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Model of a minimal risk portfolio under hybrid uncertainty

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Introduction

We investigate the architecture of some models for a minimal risk portfolio under conditions of hybrid uncertainty of possibilisticprobabilistic type.

In our work attention is paid to the study of situations when the interaction of fuzzy model factors is described by both the strongest and weakest t-norms, which allows us to assess the range of risk changes and the behavior of a set of acceptable portfolios, that is, to manage uncertainty when making investment decisions.

Necessary mathematical apparatus

Definition 1. Fuzzy random variable $Y(\omega, \gamma)$ is a real function $Y : \Omega \times \Gamma \to E^1$ σ -measurable for each fixed γ , where

$$
\mu_Y(\omega, t) = \pi \{ \gamma \in \Gamma : Y(\omega, \gamma) = t \}
$$

is called its distribution function.

It follows from Definition 1 that the distribution function of a fuzzy random variable depends on a random parameter, that is, it is a random function.

Definition 2. Let $Y(\omega, \gamma)$ be a fuzzy random variable. Its expected value $E[Y]$ is a fuzzy variable with possibility distribution function

$$
\mu_{E[Y]}(t) = \pi \{ \gamma \in \Gamma : E[Y(\omega, \gamma)] = t \},\
$$

where E is the expectation operator

$$
E[Y(\omega,\gamma)] = \int_{\Omega} Y(\omega,\gamma) P(d\omega).
$$

Necessary mathematical apparatus

Definition 3. A covariance of fuzzy random variables X and Y is defined as:

$$
cov(X,Y) = \frac{1}{2} \int_0^1 \left(cov\left(X_\omega^-\left(\alpha\right), Y_\omega^-\left(\alpha\right)\right) + cov\left(X_\omega^+\left(\alpha\right), Y_\omega^+\left(\alpha\right)\right) \right) d\alpha, \quad (1)
$$

where $X_{\omega}^-(\alpha) Y_{\omega}^-(\alpha)$, $X_{\omega}^+(\alpha) Y_{\omega}^+(\alpha)$ are left and right boundaries of α -level sets of fuzzy variables X_{ω} and Y_{ω} .

Definition 4. A variance of a fuzzy random variable Y is

 $D[Y] = cov(YY).$

Definition 5. $Z(\gamma)$ is called an LR-type fuzzy variable, if its distribution function has the form

$$
\mu_Z(t) = \begin{cases} L\left(\frac{m-t}{d}\right), \text{ for } t < \underline{m}, \\ 1, \text{ for } \underline{m} \le t \le \overline{m}, \\ R\left(\frac{t-\overline{m}}{\overline{d}}\right), \text{ for } t > \overline{m}. \end{cases}
$$

where $L(t)$ and $R(t)$ are shape functions.

Necessary mathematical apparatus

We will use triangular norms (t-norms) to aggregate fuzzy information. These norms generalize "min" operation inherent in operations on fuzzy sets and fuzzy variables (see Nguyen et al. (1997)). The following t-norms are of particular interest:

$$
T_M(x, y) = \min\{x, y\} \text{ and } T_W(x, y) = \begin{cases} \min\{x, y\}, & \text{if } \max\{x, y\} = 1, \\ 0, & \text{else,} \end{cases}
$$

 T_M is called the strongest, and T_W is called the weakest t-norm, since for any arbitrary t-norm *T* and $\forall x, y \in [0,1]$, the following inequality holds (see, for example, Nguyen et al. (1997)):

 $T_W(x, y) \leq T(x, y) \leq T_M(x, y)$.

Portfolio return under hybrid uncertainty of possibilistic-probabilistic type

Under conditions of hybrid uncertainty of possibilistic-probabilistic type, the return on an investment portfolio can be represented by a fuzzy random function

$$
R_p(w, \omega, \gamma) = \sum_{i=1}^n R_i(\omega, \gamma) w_i, \qquad (2)
$$

which is a linear function of equity shares $w = (w_1, ..., w_n)$ in the portfolio. Here $R_i(\omega, \gamma)$ are fuzzy random variables that model the returns of individual financial assets with the help of shift-scale representation (see Yazenin (2016)):

$$
R_i(\omega, \gamma) = a_i(\omega) + \sigma_i(\omega) Z_i(\gamma).
$$
 (3)

