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# Risk Adjusted Probabilities in Portfolio Optimization with Coherent Measures of Risk

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# General Portfolio Optimization Problem

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## Portfolio Optimization Problem

- We consider **n-assets** whose returns  $\mathbf{R}^j$  are integrable random variables, on some probability space  $(\Omega, \mathbf{F}, \mathbf{P})$ .
- The vector  $\mathbf{z} \in \mathbf{R}^n$  represents our asset allocation, with each  $z_j$  equal to the fraction of  $C$  invested in asset  $j$
- The set of possible asset allocations

$$\mathbf{Z} = \{z \in \mathbf{R}^n : z_1 + \dots + z_n = C, z_j \geq 0, j = 1..n\} \quad (1)$$

- The return of the portfolio is given by  $\mathbf{R}^T \mathbf{z}$
- Abstract risk-averse portfolio optimization problem.

# Coherent risk measures

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- $(\Omega, F, P) \rightarrow$  probability space
- $X : \Omega \rightarrow R \rightarrow$  uncertain outcome
- $K \rightarrow$  vector space of possible outcomes  $K \in \mathcal{L}_1(\Omega, F, P)$

**Definition:** A coherent measure of risk is a functional  $\rho : K \rightarrow R$  satisfying the following axioms:

- **Convexity:**  $\rho(\alpha X + (1 - \alpha)Y) \leq \alpha\rho(X) + (1 - \alpha)\rho(Y)$ , for all  $X, Y \in K$  and all  $\alpha \in [0, 1]$ ;
- **Monotonicity:** If  $X, Y \in K$ , and  $X(\omega) \leq Y(\omega) \forall \omega \in \Omega$ , then  $\rho(X) \geq \rho(Y)$
- **Translational Equivariance:** If  $\alpha \in R$  and  $X \in K$ , then  $\rho(X + \alpha) = \rho(X) - \alpha$
- **Positive Homogeneity:** If  $t > 0$  and  $X \in K$ , then  $\rho(tX) = t\rho(X)$

# Examples

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## Mean-risk model

$$\rho(X) = -E[X] + \lambda r[X] \quad (2)$$

for certain  $r[\cdot]$  and  $\lambda$

## Semideviation

$$r[X] = \sigma_p(X) = E[(E[X] - X)_+^p]^{\frac{1}{p}} \quad (3)$$

## Weighted Mean Deviation from Quantile

$$r_\alpha(X) = \min_{\eta \in R} E[\max(\frac{1-\alpha}{\alpha}(\eta - X), X - \eta)], \quad \alpha \in (0, 1) \quad (4)$$

## Risk-Averse Portfolio Optimization Problem

$$\min_{z \in Z} \rho(R^T z) \quad (5)$$

## Outline

- Examine this problem when  $\rho$  is a coherent risk measure
- Derive an equivalent dual problem
- Dual Optimality conditions
- Derivation of risk - adjusted probability measures
- Construction of risk-adjusted probability measures

# Representation Theorem

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- Let  $M$  denote the space of regular, countably additive signed measures,  $\mathbf{u}$  on  $(\Omega, F)$ , absolutely continuous w.r.t.  $P$ . The densities  $\frac{d\mathbf{u}}{dP} \in L_\infty(\Omega, F, P)$
- Let  $\mathbf{P}$  denote the set of probability measures in  $M$

**Representation Theorem:** If  $\rho$  is a lower semicontinuous coherent measure of risk, then there exists a convex and weakly\* closed set  $A \subset \mathbf{P}$  such that

$$\rho(X) = \sup_{\mathbf{u} \in A} \left( - \int_{\Omega} X(\omega) \mathbf{u}(d\omega) \right), \quad X \in K \quad (6)$$

The mean-risk models with semideviations and deviations from quantile satisfy assumptions of theorem. The portfolio optimization problem can be written as

$$\min_{z \in Z} \sup_{\mathbf{u} \in A} \left( - \int_{\Omega} R^T(\omega) z \mathbf{u}(d\omega) \right). \quad (7)$$

## Optimality Theorem

**Theorem:** Suppose  $\rho$  is a continuous coherent measure of risk. A point  $\bar{z}$  is an optimal solution of problem (6)  $\Leftrightarrow \exists$  a convex and weakly\* closed set  $\bar{A} \subset A$  such that  $\forall$  probability measures  $\bar{u} \in \bar{A}$  the point  $\bar{z}$  is also a solution of the problem

$$\max_{z \in Z} \int_{\Omega} R^T(\omega) z \bar{u}(d\omega). \quad (8)$$

Furthermore, the set  $\bar{A}$  is the set of solutions to the dual problem

$$\min_{u \in A} \max_{z \in Z} \int_{\Omega} R^T(\omega) z u(d\omega). \quad (9)$$

# Proof

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$F(z, u)$  function defined on  $Z \times A$ ,

$$F(z, u) = \int_{\Omega} R^T(\omega) z u(d\omega) \quad (10)$$

The optimal value of  $F(z, u)$  occurs at saddle point  $(\bar{z}, \bar{u})$ ,

$$F(z, \bar{u}) \leq F(\bar{z}, \bar{u}) \leq F(\bar{z}, u) \quad (11)$$

The optimal portfolio  $\bar{z}$  optimizes expected return w.r.t the probability measure  $\bar{u}$ .

