

# DECISIONS UNDER UNCERTAINTY, CERTAINTY EQUIVALENTS, AND GENERALIZED ENTROPY

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Attitude towards wealth	Utility
Attitude towards risk	Expected utility (EU)
Axioms for EU	Risk aversion (RA)
Generalizations of EU	Dual theory
Bad predictions of EU	Arrow-Pratt RA indices
Certainty equivalents	The Recourse CE (RCE)

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$$S_v(\mathbf{Z}) := \sup_z \{z + E v(\mathbf{Z} - z)\}$$

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Meaning of $v(\cdot)$	Recoverability
Economic models	Production, investment, insurance
Extremal principles	RCE, EU and $\phi$ -divergence

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$$I_\phi(\mathbf{p}, \mathbf{q}) := \sum q_i \phi\left(\frac{p_i}{q_i}\right)$$


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The **St. Petersburg paradox**  
Daniel Bernoulli (1738)

RV  $Z$  : Prob  $\{Z = 2^{n-1}\} = \frac{1}{2^n}, (n = 1, 2, \dots)$

The **expected value** of  $Z$ :

$$EZ = \sum_{n=1}^{\infty} 2^{n-1} \frac{1}{2^n} = \frac{1}{2} + \frac{1}{2} + \frac{1}{2} + \dots = \infty$$

Why “paradox”?

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**Game** with two players,  $A$  and  $B$  (= Bank).

A fair coin  $\{H, T\}$  is tossed until  $H$  appears.

If on trial  $n$ ,  $B$  pays  $A$  :  $2^{n-1}\$, (n = 1, 2, \dots)$

The **value** of the game for  $A$  is the RV  $Z$ .

What is a fair **ticket price** ?  $EZ$  ?

Hence the “paradox”.

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Bernoulli introduced **moral expectation**:

The **expected value** to  $A$  is:

$$\sum_{n=1}^{\infty} u(2^{n-1}) \frac{1}{2^n}$$

where  $u(W)$  is  $A$ 's **utility** of **wealth**  $W$ .

## Bernoulli's logarithmic utility

If **wealth** increases from  $W$  to  $W + \Delta W$ ,  
the **utility** increases by  $\Delta u$

$$\Delta u = K \frac{\Delta W}{W}$$

$$u(W) = \int_c^W K \frac{dW}{W} = K \log \frac{W}{c}$$

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Back to St Petersburg:  $A$ 's EU is:

$$\begin{aligned} E u(\mathbf{Z}) &= K \sum_{n=1}^{\infty} \log(2^{n-1}) \frac{1}{2^n} \\ &= K \sum_{n=1}^{\infty} \frac{n-1}{2^n} = K \end{aligned}$$

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## Attitude towards wealth

Marginal utility  $\searrow$   $\iff$   $u$  concave

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## The **Weber–Fechner law** (1860)

The **response** to a **stimulus** diminishes with each repetition of that stimulus within some specified time period.

Sensation is a logarithmic function of stimulus

**Axioms for EU theory**  
von Neumann-Morgenstern (1947)

**Preferences** between RV's  $X$ ,  $Y$ :

$X \sim Y$	<b>indifference</b>
$X \succeq Y$	<b>X better</b> than $Y$
$X \preceq Y$	<b>X worse</b> than $Y$

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**Completeness:** For any  $X$ ,  $Y$ ,

either  $X \succeq Y$  or  $X \preceq Y$ .

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**Transitivity:**  $X \succeq Y$  &  $Y \succeq Z \implies X \succeq Z$ .

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**Continuity:** Given  $X \succeq Y \succeq Z$ ,  
there exists a probability  $p$  in  $[0, 1]$  such that

$$Y \sim pX + (1 - p)Z$$

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**Independence:** If  $X \succeq Y$ , then  
for any  $p \in [0, 1]$  and any  $Z$ ,

$$pX + (1 - p)Z \succeq pY + (1 - p)Z$$

## Existence of utility

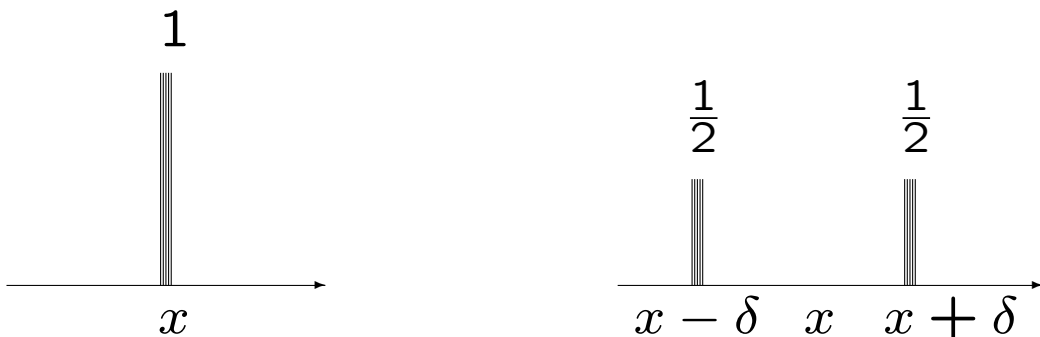
The axioms  $\implies$  existence of a **utility**  $u$ ,  
(continuous, nondecreasing) such that

$$\mathbf{X} \succeq \mathbf{Y} \iff \mathbb{E} u(\mathbf{X}) \geq \mathbb{E} u(\mathbf{Y})$$

The utility  $u$  is unique up to a positive linear transformation: For any  $\alpha > 0$ ,  $\beta$ , the utilities

$$u \quad \text{and} \quad \alpha u + \beta$$

represent the same  $\succeq$



$$u(x) \geq \frac{1}{2} u(x - \delta) + \frac{1}{2} u(x + \delta)$$

**Concavity** of  $u \iff$  **Risk Aversion**

The **Allais paradox** (1953)  
 Kahneman and Tversky (1979)

Choose between:

**A:** 4,000 (prob. .80)  
           0 (prob. .20)

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[20%]

**B:** 3,000 (certainty)

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[80%]

**C:** 4,000 (prob. .20)  
           0 (prob. .80)

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[65%]

