

# A Fourier approach to the computation of risk measures and risk contributions

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# Outline

- 1 Motivation
- 2 Optimized Certainty Equivalents
- 3 Numerical Computation: Transform Methods
- 4 Risk Contributions
- 5 Numerical Results
- 6 Conclusions

# Motivation

The financial crisis has highlighted the importance of reliable risk assessment

**Relevance:** Economically sound (Diversification, Aggregation, Basel)

**Performance:** Numerically efficient (real time, huge number of assets)

# Motivation

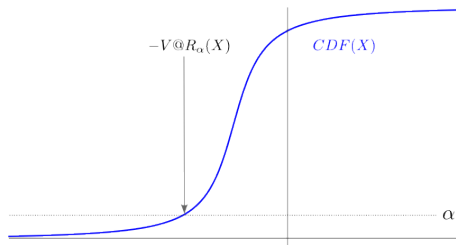
## Value at Risk (V@R)

### V@R

$$V@R_{\alpha}(X) := -q_X(\alpha)$$

- Widely used (Basel II)
- Straightforward interpretation
- Easy / efficient implementation  
↪ A single root finding

### Illustration



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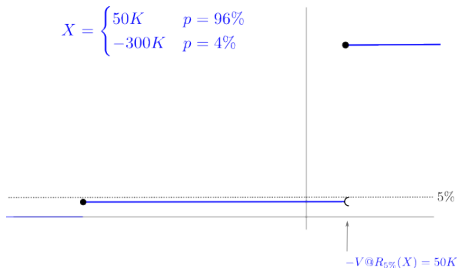
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 $\rightsquigarrow$  A single root finding

**Drawback:**

Non-consistent aggregation of risks

### Illustration

$$X = \begin{cases} 50K & p = 96\% \\ -300K & p = 4\% \end{cases}$$



# Motivation

## Value at Risk (V@R)

### V@R

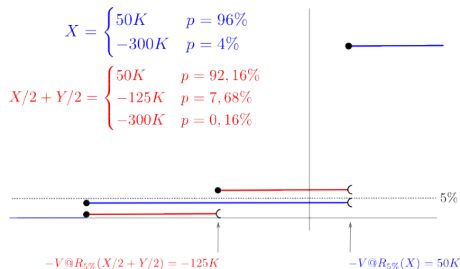
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### Illustration



$X \sim Y$  and  $X$  independent of  $Y$

$$-100K = V@R_{\alpha}(X) + V@R_{\alpha}(Y) < V@R(X + Y) = 250K$$

# Motivation

Monetary Risk Measures: Artzner, Delbaen, Eber, Heath (1999); Föllmer, Schied (2002)

“Diversification should not increase risk”

## Definition (Monetary Risk Measure)

A monetary risk measure  $\rho$  is

- **Diversifying:** for any two assets  $X$  and  $Y$  the diversified asset profile  $\lambda X + (1 - \lambda)Y$  is less risky than the worse outcome

$$\rho(\lambda X + (1 - \lambda)Y) \leq \sup \{\rho(X), \rho(Y)\}$$

- **Monotone:**  $\rho(X) \geq \rho(Y)$  if loss  $-X$  is greater than loss  $-Y$ ;
- **Monetary:**  $\rho(X + m) = \rho(X) - m$  for every amount of cash  $m$ .

Monetary and diversification implies that  $\rho$  is **convex**

$$\rho(\lambda X + (1 - \lambda)Y) \leq \lambda \rho(X) + (1 - \lambda) \rho(Y)$$

Examples: CV@R, Entropic Risk Measure, Shortfall Risk Measure, etc.

# Motivation

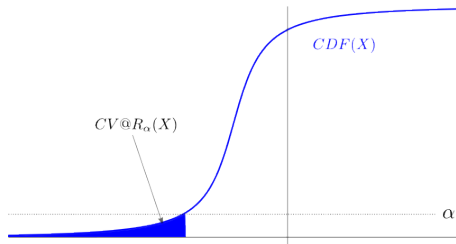
Monetary Risk Measures: Conditional Value at Risk (CV@R)

CV@R (Artzner et al.)

$$CV@R_{\alpha}(X) := -\frac{1}{\alpha} \int_0^{\alpha} q_X(s) ds$$

- Consistent aggregation
- Basel III / Swiss Solvency Test
- Good interpretation

Illustration





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Monetary Risk Measures: Conditional Value at Risk (CV@R)

CV@R (Artzner et al.)