**$u$  is the risk-adjusted probability measure**

## Discrete case

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- Assume our probability space is finite, with  $N$  elementary events  $\omega_1, \dots, \omega_N$ , and corresponding probabilities  $\mathbf{p}_1, \dots, \mathbf{p}_N$
- The **Portfolio return** is given by  $\mathbf{X}_z = \sum_{j=1}^N z_j \mathbf{R}_j$
- Set of possible portfolios is given by the simplex  
 $\mathbf{Z} = \{z \in \mathbf{R}^n : z_1 + z_2 + \dots + z_n = 1, z_j \geq 0, j = 1 \dots n\}$

The portfolio problem in this case can be written as

$$\max_{z \in \mathbf{Z}} \min_{u \in A} \langle u, R^T z \rangle \quad (12)$$

The dual problem has form

$$\min_{u \in A} \max_{z \in \mathbf{Z}} \langle u, R^T z \rangle \quad (13)$$

This can be interpreted as a matrix game, with payoff matrix  $R^T$  and mixed strategies of players represented by portfolio allocation  $z$  and measure  $u$

# mean -semideviation

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## The mean-semideviation model

$$\min_{z \in Z} -E[X] + \lambda \sigma_1(X) \quad (14)$$

where  $\sigma_1$  is the semideviation risk measure, with  $p = 1$  and  $\lambda \in [0, 1]$  some fixed constant.

$$\sigma_1 = E \max(E[X] - X, 0) \quad (15)$$

## Discrete case

$$\min_{z \in Z} -\langle p, R^T z \rangle + \lambda \sum_{i=1}^N p_i \max(\langle p, R^T z \rangle - \langle r_i, z \rangle, 0) \quad (16)$$

where  $r_i \in R^n$  represents vector of asset returns in event  $i$ .

# Lagrangian

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Equivalent formulation of (12)

$$\begin{aligned} \text{Minimize} \quad & -\langle p, R^T z \rangle + \lambda \langle p, s \rangle \\ \text{s.t.} \quad & s_i \geq \langle p, R^T z \rangle - \langle r_i, z \rangle \quad (1) \\ \text{s.t.} \quad & s \geq 0 \quad z \in Z \end{aligned}$$

## The Lagrange Function

$$L(z, s, \xi) = (\langle \xi, 1 \rangle - 1) \langle p, R^T z \rangle - \langle \xi, R^T z \rangle + \langle \lambda p - \xi, s \rangle \quad (17)$$

where  $\xi_i$  denote lagrange multipliers associated with constraints in (1)

# Game-Theoretic model

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**Theorem:** Suppose  $\rho(X) = -E(X) + \lambda\sigma_1(X)$  with  $\lambda \in [0, 1]$ . A vector  $\bar{z}$  and a measure  $\bar{u}$  constitute a saddle point of game (9)  $\Leftrightarrow$  the vector  $z$  is a solution of problem (1) and

$$\bar{u} = (\mathbf{1} - \langle \bar{\xi}, \mathbf{1} \rangle \mathbf{p} + \bar{\xi}, \quad (18)$$

where  $\bar{\xi}$  are the lagrange multipliers associated with constraints in (1).

The convex programming dual problem coincides with game-theoretic dual

$$\max_{u \in A} \min_{z \in Z} \langle -u, R^T z \rangle \quad (19)$$

where the set of probability measures  $A$  is given by

$$A = -\partial\rho[0] = \{(1 - \lambda\langle g, \mathbf{1} \rangle)p + \lambda g : |g_i| \leq p_i, i = 1, \dots, N\} \quad (20)$$

# Quantile

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## The mean-deviation from quantile model

$$\rho(X) = -E[X] + \lambda r_\alpha[X] \quad (21)$$

where  $\lambda \in [0, 1]$  is fixed. and

$$r_\alpha(X) = \min_{\eta \in R} E[\max(\frac{1-\alpha}{\alpha}(\eta - X), X - \eta)], \quad \alpha \in (0, 1) \quad (22)$$

## Discrete Case

$$\rho(X) = -\langle p, X \rangle + \lambda \min_{\eta \in R} \sum_{i=1}^N p_i \max(\frac{1-\alpha}{\alpha}(\eta - x_i), x_i - \eta). \quad (23)$$

