x \left[ \int_x^\infty e^{-\rho t} \log(c_t) dt \right]$$

$$s.t. \quad dW = [r_x W_x + \alpha_x \mu_x - c_x] dt + \alpha_x \sigma_x dz$$

$$c \rightarrow \theta c$$

$$W \rightarrow \theta W$$

$$\alpha \rightarrow \theta \alpha$$

$$v \rightarrow v + \frac{1 - e^{-\rho T}}{\rho} \log(\theta)$$

$$V(\theta W, t) = V(W, t) + \frac{1-e^{-\rho T}}{\rho} \log(\theta)$$

$$\text{let } \theta = \frac{1}{W} \Rightarrow V(1, t) = V(W, t) - \frac{1-e^{-\rho T}}{\rho} \log(W)$$

$$\Rightarrow V(W, t) = V(1, t) + \frac{1-e^{-\rho T}}{\rho} \log(W)$$

$$\frac{1}{c} = \frac{1-e^{-\rho T}}{\rho} W^{-1} \Rightarrow \frac{c}{W} = \frac{\rho}{1-e^{-\rho T}}$$

$$\text{MAX } E_t \left[ \int_t^T e^{-\rho t} \frac{e^{-\rho c}}{-\rho} dt \right] \quad \text{s.t. } dW = [rW + \alpha\mu - c]dt + \alpha\sigma dz$$

$$c \rightarrow c + \theta \quad v \rightarrow e^{-\alpha\theta} v$$

let  $r$  be constant

$$W \rightarrow W + \frac{\theta}{r}$$

$$\alpha \rightarrow \alpha$$

$$V(W + \frac{\theta}{r}, t) = e^{-\alpha\theta} V(W, t)$$

$$\text{let } \theta = -rW$$

$$V(0, t) = e^{\alpha r W} V(W, t) \Rightarrow V(W, t) = e^{-\alpha r W} V(0, t)$$

Capitalization symmetries ( $v \rightarrow v$ )

noncapital income

$$V(W, \gamma) = \max \int_t^{\infty} e^{-\rho t} u(c_t) dt$$

$$dW = [rW + \alpha\mu + \gamma - c]dt + \alpha\sigma dz$$

$$W \rightarrow W + \frac{\theta}{r} \quad (W \rightarrow W + \int_t^{\infty} e^{-\rho t} \gamma dt)$$

$$\gamma \rightarrow \gamma - \theta$$

$$V\left(W + \frac{\theta}{r}, Y - \theta, t\right) = V(W, Y, t)$$

Let  $\theta = Y \Rightarrow V\left(W + \frac{Y}{r}, 0, t\right) = V(W, Y, t)$  *capitalized labor income*  
 $\alpha = \frac{W}{Y} + \frac{Y}{r}$

CRTS

competitive output & factor markets

CRTS adjustment cost function

$$\Rightarrow V(\theta K) = \theta V(K) \quad \theta = \frac{1}{K} \Rightarrow V(1) = \frac{1}{K} V(K)$$

$$\Rightarrow V(K) = K V(1)$$

$$\frac{V(K, t)}{K} = V(1, t) = \text{avg } q = \text{marginal } q = V_K(K, t) = V(1, t)$$

Chris Carroll Habit formation  $\Rightarrow$  can place \$ value of habit burden  
 (Joe Lupton)

Horizontal & Vertical Aggregation  
 Legendre Conjugate functions

$$V(W_t, Z_t) = \max_{C, S_i} U(C_t) + \sum_i \pi_i(Z_t) \beta E_t [V_{t+1}(R_i(Z_t) S_i + Y_i(Z_t, \tilde{W}_{t+1})) - \pi_i(Z_t)]$$

s.t.  $C + \sum_i S_i = W$

Lagrange:  $+ \lambda [W - C - \sum_i S_i]$

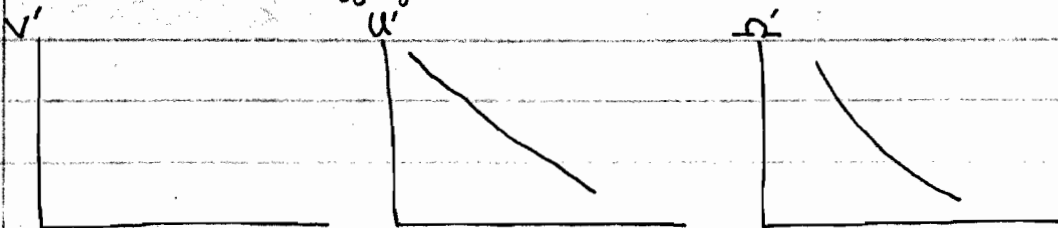
$$V(W_t, Z_t) - \lambda W \Leftrightarrow \max_C U(C_t) - \lambda C + \sum_i \left( \max_{S_i} \pi_i(Z) \beta E_t [V_{t+1}(\cdot)] - \lambda S_i \right)$$

$$- \underbrace{U^*(\lambda)}_{\tilde{U}^*(\lambda)} - \underbrace{\lambda^*(\lambda)}_{\tilde{\lambda}^*(\lambda)}$$

read  $\approx$  p. 70 2005 notes

# Horizontal + Vertical aggregation

2.22



$V'$  horizontal sum of  $U', \Omega'$  (if  $U', \Omega'$  downward sloping,  $V'$  is too)



shifting up everywhere  $\Leftrightarrow$  shifting right everywhere

anything that depends on sign of derivative, preserved under vertical aggregation.