**D:** 3,000 (prob. .25)  
           0 (prob. .75)

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[35%]

$$\mathbf{B} \succ \mathbf{A} \implies u(3,000) > .80 u(4,000)$$

$$\mathbf{C} \succ \mathbf{D} \implies .25 u(3,000) < .20 u(4,000)$$

**Stochastic programming with recourse**  
**2-stage stoch. prog., Dantzig (1955)**

$$\max \{f(z) : g(z) \leq \mathbf{Z}\}$$

$z =$  **decision variable**

$f(\cdot) =$  **profit**

$\mathbf{Z} =$  **budget**

$g(\cdot) =$  **consumption**

If  $\mathbf{Z}$  is RV, the a priori decision  $z$  may violate

$$g(z) \leq \mathbf{Z}$$

Let  $y =$  **second stage decision**, with

$h(y) =$  **consumption**,  $v(y) =$  **profit**

$$\max_z \{f(z) + E \left( \max_y \{v(y) : g(z) + h(y) \leq \mathbf{Z}\} \right) \}$$

If  $z, y$  are scalars,  $h(\cdot) \nearrow, v(\cdot) \nearrow,$

$$\max_z \{f(z) + E \left( \max_y \{v(y) : g(z) + y \leq \mathbf{Z}\} \right) \}$$

$$\max_z \{f(z) + E v(\mathbf{Z} - g(z)) \}$$



## Recourse certainty equivalent (RCE)

The **value** of a RV  $\mathbf{Z}$

$$\text{value of } \mathbf{Z} = \max \{z : z \leq \mathbf{Z}\}$$

Stoch. Prog. with Recourse interpretation:

$$\sup_z \{z + \mathbb{E} v(\mathbf{Z} - z)\}$$

$v(x)$  = current (before realization) value of  $x$

$v(\cdot)$  = the **value-risk function**

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Another interpretation:

$\mathbf{Z}$  = future income (RV)

$z$  = **loan** against  $\mathbf{Z}$  (unrestricted)

$v(\cdot)$  = **utility**

## Assumptions on $v(\cdot)$

- (v1)  $v(0) = 0$
  - (v2)  $v(\cdot)$  is strictly increasing
  - (v3)  $v(x) \leq x$  for all  $x$
  - (v4)  $v(\cdot)$  is strictly concave
  - (v5)  $v$  is continuously differentiable
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(v1) and (v2)  $\implies v(x) < 0$  for  $x < 0$ ,

$\therefore v(\cdot) =$  **penalty function** for

$$z \leq \mathbf{Z}$$

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Special class of value-risk functions

$$\mathcal{U} := \left\{ v : \begin{array}{ll} v \text{ strict. } \nearrow, & \text{strict. concave} \\ \text{cont. diff.}, & v(0) = 0, \quad v'(0) = 1 \end{array} \right\}$$

the **normalized utility functions**.

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For concave  $v$  the gradient inequality

$$v(x) \leq v(0) + v'(0)x$$

shows that all  $v \in \mathcal{U}$  satisfy (v3).

**Attainment of  $\sup_z \{z + E v(\mathbf{Z} - z)\}$**

$$\mathcal{U} = \left\{ v : \begin{array}{l} v \text{ strict. } \nearrow, \text{ strict. concave} \\ \text{cont. diff., } v(0) = 0, \quad v'(0) = 1 \end{array} \right\}$$

**Lemma.** Let the RV  $\mathbf{Z}$  have finite support

$$[z_{\min}, z_{\max}] .$$

Then  $\forall v \in \mathcal{U}$  the supremum in RCE is attained uniquely for some  $z^*$ ,

$$z_{\min} \leq z^* \leq z_{\max}$$

which is the solution of

$$E v'(\mathbf{Z} - z^*) = 1$$

so that

$$S_v(\mathbf{Z}) = z^* + E v(\mathbf{Z} - z^*)$$

**Proof.**  $\mathbf{Z} - z_{\min} \geq 0$  with probability 1.

Also  $v'(\cdot) \searrow$ ,

$$\therefore E v'(\mathbf{Z} - z_{\min}) \leq E v'(0) = 1$$

Similarly  $E v'(\mathbf{Z} - z_{\max}) \geq E v'(0) = 1$

**Properties of  $S_v(\mathbf{Z}) := \sup_z \{z + \mathbb{E} v(\mathbf{Z} - z)\}$**

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**Shift additivity.** For any  $v : \mathbf{R} \rightarrow \mathbf{R}$ , any RV  $\mathbf{Z}$  and any constant  $c$

$$S_v(\mathbf{Z} + c) = S_v(\mathbf{Z}) + c$$

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For any function  $v : \mathbf{R} \rightarrow \mathbf{R}$ ,

$$\begin{aligned} S_v(\mathbf{Z} + c) &= \sup_z \{z + \mathbb{E} v(\mathbf{Z} + c - z)\} \\ &= c + \sup_z \{(z - c) + \mathbb{E} v(\mathbf{Z} - (z - c))\} \\ &= c + S_v(\mathbf{Z}) \end{aligned}$$

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For any RV  $\mathbf{Z}$ , constant  $S$ , if

$$\mathbf{Z} \sim S$$

then

$$\mathbf{Z} + c \sim S + c$$

for all constant  $c$ .

- (v1)  $v(0) = 0$
- (v2)  $v(\cdot)$  is strictly increasing
- (v3)  $v(x) \leq x$  for all  $x$
- (v4)  $v(\cdot)$  is strictly concave
- (v5)  $v$  is continuously differentiable

**Consistency.** If  $v$  satisfies (v1), (v3) then,

$$S_v(c) = c, \quad \forall \text{ constant } c$$

**Subhomogeneity.** If  $v$  satisfies (v1) and (v4) then, for any RV  $\mathbf{Z}$

$$\frac{1}{\lambda} S_v(\lambda \mathbf{Z}) \text{ is decreasing in } \lambda, \quad \lambda > 0$$

$$S_v(\lambda \mathbf{Z}) \leq \lambda S_v(\mathbf{Z}), \quad \forall \lambda > 1$$

$$\lambda \mathbf{Z} \preceq \lambda S_v(\mathbf{Z})$$

$$\text{since } E(\lambda \mathbf{Z}) = \lambda \mathbf{Z}$$

$$\text{Var}(\lambda \mathbf{Z}) = \lambda^2 \text{Var } \mathbf{Z} > \lambda \text{Var } \mathbf{Z} \text{ if } \lambda > 1$$

An interesting result: For  $v \in \mathcal{U}$ ,

$$\lim_{\lambda \rightarrow 0^+} \frac{1}{\lambda} S_v(\lambda \mathbf{Z}) = E \mathbf{Z}$$

