

# Portfolio Theory

## Lecture 4

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# Structure

- 1 Short sell
- 2 Portfolio optimization

# Short selling

- The assumption for the technique:  $P_{t+n} < P_t$
- Investor has to borrow securities, which will sell and use the sources for a portfolio construction
- When the portfolio will be realized, then the securities must be returned
- At that point the investor must purchase on the market the security
- The owner of the security has rights on all CF's
- *An example...*

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# The impact of SS on the EPF

- The Short Sell expands the feasible set of portfolios
- ...expands the Efficient Portfolio Frontier
- The SS could be used even the  $\bar{r}_i > 0$
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- The graphical representation ...

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# Calculation algorithm

- The purpose is to find an extremum of a given function
- There are two feasible approaches:
  - ...to maximize the expected return of the portfolio
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# The minimum risk portfolio

- Two ways of problem solving:
  - ... to find an absolute minimum risk
  - ... to find a minimum risk for a given return

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# The absolute minimum risk

- Solving the optimization problem
- The weights are found by solving the objective function, assuming the restriction...
- Objective function:  $\sigma_p^2 \rightarrow \min$
- Restrictive conditions:  $\sum_{i=1}^N w_i = 1$

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# Searching the extremis

- $f(\vec{W}) \rightarrow \min$
- Lagrange function:  $L(\vec{W}) = L(\vec{W}, \vec{\lambda}) = \sum_{i=1}^N \lambda_i f_i(\vec{W})$
- For finding the solution will be used the Lagrange multipliers:
  - $\frac{\partial L(\vec{W})}{\partial \lambda_i} = 0, \forall_i$

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# Lagrange Multipliers

- $L(\vec{Y}) = \sigma_p^2(\vec{W}) + \lambda_1(\sum_{i=1}^N w_i - 1)$
- Deriving with respect to all variables we obtain  $n+1$  equations
- The first  $n$  equations will be equal to zero
- $2C\vec{W} + \lambda_1\vec{e} = 0$
- At the last equation transform the “1” to the right site
- $\vec{W}^T\vec{e} = 1$
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# Minimizing risk by given return

- Restrictions:

- $\sum_{i=1}^N w_i = 1$
- $\bar{r}_p = \sum_{i=1}^N w_i * \bar{r}_i$

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- Lagrangian:

- $L(\vec{W}) = \sigma_p^2(\vec{W}) + \lambda_1 * (\sum_{i=1}^N w_i - 1) + \lambda_2 * (\sum_{i=1}^N r_i * w_i - \bar{r}_p)$

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