

From set-valued quantiles to risk measures:
A set optimization approach to markets with
frictions

ANDREAS H. HAMEL, DANIEL KOSTNER
Free University of Bozen-Bolzano

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Theorem (Fenchel–Moreau, Hamel 2009)

$f: X \rightarrow \mathcal{G}(Z, C)$ proper closed convex, or identically \emptyset or Z
if, and only if, $f = f^{**}$.

Consequence. (Kabanov 1999, superhedging in discrete time).

$$\begin{aligned} \Gamma &:= \left\{ v \in \mathbb{R}^d : V_T^{v,L} \succeq C \text{ for some } L \in \mathfrak{A} \right\} \\ &= \bigcap_{Z \in \mathfrak{F}_0} \left\{ v \in \mathbb{R}^d : \widehat{Z}_0 v \geq E \widehat{Z}_T C \right\} =: D. \end{aligned}$$

Proof. Γ is the value of a set-valued proper closed sublinear risk measure at $-C$, and D is the value of its biconjugate at $-C$. (Note: C here corresponds to x in the general theory. The additional dual variable z^* is \widehat{Z}_0 .)

What is a quantile of a multivariate random variable?

For example, its median?

The question.

Let $X: \Omega \rightarrow \mathbb{R}$ be a (univariate) random variable on a probability space (Ω, \mathcal{F}, P) .

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where $F_X: \mathbb{R} \rightarrow [0, 1]$, $q_X^-, q_X^+: [0, 1] \rightarrow \mathbb{R}$ (inverse!).

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Question. What about F_X, q_X^-, q_X^+ for $X: \Omega \rightarrow \mathbb{R}^d$, $d > 1$?

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Question. What if \leq is replaced by \leq_C , $C \subseteq \mathbb{R}^d$ a closed convex cone?

Bad news.

- Even if $C = \mathbb{R}_+^d$, i.e., the case of joint distribution function $F_X^{jdf}(z) = P(X \leq_{\mathbb{R}_+^d} z)$, the formula

$$Q_X^-(p) = \inf \left\{ z \in \mathbb{R}^d \mid F_X^{jdf}(z) \geq p \right\}$$

doesn't work.

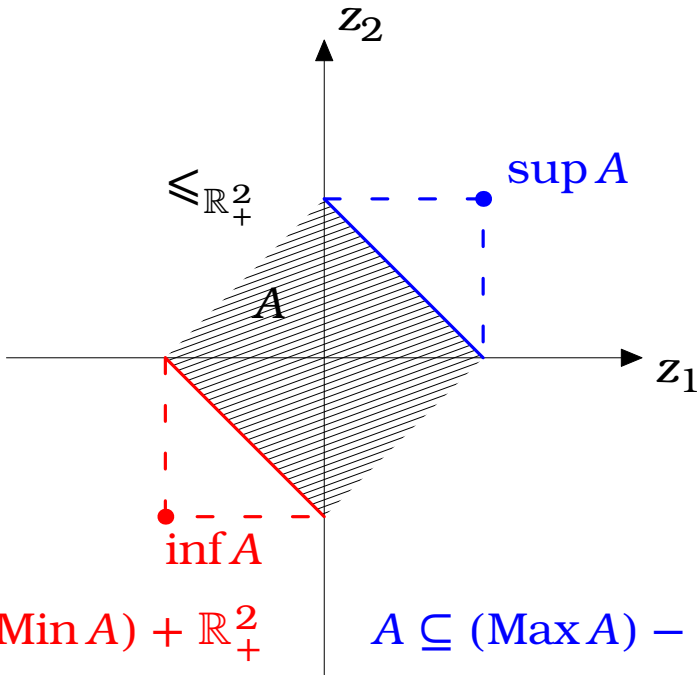
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doesn't work.

