

Parametric Linear Programming and Portfolio Optimization

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[Home Page](#)

[Title Page](#)

[Contents](#)



[Page 1 of 14](#)

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

ABSTRACT

1. The traditional (quadratic) Markowitz model produces portfolios that are stochastically dominated by portfolios not on the efficient frontier.
2. Replacing the quadratic risk measure with a mean absolute deviation (MAD) measure corrects this defect.
3. The MAD model can be formulated as a parametric linear programming problem (the risk parameter λ is the parameter).
4. The *parametric* simplex method (described in detail in my book) can be used with λ as the parameter of the parametric method.
5. Doing so, one finds ALL portfolios on the efficient frontier in roughly the same time as it takes to find just one portfolio (corresponding, say, to $\lambda = 0$).
6. The speedup is huge.



[Home Page](#)

[Title Page](#)

[Contents](#)



[Page 2 of 14](#)

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

The Ingredients: Risk and Reward



Raw Data:

$R_j(t)$ = return on asset j
in time period t

⇒ Derived Data:

$$\mu_j = \frac{1}{T} \sum_{t=1}^T R_j(t)$$
$$D_{tj} = R_j(t) - \mu_j.$$

Decision Variables:

x_j = fraction of portfolio
to invest in asset j

$$R(x) = \sum_j x_j R_j$$

Decision Criteria:

$$\mu(x) = \sum_j \mu_j x_j$$

$$\rho_2(x) = \frac{1}{T} \sum_{t=1}^T \left(\sum_j D_{tj} x_j \right)^2$$

$$\rho_1(x) = \frac{1}{T} \sum_{t=1}^T \left| \sum_j D_{tj} x_j \right|$$

[Home Page](#)

[Title Page](#)

[Contents](#)



[Page 3 of 14](#)

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Quadratic Markowitz Problem

$$\text{maximize } \lambda \sum_j \mu_j x_j - \frac{1}{T} \sum_{t=1}^T \left(\sum_j D_{tj} x_j \right)^2$$

$$\text{subject to } \sum_j x_j = 1$$
$$x_j \geq 0 \quad \text{for all investments } j$$

λ is the risk parameter.



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 4 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

MAD Markowitz Problem

$$\text{maximize } \lambda \sum_j \mu_j x_j - \frac{1}{T} \sum_{t=1}^T \left| \sum_j D_{tj} x_j \right|$$

$$\text{subject to } \sum_j x_j = 1$$
$$x_j \geq 0 \quad \text{for all investments } j$$

Not a linear programming problem. But it's easy to convert.



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 5 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Stochastic Dominance

Second order stochastic dominance characterizes those random variables that every risk averse decision maker would prefer to a given random variable:

Definition *Random variable V stochastically dominates random variable S if and only if $\mathbb{E}(U(V)) \geq \mathbb{E}(U(S))$ for every increasing concave function $U(\cdot)$.*

Theorem *There are optimal solutions to the quadratic Markowitz model that are stochastically dominated by other (non-optimal) portfolios.*

Theorem *In the MAD Markowitz model, optimal portfolios are never stochastically dominated provided for all $\lambda \geq 2$.*



[Home Page](#)

[Title Page](#)

[Contents](#)

[◀](#) [▶](#)

[◀](#) [▶](#)

Page 6 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

MAD Markowitz: LP Formulation



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 7 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

$$\text{maximize} \quad \lambda \sum_j \mu_j x_j - \frac{1}{T} \sum_{t=1}^T y_t$$

$$\text{subject to} \quad -y_t \leq \sum_j D_{tj} x_j \leq y_t \quad \text{for all times } t$$

$$\sum_j x_j = 1$$

$$x_j \geq 0 \quad \text{for all investments } j$$

$$y_t \geq 0 \quad \text{for all times } t$$

Adding Slack Variables w_t^+ and w_t^-

$$\text{maximize } \lambda \sum_j \mu_j x_j - \frac{1}{T} \sum_{t=1}^T y_t$$

$$\text{subject to } -y_t - \sum_j D_{tj} x_j + w_t^- = 0 \quad \text{for all times } t$$

$$-y_t + \sum_j D_{tj} x_j + w_t^+ = 0 \quad \text{for all times } t$$

$$\sum_j x_j = 1$$

$$x_j \geq 0 \quad \text{for all investments } j$$

$$y_t, w_t^-, w_t^+ \geq 0 \quad \text{for all times } t$$



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 8 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

The Solution for Large λ



Varying the risk bound $0 \leq \lambda < \infty$ produces the *efficient frontier*.

