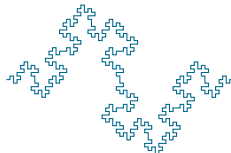


Accounting for Risk Measure Ambiguity when Optimizing Financial Positions

Erick Delage, Jonathan Y. Li



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INTRODUCTION

- ▶ Since last financial crisis, there are no more “best practice” measures of risk
 - ▶ Variance assumes symmetric distribution and considers all random variables as risky, even positive ones
 - ▶ VaR ignores what happens in the tail of distributions and does not encourage diversification of risks

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- ▶ While the axioms proposed by Artzner et al. (1999) provide good guidance, it is never easy to choose which specific measure to use

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- ▶ Since last financial crisis, there are no more “best practice” measures of risk
 - ▶ Variance assumes symmetric distribution and considers all random variables as risky, even positive ones
 - ▶ VaR ignores what happens in the tail of distributions and does not encourage diversification of risks
- ▶ While the axioms proposed by Artzner et al. (1999) provide good guidance, it is never easy to choose which specific measure to use
- ▶ We propose a framework for accounting precisely for what is known of the risk preferences of a decision maker when optimizing financial positions

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RISK MINIMIZATION

$Z = \xi^\top x$: the return of a financial portfolio composed by a wealth allocation vector x and securities with risky returns ξ .

The goal is to solve

$$\begin{aligned} & \underset{x \in \mathcal{X}}{\text{minimize}} && \rho(Z(x, \xi)) \\ & \text{s.t.} && \mathbb{E}[Z(x, \xi)] \geq \bar{r}, \end{aligned}$$

where $\rho(\cdot)$ is a risk measure and $\rho(Z_1) \geq \rho(Z_2)$ means portfolio Z_1 is perceived at least as risky as Z_2 .

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Popular instances:

- ▶ **Variance:** $\rho(Z) = \mathbb{E}[(Z - \mathbb{E}[Z])^2]$: Markowitz (1952)
- ▶ **CVaR:** $\rho(Z) = -1 \cdot \mathbb{E}[Z | Z \leq Z_{10\%}]$: Rockafellar and Uryasev (2000)

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Which one and why?

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AXIOMS OF RISK MEASURES

Convex risk measures (based on diversification principle) satisfy:

1. **Monotonicity** : if $X_1 \geq X_2$ then $\rho(X_1) \leq \rho(X_2)$;
2. **Translation Invariance** : if $c \in \mathfrak{R}$, then
$$\rho(X_1 + c) = \rho(X_1) - c,$$
3. **Convexity** :
$$\rho(\lambda X_1 + (1 - \lambda)X_2) \leq \lambda\rho(X_1) + (1 - \lambda)\rho(X_2) \quad \forall \lambda \in [0, 1].$$

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Coherent risk measures (e.g. CVaR) satisfy:

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5. **Law invariance** : if $Z_i \sim F_i$, $Z_j \sim F_j$ and $F_i = F_j$, then
$$\rho(Z_i) = \rho(Z_j)$$

i.e. Risk only depends on distribution

AXIOMS OF RISK MEASURES

Decision maker's risk measure satisfies :

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Decision maker's risk measure satisfies :

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3. **Convexity** :
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6. **What else ???**

... We can ask or observe the DM.

