MCDA Applications in Finance

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EURO PhD Summer School on MCDA/M
Chania, Greece, 2018

Outline

- Financial decisions
  - Types, problematics, multicriteria character
- Portfolio selection
  - Multi-objective optimization
- Credit rating
  - Disaggregation approach
- Bank rating
  - Constructive approach with outranking and MAVT methods implemented in a DSS
- Conclusions & perspectives

The nature of finance

- Main areas of interest
  - Corporate finance
  - Financial economics, behavioral finance
  - Valuation
  - Risk management
  - Financial engineering
- Fundamental works that shaped the new era of finance
  - Markowitz (1950s) – portfolio theory (John von Neumann Theory Prize by INFORMS in 1989, Nobel 1990)
  - Black-Scholes-Merton (1970s) – contingent valuation (option pricing), Scholes & Merton Nobel 1997
- Financial decision making has become analytical with a high level of modeling and methodological sophistication

Some characteristics

- Heavy regulation with direct methodological and modeling implications
  - Basel Committee accords for capital requirements, IFRS accounting/reporting standards, etc.
  - **Implication:** models should comply with regulatory requirements
- Dynamic environment with constant changes and deep uncertainties
  - **Implication:** data-driven validation, robustness checks
- Large-scale data (in many cases real-time)
  - **Implication:** scalable methodologies to large data

Wealth maximization principle

- Jensen (2001):
  - “Managers must have a criterion for evaluating performance and deciding between alternative courses of action, and that criterion should be maximization of the long-term market value of the firm”
    - Value stands for the sum of equity, debt and any other contingent claims outstanding on the firm
  - “It is logically impossible to maximize in more than one dimension … it leaves the manager with no objective. The result will be confusion and a lack of purpose”
  - The wealth maximization principle is in accordance with social welfare assuming there are no monopolies and externalities

Jensen, M.C. (2001), “Value maximization, stakeholder theory, and the corporate objective function”, *Journal of Applied Corporate Finance* 14(3), 8–21.

Stakeholder theory

- Different stakeholders (shareholders, employees, customers, suppliers, local society)
- Financial performance measures do not fully describe the value creation process
- Issues like business ethics, corporate governance, social responsibility, enhance the wealth maximization perspective
- Even if one focuses on one group of stakeholders, it is likely that there will be different perceptions of value and information asymmetries

Freeman, R.E., Harrison, J.S., Wicks, A.C., Parmar, B.L., and de Coll, S. (2010), *Stakeholder Theory: The State of the Art*, Cambridge University Press, New York.

Multiple objectives in finance

- The long-term and sustainable creation of value can not be ensured unless one considers the whole range of corporate operations (personnel, investments, R&D, …)
  - Jensen (2001): *enlightened value maximization*
- MCDA fits well this point of view
- Even if we accept the wealth maximization principle, its implementation raises a lot of challenges
  - Vague concept
  - Needs the specification of several operational goals

Some empirical evidence

- Graham and Harvey (2001)
  - Survey among 392 chief financial officers from the USA and Canada
  - Strategic financial decisions are based of various factors, such as flexibility, credit ratings, profits per share, capitalization, etc.
- Similar empirical results have been found for European firms (Brounen et al., 2006)

Graham, J.R. and Harvey, C.R. (2001), “The theory and practice of corporate finance: Evidence from the field”, *Journal of Financial Economics* 60(2–3), 187–243.

Brounen, D., de Jong, A., and Koedijk, K. (2006), “Capital structure policies in Europe: Survey evidence”, *Journal of Banking & Finance* 30(5), 1409–1442.

Multidimensional nature of risk

- The traditional point of view focuses on volatility
- Recent trends focus on losses under adverse conditions (e.g., value-at-risk systems)
- Many different risk measures are now available (Szegö, 2005)
  - Market risk, operational risk, liquidity risk, credit risk
  - Idiosyncratic, systematic, systemic risk
- The perception of risk is subjective
- A single measure of risk cannot fully capture all risk dimensions

Doumpos & Zopounidis (2014)
Zopounidis, Galariotis, Doumpos, Sarri, Andriosopoulos (2015)

Portfolio selection

Asset screening and selection

- Macroeconomic conditions
- Sectoral analysis
- Corporate data
- Market trends

Portfolio optimization

- Risk-return measures
- Investment policy objectives
- Diversification constraints & goals

Management

- Portfolio rebalancing
- Trading strategies

Xidonas, Mavrotas, Krintas, Psarras, Zopounidis (2012)

Portfolio optimization

- Given a set of m assets find a portfolio that maximizes the investor's expected utility
  - Different asset classes can be considered, such as stocks, funds, commodities, investment projects, etc.
- A portfolio is defined by:
  - The proportion of the available capital invested in each asset $(x_1, \ldots, x_m)$
  - The amount of capital invested in each asset
- Basic information
  - Time series of assets' returns $r_{i1}, r_{i2}, \ldots, r_{iT}$
  - Expected returns $r_1, r_2, \ldots, r_m$
  - Covariances between the assets' returns σ_{ij}

The mean-variance model

- An investor's expected utility function of wealth $\mathbb{E}[U(W)]$ is a quadratic function of the expected return (r) and the variance of returns (σ^2)

$$\mathbb{E}[U(W)] = r - \frac{\beta}{2}(\sigma^2 + r^2),$$

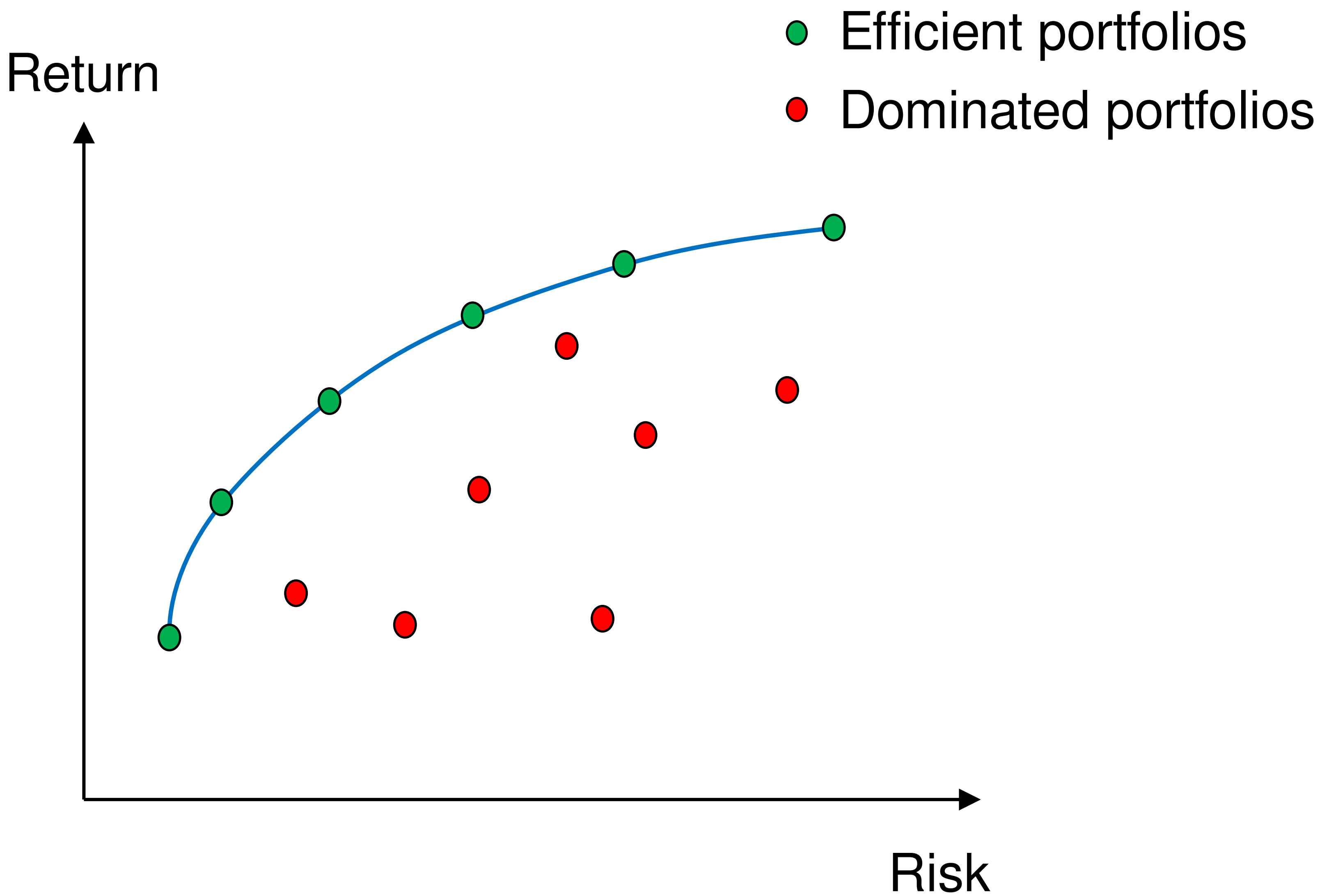
$\beta > 0$ (risk aversion parameter)

- Bi-objective quadratic optimization model

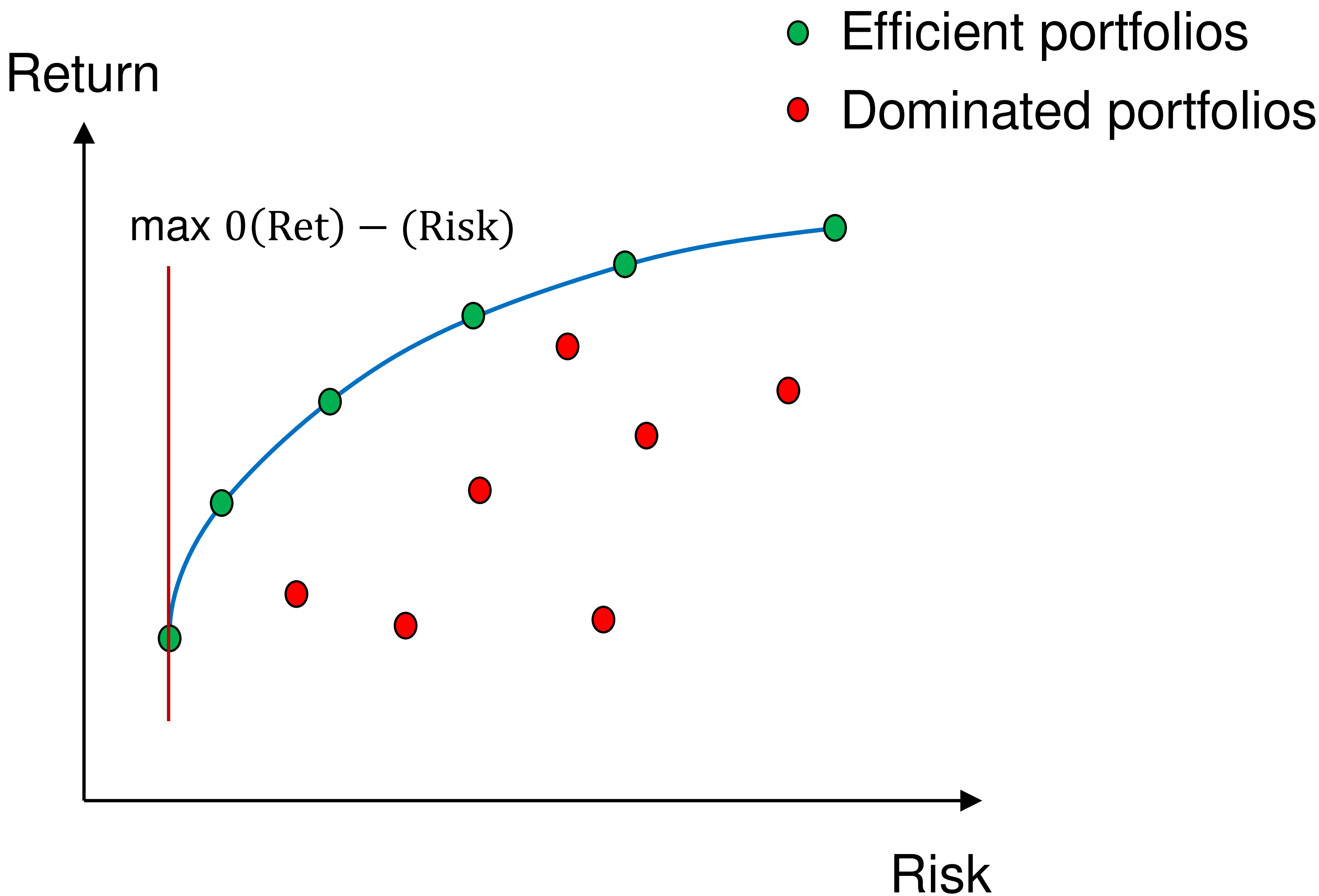
$$\begin{aligned} \max \quad & \sum_i r_i x_i - \lambda \sum_{i,j} x_i x_j \sigma_{ij} \\ \text{s.t.} \quad & x_1 + x_2 + \cdots + x_m = 1 \\ & l_i \leq x_i \leq u_i \end{aligned}$$

$$\begin{aligned} \min \quad & \sum_{i,j} x_i x_j \sigma_{ij} \\ \text{s.t.} \quad & r_1 x_1 + r_2 x_2 + \cdots + r_m x_m \geq R \\ & x_1 + x_2 + \cdots + x_m = 1 \\ & l_i \leq x_i \leq u_i \end{aligned}$$