Expected Portfolio Return Under Conditions of Hybrid Uncertainty

Further we assume that fuzzy variables $Z_i(\gamma) = \left[\underline{m}_i, \overline{m}_i, \underline{d}_i, d_i\right]_{LR}$ in representation (3) are mutually T-related, where $T \in \{T_M, T_W\}$, and $a_i(\omega), \sigma_i(\omega)$ are shift and scale coefficients – random variables defined on a probability space (Ω, B, P) , with $\sigma_i(\omega) \geq$ 0. Then possibilities distribution of the portfolio return (2) takes the following form

$$
R_p^T(w, \omega, \gamma) = \left[\underline{m}_{R_p}(w, \omega), \overline{m}_{R_p}(w, \omega) \underline{d}_{R_p^T}(w, \omega), \overline{d}_{R_p^T}(w, \omega) \right]_{LR}, \tag{4}
$$

where

$$
\underline{m}_{R_p}(w,\omega)=\sum_{i=1}^n (a_i(\omega)+\sigma_i(\omega)\underline{m}_i)w_i, \qquad \overline{m}_{R_p}(w,\omega)=\sum_{i=1}^n (a_i(\omega)+\sigma_i(\omega)\overline{m}_i)w_i,
$$

and the coefficients of fuzziness take the form depending on the type of T:

$$
\underline{d}_{R_p^M}(w,\omega) = \sum_{i=1}^n \sigma_i(\omega) \underline{d}_i w_i, \qquad \overline{d}_{R_p^M}(w,\omega) = \sum_{i=1}^n \sigma_i(\omega) \overline{d}_i w_i,
$$

when $T = T_M$, and in case of $T = T_W$:

$$
\underline{d}_{R_p^W}(w,\omega) = \max_{i=1\ldots n} \{\sigma_i(\omega) \underline{d}_i w_i\}, \qquad \overline{d}_{R_p^W}(w,\omega) = \max_{i=1\ldots n} \{\sigma_i(\omega) \overline{d}_i w_i\}.
$$

Expected Portfolio Return Under Conditions of Hybrid Uncertainty

Theorem 1. Let $T = T_M$. Then expected portfolio return $\widehat{R}_p^M(w, \gamma)$ is characterized by the *possibilities distribution function*

$$
\widehat{R}_p^M(w,\gamma) = \mathbf{E}\big[R_p^M(w,\omega,\gamma)\big] = \Big[\underline{m}_{\widehat{R}_p}(w),\overline{m}_{\widehat{R}_p}(w),\underline{d}_{\widehat{R}_p^M}(w),\overline{d}_{\widehat{R}_p^M}(w)\Big]_{LR},
$$

where

$$
\underline{m}_{\hat{\mathcal{R}}_p}(w) = \sum_{i=1}^n (\hat{a}_i + \hat{\sigma}_i \underline{m}_i) w_i, \qquad \overline{m}_{\hat{\mathcal{R}}_p}(w) = \sum_{i=1}^n (\hat{a}_i + \hat{\sigma}_i \overline{m}_i) w_i,
$$

$$
\underline{d}_{\hat{\mathcal{R}}_p^M}(w) = \sum_{i=1}^n \hat{\sigma}_i \underline{d}_i w_i, \overline{d}_{\hat{\mathcal{R}}_p^M}(w) = \sum_{i=1}^n \hat{\sigma}_i \overline{d}_i w_i, \hat{a}_i = \mathbf{E}[a_i(\omega)], \hat{\sigma}_i = \mathbf{E}[\sigma_i(\omega)].
$$

Theorem 2. Let $T = T_W$. Then expected portfolio return $\widehat{R}_p^W(w, \gamma)$ is characterized by the *possibilities distribution function*

$$
\widehat{R}_p^W(w,\gamma) = \mathbf{E}\big[R_p^W(w,\omega,\gamma)\big] = \left[\underline{m}_{\widehat{R}_p}(w),\overline{m}_{\widehat{R}_p}(w),\underline{d}_{\widehat{R}_p^W}(w),\overline{d}_{\widehat{R}_p^W}(w)\right]_{LR},
$$

where

$$
\underline{d}_{\hat{R}_p^W}(w) = \mathbf{E}\Big[\max_{i=1\ldots n} \{\sigma_i(\omega)\underline{d}_i w_i\}\Big], \overline{d}_{\hat{R}_p^W}(w) = \mathbf{E}\Big[\max_{i=1\ldots n} \{\sigma_i(\omega)\overline{d}_i w_i\}\Big].
$$

