

# Portfolios that Contain Risky Assets

## 5.3. Limited-Leverage with Risk-Free Assets

**C. David Levermore**

University of Maryland, College Park, MD

Math 420: *Mathematical Modeling*

March 15, 2022 version

© 2022 Charles David Levermore

# Portfolios that Contain Risky Assets

## Part I: Portfolio Models

1. Preliminary Topics
2. Markowitz Portfolio Model
3. Models for Portfolios with Risk-Free Assets
4. Models for Long Portfolios
5. **Models for Limited-Leverage Portfolios**

# Portfolios that Contain Risky Assets

## Part I: Portfolio Models

### 5. Models for Limited-Leverage Portfolios

- 5.1. Limited-Leverage Portfolios
- 5.2. Limited-Leverage Frontiers
- 5.3. Limited-Leverage with Risk-Free Assets
- 5.4. Limited-Leverage and Return Bounds

# Limited-Leverage with Risk-Free Assets

- 1 Limited-Leverage One-Rate Model
- 2 Computing the One-Rate Model

# Limited-Leverage One-Rate Model: $\mathcal{M}_1$ and $\Pi_1^\ell$

The set of Markowitz allocations for the one-rate model is

$$\mathcal{M}_1 = \left\{ (\mathbf{f}, f_{\text{rf}}) \in \mathbb{R}^{N+1} : \mathbf{1}^\top \mathbf{f} + f_{\text{rf}} = 1 \right\}. \quad (1.1)$$

The return mean and volatility for a portfolio with allocation  $(\mathbf{f}, f_{\text{rf}})$  are

$$\mu(\mathbf{f}, f_{\text{rf}}) = \mathbf{m}^\top \mathbf{f} + \mu_{\text{rf}} f_{\text{rf}}, \quad \sigma(\mathbf{f}, f_{\text{rf}}) = \sqrt{\mathbf{f}^\top \mathbf{V} \mathbf{f}}. \quad (1.2)$$

The leverage ratio of this portfolio can be expressed as

$$\lambda(\mathbf{f}, f_{\text{rf}}) = \frac{1}{2} (\|\mathbf{f}\|_1 + |f_{\text{rf}}| - 1). \quad (1.3)$$

Therefore for every  $\ell \geq 0$  the set of Markowitz allocations with leverage ratio no greater than  $\ell$  is

$$\Pi_1^\ell = \left\{ (\mathbf{f}, f_{\text{rf}}) \in \mathcal{M}_1 : \|\mathbf{f}\|_1 + |f_{\text{rf}}| \leq 1 + 2\ell \right\}. \quad (1.4)$$

# Limited-Leverage One-Rate Model: Tobin Frontier

The efficient Tobin frontier for  $\mathcal{M}_1$  is given by

$$\mu = \mu_{\text{rf}} + \nu_{\text{rf}}\sigma \quad \text{for } \sigma \geq 0, \quad (1.5)$$

where  $\nu_{\text{rf}} > 0$  is determined by

$$\nu_{\text{rf}}^2 = (\mathbf{m} - \mu_{\text{rf}}\mathbf{1})^T \mathbf{V}(\mathbf{m} - \mu_{\text{rf}}\mathbf{1}),$$

and the Tobin frontier allocation is given by

$$\mathbf{f}_{\text{tf}}(\mu) = \frac{\mu - \mu_{\text{rf}}}{\nu_{\text{rf}}^2} \mathbf{V}^{-1}(\mathbf{m} - \mu_{\text{rf}}\mathbf{1}). \quad (1.6)$$

The associated risk-free frontier allocation is

$$f_{\text{rff}}(\mu) = 1 - \mathbf{1}^T \mathbf{f}_{\text{tf}}(\mu) = 1 - \frac{(\mu - \mu_{\text{rf}})(\mu_{\text{mv}} - \mu_{\text{rf}})}{\nu_{\text{rf}}^2 \sigma_{\text{mv}}^2}. \quad (1.7)$$

