

Time consistency of multivariate dynamic risk measures

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1. Set-valued risk measures: Setup

- Probability space $(\Omega, (\mathcal{F}_t)_{t \in [0, T]}, \mathbb{P})$
- d assets (may include different currencies)
- Portfolio vectors in physical units (numéraire free), i.e. number of units in d assets
- Claim: $X \in L_d^p(\mathcal{F}_T)$ payoff (in physical units) at time T
- Convex transaction costs at time t : closed convex set $\mathbb{R}_+^d \subseteq K_t[\omega] \subseteq \mathbb{R}^d$ (solvency region), positions transferable into non-negative portfolios
- Eligible portfolios M , linear subspace of \mathbb{R}^d of portfolios that can be used to compensate risk (e.g. Dollars & Euros)

1.1 Set-valued risk measures: Primal representation

- $M_t := L_d^p(\mathcal{F}_t; M)$, $M_{t,+} := M_t \cap L_d^p(\mathcal{F}_t)_+$
- $\mathcal{P}(\mathcal{Z}; C) := \{A \subseteq \mathcal{Z} : A = A + C\}$
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A set-valued function $R_t : L_d^p(\mathcal{F}_T) \rightarrow \mathcal{P}(M_t; M_{t,+})$ is a conditional risk measure if

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- 1 Finite at zero: $\emptyset \neq R_t(0) \neq M_t$;
- 2 M_t translative: $R_t(X + m) = R_t(X) - m$ for any $m \in M_t$;
- 3 $L_d^p(\mathcal{F}_T)_+$ monotone: if $X - Y \in L_d^p(\mathcal{F}_T)_+$ then $R_t(X) \supseteq R_t(Y)$.

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 - 3 $L_d^p(\mathcal{F}_T)_+$ monotone: if $X - Y \in L_d^p(\mathcal{F}_T)_+$ then $R_t(X) \supseteq R_t(Y)$.
- **Normalized:** for every $X \in L_d^p(\mathcal{F}_t) : R_t(X) = R_t(X) + R_t(0)$.
 - Normalized version:
 $\bar{R}_t(X) := R_t(X) - R_t(0) = \{u \in M_t : R_t(0) + u \subseteq R_t(X)\}$.

1.1 Set-valued risk measures: Primal representation

- **(Conditionally) convex:** for all $X, Y \in L_d^p(\mathcal{F}_T)$, for all $0 \leq \lambda \leq 1$ ($\lambda \in L^\infty(\mathcal{F}_t)$ such that $0 \leq \lambda \leq 1$)

$$R_t(\lambda X + (1 - \lambda)Y) \supseteq \lambda R_t(X) + (1 - \lambda)R_t(Y).$$

- **(Conditionally) positive homogeneous:** for all $X \in L_d^p(\mathcal{F}_T)$, for all $\lambda > 0$ ($\lambda \in L^\infty(\mathcal{F}_t)_{++}$)

$$R_t(\lambda X) = \lambda R_t(X).$$

- **(Conditionally) coherent:** if it is (conditionally) convex and (conditionally) positive homogeneous.
- **K -compatible** for some set $K \subseteq L_d^p(\mathcal{F}_T)$ if there exists a risk measure \tilde{R} such that $R_t(X) = \bigcup_{k \in K} \tilde{R}_t(X - k)$.

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- Acceptance set: $A_t = \{X \in L_d^p(\mathcal{F}_T) : 0 \in R_t(X)\}$
- Risk measure: $R_t(X) = \{u \in M_t : X + u \in A_t\}$

1.1 Set-valued risk measures: Primal representation

Properties	
Risk measure	Acceptance set
(Conditionally) convex	(Conditionally) convex
(Conditionally) coherent	(Conditionally) convex cone
Closed graph	Closed
$B \subseteq L_d^p(\mathcal{F}_T)$ B -monotone	$A_t + B = A_t$
$C \subseteq M_t$ $R_t(X) : L_d^p(\mathcal{F}_T) \rightarrow \mathcal{P}(M_t; C)$	$A_t + C \subseteq A_t$
$R_t(X) \neq \emptyset \forall X \in L_d^p(\mathcal{F}_T)$	$L_d^p(\mathcal{F}_T) = A_t + M_t$
$R_t(X) \neq M_t \forall X \in L_d^p(\mathcal{F}_T)$	$L_d^p(\mathcal{F}_T) = (L_d^p(\mathcal{F}_T) \setminus A_t) + M_t$