- (v1)  $v(0) = 0$
  - (v2)  $v(\cdot)$  is strictly increasing
  - (v3)  $v(x) \leq x$  for all  $x$
  - (v4)  $v(\cdot)$  is strictly concave
  - (v5)  $v$  is continuously differentiable
- 

**Monotonicity.** If  $v$  satisfies (v2) then, for any RV  $\mathbf{X}$  and any nonnegative RV  $\mathbf{Y}$ ,

$$S_v(\mathbf{X} + \mathbf{Y}) \geq S_v(\mathbf{X})$$

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If  $v$  satisfies (v1) and (v2), and if

$$\mathbf{Z} \geq z_{\min} \text{ with probability } 1,$$

then

$$S_v(\mathbf{Z}) \geq z_{\min}$$

Take:  $\mathbf{X} = z_{\min}$  (degenerate RV)

$$\mathbf{Y} = \mathbf{Z} - z_{\min}$$

- (v1)  $v(0) = 0$
- (v2)  $v(\cdot)$  is strictly increasing
- (v3)  $v(x) \leq x$  for all  $x$
- (v4)  $v(\cdot)$  is strictly concave
- (v5)  $v$  is continuously differentiable

$$\mathcal{U} := \left\{ v : \begin{array}{l} v \text{ strict. } \nearrow, \text{ strict. concave} \\ \text{cont. diff.}, v(0) = 0, v'(0) = 1 \end{array} \right\}$$


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**Risk aversion.**  $v$  satisfies (v3) iff

$$S_v(\mathbf{Z}) \leq \mathbf{E} \mathbf{Z} \text{ for all RV's } \mathbf{Z}$$

**Concavity.** For any  $v \in \mathcal{U}$ , RV's  $\mathbf{X}_0, \mathbf{X}_1$  and  $0 < \alpha < 1$ ,

$$S_v(\alpha \mathbf{X}_1 + (1 - \alpha) \mathbf{X}_0) \geq \alpha S_v(\mathbf{X}_1) + (1 - \alpha) S_v(\mathbf{X}_0)$$

**2<sup>nd</sup> order stochastic dominance.** Let  $\mathbf{X}, \mathbf{Y}$  be RV's with compact support. Then

$$S_v(\mathbf{X}) \geq S_v(\mathbf{Y}) \text{ for all } v \in \mathcal{U}$$

if and only if

$$\mathbf{E} v(\mathbf{X}) \geq \mathbf{E} v(\mathbf{Y}) \text{ for all } v \in \mathcal{U}$$

## Exponential value-risk function

$$u(z) := 1 - e^{-z}$$

The optimality condition  $\mathbb{E} u'(\mathbf{Z} - z^*) = 1$  gives  $\mathbb{E} e^{-\mathbf{Z} + z^*} = 1$  or  $z^* = -\log \mathbb{E} e^{-\mathbf{Z}}$

$$\therefore S_u(\mathbf{Z}) = -\log \mathbb{E} e^{-\mathbf{Z}}$$

For the **exponential utility**  $u(z) = 1 - e^{-z}$ ,

$$u^{-1} \mathbb{E} u(\mathbf{Z}) = -\log \mathbb{E} e^{-\mathbf{Z}}$$

## Quadratic value-risk function

$$u(z) := z - \frac{1}{2} z^2, \quad z \leq 1$$

For RV  $\mathbf{Z} : z_{\max} \leq 1$ ,  $\mathbb{E} \mathbf{Z} = \mu$ ,  $\text{Var} \mathbf{Z} = \sigma^2$ ,

$$z^* = \mu, \quad S_u(\mathbf{Z}) = \mu - \frac{1}{2} \sigma^2$$

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In both exponential & quadratic  $u(\cdot)$

$$S_u \left( \sum_{i=1}^n \mathbf{Z}_i \right) = \sum_{i=1}^n S_u(\mathbf{Z}_i)$$

for independent RV's  $\{\mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_n\}$



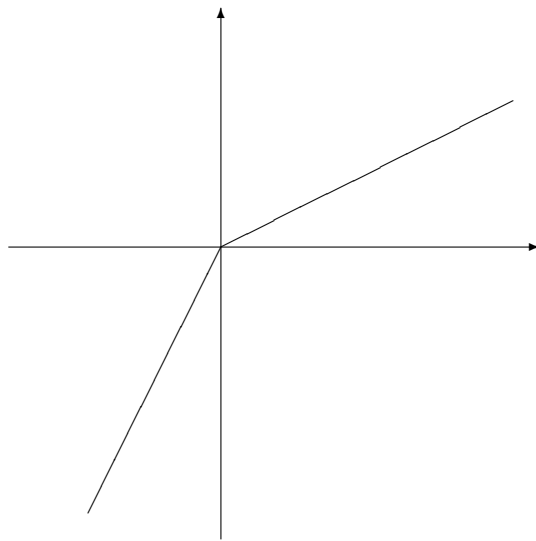
## The hybrid model

$u =$  exponential utility,  $\mathbf{Z} \sim N(\mu, \sigma^2)$ ,

$$S_u(\mathbf{Z}) = \mu - \frac{1}{2}\sigma^2$$

## Piecewise linear value-risk function

$$v(t) = \begin{cases} \beta t, & t \leq 0 \\ \alpha t, & t > 0 \end{cases}, \quad 0 < \alpha < 1 < \beta$$



$$z^* = F^{-1}\left(\frac{1-\alpha}{\beta-\alpha}\right)$$

where  $F$  is the c.d.f. of  $\mathbf{Z}$ .

$$S_v(\mathbf{Z}) = \beta \int^{z^*} t dF(t) + \alpha \int_{z^*} t dF(t).$$

# Convexity

$$\mathbf{P}^n := \left\{ \mathbf{p} \in \mathbf{R}_+^n : \sum_{i=1}^n p_i = 1 \right\}$$

For any  $\mathbf{x} = (x_i) \in \mathbf{R}^n$ ,  $\mathbf{p} = (p_i) \in \mathbf{P}^n$ , let  $[\mathbf{x}, \mathbf{p}]$  denote the RV  $\mathbf{X}$ ,  $\text{Prob} \{ \mathbf{X} = x_i \} = p_i$   
 The RCE of  $[\mathbf{x}, \mathbf{p}]$  is

$$S_v([\mathbf{x}, \mathbf{p}]) = \max_z \left\{ z + \sum_{i=1}^n p_i v(x_i - z) \right\}$$