# Limited-Leverage One-Rate Model: Tangent Portfolio

When  $\mu_{\text{rf}} \neq \mu_{\text{mv}}$  the tangent portfolio exists and is given by

$$\mathbf{f}_{\text{tg}} = \mathbf{f}_{\text{tf}}(\mu_{\text{tg}}) = \frac{\mu_{\text{tg}} - \mu_{\text{rf}}}{\nu_{\text{rf}}^2} \mathbf{V}^{-1}(\mathbf{m} - \mu_{\text{rf}}\mathbf{1}),$$

where  $\mu_{\text{tg}}$  is determined by

$$\frac{(\mu_{\text{tg}} - \mu_{\text{rf}})(\mu_{\text{mv}} - \mu_{\text{rf}})}{\nu_{\text{rf}}^2 \sigma_{\text{mv}}^2} = 1.$$

The analysis of the Tobin frontier allocations falls into three cases:

$\mu_{\text{rf}} < \mu_{\text{mv}},$	tangent portfolio is efficient ;
$\mu_{\text{mv}} = \mu_{\text{rf}},$	tangent portfolio does not exist ;
$\mu_{\text{mv}} < \mu_{\text{rf}},$	tangent portfolio is inefficient .

# Limited-Leverage One-Rate Model: Tangent Efficient

When  $\mu_{rf} < \mu_{mv}$  the tangent portfolio is efficient. The efficient frontier allocation is

$$\mathbf{f}_{\text{etf}}(\sigma) = \frac{\sigma}{\sigma_{\text{tg}}} \mathbf{f}_{\text{tg}}, \quad f_{\text{rfef}}(\sigma) = 1 - \frac{\sigma}{\sigma_{\text{tg}}}.$$

The leverage ratio is

$$\begin{aligned} \lambda_{\text{etf}}(\sigma) &= \lambda(\mathbf{f}_{\text{etf}}(\sigma), f_{\text{rfef}}(\sigma)) \\ &= \begin{cases} \frac{1}{2} \frac{\sigma}{\sigma_{\text{tg}}} (\|\mathbf{f}_{\text{tg}}\|_1 - 1) & \text{for } \sigma \in [0, \sigma_{\text{tg}}], \\ \frac{1}{2} \left( \frac{\sigma}{\sigma_{\text{tg}}} (\|\mathbf{f}_{\text{tg}}\|_1 + 1) - 2 \right) & \text{for } \sigma \in (\sigma_{\text{tg}}, \infty). \end{cases} \end{aligned}$$

Notice that  $\lambda_{\text{etf}}(\sigma) \leq \ell$  for sufficiently small  $\sigma$ .



# Limited-Leverage One-Rate Model: Tangent Inefficient

When  $\mu_{\text{mv}} < \mu_{\text{rf}}$  the tangent portfolio is inefficient. The efficient frontier allocation is

$$\mathbf{f}_{\text{etf}}(\sigma) = -\frac{\sigma}{\sigma_{\text{tg}}} \mathbf{f}_{\text{tg}}, \quad f_{\text{rfef}}(\sigma) = 1 + \frac{\sigma}{\sigma_{\text{tg}}}.$$

The leverage ratio is

$$\lambda_{\text{etf}}(\sigma) = \lambda(\mathbf{f}_{\text{etf}}(\sigma), f_{\text{rfef}}(\sigma)) = \frac{1}{2} \frac{\sigma}{\sigma_{\text{tg}}} (\|\mathbf{f}_{\text{tg}}\|_1 + 1), \quad \text{for } \sigma \in [0, \infty).$$

Notice that  $\lambda_{\text{etf}}(\sigma) \leq \ell$  for sufficiently small  $\sigma$ .

**Remark.** This shows that for sufficiently small  $\sigma$  the efficient frontier for  $\Pi_1^\ell$  coincides with the efficient Tobin frontier for  $\mathcal{M}_1$ . In particular, it is linear with slope  $\nu_{\text{rf}}$  for small  $\sigma$ .