if  $V''_{t+1}(K_{t+1}) \geq 0 \forall K_{t+1} \Rightarrow E_t [V'''(\tilde{R}S + \tilde{Y})] \geq 0$



$$-\frac{V''(K_{t+1})}{V'(K_{t+1})} \geq a \Leftrightarrow E_t [V''_{t+1}(K_{t+1}) - a V'_{t+1}(K_{t+1})] \geq 0$$

$$-\frac{\Omega''}{\Omega'} = \frac{-E[V''_{t+1}]}{E[V'_{t+1}]} \geq a$$

$$-K V''_{t+1}(K) - \gamma V'_{t+1}(K) \geq 0$$

$$F(K) = V(RK) \Rightarrow F'(K) = R V'(RK)$$

$$F''(K) = R^2 V''(RK)$$

$$KF''(K) = R^2 K V''(RK)$$

$$K \rightarrow K + \tilde{\epsilon} \Rightarrow E[(K + \tilde{\epsilon}) V''(K + \tilde{\epsilon}) - \gamma V'(K + \tilde{\epsilon})] \geq 0$$

if  $\Omega(K) = E[V(K + \tilde{\epsilon})]$ , want  $-K \Omega''(K) - \gamma \Omega'(K)$

$$-K E[V''(K + \tilde{\epsilon})] - \gamma E[V'(K + \tilde{\epsilon})]$$

$$E[(K + \tilde{\epsilon}) V''(K + \tilde{\epsilon})] \stackrel{?}{\geq} E[K V''(K + \tilde{\epsilon})] \text{ if } \tilde{\epsilon} = 0$$

$$E[\tilde{\epsilon} V''(K+\tilde{\epsilon})] \stackrel{!}{=} 0$$

$$E[\tilde{\epsilon}^2] E[V''(K+\tilde{\epsilon})] + \text{COV}(\tilde{\epsilon}, V''(K+\tilde{\epsilon}))$$

$$\stackrel{!}{=} 0 \Rightarrow V'''(\cdot) \geq 0$$

$$V''' V' - (V'')^2 \geq 0 \quad \text{DARA}$$

$$V_{KK} V_{PP} - (V_{KP})^2 \geq 0$$

$$\begin{bmatrix} V''' & V'' \\ V'' & V' \end{bmatrix} \text{ positive definite}$$

$$\begin{bmatrix} V_{KK} & V_{KP} \\ V_{KP} & V_{PP} \end{bmatrix} \text{ neg def.}$$

Vertical aggregation often straightforward.

$$V^t(w_t, z_t) = \max_{c, s_i, \beta} u^t(c) + \sum_i \pi_i(z_t) \beta E_t \left[ R_i(z_t) s_i + \gamma_i(z_t, \tilde{\omega}_{t+1}) \right], \beta, \pi^i(z_t, \tilde{\omega}_t)$$

$$= \max_{c, s_i} u^t(c) + \sum_i \Omega^{i,t}(s_i, \beta, z_t)$$

$$= \max_{c, s_i} u^t(c) + \sum_i \Omega^{i,t}(s_i, \beta, z_t) + \lambda [w_t - c - \sum_i s_i]$$

envelope theorem:  $V_w = \lambda$

$$\max_{w_t} V(w_t, \beta, z_t) - \lambda w_t = \max_c (u(c) - \lambda c) + \sum_i \max_{s_i} (\Omega^{i,t}(s_i, \beta, z_t) - \lambda s_i)$$

assume concavity (Rockafellar's Convex Analysis)

$$= -u^*(\lambda) - \sum_i \Omega^{i,*}(\lambda, \beta, z_t)$$

$\Omega^*, u^*$  = Legendre conjugate functions

$$V^*(\lambda, p) = \max_w V(w, p) - \lambda w = \lambda \underbrace{V_w^{-1}(\lambda, p)}_{w} - V(\underbrace{V_w^{-1}(\lambda, p)}_w, p) \stackrel{\sum s_i}{=} \lambda \underbrace{u_c^{-1}(\lambda)}_c - u(u_c^{-1}(\lambda)) + \sum_i \lambda \underbrace{\Omega_{s_i}^{-1}(\lambda, p)}_{s_i} - \Omega_{s_i}^i(\underbrace{\Omega_{s_i}^{-1}(\lambda, p)}_{s_i}, p)$$