In accordance with the classical Markowitz (1952) approach, we need to construct a portfolio risk function in the minimal risk portfolio model.

$$
F_p^{\tau E}(\omega) = \begin{cases} \tau \{\hat{R}_p^T(\omega, \gamma) \ \mathcal{R} \ m_d\} \ge \alpha, \\ \sum_{i=1}^n w_i = 1, \\ w \in \mathbb{E}^n_+, \end{cases}
$$

where $\mathbb{E}_{+}^{n} = \{x \in \mathbb{E}^{n} : x \ge 0\}$, $\hat{R}_{p}^{T}(w, \gamma)$ – expected return, \mathcal{R} – crisp relation $\{\ge,$ =}; $\alpha \in (0, 1]$, m_d – level of profitableness, acceptable to an investor, $T \in$ $\{T_M, T_W\}.$

The following theorems allow us to construct equivalent deterministic analogs of acceptable portfolio models.

Theorem 3. Let in the constraint model $F_p^{\tau E} \tau = ' \pi', \mathcal{R} = ' \ge '$. Then the *equivalent deterministic model of acceptable portfolios has the form:*

$$
F_p^{\pi E}(w) = \begin{cases} \sum_{i=1}^n (\hat{a}_i + \hat{\sigma}_i \overline{m}_i) w_i + \overline{d}_{\hat{R}_p^T}(w) * R^{-1}(\alpha) \ge m_d, \\ \sum_{i=1}^n w_i = 1, \\ w \in \mathbb{E}_+^n. \end{cases}
$$

Theorem 4. Let in the model of acceptable portfolios $F_p^{\tau E}$ $\tau = \tau \nu$, $\mathcal{R} = \Sigma$. *Then the equivalent deterministic model of acceptable portfolios takes the form*:

$$
F_p^{\nu E}(\omega) = \begin{cases} \sum_{i=1}^n (\hat{a}_i + \hat{\sigma}_i \underline{m}_i) w_i - \underline{d}_{\hat{R}_p^T}(\omega) * L^{-1}(1-\alpha) \ge m_d, \\ \sum_{i=1}^n w_i = 1, \\ w \in \mathbb{E}_+^n. \end{cases}
$$

From theorems 3, 4 we get

Corollary 1. $F_p^{\nu}E(\omega) \subseteq F_p^{\pi}E(\omega)$.

For further analysis we will need the following notation and concepts. We denote by $t = (t_1, ..., t_n) - a$ vector whose components are possible values of fuzzy variables $Z_1(y)$, …, $Z_n(y)$ respectively. For the strongest t-norm with the possibility of $\mu_{Z_i}(t_i)$, the return of the i-th financial asset is a random variable $Z_i^{t_i}(\omega) = a_i(\omega) + \sigma_i(\omega)t_i$, and $R_p^{t}(\omega,\omega) =$ $\sum_{i=1}^{n} (a_i(\omega) + \sigma_i(\omega)t_i) w_i$ is return on the portfolio with the possibility of $\mu_p(t) = \min_{1 \le i \le n}$ $\min_{1 \le i \le n} {\mu_{Z_i}(t_i)}$.

Then, following Yazenin (2016), with the possibility of $\mu_p(t)$, the expected return and risk of the portfolio are determined by the formulas

n

$$
m_{R_p}(w, t) = \mathbf{E}[R_p^t(w, \omega)] = \sum_{i=1}^{N} (\hat{a}_i + \hat{\sigma}_i t_i) w_i
$$

and

$$
d_{R_p}(w,t) = \mathbf{E}\left[\left(R_p^t(w,\omega) - m_{R_p}(w,t)\right)^2\right],
$$

respectively.