# Lagrange function

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Equivalent formulation of (18)

$$\begin{aligned} \text{Minimize} \quad & -\langle p, R^T z \rangle + \lambda \min_{\eta \in R} \sum_{i=1}^N p_i \left( \frac{1-\alpha}{\alpha} v_i + u_i \right) \\ \text{s.t.} \quad & \langle r_i, z \rangle - \eta = u_i - v_i, \quad i = 1, \dots, N, \quad (1) \\ \text{s.t.} \quad & u_i, v_i \geq 0, \quad i = 1, \dots, N, \\ \text{s.t.} \quad & \eta \in R \end{aligned}$$

## The Lagrange Function

$$\begin{aligned} L(z, \eta, u, v, \xi) \\ = -\langle p - \xi, R^T z \rangle - \eta \langle \xi, 1 \rangle + \left\langle \frac{\lambda(1-\alpha)}{\alpha} p + \xi, v \right\rangle + \langle \lambda p - \xi, u \rangle \end{aligned}$$

# Theorem

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**Theorem:** Suppose  $\rho(X) = -E[X] + \lambda r_\alpha(X)$  with  $\lambda \in [0, 1]$ . A vector  $\bar{z}$  and a vector  $\bar{u}$  constitute a saddle point of the game (9)  $\Leftrightarrow$  the vector  $z$  is a solution of problem (1) and

$$\bar{u} = p - \bar{\xi}, \quad (24)$$

where  $\bar{\xi}$  are the lagrange multipliers.

The convex programming dual problem coincides with game-theoretic dual

$$\max_{u \in A} \min_{z \in Z} \langle -u, R^T z \rangle \quad (25)$$

where the set of probability measures  $A$  is given by

$$A = -\partial\rho[0] = \left\{ (1 - \lambda)p + \lambda g : 0 \leq g_i \leq \frac{p_i}{\alpha}, i = 1, \dots, N, \sum_{i=1}^N g_i = 1 \right\} \quad (26)$$

# Law invariant risk

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**Kusuoka Theorem:** For every lower semicontinuous law invariant coherent risk measure  $\rho$  on  $L_\infty(\Omega, F, 1)$ , there exists a convex set  $N$  of probability measures on  $[0,1]$  such that

$$\rho(X) = \sup_{v \in N} \int_0^1 AVaR_\alpha[X] v(d\alpha). \quad (27)$$

Using the the following identity for  $AVaR_\alpha(X)$ ,

$$AVaR_\alpha(X) = -\frac{1}{\alpha} \int_0^\alpha q_t(X) dt = -E[X] + r_\alpha[X] \quad (28)$$

we can give an equivalent formulation

$$\rho(X) = -E[X] + \sup_{v \in N} \int_0^1 r_\alpha[X] v(d\alpha). \quad (29)$$

where  $r_\alpha(X)$  is the weighted mean deviation from quantile.

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## Kusuoka model discrete case

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Every coherent law invariant risk measure corresponds to a mean-risk model, with the risk functional

$$\kappa_N[X] = \sup_{v \in \mathcal{N}} \int_0^1 r_\alpha[X] v(d\alpha) \quad (30)$$

In the discrete case, the risk-functional (29) takes the form

$$\kappa_N[X] = \sup_{v \in \mathcal{N}} \sum_{k=1}^N v_k r_{\alpha_k}[X], \quad (31)$$

with  $\alpha_k = k/N$ .

### Mean-Risk Portfolio Optimization

$$\text{Minimize}_{z \in Z} - E[X R^T z] + \lambda \kappa_N[R^T z] \quad (32)$$

# Spectral Risk Measure

## Portfolio Optimization problem for spectral measure of risk

$$\begin{aligned} \text{Minimize} \quad & -\langle p, R^T z \rangle + \lambda \sum_{k=1}^N v_k \sum_{i=1}^N p_i \left( \frac{1 - \alpha_k}{\alpha_k} v_{ik} + u_{ik} \right) \quad (A) \\ \text{s.t.} \quad & \langle r_i, z \rangle - \eta_k = u_{ik} - v_{ik}, \quad i, k = 1, \dots, N \\ & u_{ik}, v_{ik} \geq 0, \quad i, k = 1, \dots, N, \\ & \eta_k \in R, \quad k = 1, \dots, N \\ & z \in Z \end{aligned}$$

We denote by  $\xi_{ik}$  the lagrange multipliers associated with constraints in (A). The matrix of lagrangian multipliers is denoted by  $\Xi$ .

# Theorem

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**Theorem** Suppose  $\rho(X) = -E[X] + \lambda\kappa_N[X]$  with  $\lambda \in [0, 1]$  and  $N = \{v\}$ . A vector  $\bar{z}$  and a measure  $\bar{u}$  constitute a saddle point of the game(9)  $\Leftrightarrow$  the vector  $z$  is a solution of problem (A) and

$$\bar{u} = \mathbf{p} - \bar{\Xi}\mathbf{1}, \quad (33)$$

where  $\bar{\Xi}$  is a solution of the dual problem (34).

