Formulations of Stochastic Programming Problems and Risk Aversion

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Why Probabilistic Models?

- Wealth of results of probability theory
- Connection to real data via statistics
- Universal language (engineering, economics, medicine, ...)
- Probability space (Ω, \mathcal{F}, P)
- Decision space X
- Random outcome (*e.g.*, cost) $Z_{X}(\omega)$, $Z: X \times \Omega \to \mathbb{R}$

Expected Value Model

$$\min_{x} \mathbb{E}[Z_{x}] = \int_{\Omega} Z_{x}(\omega) P(d\omega)$$

It optimizes the outcome on average (Law of Large Numbers?)

What is Risk?

Existence of unlikely and undesirable outcomes - high $Z_x(\omega)$ for some ω

Expected Utility Models (von Neumann and Morgenstern, 1944)

$$\min_{x \in X} \mathbb{E}\left[u(Z_x)\right] \qquad \left(=\int_{\Omega} u(Z_x(\omega)) dP(\omega)\right)$$

 $u: \mathbb{R} \to \mathbb{R}$ is a nondecreasing disutility function

Rank Dependent Utility (Distortion) Models (Quiggin, 1982; Yaari, 1987)

$$\min_{x \in X} \int_0^1 F_{Z_x}^{-1}(p) \, dw(p) \qquad F_{Z_x}^{-1}(\cdot) \text{ - quantile function}$$

 $w : [0,1] \rightarrow \mathbb{R}$ is a nondecreasing rank dependent utility function

Existence of utility functions is derived from systems of axioms, but in practice they are difficult to elicit *W* is a lottery of *Z* and *V* with probabilities $\alpha \in (0, 1)$ and $(1 - \alpha)$, if the probability measure μ_W induced by *W* on \mathbb{R} is the corresponding convex combination of the probability measures μ_Z and μ_V of *Z* and *V*:

$$\mu_W = \alpha \mu_Z + (1 - \alpha) \mu_V.$$

We write the lottery symbolically as

$$W = \alpha Z \oplus (1 - \alpha) V.$$

For law invariant preferences on the space of random vectors with values in \mathbb{R} , von Neumann introduced the axioms:

Independence Axiom: For all $Z, V, W \in \mathcal{Z}$ one has

$$Z \triangleleft V \implies \alpha Z \oplus (1-\alpha)W \triangleleft \alpha V \oplus (1-\alpha)W, \quad \forall \alpha \in (0,1)$$

Archimedean Axiom: If $Z \triangleleft V \triangleleft W$, then $\alpha, \beta \in (0, 1)$ exist such that

$$\alpha Z \oplus (1-\alpha)W \triangleleft V \triangleleft \beta Z \oplus (1-\beta)W$$

Integral Representation

Suppose the total preorder \trianglelefteq on \mathcal{Z} is law invariant, and satisfies the independence and Archimedean axioms. Then it has an "affine" numerical representation $U : \mathcal{Z} \to \mathbb{R}$:

$$U(\alpha Z \oplus (1-\alpha)V) = \alpha U(Z) + (1-\alpha)U(V).$$

If \leq is weakly continuous, then a continuous and bounded function $u : \mathbb{R} \to \mathbb{R}$ exists, such that

$$U(Z) = \mathbb{E}[u(Z)] = \int_{\Omega} u(Z(\omega)) P(d\omega).$$

New proof by separation theorem - D. & R. 2012

In a more general setting, we may consider only r.v. with finite moments, and then the boundedness condition on $u(\cdot)$ can be relaxed.

$$U(Z) = \mathbb{E}[u(Z)] = \int_{\Omega} u(Z(\omega)) P(d\omega)$$

Monotonicity

The total preorder \trianglelefteq is monotonic with respect to the partial order \le , if $Z \le V \implies Z \trianglelefteq V$.

We focus on \mathcal{Z} containing integrable random vectors.

Risk Aversion

A preference relation \trianglelefteq on \mathcal{Z} is *risk-averse*, if $\mathbb{E}[Z|\mathcal{G}] \trianglelefteq Z$, for every $Z \in \mathcal{Z}$ and every σ -subalgebra \mathcal{G} of \mathcal{F} .

