

11/6

Levon

Expected Utility Theory will not get us that far

State is the most important thing
↳ events

States have to be payoff relevant

↳ X := collection of possible realizations
= $\{X_1, \dots, X_N\}$

$$P = \{p = \{p_1, \dots, p_N\}\}$$

$$\sum_{i=1}^N p_i = 1, p_i > 0$$

Can we expectation to derive stuff

$$EV = \sum_{i=1}^N p_i X_i$$

Suppose $EV = \$72$

How much you are willing to pay to play determines if you are risk averse

Say we have another $q := \{q_1, \dots, q_N\}$

↓ Probabilities

$p \succsim q$

→ complete and transitive

→ continuous

→ independence

If I prefer p to q
then I prefer a mixture of p and r
to a mix of q and r

X (states) are fixed

$$\alpha p + (1-\alpha)r \succsim \alpha q + (1-\alpha)r$$

EU's are linear in probabilities

$p \succsim q$

$$\Rightarrow \sum_{i=1}^N p_i U(x_i) \geq \sum_{i=1}^N q_i U(x_i)$$

Must know U !

Let's do stuff with U

① U is concave (risk averse)

convex (risk preferred)

U is "shape restricted" because
of patterns in the data

U depends on wealth

We define

$$V = EU = \sum_{i=1}^N p_i U(x_i)$$

Flip 2 coins

heads → 0

tails → I pay you $-T$

$$\begin{matrix} \{0 & ; & -T\} \\ p_1 & & p_2 \end{matrix}$$

Utility fn: $-\exp(-\sigma x)$

$$\left\{ \begin{aligned} &\rightarrow p_1 (-\exp(0)) + p_2 (-\exp(\sigma T)) \\ &\quad - (p_1 + (1-p_1) \exp(\sigma T)) \end{aligned} \right\} \text{How much you should pay to play}$$

Certainty Equivalent

$$\rightarrow -\exp(-\sigma CE)$$

Take logs,

$$-\frac{1}{\sigma} \log(p_1 + (1-p_1) \exp(\sigma T)) = CE$$

The assumption you make about utility and probability are what's important

"If you raise your hand and are right,
I'll bring you a potato" - Levon

$$\begin{matrix} & 0.1-E & E \\ \rightarrow 0 & +1_m & -10 \end{matrix}$$

$$\rightarrow 0 \quad +2_m$$

Ch 6 of MWG

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TA

SEU: A & A

S: states

X: outcomes

P: all possible distribution over X

H: acts = $\{h \mid h: S \rightarrow P\}$

π : prior / belief over states

SEU: one belief $\pi \in \Delta(S) = P$

$$SEU(h) = \sum_{s \in S} \pi(s) \sum_{x \in X} h(x|s) u(x)$$

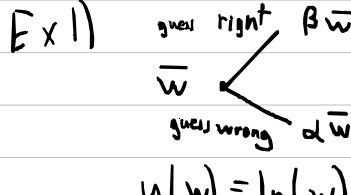
$$\max_h SEU(h)$$

Beyond SEU (Gilboa-Schmeidler type)

Only have a set of beliefs Q

max-min utility

$$\max_{\pi \in Q} \{ \min_{\pi \in Q} [\sum_{s \in S} \pi(s) \sum_{x \in X} h(x|s) u(x)] \}$$



In state H: heads is $\frac{2}{3}$

$$\begin{aligned} SEU &= P\{\text{heads} | \text{guess heads}\} \ln(\beta \bar{w}) \\ &\quad + P\{\text{heads} | \text{guess tails}\} \ln(\alpha \bar{w}) \\ &\quad + P\{\text{tails} | \text{guess heads}\} \ln(\alpha \bar{w}) \\ &\quad + P\{\text{tails} | \text{guess tails}\} \ln(\beta \bar{w}) \\ &= \frac{2}{3} \ln(\beta \bar{w}) + \frac{2}{3} \ln(\alpha \bar{w}) \\ &\quad + \frac{1}{3} \ln(\alpha \bar{w}) + \frac{1}{3} \ln(\beta \bar{w}) \end{aligned}$$

