

# DATA SCIENCE

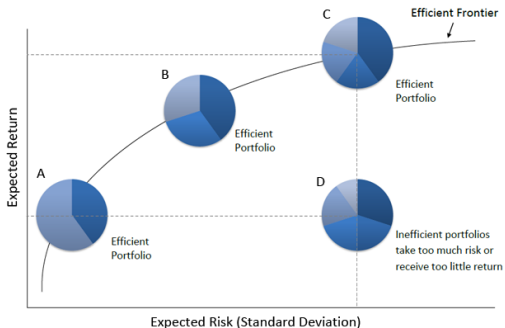
## The Markowitz's model

Antonio VIOLI

[antonio.violi@unirc.it](mailto:antonio.violi@unirc.it)

# The efficient frontier

- ▶ How can we determine the efficient frontier?
- ▶ By using the mathematical programming tools!



# The Markowitz's model

- ▶ Reward and risk (measured by variance) are the two criteria that should be considered in defining efficient portfolios
- ▶ For a given level of expected return, determine the portfolio with minimum variance
- ▶ For a given level of risk, determine the portfolio with maximum expected return

H. Markowitz 1990 Nobel Memorial Prize in Economic Sciences



# The Markowitz's model

- ▶ Let  $N$  denote the universe of assets
- ▶ For each asset  $i = \dots, N$  let
  - ▶  $\bar{r}_i$  the expected rate of return of asset  $i$
  - ▶  $\sigma_{ij}$  the covariance of the return of asset  $i$  and  $j$
- ▶ We denote by  $x_i$  the decision variable associated with the percentage of money invested in asset  $i$
- ▶ We assume that the decision variables are non negative (no short selling are allowed)

# The Markowitz's model

- ▶ Let  $\gamma$  be a threshold on the expected portfolio return
- ▶ The Markowitz's model is as follows

$$\min z = \sum_{i=1}^N \sum_{j=1}^N \sigma_{ij} x_i x_j$$

$$\sum_{i=1}^N \bar{r}_i x_i \geq \gamma$$

$$\sum_{i=1}^N x_i = 1$$

$$x_i \geq 0 \quad i = 1, \dots, N$$

# The Markowitz's model

- ▶ The Markowitz's model belongs to the class of nonlinear (quadratic) programming problem
- ▶ By solving several instances of the Markowitz's model associated with different  $\gamma$  values we obtain different points in the  $(\bar{r} - \sigma)$  plane
- ▶ By taking the convex combinations of these points, we get the efficient frontier

# The Markowitz's model: Compact formulation

We denote by

- ▶  $\bar{\mathbf{r}}$  the vector of expected returns
- ▶  $\mathbf{e}$  the vector of 1
- ▶  $\mathbf{x}$  the vector of decision variables
- ▶  $V$  the variance-covariance matrix

$$\begin{aligned}\min z &= \mathbf{x}^T V \mathbf{x} \\ \bar{\mathbf{r}}^T \mathbf{x} &\geq \gamma \\ \mathbf{e}^T \mathbf{x} &= 1 \\ \mathbf{x} &\geq \mathbf{0}\end{aligned}$$

# The mean-risk formulation

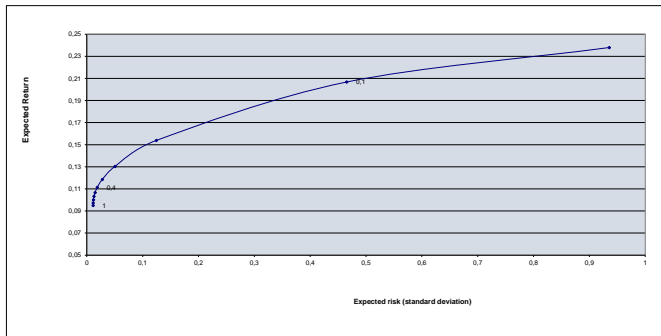
- ▶ Rather than considering different  $\gamma$  values, the efficient frontier can be determined by adopting a bi-objective approach
- ▶ Let  $\lambda$  denote a given scalar taking values in the interval  $[0,1]$
- ▶ The mean-variance formulation is as follows

$$\begin{aligned}\min z &= \lambda * (\mathbf{x}^T V \mathbf{x}) - (1 - \lambda) * (\bar{\mathbf{r}}^T \mathbf{x}) \\ &\mathbf{e}^T \mathbf{x} = 1 \\ &\mathbf{x} \geq \mathbf{0}\end{aligned}$$