1.2 Set-valued risk measures: Dual representation

- $f : \mathcal{X} \rightarrow \mathcal{G}(\mathcal{Z}; C) = \{D \subseteq \mathcal{Z} : D = \text{cl co}(D + C)\}$.
- Set-valued infimum: $\inf_{x \in A} f(x) := \text{cl co} \bigcup_{x \in A} f(x)$;
- Set-valued supremum: $\sup_{x \in A} f(x) := \bigcap_{x \in A} f(x)$.

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- Set-valued supremum: $\sup_{x \in A} f(x) := \bigcap_{x \in A} f(x)$.
- $F_{(x^*, z^*)}^{\mathcal{Z}} : \mathcal{X} \rightarrow 2^{\mathcal{Z}}$ for $x^* \in \mathcal{X}^*$ and $z^* \in \mathcal{Z}^*$

$$F_{(x^*, z^*)}^{\mathcal{Z}}(x) := \{z \in \mathcal{Z} : \langle x^*, x \rangle \leq \langle z^*, z \rangle\}.$$

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- (Negative) convex conjugate:

$$\begin{aligned} -f^*(x^*, z^*) &= \inf_{x \in \mathcal{X}} \left[F_{(x^*, z^*)}^{\mathcal{Z}}(-x) + f(x) \right] \\ &= \text{cl co} \bigcup_{x \in \mathcal{X}} \left[F_{(x^*, z^*)}^{\mathcal{Z}}(-x) + f(x) \right]. \end{aligned}$$

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- Biconjugate:

$$\begin{aligned} f^{**}(x) &= \sup_{(x^*, z^*) \in \mathcal{X}^* \times C^+ \setminus \{0\}} \left[-f^*(x^*, z^*) + F_{(x^*, z^*)}^{\mathcal{Z}}(x) \right] \\ &= \bigcap_{(x^*, z^*) \in \mathcal{X}^* \times C^+ \setminus \{0\}} \left[-f^*(x^*, z^*) + F_{(x^*, z^*)}^{\mathcal{Z}}(x) \right]. \end{aligned}$$

1.2 Set-valued risk measures: Dual representation

- f is **proper** if $f(x) \neq \mathcal{Z}$ for every $x \in \mathcal{X}$ and $f(x) \neq \emptyset$ for some $x \in \mathcal{X}$
- f is **closed** if the graph of f
(graph $f = \{(x, z) \in \mathcal{X} \times \mathcal{Z} : z \in f(x)\}$) is closed.
- Set-valued Fenchel-Moreau Theorem:

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- f is **closed** if the graph of f (graph $f = \{(x, z) \in \mathcal{X} \times \mathcal{Z} : z \in f(x)\}$) is closed.
- Set-valued Fenchel-Moreau Theorem:
A proper function $f : \mathcal{X} \rightarrow \mathcal{G}(\mathcal{Z}; C)$ is closed and convex if and only if $f(x) = f^{**}(x)$ for every $x \in \mathcal{X}$.