For any  $v : \mathbf{R} \rightarrow \mathbf{R}$ , and  $\mathbf{x} \in \mathbf{R}^n$ ,

$S_v([\mathbf{x}, \mathbf{p}])$  is convex in  $\mathbf{p}$

For  $v$  concave, and any  $\mathbf{p} \in \mathbf{P}^n$ ,

$S_v([\mathbf{x}, \mathbf{p}])$  is concave in  $\mathbf{x}$

	Function of $\mathbf{p}$	Function of $\mathbf{x}$
$Eu, u$ concave	linear	concave
$u^{-1}Eu, u$ concave	convex	?
$Y_f$	convex	linear
$S_v$	convex	concave (if $v$ )

**Recoverability & meaning of  $v(\cdot)$** 

Let  $\mathbf{X} = (x, p)$  denote the RV

$$\mathbf{X} = \begin{cases} x, & \text{with probability } p \\ 0, & \text{with probability } \bar{p} = 1 - p \end{cases}$$

$$S_v(x, p) = \sup_z \{z + pv(x - z) + \bar{p}v(-z)\}$$

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**Theorem.** If  $v \in \mathcal{U}$  then

$$v(x) = \left. \frac{\partial}{\partial p} S_v(x, p) \right|_{p=0}$$
$$p = \left. \frac{\partial}{\partial x} S_v(x, p) \right|_{x=0}$$

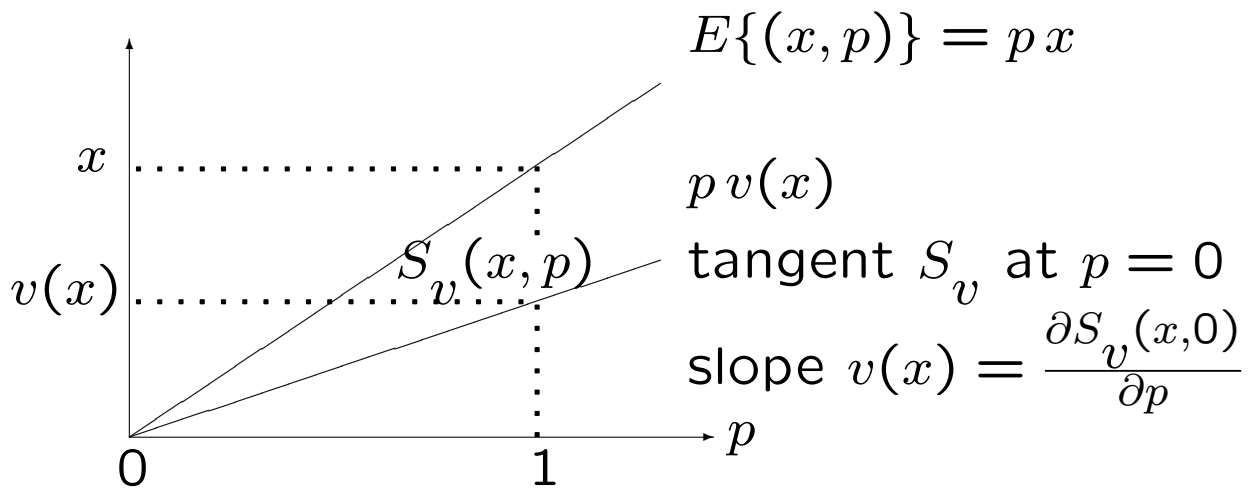
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Going from  $(x, 0)$  to  $(x, p)$  changes the RCE by

$$\Delta(x, p) = S_v(x, p) - S_v(x, 0)$$

The **rate of change** is

$$\frac{S_v(x, p) - S_v(x, 0)}{p} \approx v(x) \quad \text{for } p \ll 1$$



**Risk functions**

For any certainty equivalent  $CE(x, p)$ ,

$\frac{\partial}{\partial p} CE(x, 0)$  **value risk function** of CE

$\frac{\partial}{\partial x} CE(0, p)$  **probability risk function** of CE

$CE(x, p)$	$\frac{\partial}{\partial p} CE(x, 0)$	$\frac{\partial}{\partial x} CE(0, p)$
$C_u = u^{-1} E u$	$\frac{u(x) - u(0)}{u'(0)}$	$p$
$M_u$	$\frac{u(x) - u(0)}{u'(0)}$	$p$
$S_v$	$v(x)$	$p$

where  $M_u(\mathbf{Z})$  is defined by

$$E u(\mathbf{Z} - M_u(\mathbf{Z})) = 0$$

**Strong risk aversion**  
Rothschild-Stiglitz (1970,1971)  
Diamond-Stiglitz (1974)

In EU Theory, **risk aversion** of EU, i.e.

$$E u(\mathbf{Z}) \leq E \mathbf{Z}, \quad \forall RV \mathbf{Z}$$

is equivalent to the concavity of  $u(\cdot)$ .

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$$S_v(\mathbf{Z}) := \sup_z \{z + E v(\mathbf{Z} - z)\} \quad (\text{RCE})$$

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In RCE Theory, **risk aversion** of  $S_v$ , i.e.

$$S_v(\mathbf{Z}) \leq E \mathbf{Z}, \quad \forall RV \mathbf{Z}$$

is equivalent to

$$v(x) \leq x, \quad \forall x$$

What corresponds to  $v(\cdot)$  concave ?

## Risk increases

Let  $F_{\mathbf{X}}$ ,  $F_{\mathbf{Y}}$  be the c.d.f.'s of RV  $\mathbf{X}$ ,  $\mathbf{Y}$  with support  $[a, b]$ .

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If  $E\mathbf{X} = E\mathbf{Y}$  and there is a  $c \in [a, b]$  such that

$$\begin{aligned} F_{\mathbf{Y}}(t) &\leq F_{\mathbf{X}}(t), & a \leq t \leq c \\ F_{\mathbf{X}}(t) &\geq F_{\mathbf{Y}}(t), & c \leq t \leq b \end{aligned}$$

then  $F_{\mathbf{Y}}$  differs from  $F_{\mathbf{X}}$  by a **mean preserving simple increase in risk** (MPSIR).