PREFERENCE ELICITATION

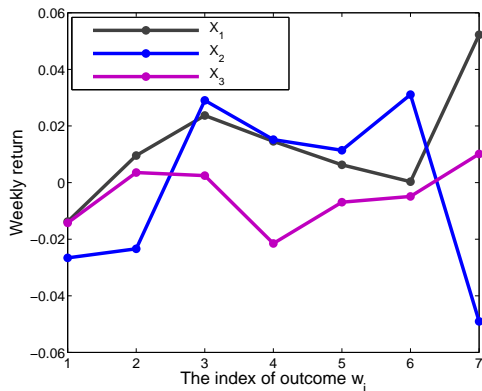


Figure: Three risk profiles

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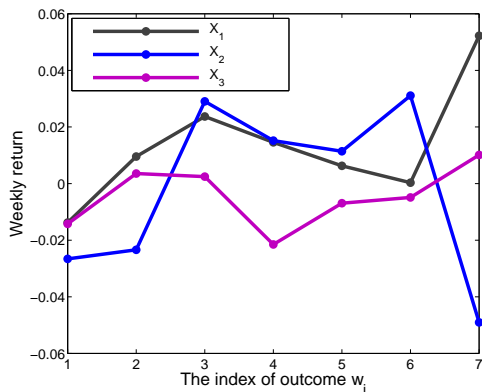


Figure: Three risk profiles

1. **Q1**: $X_1? \succeq X_3$

PREFERENCE ELICITATION

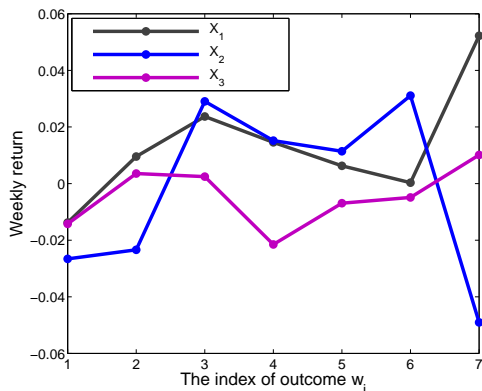


Figure: Three risk profiles

- Q1** : $X_1 \succcurlyeq X_3$ **A1** : Monotonicity $\Rightarrow \rho(X_1) \geq \rho(X_3)$

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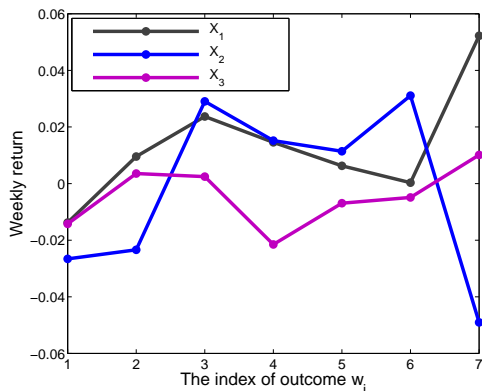


Figure: Three risk profiles

- Q1** : $X_1 \succcurlyeq X_3$ **A1** : Monotonicity $\Rightarrow \rho(X_1) \geq \rho(X_3)$
- Q2** : $X_1 \succcurlyeq X_2$

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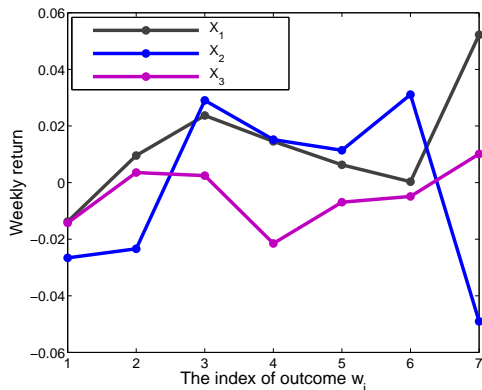


Figure: Three risk profiles

- Q1** : $X_1 \succcurlyeq X_3$ **A1** : Monotonicity $\Rightarrow \rho(X_1) \geq \rho(X_3)$
- Q2** : $X_1 \succcurlyeq X_2$ **A2** : ??(we can learn from the DM)

WHAT WE KNOW ABOUT ρ

1. **Monotonicity**
2. **Translation Invariance**
3. **Convexity**
4. **Positive homogeneity**
5. **Law invariance**
6. **Elicitation Results** : $\{\rho(X_j) \leq \rho(X_k)\}_{(j,k) \in \mathcal{I}}$

Back to the problem :

$$\min_{x \in \mathcal{X}} \rho(Z(x, \xi))$$

Question : How should we choose the portfolio x when only the above information about ρ is known ?