Nondecreasing Convex Disutility

Suppose a total preorder \trianglelefteq on \mathcal{Z} is weakly continuous, monotonic, risk-averse, and satisfies the independence axiom. Then the utility function $u : \mathbb{R} \to \mathbb{R}$ is nondecreasing and convex.

Axioms of Dual Utility Theory (Yaari 1987)

Real random variables Z_i , i = 1, ..., n, are comonotonic, if

$$(Z_i(\omega) - Z_i(\omega'))(Z_j(\omega) - Z_j(\omega')) \ge 0$$

for all $\omega, \omega' \in \Omega$ and all $i, j = 1, \ldots, n$.

Dual Independence Axiom: For all comonotonic random variables Z, V, and W in \mathcal{Z} one has

$$Z \triangleleft V \implies \alpha Z + (1 - \alpha)W \triangleleft \alpha V + (1 - \alpha)W, \quad \forall \, \alpha \in (0, 1)$$

Dual Archimedean Axiom: For all comonotonic random variables Z, V, and W in Z, satisfying the relations

$$Z \triangleleft V \triangleleft W,$$

there exist $\alpha, \beta \in (0, 1)$ such that

$$\alpha Z + (1-\alpha)W \triangleleft V \triangleleft \beta Z + (1-\beta)W$$

Affine Representation

If the total preorder \trianglelefteq on \mathcal{Z} is law invariant, and satisfies the dual independence and Archimedean axioms, then a numerical representation $U : \mathcal{Z} \to \mathbb{R}$ of \trianglelefteq exists, which satisfies for all comonotonic $Z, V \in \mathcal{Z}$ and all $\alpha, \beta \in \mathbb{R}_+$ the equation

$$U(\alpha Z + \beta V) = \alpha U(Z) + \beta U(V).$$

Integral Representation

Suppose \mathcal{Z} is the set of bounded random variables. If, additionally, \trianglelefteq is continuous in \mathcal{L}_1 and monotonic, then a bounded, nondecreasing, and continuous function $w : [0, 1] \rightarrow \mathbb{R}_+$ exists, such that

$$U(Z)=\int_0^1 F_Z^{-1}(p) \ dw(p), \quad Z\in \mathcal{Z}.$$

Proof by separation - D. & R. 2012

$$U(Z) = \int_0^1 F_Z^{-1}(p) \, dw(p), \quad Z \in \mathcal{Z}$$
 (*)

Risk Aversion

A preference relation \trianglelefteq on \mathcal{Z} is *risk-averse*, if $\mathbb{E}[Z|\mathcal{G}] \trianglelefteq Z$, for every $Z \in \mathcal{Z}$ and every σ -subalgebra \mathcal{G} of \mathcal{F} .

Convex Rank-Dependent Utility

Suppose a total preorder \leq on Z is continuous, monotonic, and satisfies the dual independence axiom. Then it is risk-averse if and only if it has the integral representation (*) with a nondecreasing and convex function $w : [0, 1] \rightarrow [0, 1]$ such that w(0) = 0 and w(1) = 1.

Two Objectives

- Minimize the expected outcome, the mean $\mathbb{E}[Z_x]$
- Minimize a scalar measure of uncertainty of Z_x , the risk $r[Z_x]$

$$\begin{split} r[Z] &= \mathbb{V}ar[Z] \qquad (Markowitz' model) \\ \sigma_{\rho}^{+}[Z] &= \left(\mathbb{E}[(Z - \mathbb{E}Z)_{+}^{\rho}]\right)^{1/\rho} \qquad (semideviation) \\ \delta_{\alpha}^{+}[Z] &= \min_{\eta} \mathbb{E}\left[\max\left(\eta - Z, \frac{\alpha}{1 - \alpha}(Z - \eta)\right)\right] \qquad (deviation from quantile) \end{split}$$

 $r Z_x$ is nonlinear w.r.t. probability and possibly nonconvex in x

Example: Portfolio Optimization

 R_1, R_2, \ldots, R_n - random return rates of securities x_1, x_2, \ldots, x_n - fractions of the capital invested in the securities