1.2 Set-valued risk measures: Dual representation

- $\mathcal{X} = L_d^p(\mathcal{F}_T)$ and $\mathcal{X}^* = L_d^q(\mathcal{F}_T)$
- $\mathcal{Z} = M_t$ and $\mathcal{Z}^* = L_d^q(\mathcal{F}_t)$

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- $\mathcal{Z} = M_t$ and $\mathcal{Z}^* = L_d^q(\mathcal{F}_t)$
- Dual variables:

$$\mathcal{W}_t := \left\{ (\mathbb{Q}, w) \in \mathcal{M}_d \times \left(M_{t,+}^+ \setminus M_t^\perp \right) : \right. \\ \left. \mathbb{Q} = \mathbb{P}|_{\mathcal{F}_t}, w_t^T(\mathbb{Q}, w) \in L_d^q(\mathcal{F}_T)_+ \right\};$$

where $w_t^s(\mathbb{Q}, w) = w \cdot \mathbb{E}_s \left[\frac{d\mathbb{Q}}{d\mathbb{P}} \right] = \left(w_1 \mathbb{E}_s \left[\frac{d\mathbb{Q}_1}{d\mathbb{P}} \right], \dots, w_d \mathbb{E}_s \left[\frac{d\mathbb{Q}_d}{d\mathbb{P}} \right] \right)^\top$.

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- $G_t(w) := \{ u \in L_d^p(\mathcal{F}_t) : \mathbb{E} [w^T u] \geq 0 \}$

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- $G_t(w) := \{ u \in L_d^p(\mathcal{F}_t) : \mathbb{E} [w^\top u] \geq 0 \}$
- $F_{(\mathbb{Q}, w)}^M(X) = \left\{ u \in M_t : \mathbb{E} [w^\top u] \geq \mathbb{E} [w^\top \mathbb{E}_t^\mathbb{Q} [X]] \right\} = \left(\mathbb{E}_t^\mathbb{Q} [X] + G_t(w) \right) \cap M_t$.

1.2 Set-valued risk measures: Dual representation

Convex Risk Measures

A function $R_t : L_d^p(\mathcal{F}_T) \rightarrow \mathcal{G}(M_t; M_{t,+})$ is a *closed convex risk measure* if and only if

$$R_t(X) = \bigcap_{(\mathbb{Q}, w) \in \mathcal{W}_t} \left[-\beta_t^{\min}(\mathbb{Q}, w) + \left(\mathbb{E}_t^{\mathbb{Q}}[-X] + G_t(w) \right) \cap M_t \right],$$

where $-\beta_t^{\min}$ is the minimal penalty function given by

$$-\beta_t^{\min}(\mathbb{Q}, w) = \text{cl} \bigcup_{Z \in A_t} \left(\mathbb{E}_t^{\mathbb{Q}}[Z] + G_t(w) \right) \cap M_t.$$

1.2 Set-valued risk measures: Dual representation

Coherent Risk Measures

A function $R_t : L_d^p(\mathcal{F}_T) \rightarrow \mathcal{G}(M_t; M_{t,+})$ is a **closed coherent risk measure** if and only if

$$R_t(X) = \bigcap_{(\mathbb{Q}, w) \in \mathcal{W}_t^{\max}} \left(\mathbb{E}_t^{\mathbb{Q}}[-X] + G_t(w) \right) \cap M_t,$$

where \mathcal{W}_t^{\max} is the maximal set of dual variables given by

$$\mathcal{W}_t^{\max} = \{(\mathbb{Q}, w) \in \mathcal{W}_t : w_t^T(\mathbb{Q}, w) \in A_t^+\}.$$

1.2 Set-valued risk measures: Dual representation

- $\Gamma_t(w) := \{u \in L_d^p(\mathcal{F}_t) : w^\top u \geq 0 \text{ a.s.}\}$

Conditionally Convex and Coherent Risk Measures

A function $R_t : L_d^p(\mathcal{F}_T) \rightarrow \mathcal{G}(M_t; M_{t,+})$ is a **closed conditionally convex risk measure** if and only if

$$R_t(X) = \bigcap_{(\mathbb{Q}, w) \in \mathcal{W}_t} \left[-\alpha_t^{\min}(\mathbb{Q}, w) + \left(\mathbb{E}_t^{\mathbb{Q}}[-X] + \Gamma_t(w) \right) \cap M_t \right],$$

where $-\alpha_t^{\min}$ is the conditional penalty function given by

$$-\alpha_t^{\min}(\mathbb{Q}, w) = \text{cl} \bigcup_{Z \in A_t} \left(\mathbb{E}_t^{\mathbb{Q}}[Z] + \Gamma_t(w) \right) \cap M_t.$$