# Numerical Examples

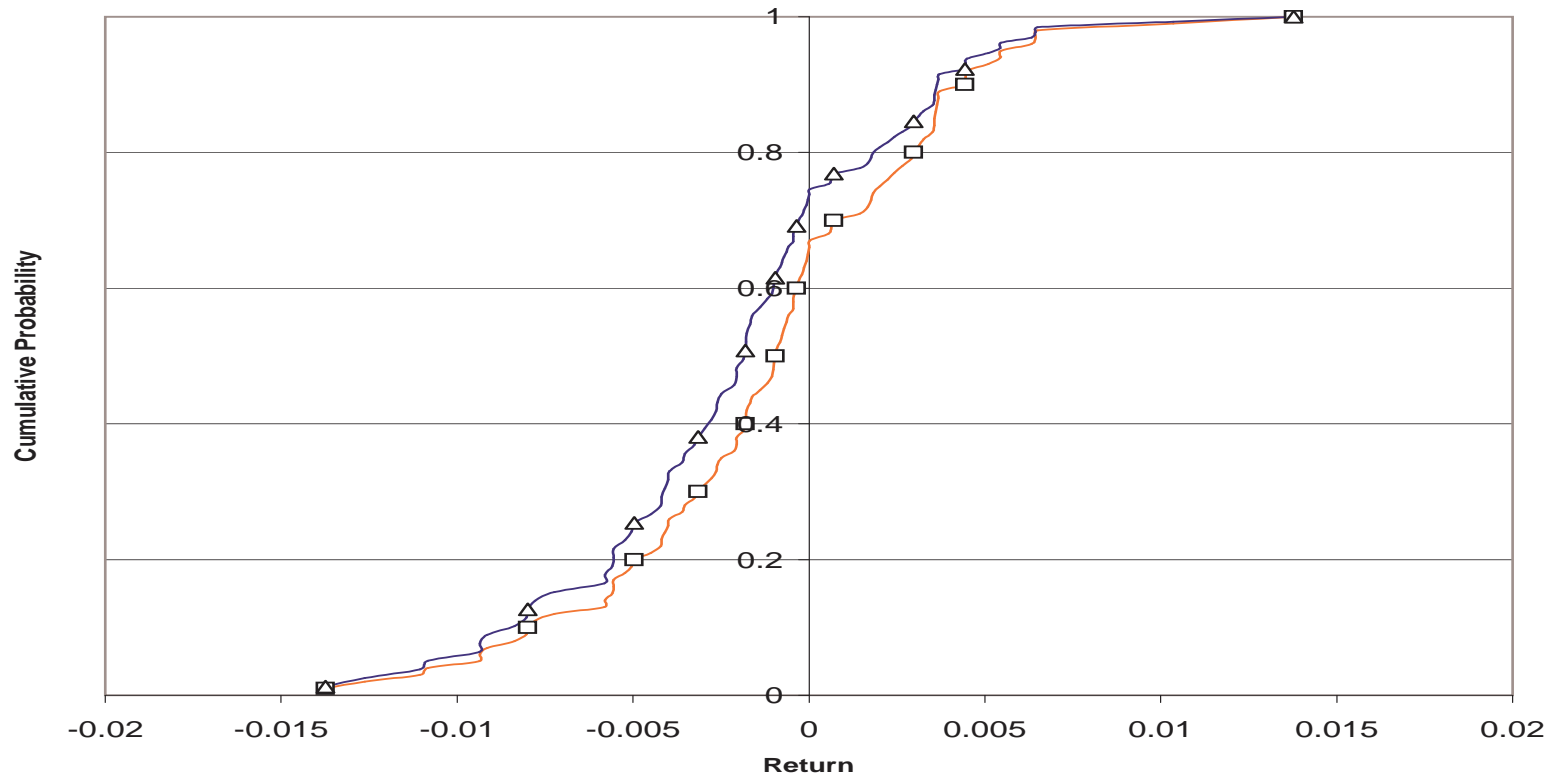


Figure 1: Cumulative distribution curves of market portfolio for the semideviation measure.