- ▶ The parameter  $\lambda$  measures the risk aversion attitude
  - ▶  $\lambda$  values close to 1 are used to model a high risk aversion level
  - ▶  $\lambda$  values close to 0 denote a risk neutrality position

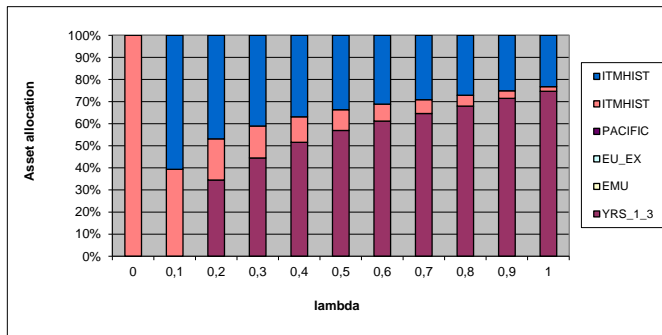


# The efficient frontier



# The optimal allocation

- ▶ The higher  $\lambda$ , the more diversified the portfolio



# Limitations of Markowitz Portfolio Theory

The basic Markowitz model presents several limitations(drawback)

- ▶ Data estimation
- ▶ Lack of real features
- ▶ Inadequacy of variance as risk measure
- ▶ Single-period perspective

- ▶ The information required by the Markowitz model grows substantially as the number  $N$  of assets increases
- ▶ For example, for a portfolio of small size ( $N = 50$ ), it is necessary to calculate:
  1.  $N = 50$  estimates of expected returns
  2.  $N = 50$  estimates of the variance
  - 3.

$$\frac{N * (N - 1)}{2} = 1255$$

estimates of covariance

- ▶ 1325 total estimates

- ▶ The randomness displayed by the returns of  $N$  assets often can be traced back to a smaller number of underlying basic sources of randomness (termed factor)
- ▶ For common stocks, the main factor is a proper market index
- ▶ If we denote by  $\tilde{r}_m$  the random variable associated with the index return, then we assume that

$$\tilde{r}_i = f(\tilde{r}_m)$$

- ▶ We assume that the rates of return and the factor are related by the following equation:

$$\tilde{r}_i = \alpha_i + \beta_i * \tilde{r}_m + e_i$$

- ▶  $\alpha_i$  and  $\beta_i$  are fixed constants
- ▶  $e_i$  are random quantities which represent errors

# Single-Factor model: assumptions

We shall assume that

- ▶ The errors have zero mean

$$\mathbb{E}[e_i] = 0$$

- ▶ The errors are uncorrelated with the market index

$$\mathbb{E}[e_i(\tilde{r}_m - \bar{r}_m)] = 0$$

- ▶ The errors are uncorrelated

$$\mathbb{E}[e_i e_j] = 0 \quad j \neq i$$

The parameters for the mean-variance analysis are

$$\bar{r}_i = \alpha_i + \beta_i \bar{r}_m$$

$$\sigma_i^2 = \beta_i^2 \sigma_m^2 + \sigma_{e_i}^2$$

$$\sigma_{ij} = \beta_i \beta_j \sigma_m^2$$



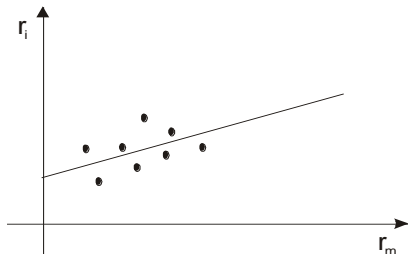
These equations reveal the primary advantage of a factor model

- ▶ For a portfolio of small size ( $N = 50$ ) we have to calculate:
  - ▶ 1 estimate of the expected rate of the market index return
  - ▶ 1 estimate of the variance of the return of the market index
  - ▶ 50 estimates of the  $\alpha$ ,  $\beta$  and the variance of the errors
- ▶ 152 total estimates
- ▶ In general for  $N$  assets

$$3N + 2$$

# Parameter estimation

- ▶ The values of  $\beta_j$  are estimated using the method of least squares
- ▶ Given a set of observations, represented as points in the plane  $(r_i, r_m)$ , we look for the "best" straight line that interpolates them
- ▶ "Better" in the sense of minimizing the mean square error between the observed data and the estimated