R_t is additionally **conditionally coherent** if and only if

$$R_t(X) = \bigcap_{(\mathbb{Q}, w) \in \mathcal{W}_t^{\max}} \left(\mathbb{E}_t^{\mathbb{Q}}[-X] + \Gamma_t(w) \right) \cap M_t.$$

Multi-Portfolio Time Consistency

A dynamic risk measure $(R_t)_{t=0}^T$ is *multi-portfolio time consistent* if the relation

$$R_s(X) \subseteq \bigcup_{Y \in \mathbf{Y}} R_s(Y) \Rightarrow R_t(X) \subseteq \bigcup_{Y \in \mathbf{Y}} R_t(Y)$$

for any times $t < s$, any $X \in L_d^p(\mathcal{F}_T)$ and any $\mathbf{Y} \subseteq L_d^p(\mathcal{F}_T)$

2.1 Time consistency: Multi-portfolio time consistency

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- Multi-portfolio time consistency implies “time consistency” defined by

$$R_s(X) \subseteq R_s(Y) \Rightarrow R_t(X) \subseteq R_t(Y)$$

for any times $t < s$ and $X, Y \in L_d^p(\mathcal{F}_T)$.

Multi-Portfolio Time Consistency

If $(R_t)_{t=0}^T$ is normalized ($R_t(X) = R_t(X) + R_t(0)$ for every X and t) then the following are equivalent:

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- $R_s(\mathbf{X}) \subseteq R_s(\mathbf{Y}) \Rightarrow R_t(\mathbf{X}) \subseteq R_t(\mathbf{Y})$ for $\mathbf{X}, \mathbf{Y} \subseteq L_d^p(\mathcal{F}_T)$ and $R_\tau(\mathbf{X}) := \bigcup_{X \in \mathbf{X}} R_\tau(X)$;

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- $R_t(X) = \bigcup_{Z \in R_s(X)} R_t(-Z) =: R_t(-R_s(X))$;

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- $R_t(X) = \bigcup_{Z \in R_s(X)} R_t(-Z) =: R_t(-R_s(X))$;
- $A_t = A_s + A_{t,s}$ where $A_{t,s} := A_t \cap M_s$.

2.1 Time consistency: Multi-portfolio time consistency

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 - $R_t(X) = \bigcup_{Z \in R_s(X)} R_t(-Z) =: R_t(-R_s(X))$;
 - $A_t = A_s + A_{t,s}$ where $A_{t,s} := A_t \cap M_s$.
- If discrete time $t, s \in \{0, 1, \dots, T\}$ then sufficient to have any of these conditions with $s = t + 1$.

Stepped Risk Measures

A *stepped risk measure* $R_{t,s} : M_s \rightarrow \mathcal{P}(M_t; M_{t,+})$ from time t to s is the restriction of a risk measure R_t to M_s .

2.1 Time consistency: Multi-portfolio time consistency

Stepped Risk Measures

A *stepped risk measure* $R_{t,s} : M_s \rightarrow \mathcal{P}(M_t; M_{t,+})$ from time t to s is the restriction of a risk measure R_t to M_s .

- If $R_{t,s}$ is closed and convex (coherent, conditionally convex) then it can be defined by the penalty function (dual set, conditional penalty function)

$$-\beta_{t,s}^{\min}(\mathbb{Q}, w) := \text{cl} \bigcup_{Z \in A_{t,s}} \left(\mathbb{E}_t^{\mathbb{Q}} [Z] + G_t(w) \right) \cap M_t$$

$$\mathcal{W}_{t,s}^{\max} := \{(\mathbb{Q}, w) \in \mathcal{W}_{t,s} : w_t^s(\mathbb{Q}, w) \in L_d^q(\mathcal{F}_s)_+\}$$

$$-\alpha_{t,s}^{\min}(\mathbb{Q}, w) := \text{cl} \bigcup_{Z \in A_{t,s}} \left(\mathbb{E}_t^{\mathbb{Q}} [Z] + \Gamma_t(w) \right) \cap M_t$$

over the set of stepped dual variables

$$\begin{aligned} \mathcal{W}_{t,s} &:= \{(\mathbb{Q}, w) \in \mathcal{M}_d \times (M_{t,+}^+ \setminus M_t^\perp) : \\ &\quad \mathbb{Q} = \mathbb{P}|_{\mathcal{F}_t}, w_t^s(\mathbb{Q}, w) \in M_{s,+}^+\} \supseteq \mathcal{W}_t. \end{aligned}$$