# Numerical examples

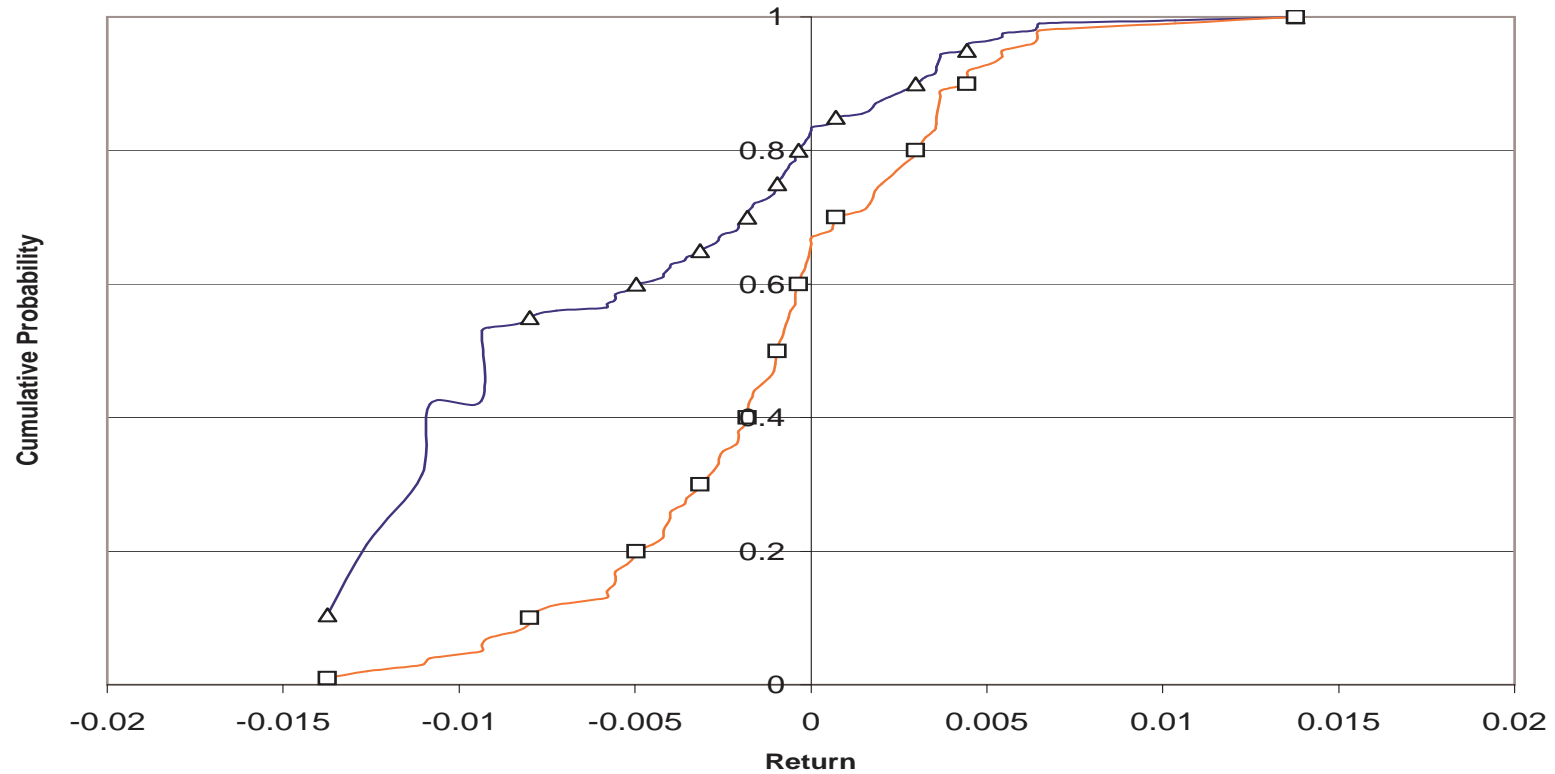


Figure 2: Cumulative distribution curves of market portfolio for the deviation from quantile measure.