# Limited-Leverage One-Rate Model: $\mu_{\text{mx}}^\ell$

It can be shown that  $\Pi_1^\ell = \text{Hull}(\mathcal{E}_1^\ell)$  where

$$\mathcal{E}_1^\ell = \left\{ (\mathbf{e}_{ij}^\ell, 0), ((1 + \ell)\mathbf{e}_i, -\ell), (-\ell\mathbf{e}_j, 1 + \ell) \right\}.$$

Therefore

$$\begin{aligned} \mu_{\text{mx}}^\ell &= \max \left\{ \mu(\mathbf{f}, f_{\text{rf}}) : (\mathbf{f}, f_{\text{rf}}) \in \Pi_1^\ell \right\} \\ &= \max \left\{ \mu(\mathbf{f}, f_{\text{rf}}) : (\mathbf{f}, f_{\text{rf}}) \in \mathcal{E}_1^\ell \right\} \\ &= \max \left\{ (1 + \ell)\mu_{\text{mx}} - \ell\mu_{\text{mn}}, \right. \\ &\quad (1 + \ell)\mu_{\text{mx}} - \ell\mu_{\text{rf}}, \\ &\quad \left. (1 + \ell)\mu_{\text{rf}} - \ell\mu_{\text{mn}} \right\}, \end{aligned}$$

where

$$\mu_{\text{mn}} = \min_i \{m_i\}, \quad \mu_{\text{mx}} = \max_i \{m_i\}.$$

# Limited-Leverage One-Rate Model: Tangent Inefficient

Because

$$\frac{\ell}{1+2\ell} \left( (1+\ell)\mu_{\text{mx}} - \ell\mu_{\text{rf}} \right) + \frac{1+\ell}{1+2\ell} \left( (1+\ell)\mu_{\text{rf}} - \ell\mu_{\text{mn}} \right) = \mu_{\text{rf}},$$

and because

$$(1+\ell)\mu_{\text{mx}} - \ell\mu_{\text{rf}} > (1+\ell)\mu_{\text{rf}} - \ell\mu_{\text{mn}},$$

we see that  $\mu_{\text{rf}} < (1+\ell)\mu_{\text{mx}} - \ell\mu_{\text{rf}} \leq \mu_{\text{mx}}^{\ell}$ . Therefore the efficient frontier of  $\Pi_1^{\ell}$  exists for  $\mu \in [\mu_{\text{rf}}, \mu_{\text{mx}}^{\ell}]$ . We can approximate it numerically using the Matlab “quadprog” command.

# Computing the One-Rate Model: Quadratic Programming

Because the function being minimized is quadratic in  $\mathbf{f}$  while the constraints are linear in  $\mathbf{f}$ , this is called a *quadratic programming problem*. It can be solved for a particular  $\mathbf{V}$ ,  $\mathbf{m}$ , and  $\mu$  by using either the Matlab command “**quadprog**” or an equivalent command in some other language.

Recall that the Matlab command `quadprog(A, b, C, d, Ceq, deq)` returns the solution of a quadratic programming problem in the *standard form*

$$\arg \min \left\{ \frac{1}{2} \mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{b}^T \mathbf{x} : \mathbf{x} \in \mathbb{R}^M, \mathbf{C} \mathbf{x} \leq \mathbf{d}, \mathbf{C}_{\text{eq}} \mathbf{x} = \mathbf{d}_{\text{eq}} \right\},$$

where  $\mathbf{A} \in \mathbb{R}^{M \times M}$  is nonnegative definite,  $\mathbf{b} \in \mathbb{R}^M$ ,  $\mathbf{C} \in \mathbb{R}^{K \times M}$ ,  $\mathbf{d} \in \mathbb{R}^K$ ,  $\mathbf{C}_{\text{eq}} \in \mathbb{R}^{K_{\text{eq}} \times M}$ , and  $\mathbf{d}_{\text{eq}} \in \mathbb{R}^{K_{\text{eq}}}$ . Here  $K$  and  $K_{\text{eq}}$  are the number of inequality and equality constraints respectively.