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$F_{\mathbf{Y}}$  differs from  $F_{\mathbf{X}}$  by a **mean preserving increase in risk** (MPIR) if it differs from  $F_{\mathbf{X}}$  by a sequence of MPSIR's.

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A CE maximizing DM exhibits **strong risk aversion** if

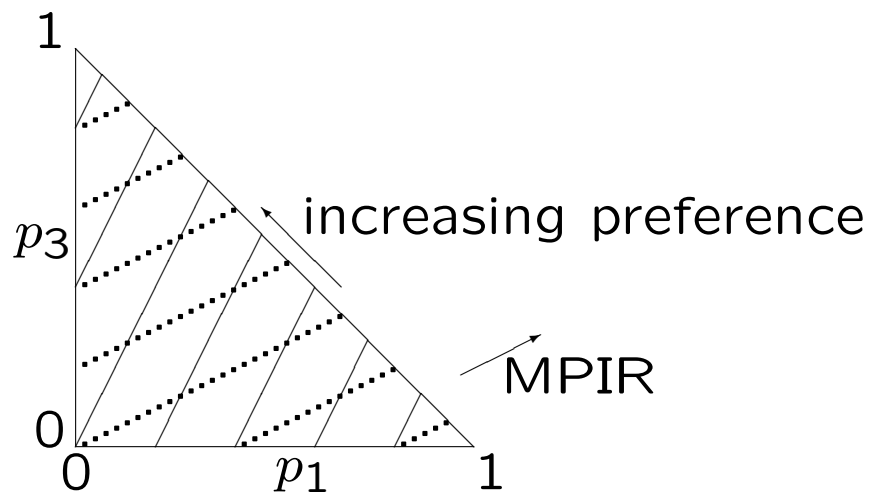
$$\left\{ \begin{array}{l} F_{\mathbf{Y}} \text{ differs from } F_{\mathbf{X}} \\ \text{by a MPIR} \end{array} \right\} \implies CE(\mathbf{Y}) \leq CE(\mathbf{X})$$

## Strong risk aversion in EU Theory

Fix  $x_1 < x_2 < x_3$ , and let

$$D\{x_1, x_2, x_3\} := \left\{ \begin{array}{l} \text{probability distributions} \\ \text{over } x_1, x_2, x_3 \end{array} \right.$$

Each  $\mathbf{p} = (p_1, p_2, p_3) \in D\{x_1, x_2, x_3\}$  is represented as a point in a unit triangle in the  $(p_1, p_3)$ -plane, where  $p_2 = 1 - p_1 - p_3$



Iso-mean and iso-EU lines in  $D\{x_1, x_2, x_3\}$

$$\text{Strong RA} \iff \underbrace{\frac{u(x_2) - u(x_1)}{u(x_3) - u(x_2)}}_{\text{slope iso-EU}} > \underbrace{\frac{x_2 - x_1}{x_3 - x_2}}_{\text{slope iso-mean}}$$

## Functionals & approximations

RV  $\vec{Z} = (Z_i) \in \mathbf{R}^n$ ,  $E \vec{Z} = \vec{\mu}$ ,  $\text{Cov } \vec{Z} = \Sigma$ .  
 For any  $\vec{y} \in \mathbf{R}^n$

$$s_u(\vec{y}) := S_u(\vec{y} \cdot \vec{Z})$$

If  $u \in \mathcal{U} \cap \mathcal{C}^{(2)}$ , then

(a) The functional  $s_u(\cdot)$  is concave, and given by

$$s_u(\vec{y}) = z^*(\vec{y}) + Eu(\vec{y} \cdot \vec{Z} - z^*(\vec{y}))$$

where  $z^*(\vec{y})$  is the unique solution  $z$  of

$$E u'(\vec{y} \cdot \vec{Z} - z) = 1$$

(b) Moreover,

$$\begin{aligned} s_u(\vec{0}) &= 0, \quad \nabla s_u(\vec{0}) = \vec{\mu}, \quad \nabla^2 s_u(\vec{0}) = u''(0)\Sigma \\ z^*(\vec{0}) &= 0, \quad \nabla z^*(\vec{0}) = \vec{\mu} \end{aligned}$$

and if  $u \in \mathcal{C}^{(3)}$ ,

$$\nabla^2 z^*(\vec{0}) = \frac{u'''(0)}{u''(0)}\Sigma$$

$$s_u(\vec{y}) = \vec{\mu} \cdot \vec{y} + \frac{1}{2} u''(0) \vec{y} \cdot \Sigma \vec{y} + o(\|\vec{y}\|^2)$$



$$s_u(\mathbf{y}) = \mu \cdot \mathbf{y} + \frac{1}{2} u''(0) \mathbf{y} \cdot \Sigma \mathbf{y} + o(\|\mathbf{y}\|^2)$$

For  $n = 1$  and  $y = 1$ ,

$$\begin{aligned} S_u(\mathbf{Z}) &\approx \mu + \frac{1}{2} u''(0) \sigma^2 \\ &= \mu - \frac{1}{2} r(0) \sigma^2 \end{aligned}$$

$$\text{where } r(z) = -\frac{u''(z)}{u'(z)}$$

the **Arrow-Pratt absolute risk-aversion index**

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The approximation is exact if

- (i)  $u$  is quadratic, or
  - (ii)  $u$  is exponential,  $\mathbf{Z}$  is normal
- 

Comparing with the Taylor expansion of the classical CE

$$c_u(y) := u^{-1} E u(y \cdot \mathbf{Z})$$

$$\text{we get } c_u(y) - s_u(y) = o(\|y\|^2)$$

# Competitive firm under price uncertainty

Sandmo (1971)

$$\Pi(q) = qP - c(q) - B$$

$P =$  price (RV)

$q =$  production

$B =$  fixed cost

$c(q) =$  variable cost

$\Pi =$  profit

Assume:

$$c(0) = 0, \quad c' > 0, \quad c'' > 0$$

$$u \in \mathcal{U}$$

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$$\max_{q \geq 0} E u(\Pi(q)) \quad (\text{EU Model})$$

$$\max_{q \geq 0} S_u(\Pi(q)) \quad (\text{RCE Model})$$

$$\Pi(q) = qP - c(q) - B$$

EU	RCE
$q^* > 0$ iff $\mu > c'(0)$	same
$q^* < q_{\text{cer}}$	same
$q^* \nearrow$ as $B \nearrow$ if $r \nearrow$  $q^* \searrow$ as $B \nearrow$ if $r \searrow$	$q^*$ is independent of $B$ , $\forall u$
$q^* \nearrow$ as $P \rightarrow P + \epsilon$ if $r \searrow$	$q^* \nearrow$ as $P \rightarrow P + \epsilon$ $\forall u \in \mathcal{U}$
Profit tax $(1 - t)\Pi(q)$	Profit tax $(1 - t)\Pi(q)$
$q^* \nearrow$ with $t$ if $r = \text{const}$ and $R \nearrow$ or $r \searrow$ and $R \nearrow$ $r \searrow$ and $R = \text{const}$	$q^* \nearrow$ with $t$ for all $u \in \mathcal{U}$

$$r(z) := -\frac{u''(z)}{u'(z)}, \quad R(z) := zr(z)$$

## Investment in risky & safe assets Arrow (1971)

$$Y(a) = A - a + (1 + X)a = A + aX$$

$A =$  initial wealth,       $Y =$  final wealth.