Large values of λ favor reward whereas small values favor minimizing risk.

Beyond some finite threshold value for λ , the optimal solution will be a portfolio consisting of just one asset—the asset j^* with the largest average return:

$$\mu_{j^*} \geq \mu_j \quad \text{for all } j.$$

It's easy to identify basic vs. nonbasic variables:

- Variable x_{j^*} is basic whereas the remaining x_j 's are nonbasic.
- All of the y_t 's are basic.
- If $D_{tj^*} > 0$, then w_t^- is basic and w_t^+ is nonbasic. Otherwise, it is switched.

[Home Page](#)

[Title Page](#)

[Contents](#)



Page 9 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

The Basic Optimal Solution for Large λ

Let

$$T^+ = \{t : D_{tj^*} > 0\}, \quad T^- = \{t : D_{tj^*} < 0\}, \quad \text{and} \quad \epsilon_t = \begin{cases} 1, & \text{for } t \in T^+ \\ -1, & \text{for } t \in T^- \end{cases}$$

It's tedious, but here's the optimal dictionary:

$$\begin{aligned} \zeta &= \frac{1}{T} \sum_{t=1}^T \epsilon_t D_{tj^*} + \lambda \mu_{j^*} - \frac{1}{T} \sum_{j \neq j^*} \sum_{t=1}^T \epsilon_t (D_{tj} - D_{tj^*}) x_j + \lambda \sum_{j \neq j^*} (\mu_j - \mu_{j^*}) x_j - \frac{1}{T} \sum_{t \in T^-} w_t^- - \frac{1}{T} \sum_{t \in T^+} w_t^+ \\ \hline y_t &= -D_{tj^*} - \sum_{j \neq j^*} (D_{tj} - D_{tj^*}) x_j + w_t^- & t \in T^- \\ w_t^- &= 2D_{tj^*} + 2 \sum_{j \neq j^*} (D_{tj} - D_{tj^*}) x_j + w_t^+ & t \in T^+ \\ y_t &= D_{tj^*} + \sum_{j \neq j^*} (D_{tj} - D_{tj^*}) x_j + w_t^+ & t \in T^+ \\ w_t^+ &= -2D_{tj^*} - 2 \sum_{j \neq j^*} (D_{tj} - D_{tj^*}) x_j + w_t^- & t \in T^- \\ x_{j^*} &= 1 - \sum_{j \neq j^*} x_j \end{aligned}$$



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 10 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Computing the Efficient Frontier



Using a reasonably efficient code for the *parametric simplex method* (simpo), it took *22,000* pivots and *1.5 hours* to solve for *one point* on the efficient frontier.

Customizing this same code to solve parametrically for every point on the efficient frontier, it took *23,446* pivots and *57 minutes* to compute *every point* on the frontier.

The efficient frontier consists of *23,446* distinct portfolios. Click [here](#) for a partial list (*warning: the file is 2.5 MBytes*). The complete list makes a 37 MByte file.

[Home Page](#)

[Title Page](#)

[Contents](#)



Page *12* of *14*

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

REVIEW

- A portfolio is *bad* if another portfolio dominates it (stochastically).
- Many portfolios on Markowitz's "efficient frontier" are bad.
- MAD Markowitz isn't bad.
- MAD Markowitz is a parametric LP.
- Even more, using the parametric simplex method the entire efficient frontier can be computed in the time normally required to find just one point on the frontier.
- Lastly, our efficient frontier is completely determined by a finite set of portfolios (vs. a continuum).

Paper was published a year ago in *Econometrica*.



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 13 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)



[Home Page](#)

[Title Page](#)

[Contents](#)



Page 14 of 14

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

Contents

1	The Ingredients: Risk and Reward	3
2	Quadratic Markowitz Problem	4
3	MAD Markowitz Problem	5
4	Stochastic Dominance	6
5	MAD Markowitz: LP Formulation	7
6	The Solution for Large λ	9
7	Computing the Efficient Frontier	12