Return rate of the portfolio (negative of)

$$Z_x = -(R_1x_1 + R_2x_2 + \cdots + R_nx_n)$$

Risk Optimization with Fixed Mean

$$\min_{x} r[Z_{x}]$$
s.t. $\mathbb{E}[Z_{x}] = \mu$ (parameter)
 $x \in X_{0}.$

Combined Mean–Risk Optimization

$$\min_{x \in X_0} \rho[Z_x] = \mathbb{E}[Z_x] + \kappa r[Z_x], \qquad 0 \le \kappa \le \kappa_{\max}$$

Interesting applications of parametric optimization

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Nonlinear Programming Formulations for Discrete Distributions

Suppose *Z* has finitely many realizations $z_1, z_2, ..., z_S$ with probabilities $p_1, p_2, ..., p_S$

$$\rho(Z) = \mathbb{E}[Z] + \kappa \sigma_m^+[Z] = \mathbb{E}[Z] + \kappa \left(\mathbb{E}[(Z - \mathbb{E}Z)_+^m]\right)^{1/m}$$
$$= \sum_{s=1}^S p_s z_s + \kappa \left(\sum_{s=1}^S p_s \left(z_s - \sum_{j=1}^S p_j z_j\right)_+^m\right)^{1/m}$$

Equivalent Problem (for m = 1 - linear programming)

$$p(Z) = \min_{v,\mu} \quad \mu + \kappa \left(\sum_{s=1}^{S} p_s v_s^m\right)^{1/m}$$

s.t.
$$\mu = \sum_{s=1}^{S} p_s z_s$$
$$v_s \ge z_s - \mu, \quad s = 1, \dots, S$$
$$v_s \ge 0, \qquad s = 1, \dots, S$$

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Formulations and Risk Aversion

Application to Portfolios

Suppose the vector of return rates has *S* realizations with probabilities p_1, p_2, \ldots, p_S

 R_{js} - return rate of asset j = 1, ..., n in scenario s = 1, ..., S

Equivalent Problem (for m = 1 - linear programming)

n x,z

$$\min_{z,v,\mu} \quad \mu + \kappa \left(\sum_{s=1}^{S} v_s^m\right)^{1/m}$$
s.t.
$$\mu = \sum_{s=1}^{S} p_s z_s$$

$$z_s = -\sum_{j=1}^{n} R_{sj} x_j, \quad s = 1, \dots, S$$

$$v_s \ge z_s - \mu, \qquad s = 1, \dots, S$$

$$v_s \ge 0, \qquad s = 1, \dots, S$$

$$x \in X_0$$

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Basket of 719 Securities. Mean–Semideviation Model



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Formulations and Risk Aversion

$$\rho(Z) = \mathbb{E}[Z] + \kappa r[Z]$$

Consistency with Stochastic Dominance (Ogryczak-R., 1997)

 $\mathbb{E}[u(Z)] \leq \mathbb{E}[u(W)], \forall \text{ nondecreasing and convex } u(\cdot) \Rightarrow \rho[Z] \leq \rho[W]$

Consistency with Pointwise Order (Artzner et. al., 1999)

$$Z \leq W$$
 a.s. $\Rightarrow \rho[Z] \leq \rho[W]$

Mean–semideviation and mean–deviation from quantile models are consistent for $0 \le \kappa \le 1$, but not mean–variance.

Unique optimal solutions of consistent optimization models

 $\min_{x\in X} \rho(Z_x)$

cannot be strictly dominated (in the corresponding sense)

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Formulations and Risk Aversion

A functional $\rho: \mathbb{Z} \to \mathbb{R}$ is a coherent risk measure if it satisfies the following axioms

- Convexity: $\rho(\lambda Z + (1 \lambda)W) \le \lambda \rho(Z) + (1 \lambda)\rho(W)$ $\forall \lambda \in (0, 1), Z, W \in \mathbb{Z}$
- Monotonicity: If $Z \leq W$ then $\rho(Z) \leq \rho(W)$, $\forall Z, W \in \mathcal{Z}$
- Translation Equivariance: $\rho(Z + a) = \rho(Z) + a$, $\forall Z \in \mathbb{Z}, a \in \mathbb{R}$
- Positive Homogeneity: $\rho(\tau Z) = \tau \rho(Z), \quad \forall Z \in \mathbb{Z}, \ \tau \geq 0$