- *Convex upper continuous (c.u.c.)*: for any $D \in \mathcal{G}(M_t; M_{t,-})$

$$R_t^{-1}(D) := \{X \in L_d^p(\mathcal{F}_T) : R_t(X) \cap D \neq \emptyset\}$$

is closed.

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is closed.

- If $(R_t)_{t=0}^T$ is c.u.c. and convex then $\tilde{R}_t(\cdot) := R_t(-R_s(\cdot))$ is closed and convex.

Multi-Portfolio Time Consistency

If $(R_t)_{t=0}^T$ is normalized, c.u.c., and convex then the following are equivalent:

- $R_s(X) \subseteq \bigcup_{Y \in \mathbf{Y}} R_s(Y) \Rightarrow R_t(X) \subseteq \bigcup_{Y \in \mathbf{Y}} R_t(Y)$;
- For every $(\mathbb{Q}, w) \in \mathcal{W}_t$

$$-\beta_t^{\min}(\mathbb{Q}, w) = \text{cl} \left(-\beta_{t,s}^{\min}(\mathbb{Q}, w) + \mathbb{E}_t^{\mathbb{Q}} \left[-\beta_s^{\min}(\mathbb{Q}, w_t^s(\mathbb{Q}, w)) \right] \right).$$

2.1 Time consistency: Multi-portfolio time consistency

Multi-Portfolio Time Consistency

If $(R_t)_{t=0}^T$ is normalized, c.u.c., and conditionally convex where

$$R_\tau(X) := \bigcap_{(\mathbb{Q}, w) \in \mathcal{W}_\tau^e} \left[-\alpha_\tau^{\min}(\mathbb{Q}, w) + \left(\mathbb{E}_\tau^{\mathbb{Q}}[-X] + \Gamma_\tau(w) \right) \cap M_\tau \right]$$

then the following are equivalent:

- $R_s(X) \subseteq \bigcup_{Y \in \mathbf{Y}} R_s(Y) \Rightarrow R_t(X) \subseteq \bigcup_{Y \in \mathbf{Y}} R_t(Y)$;
- For every $(\mathbb{Q}, w) \in \mathcal{W}_t^e$

$$-\alpha_t^{\min}(\mathbb{Q}, w) = \text{cl} \left(-\alpha_{t,s}^{\min}(\mathbb{Q}, w) + \mathbb{E}_t^{\mathbb{Q}} \left[-\alpha_s^{\min}(\mathbb{Q}, w_t^s(\mathbb{Q}, w)) \right] \right).$$

2.1 Time consistency: Multi-portfolio time consistency

- Let $\mathbb{Q}, \mathbb{R} \in \mathcal{M}_d$ then $\mathbb{S} = \mathbb{Q} \oplus^s \mathbb{R}$ if $\frac{d\mathbb{S}}{d\mathbb{P}} := \xi_{0,s}(\mathbb{Q}) \cdot \xi_{s,T}(\mathbb{R})$ where

$$\xi_{t,s}^i(\mathbb{Q}) := \begin{cases} \mathbb{E}_s \left[\frac{dQ_i}{d\mathbb{P}} \right] / \mathbb{E}_t \left[\frac{dQ_i}{d\mathbb{P}} \right] & \text{on } \left\{ \mathbb{E}_t \left[\frac{dQ_i}{d\mathbb{P}} \right] > 0 \right\} \\ 1 & \text{else} \end{cases}$$