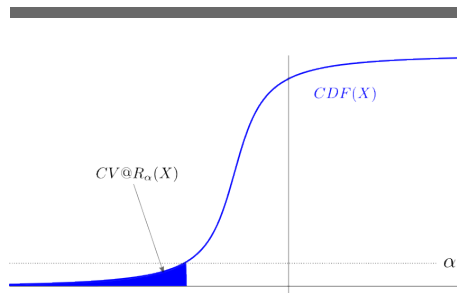
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- Consistent aggregation
- Basel III / Swiss Solvency Test
- Good interpretation

**Drawbacks:**

- Increased numerical complexity
- Backtesting – Elicitability
- Statistical robustness

Illustration



# Optimized Certainty Equivalents

## Definition

OCE (Ben-Tal, Teboulle [86,06])

- Today's expected loss of  $X$

$$E [I(-X)]$$

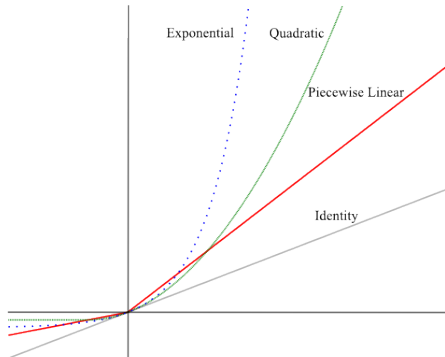
- Allocating cash  $\eta$

$$E [I(\eta - X)] - \eta$$

- Optimal allocation  $\rightsquigarrow$  OCE

$$\rho(X) := \inf_{\eta} \{E [I(\eta - X)] - \eta\}$$

Typical Loss Functions  $I$



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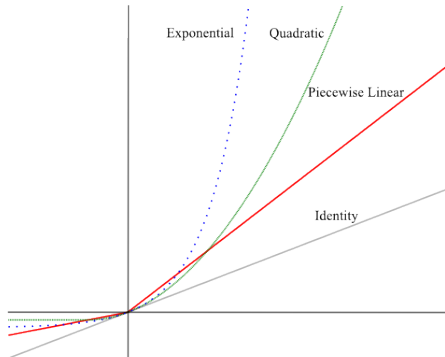
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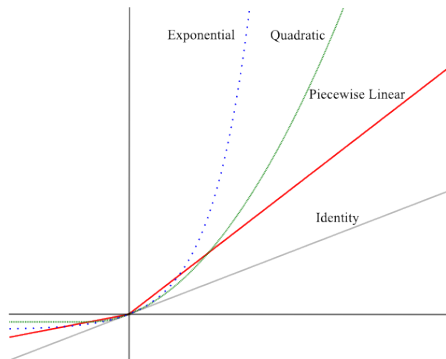
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# Optimized Certainty Equivalents

## OCE as a Risk Measure

### Theorem

- The optimized certainty equivalent  $\rho$  is a **monetary risk measure**
- **Optimal allocation**

$$\rho(X) = \inf_{\eta} \{E[l(\eta - X)] - \eta\} = E[l(\eta^* - X)] - \eta^*$$

where  $\eta^*$  fulfills

$$E[l'(\eta^* - X)] = 1$$

- **Robust Representation**

$$\rho(X) = \sup_Q \left\{ E_Q[-X] - E \left[ l^* \left( \frac{dQ}{dP} \right) \right] \right\} = E_{Q^*}[-X] - E \left[ l^* \left( \frac{dQ^*}{dP} \right) \right]$$

where  $l^*$  is the convex conjugate of  $l$  and  $dQ^*/dP = l'(\eta^* - X)$

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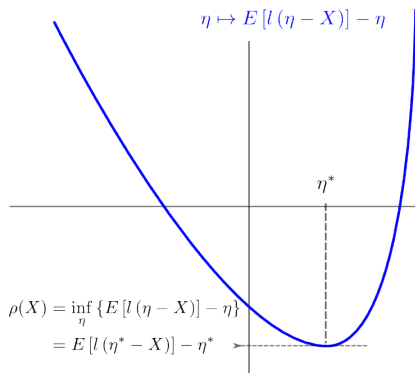
### Sketch of Proof

- The function  $\eta \mapsto E[l(\eta - X)] - \eta$  is real-valued, convex and coercive.
- **Optimal allocation:** first order conditions imply that  $\eta^*$  fulfills

$$E[l'(\eta^* - X)] = 1$$

and then

$$\begin{aligned} \rho(X) &:= \inf_{\eta} \{E[l(\eta - X)] - \eta\} \\ &= E[l(\eta^* - X)] - \eta^* \end{aligned}$$





# Optimized Certainty Equivalents

In a Nutshell

- Easy interpretation: optimal allocation of losses
- Adequate for financial optimization problems (Cherny, Kupper)
- Wide class of monetary risk measures by specifying the loss function  $l$