- Even worse, the joint distribution function is not very useful for statistical analysis: it 'does not mean much' (M. Hallin 2017). Instead, so-called *depth functions* are used.



$$A \subseteq (\text{Min } A) + \mathbb{R}_+^2$$

$$A \subseteq (\text{Max } A) - \mathbb{R}_+^2$$

Remaining question.

What is a quantile of a multivariate random variable
in the presence of an order relation for its values?

Naturally, the quantiles of a multivariate random variable are also of interest, and the search for a multidimensional counterpart of the quantiles of a random variable has attracted considerable attention in the statistical literature.

The fundamental difficulty in reaching agreement on a suitable generalization of univariate quantiles is arguably **the lack of a natural ordering in a multidimensional setting.**

Belloni/Winkler 2011, The Annals of Statistics

Unlike the real line, the d -dimensional space \mathbb{R}^d , for $d \geq 2$, is not canonically ordered. As a consequence, such fundamental and strongly order-related univariate concepts as quantile and distribution functions, and their empirical counterparts, involving ranks and signs, do not canonically extend to the multivariate context.

Hallin 2017, ECARES Working Paper

If $X: \Omega \rightarrow \mathbb{R}$ is univariate, the set

$$LQ_X(p) = \{r \in \mathbb{R} \mid P(X \leq r) \geq p\}$$

is “directed upward,” i.e.,

$$LQ_X(p) + \mathbb{R}_+ = LQ_X(p) \quad \text{and} \quad q_X^-(p) = \inf LQ_X(p).$$

On the other hand, the set

$$UQ_X(p) = \{r \in \mathbb{R} \mid P(X < r) \leq p\}$$

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$$UQ_X(p) - \mathbb{R}_+ = UQ_X(p) \quad \text{and} \quad q_X^+(p) = \sup UQ_X(p).$$

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Note. (lower quantiles are sufficient)

$$q_X^+(p) = -q_{-X}^-(1-p).$$

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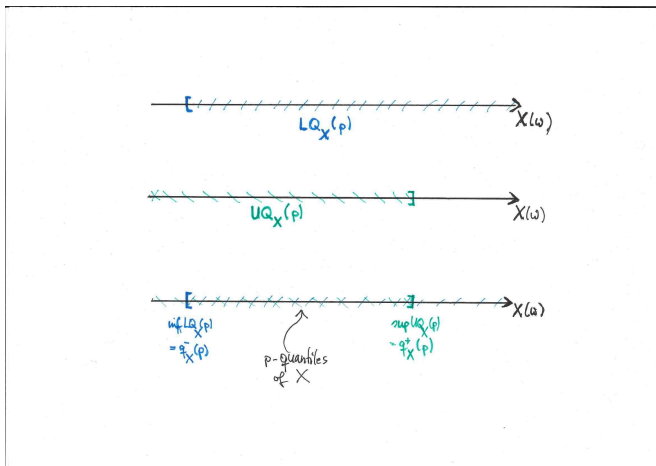
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Recall. ($V@R$ is a quantile)

$$V@R_\alpha(X) = q_{-X}^-(1-\alpha) \quad \text{for} \quad \alpha \in (0, 1).$$

Observation.

$$LQ_X(p) \cap UQ_X(p) = [\inf LQ_X(p), \sup UQ_X(p)] = [q_X^-(p), q_X^+(p)].$$



- ◆ Lower (real-valued) C -distribution functions
- ◆ Lower & upper (set-valued) C -quantiles
- ◆ Set-valued $V@R$ & first order stochastic dominance
- ◆ Multivariate $V@R$ for conical market models

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Bipolar theorem. $C = \bigcap_{w \in C^+} H^+(w)$.

Let (Ω, \mathcal{F}, P) be a probability space and $X: \Omega \rightarrow \mathbb{R}^d$ a random variable.