BOS/SOR 2020 (December 14-15) 12

Using standard transformations we obtain the following formula for the variance with the possibility of $\mu_p(t)$ (see, for example, Yazenin (2016)):

$$
d_{R_p}(w,t) = \sum_{i=1}^n \sum_{j=1}^n c_{ij}(t_i, t_j) w_i w_j,
$$

in which

$$
c_{ij}(t_i, t_j) = C_{a_i a_j} + C_{a_j \sigma_i} t_j + C_{\sigma_j a_i} t_i + C_{\sigma_i \sigma_j} t_i t_j,
$$

\n
$$
C_{a_i a_j} = cov(a_i, a_j), C_{a_j \sigma_i} = cov(a_j, \sigma_i), C_{\sigma_j a_i} = cov(\sigma_j, a_i), C_{\sigma_i \sigma_j} = cov(\sigma_i, \sigma_j).
$$

\nFunction $d_{R_p}(w, t)$ has properties that are due to the properties of the covariance matrix **C** with elements $c_{ij}(t_i, t_j)$:

- $d_{R_p}(w,t)$ is a convex function on w for a fixed t;
- for any vectors w and t function $d_{R_p}(w,t)$ is nonnegative;
- $d_{R_p}(w,t)$ is a convex function on t for a fixed w .

The function $d_{R_p}(w,t)$ can be written with the help of matrix $\mathbf C$ as

$$
d_{R_p}(w,t) = (\mathbf{C} w, w).
$$

Lemma 1. Let in the constraint model $F_p^{\tau P}(w)$ random parameters are *normally* distributed: $a_i(\omega) \in N_p(\hat{a}_i, \hat{d}_{a_i}), \quad \sigma_i(\omega) \in N_p(\hat{\sigma}_i, \hat{d}_{\sigma_i}), i =$ 1, ..., *n*; fuzzy parameters $Z_1(\gamma)$, ..., $Z_N(\gamma)$ are T_M -related, $\mu_p(t) \ge \alpha_0$. *Then* with the possibility of $\mu_p(t)$ system of restrictions $F_p^{\tau P}(w)$ is *equivalent to the system*

$$
F_p^{\mu P}(w) = \begin{cases} m_{R_p}(w, t) + \beta_0 \sqrt{d_{R_p}(w, t)} \ge m_d, \\ \sum_{i=1}^n w_i = 1, \\ w \in \mathbb{E}_+^n, \end{cases}
$$

where β_0 – *is a solution to the equation* $\mathcal{F}_0^1(x) = 1 - p_0$ *, and* $\mathcal{F}_0^1(x) - i$ *s a function of the standard normal probabilities distribution.*

The Lemma proved above allows us to prove a theorem with the help of which an equivalent deterministic analog of the system $F_p^{\tau P}(w)$ can be constructed.

Theorem 5. Let in the constraint model $F_p^{\tau P}(w)$ random parameters are normally *fuzzy* α *parameters* $Z_1(\gamma)$, ..., $Z_N(\gamma)$ are T_M -related, $\tau = ' \pi'$. Then the system of *restrictions* $F_p^{\tau P}(w)$ *is equivalent to the system*

$$
F_p^{\pi P}(w) = \begin{cases} m_{R_p}(w, t^+) + \beta_0 \sqrt{d_{R_p}(w, t^+)} \ge m_d, \\ \sum_{i=1}^n w_i = 1, \\ w \in \mathbb{E}^n_+, \end{cases}
$$

where $m_{R_p}(w, t^+) = \sum_{i=1}^n (\hat{a}_i + \hat{\sigma}_i t_i^+) w_i, d_{R_p}(w, t^+) =$ $\sum_{i=1}^n \sum_{j=1}^n c_{ij}(t_i^+, t_j^+) w_i w_j$, and t_i^+, t_j^+ are right borders of α_0 -level sets of fuzzy *variables* $Z_i(\gamma)$, $Z_j(\gamma)$, *respectively.*

In accordance with the indicated approach to determining second-order moments, we can determine the variance of the portfolio to assess its risk. We need to obtain formulas (variances) for the case of both the strongest and weakest t-norms.