$l$	RM	$\eta^*$	$\rho(X)$
$e^x - 1$	Entropic	$-\ln E[e^{-X}]$	$\ln E[e^{-X}]$
$x^+/\alpha$	$CV@R_\alpha$	$q_X(\alpha)$	$-\frac{1}{\alpha} \int_0^\alpha q_X(s) ds$
$x + x^2/2$	Quadratic RM	$\rightsquigarrow$ monotone mean variance	
$\frac{([x+1]^+)^n - 1}{n}$	Polynomial RM		

# Optimized Certainty Equivalents

In a Nutshell

An easy two step computation

- 1 Find the root  $\eta^*$  of

$$\eta \mapsto E \left[ I'(\eta - X) \right] - 1 \quad (1)$$

- 2 Compute an integral

$$\rho(X) = E [I(\eta^* - X)] - \eta^* \quad (2)$$

# Numerical Computation: Transform Methods

## General Result

Ingredients to compute the risk of  $X$

- Moment generating function:  $M_X(u) = E[e^{uX}]$
- Fourier transform  $\hat{f}(u) = \int e^{iux} f(x) dx$

### Theorem

The optimal allocation  $\eta^*$  is the unique root of

$$\eta \mapsto \frac{1}{2\pi} \int_{\mathbb{R}} e^{(a-iu)\eta} M_X(iu - a) \hat{f}(u + ia) du - 1,$$

and the Optimized Certainty Equivalent is given by

$$\rho(X) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{(b-iu)\eta^*} M_X(iu - b) \hat{f}(u + ib) du - \eta^*$$

Here  $a, b$  are adequate constants.

# Numerical Computation: Transform Methods

## Conditional Value at Risk

### Proposition

Given  $\eta^* = q_X(\alpha)$  it holds

$$CV@R_\alpha(X) = -\frac{1}{2\pi\alpha} \int_{\mathbb{R}} \frac{e^{(b-iu)\eta^*}}{(u+ib)^2} M_X(iu-b) du - \eta^*,$$

Alternative representations

- Quantile Integration

$$CV@R_\alpha(X) = -\frac{1}{\alpha} \int_0^\alpha q_X(s) ds$$

Increased complexity.

- Rockafellar and Uryasev

$$CV@R_\alpha(X) = \frac{1}{\alpha} E \left[ [q_X(\alpha) - X]^+ \right] - q_X(\alpha)$$

Either Monte Carlo or direct integration if density  $P_X(dx) = f_X(x)dx$  is known.

# Numerical Computation: Transform Methods

## Polynomial loss functions

### Proposition

The optimal allocation is the unique root of

$$\eta \mapsto \frac{(\gamma - 1)!}{2\pi} \int_{\mathbb{R}} M_X(iu - R) \frac{e^{(R-iu)(1+\eta)}}{(R-iu)^\gamma} du - 1. \quad (3)$$

Once  $\eta^*$  is determined, then

$$\rho(X) = \frac{(\gamma - 1)!}{2\pi} \int_{\mathbb{R}} M_X(iu - R) \frac{e^{(R-iu)(1+\eta^*)}}{(R-iu)^{\gamma+1}} du - \frac{1}{\gamma} - \eta^*. \quad (4)$$

### Remark

The same method applies to other risk measures, e.g. expectiles or shortfall risk measures

$$\rho_{SR} \mapsto E[(-\rho_{SR} - X)] - \lambda$$

# Numerical Computation: Transform Methods

## Scenarios

This approach is particularly flexible for the following reasons:

- We only need the moment generating function of  $X$
- A whole class of risk instruments parametrized by  $\hat{l}$ ;
- We can immediately aggregate portfolios if the factors are independent, e.g.  $X = \sum_{i=1}^N X_i$  where  $N$  is a random variable and  $X_i$  independent, then

$$M_X(v) = \sum_{k=1}^{\infty} P[N = k] \prod_{i=1}^k M_{X_i}(v)$$

- Weighted portfolios and loss models à la Dembo et al.
- Linear mixture models for dependence:  $Y_1, \dots, Y_m$  independent random variables, then the dependent factors  $U = (U_1, \dots, U_n)$  are defined via  $U = AY$  for  $A \in \mathbb{R}^{n \times m}$ . The moment generating function of the risk factor  $X = \sum_{i=1}^n U_i$  is provided by

$$M_X(u) = \prod_{l=1}^m M_{Y_l}(u\alpha_l), \quad \alpha_l := \sum_{i=1}^n A_{il}$$

- Elliptical distributions, ...

# Risk Contribution

## OCE and Risk Contributions

OCE  $\rightsquigarrow$  straightforward expression for risk contributions

### Theorem

The contribution of a factor  $Y$  to the risk of a financial position  $X$  is given by

$$RC(X; Y) := \lim_{\varepsilon \downarrow 0} \frac{\rho(X + \varepsilon Y) - \rho(X)}{\varepsilon} = E \left[ l'(\eta^* - X) Y \right]$$

where  $\eta^*$  fulfills

$$E \left[ l'(\eta^* - X) \right] = 1$$

- Once again a two step computation with a root finding and an expectation.
- The optimal allocation  $\eta^*$  is already computed!