Definition

The w -distribution function $F_{X,w}: \mathbb{R}^d \rightarrow [0, 1]$ of X is the composition of the cdf of $w^T X$ and $w \in \mathbb{R}^d \setminus \{0\}$, i.e.,

$$F_{X,w}(z) = F_{w^T X}(w^T z) = P(X \in z - H^+(w)).$$

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The lower C -distribution function $F_{X,C}: \mathbb{R}^d \rightarrow [0, 1]$ of X is

$$F_{X,C}(z) = \inf_{w \in C^+ \setminus \{0\}} F_{X,w}(z).$$

Lower C -distribution function:

$$F_{X,C}(z) = \inf_{w \in C^+ \setminus \{0\}} F_{X,w}(z) = \inf_{w \in C^+ \setminus \{0\}} P(X \in z - H^+(w)).$$

Observation. (since $C \subseteq H^+(w)$ for all $w \in C^+ \setminus \{0\}$)

$$\forall z \in \mathbb{R}^d: F_{X,C}(z) \geq P(X \in z - C),$$

and this inequality is strict in general even for $C = \mathbb{R}_+^d$ (already for X bivariate normal and $z = 0 \in \mathbb{R}^2$).

Proposition

(a) Affine invariance: if $b \in \mathbb{R}^d$, $A \in \mathbb{R}^{d \times d}$ invertible, then

$$\forall z \in \mathbb{R}^d: F_{AX+b, A^T C}(Az + b) = F_{X, C}(z).$$

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(d) Right-continuity: if $\{z_n\}_{n \in \mathbb{N}} \subseteq \mathbb{R}^d$ with $\lim_{n \rightarrow \infty} z_n = \bar{z} \in \mathbb{R}^d$ and $z_{n+1} \leq_C z_n$ for all $n \in \{1, 2, \dots\}$, then

$$\lim_{n \rightarrow \infty} F_{X, C}(z_n) = F_{X, C}(\bar{z}).$$

Proposition

(e) Behavior at infinity: If $L^+(z) = \{w \in C^+ \mid w^T z = 0\}$, then

$$\lim_{t \rightarrow \infty} F_{X,C}(tz) = \begin{cases} \min\{a, b\} & \text{if } z \in C \\ 0 & \text{if } z \notin C \end{cases}$$

where $a = \inf_{w \in L^+(z) \setminus \{0\}} F_{X,w}(0)$, $b = \lim_{t \rightarrow \infty} \inf_{w \in C^+ \setminus L^+(z)} F_{X,w}(z)$ and

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$$\lim_{t \rightarrow -\infty} F_{X,C}(tz) = \begin{cases} 0 & \text{if } z \notin -C \\ \min\{a, c\} & \text{if } z \in -C \end{cases}$$

where $c = \lim_{t \rightarrow -\infty} \inf_{w \in C^+ \setminus L^+(z)} F_{X,w}(z)$.

Summary.

- The lower C -distribution function $F_{X,C}$ almost behaves like a (univariate) cdf.
- It is, however, different from the joint distribution function even if $C = \mathbb{R}_+^d$.
- For $d = 1$, $C = \mathbb{R}_+$, one gets back the univariate cdf.

- ◆ Lower & upper C -quantiles

$$\mathcal{P}(\mathbb{R}^d) = \{D \mid D \subseteq \mathbb{R}^d\} \quad \text{power set}$$

Definition

The lower w -quantile of X is $Q_{X,w}^-: [0, 1) \rightarrow \mathcal{P}(\mathbb{R}^d)$ defined by

$$Q_{X,w}^-(p) = \{z \in \mathbb{R}^d \mid F_{X,w}(z) \geq p\}.$$

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$$\forall p \in [0, 1): Q_{X,C}^-(p) = \bigcap_{w \in C^+ \setminus \{0\}} Q_{X,w}^-(p).$$

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$$\forall z \in \mathbb{R}^d: F_{X,C}(z) = \sup \left\{ p \in [0, 1) \mid z \in Q_{X,C}^-(p) \right\}$$

($F_{X,C}$ can be reconstructed from the quantile function.)