# Computing the One-Rate Model: Standard Form

Given  $\mathbf{V}$ ,  $\mathbf{m}$ , and  $\mu \in [\mu_{\text{rf}}, \mu_{\text{mx}}^\ell]$ , the problem that we want to solve to obtain  $\mathbf{f}_f^\ell(\mu)$  and  $f_{\text{rf}}(\mu)$  is

$$\arg \min \left\{ \frac{1}{2} \mathbf{f}^T \mathbf{V} \mathbf{f} : (\mathbf{f}, f_{\text{rf}}) \in \mathbb{R}^{N+1}, \|\mathbf{f}\|_1 + |f_{\text{rf}}| \leq 1 + 2\ell, \right. \\ \left. \mathbf{1}^T \mathbf{f} + f_{\text{rf}} = 1, \mathbf{m}^T \mathbf{f} + \mu_{\text{rf}} f_{\text{rf}} = \mu \right\}.$$

By comparing this with the standard form on the previous slide we see that if we set  $\mathbf{x}^T = (\mathbf{f} \ f_{\text{rf}})$  then  $M = N + 1$ ,  $K_{\text{eq}} = 2$ , and

$$\mathbf{A} = \begin{pmatrix} \mathbf{V} & \mathbf{0} \\ \mathbf{0}^T & 0 \end{pmatrix}, \quad \mathbf{b} = \begin{pmatrix} \mathbf{0} \\ 0 \end{pmatrix}, \quad \mathbf{C}_{\text{eq}} = \begin{pmatrix} \mathbf{1}^T & 1 \\ \mathbf{m}^T & \mu_{\text{rf}} \end{pmatrix}, \quad \mathbf{d}_{\text{eq}} = \begin{pmatrix} 1 \\ \mu \end{pmatrix}.$$

However, the inequality constraint  $\|\mathbf{f}\|_1 + |f_{\text{rf}}| \leq 1 + 2\ell$  is not in the standard form  $\mathbf{C}\mathbf{x} \leq \mathbf{d}$ .

# Computing the One-Rate Model: Two Reformulations

As was done for the limited-leverage allocations  $\Pi^\ell$  without risk-free assets, we enlarge the dimension of  $\mathbf{x}$  and consider the following reformulations  $\Pi_1^\ell$ .

$$\begin{aligned} \Pi_1^\ell &= \left\{ (\mathbf{f}, f_{\text{rf}}) \in \mathbb{R}^{N+1} : \mathbf{1}^\top \mathbf{f} + f_{\text{rf}} = 1, \|\mathbf{f}\|_1 + |f_{\text{rf}}| \leq 1 + 2\ell \right\} \\ &= \left\{ (\mathbf{f}, f_{\text{rf}}) \in \mathbb{R}^{N+1} : \mathbf{1}^\top \mathbf{f} + f_{\text{rf}} = 1, \exists (\mathbf{s}, s_{\text{rf}}) \in \mathbb{R}^{N+1} : \right. \\ &\quad \left. \mathbf{s} \geq \mathbf{0}, (\mathbf{f} + \mathbf{s}) \geq \mathbf{0}, s_{\text{rf}} \geq 0, (f_{\text{rf}} + s_{\text{rf}}) \geq 0, \mathbf{1}^\top \mathbf{s} + s_{\text{rf}} \leq \ell \right\} \\ &= \left\{ (\mathbf{f}, f_{\text{rf}}) \in \mathbb{R}^{N+1} : \mathbf{1}^\top \mathbf{f} + f_{\text{rf}} = 1, \exists (\mathbf{g}, g_{\text{rf}}) \in \mathbb{R}^{N+1} : \right. \\ &\quad \left. (\mathbf{g} \pm \mathbf{f}) \geq \mathbf{0}, (g_{\text{rf}} \pm f_{\text{rf}}) \geq 0, \mathbf{1}^\top \mathbf{g} + g_{\text{rf}} \leq 1 + 2\ell \right\}. \end{aligned}$$

The proofs of these reformulations are left as exercises.