With $T = T_M$ formula (1) takes the form

$$
D_p^M(w) = \frac{1}{2} \int_0^1 \left(\mathbf{D} \left[R_p^{M-}(w, \omega, \alpha) \right] + \mathbf{D} \left[R_p^{M+}(w, \omega, \alpha) \right] \right) d\alpha,
$$

where $R_p^{M-}(w, \omega, \alpha)$ and $R_p^{M+}(w, \omega, \alpha)$ – are left and right boundaries of α -level set of fuzzy random variable $R_p^M(w, \omega, \alpha)$:

$$
R_p^{M-}(w, \omega, \alpha) = \sum_{\substack{i=1 \ i \neq j}}^n (a_i(\omega) + \sigma_i(\omega) \underline{m}_i) w_i - \sum_{\substack{i=1 \ i \neq j}}^n \sigma_i(\omega) \underline{d}_i w_i * L^{-1}(\alpha),
$$

$$
R_p^{M+}(w, \omega, \alpha) = \sum_{i=1}^n (a_i(\omega) + \sigma_i(\omega) \overline{m}_i) w_i + \sum_{i=1}^n \sigma_i(\omega) \overline{d}_i w_i * R^{-1}(\alpha).
$$

If all random parameters of distributions are independent, then after standard transformations we get the formula for the variance:

$$
D_p^M(w)
$$

= $\sum_{i=1}^n \left(\mathbf{D}[a_i(\omega)] \left(\frac{m_i^2 + \overline{m}_i^2 + 2\overline{m}_i \overline{d}_i \int_0^1 R^{-1}(\alpha) d\alpha - 2 \underline{m}_i \underline{d}_i \int_0^1 L^{-1}(\alpha) d\alpha \right) + \overline{d}_i^2 \int_0^1 (R^{-1}(\alpha))^2 d\alpha + \underline{d}_i^2 \int_0^1 (L^{-1}(\alpha))^2 d\alpha \right) \right) w_i^2.$

Note that if in fuzzy random variables the fuzzy components are given by LRtype fuzzy numbers with the same left and right shapes and coefficients of fuzziness, i.e. $L(\alpha) = R(\alpha) = S(\alpha)$, $\forall \alpha$ and $\overline{m}_i = \underline{m}_i = m_i$, $d_i = \underline{d}_i = d_i$, $i =$ 1, \ldots , n, then the variance formula can be simplified:

$$
D_p^M(w) = \sum_{i=1}^n \left(\mathbf{D}[a_i(\omega)] + \mathbf{D}[\sigma_i(\omega)] \left(m_i^2 + d_i^2 \int_0^1 (S^{-1}(\alpha))^2 d\alpha \right) \right) w_i^2.
$$

Example 1. In case when shift and scale coefficients $a_i(\omega)$, $\sigma_i(\omega)$ are uniformly distributed over the segment [0,1] and independent, and the shape function $S(t) = max{0, 1 - t}$, $t \ge 0$, we obtain the following formula for the variance:

$$
D_p^M(w) = \frac{1}{12} \sum_{i=1}^n \left(m_i^2 + \frac{1}{3} d_i^2 + 1 \right) w_i^2.
$$

We now define the variance for the t-norm T_w . To do this, we will again use formula (1) to find the covariance of two fuzzy random variables. For the weakest t-norm, the formula for finding the variance takes the form:

$$
D_p^W(w) = \frac{1}{2} \int_0^1 \left(\mathbf{D} \left[R_p^{W-}(w, \omega, \alpha) \right] + \mathbf{D} \left[R_p^{W+}(w, \omega, \alpha) \right] \right) d\alpha,
$$

where $R_p^{W-}(w, \omega, \alpha)$ and $R_p^{W+}(w, \omega, \alpha)$ are respectively left and right boundaries of α -level set of portfolio return – fuzzy random variable $R_p^W(w, \omega, \gamma)$:

$$
R_p^{W-}(w, \omega, \alpha) = \sum_{i=1}^n (a_i(\omega) + \sigma_i(\omega) \underline{m}_i) w_i - \max_{i=1\ldots n} {\{\sigma_i(\omega) \underline{d}_i w_i\}} * L^{-1}(\alpha),
$$

$$
R_p^{W+}(w, \omega, \alpha) = \sum_{i=1}^n (a_i(\omega) + \sigma_i(\omega) \overline{m}_i) w_i + \max_{i=1\ldots n} {\{\sigma_i(\omega) \overline{d}_i w_i\}} * R^{-1}(\alpha).
$$

