

# Topics in Behavioral Decisions in Finance

Discussion by Christian Hilpert  
November 6, 2023

## 5. Alternative Theories of Choice under Risk

### 5.1 Reference-Dependent Risk Attitudes

#### **Kszegi, Rabin (2007, AER)**

- ▶ choice of reference point in CPT exogenous.
- ▶ has huge impact for economic choices
- ▶  $\Rightarrow$  literature on disposition effect
- ▶ new model:
  - ▶ combines gain/loss utility with standard consumption utility
  - ▶ Rabin(2000):  $(50/50, +550, -500) \Rightarrow (+100, 000, 000, 000, 000, -4, 000) \Rightarrow$  reject
  - ▶ endogenously determines reference point
  - ▶ allows for stochastic reference points.

## 5.1 Reference-Dependent Risk Attitudes

1. surprise, low probability decisions, exogenous expectations; say pay \$55 to insure \$100 risk, 50%
  - (a) status quo: 0.  $\rightarrow$  diminishing sensitivity do not insure
  - (b) expect to pay 55: lose 45 gain 55 . loss aversion  $\rightarrow$  insure.
2. anticipated risks
  - (a) maximizing personal equilibrium (UPE)  
behaviour where the stochastic outcome generated by utility-maximizing choices conditional on expectations equals expectations. i.e. follows planned behavior  
 $\Rightarrow$  selects preferred personal equilibrium (PPE)
  - (b) choice-acclimating personal equilibrium (CPE)  
committed decision long before outcomes  $\Rightarrow$  reference point influenced by choice.  
maximize expected utility given that it determines reference lottery and outcome lottery.
3. 1&2 : linear consumption utility  $\Rightarrow$  small gambles.  
now large gambles, consumption utility non-linear  $\Rightarrow$  reference point not very important.

# Model

- ▶  $w \in \mathbb{R}$  wealth,  $r \in \mathbb{R}$  reference:  
$$U(w|r) = m(w) + \mu(m(w) - m(r))^2$$
- ▶ reference point: belief of outcomes,  $g$  probability measure  
$$U(w|g) = \int u(w|r) dg(r)$$
  
 $\Rightarrow$  mixed feelings, 50 : 500/100; 50:gain to 0, loss to 100.
- ▶  $w$  has measure  $F$   
$$U(F|g) = \iint u(w|r) dg(r) dF(w),$$
 no probability weighting for simplicity.

## Assumptions on $\mu$

- ▶ A0:  $\mu(x)$  continuous , twice differentiable for  $x \neq 0$ ,  $\mu(0) = 0$ .
- ▶ A1:  $\mu(x)$  strictly increasing.
- ▶ A2: if  $y > x \geq 0$ , then  $\mu(y) + \mu(-y) < \mu(x) + \mu(-x)$ .
- ▶ A3:  $\mu''(x) \leq 0$  for  $x > 0$  and  $\mu''(x) \geq 0$  for  $x < 0$ .
- ▶ A4:  $\frac{\mu'_-(0)}{\mu'_+(0)} \equiv \lambda > 1$ ,  
where  $\mu'_+(0) \equiv \lim_{x \rightarrow 0} \mu'(|x|)$  and  $\mu'_-(0) \equiv \lim_{x \rightarrow 0} \mu'(-|x|)$ .
- ▶ A2,A4: loss aversion
- ▶ A3: diminishing sensitivity
- ▶ A3':  $\forall x \neq 0, \mu''(x) = 0 \Rightarrow$  no diminishing sensitivity.
- ▶ general assumption, reference point  $\neq$  expectations; rational expectations, generally people have some idea how they behave and their own environment.

## 1. Risk aversion in surprise situations

- ▶  $m$  is linear:  $m(w) = w$
- ▶ reference point fixed

### Proposition (1)

*Suppose  $m(\cdot)$  is linear and  $\mu(\cdot)$  satisfies A3' (no diminishing sensitivity). For any lotteries  $F, G, H$ , and constant  $w$ , if  $U(w + F|g) \geq U(w|w)$ , the  $U(H + F|G) \geq U(H|G)$ .*

$\Rightarrow$

- ▶ If willing to accept  $F$  relative to riskless  $r$ , positive values of  $F$  are gains, negative ones are losses.
- ▶ If  $F$  is added to lottery  $H$  relative to lottery  $G$ , positive outcomes of  $F$  eliminate losses from  $H$  relative to  $G$ , losses from  $F$  merely eliminate gains from  $H$ .
- ▶  $\Rightarrow$  more willing to accept  $F$ .
- ▶ If  $H = w, G = F \Rightarrow$  less risk averse in eliminating risk that is expected.