$$\Omega_s = \lambda, u_c = \lambda$$

$$(V^*(\lambda, p))^* = V(w, p)$$

$$V^*(\lambda, p) = \lambda V_w^{-1}(\lambda, p) - V(V_w^{-1}(\lambda, p), p)$$

$$V^{**}(\lambda) = \min_w \lambda w - V^*(\lambda) = \min_w \lambda w - \lambda V_w^{-1}(\lambda) + V(V_w^{-1}(\lambda, p), p)$$

$$= \min_w \frac{V'(w)}{w} w - \frac{V'(w)}{w} w + V(w)$$

$$\Rightarrow V'(w) \neq \lambda \quad V''(w)w - V''(w)w - V'(w) + V'(w) = 0$$

$$\Rightarrow w = w \text{ so long as } V'' \neq 0$$

$$w = V_w^{-1}(\lambda, p)$$

$$V_w(w, p) = \lambda$$

$$V_{ww}(w, p)dw + V_{wp}(w, p)dp = d\lambda$$

$$dw = \frac{d\lambda}{V_{ww}} - \frac{V_{wp}}{V_{ww}}$$

$$\frac{\partial}{\partial \lambda} V_w^{-1}(\lambda, p) = \frac{1}{V_{ww}(V_w^{-1}(\lambda, p))}$$

$$\frac{\partial}{\partial p} V_w^{-1}(\lambda, p) = \frac{-V_{wp}(V_w^{-1}(\lambda, p), p)}{V_{ww}(V_w^{-1}(\lambda, p), p)}$$

$$V^*(\lambda, p) = -\max_w (V(w, p) - \lambda w) = \lambda V_w^{-1}(\lambda, p) - V(V_w^{-1}(\lambda, p), p)$$

$$V_\lambda^*(\lambda, p) = V_w^{-1}(\lambda, p) = w$$

$$\lambda = V_w(w) \quad w = V_\lambda(\lambda)$$

$$V(w, p) = -\max_\lambda (V^*(\lambda, p) - \lambda w) = w V_\lambda^*(w, p) - V^*(V_\lambda^*(w, p), p)$$

$$V_w(w, p) = V_\lambda^{*-1}(w, p) = \lambda$$

$$V_\lambda^* = w \quad (w = V_w^{-1}(\lambda, p))$$

$$V_p^* = -V_p$$

$$V_{\lambda\lambda}^* = \frac{1}{V_{ww}}$$

$$V_{p\lambda}^* = -V_{pw} / V_{ww}$$

$$V_{\lambda\lambda\lambda}^* = \frac{-V_{www}}{V_{ww}^2}$$



$$V_w = \lambda$$

$$\lambda = (V_{\lambda}^*)^{-1}(w, p)$$

$$V_p = -V_p^*$$

$$V_{ww} = \frac{1}{V_{\lambda}^*}$$

$$V_{pp} = -V_{p\lambda}^* / V_{\lambda}^*$$

$$V_{www} = -\frac{V_{\lambda\lambda}^*}{V_{\lambda}^{*2}}$$

$$V_{pw} \geq 0 \Leftrightarrow V_{p\lambda}^* \geq 0$$

assuming concavity

$$-\frac{V_{KK} \cdot K}{V_K} \geq \gamma \quad (K=W)$$

$$-\frac{V_{\lambda}^*}{\lambda V_{\lambda}^*} \geq \gamma \quad \text{relative risk tolerance of conjugate function}$$

$$V^* = u^* + \sum_i \Omega_i^*$$

$$V(K, Z) = \Pi(K, Z) + \max_{I \geq 0} \pi \Omega + \Phi(I, Z) + E_z [D(\beta, Z_{t+1}) V^{t+1}(s, \beta, Z_{t+1})]$$

$$s = (1-\delta)K + I$$

$$\Leftrightarrow V(K, Z) - \Pi(K, Z) = \max_I \Phi(I, Z) + E_z [\cdot] + \lambda [(1-\delta)K + I - s]$$

ex profit value  $\checkmark$   $F(K, Z)$

$$\max_K (F(K, Z) - \lambda(1-\delta)K) = \max_I (\Phi(I, Z) + \lambda I) + \max_s (\Omega(s, \beta, Z) - \lambda s)$$

$$-F^*((1-\delta)\lambda, Z) = -\Phi^*(-\lambda, Z) - \Omega^*(\lambda, \beta, Z)$$

$$\Leftrightarrow F^*((1-\delta)\lambda, Z) = \Phi^*(-\lambda, Z) + \Omega^*(\lambda, \beta, Z)$$

Extra Credit: max of  $x$  = get  $S$  times conjugate function

$$F^*(\lambda(1-\delta), Z) = \Omega^*(\lambda + \Phi^*(-\lambda, Z), Z)$$