Proposition

(a) $Q_{X,C}^-: [0, 1) \rightarrow \mathcal{P}(\mathbb{R}^d)$ has closed convex values and satisfies

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(b) For all $b \in \mathbb{R}^d$ and all invertible $A \in \mathbb{R}^{d \times d}$,

$$Q_{X+b,C}^-(p) = Q_{X,C}^-(z) + b \quad \text{and} \quad Q_{AX,ATC}^-(p) = A Q_{X,C}^-(p).$$

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Note. (a): $Q_{X,C}^-$ maps into the complete lattice ordered by \supseteq :

$$\mathcal{G}(\mathbb{R}^d, C) := \left\{ D \subseteq \mathbb{R}^d \mid D = \text{cl co}(D + C) \right\}.$$

Tukey depth function.

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Tukey depth region.

$$D_X(p) = \left\{ z \in \mathbb{R}^d \mid HD_X(z) \geq p \right\}, \quad p \in [0, 1/2].$$

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Observation. Special cases of $F_{X,C}$ and $Q_{X,C}^-$, respectively, for $C = \{0\}$, $C^+ = \mathbb{R}^d$: one looks for “deepest points.”

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Observation. Univariate quantile: $d = 1$, $C = C^+ = \mathbb{R}_+$.

Definition

For $w \in C^+ \setminus \{0\}$, the function $Q_{X,w}^+ : (0, 1] \rightarrow \mathcal{P}(\mathbb{R}^d)$ defined by

$$Q_{X,w}^+(p) = \left\{ z \in \mathbb{R}^d \mid P(w^T X < w^T z) \leq p \right\}$$

is called the *upper w -quantile function* of X . The function $Q_{X,C}^+ : (0, 1] \rightarrow \mathcal{P}(\mathbb{R}^d)$ defined by

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Remark. $Q_{X,C}^+ : \mathbb{R}^d \rightarrow \mathcal{G}(\mathbb{R}^d, -C)$ (opposite to $Q_{X,C}^-$).

Surprising result. (no other concept known with this type of property)

$$Q_{X,C}^+(p) = Q_{X,-C}^-(1-p).$$

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Compare this to

$$q_X^+(p) = -q_X^-(1-p).$$

Summary.

- The lower C -quantile $Q_{X,C}^-$ is a set-valued inverse of $F_{X,C}$.
- It shares most properties with scalar quantiles.
- It also generalizes the Tukey (halfspace) depth function as well as the univariate quantile.

Example. (a four point uniform distribution)

- $\Omega = \{(-1, 2)^T, (0, 0)^T, (1, 1)^T, (2, -1)^T\} \subseteq \mathbb{R}^2$,
- X uniformly distributed over Ω .

Lower and upper quantile sets for the seven cases

$$p \in (0, \frac{1}{4}), p = \frac{1}{4}, p \in (\frac{1}{4}, \frac{1}{2}), p = \frac{1}{2}, p \in (\frac{1}{2}, \frac{3}{4}), p = \frac{3}{4}, p \in (\frac{3}{4}, 1).$$

Lower & upper C -quantiles: how do they look like?

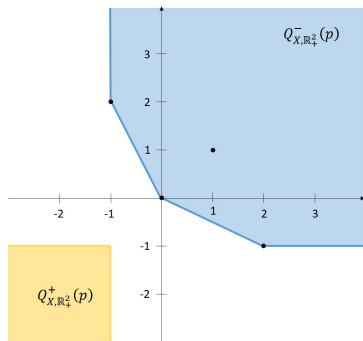


Figure : $p \in (0, \frac{1}{4})$

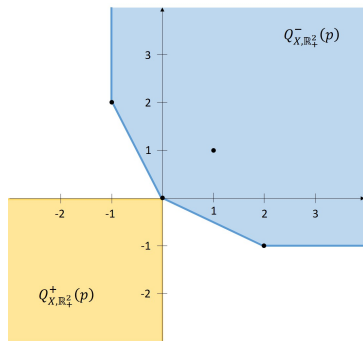


Figure : $p = \frac{1}{4}$

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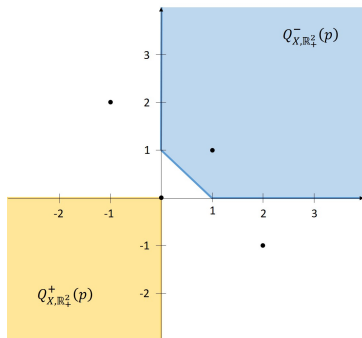