In state T: heads is $\frac{1}{3}$

$$\begin{aligned} SEU &= P\{\text{heads} | \text{guess heads}\} \ln(\beta \bar{w}) \\ &\quad + P\{\text{heads} | \text{guess tails}\} \ln(\alpha \bar{w}) \\ &\quad + P\{\text{tails} | \text{guess heads}\} \ln(\alpha \bar{w}) \\ &\quad + P\{\text{tails} | \text{guess tails}\} \ln(\beta \bar{w}) \\ &= \frac{1}{3} \ln(\beta \bar{w}) + \frac{1}{3} \ln(\alpha \bar{w}) \\ &\quad + \frac{2}{3} \ln(\alpha \bar{w}) + \frac{2}{3} \ln(\beta \bar{w}) \end{aligned}$$

$$\begin{aligned} &\frac{2}{3} \ln(\beta \bar{w}) + \frac{2}{3} \ln(\alpha \bar{w}) + \frac{1}{3} \ln(\alpha \bar{w}) + \frac{1}{3} \ln(\beta \bar{w}) \\ &= \frac{1}{3} \ln(\beta \bar{w}) + \frac{1}{3} \ln(\alpha \bar{w}) + \frac{1}{3} \ln(\alpha \bar{w}) + \frac{2}{3} \ln(\beta \bar{w}) \end{aligned}$$

$$a) \pi(T) = \pi(H) = \frac{1}{2}$$

If accept,

You choose which gives higher SEU

$$\begin{aligned} SEU(h) &= \frac{1}{2} \left[\frac{2}{3} \ln(\beta \bar{w}) + \frac{1}{3} \ln(\alpha \bar{w}) \right. \\ &\quad \left. + \frac{1}{2} \left(\frac{1}{3} \ln(\beta \bar{w}) + \frac{2}{3} \ln(\alpha \bar{w}) \right) \right] \\ &= \frac{1}{2} \ln(\beta \alpha \bar{w}^2) \\ SEU(t) &= \frac{1}{2} \ln(\beta \alpha \bar{w}^2) \end{aligned}$$

If no accept,

$$SEU(n) = \ln(\bar{w})$$

$$\Rightarrow \ln(\bar{w}) = \frac{1}{2} \ln(\beta \alpha \bar{w}^2)$$

$$= \ln(\sqrt{\beta \alpha \bar{w}})$$

$$w = \sqrt{\beta \alpha \bar{w}}$$

$$\alpha \beta = 1$$

b)

$$SEU(h) = \min_{\pi(H) \in [0,1]} \pi(H) \left[\frac{2}{3} \ln(\beta \bar{w}) + \frac{1}{3} \ln(\alpha \bar{w}) \right] + (1 - \pi(H)) \left[\frac{1}{3} \ln(\beta \bar{w}) + \frac{2}{3} \ln(\alpha \bar{w}) \right]$$

"worst case" occurs when $\pi(H) = 0$

$$= \frac{1}{3} \ln(\beta \bar{w}) + \frac{2}{3} \ln(\alpha \bar{w})$$

$$SEU(t) = \frac{1}{3} \ln(\beta \bar{w}) + \frac{2}{3} \ln(\alpha \bar{w})$$

no bet

$$SEU(n) = \ln(\bar{w})$$

$$\Rightarrow \ln(\bar{w}) = \frac{1}{3} \ln(\beta \bar{w}) + \frac{2}{3} \ln(\alpha \bar{w})$$

$$\Rightarrow (\beta \bar{w})^{1/3} (\alpha \bar{w})^{2/3} = w$$

$$\alpha^2 \beta = 1$$

c) For part (a),
It holds

For part (b),

$$SEU(h) = \frac{9}{10} \ln(\alpha \bar{w}) + \frac{1}{10} \ln(\beta \bar{w})$$

$$SEU(n) = \ln(\bar{w})$$

$$\alpha^9 \beta = 1$$

because worst case vs. worst

2) a)