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ROBUST OPTIMIZATION FORMULATION

We propose the following minmax formulation

$$\min_{x \in \mathcal{X}} \sup_{\rho \in \mathcal{R}} \rho(Z(x, \xi)),$$

where $\mathcal{R} := \{\rho \mid \rho \text{ satisfies a subset of (1) to (6)}\}$

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THE ROBUST MEASURE AND OPTIMIZATION

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Fact 1 :

If ρ is a convex/coherent/law inv. risk measure, then

$\rho' = \sup_{\rho \in \mathcal{R}} \rho$ is also a convex/coherent/law inv. risk measure.

THE ROBUST MEASURE AND OPTIMIZATION

Fact 1 :

If ρ is a convex/coherent/law inv. risk measure, then $\rho' = \sup_{\rho \in \mathcal{R}} \rho$ is also a convex/coherent/law inv. risk measure.

Fact 2 :

Assuming that

- ▶ Set \mathcal{X} is convex
- ▶ Random vector ξ has N possible outcomes

then the risk vs. return optimization problem is a convex optimization problem that can be solved in polynomial time.

ROBUST CONVEX RISK MEASURE

Let's consider the problem

$$\underset{x \in \mathcal{X}}{\text{minimize}} \quad \sup_{\rho \in \mathcal{R}_1} \rho(Z(x, \xi)) ,$$

where $\mathcal{R}_1 := \{\rho \mid \rho \text{ satisfies conditions (1), (2), (3), and (6)}\}$

1. **Monotonicity**
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ROBUST CONVEX RISK MEASURE

The optimization problem can be equivalently formulated as the following **finite dimensional convex optimization problem**

$$\begin{aligned}
 (P) \quad & \min_{x \in \mathcal{X}, t, \theta} \quad t \\
 & \text{s.t.} \quad Z(x, \xi_i) + t \geq [X_1(\xi_i) \cdots X_m(\xi_i)]\theta + \delta^{*\top} \theta, \quad \forall i = 1, \dots, N \\
 & \quad \mathbf{1}^\top \theta = 1, \quad \theta \geq 0,
 \end{aligned}$$

where δ^* is the optimal solution of

$$\begin{aligned}
 \max_{\delta, \lambda} \quad & \sum_i \delta_i \\
 \text{s.t.} \quad & \delta_j \leq \delta_k, \quad \forall (j, k) \in \mathcal{I} \\
 & \delta_j \geq \delta_i - \lambda_i^\top (X_j - X_i), \quad \forall i, j \\
 & \mathbf{1}^\top \lambda = 1 \quad \& \quad \lambda_i \geq 0, \quad \forall i
 \end{aligned}$$

OUTLINE OF THE REFORMULATION PROCEDURE

We reformulate the problem from the perspective of acceptance sets (Föllmer and Schied 2002)

$$\rho_{\mathcal{A}}(Z) := \inf_{t \in \mathbb{R}} \{t \mid Z + t \in \mathcal{A}\}.$$

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Our goal is to characterize the **worst-case** set \mathcal{A}^* for a risk profile Z

$$\sup_{\mathcal{A} \in \mathbb{A}} \rho_{\mathcal{A}}(Z),$$

where $\mathbb{A} := \left\{ \mathcal{A} \mid \begin{array}{l} \rho_{\mathcal{A}} = \text{convex risk measure} \\ \rho_{\mathcal{A}}(X_j) \leq \rho_{\mathcal{A}}(X_k), \forall (j, k) \in \mathcal{I} \end{array} \right\}$ denotes a **set of acceptance sets** that are consistent with given information.