Kijima-Ohnishi (1993) – no monotonicity Artzner-Delbaen-Eber-Heath (1999–) - space \mathcal{L}_{∞} R.-Shapiro (2005) – spaces \mathcal{L}_{n}, \ldots

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Kijima-Ohnishi (1993) – no monotonicity Artzner-Delbaen-Eber-Heath (1999–) - space \mathcal{L}_{∞} R.-Shapiro (2005) – spaces \mathcal{L}_{p}, \ldots

For simplicity, semideviation of order m = 1 with $\kappa = 1$:

$$\rho(Z) = \mathbb{E}[Z] + \mathbb{E}[(Z - \mathbb{E}Z)_+] = \mathbb{E}\{\max(\mathbb{E}[Z], Z)\}$$

Convexity follows from the convexity of $Z \mapsto \max(\mathbb{E}[Z], Z)$ a.s. Monotonicity follows from monotonicity of $Z \mapsto \max(\mathbb{E}[Z], Z)$ a.s. Translation follows from translation of $Z \mapsto \max(\mathbb{E}[Z], Z)$ a.s. Pos. Homogeneity follows from pos. homogeneity of $\max(\mathbb{E}[Z], Z)$ a.s.

Convex combination of coherent measures of risk is coherent $\rho(Z) = \lambda_1 \rho_1(Z) + \lambda_2 \rho_2(Z) + \dots + \lambda_L \rho_L(Z)$ $\lambda_1 + \lambda_2 + \dots + \lambda_L = 1,$ $\lambda_1 \ge 0, \ \lambda_2 \ge 0, \dots, \lambda_L \ge 0$

 $\rho(Z) = \mathbb{E}[Z] + \kappa \mathbb{E}[(Z - \mathbb{E}Z)_+]$ is coherent for $\kappa \in [0, 1]$

The Value at Risk at level $\alpha \in (0, 1)$ of a random cost $Z \in \mathcal{Z}$:

$$\mathsf{VoR}^+_{\alpha}(Z) \stackrel{\scriptscriptstyle \Delta}{=} \inf \{\eta : F_Z(\eta) \ge 1 - \alpha\} = F_Z^{-1}(1 - \alpha)$$

Monotonicity: $Z \leq V \Longrightarrow \operatorname{VeR}^+_{\alpha}(Z) \leq \operatorname{VeR}^+_{\alpha}(V)$ Translation: $\operatorname{VeR}^+_{\alpha}(Z+c) = \operatorname{VeR}^+_{\alpha}(Z) + c$, for all $c \in \mathbb{R}$ Positive Homogeneity: $\operatorname{VeR}^+_{\alpha}(\gamma Z) = \gamma \operatorname{VeR}^+_{\alpha}(Z)$, for all $\gamma \geq 0$ However, it is not convex

Counterexample: Two independent variables $Z = \begin{cases} 0 & \text{with probability } 1 - p \\ 1 & \text{with probability } p \end{cases} V = \begin{cases} 0 & \text{with probability } 1 - p \\ 1 & \text{with probability } p \end{cases}$

For $p < \alpha < 1$ we have $\operatorname{VeR}^+_{\alpha}(Z) = \operatorname{VeR}^+_{\alpha}(V) = 0$ If $p < \alpha < 1 - (1 - p)^2$, we have non-convexity

$$\operatorname{VeR}^+_{\alpha}\left(\lambda Z + (1-\lambda)V\right) > 0 = \lambda \operatorname{VeR}^+_{\alpha}(Z) + (1-\lambda)\operatorname{VeR}^+_{\alpha}(V)$$

Average Value at Risk

$$\mathsf{AVeR}^+_lpha(Z) riangleq rac{1}{lpha} \int_0^lpha \mathsf{VeR}^+_eta(Z) \, \mathsf{d}eta$$

If the $(1 - \alpha)$ -quantile of Z is unique

$$\mathsf{AVeR}^+_{\alpha}(Z) = \frac{1}{\alpha} \int_{\mathsf{VOR}^+_{\alpha}(Z)}^{\infty} z \, \mathsf{d}F_Z(z) = \mathbb{E}\Big[Z \,|\, Z \ge \mathsf{VOR}^+_{\alpha}(Z)\Big]$$