# 1. Risk aversion in surprise situations

## Proposition (2)

*Suppose  $m(\cdot)$  is linear. For any lottery  $F$  with positive expected value:*

- (i) There exist  $A, \varepsilon > 0$  such that if  $G$  has  $\Pr_G[r \in (k - A, k + A)] < \varepsilon$  for all constants  $k$ , then  $U(H + F|G) > U(H|G) > U(H - F|G)$  for any lottery  $H$ .*
- (ii) For any continuously distributed lottery  $G$ , there is a  $\bar{t} > 0$  s.t. for any  $t \in (0, \bar{t}]$  and any lottery  $H$ ,  $U(H + t \cdot F|G) > U(H|G) > U(H - t \cdot F|G)$ .*

Identifies attitudes towards  $F$  in which risk neutral.

- (i) If sufficiently widely distributed reference lottery, accept  $F$ , and reject  $-F$ .
- (ii) If fixed continuously distributed reference lottery, accept sufficiently small multiple of  $F$ , reject the same multiple of  $-F$ .

Prop. 1&2 do not imply no risk aversion, just lower risk aversion!

## 2. UPE and PPE Risk Attitudes

- ▶ now correctly anticipates choice set.
- ▶ cannot commit to choice until shortly before outcome  
 $L = \{D_1, 1 - q; D_2, q\}, D_1, D_2 \in \Delta(\mathbb{R})$
- ▶ for now  $q = 0 \Rightarrow$  choice set is certain
- ▶ beliefs are set, reference point exogenous.

### Definition (UPE)

A selection  $F_1 \in D_1, F_2 \in D_2$  is an unacclimating personal equilibrium (UPE) if for each  $l \in 1, 2$  and any  $F'_l \in D_l$ ,  $U(F_l \mid (1 - q)F_1 + qF_2) \geq U(F'_l \mid (1 - q)F_1 + qF_2)$ .  
(Koszegi, 2005 proves existence.)

- ▶ If the person expects to choose  $F_1$  and  $F_2$  from choice sets  $D_1$  and  $D_2$ , then she expects the distribution of outcomes  $(1 - q)F_1 + qF_2$ .
- ▶ Def. 1: If this is the expectation. she should be willing to choose  $F_1$  and  $F_2$ .



## 2. UPE and PPE Risk Attitudes

Example:

wealth  $w$ , 50/50 chance 0,  $-100$  or pay  $-55$ , when is the lottery a UPE?

$$\begin{aligned} & \left[ \frac{1}{2}(w - 100) + \frac{1}{2}w \right] \\ & + \left[ \frac{1}{4}\mu(100) + \frac{1}{4}\mu(-100) \right] \\ & \geq [w - 55] \\ & + \left[ \frac{1}{2}\mu(45) + \frac{1}{2}\mu(-55) \right] \end{aligned}$$

- ▶ UPE generally not unique.
- ▶ expectation: plan what to do at the time.
- ▶ idea: select best plan she will follow through on.

## 2. UPE and PPE Risk Attitudes

### Definition (PPE)

A selection  $F_1 \in D_1, F_2 \in D_2$  is a preferred personal equilibrium (PPE) if it is a UPE, and

$U((1-q)F_1 + qF_2 \mid (1-q)F_1 + qF_2) \geq U((1-q)F'_1 + qF'_2 \mid (1-q)F'_1 + qF'_2)$  for all UPE selections  $F'_1 \in D_1, F'_2 \in D_2$ .

$\Rightarrow$  choice optimal given expectations!

## 2. UPE and PPE Risk Attitudes

### Proposition (3)

*Suppose  $m(\cdot)$  is linear. For any  $w \in \mathbb{R}$  and mean-zero lottery  $F \neq 0$  with bounded support, there exist  $\bar{k}, \bar{t} > 0$  such that for any positive  $t < \bar{t}, k < \bar{k}$ , the unique PPE with the choice set  $\{w, w + t(F + k)\}$  is to choose  $w$ .*

- ▶ select riskless  $w$  over a sufficiently small, better-than-fair but unattractive bet.
- ▶ loss aversion makes gamble unattractive.
- ▶ key point: CPT: costs  $\neq$  loss in status quo.  
here: expected costs, such as insurance premium is a cost, not a loss.
- ▶  $\Rightarrow$  explain insurance for likely events

## 2. UPE and PPE Risk Attitudes

### Proposition (4)

*Suppose  $m(\cdot)$  is linear,  $\mu(\cdot)$  satisfies A3'.*

*If  $w + F$  is a PPE in the choice set  $\{w, w + F\}$ , then for any lottery  $H$ ,  $U(w + F | H) > U(w | H)$ .*

⇒ If choose between risk and insurance, at least a risk aversion as ????