Figure : $p \in (\frac{1}{4}, \frac{1}{2})$

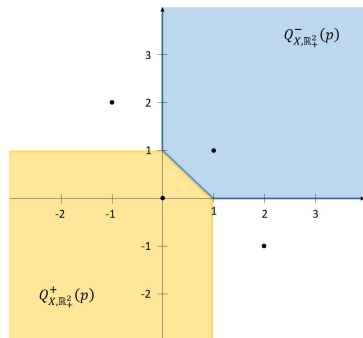


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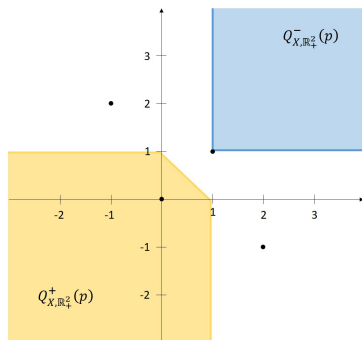


Figure : $p \in (\frac{1}{2}, \frac{3}{4})$

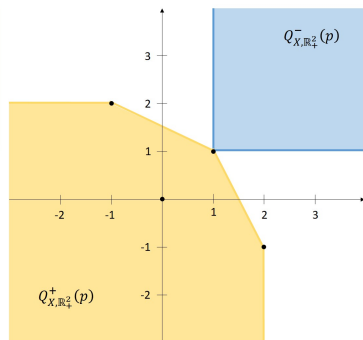


Figure : $p = \frac{3}{4}$

Lower & upper C -quantiles: how do they look like?

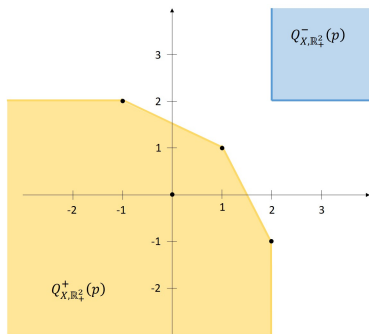


Figure : $p \in (\frac{3}{4}, 1)$

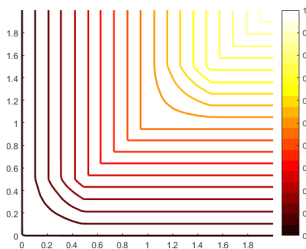
Remark. In general,

$$Q_{X,C}^-(p) \cap Q_{X,C}^+(p) = \emptyset.$$

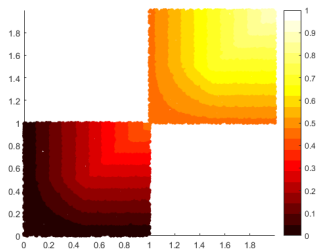
Compare this to

$$LQ_X(p) \cap UQ_X(p) = [\inf LQ_X(p), \sup UQ_X(p)] = [q_X^-(p), q_X^+(p)].$$

Lower & upper C -quantiles: how do they look like?



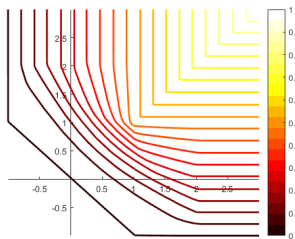
Contours of $Q_{X, \mathbb{R}_+^2}^-(p)$



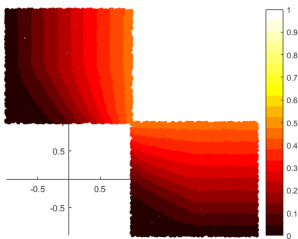
Sample points in $Q_{X, \mathbb{R}_+^2}^-(p)$

Figure : Lower C -quantiles in 5% increments for $C = \mathbb{R}_+^2$ and $X \sim \text{Uniform}((0, 1) \times (0, 1) \cup (1, 2) \times (1, 2))$.