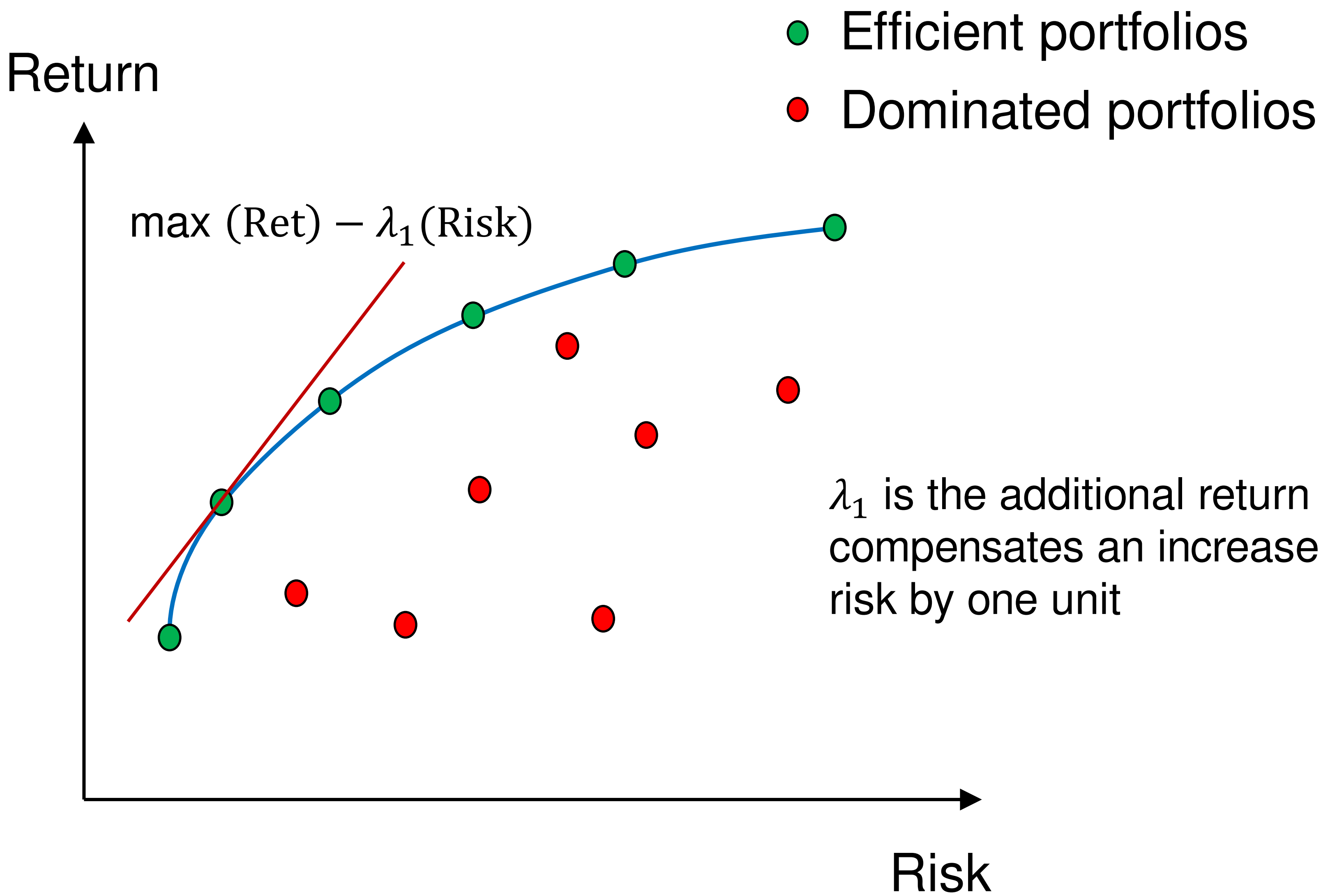
The Pareto frontier



Weighted sum

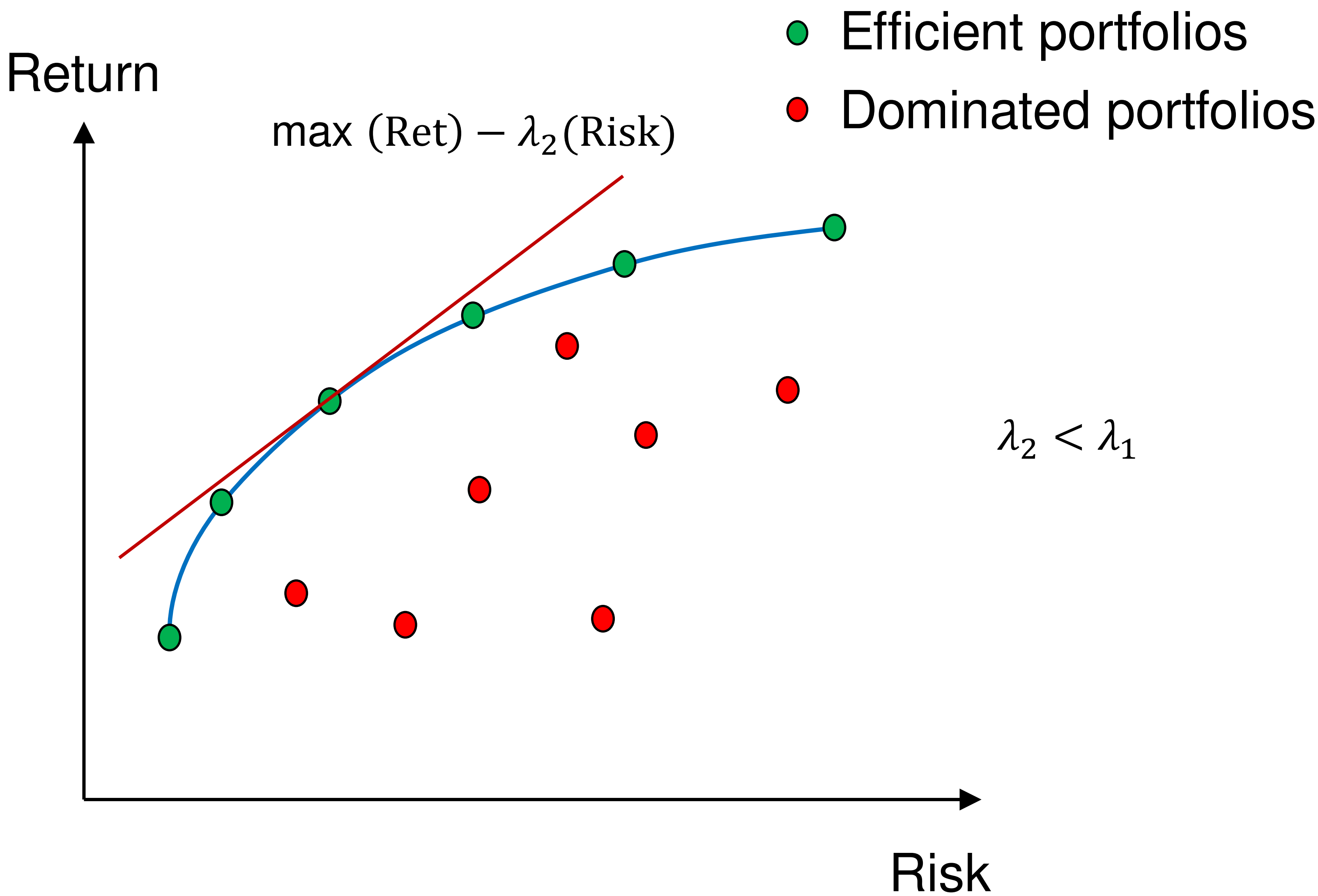


Weighted sum

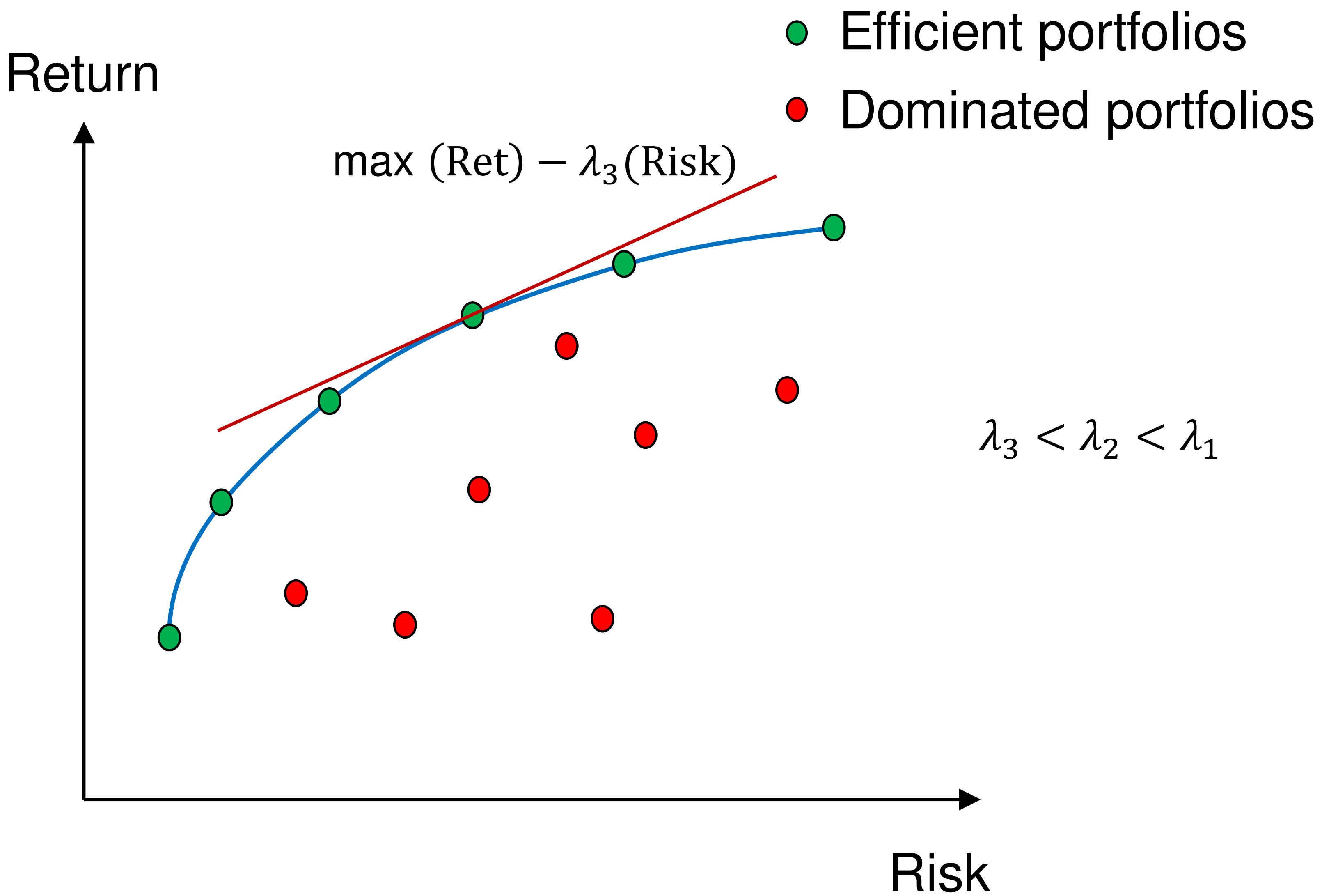


λ_1 is the additional return that compensates an increase in risk by one unit

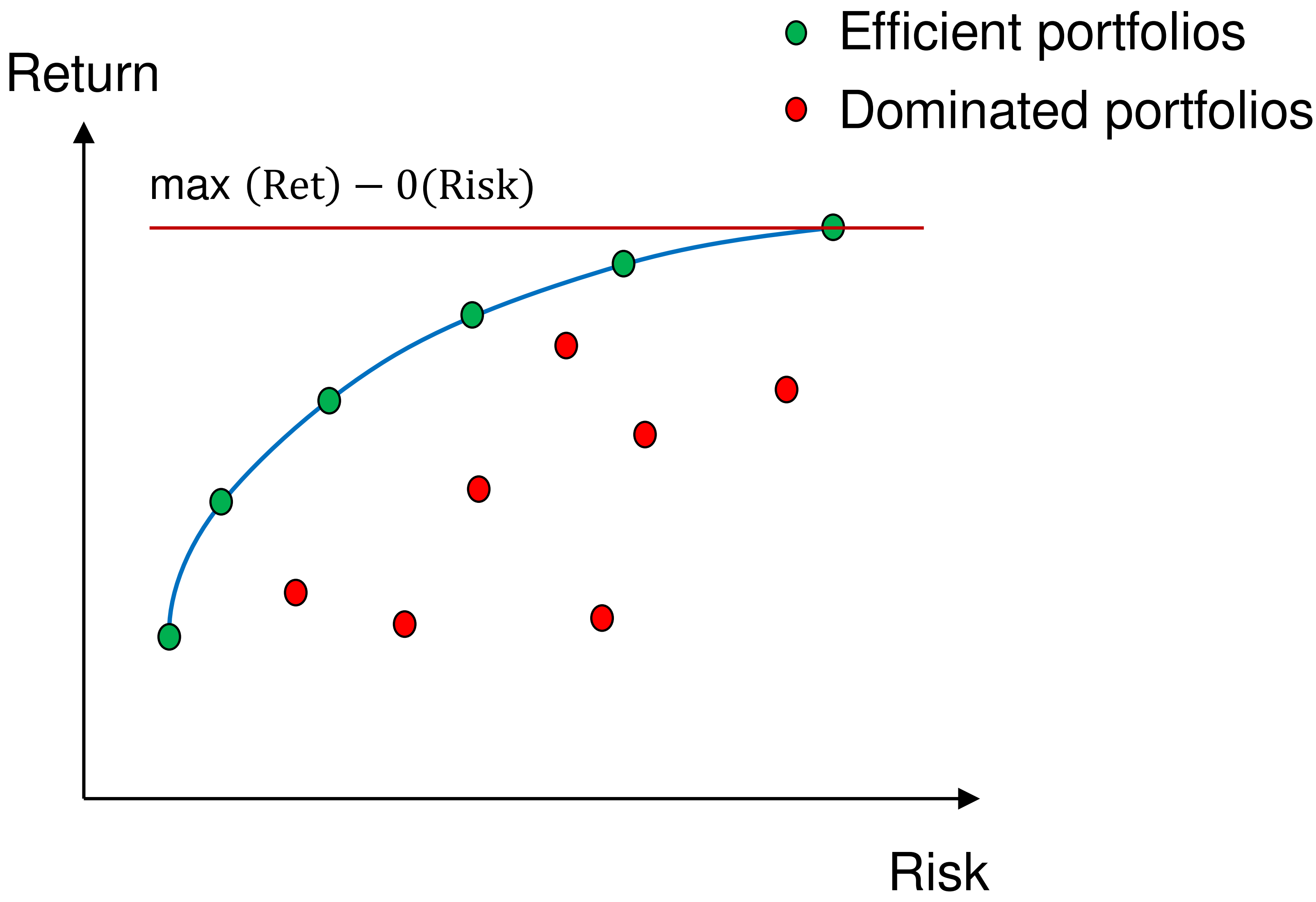
Weighted sum



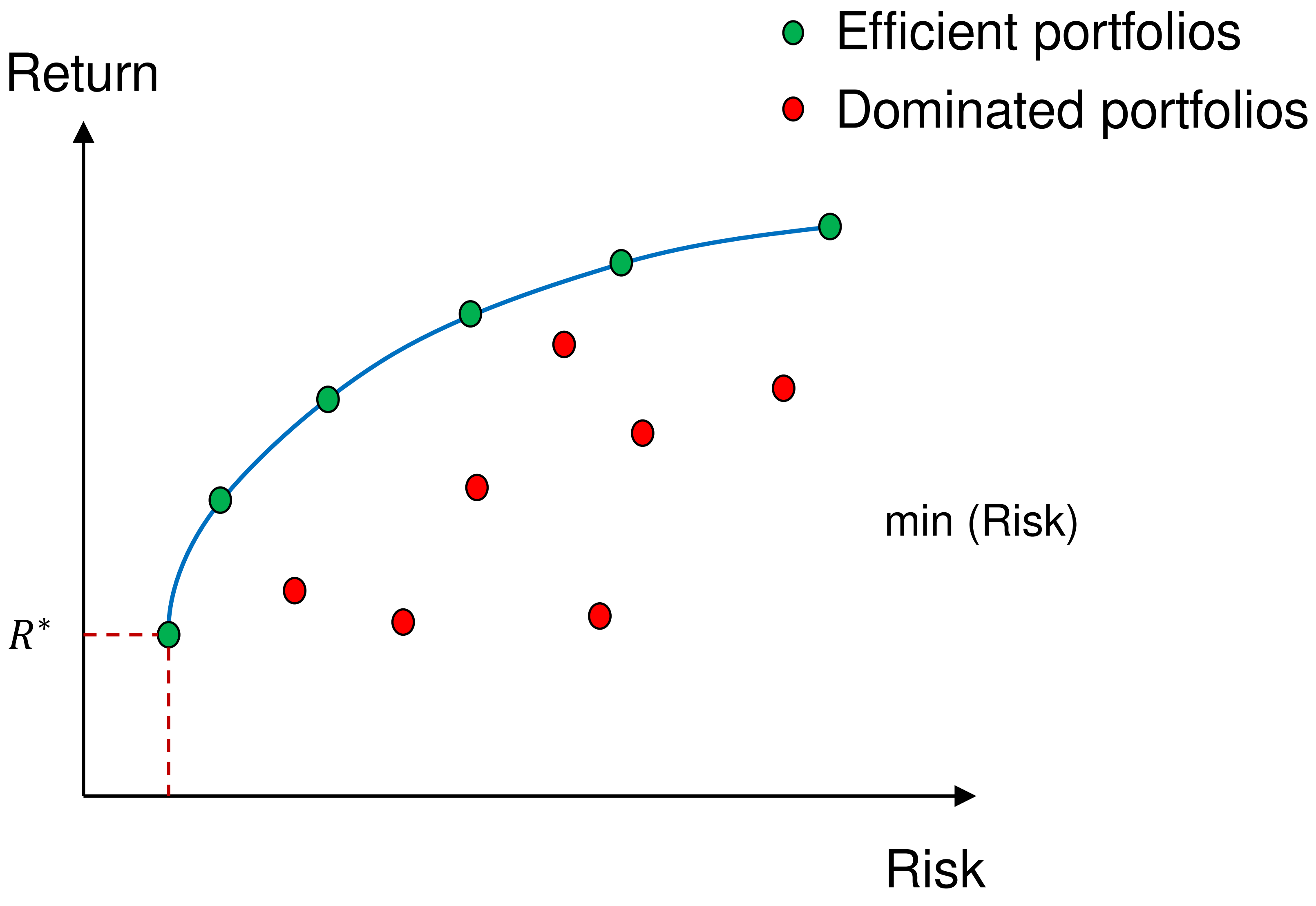
Weighted sum



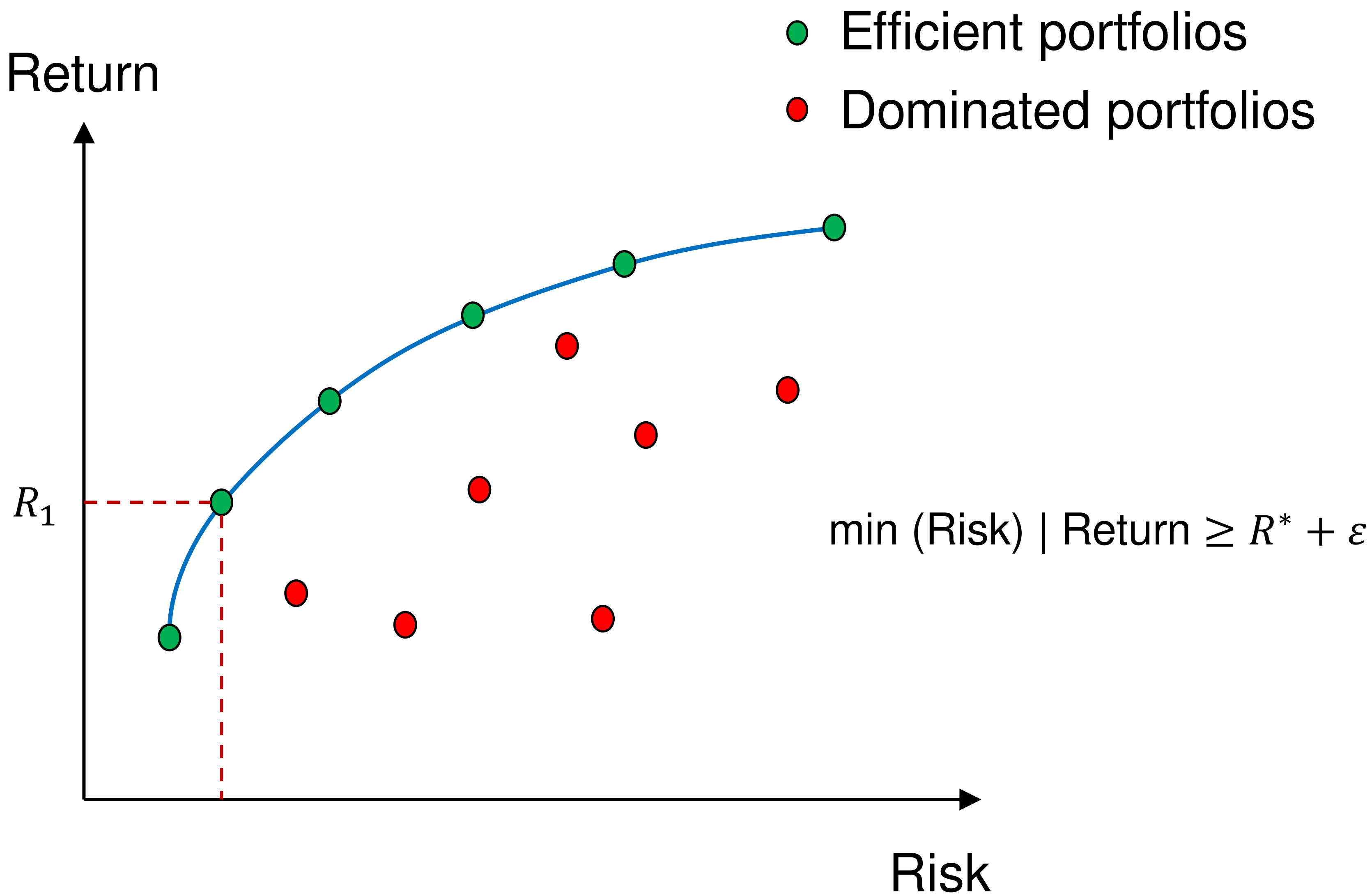
Weighted sum



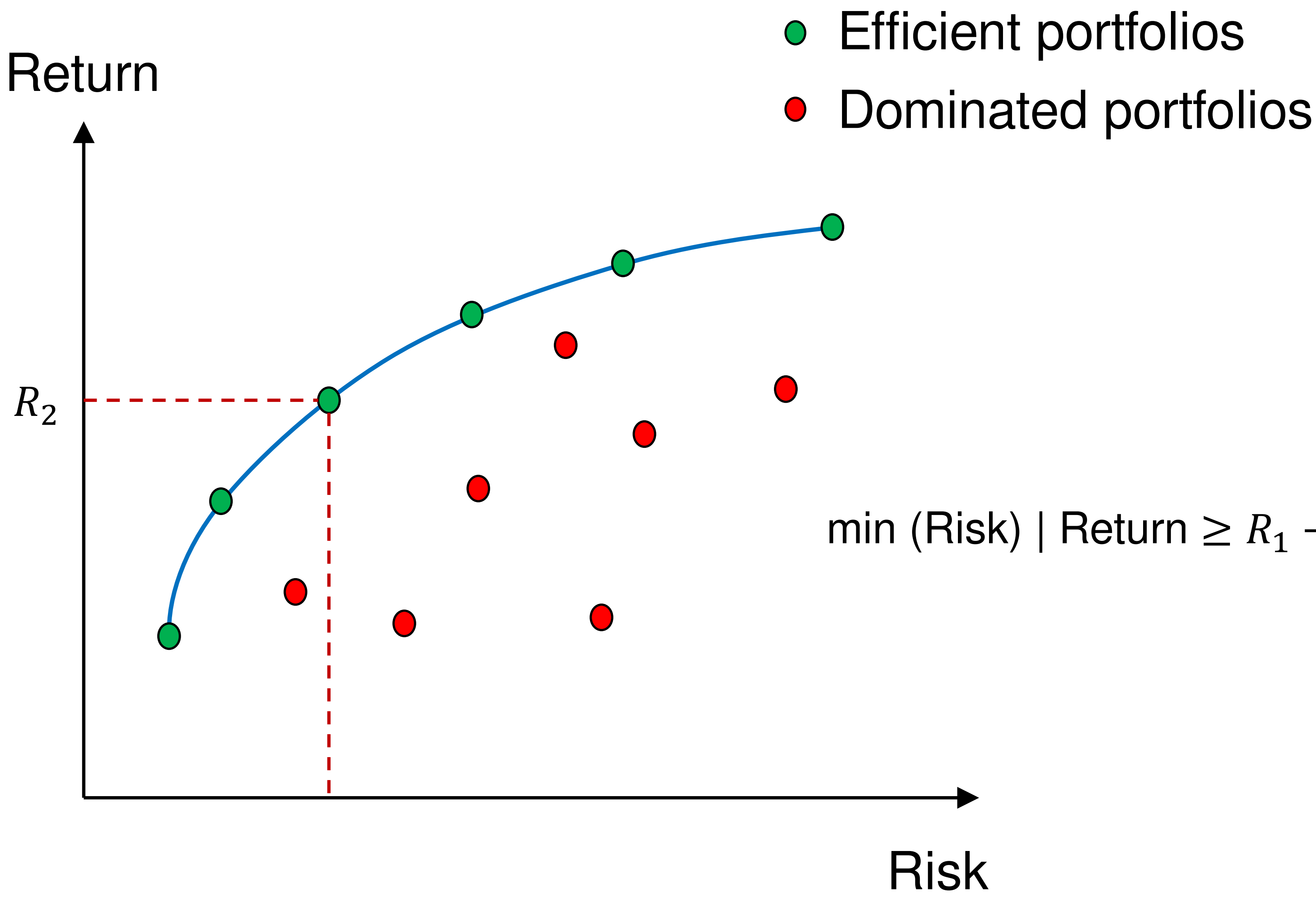
ε-constraint method



ε-constraint method

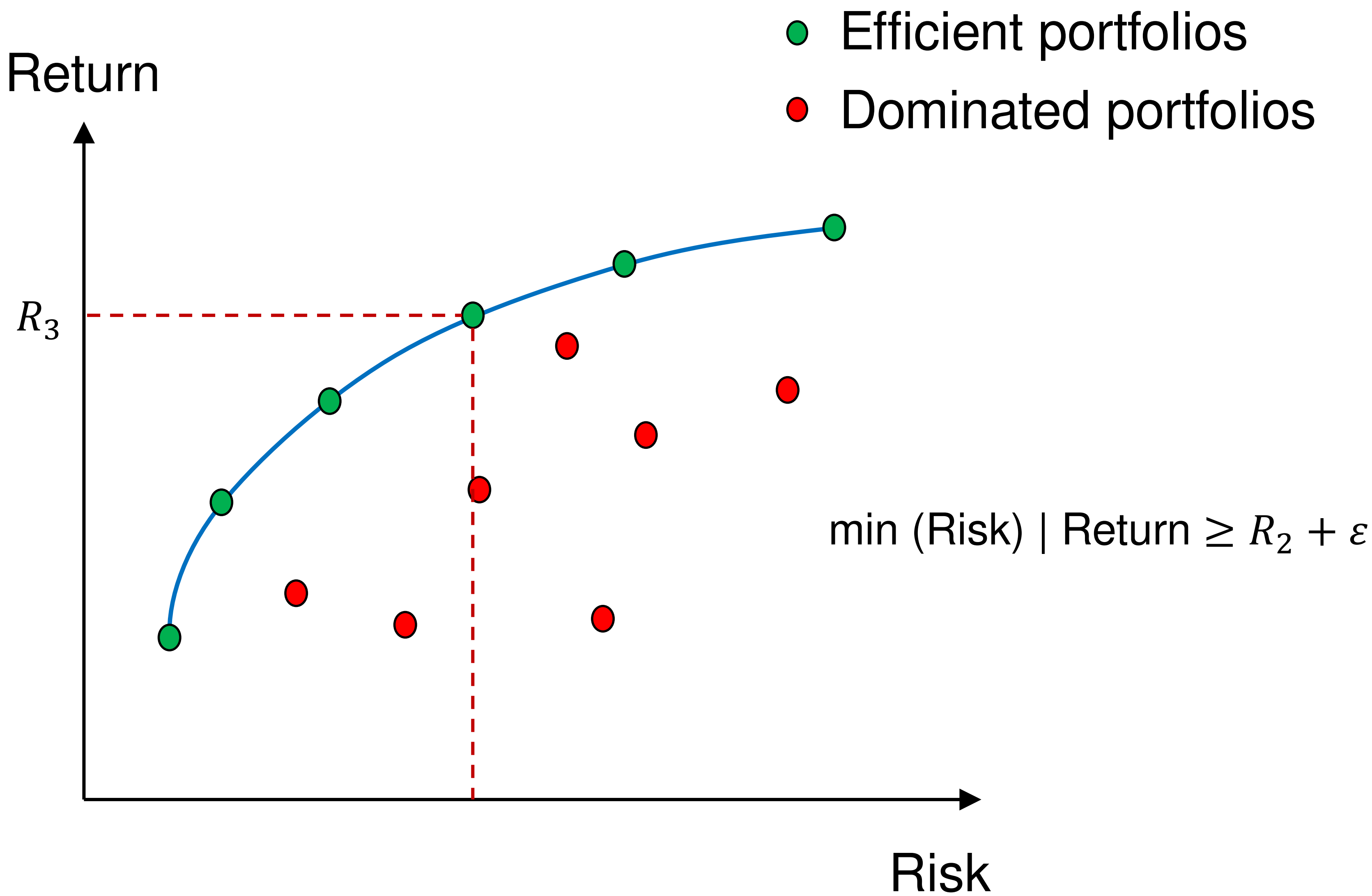