Correct $\rightarrow \delta$

Wrong $\rightarrow -\delta$

$$P\{H | s_A\} = \frac{1}{3}$$

$$P\{H | s_B\} = \frac{3}{4}$$

$$u(w) = \log(w)$$

$$\begin{aligned} &\ln(1) \\ &u(1) = 1 \end{aligned}$$

$$\begin{aligned} SEU(h) &= \frac{1}{2} [P\{H | s_A\} \cdot 1 + P\{T | s_A\} \cdot (-1)] \\ &\quad + \frac{1}{2} [P\{H | s_B\} \cdot 1 + P\{T | s_B\} \cdot (-1)] \\ &= \frac{1}{2} \left(\frac{1}{3} - \frac{2}{3} \right) + \frac{1}{2} \left(\frac{3}{4} - \frac{1}{4} \right) \\ &= -\frac{1}{6} + \frac{1}{4} = \frac{1}{12} \end{aligned}$$

$$\begin{aligned} SEU(t) &= \frac{1}{2} [P\{H | s_A\} \cdot (-1) + P\{T | s_A\} \cdot 1] \\ &\quad + \frac{1}{2} [P\{H | s_B\} \cdot (-1) + P\{T | s_B\} \cdot 1] \\ &= \frac{1}{2} \left(-\frac{1}{3} + \frac{2}{3} \right) + \frac{1}{2} \left(-\frac{3}{4} + \frac{1}{4} \right) \\ &= \frac{1}{6} - \frac{1}{4} = -\frac{1}{12} \end{aligned}$$

$$SEU(n) = 0$$

Yes, bet on h

$$b) EU(H) = \min_{p \in [\frac{1}{3}, \frac{2}{3}]} p \left(\frac{1}{3} (w+1) + \frac{2}{3} (w-1) \right) + (1-p) \left(\frac{3}{4} (w+1) + \frac{1}{4} (w-1) \right)$$

Let $p = \frac{2}{3}$ to minimize RHS

$$= \frac{2}{3} \left(w - \frac{1}{3} \right) + \frac{1}{3} \left(w + \frac{1}{2} \right)$$

$$= w - \frac{1}{18}$$

$$EU(T) = w - \frac{2}{9}$$

$$EU(N) = w$$

Choose not to bet

Check Online

11/11

HW due Friday

States of the World

Potential outcomes

$\hookrightarrow X_1, \dots, X_N$

Probability

$\hookrightarrow p_1, \dots, p_N$

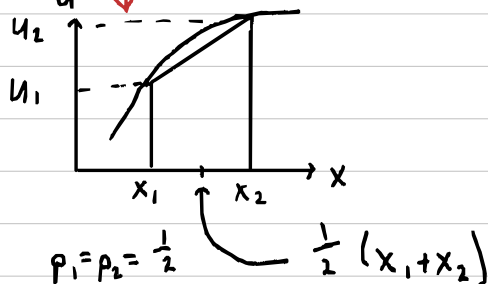
Expected Value = $\sum_{i=1}^N p_i X_i$

Expected Utility = $\sum_{i=1}^N p_i U(X_i)$

There is a transformation from X_i 's to Utility

The utility curve is the "certain" lottery

The expected value is less
 \hookrightarrow people are risk averse



You should only gamble if your preferences are convex!