⇒ in experiments , people generally are in surprise settings / don't know what comes

⇒ underestimate risk aversion

Additionally (see papers) expecting risk decreases risk aversion.

### 3. CPE Risk Attitudes

- ▶ long committed choices

#### Definition (CPE)

For any choice set  $D$ ,  $F \in D$  is a choice-acclimating personal equilibrium (CPE) if  $U(F | F) \geq U(F' | F')$  for all  $F' \in D$ .

$\Rightarrow$  selecting  $F$  determines it as reference point.

Example:

lottery 50/50 with (0,-100) is CPE if:

$$\begin{aligned} & \left[ \frac{1}{2}(w - 100) + \frac{1}{2}w \right] \\ & + \left[ \frac{1}{4}\mu(100) + \frac{1}{4}\mu(-100) \right] \\ & \geq [w - 55] + [0]. \end{aligned}$$

- ▶ UPE: premium 55 can be gain or loss;
- ▶ CPE: premium 55 is neither gain nor loss.

### 3. CPE Risk Attitudes

Some implications:

- ▶ unlike as UPE,PPE, for CPE people may want to choose stochastically dominated options
- ▶ idea: give up unlikely gain to avoid losses

## 5.2 Salience Theory

### **Bordalo, Gennaioli, Shleifer (2012,QJE)**

- ▶ risk preferences not stable
- ▶ Allais (1953) paradoxes: irrelevant choice implies risk lottery behavior.
- ▶ idea: salience to prominent outcomes
- ▶ building blocks:
  - ▶ ordering
  - ▶ diminishing sensitivity
  - ▶ salience weighting ( $\neq$  probability weighting)
- ▶ say consumer choice: speed, price, design

## 5.2 Salience Theory

### Allais (1953) paradoxes

$$L_1(z) = \begin{cases} \$2500 & \text{with prob.} & 0.33 \\ \$0 & & 0.01 \\ \$z & & 0.66 \end{cases}$$

$$L_2(z) = \begin{cases} \$2400 & \text{with prob.} & 0.34 \\ \$z & & 0.66 \end{cases}$$

In experiments:  $z = 2400$

$$L_1(2400) = \begin{cases} 2500 \text{ with prob.} & 0.33 \\ 0 & 0.01 \\ 2400 & 0.66 \end{cases} \prec L_2(2400) = 2400$$

$\Rightarrow$  risk averse



## 5.2 Salience Theory

In experiments:  $z = 0$

$$L_1(0) = \begin{cases} 2500 & \text{with prob. } 0.33 \\ 0 & 0.67 \end{cases} \succ L_2(0) = \begin{cases} 2400 & \text{with prob. } 0.34 \\ 0 & 0.66 \end{cases}$$

$\Rightarrow$  risk loving

- ▶ CPT: in last gamble  $w(p = 0.01)$  overweighted
- ▶ Salience theory:  $L_1(2400), L_2(2400) \rightarrow 2500$  only slightly higher than 2400; 0 a lot lower than 2400.
- ▶ Salience theory:  $L_1(0), L_2(0) \rightarrow$  outcome zero is standard; 2500 stands out more.

## Model

- ▶  $s \in S$ : state
- ▶  $\pi_s$ : probability, s.t.  $\sum_{s \in S} \pi_s = 1$
- ▶  $\{L_1, L_2\}$ : choice set
- ▶  $x_s^i$ : payoffs
- ▶ value function as before, reference dependent  $V$  without decision weights, only local thinking:

$$V(L_i) = \sum_{s \in S} \pi_s v(x_s^i).$$

- ▶ With salience distortion:
- ▶ two steps: salience ranking, then decision weight  $\pi_s^i$
- ▶ Formally:  $x_s = (x_s^i)_{i=1,2}$ , payoffs in state  $s$
- ▶  $x_s^{-i}$ : payoff of lottery  $L_j$ ,  $j \neq i$
- ▶  $x_s^{\min}, x_s^{\max}$ : largest / smallest payoffs in  $x_s$