ε-constraint method



min (Risk) | Return $\geq R_1 + \varepsilon$

ε-constraint method

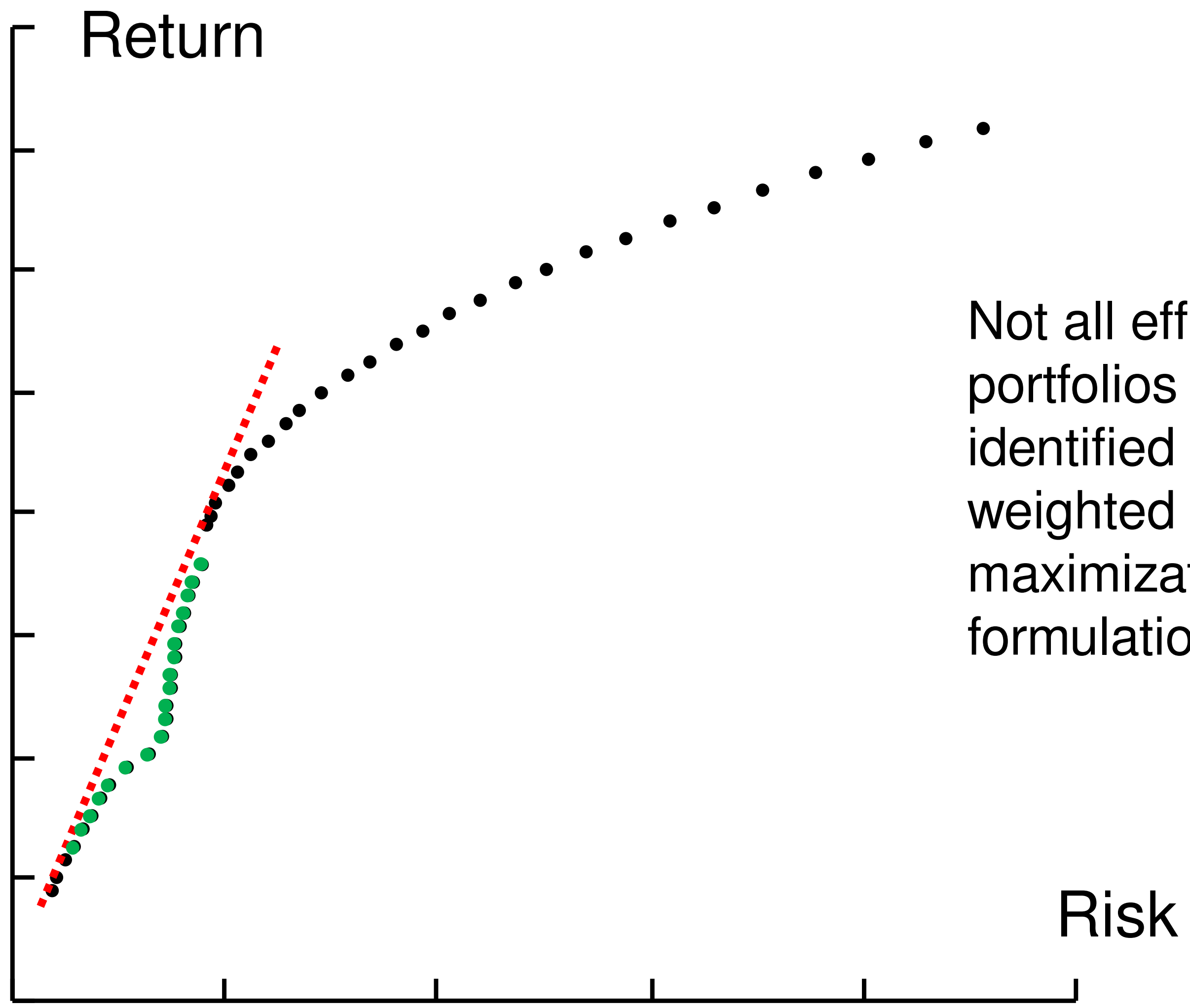


Cardinality constrained variant

- Construct portfolios consisting of at most K assets

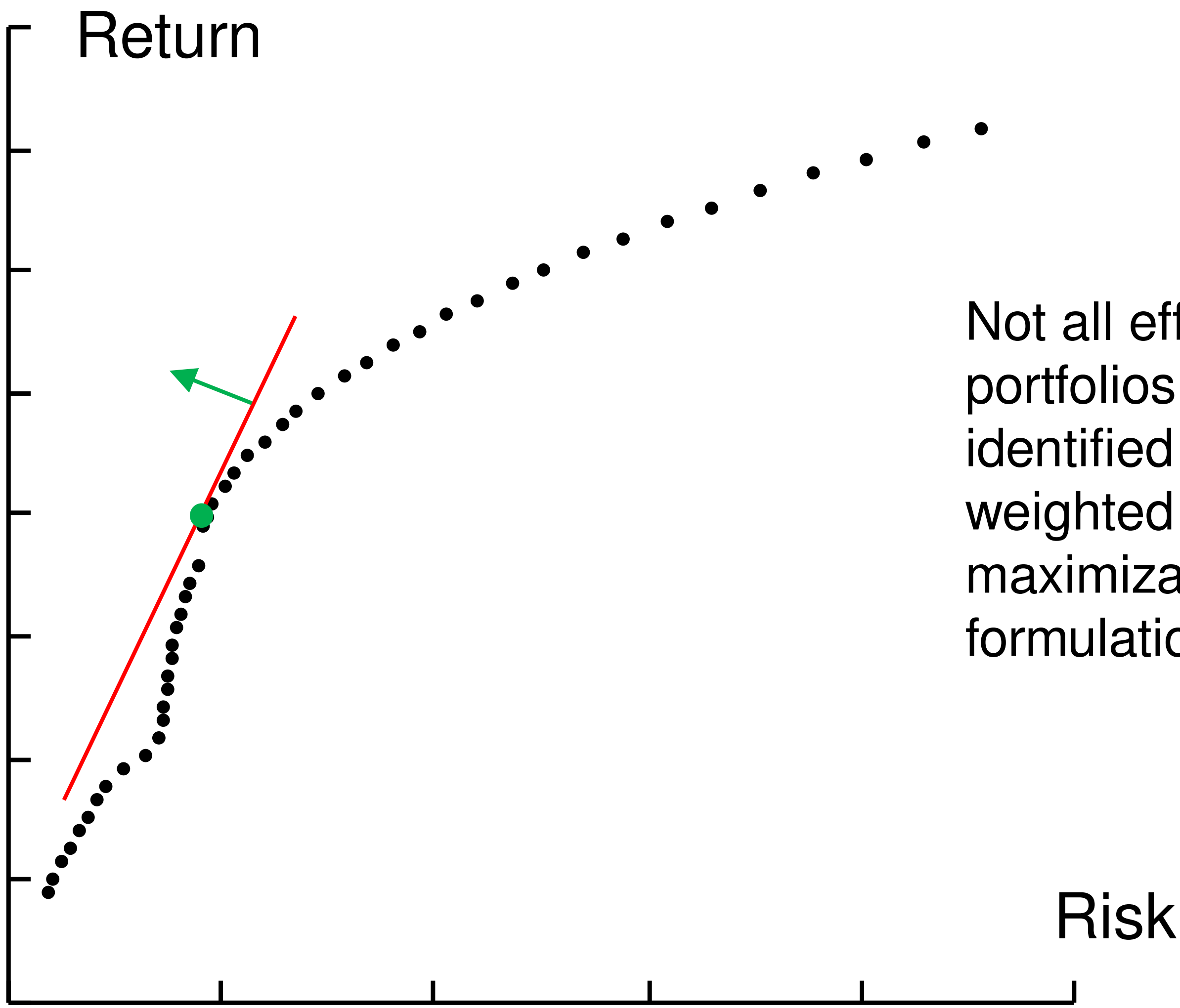
$$
\begin{aligned}
\min \quad & \sum_{i,j} x_i x_j \sigma_{ij} \\
\text{s.t.} \quad & r_1 x_1 + r_2 x_2 + \cdots + r_m x_m \geq R \\
& x_1 + x_2 + \cdots + x_m = 1 \\
& y_1 + y_2 + \cdots + y_m \leq K \\
& l_i y_i \leq x_i \leq u_i y_i \\
& y_i \in \{0, 1\}
\end{aligned}
$$