Certainty Equivalent

\hookrightarrow allows you to evaluate any lottery in the world of outcomes by which the lottery is realized

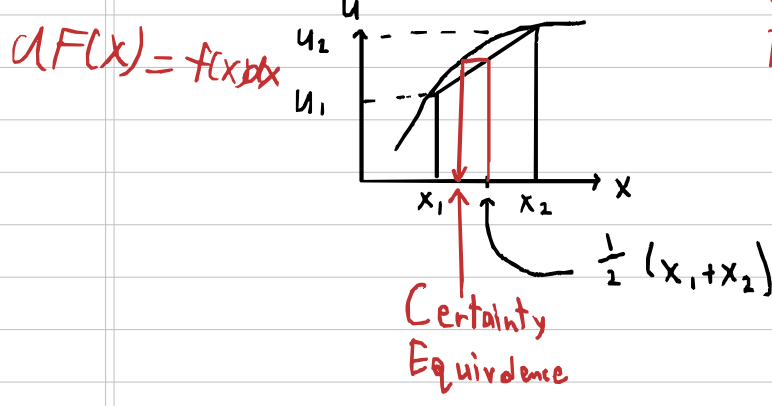
\hookrightarrow e.g. the dollar amount between certainty and lottery

$$U\left(\sum_{i=1}^N p_i X_i\right) \geq \sum_{i=1}^N p_i U(X_i)$$

$$U(CE) := \sum_{i=1}^N p_i U(X_i)$$

\hookrightarrow You are willing to accept a lower payoff in order to receive less risk

$$\frac{dF(x)}{dx} = f(x)$$



$$E = \int x f(x) dx$$

Lower CE \Rightarrow More Risk Averse

How do convex preferences \Rightarrow quasi-concave utility?

$$\min X_i \leq CE \leq \max X_i \leq \sum_{i=1}^N p_i X_i$$

Continuous Case

$$\text{Expected Value} = \int_{\mathcal{M}} x dF(x)$$

$$\text{Expected Utility} = \int_{\mathcal{M}} u(x) dF(x)$$

Two losses (will come out of initial wealth w)

		prob.	price	how much you buy
Loss 1	$w - L_1$	p_1	q_1	π_1
Loss 2	$w - L_2$	p_2	q_2	π_2
No Loss	$w - 0$	p_0 $\uparrow 1 - p_1 - p_2$	q_0	π_0

$$\text{Loss 1: } w - L_1 - q_1 \pi_1 - q_2 \pi_2 + \pi_1$$

$$\text{Loss 2: } w - L_2 - q_1 \pi_1 - q_2 \pi_2 + \pi_2$$

$$\text{No Loss: } w - 0 - q_1 \pi_1 - q_2 \pi_2$$

Maximize this guy's utility

$$\max_{\{\pi_1, \pi_2\}} p_1 U(w - L_1 - q_1 \pi_1 - q_2 \pi_2 + \pi_1) + p_2 U(w - L_2 - q_1 \pi_1 - q_2 \pi_2 + \pi_2) + (1 - p_1 - p_2) U(w - q_1 \pi_1 - q_2 \pi_2)$$

FOC

$$[\pi_1] \quad p_1(1 - q_1)U'(z_1) + p_2(-q_2)U'(z_2) + (1 - p_1 - p_2)q_1U'(z_3) = 0$$

$$[\pi_2] \quad -p_1 q_2 U'(z_1) + p_2(1 - q_2)U'(z_2) - (1 - p_1 - p_2)q_2 U'(z_3) = 0$$

$$\hookrightarrow p_2 U'(z_1) - p_1 q_2 U'(z_1) + -(p_2 q_2)U'(z_2) - (1 - p_1 - p_2)q_2 U'(z_3) = 0$$

$$\frac{p_1 U'(z_1)}{p_2 U'(z_2)} = \frac{q_1}{q_2}$$

\hookrightarrow the rate at which you can transfer resources between states

A perfectly competitive firm would price:

$$q_1 = p_1$$

$$q_2 = p_2$$

If $p_1, p_2 \uparrow$ by scalar α then you will be poorer because you are paying more not to take heavy losses in L_1 or L_2

This required assuming that

\hookrightarrow we knew u

\hookrightarrow we knew p

\hookrightarrow we knew w

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"Actuarially fair" means that the expected value of the loss equals the price