# Computing the One-Rate Model: First Reformulation

If we use the first reformulation then the problem that we want to solve to obtain  $\mathbf{f}_f^\ell(\mu)$  and  $f_{\text{rf}}(\mu)$  is

$$\arg \min \left\{ \frac{1}{2} \mathbf{f}^T \mathbf{V} \mathbf{f} : (\mathbf{f}, \mathbf{s}, f_{\text{rf}}, s_{\text{rf}}) \in \mathbb{R}^{2N+2}, \mathbf{1}^T \mathbf{f} + f_{\text{rf}} = 1, \mathbf{m}^T \mathbf{f} + \mu_{\text{rf}} f_{\text{rf}} = \mu, \right. \\ \left. \mathbf{s} \geq \mathbf{0}, (\mathbf{f} + \mathbf{s}) \geq \mathbf{0}, s_{\text{rf}} \geq 0, (f_{\text{rf}} + s_{\text{rf}}) \geq 0, \mathbf{1}^T \mathbf{s} + s_{\text{rf}} \leq \ell \right\}.$$

By comparing this with the standard form we see that if we set

$\mathbf{x} = (\mathbf{f}^T \mathbf{s}^T f_{\text{rf}} s_{\text{rf}})^T$  then  $M = 2N + 2$ ,  $K = 2N + 3$ ,  $K_{\text{eq}} = 2$ , and

$$\mathbf{A} = \begin{pmatrix} \mathbf{V} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0}^T & \mathbf{0}^T & 0 & 0 \\ \mathbf{0}^T & \mathbf{0}^T & 0 & 0 \end{pmatrix}, \quad \mathbf{b} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{C} = \begin{pmatrix} -\mathbf{1} & -\mathbf{1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & -\mathbf{1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0}^T & \mathbf{1}^T & 0 & 1 \end{pmatrix}, \quad \mathbf{d} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \\ \ell \end{pmatrix}, \\ \mathbf{C}_{\text{eq}} = \begin{pmatrix} \mathbf{1}^T & \mathbf{0}^T & 1 & 0 \\ \mathbf{m}^T & \mathbf{0}^T & \mu_{\text{rf}} & 0 \end{pmatrix}, \quad \mathbf{d}_{\text{eq}} = \begin{pmatrix} 1 \\ \mu \end{pmatrix}.$$

# Computing the One-Rate Model: Second Reformulation

If we use the second reformulation then the problem that we want to solve to obtain  $\mathbf{f}_f^\ell(\mu)$  and  $f_{\text{rf}}(\mu)$  is

$$\arg \min \left\{ \frac{1}{2} \mathbf{f}^\top \mathbf{V} \mathbf{f} : (\mathbf{f}, \mathbf{g}, f_{\text{rf}}, g_{\text{rf}}) \in \mathbb{R}^{2N+2}, \mathbf{1}^\top \mathbf{f} + f_{\text{rf}} = 1, \mathbf{m}^\top \mathbf{f} + \mu_{\text{rf}} f_{\text{rf}} = \mu, \right. \\ \left. (\mathbf{g} \pm \mathbf{f}) \geq \mathbf{0}, (g_{\text{rf}} \pm f_{\text{rf}}) \geq 0, \mathbf{1}^\top \mathbf{g} + g_{\text{rf}} \leq 1 + 2\ell \right\}.$$

By comparing this with the standard form we see that if we set

$\mathbf{x} = (\mathbf{f}^\top \mathbf{g}^\top f_{\text{rf}} g_{\text{rf}})^\top$  then  $M = 2N + 2$ ,  $K = 2N + 3$ ,  $K_{\text{eq}} = 2$ , and

$$\mathbf{A} = \begin{pmatrix} \mathbf{V} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0}^\top & \mathbf{0}^\top & 0 & 0 \\ \mathbf{0}^\top & \mathbf{0}^\top & 0 & 0 \end{pmatrix}, \mathbf{b} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \\ 0 \\ 0 \end{pmatrix}, \mathbf{C} = \begin{pmatrix} -\mathbf{I} & -\mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{I} & -\mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{0}^\top & \mathbf{1}^\top & 0 & 1 \end{pmatrix}, \mathbf{d} = \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \\ 1 + 2\ell \end{pmatrix}, \\ \mathbf{C}_{\text{eq}} = \begin{pmatrix} \mathbf{1}^\top & \mathbf{0}^\top & 1 & 0 \\ \mathbf{m}^\top & \mathbf{0}^\top & \mu_{\text{rf}} & 0 \end{pmatrix}, \mathbf{d}_{\text{eq}} = \begin{pmatrix} 1 \\ \mu \end{pmatrix}.$$