Cardinality constrained Pareto set



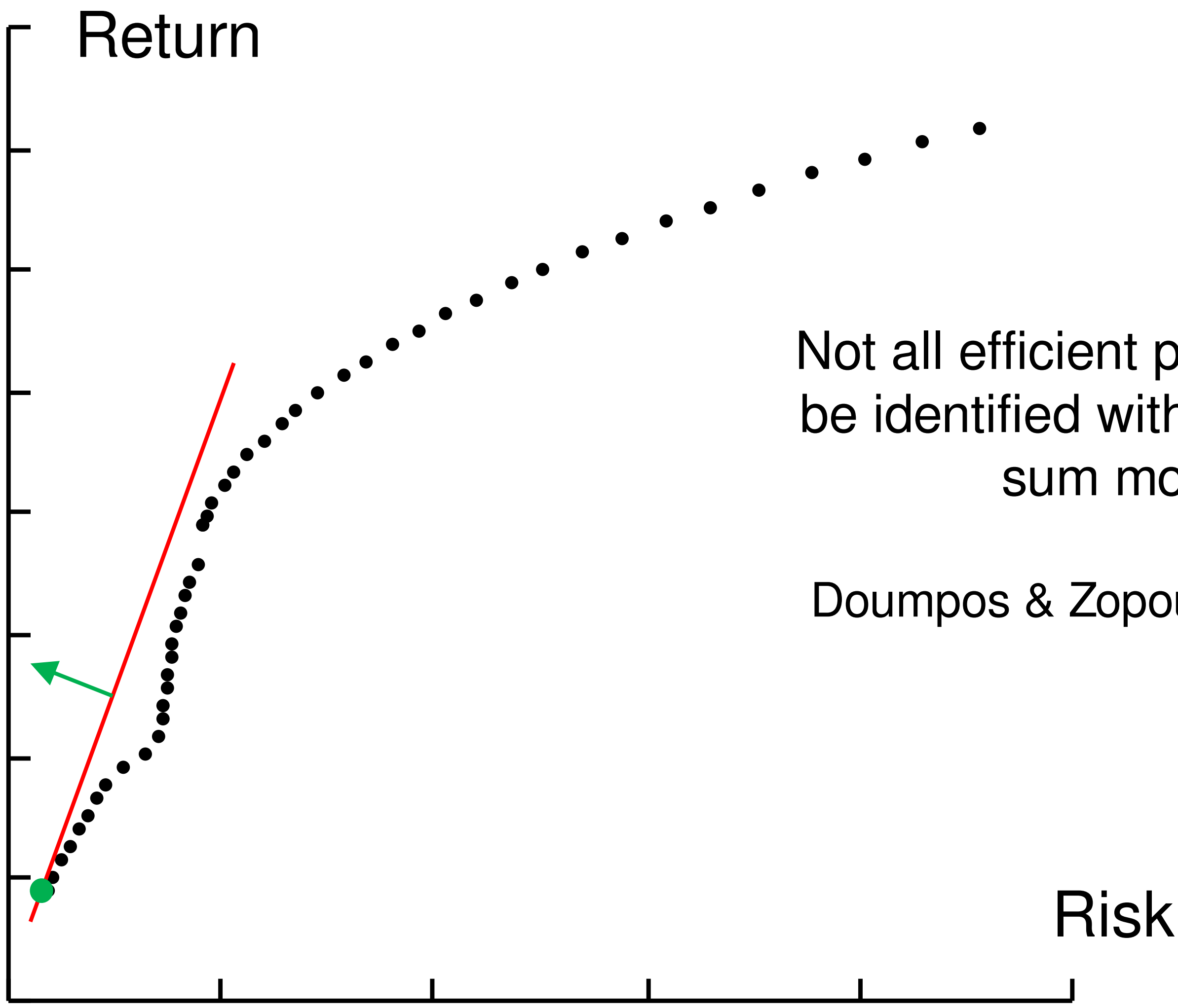
Not all efficient portfolios can be identified with a weighted sum maximization formulation

Cardinality constrained Pareto set



Not all efficient portfolios can be identified with a weighted sum maximization formulation

Cardinality constrained Pareto set



Not all efficient portfolios can be identified with a weighted sum model

Doumpos & Zopounidis (2014)

Some criticisms

- Investors care about more than just mean and variance
- Expected returns and covariances are hard to estimate and they do not provide a complete description of market returns
- Returns are not linear functions of the investment weights (e.g., transaction costs)
- Investment strategies are not simple

Other risk measures

- Semi-variance: the variance of returns below the mean

$$SV = \mathbb{E}[(\min(0, r_t - r))^2]$$

  - Quadratic optimization problem (Markowitz, Todd, Xu, Yamane, 1993)

- Mean absolute deviation

$$MAD = \mathbb{E}[|r_t - r|]$$

  - Linear programming (Konno & Yamazaki, 1991)

- Higher-order moments: Skewness and kurtosis
  - Investors prefer portfolios with high positive skewness (long right tail) and low kurtosis so that the probability of losses will be reduced
  - Non-convex, not easy to optimize (Lai, 1991)

Other risk measures

- Value-at-risk (VaR_α): the maximum expected loss at a specific confidence level $\alpha\%$

$$\text{VaR}_\alpha(L) = \min\{z : \Pr(L \geq z) \leq 1 - \alpha\}$$

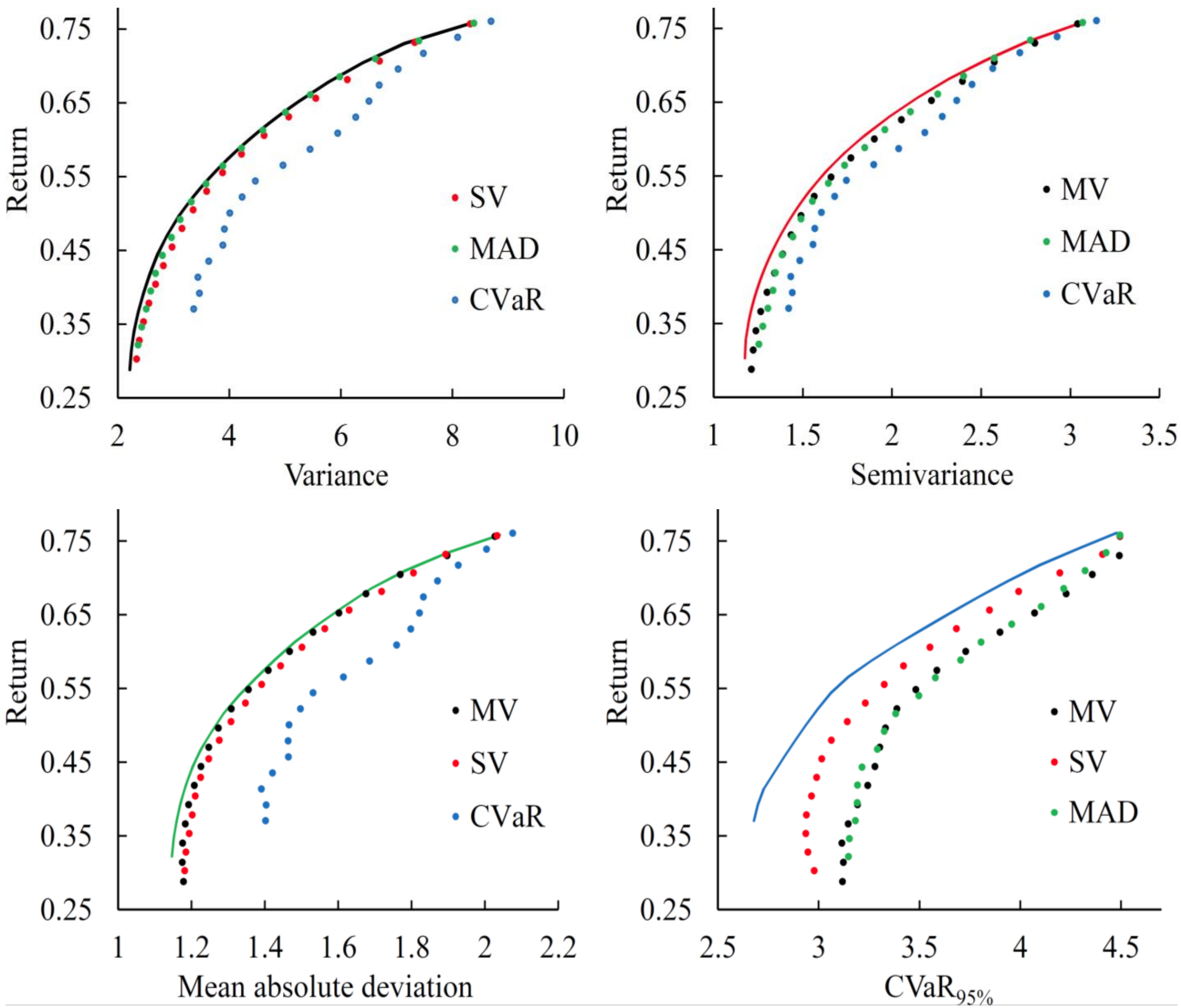
  - Non-convex, not easy to optimize (Gaivoronski & Pflug, 2005)

- Conditional value-at-risk: the mean losses exceeding VaR_α

$$\text{CVaR}_\alpha(L) = \mathbb{E}[L \mid L \geq \text{VaR}_\alpha(L)]$$

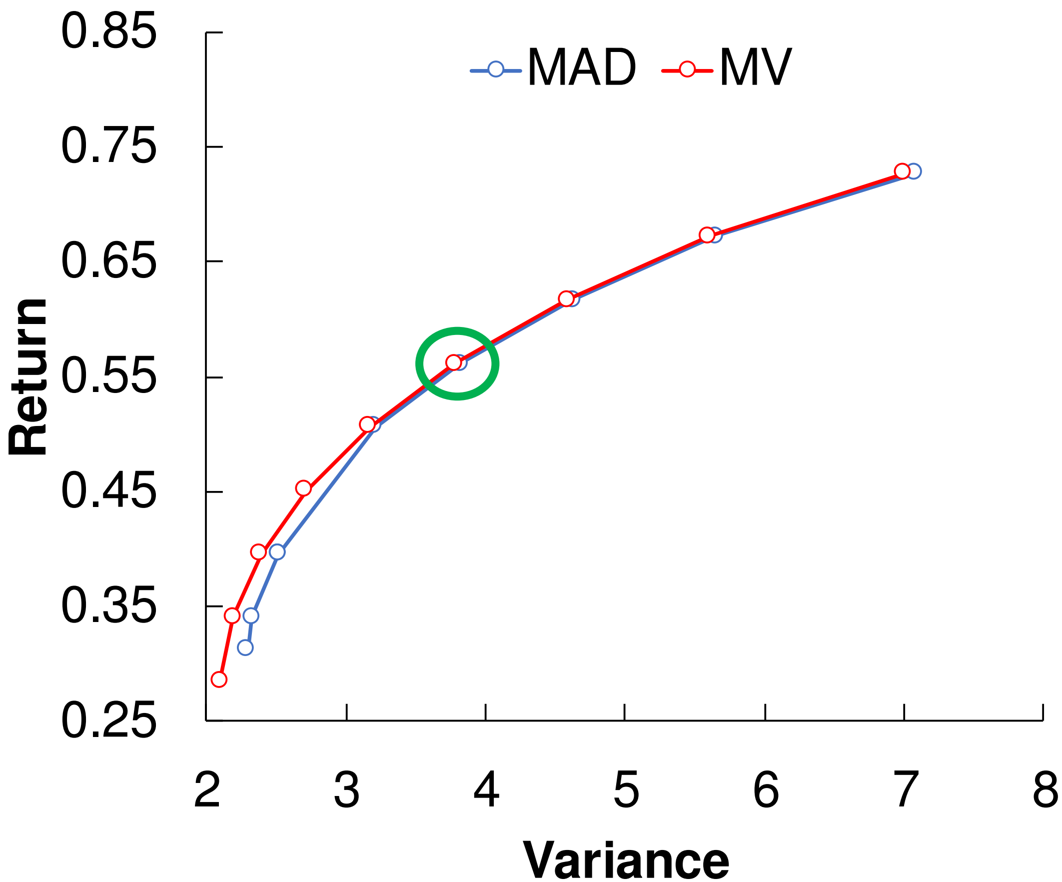
  - Linear programming (Rockafellar & Uryasev, 2000)

30 stocks from DJIA, over the period 2011–2013 (weekly data)



Pareto frontiers for different portfolio performance criteria

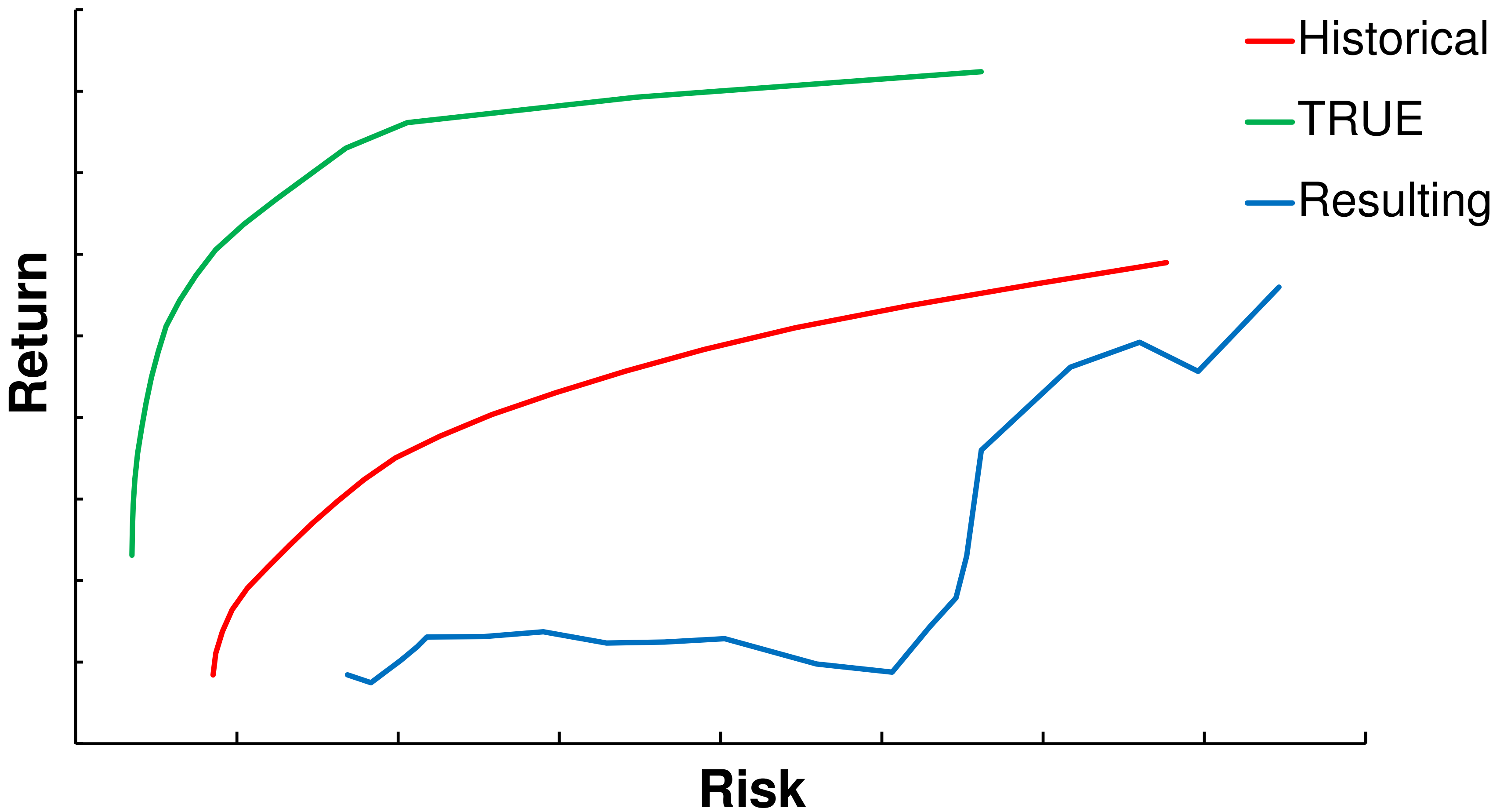
Objective vs decision spaces



Portfolio compositions

Stocks	MV	MAD
A1	32%	34%
A2	19%	14%
A3	14%	19%
A4	13%	11%
A5	13%	12%
A6	5%	9%
A7	3%	0%

Out-of-sample frontiers



Pavlou, A., Doumpos, M. & Zopounidis, C. (2018), “The robustness of portfolio efficient frontiers: A comparative analysis of bi-objective and multi-objective approaches”, *Management Decision* (forthcoming)

Risk-adjusted performance

- Sharpe ratio: excess return (over risk-free rate) to volatility
- Treynor ratio: excess return to systematic risk
- Sortino ratio: excess return to standard deviation of negative returns
- Jensen's alpha: return attributable to management skill
- Omega ratio: excess return over a threshold τ to mean return below the threshold

$$\text{Sharpe} = \frac{r - r_f}{\sigma} \qquad \text{Treynor} = \frac{r - r_f}{\beta} \qquad \text{Sortino} = \frac{r - r_f}{\sigma_N}$$

$$\alpha = r - \left[r_f + \beta\left(r_m - r_f\right)\right] \qquad \Omega(\tau) = \frac{\mathbb{E}[\max(0, r_t - \tau)\ ]}{\mathbb{E}[\max(0, \tau - r_t)]}$$

Other considerations

- Transaction costs and management fees
- Portfolio diversification
- Liquidity
- Social responsibility (Ballestero et al., 2012; Utz et al., 2014)
  - Socially responsible investments (SRI) in the USA exceeded $8.7 trillion at the end of 2016 (>21% of assets under professional management)
- Such issues can be stated in the form of objectives or “soft” constraints (e.g., goal programming; Aouni, Colapinto, & La Torre, 2014)

A goal programming example

- Construct a portfolio with $\beta \approx 1$ with expected daily return preferably $\geq 0.1\%$ that consists (preferably) of 25-50% in stocks from a SRI index $\mathcal{S}$

$$
\begin{array}{ll}
\min & w_1 s_1 + w_2(s_2^+ + s_2^-) + w_3(s_3^+ + s_3^-) \\
\text{s.t.} & r_1 x_1 + r_2 x_2 + \cdots + r_m x_m + s_1 \geq 0.1 \\
& \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m + s_2^- - s_2^+ = 1 \\
& \displaystyle\sum_{i \in \mathcal{S}} x_i + s_3^- \geq 0.25 \qquad \sum_{i \in \mathcal{S}} x_i - s_3^+ \leq 0.5 \\
& x_1 + x_2 + \cdots + x_m = 1 \\
& x_i, s_1, s_2^{\pm}, s_3^{\pm} \geq 0
\end{array}
$$

Credit risk

- Credit risk refers to the probability that borrowers will not be able to meet their debt obligations (default)
  - Major component of all regulatory frameworks
  - Timely issue due to the outbreak of the credit crisis
- Credit risk is not only relevant for financial institutions
  - Non-financial firms
  - Investors
  - New areas (e.g., online transactions, social lending, crowdfunding)

Credit risk management

- Estimation of the expected loss $\mathbb{E}(L)$ for a given period

$$\mathbb{E}(L) = PD \times LGD \times EAD$$

  - PD = Probability of default
  - EAD = Exposure at default
  - LGD = Loss given default (% of EAD)
- Each of the three elements (PD, EAD, LGD) is modeled separately using different approaches