# Model

## Definition (1)

The salience of state  $s$  for lottery  $L_i, i = 1, 2$ , is a continuous and bounded function  $\sigma(x_s^i, x_s^{-i})$  that satisfies three conditions:

- ▶ 1. Ordering. If for states  $s, \tilde{s} \in S$  we have that  $[x_s^{\min}, x_s^{\max}] \in [x_{\tilde{s}}^{\min}, x_{\tilde{s}}^{\max}]$ , then

$$\sigma(x_s^i, x_s^{-i}) < \sigma(x_{\tilde{s}}^i, x_{\tilde{s}}^{-i}).$$

- ▶ 2. Diminishing sensitivity. If  $x_s^j > 0$  for  $j = 1, 2$ , then for any  $\epsilon > 0$ ,

$$\sigma(x_s^i + \epsilon, x_s^{-i} + \epsilon) < \sigma(x_s^i, x_s^{-i}).$$

- ▶ 3. Reflection. For any two states  $s, \tilde{s} \in S$  s.t.  $x_s^j, x_{\tilde{s}}^j > 0, (j = 1, 2)$ , we have  
 $\sigma(x_s^i, x_s^{-i}) < \sigma(x_{\tilde{s}}^i, x_{\tilde{s}}^{-i})$   
if and only if  $\sigma(-x_s^i, -x_s^{-i}) < \sigma(-x_{\tilde{s}}^i, -x_{\tilde{s}}^{-i})$ .

# Model

## Example:

$$\sigma(x_s^i, x_s^{-i}) = \frac{|x_s^i - x_s^{-i}|}{|x_s^i| + |x_s^{-i}| + \theta}, \theta > 0$$

- ▶ ordering: salience rises if distance of  $x_s^i$  and  $x_s^{-i}$  rises
- ▶ diminishing sensitivity: as average payoff gets farther from zero, salience reduces  $|x_s^1| + |x_s^2|$
- ▶ reflection: salience is shaped by the magnitude, not sign
- ▶ (example: symmetric additional dropped for  $N > 2$ )
- ▶ Results mostly driven by ordering and diminishing sensitivity.

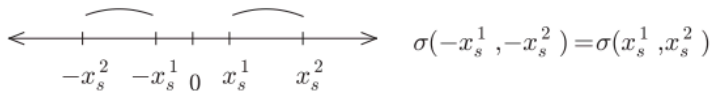
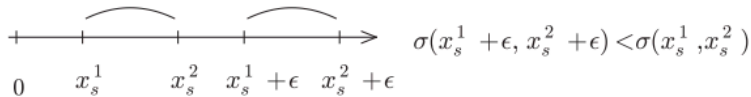
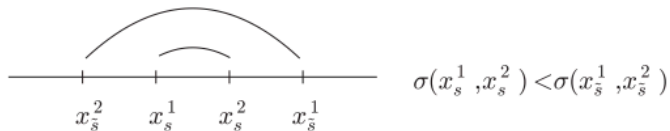


FIGURE I

Properties of a Saliency Function, Equation (5)

# Model

## Definition (2)

Given states  $s, \tilde{s} \in S$ , we say that for lottery  $L_i$   $s$  is more salient than  $\tilde{s}$  if  $\sigma(x_s^i, x_s^{-i}) > \sigma(x_{\tilde{s}}^i, x_{\tilde{s}}^{-i})$ . Let  $k_s^i \in \{1, \dots, |S|\}$  be the salience ranking of state  $s$  for  $L_i$ , with lower  $k_s^i$  indicating higher salience. All states with the same salience obtain the same ranking (no jumps). Then the local thinker transforms the odds  $\frac{\pi_{\tilde{s}}}{\pi_s}$  of  $\tilde{s}$  relative to  $s$  into the odds  $\frac{\pi_{\tilde{s}}^i}{\pi_s^i}$ , given by:

$$\frac{\pi_{\tilde{s}}^i}{\pi_s^i} = \delta^{k_{\tilde{s}}^i - k_s^i} \cdot \frac{\pi_{\tilde{s}}}{\pi_s}, \quad \text{where } \delta \in (0, 1]$$

By normalizing  $\sum_s \pi_s^i = 1$  and defining  $\omega_s^i = \frac{\delta^{k_s^i}}{\left(\sum_r \delta^{k_r^i} \cdot \pi_r\right)}$

the decision weight is:  $\pi_s^i = \pi_s \cdot \omega_s^i$

$\Rightarrow$  local thinker overweights most salient states.