## Computing the One-Rate Model: quadprog Command

In either case  $\mathbf{f}_f^\ell(\mu)$  and  $f_{\text{rff}}^\ell(\mu)$  are the first  $N$  entries and the  $2N + 1$  entry of the output  $\mathbf{x}$  of a `quadprog` command that is formatted as

$$\mathbf{x} = \text{quadprog}(\mathbf{A}, \mathbf{b}, \mathbf{C}, \mathbf{d}, \mathbf{C}_{\text{eq}}, \mathbf{d}_{\text{eq}}),$$

where the matrices  $\mathbf{A}$ ,  $\mathbf{C}$ , and  $\mathbf{C}_{\text{eq}}$ , and the vectors  $\mathbf{b}$ ,  $\mathbf{d}$ , and  $\mathbf{d}_{\text{eq}}$  are given on the previous slides.

**Remark.** By doubling the dimension of the vector  $\mathbf{x}$  from  $N + 1$  to  $2N + 2$ , the number of inequality constraints becomes  $2N + 3$ . If  $N = 9$  then this is 21!

**Remark.** There are other ways to use `quadprog` to find  $\mathbf{f}_f^\ell(\mu)$  and  $f_{\text{rff}}^\ell(\mu)$ . Documentation for this command is easy to find on the web. The similar command in R is also called “`quadprog`”.

## Computing the One-Rate Model: Properties of $\sigma_f^\ell(\mu)$

When computing an  $\ell$ -limited efficient frontier, it helps to know some general properties of the function  $\sigma_f^\ell(\mu)$  over the interval  $[\mu_{rf}, \mu_{mx}^\ell]$ . These include:

- $\sigma_f^\ell(\mu)$  is **continuous** over  $[\mu_{rf}, \mu_{mx}^\ell]$ ;
- $\sigma_f^\ell(\mu)$  is **increasing** and **convex** over  $[\mu_{rf}, \mu_{mx}^\ell]$ ;
- $\sigma_f^\ell(\mu)$  is **piecewise hyperbolic** over  $[\mu_{rf}, \mu_{mx}^\ell]$ .

This means that  $\sigma_f^\ell(\mu)$  is built up from segments of a line and hyperbolas that are connected at a finite number of **nodes** that correspond to points in the interval  $(\mu_{rf}, \mu_{mx}^\ell)$  where  $\sigma_f^\ell(\mu)$  has either

- *a jump discontinuity in its first derivative* or
- *a jump discontinuity in its second derivative.*

Guided by these facts we now show how **an  $\ell$ -limited efficient frontier can be approximated numerically with the Matlab “quadprog” command.**

# Computing the One-Rate Model: Approximating $\sigma_f^\ell(\mu)$

**First**, partition the interval  $[\mu_{\text{rf}}, \mu_{\text{mx}}^\ell]$  as

$$\mu_{\text{rf}} = \mu_0 < \mu_1 < \dots < \mu_{n-1} < \mu_n = \mu_{\text{mx}}^\ell.$$

For example, set  $\mu_k = \mu_{\text{mn}}^\ell + k(\mu_{\text{mx}}^\ell - \mu_{\text{rf}})/n$  for a uniform partition. Pick  $n$  large enough to resolve all the features of the  $\ell$ -limited efficient frontier. There should be at most one node in each subinterval  $[\mu_{k-1}, \mu_k]$ .

**Second**, for every  $k = 1, \dots, n-1$  use quadprog to compute  $\mathbf{f}_f^\ell(\mu_k)$  and  $\mathbf{f}_{\text{rff}}^\ell(\mu_k)$ . (This computation will not be exact, but we will speak as if it is.)  
**The allocations  $\{\mathbf{f}_f^\ell(\mu_k)\}_{k=0}^n$  should be saved.**

**Third**, for every  $k = 1, \dots, n-1$  compute  $\sigma_k$  by

$$\sigma_k = \sigma_f^\ell(\mu_k) = \sqrt{\mathbf{f}_f^\ell(\mu_k)^T \mathbf{V} \mathbf{f}_f^\ell(\mu_k)}.$$