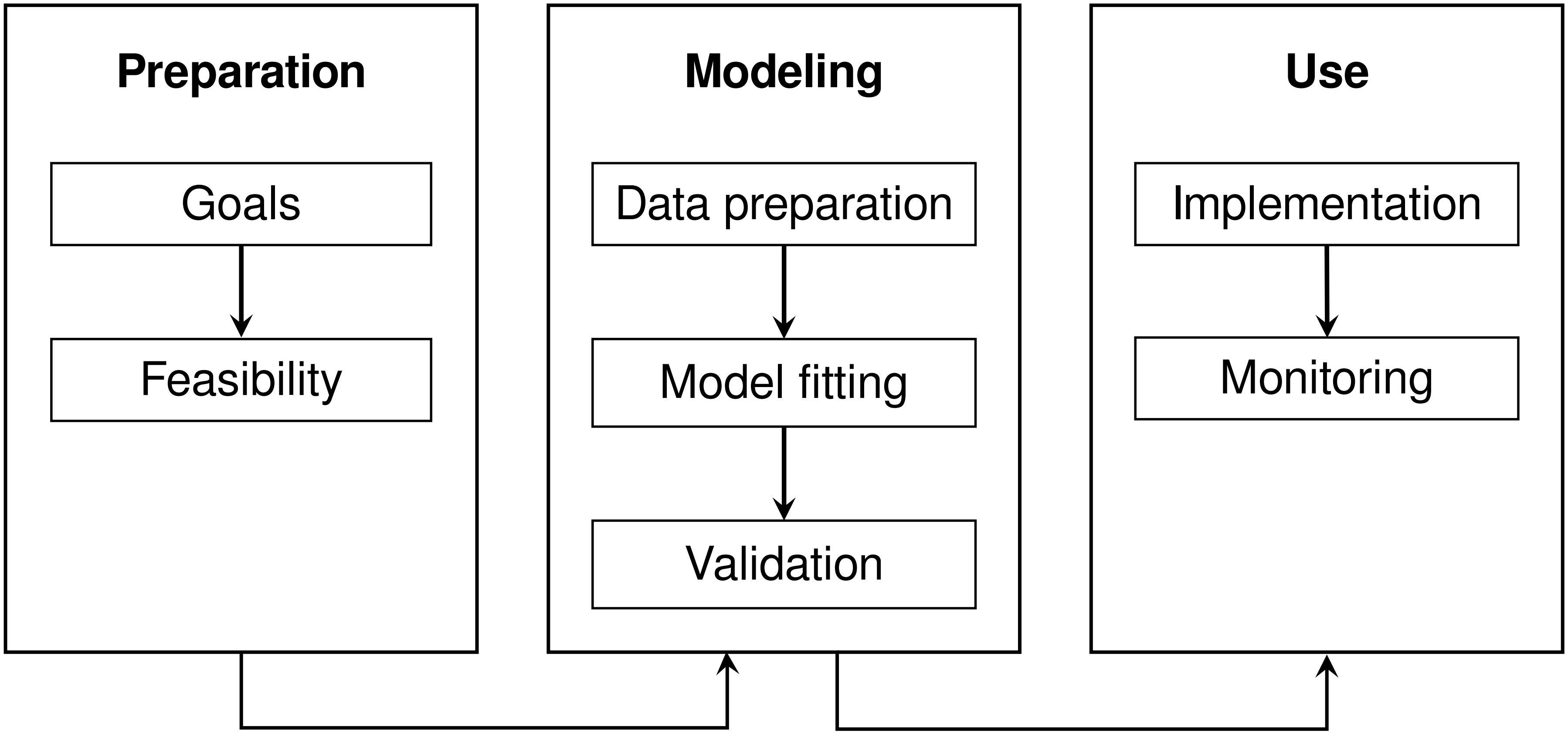
Credit scoring & rating models

- Models that evaluate the creditworthiness of a borrower, estimate the probabilities of default and classify the borrowers into risk groups
- Credit scoring vs credit rating (Van Gestel & Baesens, 2009; Doumpos et al., 2018)
  - Credit scores are expressed in numeric form and they usually refer to consumers
  - Credit ratings are expressed in symbolic form (e.g., AAA, B+, CCC, etc.) and usually refer to corporate and sovereign debt

Three main approaches

- Judgmental models
  - Applicable when there is a lack of historical data
  - Expert judgments and experience of the credit analysts
  - Elaborate structure providing rich information on all aspects of assessment process
- Empirical analytical models
  - Linear or non-linear models
  - Reliance of historical databases (internal & external)
  - Quantitative and qualitative data
- Financial models
  - Based on theories like option pricing and market data (equities, bonds, CDSs)
- Each approach has its pros and cons
  - Empirical and financial models dominate the industry, unless data are lacking

The process



Preparation
Goals
Feasibility
Modeling
Data preparation
Model fitting
Validation
Use
Implementation
Monitoring

Data for model development

- Training sample / reference set
  - A set of data upon which the development of the model will be based
  - *m* observations corresponding to obligors from a historical data base
    - Information about a set of *n* attributes (financial data, business data, credit history, etc.)
    - Separation into defaulted and non-defaulted cases (two groups)
- Validation / holdout sample
  - A set of data which will be used to test the performance of the model

Multicriteria aspects of credit risk analysis

- Multicriteria classification setting
  - Risk scores/grades are ordinal
  - Risk attributes are monotonically related to the probability of default

$$\Pr(D|\mathbf{x}_i) \leq \Pr(D|\mathbf{x}_j),\ \forall \mathbf{x}_i \succ \mathbf{x}_j$$

- Credit analysts often expect (or would like) the model to have specific characteristics
  - Domain (expert) knowledge has been shown to ameliorate statistical issues (noise) with the data
  - Transparency, comprehensibility, argumentation

How MCDA techniques are used?

- Judgmental rating models
    - Angilella & Mazzù (2015), EJOR 244(2), 540–554
- In combination with other analytical models
  - Fuzzy models, case-based reasoning, neural networks, etc.
    - Hu (2009), Neurocomputing 72, 3150–3157
    - Capotorti & Barbanera (2012), Comp. Stat. Data Anal. 56(4), 981–994
- Model fitting with multiple performance measures
  - Different model performance criteria (statistical & financial)
    - He et al. (2010), IEEE Trans. Knowl. Data Eng. 22(6), 826–838
    - Zhang et al. (2014), EJOR 237(1), 335–348
- Alternatives to statistical/data mining techniques
    - Doumpos & Zopounidis (2011), Decis. Sci. 42(3), 721–742

Value function models

- Evaluation of a borrower's creditworthiness through an additive value function (AVF)

$$V(\mathbf{x}) = w_1 v_1(x_1) + w_2 v_2(x_2) + \cdots + w_n v_n(x_n)$$

  - $w_1, \ldots, w_n$: non-negative weights summing up to 1
  - $v_1, \ldots, v_n$: monotone marginal value functions (usually defined in [0, 1])
- Most rating models have the form of an additive value function

  Krahnen & Weber (2001), Journal of Banking and Finance, 25, 3–23
- Advantages / disadvantages
  - Comprehensibility, easy to use and construct with PDA
  - The additivity assumption may be strong in some cases

Outranking models

- Relational models developed on the basis of an outranking (or preference) relation

  x S **y** : **x** is at least as good as **y**

  x P **y** : **x** is preferred over **y**

- Non-compensatory models
  - It might be unacceptable to compensate a low performance on some criteria with high performance on the others
- Advantages / disadvantages
  - They can provide rich insights (class boundaries, incomparabilities, irregular cases, etc.; see Doumpos & Zopounidis, 2011)
  - Less transparent, difficult to construct (metaheuristics can be useful)
  - Deriving credit scores and PDs may not be straightforward

Decision rules

- Symbolic models expressed in natural language

  IF (conditions) **THEN** (conclusion)

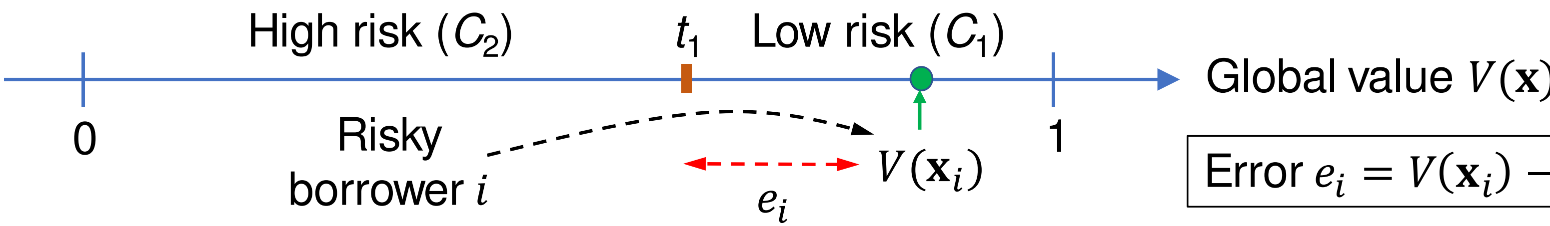
- Advantages / disadvantages
  - Easy to interpret (if the rules are not many and not too complex)
  - Computationally efficient procedures for large data sets
  - Deriving (continuous) credit scores and PDs is not straightforward

Constructing AVF credit rating

- q ordinal categories $C_1, C_2, \dots, C_q$ (C_1 = low risk)
- A threshold-based classification rule
  - Borrower i is classified in category k if $t_k < V(\mathbf{x}_i) < t_{k-1}$
- Inputs: a reference set X of m borrowers classified in the pre-defined risk categories
- Objective: infer an AVF model and class boundaries as consistently as possible with the instances in X

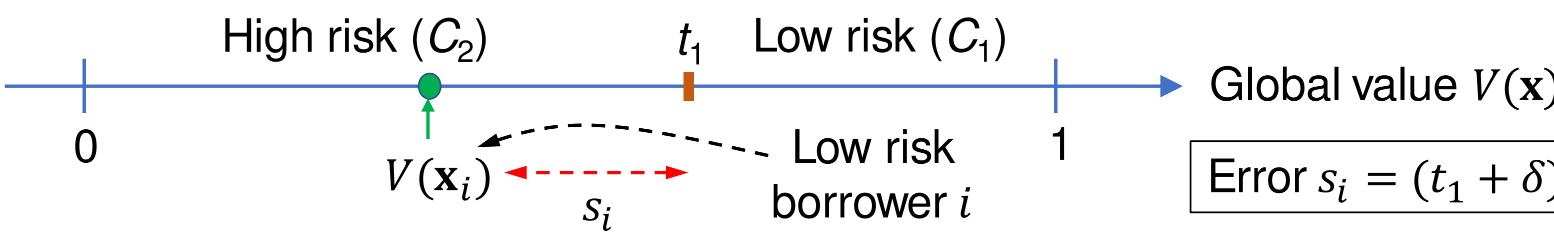
Classification errors

- The model overestimates the creditworthiness of borrower i



Error $e_i = V(\mathbf{x}_i) - (t_1 - \delta)$

- The model underestimates the creditworthiness of borrower i



Error $s_i = (t_1 + \delta) - V(\mathbf{x}_i)$

Basic formulation (UTADIS method)

- Assume a linear value function with all criteria scaled in 0-1:

$$V(\mathbf{x}_i) = w_1 x_{i1} + w_2 x_{i2} + \cdots + w_n x_{in}$$

- Linear programming model (Doumpos & Zopounidis, 2002)

$$
\begin{aligned}
\min \quad & \sum_{i=1}^{m} \omega_i (e_i + s_i) & \\
\text{s.t.} \quad & \sum_{j=1}^{n} w_j x_{ij} + s_i \geq t_k + \delta & \forall i \in \{C_1 \cup C_2 \cup \cdots \cup C_{q-1}\} \\
& \sum_{j=1}^{n} w_j x_{ij} - e_i \leq t_{k-1} - \delta & \forall i \in \{C_2 \cup C_3 \cup \cdots \cup C_q\} \\
& t_{k-1} - t_k \geq \varepsilon & k = 2, \ldots, q-1 \\
& w_1 + w_2 + \cdots + w_n = 1 & \\
& w_j, t_k, e_i, s_i \geq 0 &
\end{aligned}
$$

Example

Borrowers	Criterion x_1	Criterion x_2	Risk class
A_1	0.73	0.97	Low (C_1)
A_2	0.78	0.80	Low (C_1)
A_3	0.60	0.64	Low (C_1)
A_4	0.68	0.62	Medium (C_2)
A_5	0.51	0.32	Medium (C_2)
A_6	0.31	0.68	Medium (C_2)
A_7	0.37	0.35	Medium (C_2)
A_8	0.10	0.02	High (C_3)
A_9	0.12	0.37	High (C_3)
A_{10}	0.36	0.01	High (C_3)

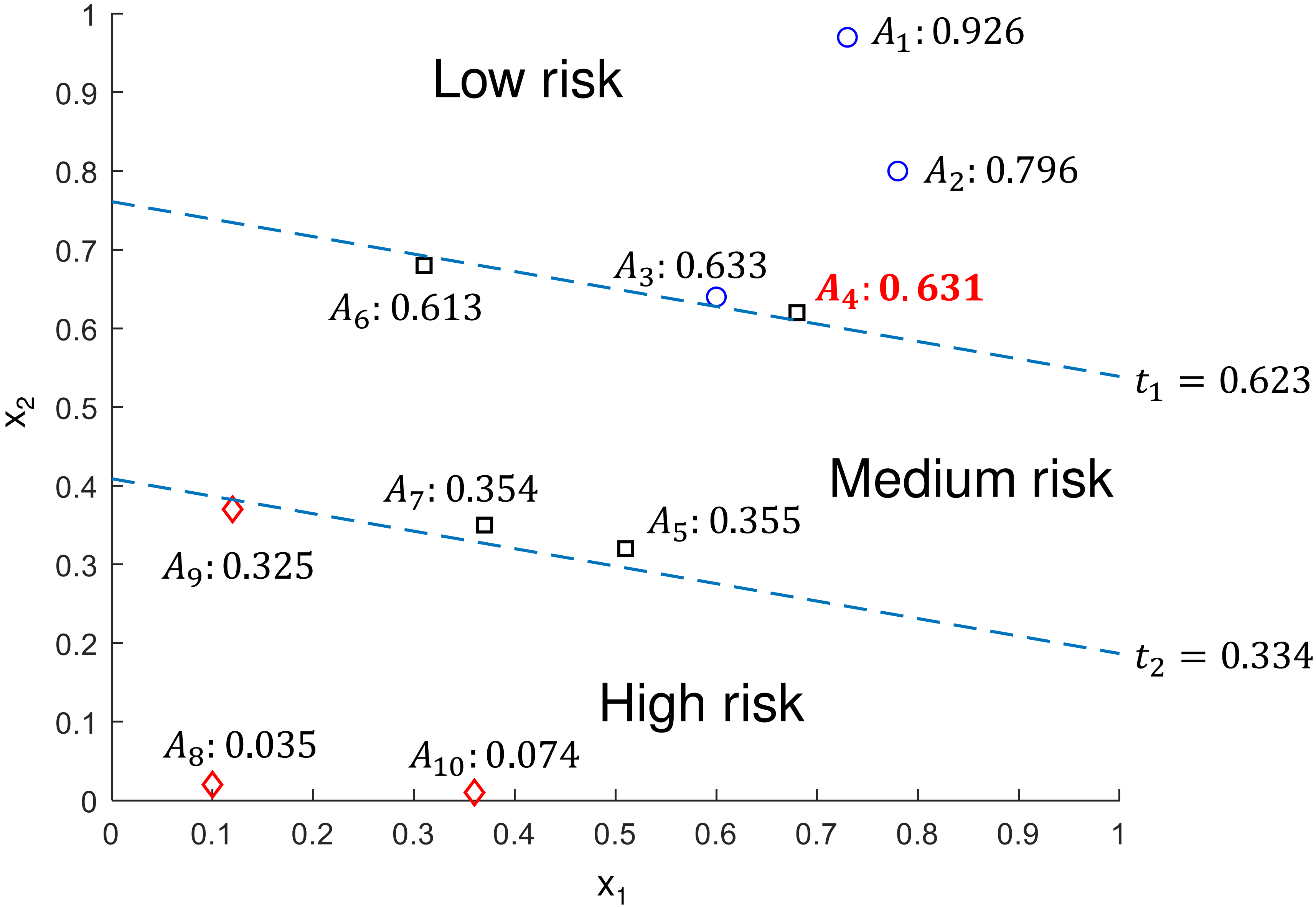
LP formulation

$$
\begin{aligned}
\min \quad & \frac{1}{3}(s_1 + s_2 + s_3) + \frac{1}{4}(s_4 + e_4 + \cdots + s_7 + e_7) + \frac{1}{3}(e_8 + e_9 + e_{10}) \\
\text{s.t.} \quad & 0.73w_1 + 0.97w_2 + s_1 \geq t_1 + 0.01 \quad \text{(Borrower } A_1\text{)} \\
& \text{Similar constraints for } A_2,\ A_3 \\
& 0.68w_1 + 0.62w_2 + s_4 \geq t_2 + 0.01 \quad \text{(Borrower } A_4\text{)} \\
& 0.68w_1 + 0.62w_2 - e_4 \leq t_1 - 0.01 \quad \text{(Borrower } A_4\text{)} \\
& \text{Similar constraints for } A_5,\ A_6, A_7 \\
& 0.10w_1 + 0.02w_2 - e_8 \leq t_2 - 0.01 \quad \text{(Borrower } A_8\text{)} \\
& \text{Similar constraints for } A_9,\ A_{10} \\
& t_1 - t_2 \geq 0.2 \\
& w_1 + w_2 = 1 \\
& w_j, w_2, t_1, t_2, e_i, s_i \geq 0
\end{aligned}
$$