Former example (where to put wine tree)

		Returns w/o flood	Prob. of flood
L Left	200	l	f_l
R Right	200	r	f_r
M Middle	50	m	0

If L and R are divisible and their combinations dominate M then M is useless

We should ask if the floods are mutually exclusive (ME)

Reservation price to pay insurance is $M(50)$

Now with math,

$$\max_{x_l + x_r + x_m \leq 1} \sum_{i \in \{0, l, r, lr\}} f_i U(w_i) \quad \text{states of the world}$$

$$w_0 = x_m m$$

Let's say the floods are indep.
Then,

$$P\{\text{no flood}\} = (1-f_l)(1-f_r) \rightarrow x_l l + x_r r + x_m m$$

$$P\{l \text{ flood}\} = f_l(1-f_r) \rightarrow x_r r + x_m m$$

$$P\{r \text{ flood}\} = f_r(1-f_l) \rightarrow x_l l + x_m m$$

$$P\{lr \text{ flood}\} = f_l f_r \rightarrow x_m m$$

Suppose preferences are CARA

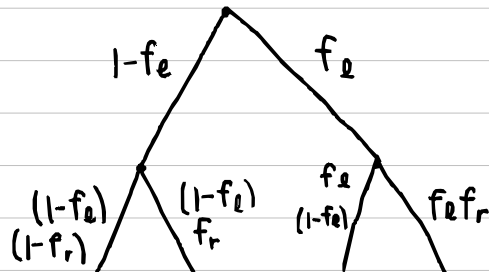
$$\text{then we maximize } - \sum f_i \underbrace{\exp(-\gamma \cdot w_i)}_{\text{CARA}}$$

$$\rightarrow f_l(1-f_r) \exp(-\gamma(x_r r + x_m m))$$

$$\rightarrow (1-f_l)(1-f_r) \exp(-\gamma(x_l l + x_r r + x_m m))$$

$$\rightarrow (1-f_l)f_r \exp(-\gamma(x_l l + x_m m))$$

$$\rightarrow f_l f_r \exp(-\gamma(x_m m))$$



Recall that $x_l + x_r + x_m \leq 1$

she will never leave the constraints slack

We rewrite

$$\rightarrow f_l(1-f_r) \exp(-\gamma(x_r r + (1-x_r-x_l)m))$$

$$\rightarrow (1-f_l)(1-f_r) \exp(-\gamma(x_l l + x_r r + (1-x_r-x_l)m))$$

$$\rightarrow (1-f_l)f_r \exp(-\gamma(x_l l + (1-x_r-x_l)m))$$

$$\rightarrow f_l f_r \exp(-\gamma((1-x_r-x_l)m))$$

So we maximize

$$f_l \left[(1-f_r) \exp(-\gamma(x_r r + (1-x_r-x_l)m)) + f_r \exp(-\gamma((1-x_r-x_l)m)) \right]$$

$$+ (1-f_l) \left[(1-f_r) \exp(-\gamma(x_l l + x_r r + (1-x_r-x_l)m)) + f_r \exp(-\gamma(x_l l + (1-x_r-x_l)m)) \right]$$



$$f_l \left[(1-f_r) \exp(-\gamma(x_r r + (1-x_r-x_l)m)) + f_r \exp(-\gamma((1-x_r-x_l)m)) \right]$$

$$+ (1-f_l) \exp(-\gamma x_l l) \left[(1-f_r) \exp(-\gamma(x_r r + (1-x_r-x_l)m)) + f_r \exp(-\gamma((1-x_r-x_l)m)) \right]$$

Since the term with x_r is the same, the amount of x_r you choose doesn't depend on the state

Can see more clearly by

$$\exp(\gamma x_l m) \left\{ f_l \left[(1-f_r) \exp(-\gamma(x_r r + (1-x_r)m)) + f_r \exp(-\gamma((1-x_r)m)) \right] \right.$$

$$\left. \exp(-\gamma x_l l) (1-f_l) \left[(1-f_r) \exp(-\gamma(x_r r + (1-x_r)m)) + f_r \exp(-\gamma((1-x_r)m)) \right] \right\}$$



Background risk simply means an event that can occur with simple prob., but the occurrence (not the prob.) is independent from something?