$X =$  rate of return of risky investment

$a =$  amount invested in risky assets

EU	RCE
$a^* > 0$ iff $EX > 0$	same
Wealth elasticity of cash balance $m = A - a^*$ $\frac{dm/dA}{m/A} \geq 1$ if $R \nearrow$	$\frac{dm/dA}{m/A} \geq 1 \quad \forall u \in \mathcal{U}$
$X \rightarrow X + h \implies a^*(h) \nearrow$	same
$X \rightarrow (1 + h)X$ $\implies a^*(h) = \frac{a^*}{1 + h}$  Tobin (1958)	same

**Investment in risky & safe assets**  
 Cass-Stiglitz (1970), Fishburn-Porter (1976)

$$Y(k) = kW_0X + (1 - k)W_0\rho$$

$W_0$  = initial wealth

$X$  = rate of return, risky asset

$\rho$  = rate of return, safe asset

$k$  = fraction invested in risky asset

EU	RCE
If $0 < k^* < 1$ $\rho \nearrow \implies (1 - k^*) \nearrow$ if $r \nearrow$ or $R \leq 1$	Conclusion holds for all $u \in \mathcal{U}$

**Insurance**  
 Ehrlich-Becker (1972)  
 Lippman-McCall (1981)

- $n$     **states of nature**
- $\mathbf{p}$     =     $(p_1, \dots, p_n)$  their **probabilities**
- $\bar{q}_i$     =    **premium** for 1\$ coverage in state  $i$
- $\bar{B}$     =    **insurance budget**
- $q_i$     =     $\bar{q}_i / \sum_{j=1}^n \bar{q}_j$  = **normalized premium**
- $B$     =     $\bar{B} / \sum_{j=1}^n \bar{q}_j$  = **normalized budget**
- $x_i$     =    **income** in state  $i$
- $\mathbf{x}$     =     $(x_1, \dots, x_n)$  **decision variable**

$$\sum_{i=1}^n q_i x_i = B \quad \text{budget constraint}$$

The **optimal value** is

$$\begin{aligned} I^* &= \max_{\mathbf{x}} \left\{ S_v([\mathbf{x}, \mathbf{p}]) : \sum_{i=1}^n q_i x_i = B \right\} \\ &= \max_{\mathbf{x}, \sum q_i x_i = B} \max_z \left\{ z + \sum_{i=1}^n p_i v(x_i - z) \right\} \\ &= S_v([\mathbf{x}^*, \mathbf{p}]) \end{aligned}$$

$\mathbf{x}^* = (x_i^*)$  is the **optimal insurance coverage**.

## Insurance: The solution

$$\begin{aligned} I^* &= \max_{\mathbf{x}} \{S_v([\mathbf{x}, \mathbf{p}]) : \sum_{i=1}^n q_i x_i = B\} \\ &= \max_{\mathbf{x}, \sum q_i x_i = B} \max_z \left\{ z + \sum_{i=1}^n p_i v(x_i - z) \right\} \\ &= S_v([\mathbf{x}^*, \mathbf{p}]) \end{aligned}$$

---

The optimal insurance coverage is

$$x_i^* = B + \phi \left( \frac{q_i}{p_i} \right) - \sum_{j=1}^n q_j \phi \left( \frac{q_j}{p_j} \right)$$

where

$$\phi = (v')^{-1}$$

Moreover,

$$I^* = B - \sum q_i \phi \left( \frac{q_i}{p_i} \right) + \sum p_i v \left( \phi \left( \frac{q_i}{p_i} \right) \right)$$

## The $\phi$ -divergence functional Csiszár (1978)

Given a convex function  $\phi : \mathbf{R}_+ \rightarrow \mathbf{R}$ ,  
the  $\phi$ -divergence functional,

$$I_\phi(\mathbf{p}, \mathbf{q}) := \sum_{i=1}^n q_i \phi \left( \frac{p_i}{q_i} \right)$$

is a “distance function” on  $\mathbf{P}^n$ .

---

$\phi : \mathbf{R}_+ \rightarrow \mathbf{R}$  convex

$\implies I_\phi(\mathbf{p}, \mathbf{q})$  jointly convex in  $\mathbf{p}$  and  $\mathbf{q}$ .

---

Let  $\phi : \mathbf{R}_+ \rightarrow \mathbf{R}$  be convex.

Then for any  $\mathbf{p}, \mathbf{q} \in \mathbf{R}_{++}^n$ ,

$$I_\phi(\mathbf{p}, \mathbf{q}) \geq \left( \sum_{i=1}^n q_i \right) \phi \left( \frac{\sum_{i=1}^n p_i}{\sum_{i=1}^n q_i} \right)$$

If  $\phi$  is strictly convex, equality holds iff

$$\frac{p_1}{q_1} = \frac{p_2}{q_2} = \dots = \frac{p_n}{q_n}$$



## Adjoints

Let  $\phi : \mathbf{R}_+ \rightarrow \mathbf{R}$  be convex,  $\phi(1) = 0$ .  
The **adjoint** of  $\phi$  is

$$\phi^\diamond(t) := t \phi\left(\frac{1}{t}\right), \quad t > 0.$$

- 
- (a)  $\phi^{\diamond\diamond} = \phi$ .
  - (b)  $\phi^\diamond(\cdot)$  is convex.
  - (c)  $\phi^\diamond(1) = 0$
  - (d) For any  $\mathbf{p}, \mathbf{q} \in \mathbf{R}_{++}^n$

$$I_\phi(\mathbf{p}, \mathbf{q}) = I_{\phi^\diamond}(\mathbf{q}, \mathbf{p})$$

- (e)  $\phi^\diamond(t)$  is increasing for  $t > 1$ .