Results

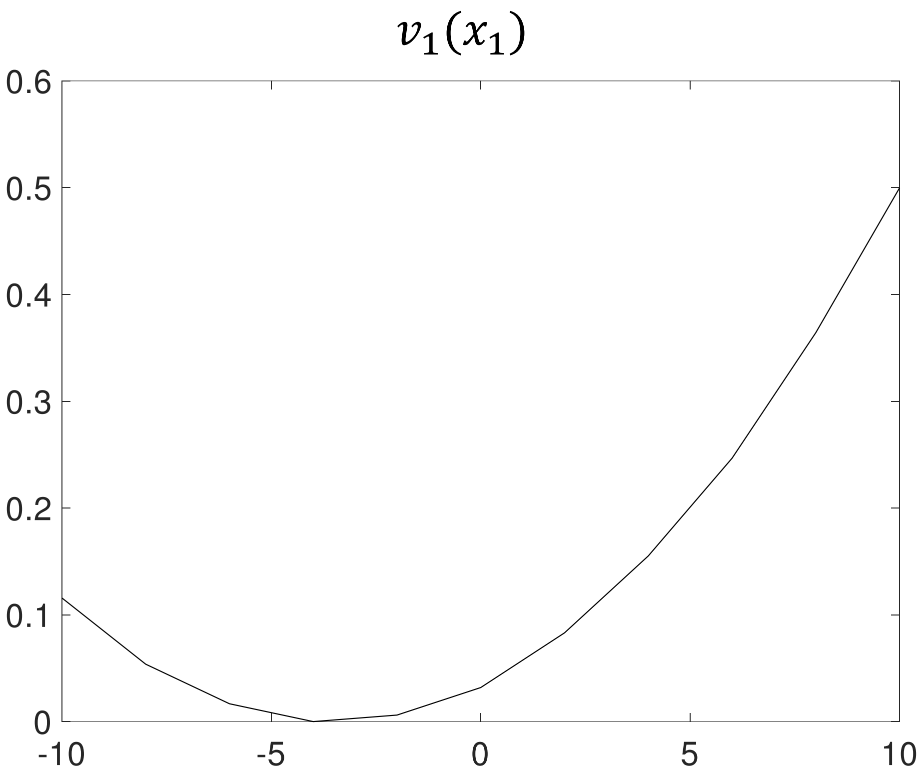
Value function

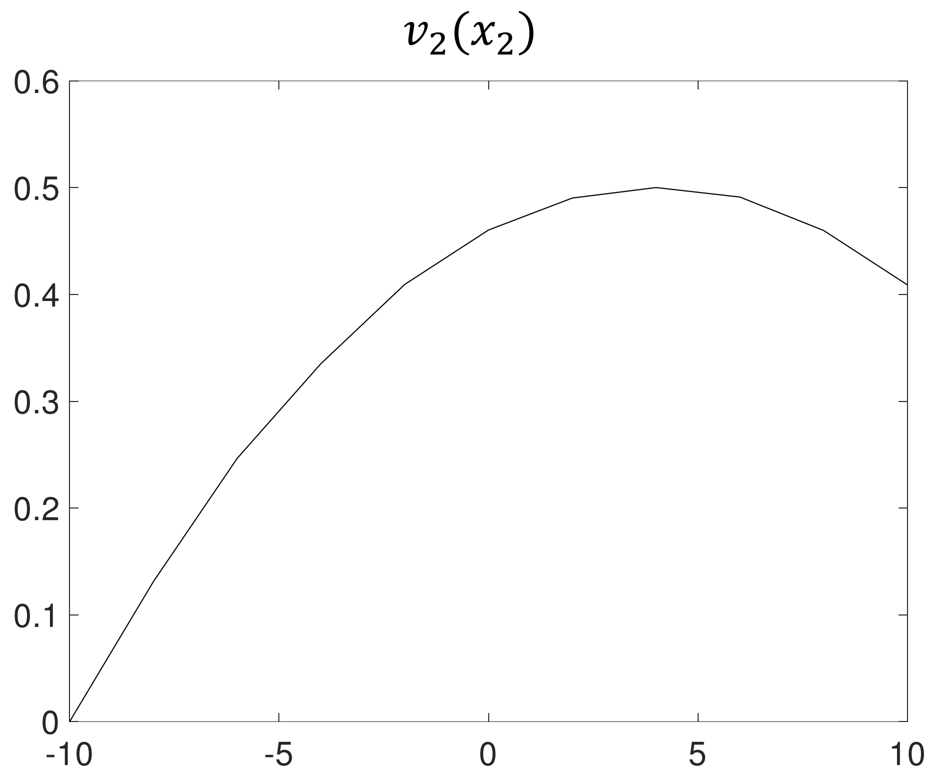
$V(\mathbf{x}) = 0.182x_1 + 0.818x_2$



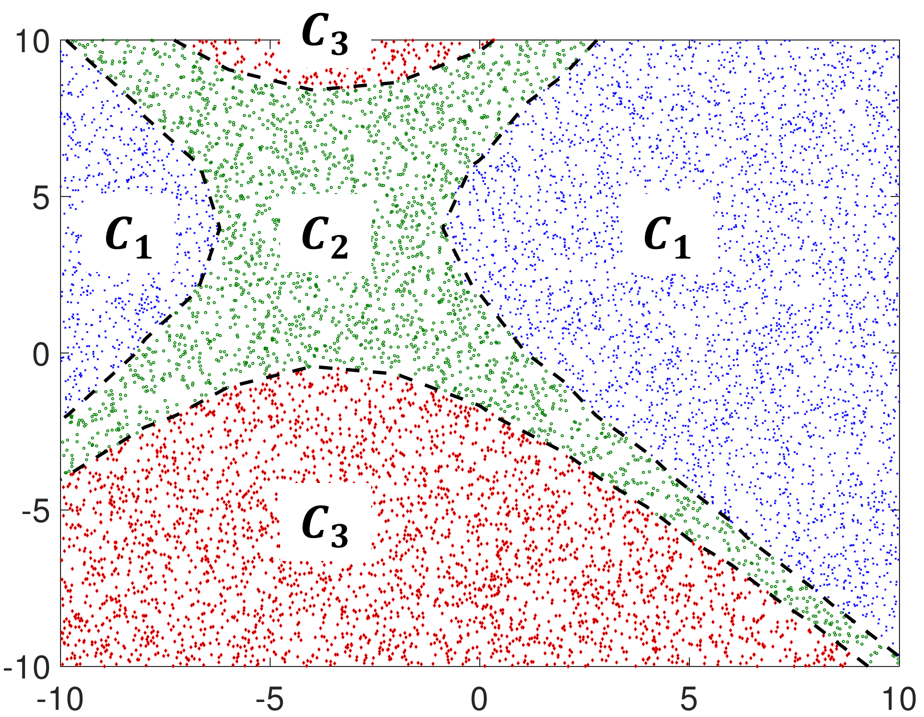
Non-monotonic value functions

- Additive model $V(\mathbf{x}) = v_1(x_1) + v_2(x_2)$

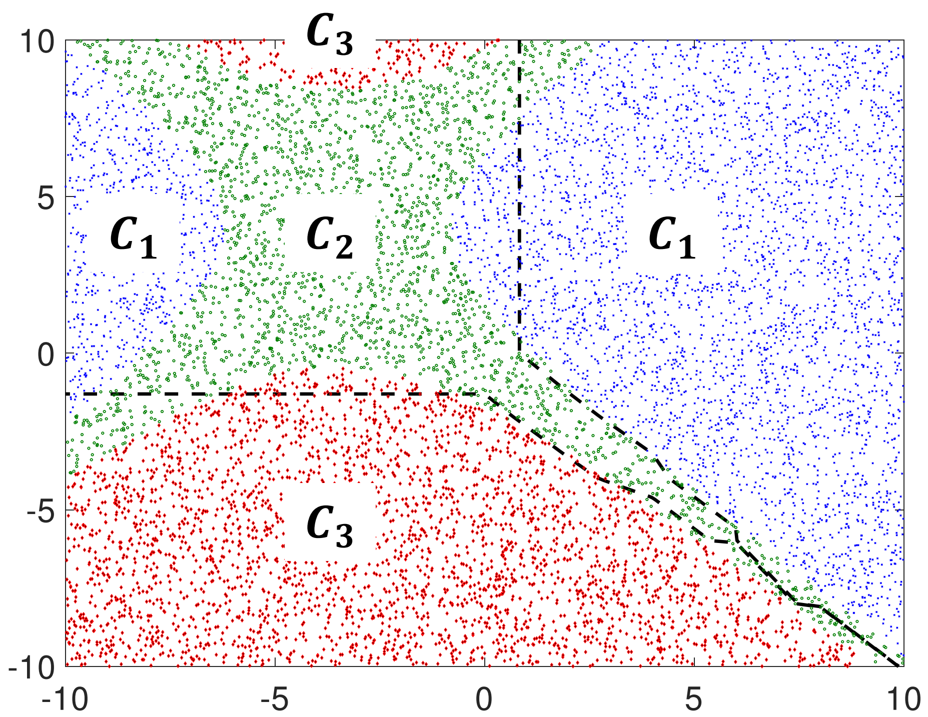




Non-monotonic value functions



Non-monotonic model



Monotonic model

Doumpos, M. (2012), "Learning non-monotonic additive value functions for multicriteria decision making", *OR Spectrum*, 34, 89-106

Criteria + nominal features

- Nominal features often affect a decision, without having an ordinal interpretation
  - R_{ikj} = distress risk score of firm *i* from country *k* & sector *j* (higher risk scores $\rightarrow$ lower risk of failure)

$$R_{ikj} = \underbrace{V(\mathbf{x}_i)}_{\text{criteria}} + \underbrace{c_k + r_j}_{\text{country+sector dummies}}$$

- Application to the prediction of corporate failures for European firms in the energy sector
  - Significant improvements by considering indicators about the status of the countries' energy markets, as well as country-sector effects

Doumpos, Andriosopoulos, Galariotis, Makridou, Zopounidis (2017)

Firm and country indicators

Indicators	D	ND
LNAGE: Ln(age)	1.59	1.71
LNTA: Ln(total assets)	7.45	7.69
ROA: Return on assets	-2.44	3.86
CL/TA: Current liabilities / Total assets	0.54	0.32
S/CL: Sales / Current liabilities	5.02	5.31
GDPG: Annual GDP growth	-0.05	0.10
INFL: Abs(Inflation GDP deflator)	1.54	1.18
INVF: Investment freedom index	77.06	75.32
EPTDL: Electric power transm. & distr. losses (% of output)	7.75	7.35
CO2INT: CO2 intensity (kg per kg of oil equivalent energy use)	2.11	2.00
LNRET: Ln(total number of electr. retailers to final consumers)	4.90	5.09
SAIDI: Unplanned SAIDI including exceptional events	134.34	99.35
SWITCH: External electricity switching rates	7.28	7.66
POLICY: Energy efficiency policy score for industry	2.13	2.55

Criteria + nominal features

- Quadratic programming formulation

$$\min \ \lambda\left(\frac{1}{m_{ND}}\sum_{i\in ND} s_i^2 + \frac{1}{m_D}\sum_{i\in D} e_i^2\right) + \frac{1}{2}\left(\|\mathbf{w}\|^2 + \|\mathbf{c}\|^2 + \|\mathbf{r}\|^2\right)$$

$$\text{s.t.} \quad V(\mathbf{x}_i) + c_k + r_j + s_i \geq t + 1 \quad \forall i \in ND, \text{ country } k, \text{ sector } j$$

$$V(\mathbf{x}_i) + c_k + r_j - e_i \leq t - 1 \quad \forall i \in D, \text{ country } k, \text{ sector } j$$

$$\mathbf{w}, s_i, e_i, t \geq 0, \quad c_k, r_j \in \mathbb{R}$$

  - The optimal solution can be rescaled so that the additive value function $V(\mathbf{x}_i)$ ranges in [0, 1]

An application

- Construction of a model for predicting corporate defaults
- Sample of Greek firms from the sector of commerce
- Period 2007 – 2010
  - Construction of the model using the data for 2007 – 2008
  - Validation of the model on the data for 2009 – 2010

Years	Non-defaults	Defaults	Total
2007	2748	52	2800
2008	2846	53	2899
2009	2731	99	2830
2010	2143	44	2187
Total	10468	248	10716

Risk assessment attributes

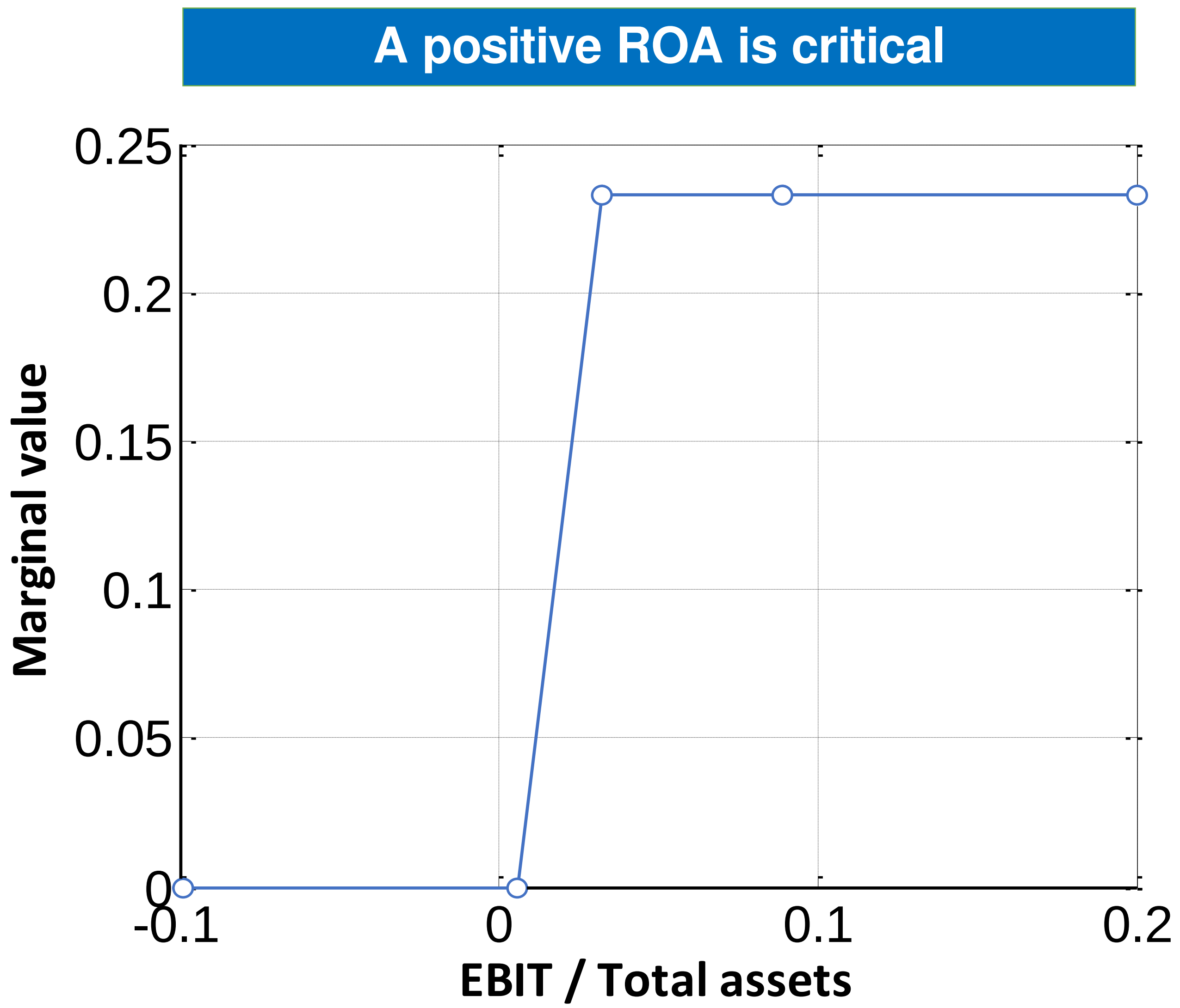
- The status of the firms in year t is analyzed in terms of the financial data in year $t-1$ (one year lag)

		Expected sign	Class averages	
			Defaulted	Non-defaulted
GP / S	Gross profit / Sales	+	0.232	0.299
EBIT / TA	Earnings before taxes / Total assets	+	–0.039	0.040
TL / TA	Total liabilities / Total assets	–	0.879	0.716
IE / S	Interest expenses / Sales	–	0.068	0.029
CA / STL	Current assets / Short-term liabilities	+	1.223	1.674
S / STL	Sales / Short-term liabilities	+	1.509	2.572
AR / S	(Accounts receivable 365) / Sales	–	342	237