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Stability

A set $W_t \subseteq \mathcal{W}_t$ is **stable** at time t with respect to $W_{t,s}$ and W_s if

- $(\mathbb{Q}, w) \in W_t$ implies $(\mathbb{Q}, w_t^s(\mathbb{Q}, w)) \in W_s$ and
- $(\mathbb{Q}, w) \in W_{t,s}$ and $\mathbb{R} \in \mathcal{M}_d$ such that $(\mathbb{R}, w_t^s(\mathbb{Q}, w)) \in W_s$ implies $(\mathbb{Q} \oplus^s \mathbb{R}, w) \in W_t$

Multi-Portfolio Time Consistency

If $(R_t)_{t=0}^T$ is normalized, c.u.c., and coherent then the following are equivalent:

- $R_s(X) \subseteq \bigcup_{Y \in \mathbf{Y}} R_s(Y) \Rightarrow R_t(X) \subseteq \bigcup_{Y \in \mathbf{Y}} R_t(Y)$;
- \mathcal{W}_t^{\max} is stable with respect to $\mathcal{W}_{t,s}^{\max}$ and \mathcal{W}_s^{\max} ;
- $\mathcal{W}_t^{\max} = \{(\mathbb{Q} \oplus^s \mathbb{R}, w) : (\mathbb{Q}, w) \in \mathcal{W}_{t,s}^{\max}, (\mathbb{R}, w_t^s(\mathbb{Q}, w)) \in \mathcal{W}_s^{\max}\}$;
- $\mathcal{W}_t^{\max} = \mathcal{W}_{t,s}^{\max} \cap H_t^s(\mathcal{W}_s^{\max})$ where
 $H_t^s(W) := \{(\mathbb{Q}, w) \in \mathcal{W}_t : (\mathbb{Q}, w_t^s(\mathbb{Q}, w)) \in W\}$.

2.2 Time consistency: Composition of risk measures

Composition of One-Step Risk Measures

Let $(R_t)_{t=0}^T$ be a risk measure then $(\tilde{R}_t)_{t=0}^T$ is the multi-portfolio time consistent version if

$$\tilde{R}_T(X) := R_T(X); \quad \tilde{R}_t(X) := \bigcup_{Z \in \tilde{R}_{t+1}(X)} R_t(-Z)$$

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- Also given by:

$$\begin{aligned} \tilde{A}_t &:= A_{t,t+1} + \tilde{A}_{t+1}; \\ -\tilde{\beta}_t(\mathbb{Q}, w) &:= \text{cl} \left(-\beta_{t,t+1}^{\min}(\mathbb{Q}, w) + \mathbb{E}_t^{\mathbb{Q}} \left[-\tilde{\beta}_{t+1}(\mathbb{Q}, w_t^{t+1}(\mathbb{Q}, w)) \right] \right); \\ \tilde{\mathcal{W}}_t &:= \mathcal{W}_{t,t+1}^{\max} \cap H_t^{t+1}(\tilde{\mathcal{W}}_{t+1}); \\ -\tilde{\alpha}_t(\mathbb{Q}, w) &:= \text{cl} \left(-\alpha_{t,t+1}^{\min}(\mathbb{Q}, w) + \mathbb{E}_t^{\mathbb{Q}} \left[-\tilde{\alpha}_{t+1}(\mathbb{Q}, w_t^{t+1}(\mathbb{Q}, w)) \right] \right). \end{aligned}$$

3.1 Examples: Superhedging

- Convex transaction costs at time t : closed convex set $\mathbb{R}_+^d \subseteq K_t[\omega] \subseteq \mathbb{R}^d$ (solvency region), positions transferable into non-negative portfolios.

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Self-Financing Portfolio Process

A **self-financing portfolio process** $(V_t)_{t=0}^T$ is a stochastic process of portfolio vectors (of “physical units”) if starting with no assets you can trade for V_t from the portfolio V_{t-1} .

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- Let $K_{t,s} := \sum_{r=t}^s L_d^p(\mathcal{F}_r; K_r)$ denote the portfolios reachable from time t at time s .