After appropriate transformations, the final formula for variance, which allows us to determine the risk of the portfolio, has the form:

$$
D_p^W(w)
$$

\n
$$
= \frac{1}{2} \sum_{i=1}^n w_i^2 (\mathbf{D}[a_i(\omega) + \sigma_i(\omega) \underline{m}_i] + \mathbf{D}[a_i(\omega) + \sigma_i(\omega) \overline{m}_i])
$$

\n
$$
+ \frac{1}{2} \mathbf{D} \Big[\max_{j=1...n} {\sigma_j(\omega) \overline{d}_j w_j} \Big] \int_0^1 (R^{-1}(\alpha))^2 d\alpha + \frac{1}{2} \mathbf{D} \Big[\max_{j=1...n} {\sigma_j(\omega) \underline{d}_j w_j} \Big] \int_0^1 (L^{-1}(\alpha))^2 d\alpha
$$

\n
$$
+ \sum_{1 \le i < j \le n} w_i w_j \Big(cov \Big((a_i(\omega) + \sigma_i(\omega) \underline{m}_i), (a_j(\omega) + \sigma_j(\omega) \underline{m}_j) \Big)
$$

\n
$$
+ cov \Big((a_i(\omega) + \sigma_i(\omega) \overline{m}_i), (a_j(\omega) + \sigma_j(\omega) \overline{m}_j) \Big) \Big)
$$

\n
$$
+ \sum_{i=1}^n w_i \Big(\int_0^1 R^{-1}(\alpha) d\alpha cov \Big((a_i(\omega) + \sigma_i(\omega) \overline{m}_i), \max_{j=1...n} {\sigma_j(\omega) \overline{d}_j w_j} \Big) - \int_0^1 L^{-1}(\alpha) d\alpha cov \Big((a_i(\omega) + \sigma_i(\omega) \underline{m}_i), \max_{j=1...n} {\sigma_j(\omega) \underline{d}_j w_j} \Big) \Big).
$$

If all random parameters of distributions are independent, then: $D_{p}^{W}(w)$

$$
= \frac{1}{2} \sum_{i=1}^{n} w_i^2 \left(2 \mathbf{D} [a_i(\omega)] + \mathbf{D} [\sigma_i(\omega)] \left(\underline{m}_i^2 + \overline{m}_i^2 \right) \right)
$$

+
$$
\frac{1}{2} \mathbf{D} \Big[\max_{j=1...n} \left\{ \sigma_j(\omega) \overline{d}_j w_j \right\} \Big] \int_0^1 \left(R^{-1}(\alpha) \right)^2 d\alpha + \frac{1}{2} \mathbf{D} \Big[\max_{j=1...n} \left\{ \sigma_j(\omega) \underline{d}_j w_j \right\} \Big] \int_0^1 \left(L^{-1}(\alpha) \right)^2 d\alpha
$$

+
$$
\sum_{i=1}^{n} w_i \left(\int_0^1 R^{-1}(\alpha) d\alpha \, cov \left((a_i(\omega) + \sigma_i(\omega) \overline{m}_i), \max_{j=1...n} \left\{ \sigma_j(\omega) \overline{d}_j w_j \right\} \right) \Big] - \int_0^1 L^{-1}(\alpha) d\alpha \, cov \left((a_i(\omega) + \sigma_i(\omega) \underline{m}_i), \max_{j=1...n} \left\{ \sigma_j(\omega) \underline{d}_j w_j \right\} \right).
$$

If in all distributions the fuzzy component is given by LR-type fuzzy numbers with the same left and right shape functions and coefficients of fuzziness, then the terms with covariance are mutually eliminated and the variance formula can be simplified:

$$
D_p^W(w)
$$

=
$$
\sum_{i=1}^n w_i^2 (\mathbf{D}[a_i(\omega)] + \mathbf{D}[\sigma_i(\omega)]m_i^2)
$$

+
$$
\mathbf{D} \Big[\max_{j=1...n} {\{\sigma_j(\omega)d_jw_j\}} \Big] \int_0^1 (S^{-1}(\alpha))^2 d\alpha.
$$
 (5)