# Computing the One-Rate Model: Interpolation in $\sigma\mu$ -Plane

## Fourth. Set

$$\mathbf{f}_f^\ell(\mu_0) = \mathbf{0}, \quad f_{\text{rff}}^\ell(\mu_0) = 1, \quad \sigma_0 = 0.$$

There is typically a unique long-short pair allocation  $\mathbf{e}_{ij}^\ell$  such that  $\mu_{\text{mx}}^\ell = (1 + \ell) m_i - \ell m_j$  that is most efficient, in which case we have

$$\mathbf{f}_f^\ell(\mu_n) = \mathbf{e}_{ij}^\ell, \quad f_{\text{rff}}^\ell(\mu_n) = 0, \quad \sigma_n = \sigma_{ij}^\ell = \sqrt{(\mathbf{e}_{ij}^\ell)^\top \mathbf{V} \mathbf{e}_{ij}^\ell}.$$

**Finally**, we “connect the dots” between the points  $\{(\sigma_k, \mu_k)\}_{k=0}^n$  to build an approximation to the  $\ell$ -limited frontier in the  $\sigma\mu$ -plane. This can be done by linear interpolation. Specifically, for every  $\mu \in (\mu_{k-1}, \mu_k)$  we set

$$\tilde{\sigma}_f^\ell(\mu) = \frac{\mu_k - \mu}{\mu_k - \mu_{k-1}} \sigma_{k-1} + \frac{\mu - \mu_{k-1}}{\mu_k - \mu_{k-1}} \sigma_k.$$

# Computing the One-Rate Model: Linear Interpolation in $\Pi_1^\ell$

A better way to “connect the dots” between the points  $\{(\sigma_k, \mu_k)\}_{k=0}^n$  is motivated by the two-fund property. Specifically, for every  $\mu \in (\mu_{k-1}, \mu_k)$  we set

$$\tilde{\mathbf{f}}_f^\ell(\mu) = \frac{\mu_k - \mu}{\mu_k - \mu_{k-1}} \mathbf{f}_f^\ell(\mu_{k-1}) + \frac{\mu - \mu_{k-1}}{\mu_k - \mu_{k-1}} \mathbf{f}_f^\ell(\mu_k),$$

$$\tilde{f}_{\text{rff}}^\ell(\mu) = \frac{\mu_k - \mu}{\mu_k - \mu_{k-1}} f_{\text{rff}}^\ell(\mu_{k-1}) + \frac{\mu - \mu_{k-1}}{\mu_k - \mu_{k-1}} f_{\text{rff}}^\ell(\mu_k),$$

and then set

$$\tilde{\sigma}_f^\ell(\mu) = \sqrt{\tilde{\mathbf{f}}_f^\ell(\mu)^T \mathbf{V} \tilde{\mathbf{f}}_f^\ell(\mu)}.$$

**Remark.** This will be a very good approximation if  $n$  is large enough. Over each interval  $(\mu_{k-1}, \mu_k)$  it generally approximates  $\sigma_f^\ell(\mu)$  with a hyperbola rather than with a line.

# Computing the One-Rate Model: Linear Interpolation in $\Pi_1^\ell$

**Remark.** Because  $\mathbf{f}_f^\ell(\mu_k) \in \Pi^\ell(\mu_k)$  and  $\mathbf{f}_f^\ell(\mu_{k-1}) \in \Pi^\ell(\mu_{k-1})$ , we can show that

$$\tilde{\mathbf{f}}_f^\ell(\mu) \in \Pi^\ell(\mu) \quad \text{for every } \mu \in (\mu_{k-1}, \mu_k).$$

Therefore  $\tilde{\sigma}_f^\ell(\mu)$  gives an approximation to the  $\ell$ -limited frontier that lies on or to the right of the  $\ell$ -limited frontier in the  $\sigma\mu$ -plane.

**Remark.** When there are no nodes in the interval  $(\mu_{k-1}, \mu_k)$  then we can use the two-fund property to show that  $\tilde{\sigma}_f^\ell(\mu) = \sigma_f^\ell(\mu)$ .