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TA

$$\begin{aligned} & \text{EU} \\ & \max_{\{x_1, x_2\}} \pi U(x_1 + ax_2) + (1-\pi)U(x_1 + bx_2) \\ & \text{s.t. } x_1 + x_2 = 1 \\ & \quad x_1, x_2 \in [0, 1] \end{aligned}$$

by substitution

$$\Leftrightarrow \max_{x_2 \in [0, 1]} \pi U(1 - x_2 + ax_2) + (1-\pi)U(1 - x_2 + bx_2)$$

a)

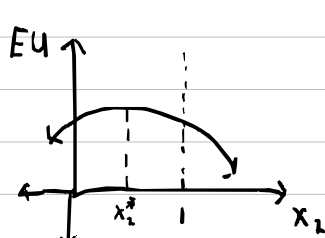
Assume $U'' \leq 0$ (by risk aversion)

$$\frac{\partial EU(x_2)}{\partial x_2} = \pi U'(1 - x_2 + ax_2)(a-1) + (1-\pi)U'(1 - x_2 + bx_2)(b-1)$$

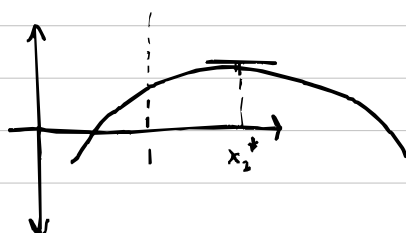
$$\frac{\partial^2 EU(x_2)}{\partial x_2^2} = \underbrace{\pi U''(1 - x_2 + ax_2)(a-1)^2}_{\leq 0} + \underbrace{(1-\pi)U''(1 - x_2 + bx_2)(b-1)^2}_{\leq 0}$$

$$\Rightarrow \frac{\partial^2 EU(x_2)}{\partial x_2^2} \leq 0$$

One necessary condition is $\frac{\partial EU(x)}{\partial x_2} \Big|_{x_2=1} < 0$



If $x_2^* > 1$



So,

$$\pi U'(a)(a-1) + (1-\pi)U'(b)(b-1) < 0$$

is a suff. and necessary condition due to concavity.

A simple necessary condition is $\min\{a, b\} < 1$

↳ Not sufficient

$$b) \frac{\partial EU(x_2)}{\partial x_2} \Big|_{x_2=0} > 0$$

$$\text{So, } \underbrace{\pi U'(1)(a-1)}_{\text{cancel}} + \underbrace{(1-\pi)U'(1)(b-1)}_{\text{cancel}} > 0$$

c) Assuming (a) and (b) hold let's us ignore corner solutions

$$\frac{\partial EU(x_2)}{\partial x_2} = \pi U'(1 - x_2 + ax_2)(a-1) + (1-\pi)U'(1 - x_2 + bx_2)(b-1) \stackrel{\text{set}}{=} 0$$

$$d) \quad x_1 = 1 - x_2 \\ dx_1 = -dx_2$$

$$\frac{dx_1}{da} \leq 0 \Leftrightarrow \frac{dx_2}{da} \geq 0$$

Recall our FOC

$$\frac{\partial EU(x_2)}{\partial x_2} = \pi U'(1 - x_2 + ax_2)(a-1) + (1-\pi)U'(1 - x_2 + bx_2)(b-1) = 0$$

Take deriv. of a on FOC

$$\pi U''(1 - x_2 + ax_2)(a-1) \left(-\frac{dx_2}{da} + x_2 + a \frac{dx_1}{da} \right) + \pi U'(1 - x_2 + ax_2) + (1-\pi)U''(1 - x_2 + bx_2)(b-1) \frac{dx_2}{da} = 0$$