Lower & upper C -quantiles: how do they look like?



Contours of $Q_{X, \mathbb{R}_+^2}^-(p)$



Sample points in $Q_{X, \mathbb{R}_+^2}^-(p)$

Figure : Lower C -quantiles in 5% increments for $C = \mathbb{R}_+^2$ and $X \sim \text{Uniform}((-1, 1) \times (1, 3) \cup (1, 3) \times (-1, 1))$.

The joint distribution lower quantile.

$$Q_X^{jdf}(p) := \left\{ z \in \mathbb{R}^2 \mid F_X^{jdf}(z) \geq p \right\}$$

Example. (same as before)

- $Q_X^{jdf}(p)$ is different from lower C -quantile in general.
- $Q_X^{jdf}(p)$ is non-convex in general.
- $Q_{X,C}^-(p)$ is also different from the convex hull of $Q_X^{jdf}(p)$.

Lower & upper C -quantiles.

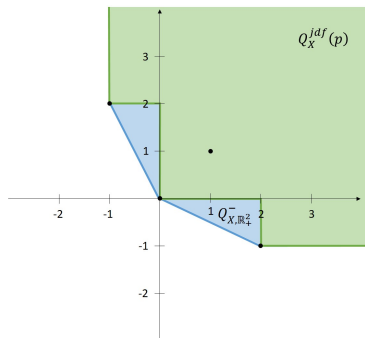


Figure : $p = \frac{1}{4}$

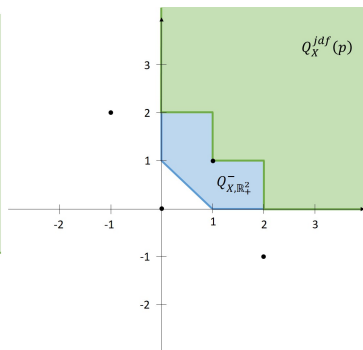


Figure : $p = \frac{1}{2}$

- ◆ Set-valued V@R & first order stochastic dominance

Definition

The Value-at-Risk of $X : \Omega \rightarrow \mathbb{R}^d$ at level $\alpha \in (0, 1)$ is

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Recall. (univariate V@R)

$$V@R_{\alpha}(X) = q_{-X}^-(1 - \alpha) \quad \text{for } \alpha \in (0, 1).$$

Basic formula.

$$\begin{aligned} V@R_{\alpha,C}(X) &= \left\{ z \in \mathbb{R}^d \mid \sup_{w \in C^+ \setminus \{0\}} P(X + z \in -\text{int } H^+(w)) \leq \alpha \right\} \\ &= \bigcap_{w \in C^+ \setminus \{0\}} \left\{ z \in \mathbb{R}^d \mid P(X + z \in -\text{int } H^+(w)) \leq \alpha \right\} \end{aligned}$$

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 \end{aligned}$$

Interpretation. $V@R_{\alpha,C}(X)$ includes all deterministic portfolios z (= deposits) which keep the probability of bankruptcy $\leq \alpha$ when added to the random position X – for all “price” vectors $w \in C^+$ since

$$X + z \in -\text{int } H^+(w) \quad \Leftrightarrow \quad w^T(X + z) < 0.$$

Proposition

(1) *The function $X \mapsto V@R_{\alpha,C}(X)$ maps into $\mathcal{G}(\mathbb{R}^d, C)$ and is positively homogeneous. In particular, $V@R_{\alpha,C}(0) = C$.*