Example 2. Let the shift and scale coefficients $a_i(\omega)$, $\sigma_i(\omega)$ are uniformly distributed over the segment [0,1] and independent the formula (5) under the corresponding assumptions and for $S(t) = max\{0, 1 - t\}, t \ge 0$ takes the form:

$$
D_p^W(w) = \frac{1}{12} \sum_{i=1}^n w_i^2 (m_i^2 + 1) + \frac{1}{3} (EMax2(dw) - (EMax(dw))^2),
$$

where

$$
EMax(dw) := \mathbf{E} \left[\max_{i=1...n} \{ \sigma_i(\omega) d_i w_i \} \right]
$$

=
$$
\sum_{i=1}^n \frac{(dw)_{(i)}^{n-i+1}}{(n-i+1)(n-i+2)(dw)_{(i+1)} \cdots (dw)_{(n)}},
$$

$$
EMax2(dw) := \mathbf{E} \left[\left(\max_{i=1...n} \{ \sigma_i(\omega) d_i w_i \} \right)^2 \right]
$$

=
$$
\sum_{i=1}^n \frac{2(dw)_{(i)}^{n-i+2}}{(n-i+2)(n-i+3)(dw)_{(i+1)} \cdots (dw)_{(n)}},
$$

and $(dw)_{(1)}, \ldots, (dw)_{(n)}$ is an ascending permutation of elements $\{d_1w_1, \ldots, d_nw_n\}$.

Minimum Risk Portfolio Models

Based on the results presented above, the minimum risk portfolio models can be written as:

$$
D_p^T(w) \to \min,\tag{6}
$$

\n
$$
w \in F_p(w),
$$
\n
$$
(7)
$$

where
$$
F_p(w) \in \{F_p^{\mu E}, F_p^{\nu E}, F_p^{\mu P}, F_p^{\nu P}\}.
$$

We consider an example of two-dimensional portfolio ($n = 2$). Let $Z_1 =$ $[2.2, 2.2, 0.3, 0.3]_{LR}$, $Z_2 = [1.2, 1.2, 0.4, 0.4]_{LR}$, $L(t) = R(t) = \max\{0, 1 - t\}, t \ge$ $0, \alpha = 0.75$. Recall that all $a_i(\omega)$, $\sigma_i(\omega)$ are independent random variables with a uniform distribution on the segment $[0,1]$. We first specify the minimum risk portfolio models for the weakest t-norm:

$$
\frac{73}{150}w_1^2 + \frac{61}{300}w_2^2 + \frac{1}{3}\Big(EMax2(dw) - (EMax(dw))^2\Big) \to min,
$$

$$
F_p^{\pi E}(w) = \begin{cases} 1.6w_1 + 1.1w_2 + 0.25 * EMax(dw) \ge m_d, \\ w_1 + w_2 = 1, \\ w_1, w_2 \ge 0, \end{cases}
$$

and in the context of a necessity measure:

$$
\frac{73}{150}w_1^2 + \frac{61}{300}w_2^2 + \frac{1}{3}\Big(EMax2(dw) - (EMax(dw))^2\Big) \to min,
$$

$$
F_p^{\nu E}(w) = \begin{cases} 1.6w_1 + 1.1w_2 - 0.75 * EMax(dw) \ge m_d, \\ w_1 + w_2 = 1, \\ w_1, w_2 \ge 0. \end{cases}
$$

Let us now consider the same problem for the strongest t-norm. Under the assumptions made, the equivalent deterministic analog of the minimum risk portfolio (6)-(7) in the context of the possibility measure takes the form:

$$
\frac{587}{1200}w_1^2 + \frac{187}{900}w_2^2 \to min,
$$

$$
F_p^{\pi E}(w) = \begin{cases} 1.6375w_1 + 1.15w_2 \ge m_d, \\ w_1 + w_2 = 1, \\ w_1, w_2 \ge 0, \end{cases}
$$

and in the context of a necessity measure:

$$
\frac{587}{1200}w_1^2 + \frac{187}{900}w_2^2 \to min,
$$

$$
F_p^{\text{vE}}(w) = \begin{cases} 1.4875w_1 + 0.95w_2 \ge m_d, \\ w_1 + w_2 = 1, \\ w_1, w_2 \ge 0. \end{cases}
$$

Fig. 1: Sets of quasi-efficient portfolios depending on the measure of possibility/necessity and the t-norm

Fig. 2: Influence of the random parameter σ_i (scaling) on the set of quasi-efficient *portfolios in the case of the strongest t-norm in the context of the measure of possibility*

Thank you!