Collect terms of $\frac{\partial x_2}{\partial a}$

$$\Rightarrow \pi U''(1 - x_2 + ax_2)(a-1)x_2 + \pi U'(1 - x_2 + ax_2)$$

$$= - \left[\pi U''(1 - x_2 + ax_2)(a-1)^2 \frac{dx_2}{da} + (1-\pi)U''(1 - x_2 + bx_2)(b-1)^2 \frac{dx_2}{da} \right]$$

$$= - \left[\pi U''(1 - x_2 + ax_2)(a-1)^2 + (1-\pi)U''(1 - x_2 + bx_2)(b-1)^2 \right] \frac{dx_2}{da}$$

$$\frac{dx_2}{da} = - \frac{\pi U''(1 - x_2 + ax_2)(a-1)x_2 + \pi U'(1 - x_2 + ax_2)}{[\pi U''(1 - x_2 + ax_2)(a-1)^2 + (1-\pi)U''(1 - x_2 + bx_2)(b-1)^2]} \quad \begin{matrix} \geq 0 \\ \leq 0 \end{matrix}$$

$$\Rightarrow \frac{dx_2}{da} \geq 0$$

e) π is probability of bad state/lose

So the more likely you are going to lose, the less you will invest in risky asset.

$$\text{So, } \frac{\partial x_1}{\partial \pi} < 0 \quad \text{and} \quad \frac{\partial x_2}{\partial \pi} > 0$$

e) Recall our FOC

$$\frac{\partial EU(x_2)}{\partial x_2} = \pi U'(1 - x_2 + ax_2)(a-1) + (1-\pi)U'(1 - x_2 + bx_2)(b-1) = 0$$

Take deriv w.r.t. π ?

"Take derivative of π on FOC"

11/18

Short Quiz on Friday

$\int U(w) dF(w)$ is the bread and butter of Expected Utility

Equity Premium
↳ return of risky asset minus safe asset?

- ① Risk free asset $\mapsto r$, $r > 1$
 ② Stochastic return $\mapsto q$, $\underbrace{E[q] < r}$

Inconsistent with what we expect so it better be that $E[q] > r$

Consider $E[q] > r$

$$\max_x \int U(w\{(1-x) \cdot r + xq\}) dF(q)$$

Deriv. w.r.t. x

The sum of 2 concave fns. is concave so the sum of n (aka the integral) is still concave

$$\int U'(w(1-x)r + xq) \cdot W(-r+q) dF(q) = 0$$

If $x=0$ and it is the optimum, then $U'(wr)W(q-r) dF = 0$

Since this is never true, $x=0$ is not optimal.

Asset 1	Rain $\frac{1}{2}$	No Rain $\frac{1}{2}$
Asset 2	Chiefs W $\frac{1}{2}$	Chiefs Lose $\frac{1}{2}$
Asset 3	People Drunk in Kansas City $\frac{1}{2}$	People Not Drunk in Kansas City $\frac{1}{2}$

Correlated ↘ So one of these assets is irrelevant

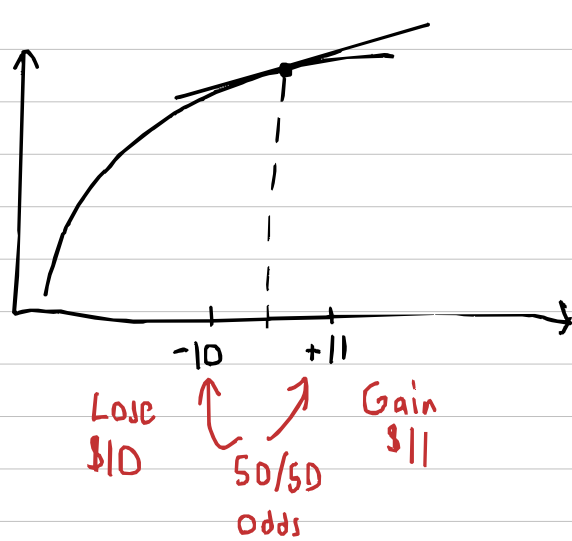
Now we choose between Asset 1 and 2

If two assets have the same profile then their price profile should be basically the same