Extremal representation

$$\mathsf{AVeR}^+_lpha(Z) = \inf_{\eta \in \mathbb{R}} \left\{ \eta + rac{1}{lpha} \mathbb{E}[(Z - \eta)_+]
ight\}$$

The minimizer $\eta = V \circ R_{\alpha}(Z)$

Connection to weighted deviation from α -quantile:

$$\delta^+_{lpha}(Z) = \mathsf{AV}_{\mathfrak{A}}^+(Z) - \mathbb{E}[Z], \quad lpha \in [0, 1].$$

Extremal representation

$$\mathsf{AVeR}^+_{\alpha}(Z) = \inf_{\eta \in \mathbb{R}} \left\{ \eta + \frac{1}{\alpha} \mathbb{E} \left[(Z - \eta)_+ \right] \right\}$$

Convexity follows from joint convexity in (η, Z) of $\{\cdots\}$

Monotonicity follows from monotonicity w.r.t. Z of $\{\cdots\}$

Translation follows from $\eta \leftrightarrow \eta - c$ in $\{\cdots\}$

Pos. Homogeneity follows from pos. homogeneity in (η, Z) of $\{\cdots\}$

Linear Programming Representation of AV@R

Suppose *Z* has finitely many realizations $z_1, z_2, ..., z_S$ with probabilities $p_1, p_2, ..., p_S$

$$\min_{\boldsymbol{v},\eta} \quad \eta + \frac{1}{\alpha} \sum_{s=1}^{S} p_s \boldsymbol{v}_s$$
s.t. $\boldsymbol{v}_s \ge \boldsymbol{z}_s - \eta, \quad \boldsymbol{s} = 1, \dots, S$
 $\boldsymbol{v}_s \ge 0, \qquad \boldsymbol{s} = 1, \dots, S$

For portfolios we have to add the constraints

$$z_s = -\sum_{j=1}^n R_{sj} x_j, \quad s = 1, \dots, S$$
$$x \in X_0$$

and include z and x into the decision variables

Conjugate Duality of Risk Measures

Pairing of a linear topological space Z with a linear topological space Y of regular signed measures on Ω with the bilinear form

$$ig\langle \mu, Z ig
angle = \mathbb{E}_{\mu}[Z] = \int_{\Omega} Z(\omega) \, \mu(\mathsf{d}\omega)$$

We assume standard conditions on pairing and the polarity: $(\mathcal{Z}_+)^\circ = \mathcal{Y}_-$

Dual Representation Theorem

If $\rho : \mathbb{Z} \to \overline{\mathbb{R}}$ is a lower semicontinuous^{*} coherent risk measure, then $\rho(Z) = \max_{\mu \in \mathcal{R}} \int_{\Omega} Z(\omega) \mu(d\omega), \quad \forall Z \in \mathbb{Z}$

with a convex closed $\mathcal{A} \subset \mathcal{P}$ (set of probability measures in \mathcal{Y}).

Delbaen (2001), Föllmer-Schied (2002), R.-Shapiro (2005),

Rockafellar–Uryasev–Zabarankin (2006), ...

 * Lower semicontinuity is automatic if ho is finite and $\mathcal Z$ is a Banach lattice

Universality of AV_@R

 $Z \sim V$ means that Z and V have the same distribution, $\mu_Z = \mu_V$. $\rho : \mathcal{Z} \rightarrow \mathbb{R}$ is law invariant if $Z \sim V \Longrightarrow \rho(Z) = \rho(V)$

Kusuoka Theorem

If (Ω, \mathcal{F}, P) is atomless and $\rho : \mathcal{L}_1(\Omega, \mathcal{F}, P) \to \mathbb{R}$ is law invariant, then

$$ho(Z) = \sup_{\textit{m} \in \mathcal{M}} \int_{0}^{1} \mathsf{AVeR}^{+}_{lpha}(Z) \; \textit{m}(\textit{d}lpha)$$

where \mathcal{M} is a convex set of probability measures on (0, 1].