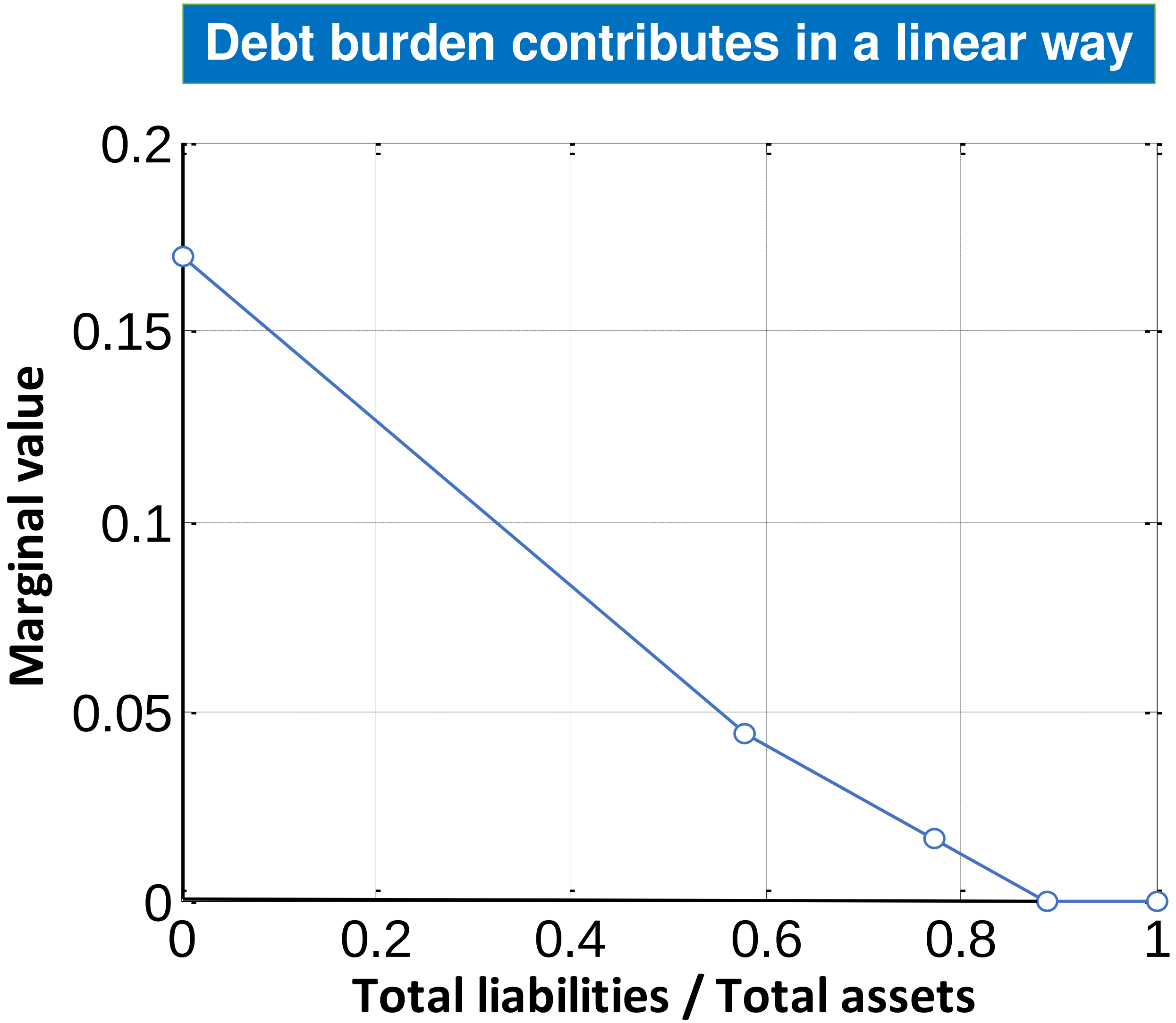
The attributes' contributions

Ratios	Stepwise LR*	UTADIS
GP / S	1.043	0.010
EBIT / TA	2.145	0.233
TL / TA	–1.346	0.170
IE / S	–8.559	0.128
CA / STL	0.189	0.178
S / STL	–	0.128
AR / S	–0.001	0.153

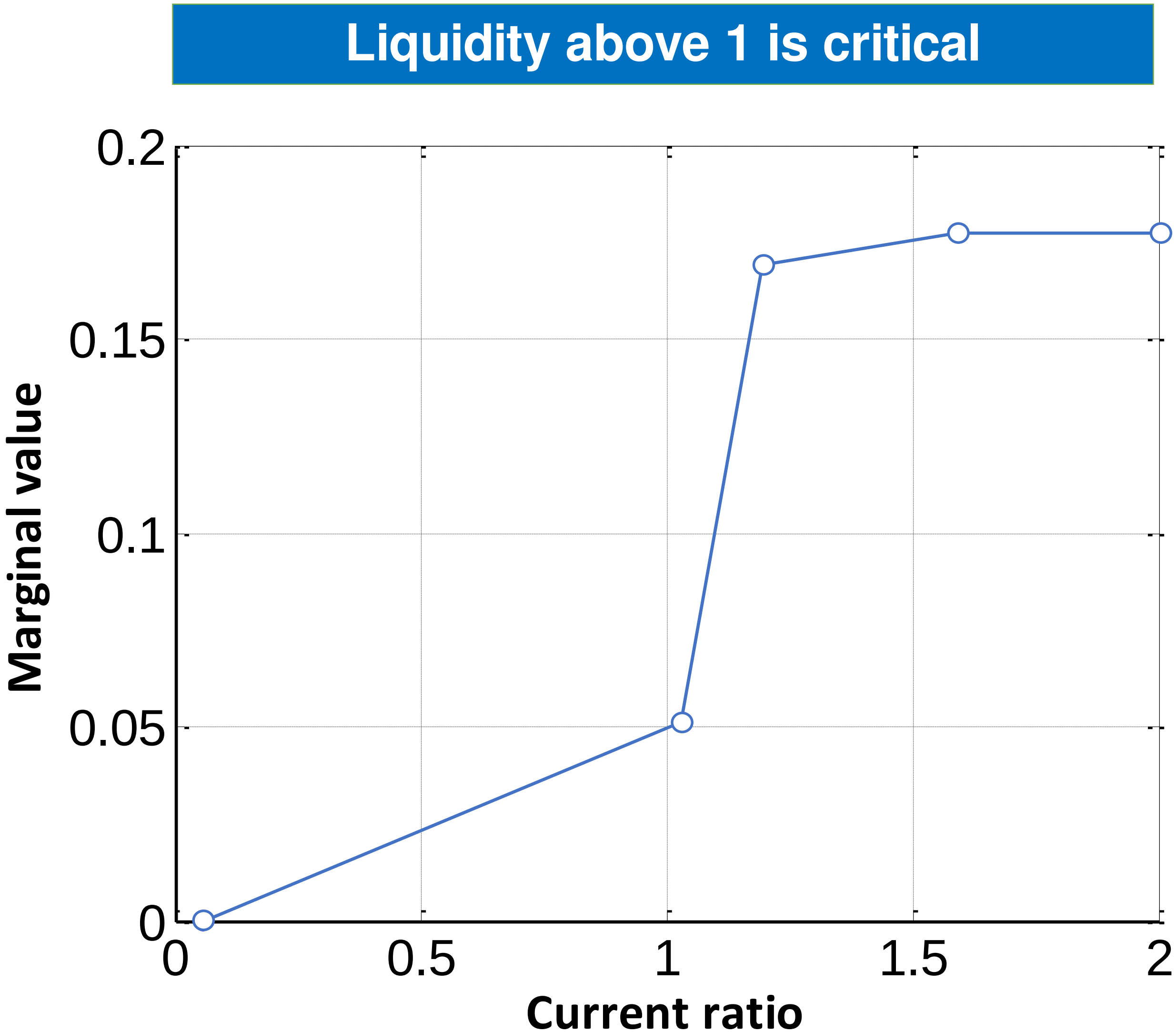
Marginal value functions



Marginal value functions



Marginal value functions



Bank rating

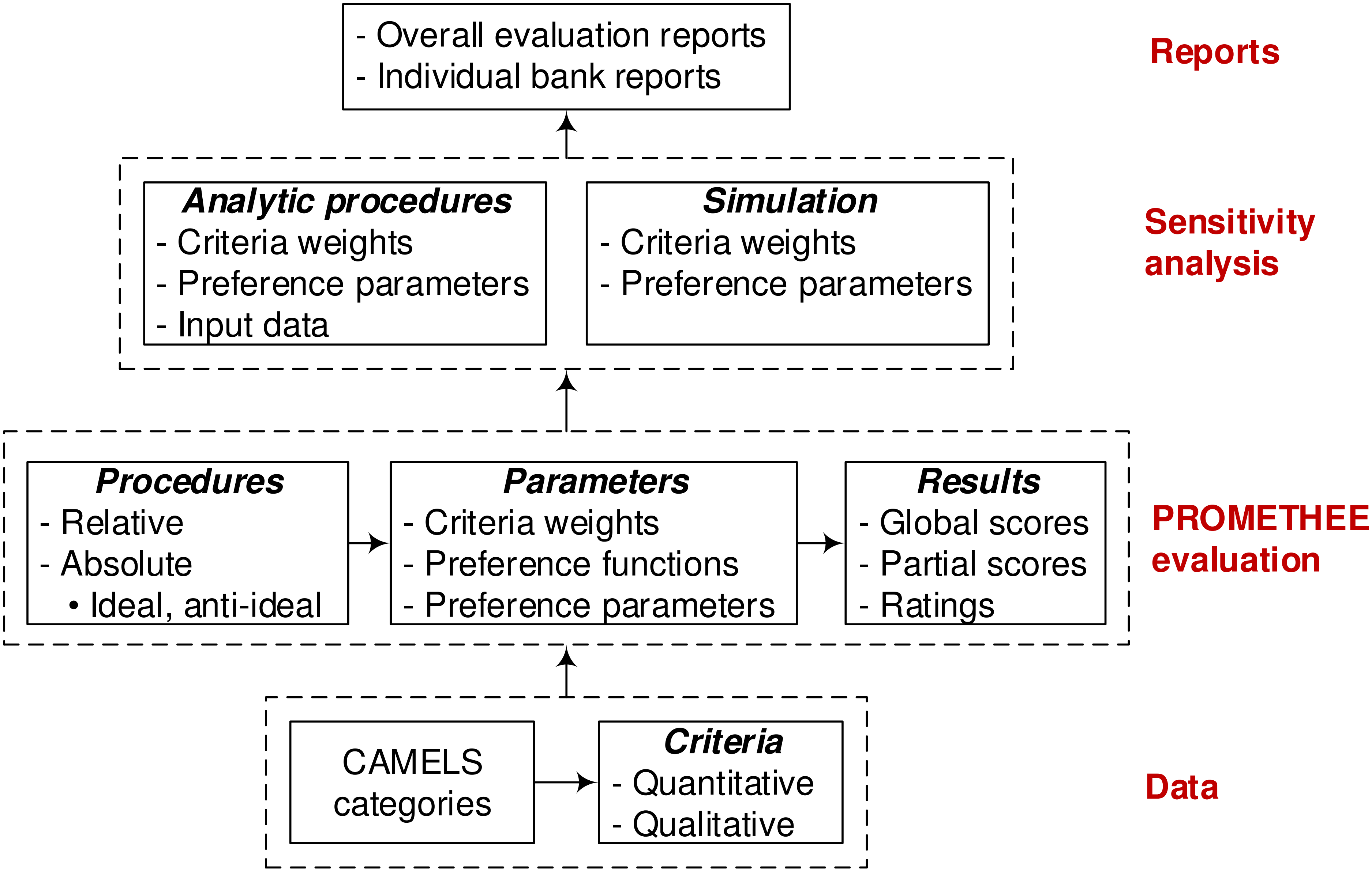
- Lack of historical bank default data
- Empirical rating systems based on quantitative and qualitative criteria
  - Financial analysis
  - *CAMELS* (**C**apital, **A**ssets, **M**anagement, **E**arnings, **L**iquidity, **S**ensitivity to market risk)
- Early warning systems
  - Bankruptcy prediction
  - Prediction of capital adequacy
  - Estimation of downgrade probability

Doumpos, M. and Zopounidis, C. (2010), “A multicriteria decision support system for bank rating”, *Decision Support Systems* 50(1), 55–63.

MCDA methodology

- Relative evaluation
  - Identification of the strengths and weaknesses of a bank relative to the others
- Absolute evaluation
  - Comparison to a predefined reference point (ideal or anti-ideal)
- Rating in 5 risk groups (1=low risk, …, 5=high risk)
- Overall and partial evaluation
- Impact of model’s parameters
  - Sensitivity and scenario analysis

Methodology



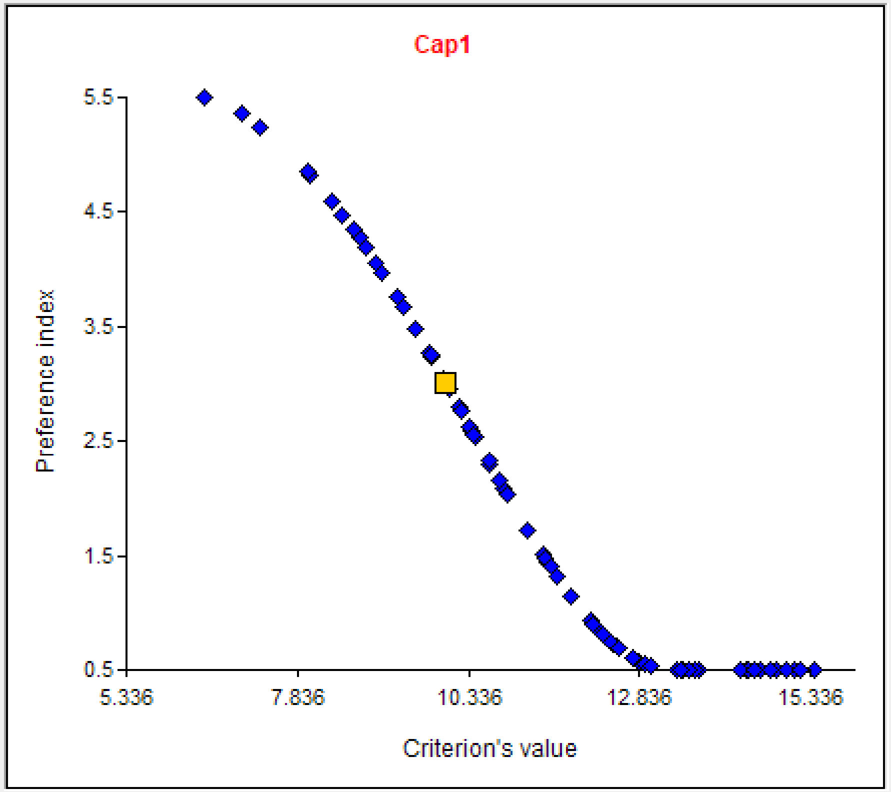
Evaluation criteria

- 31 criteria grouped in 6 categories
- Financial statements
  - Capital adequacy ratio
  - TIER I & II capital
  - Profits/Assets
  - Interest income/Assets
  - Loans/Deposits
  - Insecure loans/Total loans
- Qualitative criteria
  - Management (operating expenses, managers experience, management information systems)
  - Risk management systems
  - Control procedures

MCDA methodologies

- A linear value function model (compatible with the CAMELS framework)
- PROMETHEE II
- Criteria weights
  - Direct specification by the analyst
  - Rank-order weights obtained by ranking the criteria according to their relative importance (Jia, Fischer & Dyer, 1998)
  - Descriptive statistical tools (factor analysis)

Partial net flows



Function type Gauss

Evaluation type
- Absolute evaluation
- Relative evaluation

Reference point
- Ideal point
- Anti-ideal point

Update

Close

Criteria	Function	Parameter	Ideal point	Anti-ideal point	Benchmark
Cap1	Gauss	3.00	13.33	6.67	10.00
Cap2	Gauss	35.00	0.00	80.00	40.00
Cap3	Linear	5.00	0.50	5.50	3.00
Ass1	Gauss	22.00	35.00	85.00	60.00
Ass2	Gauss	3.30	-1.50	6.00	2.25
Ass3	Gauss	2.20	0.00	5.00	2.50
Ass4	Gauss	2.20	-1.50	3.50	1.00
Ass5	Linear	5.00	0.50	5.50	3.00
Man1	Gauss	22.00	40.00	90.00	65.00
Man2	Gauss	0.65	0.70	2.20	1.45
Man3	Gauss	2.20	5.00	0.00	2.50
Man4	Linear	5.00	0.50	5.50	3.00
Man5	Linear	5.00	0.50	5.50	3.00
Man6	Linear	5.00	0.50	5.50	3.00
Man7	Linear	5.00	0.50	5.50	3.00
Man8	Linear	5.00	0.50	5.50	3.00
Man9	Linear	5.00	0.50	5.50	3.00
Man10	Linear	5.00	0.50	5.50	3.00
Man11	Linear	5.00	0.50	5.50	3.00
Man12	Linear	5.00	0.50	5.50	3.00
Ear1	Gauss	0.90	1.60	-0.40	0.60
Ear2	Gauss	11.00	20.00	-5.00	7.50
Ear3	Gauss	4.00	9.00	0.00	4.50
Ear4	Gauss	0.95	2.00	0.00	1.00
Ear5	Linear	5.00	0.50	5.50	3.00
Liq1	Gauss	11.00	35.00	10.00	22.50
Liq2	Gauss	33.00	45.00	120.00	82.50
Liq3	Gauss	6.50	-3.00	12.00	4.50
Liq4	Linear	5.00	0.50	5.50	3.00
Mar1	Gauss	13.00	0.00	30.00	15.00
Mar2	Linear	5.00	0.50	5.50	3.00

Results report & interactive sensitivity (weights)

Banks	2001	2002	2003	2004	2005
Average	1.93	2.11	1.63	1.64	1.66
B1	2.38	2.76	2.47	2.15	2.55
B10	0.08	2.32	2.21	2.61	3.73
B11	N/A	2.21	2.26	2.73	2.09
B12	2.51	3.44	2.76	2.74	2.38
B13	2.76	3.25	3.33	3.27	3.11
B14	0.83	2.58	2.43	2.40	2.57
B15	N/A	2.51	2.26	2.30	1.91
B16	N/A	2.18	2.33	1.95	1.96
B17	N/A	2.08	2.31	2.36	2.60
B18	N/A	2.84	3.00	3.12	3.11
B2	2.28	2.41	1.89	1.80	2.08
B3	2.95	3.66	3.49	3.78	3.55
B4	3.08	2.95	2.59	2.92	3.22
B5	2.45	2.54	2.30	2.26	2.26
B6	2.37	2.56	2.36	2.36	2.35
B7	1.44	1.78	1.98	1.87	1.97
B8	2.24	2.32	2.38	2.48	2.60
B9	2.10	2.58	2.44	2.49	2.54
Benchmark			3.04		