If Taylor Swift benefits from KC winning, then she should bet on weather in Ithaca

↳ A Ford worker should invest in Tesla

Must know (W) $F(w)$ $U(w)$
 ↳ states



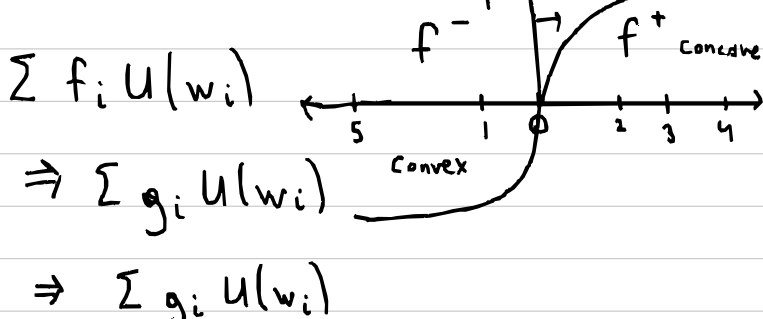
Ex: $\frac{1}{2} U(w+L-p) + \frac{1}{2} U(w-p)$
 $\pi(\frac{1}{2}) U(w+L-p) + \pi(\frac{1}{2}) U(w-p)$

Rank dependence

$$[1-\pi](\frac{1}{2}) U(w+L-p) + \pi(\frac{1}{2}) U(w-p)$$

<u>$(w-p_1, -p_2)$</u>	<u>$w-p_1, -p_2+L_1$</u>	<u>$w-p_1, -p_2+L_2$</u>	<u>$w-p_1, -p_2+L_1+L_2$</u>
f_1	f_2	f_3	f_4
$\pi(f_1)$	$\pi(f_1+f_2) - \pi(f_1)$	$\pi(f_1+f_2+f_3) - \pi(f_1+f_2)$	\uparrow $1 - \pi(f_1+f_2+f_3)$

Learn the sliders he posts



11/20

Review of Decision Making under Risk

Probability is measure of likelihood

Know the paradoxes!

↳ Which assumptions they violate

↳ Ellsberg, St. Petersburg, etc.

MWG 6.C.17

$$W_t = [(1 - \alpha_{t-1})R + \alpha_{t-1}X] w_{t-1}$$

$$\max E[U(w_2)]$$

s.t. $w_2 = [(1 - \alpha_1)R + \alpha_1 X] w_1$

$$= \max \int U([(1 - \alpha_1)R + \alpha_1 X] w_1) dF(x)$$

$$\Rightarrow \int w_1 U'(\cdot) (X - R) dF(x) = 0 \quad \text{by FOC}$$

Using our functional form:

$$U' = [(1 - \alpha_1)R + \alpha_1 X]^{-\sigma} w_1^{-\sigma}$$

$$\int [(1 - \alpha_1)R + \alpha_1 X]^{-\sigma} w_1^{-\sigma} (X - R) dF(x) = 0$$

by FOC

$$= \int w_1 \{ \exp \{ -\sigma [(1 - \alpha_1)R + \alpha_1 X] w_1 \} \} (X - R) dF(x) = 0$$

$$= \int (X - R) \exp \{ -\sigma [(1 - \alpha_1)X] w_1 \} dF(x) = 0$$

Tangent } Apply basic IFT,

$$A(\alpha_1, w_1) = 0$$

$$A(\alpha_1, (w_1), w_1) = 0$$

$$A_\alpha \cdot \frac{d\alpha_1}{dw_1} + A_w = 0$$

A