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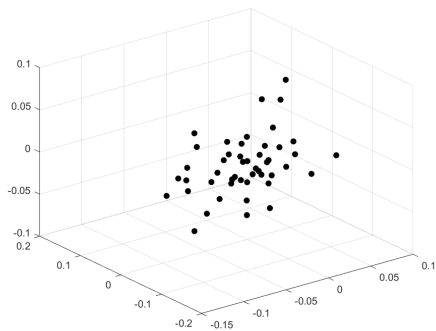
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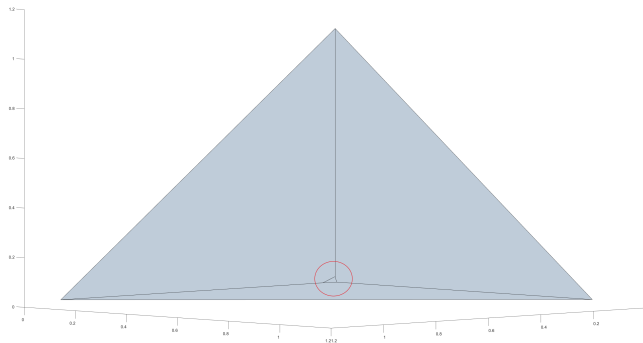
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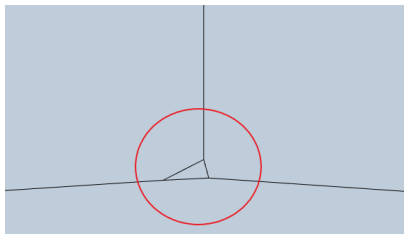
Note. This qualifies $V@R$ as a set-valued risk measure in the sense of Hamel/Heyde 2010 SIFIN.



$$\tilde{X} = (R_{DAX} \mid R_{HSI} \mid R_{S\&P})$$



$$V@R_{10\%, \mathbb{R}_+^3}(\tilde{X})$$



Vertices of $V@R$

Figure : Value-at-Risk with $C = \mathbb{R}_+^3$ for the monthly return of three major stock indexes.

Scalarization formula.

$$V@R_{\alpha,C}(X) = \bigcap_{w \in C^+ \setminus \{0\}} \left\{ z \in \mathbb{R}^d \mid w^T z \geq V@R_{\alpha}^{sca}(w^T X) \right\}$$

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Special case. $C = \mathbb{R}_+^d$

$$\begin{aligned} V@R_{\alpha, \mathbb{R}_+^d}(X) &= \bigcap_{w \in \mathbb{R}_+^d \setminus \{0\}} \left\{ z \in \mathbb{R}^d \mid w^T z \geq V@R_{\alpha}^{sca}(w^T X) \right\} \\ &\subseteq \bigcap_{i \in \{1, \dots, d\}} \left\{ z \in \mathbb{R}^d \mid z_i \geq V@R_{\alpha}^{sca}(X_i) \right\}, \end{aligned}$$

i.e., $V@R_{\alpha, \mathbb{R}_+^d}$ is “more conservative” than the component-wise Value-at-Risk.

Embrechts/Puccetti 06. F_X^{jdf} jdf and

$$V@R_\alpha^{jdf}(X) = \partial \left\{ z \in \mathbb{R}^d \mid F_X^{jdf}(z) \geq \alpha \right\}.$$

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$$V@R_\alpha^{jdf}(X) = \partial \left\{ z \in \mathbb{R}^d \mid F_X^{jdf}(z) \geq \alpha \right\}.$$

Associated to order generated by \mathbb{R}_+^d ; even if it is replaced by C and ∂ is dropped,

$$\begin{aligned} V@R_{\alpha,C}(X) &= Q_{-X,C}^-(1 - \alpha) = \left\{ z \in \mathbb{R}^d \mid F_{-X,C}(z) \geq 1 - \alpha \right\} \\ &\supseteq \left\{ z \in \mathbb{R}^d \mid P(-X \in z - C) \geq 1 - \alpha \right\} \end{aligned}$$

since

$$\forall z \in \mathbb{R}^d: F_{-X,C}(z) \geq P(-X \in z - C).$$

Note. $V@R_{\alpha,C}$ is “less conservative” than the E/P version.