Spectral measure

$$ho(V) = \int_0^1 \operatorname{AVeR}^+_{lpha}(Z) m(dlpha)$$

Spectral measures have dual utility form:

$$\rho(Z) = \int_0^1 F_Z^{-1}(\beta) \, dw(\beta)$$

Optimization of Risk Measures

"Minimize" over $x \in X$ a random outcome $Z_x(\omega) = f(x, \omega), \omega \in \Omega$

Composite Optimization Problem

$$\min_{x \in X} \rho(Z_x) \tag{P}$$

Theorem

Let $x \mapsto Z_x(\omega)$ be convex and $\rho(\cdot)$ be coherent. Suppose that $\hat{x} \in X$ is an optimal solution of (P) and $\rho(\cdot)$ is continuous at $Z_{\hat{x}}$. Then there exists a probability measure $\hat{\mu} \in \partial \rho(Z_{\hat{x}}) \subseteq \mathcal{A}$ such that \hat{x} solves

$$\min_{x\in X} \mathbb{E}_{\hat{\mu}}[Z_x] = \min_{x\in X} \max_{\mu\in\mathcal{A}} \mathbb{E}_{\mu}[Z_x]$$

We also have the duality relation:

$$\min_{x\in X} \rho(Z_x) = \max_{\mu\in\mathcal{A}} \inf_{x\in X} \mathbb{E}_{\mu}[Z_x]$$

Duality in Portfolio Optimization - Game Model

Suppose the vector of return rates of assets has *S* realizations R_{js} - return rate of asset j = 1, ..., n in scenario s = 1, ..., S Portfolio return (negative) in scenario *s*

$$Z_{s}(x) = -\sum_{j=1}^{n} R_{js} x_{j}$$

Portfolio Problem

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

By homogeneity, we may assume that $\sum_{j=1}^{n} x_j = 1$

Equivalent Matrix Game

$$\max_{x \in X} \min_{\mu \in \mathcal{R}} \sum_{j=1}^{n} \sum_{s=1}^{S} x_j R_{js} \mu_s$$

- x mixed strategy of the investor
- μ mixed strategy of the opponent (market)

Expected-Value Model

$$\min_{x\in X} c^T x + \mathbb{E}\big[Q(x)\big]$$

where Q(x) is the optimal value of the random second-stage problem

$$\min q^T y \\ \text{s.t. } Tx + Wy = h, \\ y \ge 0,$$

- (q, T, h) random data of the second-stage problem
- *c* is deteministic
- (q, T, h) become known after the first stage

For finite scenario case - powerful decomposition methods

$$\min_{x\in X}\rho_1(c^Tx+Q(x))$$

where Q(x) is the optimal value of the second-stage problem

$$Q(x) = \min \rho_2(q^T y)$$

s.t. $Tx + Wy = h$,
 $y \ge 0$,

and $\xi = (q, T, h)$ - random data of the second-stage problem

- *c* is random
- (T, h) become known after the first stage
- q may be still unknown (conditional distribution)

Second-stage scenarios: c_s , T_s , h_s , s = 1, ..., SFinal scenarios: q_{sj} , $j \in J(s)$

$$\min_{x\in X}\rho_1(c^Tx+Q(x))$$

where Q(x) is the optimal value of the second-stage problem; In scenario *s* its value is

$$Q_{s}(x) = \min \rho_{2s}(q_{s}^{T}y)$$

s.t. $T_{s}x + Wy = h_{s},$
 $y \ge 0,$

 q_s is random and has realizations q_{sj} , $j \in J(s)$

This structure of the problem follows from the general theory of dynamic measures of risk (lecture tomorrow)

Dual Representation of the Two-Stage Problem

Risk-averse first-stage problem

$$\min_{x \in X} \max_{\mu \in \mathcal{A}} \sum_{s=1}^{S} \mu_s \Big[c_s^{\mathsf{T}} x + Q_s(x) \Big]$$

Risk-averse second-stage problem

$$Q_{s}(x) = \min_{y} \max_{v \in \mathcal{B}_{s}} \sum_{j \in J(s)} v_{j} q_{j}^{T} y$$

s.t. $T_{s}x + W_{s}y = h_{s}$ (multipliers π_{s})
 $y \ge 0$

The sets of probability measures:

$$\begin{aligned} \mathcal{A} &= \partial \rho_1(0) \\ \mathcal{B}_s &= \partial \rho_{2s}(0) \end{aligned}$$