# Parameter estimation

- ▶ Let us denote by  $M$  the number of historical observations  $(r_{ik}, r_{mk})$  with  $k = 1, \dots, M$

$$e_{ik} = r_{ik} - \alpha_i - \beta_i r_{mk}$$

- ▶ We look for the  $\alpha_i$  and  $\beta_i$  values that minimize

$$\frac{1}{M} \sum_{k=1}^M e_{ik}^2$$

- ▶ By solving

$$\beta_i = \frac{\sigma_{im}}{\sigma_m^2}$$

$$\alpha_i = \bar{r}_i - \beta_i \bar{r}_m$$

- ▶ Portfolio variance

$$\sigma_p^2 = \sum_{i=1}^N x_i^2 \beta_i^2 \sigma_m^2 + \sum_{i=1}^N x_i^2 \sigma_{e_i}^2 + \sum_{i=1}^N \sum_{j=1, j \neq i}^N x_i x_j \beta_i \beta_j \sigma_m^2$$

- ▶ Expected return of portfolio

$$\sum_{i=1}^N x_i \alpha_i + \sum_{i=1}^N x_i \beta_i \bar{r}_m \geq \gamma$$

# Diversification limits and transactions costs

- ▶ A general problem with the mean-variance model for risk-averse investors is that the optimal portfolios often contain a large number of individual stocks, making them very expensive to purchase and to manage
- ▶ A natural question is how to limit the number of stocks in the portfolio
- ▶ There are at least two obvious ways to do so
  - ▶ Simply limit the number of stocks present in the portfolio.
  - ▶ Explicitly modeling transactions costs subtracting them out of the expected returns

# Diversification limits

- ▶ Let  $y_i$  denote a binary variables taking the value 1 if asset  $i$  is included on the portfolio and 0 otherwise
- ▶ We assume that there are lower  $l_i$  and upper  $u_i$  limitations on the fraction of capital invested capital in each asset

$$x_i \leq u_i y_i$$

$$x_i \geq l_i y_i$$

- ▶ We may want to impose that the number of assets in our portfolio is at most  $K$

$$\sum_{i=1}^N y_i \leq K$$

# Modeling transaction costs

- ▶ Typically financial institutions may charge a fixed fee each time they execute a transaction involving a particular type of security.
- ▶ Such a fee may have a limiting effect on the number of different securities in the optimal portfolio, and is significant enough in most real-world applications to be considered as a necessary part of the model.
- ▶ To model transaction cost we introduce a binary variable  $y_i$  taking the value 1 if asset  $i$  is included on the portfolio and 0 otherwise

# Modeling transaction costs

- ▶ Transaction cost determine a reduction of the portfolio expected return

$$\sum_{i=1}^N \bar{r}_i x_i - \sum_{i=1}^N f * y_i$$

- ▶ Note that variables  $x_i$  should be related to the  $y_i$

$$x_i \leq u_i y_i$$

$$x_i \geq l_i y_i$$

$l_i$  and  $u_i$  may be eventually set to 0 and 1, respectively



- ▶ A further problem with the traditional Markowitz model is the return distribution assumption on which it is implicitly based
- ▶ In the model, only the first two moments of the distribution, i.e. the expected value and the variance, are considered while higher moments such as skewness and kurtosis are ignored.
- ▶ Traditional risk/return optimization therefore assumes that returns follow a normal distribution.
- ▶ Empirical studies demonstrate, however, that normal distribution, especially during periods of market turbulence, significantly underestimates the likelihood of strongly negative returns.
- ▶ Empirical return distributions are not symmetric and exhibit fat tails.
- ▶ One way of resolving the problem is to incorporate forward-looking performance scenarios

The scenario-based approach poses a number of important issues

- ▶ **How realistic scenarios could be generated ?**

As we shall see in the course, we can adopt simulation techniques

- ▶ **Once generated, how scenarios can be included in the mathematical models?**

We have to introduce some sophisticated modeling paradigms

*The scenario-based approach will allow us to elaborate on different risk measures, overcoming the intrinsic limitations of the variance*