Definition

The random variable $Y \in L_d^0(\Omega, \mathcal{F}, P)$ is said to C -stochastically dominate $X \in L_d^0(\Omega, \mathcal{F}, P)$, written as $Y \succeq_{FSD}^C X$, iff

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Proposition

For $X, Y \in L_d^0(\Omega, \mathcal{F}, P)$, $Y \succeq_{FSD}^C X$ is true if, and only if,

$$\forall p \in (0, 1): Q_{Y,C}^-(p) \subseteq Q_{X,C}^-(p),$$

and if, and only if,

$$\forall \alpha \in (0, 1): V @ R_{\alpha,C}(X) \subseteq V @ R_{\alpha,C}(Y).$$

- ◆ Multivariate V@R for conical market models

Obvious idea. Make the cone C random.

Motivation (from finance). Conical market models.

Motivation (from statistics). I hardly have a clue, just ideas. Ilya, would it make sense to analyse data with an order relation which changes with the data point?

The model.

- $K(\omega) \subseteq \mathbb{R}^d$ closed convex cones (measurable) generating on L_d^0 the order

$$X^1 \leq_K X^2 \quad \Leftrightarrow \quad X^2 - X^1 \in K \quad (P - \text{a.s.})$$

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- Potential quantiles: $z \in \mathbb{R}^m$ ordered via closed convex cone $K_0 \subseteq \mathbb{R}^m$ with $1 \leq m \leq d$:

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- A linear operator $T: \mathbb{R}^m \rightarrow L_d^0(\Omega, \mathcal{F}, P)$ which generates a another cone $TK_0 \subseteq L_d^0$.

Example. $Z^1, \dots, Z^m \in L_d^0$ linearly independent and $Tz = \sum z_i Z^i$. In particular, $Z^i = b^i \mathbb{1}$ with $b^i \in \mathbb{R}^d$ (riskless portfolios used as deposits).

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Pointwise cones.

- $C(\omega) = (TK_0)(\omega) + K(\omega)$,
- $C^+(\omega) = [(TK_0)(\omega) + K(\omega)]^+ = (TK_0)(\omega)^+ \cap K(\omega)^+$.

This can be seen as a one-period market model with m eligible assets.

Definition

The composition of the function $F_{X,Y}: L_d^0 \rightarrow [0, 1]$ with T which is defined by

$$F_{X,Y}(Tz) = \Pr[Y^\top X \leq Y^\top (Tz)]$$

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The composition of the function $F_{X,C}: L_d^0 \rightarrow [0, 1]$ with T defined by

$$F_{X,C}(Tz) = \inf\{F_{X,Y}(Tz) \mid Y \in C^+\}$$

is called the C -distribution function of X (with respect to T).

Definition

The lower Y -quantile of X is $Q_{X,Y}^-: [0, 1) \rightarrow \mathcal{P}(\mathbb{R}^m)$ defined by

$$Q_{X,Y}^-(p) = \{z \in \mathbb{R}^m \mid F_{X,Y}(Tz) \geq p\}.$$

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Note. Many (not all) properties carry over from the constant cone case.

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Perspective. stochastic dominance, AV@R, Kusuoka representations ... data analysis etc.

Conclusion. There seems to be a canonical way to introduce quantiles in the multivariate case in the presence of an in general non-complete order relation for the values of random variables.

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Reference. Hamel/Kostner: *Cone distribution functions and quantiles for multivariate random variables*

JMVA 167 (2018) 97-113 and follow-ups

THANK YOU FOR FOLLOWING ...

... INTO THE DEPTH OF STATISTICS.

SET OPTIMIZATION for APPLICATIONS

4th International Conference on Set Optimization
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