# Risk Contribution

## Risk Contribution with CV@R

- $X = \sum_{i=1}^N X_i$  aggregation for  $N$  lines of independent risks  $X_i$
- $\eta^* = q_X(\alpha)$
- Goal: Contribution of the line  $X_i$  to the aggregated risk  $X$ .

### Example (CV@R Risk Contribution)

$$RC(X; X_i) = \frac{1}{4\pi^2\alpha} \int_{\mathbb{R}^2} M(R + iu) \frac{e^{-(R_1 + iu_1)\eta^*}}{(R_1 + iu_1)(u_1 - u_2 - iR_1 - iR_2)^2} du$$

where

$$M(u_1, u_2) = M_{X_i}(u_2) \prod_{j \neq i}^n M_{X_j}(u_1),$$

for adequate constants  $R = (R_1, R_2)$ .

**2 dimensional integration!** Monte Carlo needs to simulate  $N$  random variables.

### Remark

In the linear mixture model: replace the moment generating function.



# Numerical Results

## NIG

The Moment generating function of NIG is given by

$$M_X(u) = \exp \left( u\mu + \delta \left[ \sqrt{\alpha^2 - \beta^2} - \sqrt{\alpha^2 - (\beta + u)^2} \right] \right),$$

where  $\alpha$  = shape,  $\beta$  = skewness and  $\delta$  = scaling parameters (zero mean)

	Parameters		
	$\alpha$	$\beta$	$\delta$
NIG <sub>1</sub>	106.00	-26.00	0.0110
NIG <sub>2</sub>	26.00	-10.60	0.0070
NIG <sub>3</sub>	6.20	-3.90	0.0011
NIG <sub>4</sub>	1.00	0.00	1.0000

**Table :** Parameter sets for NIG distributions.

# Numerical Results

CV@R

Programmed in Matlab, R and Num/Sci-Py (same results)

	V@R		CV@R		
	Value	CT	Value	CT (F)	CT (S)
NIG <sub>1</sub>	0.0210	92 ms	0.0298	99 ms	212 ms
NIG <sub>2</sub>	0.0311	87 ms	0.0585	94 ms	359 ms
NIG <sub>3</sub>	0.0073	88 ms	0.0352	97 ms	636 ms
NIG <sub>4</sub>	1.5914	89 ms	2.2872	97 ms	197 ms

**Table :** Numerical results for V@R and CV@R at the 5% level.

	V@R		CV@R		
	Value	CT	Value	CT (F)	CT (S)
NIG <sub>1</sub>	0.0350	95 ms	0.0444	104 ms	211 ms
NIG <sub>2</sub>	0.0737	92 ms	0.1108	99 ms	360 ms
NIG <sub>3</sub>	0.0369	88 ms	0.1162	100 ms	507 ms
NIG <sub>4</sub>	2.7019	94 ms	3.4503	99 ms	194 ms

**Table :** Numerical results for V@R and CV@R at the 1% level.

# Numerical Results

## Polynomial loss function

Polynomial loss function, Fourier vs Stochastic Root Finding (Weber et al.)

	Fourier			SRF
	$\eta^*$	$\rho(X)$	CT(F)	CT
NIG <sub>1</sub>	0.0028	-0.0027	62 ms	455 ms
NIG <sub>2</sub>	0.0031	-0.0029	71 ms	449 ms
NIG <sub>3</sub>	0.0008	-0.0007	129 ms	443 ms
NIG <sub>4</sub>	-0.0957	0.4380	39 ms	448 ms

Table : Polynomial risk measure with  $\gamma = 2$ .

	$\gamma = 4$			$\gamma = 5$		
	$\eta^*$	$\rho(X)$	CT(F)	$\eta^*$	$\rho(X)$	CT(F)
NIG <sub>1</sub>	0.0027	-0.0026	70 ms	0.0026	-0.0026	30 ms
NIG <sub>2</sub>	0.0028	-0.0026	40 ms	0.0026	-0.0025	32 ms
NIG <sub>3</sub>	0.0006	-0.0005	39 ms	0.0005	-0.0004	27 ms
NIG <sub>4</sub>	-1.0283	1.4994	124 ms	-1.8095	2.3915	103 ms

Table : Polynomial risk measures with  $\gamma = 4$  and  $\gamma = 5$ .

# Conclusions

Optimized certainty equivalents and Fourier methods offer

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- very competitive computational times
- realistic scenarios

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