---

In general,  $I_\phi(\mathbf{p}, \mathbf{q}) \neq I_\phi(\mathbf{q}, \mathbf{p})$ .

Also  $I_\phi(\cdot, \cdot)$  does not satisfy triangle inequality.

To get symmetry use:

$$I_\phi(\mathbf{p}, \mathbf{q}) + I_{\phi^\diamond}(\mathbf{p}, \mathbf{q})$$

## The Kullback-Leibler distance

$$I_{\phi}(\mathbf{p}, \mathbf{q}) = \sum_{i=1}^n p_i \log \frac{p_i}{q_i}$$

$$\text{from } \phi(t) := t \log t, \quad t > 0,$$

$$\phi^{\diamond} = t \left( \frac{1}{t} \log \frac{1}{t} \right) = -\log t$$

In particular, for  $\mathbf{p} = \left( \frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n} \right)$

$$\begin{aligned} I_{\phi^{\diamond}}(\mathbf{p}, \mathbf{q}) &= - \sum_{i=1}^n q_i \log \frac{1}{nq_i} \\ &= \sum_{i=1}^n q_i \log q_i + \log n \end{aligned}$$

## The Hellinger distance

$$I_{\phi}(\mathbf{p}, \mathbf{q}) = \sum_{i=1}^n (\sqrt{p_i} - \sqrt{q_i})^2$$

$$\text{from } \phi(t) := (1 - \sqrt{t})^2, \quad t > 0$$

$$\phi^{\diamond} = \phi$$

## $\alpha$ -order entropy

For  $\alpha > 1$  let,

$$\phi(t) := t^\alpha, \quad t > 0$$

$$\therefore I_\phi(\mathbf{p}, \mathbf{q}) = \sum_{i=1}^n (p_i)^\alpha (q_i)^{1-\alpha}$$

the  $\alpha$ -order entropy.

$$\phi^\diamond(t) = t^{1-\alpha}$$

## The $\chi^2$ -distance

$$\phi(t) := (t - 1)^2, \quad t > 0,$$

$$I_\phi(\mathbf{p}, \mathbf{q}) = \sum_{i=1}^n \left( \frac{p_i^2 - q_i^2}{q_i} \right)$$

the  $\chi^2$ -distance.

$$\begin{aligned} \phi^\diamond(t) &= \left( \sqrt{t} - \frac{1}{\sqrt{t}} \right)^2 \\ &= t + \frac{1}{t} - 2 \end{aligned}$$

## The variation distance

$$\begin{aligned}\phi(t) &:= |t - 1|, \quad t > 0, \\ I_\phi(\mathbf{p}, \mathbf{q}) &= \sum_{i=1}^n |p_i - q_i|\end{aligned}$$

## Indicator function

Let  $\alpha < 1 < \beta$  and define

$$\phi(t) := \delta(t | [\alpha, \beta]) = \begin{cases} 0 & \text{if } \alpha \leq t \leq \beta, \\ \infty & \text{otherwise,} \end{cases}$$

**indicator function** of the interval  $[\alpha, \beta]$ ,

$$\begin{aligned}\phi^\diamond(t) &= \delta\left(t \mid \left[\frac{1}{\beta}, \frac{1}{\alpha}\right]\right) \\ I_\phi(\mathbf{p}, \mathbf{q}) &= \begin{cases} 0 & \text{if } \alpha \leq \frac{p_i}{q_i} \leq \beta, \\ & \forall i = 1, \dots, n \\ \infty & \text{otherwise.} \end{cases}\end{aligned}$$

## Convex analysis

For  $f : \mathbf{R}^n \rightarrow \mathbf{R}$ ,

$$f^*(y) := \sup_x \{y \cdot x - f(x)\} \quad \text{convex conjugate}$$

$$f_*(y) := \inf_x \{y \cdot x - f(x)\} \quad \text{concave conjugate}$$

- (a)  $\phi$  convex  $\implies (-\phi)_*(x) = -\phi^*(-x), \forall x$ ,  
 (b)  $u$  concave  $\implies (-u)^*(x) = -u_*(-x), \forall x$ .
- 

If  $u : \mathbf{R} \rightarrow \mathbf{R}$  strictly  $\nearrow$  & concave then

- (a)  $\text{dom } u_* \subset \mathbf{R}_+$   
 (b)  $\text{dom } (u^{-1})^* \subset \mathbf{R}_+$   
 (c)  $y \in \text{dom } (u^{-1})^* \iff \frac{1}{y} \in \text{dom } u_*$   
 (d) For all  $y > 0$

$$\begin{aligned} (u^{-1})^*(y) &= -y u_* \left( \frac{1}{y} \right) \\ &= -(u_*)^\diamond(y) \end{aligned}$$


---

Let  $\phi : \mathbf{R} \rightarrow \mathbf{R}$  be convex. Then

- (a)  $\text{dom } \phi = \mathbf{R}_+ \implies \phi^*$  is nondecreasing  
 (b)  $\text{dom } \phi = \mathbf{R}_{++} \implies \phi^*$  is increasing

## A special functional

For  $h : \mathbf{R}^n \rightarrow \mathbf{R}$  define  $h_+ : \mathbf{R}^n \rightarrow \mathbf{R}$  by

$$h_+(\mathbf{y}) := \sup_{\substack{z \in \mathbf{R} \\ \mathbf{x} \in \mathbf{R}^n \\ \mathbf{y} \cdot \mathbf{x} = 0}} \{z + h(\mathbf{x} - z\mathbf{e})\}$$

Then for any  $\mathbf{y} \in \mathbf{R}^n$  with  $\sum y_i \neq 0$ ,

$$h_+(\mathbf{y}) = -h_*\left(\frac{\mathbf{y}}{\sum y_i}\right)$$

If  $h$  is strictly concave and  $\mathcal{C}^{(1)}$ ,

$$\begin{aligned} z^* &= -\mathbf{v}^T \mathbf{u}^* = -\frac{\mathbf{y}^T}{\mathbf{e} \cdot \mathbf{y}} (\nabla h)^{-1} \left( \frac{\mathbf{y}}{\mathbf{e} \cdot \mathbf{y}} \right) \\ \mathbf{x}^* &= \mathbf{u}^* + z^* \mathbf{e} = \left( I - \frac{\mathbf{e}\mathbf{y}^T}{\mathbf{e}^T \mathbf{y}} \right) (\nabla h)^{-1} \left( \frac{\mathbf{y}}{\mathbf{e} \cdot \mathbf{y}} \right) \\ &= P_{\mathbf{e}^\perp} (\nabla h)^{-1} \left( \frac{\mathbf{y}}{\mathbf{e} \cdot \mathbf{y}} \right) \end{aligned}$$