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- $SHP_t(X) := \{u \in L_d^p(\mathcal{F}_t) : -X + u \in -K_{t,T}\}.$

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- If the market model $(K_t)_{t=0}^T$ satisfies proper no-arbitrage argument (robust no scalable arbitrage) then the superhedging portfolios can be found via the dual representation with penalty function:

$$-\alpha_t^{SHP}(\mathbb{Q}, w) = \sum_{s=t}^T \left\{ u \in L_d^p(\mathcal{F}_t) : \right. \\ \left. \text{ess inf}_{k \in L_d^p(\mathcal{F}_s; K_s)} w^\top \mathbb{E}_t^{\mathbb{Q}} [k] \leq w^\top u \right\}$$

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- This is multi-portfolio time consistent, but not necessarily self-recursive.

3.1 Examples: Superhedging

- If **solvency cones** (K_t is a.s. a cone) then the superhedging portfolios are conditionally coherent with dual variables defined by

$$\mathcal{W}_{\{t, \dots, T\}} = \{(\mathbb{Q}, w) \in \mathcal{W}_t : \forall s \in \{t, \dots, T\} : \} \\ w_t^s(\mathbb{Q}, w) \in L_d^q(\mathcal{F}_s; K_s^+)\}$$

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3.2 Examples: Average Value-at-Risk

- Level $\lambda^t \in L_d^\infty(\mathcal{F}_t)$ bounded away from 0.
- Average Value-at-Risk at time t is closed and conditionally coherent risk measure defined by the dual variables:

$$\mathcal{W}_t^\lambda := \left\{ (\mathbb{Q}, w) \in \mathcal{W}_t : 0 \preceq w \cdot \frac{d\mathbb{Q}}{d\mathbb{P}} \preceq w/\lambda^t \right\}$$

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- Average Value-at-Risk is not time consistent.

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- Consider $M := \mathbb{R}^d$ and $p = +\infty$
- $AV@R_t$ is c.u.c.
- Multi-portfolio time consistent version has dual variables:

$$\begin{aligned}\widetilde{\mathcal{W}}_t^\lambda &:= \{(\mathbb{Q}, w) \in \mathcal{W}_t : \forall s \in \{t, t+1, \dots, T-1\} : \\ &\quad w_t^s(\mathbb{Q}, w) / \lambda^s \succeq w_t^{s+1}(\mathbb{Q}, w)\} \\ &= \{(\mathbb{Q}, w) \in \mathcal{W}_t : \forall s \in \{t, t+1, \dots, T-1\} \forall i : \\ &\quad \mathbb{P} \left(\mathbb{E}_{s+1} \left[\frac{d\mathbb{Q}_i}{d\mathbb{P}} \right] \leq \frac{1}{\lambda_i^s} \mathbb{E}_s \left[\frac{d\mathbb{Q}_i}{d\mathbb{P}} \right] \text{ or } w_i = 0 \right) = 1 \forall i \}\end{aligned}$$

3.3 Examples: Entropic risk measure

- Utility based shortfall risk measures:

$$R_t^u(X) := \{m \in M_t : \mathbb{E}_t[u(X + m)] \in C_t\}$$

for some vector utility function u and $C_t \in \mathcal{G}(L_d^p(\mathcal{F}_t); L_d^p(\mathcal{F}_t)_+)$

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- Closed convex risk measure with penalty function

$$-\alpha_t^{ent}(\mathbb{Q}, w) = H_t(\mathbb{Q}|\mathbb{P})/\lambda + \Gamma_t(w)$$

$$-\beta_t^{ent}(\mathbb{Q}, w) = H_t(\mathbb{Q}|\mathbb{P})/\lambda + G_t(w)$$

where $\hat{H}_t(\mathbb{Q}|\mathbb{P}) = \mathbb{E}_t^{\mathbb{Q}} \left[\log\left(\frac{d\mathbb{Q}}{d\mathbb{P}}\right) \right]$

- c.u.c., normalized, and multi-portfolio time consistent.



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