# Numerical Examples

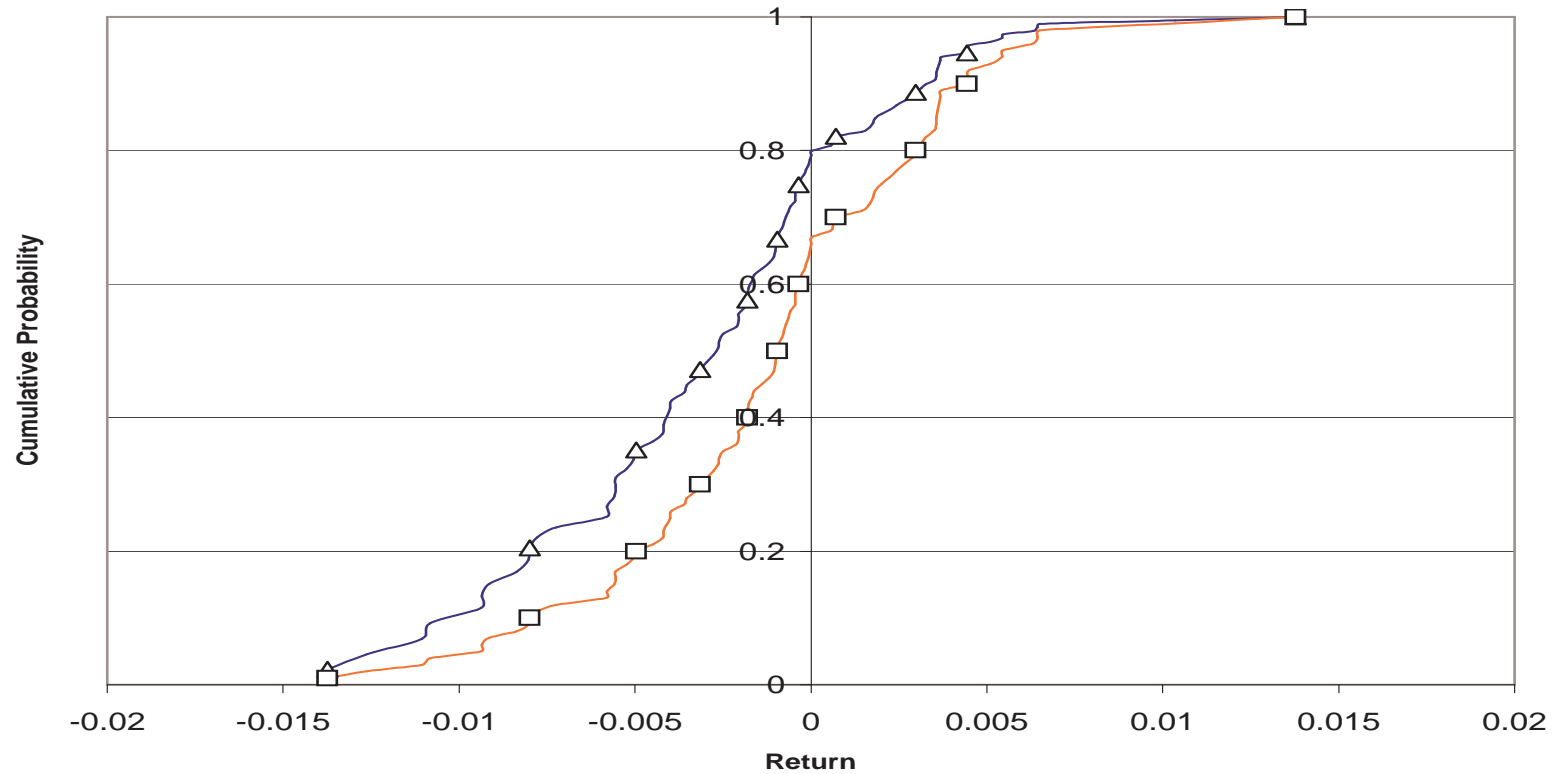


Figure 3: Cumulative distribution curves of market portfolio for the spectral measure.