OUTLINE OF THE REFORMULATION PROCEDURE

We prove that the worst-case measure satisfies for all Z :

$$\sup_{\mathcal{A} \in \mathbb{A}} \rho_{\mathcal{A}}(Z) = \sup_{\delta \in \Delta} \sup_{\mathcal{A} \in \mathbb{A}(\delta)} \rho_{\mathcal{A}}(Z)$$

where

$$\mathbb{A}(\delta) := \left\{ \mathcal{A} \mid \begin{array}{l} \rho_{\mathcal{A}} = \text{convex risk measure} \\ \rho_{\mathcal{A}}(X_i) = \delta_i, \forall i \end{array} \right\}$$

and

$$\Delta = \{ \delta \in \mathfrak{R}^m \mid \mathbb{A}(\delta) \neq \emptyset \ \& \ \delta_j \leq \delta_k, \forall (j, k) \in \mathcal{I} \}$$

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where

$$\Delta = \{\delta \in \mathbb{R}^m \mid \mathbb{A}(\delta) \neq \emptyset \text{ \& } \delta_j \leq \delta_k, \forall (j, k) \in \mathcal{I}\}$$

and $\mathcal{H}(\delta)$ is a convex polyhedron with the points $\{X_i + \delta_i\}$ as vertices

$$\mathcal{H}(\delta) = \left\{ y \in \mathbb{R}^N \mid \exists \theta \in \mathbb{R}^m, \begin{array}{l} y \geq [X_1 \ X_2 \ \cdots \ X_m] \theta + \delta^T \theta \\ \mathbf{1}^\top \theta = 1, \ \theta \geq 0 \end{array} \right\}$$

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DETAILS OF EXPERIMENTS

We consider a static portfolio optimization problem with 4 assets over a period of one week

$$\min_{x \geq 0, \mathbf{1}^\top x = 1} \rho(R^\top x)$$

We simulate a decision maker's true risk attitude using the following unknown law inv. coherent risk measure

$$\rho := 0.1 \cdot \text{CVaR}_{20\%} + 0.9 \cdot \text{CVaR}_{95\%}.$$

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DETAILS OF EXPERIMENTS

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DETAILS OF EXPERIMENTS

Use historical data about weekly returns of 14 assets from July 2007 to June 2012.

- ▶ On any given week, last 13 weeks' returns constitute the outcome space
- ▶ For elicitation, we use a number of 13 weeks risk profiles from 2007 and 2008
- ▶ We report on 4000 experiments. For each one:
 - ▶ We randomly draw a date between 2009 and 2012
 - ▶ We randomly draw 4 assets for portfolio optimization
 - ▶ Performance of obtained portfolios is measured using true risk measure

NUMERICAL RESULTS

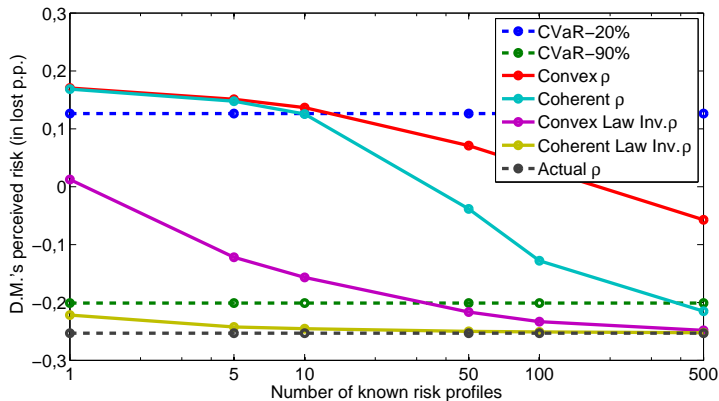


Figure: Average perceived risk for the optimized portfolios over 4000 experiments

CONCLUSION

- ▶ Assuming a particular form of CVaR can be misleading, one can instead use an ambiguity averse risk measure formulation
- ▶ Impact of information about global attitude is significant but can be replaced with information about risk profiles
- ▶ The measures that account for law invariance can achieve nearly optimal performance with a small amount of additional information

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- ▶ Impact of information about global attitude is significant but can be replaced with information about risk profiles
- ▶ The measures that account for law invariance can achieve nearly optimal performance with a small amount of additional information

- ▶ In Armbruster and Delage (2012), we develop a similar framework but for expected utility theory