 Z_x - random outcome (*e.g.*, cost)

Y - benchmark random outcome, e.g. $Y(\omega) = Z_{\bar{X}}(\omega)$ for some $\bar{x} \in X$

New Model

 $\begin{array}{ll} \min \mathbb{E}[Z_x] & (\text{or some other objective}) \\ \text{subject to } Z_x \leq_{\mathcal{U}} Y & (\text{stochastic ordering constraint}) \\ x \in X \end{array}$

 Z_x is preferred over Y by all decision makers having disutility functions in the generator \mathcal{U} :

$$\mathbb{E}[u(Z_{\mathsf{X}})] \leq \mathbb{E}[u(\mathsf{Y})] \quad \forall \ u \in \mathcal{U}$$

All nondecreasing $u(\cdot)$ - first order stochastic dominance \leq_{st} All nondecreasing convex $u(\cdot)$ - increasing convex order \leq_{icx}

Dominance Constrained Optimization

 $\begin{array}{l} \min \mathbb{E}[Z_x] \\ \text{subject to } Z_x \leq_{\text{icx}} Y \\ x \in X \end{array}$

X - convex set in *X* (separable locally convex Hausdorff vector space) $x \mapsto Z_x$ is a continuous operator from *X* to $\mathcal{L}_1(\Omega, \mathcal{F}, P)$ $x \mapsto Z_x(\omega)$ is convex for *P*-almost all $\omega \in \Omega$

Primal: $\mathbb{E}[u(Z_x)] \leq \mathbb{E}[u(Y)]$ for all convex nondecreasing $u : \mathbb{R} \to \mathbb{R}$ Inverse: $\int_0^1 F_{Z_x}^{-1}(p) dw(p) \leq \int_0^1 F_Y^{-1}(p) dw(p)$ for all convex nondecreasing $w : [0, 1] \to \mathbb{R}$

Main Results

- Utility functions *u* : ℝ → ℝ and rank dependent utility functions
 w : [0, 1] → ℝ play the roles of Lagrange multipliers
- Expected utility models and rank dependent utility models are Lagrangian relaxations of the problem

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Lagrangian in Direct Form

$$L(x, \boldsymbol{u}) = \mathbb{E} \Big[Z_x + \boldsymbol{u}(Z_x) - \boldsymbol{u}(Y) \Big]$$

 $u(\cdot)$ - convex function on $\mathbb R$

Theorem

Assume Uniform Dominance Condition (a form of Slater constraint qualification). If \hat{x} is an optimal solution of the problem then there exists a function $\hat{u} \in \mathcal{U}$ such that

$$L(\hat{x}, \hat{u}) = \min_{x \in X} L(x, \hat{u})$$
(1)
$$\mathbb{E}[\hat{u}(Z_{\hat{x}})] = \mathbb{E}[\hat{u}(Y)]$$
(2)

Conversely, if for some function $\hat{u} \in \mathcal{U}$ an optimal solution \hat{x} of (1) satisfies the dominance constraint and (2), then \hat{x} is optimal

Lagrangian in Inverse Form

$$\Phi(x, w) = \int_0^1 F_{Z_x}^{-1}(p) d(p + w(p)) - \int_0^1 F_Y^{-1}(p) dw(p)$$

 $w(\cdot)$ - convex function on [0, 1]

Theorem

Assume Uniform Dominance Condition (a form of Slater constraint qualification). If \hat{x} is an optimal solution of the problem, then there exists a function $\hat{w} \in \mathcal{W}$ such that

$$\Phi(\hat{x}, \hat{w}) = \min_{x \in X} \Phi(x, \hat{w})$$
(3)

$$\int_0^1 F_{Z_{\hat{x}}}^{-1}(p) \, d\hat{w}(p) = \int_0^1 F_Y^{-1}(p) \, d\hat{w}(p) \tag{4}$$

If for some $\hat{w} \in \mathcal{W}$ an optimal solution \hat{x} of (3) satisfies the inverse dominance constraint and (4), then \hat{x} is optimal

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