# Model

- ▶  $\delta = 1 \Rightarrow$  standard model,  $\omega_s^i = 1$
- ▶  $\delta < 1 \Rightarrow$  local thinker
- ▶ state  $s$  is overweighted, if  $(\omega_s^i > 1, \text{ or } \delta^{k_s^i} > \sum_r \delta_r^{k_r^i} \cdot \pi_r)$
- ▶  $\delta \rightarrow 0$ : decision based on most salient state
- ▶  $\delta$  is independent of objective state probabilities!

## Some remarks:

- ▶ weighting depends on salience, not low-probability
- ▶ low-probability can be most overweighted, but also underweighted
- ▶ choice of state space / alternative lottery unclear
- ▶ some cases: no alternative  $\Rightarrow$  take zero? Open question



## Risk attitudes:

- ▶ suppose linear value function
- ▶  $L_0 = (x, 1)$ : sure prospect
- ▶  $L_1 = (x + g, \pi_g; x - l, 1 - \pi_g)$ , with  $g\pi_g = (1 - \pi_g)l$ : mean preserving spread,  $x, g, x - l > 0$
- ▶  $s_g = (x + g, x), s_l = (x - l, x)$ , :two states
- ▶  $V^{LT}(L) = \sum_{s \in S} \pi_s^i v(x_s^i) = \sum_{s \in S} \pi_s \omega_s^i v(x_s^i)$

## Risk attitudes:

- ▶  $\delta < 1 \Rightarrow$  prefer  $L_1$  if  $s_g$  more salient,  $\sigma(x + g, x) > \sigma(x - l, x)$
- ▶ Using  $g\pi_g = (1 - \pi_g)l$ ,  $\sigma\left(x + \frac{1 - \pi_g}{\pi_g} \cdot l, x\right) > \sigma(x - l, x)$
- ▶ holds, if  $\pi_g \simeq 0$  (gain unlikely) because  $g$  is high  $\Rightarrow$  risk taking
- ▶ diminishing sensitivity: if  $g = l, x - l < g + x$  implies that the loss is salient,  $\pi_g = \frac{1}{2} \Rightarrow$  risk averse
- ▶  $\Rightarrow \pi_g^* < \frac{1}{2}$ , below risk seeking, above averting

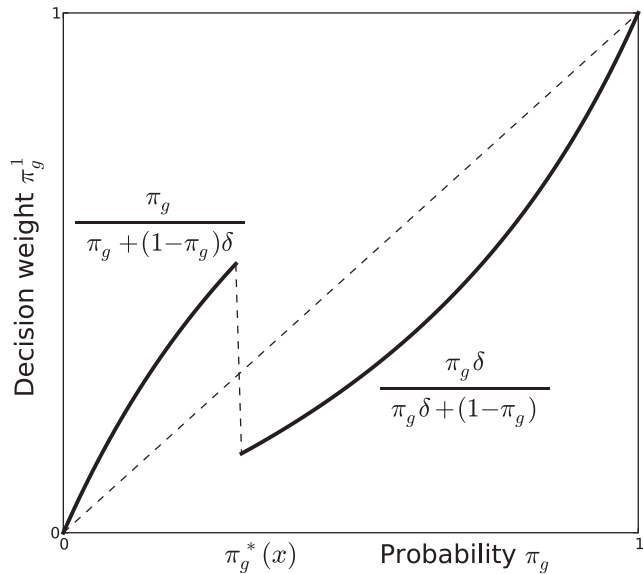


FIGURE II

Context-Dependent Probability Weighting Function

## Risk attitudes:

### Definition (3)

A salience function is convex if, for any state with positive payoffs  $(y, z)$  and any  $x, \epsilon > 0$ , the difference  $\sigma(y + x, z + x) - \sigma(y + x + \epsilon, z + x + \epsilon)$  is a decreasing function of the payoff level  $x$ .  
(concave if increasing in  $x$ ).

### Lemma (1)

*If the salience function is convex, then  $r = v^{LT}(L_0) - v^{LT}(L_1)$  weakly decreases with  $x$ .*

*(concave if increases with  $x$ ).*

$\Rightarrow$  if diminishing sensitivity weakens with  $x$ , a higher payoff level raises the relative attractiveness of  $L_1$ .

( $\pi_g^*$  increases, raises risk seeking)

## Some critical remarks:

- ▶ Kontek (2016, EL): certainty equivalent not necessarily defined
- ▶ monotonicity for  $N > 2$  violated
- ▶ mixed experimental evidence if estimated from indifference curves
- ▶ also strong empirical support
- ▶  $\Rightarrow$  room for research