# Numerical Examples

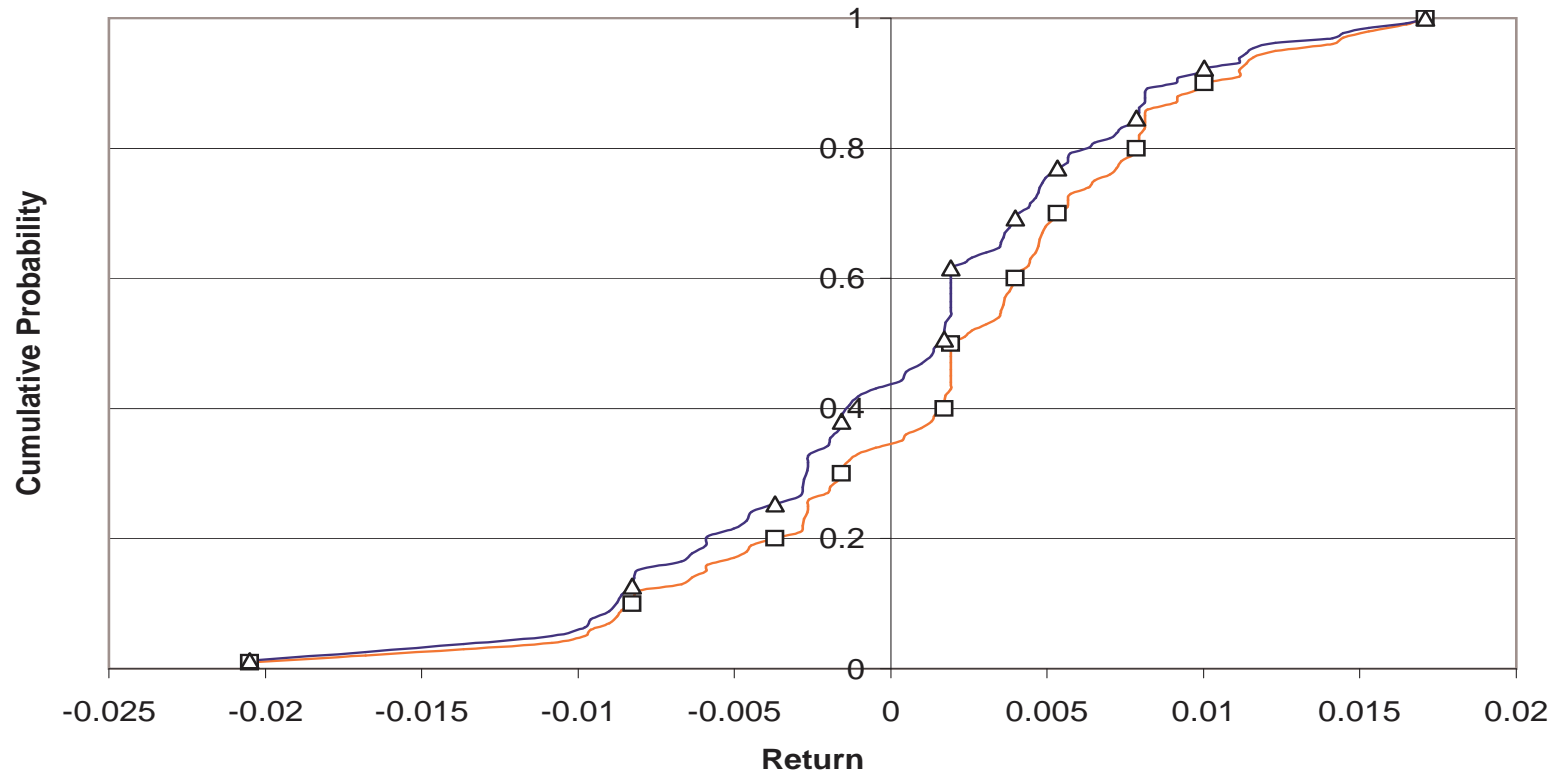


Figure 4: The CDF curves corresponding to optimal portfolio returns for the semideviation measure.

# Numerical Examples

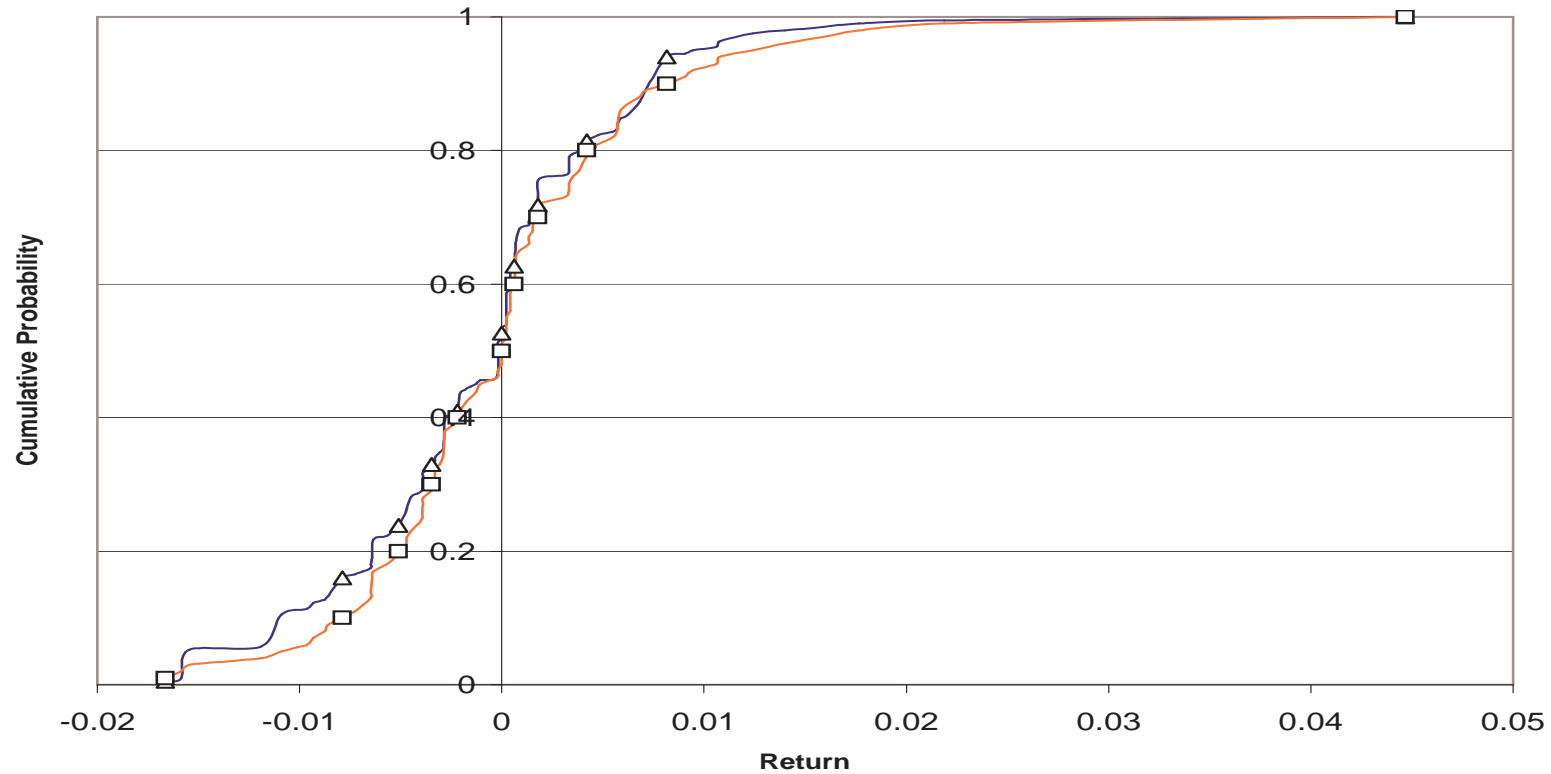


Figure 5: The CDF curves corresponding to optimal portfolio returns for the deviation from quantile measure.