$P_{\mathbf{e}^\perp} :=$  orthogonal projection  $\perp \mathbf{e}$ .

$$-z^* \mathbf{e} = \frac{\mathbf{e}\mathbf{y}^T}{\mathbf{e}^T \mathbf{y}} (\nabla h)^{-1} \left( \frac{\mathbf{y}}{\mathbf{e} \cdot \mathbf{y}} \right) = P_{\mathbf{e}} (\nabla h)^{-1} \left( \frac{\mathbf{y}}{\mathbf{e} \cdot \mathbf{y}} \right)$$

## Extremal principles for RCE, EU

If  $u : \mathbf{R} \rightarrow \mathbf{R}$  is strictly  $\nearrow$  & concave, then

$$\phi := -u_*$$

is convex and  $\phi : \mathbf{R}_+ \rightarrow \mathbf{R}$ . Also

$$\phi^\diamond = (u^{-1})^*$$

Conversely, for convex  $\phi : \mathbf{R}_+ \rightarrow \mathbf{R}$ ,

$$u(t) := -\phi^*(-t)$$

is concave.

For any RV  $\mathbf{X} = [\mathbf{x}, \mathbf{p}]$ ,

$$\begin{aligned} S_u([\mathbf{x}, \mathbf{p}]) &= \inf_{\mathbf{q} \in \mathbf{P}^n} \left\{ I_\phi(\mathbf{q}, \mathbf{p}) + \sum_{i=1}^n q_i x_i \right\} \\ &= \inf_{\mathbf{q} \in \mathbf{P}^n} \left\{ I_{\phi^\diamond}(\mathbf{p}, \mathbf{q}) + \sum_{i=1}^n q_i x_i \right\} \\ E u([\mathbf{x}, \mathbf{p}]) &= \inf_{\mathbf{q} \in \mathbf{R}_+^n} \left\{ I_\phi(\mathbf{q}, \mathbf{p}) + \sum_{i=1}^n q_i x_i \right\} \end{aligned}$$

## Duality

$$S_u([\mathbf{x}, \mathbf{p}]) = \inf_{\mathbf{q} \in \mathbf{P}^n} \left\{ I_\phi(\mathbf{q}, \mathbf{p}) + \sum_{i=1}^n q_i x_i \right\}$$

---

The RCE, in LHS, is the optimal value of

$$(P) \quad \sup \{z : "z \leq \mathbf{X}"\}$$

in the sense of **recourse optimization**.

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The RHS is the “dual” of (P),

$$(D) \quad \inf \{z : "z \geq \mathbf{X}"\}$$

using a **stochastic penalty function**  $P(\cdot)$  to “enforce” the stochastic constraint

$$"z \geq \mathbf{X}"$$

---

$$(D1) \quad \inf \{z + P(z)\}$$



## Stochastic penalty

Given the RV  $\mathbf{X} = [\mathbf{x}, \mathbf{p}]$  and  $z$ , define

$$R\{z\} := \left\{ \mathbf{q} \in \mathbf{P}^n : z \geq \sum_i q_i x_i \right\},$$

representing the RV's  $\{\mathbf{Z} := [\mathbf{x}, \mathbf{q}] : \mathbf{q} \in R\{z\}\}$  supported as  $\mathbf{X}$ , satisfying  $z \geq \mathbf{X}$  "in the mean".

$P(z)$  is the **penalty**

$$P(z) := \text{"dist"}(\mathbf{p}, R\{z\}) = \inf_{\mathbf{q} \in R\{z\}} \text{"dist"}(\mathbf{q}, \mathbf{p})$$

and "dist" is induced by the  $\phi$ -divergence,

$$P(z) = \inf_{\mathbf{q} \in R\{z\}} I_\phi(\mathbf{q}, \mathbf{p})$$

$$\begin{aligned} \inf_{\substack{z \\ \mathbf{q} \in R\{z\}}} \{z + I_\phi(\mathbf{q}, \mathbf{p})\} &= \\ &= \inf_{\mathbf{q} \in \mathbf{P}^n} \inf_{z \geq \sum q_i x_i} \{z + I_\phi(\mathbf{q}, \mathbf{p})\} \\ &= \inf_{\mathbf{q} \in \mathbf{P}^n} \{I_\phi(\mathbf{q}, \mathbf{p}) + \sum q_i x_i\} \end{aligned}$$

## Extremal principles for $\phi$ -divergence

Let  $\phi : \mathbf{R}_+ \rightarrow \mathbf{R}$  convex,  $\text{dom } \phi \subset \mathbf{R}_{++}$ . Define

$$u(t) := -\phi^*(-t)$$

Then for any  $\mathbf{p}, \mathbf{q} \in \mathbf{P}^n$ ,

$$I_\phi(\mathbf{q}, \mathbf{p}) = \sup_{\substack{\mathbf{x} \in \mathbf{R}^n \\ \mathbf{q} \cdot \mathbf{x} = 0}} S_u([\mathbf{x}, \mathbf{p}])$$

Furthermore, if  $\text{dom } \phi = \mathbf{R}_{++}$ , define the function

$$v(x) := (\phi^*)^{-1}(x),$$

Then

$$I_\phi(\mathbf{p}, \mathbf{q}) = \sup_{\substack{\mathbf{x} \in \mathbf{R}^n \\ \mathbf{q} \cdot \mathbf{x} = 0}} S_v([\mathbf{x}, \mathbf{p}])$$

For all  $\mathbf{p} \in \mathbf{P}^n$ ,  $\mathbf{q} \in \mathbf{R}_+^n$ ,

$$I_\phi(\mathbf{q}, \mathbf{p}) = \sup_{\mathbf{x} \in \mathbf{R}^n} \left\{ \sum_{i=1}^n p_i u(x_i) - \sum_{i=1}^n q_i x_i \right\}$$