Evaluation results

Detailed report: B10

Comparative evaluation: B1, B10

Cap1

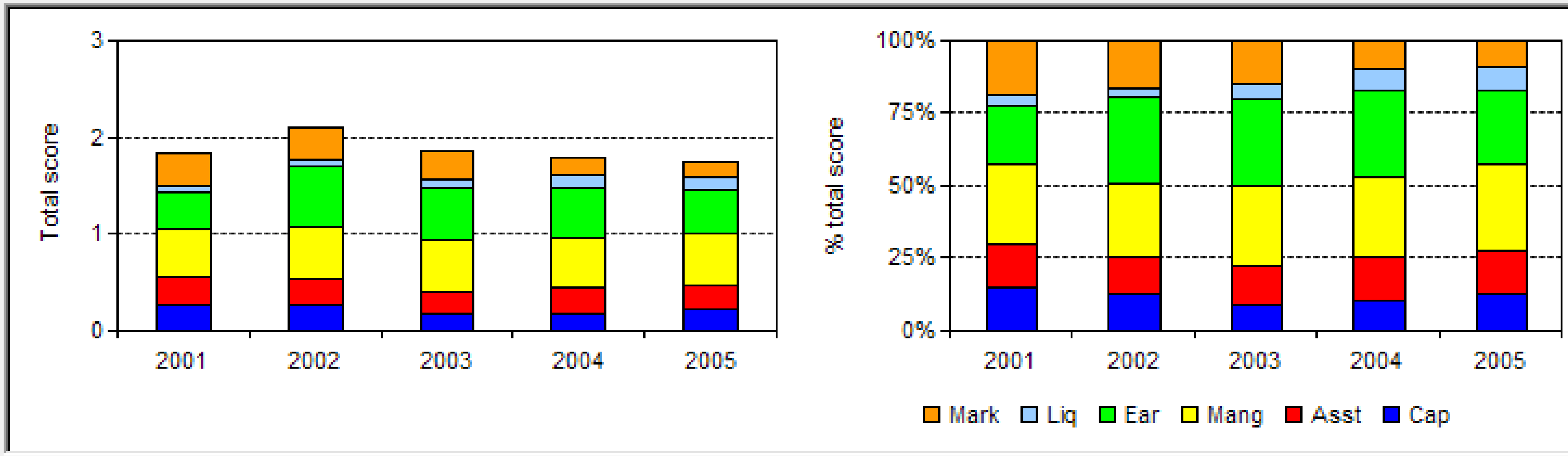
Weight 50.0%

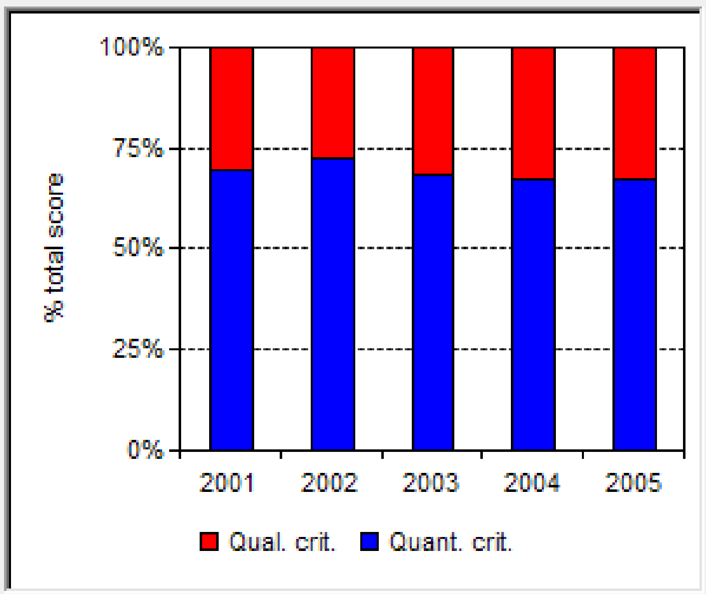
Param. 3

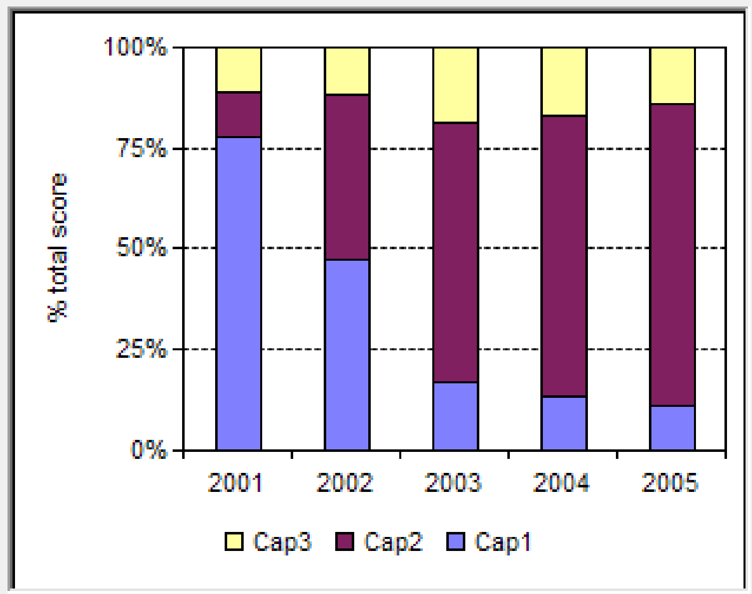
Report | Comparison

Print | Close

Analysis of a bank’s global score







Capital
Asset
Management
Earnings
Liquidity
Market

Sensitivity analysis

- Intervals of the parameters' values within which the ratings remain unchanged
  - Minimum changes that alter the ratings
- Analysis of the impact that the parameters have on the global score of the banks
- Analysis for each bank and the complete set of banks

Weight stability intervals

Categories	Criteria	Weight	Lower bound	Upper bound
Capital risk	Cap1	60.00	54.26	61.64
	Cap2	20.00	18.41	25.91
	Cap3	20.00	17.07	23.20
	Total	30.00	28.86	31.02
Asset risk	Ass1	10.00	7.49	12.97
	Ass2	20.00	16.95	23.88
	Ass3	20.00	17.00	23.52
	Ass4	20.00	9.47	21.91
	Ass5	30.00	21.86	37.39
	Total	20.00	16.86	21.82
Management risk	Man1	20.00	15.51	26.82
	Man2	15.00	9.29	21.93
	Man3	5.00	0.00	13.46
	Man4	5.00	0.00	11.36
	Man5	5.00	0.00	22.09
	Man6	5.00	0.00	13.90
	Man7	10.00	0.62	16.03
	Man8	10.00	0.00	18.43
	Man9	5.00	0.00	11.36
	Man10	5.00	0.00	13.90
	Man11	5.00	0.00	11.36

Scenario analysis

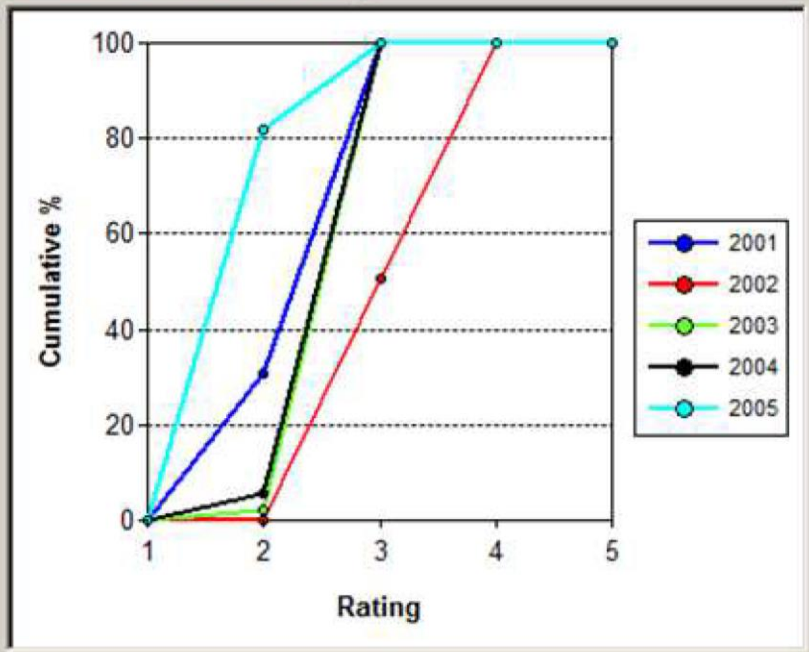
- Scenarios for the criteria weights
  - Random scenarios or scenarios with pre-specified characteristics
  - Analysis of ratings' stability
  - Statistics
    - Net flows (global scores)
    - Ratings

Scenario analysis results

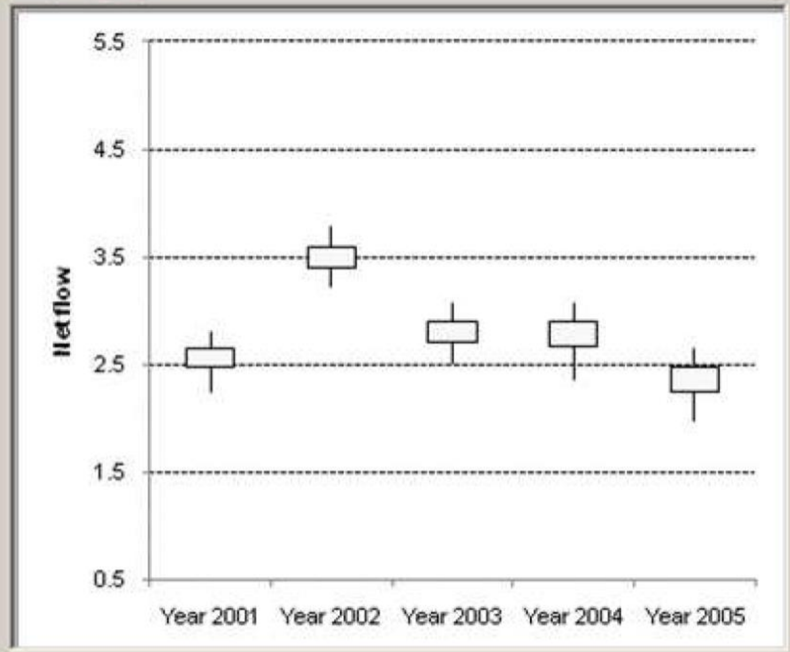
	2001					2002					2003		
Banks	Avg	Median	Std	95% CI		Avg	Median	Std	95% CI		Avg	Median	Std
B1	1.98	1.96	0.17	1.69	2.36	2.14	2.13	0.13	1.89	2.41	1.64	1.64	0.13
B10	2.38	2.39	0.15	2.04	2.63	2.80	2.80	0.15	2.50	3.08	2.45	2.45	0.13
B11	N/A	N/A	N/A	N/A	N/A	2.30	2.33	0.19	1.84	2.64	2.21	2.23	0.19
B12	2.15	2.15	0.24	1.63	2.59	2.21	2.23	0.25	1.67	2.65	2.22	2.25	0.22
B13	2.55	2.56	0.15	2.23	2.82	3.51	3.51	0.14	3.24	3.79	2.80	2.80	0.14
B14	2.81	2.82	0.21	2.37	3.16	3.33	3.32	0.18	2.97	3.71	3.45	3.44	0.20
B15	N/A	N/A	N/A	N/A	N/A	2.55	2.56	0.24	2.03	2.98	2.39	2.40	0.20
B16	N/A	N/A	N/A	N/A	N/A	2.44	2.45	0.23	1.93	2.84	2.16	2.15	0.21
B17	N/A	N/A	N/A	N/A	N/A	2.15	2.17	0.19	1.71	2.50	2.31	2.31	0.15
B18	N/A	N/A	N/A	N/A	N/A	2.00	2.00	0.18	1.62	2.35	2.23	2.22	0.19
B2	2.14	2.14	0.15	1.84	2.39	2.90	2.90	0.12	2.65	3.15	3.03	3.02	0.15
B3	2.37	2.35	0.17	2.07	2.74	2.42	2.41	0.15	2.17	2.73	1.82	1.84	0.19
B4	3.00	3.02	0.17	2.63	3.30	3.72	3.73	0.12	3.47	3.94	3.54	3.55	0.13
B5	3.11	3.10	0.18	2.75	3.48	2.99	2.99	0.17	2.67	3.33	2.60	2.61	0.16
B6	2.52	2.49	0.20	2.20	3.00	2.58	2.55	0.16	2.31	2.92	2.26	2.25	0.13
B7	2.32	2.32	0.22	1.80	2.72	2.54	2.54	0.23	2.01	2.95	2.42	2.43	0.21
B8	1.44	1.44	0.08	1.26	1.58	1.78	1.77	0.09	1.60	1.98	2.00	2.00	0.16
B9	2.25	2.26	0.18	1.90	2.57	2.35	2.36	0.16	2.03	2.64	2.40	2.40	0.17

Scenario analysis report

Cumulative distribution of ratings



Boxplot graph



Ratings' distribution

	Ratings				
Years	1	2	3	4	5
2001	0.00	30.80	69.20	0.00	0.00
2002	0.00	0.00	50.80	49.20	0.00
2003	0.00	2.00	98.00	0.00	0.00
2004	0.00	5.80	94.20	0.00	0.00
2005	0.00	82.00	18.00	0.00	0.00

Distribution

Criteria's weights

Years		Cap1	Cap2	Cap3	Ass1	Ass2	Ass3	Ass4
2001	Corr. with rating	-51.3	-31.1	23.5	11.4	24.8	-42.2	25.0
	Mean rating 1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mean rating 2	18.6	8.5	5.9	1.2	4.3	5.8	4.1
	Mean rating 3	14.1	6.2	7.6	1.6	5.0	4.5	4.8
	Mean rating 4	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mean rating 5	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2002	Corr. with rating	53.9	20.5	-12.1	-3.4	36.5	-28.5	43.2
	Mean rating 1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Mean rating 2	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Conclusions & perspectives

- Financial decision problems have a strong multicriteria aspects
- Broad range of problems for applying different MCDA methods
- Perspectives
  - Cognitive effort required by the decision makers
    - Understanding the methods and their parameters
    - Financial decision makers often also act as decision analysts
    - Integration with other disciplines into hybrid systems
  - Real-time decision making
  - Support during the implementation at the organization level
  - Regulatory compliance
  - Extensions to emerging fields in finance (e.g., fintech) and other markets (e.g., energy finance)

References

Aouni, B., Colapinto, C., and La Torre, D. (2014), "Financial portfolio management through the goal programming model: Current state-of-the-art", *European Journal of Operational Research* 234(2), 536–545.

Ballestero, E., Bravo, M., Pérez-Gladish, B., Arenas-Parra, M., and Plà-Santamaria, D. (2012), "Socially responsible investment: A multicriteria approach to portfolio selection combining ethical and financial objectives", *European Journal of Operational Research* 216 (2), 487–494.

Doumpos, M. and Zopounidis, C. (2002), *Multicriteria Decision Aid Classification Methods*, Kluwer Academic Publishers, Dordrecht.

Doumpos, M. and Zopounidis, C. (2010), "A multicriteria decision support system for bank rating", *Decision Support Systems* 50(1), 55–63.

Doumpos, M. and Zopounidis, C. (2011), "A multicriteria outranking modeling approach for credit rating", *Decision Sciences* 42(3), 721–742.

Doumpos, M. and Zopounidis, C. (2014), *Multicriteria Analysis in Finance*. Springer, Berlin-Heidelberg.

Doumpos, M., Lemonakis, C., Niklis, D., and Zopounidis, C. (2018), *Analytical Techniques in the Assessment of Credit Risk*. Springer, Berlin-Heidelberg.

Doumpos, M., Andriosopoulos, K., Galariotis, E., Makridou, G., and Zopounidis, C. (2017), "Corporate failure prediction in the European energy sector: A multicriteria approach and the effect of country characteristics", *European Journal of Operational Research*, 262(1), 347–360.

Gaivoronski, A.A. and Pflug, G. (2005), "Value-at-risk in portfolio optimization: properties and computational approach", *Journal of Risk* 7(2), 1-31.

Greco, S., Matarazzo, B., and Slowinski, R. (2013), "Beyond Markowitz with multiple criteria decision aiding", *Journal of Business Economics* 83(1), 29–60.

Jacquet-Lagrèze, E. and Siskos, Y. (2001), "Preference disaggregation: Twenty years of MCDA experience", *European Journal of Operational Research* 130, 233–245.

References

Konno, H. and Yamazaki, H. (1991), “Mean-absolute deviation portfolio optimization model and its applications to Tokyo stock market”, *Management Science* 37(5), 519–531.

Krahnen, J.P. and Weber, M. (2001), “Generally accepted rating principles: A primer”, *Journal of Banking and Finance*, 25, 3–23.

Lai, T.Y. (1991), “Portfolio selection with skewness: A multiple-objective approach”, *Review of Quantitative Finance and Accounting* 1, 293–305.

Markowitz, H., Todd, P., Xu, G., and Yamane, Y. (1993), “Computation of mean-semivariance efficient sets by the critical line algorithm”, *Annals of Operations Research* 45(1), 307–317.

Rockafellar, R.T. and Uryasev, S. (2000), “Optimization of conditional value-at-risk”, *Journal of Risk* 2, 21–41.

Szegö, G. (2005), “Measures of risk”, *Journal of Banking & Finance* 26, 1253–1272

Utz, S., Wimmer, M., Hirschberger, M., and Steuer, R.E. (2014), “Tri-criterion inverse portfolio optimization with application to socially responsible mutual funds”, *European Journal of Operational Research* 234(2), 491–498.

Van Gestel, T. and Baesens, B. (2009), *Credit Risk Management - Basic Concepts*, Oxford University Press, Oxford.

Xidonas, P., Mavrotas, G., Krintas, T., Psarras, J., and Zopounidis, C. (2012), *Multicriteria Portfolio Management*, Springer, New York.

Zopounidis, C. and Doumpos, M. (1999), “A multicriteria decision aid methodology for sorting decision problems: The case of financial distress”, *Computational Economics,* 14, 197–218.

Zopounidis, C., Galariotis, E., Doumpos, M., Sarri, S., and Andriosopoulos, K. (2015), “Multiple criteria decision aiding for finance: An updated bibliographic survey”, *European Journal of Operational Research* 247(2), 339–348