# Numerical Examples

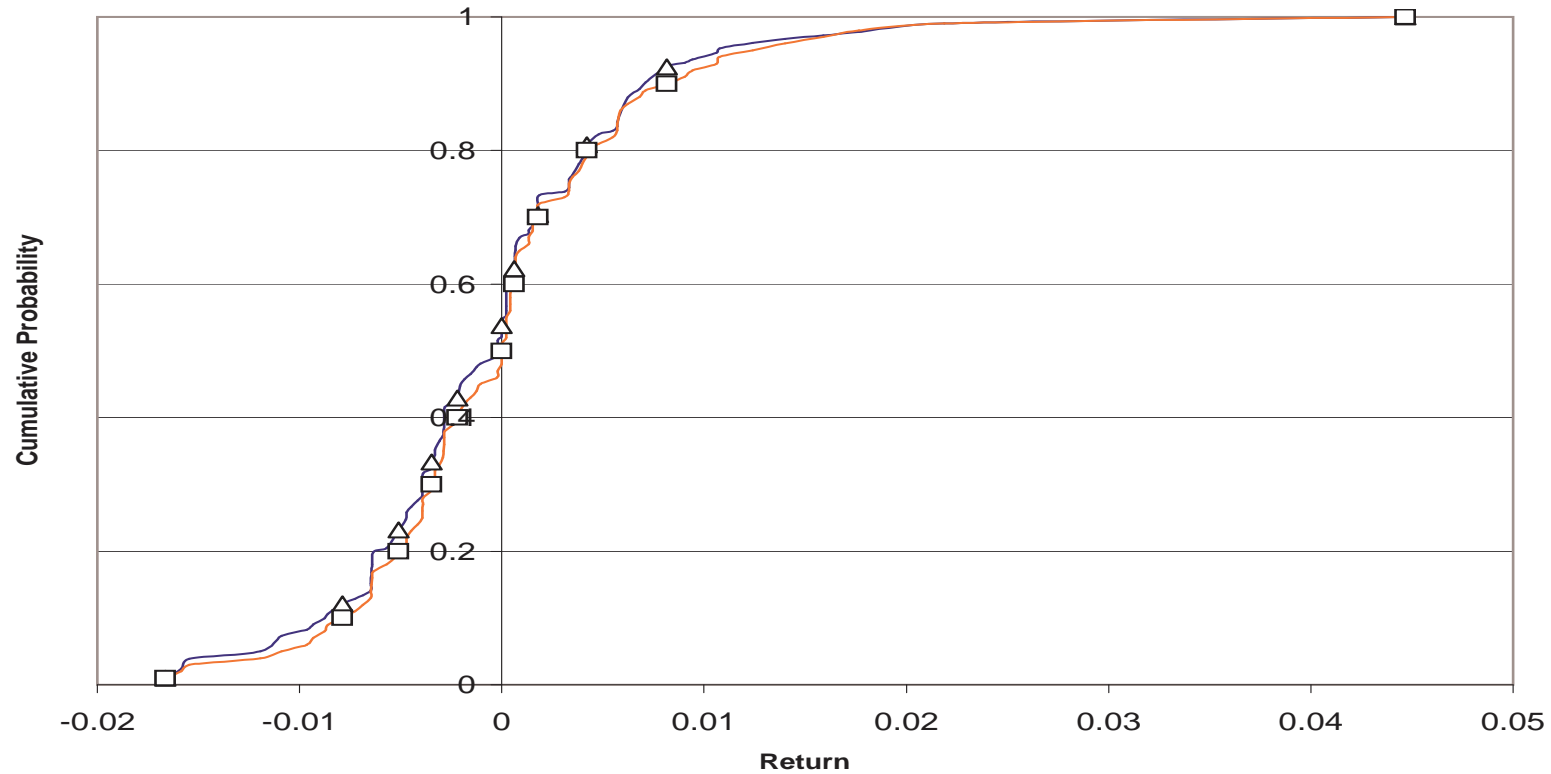


Figure 6: The CDF curves corresponding to optimal portfolio returns for the spectral measure.

## Future Research

- Two stage portfolio optimization problem
- Derive Dual problem and optimality conditions for dual
- Derive Risk-Adjusted probability measures for the two stage problem
- Construction of risk-adjusted probability measures
- Extension to multistage portfolio optimization