4. Multi-Factor Models and Optimization

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4.1. **Portfolio Risk Analysis.** We begin by reviewing the multi-factor models we introduced last time. These models assume a linear functional form

$$R_{t+1} = X_t f_t + \epsilon_t, \quad \mathbb{E}[\epsilon] = 0, \quad \mathbb{V}[\epsilon] = D \tag{4.1}$$

where R_{t+1} is an n-dimensional random vector containing the cross-section of returns in excess of the risk-free rate over some time interval $[t, t+1]$, and X_t is a (non-random) $n \times p$ matrix that can be calculated entirely from data known before time t.

Also ϵ_t is assumed to follow a mean-zero distribution with diagonal variance-covariance matrix

$$D := \operatorname{diag}(\sigma_1^2, \ldots, \sigma_n^2) \text{ with all } \sigma_i^2 > 0. \tag{4.2}$$

The variable f in (4.1) denotes a p-dimensional random vector process which cannot be observed directly; information about the f-process must be obtained via statistical inference. We assume that the f-process has finite first and second moments given by

$$\mathbb{E}[f] = \mu_f, \text{ and } \mathbb{V}[f] = F. \tag{4.3}$$

We also recall the definition of "exposure of the portfolio" to one or more factors:

Definition 4.1. For a portfolio with holdings vector $h \in \mathbb{R}^n$, the vector $\mathbf{x} = h'X \in \mathbb{R}^p$ is called the *exposure vector* of the portfolio. The j-th element of $\mathbf{x}$, denoted x_j, is called the *exposure* of h to the j-th factor.

The model (4.1), (4.2) and (4.3) entails associated reductions of the first and second moments of the asset returns:

$$\mathbb{E}[R] = X\mu_f, \text{ and } \Sigma := \mathbb{V}[R] = D + XFX' \tag{4.4}$$

where X' denotes the transpose. Eq. (4.4) is quite useful for portfolio construction and for analyzing existing portfolios. For example, it says that

$$h'\Sigma h = h'Dh + h'XFX'h = h'Dh + \mathbf{x}'F\mathbf{x} \tag{4.5}$$

which expresses the portfolio's variance in terms of the *idiosyncratic variance* $h'Dh$ and a second term computable from only the exposure vector (Def. 4.1).

We can transform (4.5) into an equivalent form which makes the relative contributions of different terms easier to interpret. Divide both sides by the total variance, $h'\Sigma h$ to get

$$1 = \frac{h'Dh}{h'\Sigma h} + \sum_{i=1}^{p} x_i \Big(\sum_j \frac{F_{ij} x_j}{h'\Sigma h} \Big), \qquad \mathbf{x} := h'X \in \mathbb{R}^p \tag{4.6}$$

where we have let $\mathbf{x}$ denote the exposure vector of the portfolio. Eq. (4.6) is known as a *variance decomposition.* It has a term for the idiosyncratic variance, plus one term for each factor.

Schematically, we can write (4.6) as

$$1 = [\text{idiosyncratic}] + \sum_i [\text{contribution from } i\text{-th factor}]$$

Note that the idiosyncratic term is never negative, but the variance contribution from a factor can be negative if a factor is acting as a hedge and reducing variance caused by exposure to other factors.

The APT relation (4.1) allows us to attribute not only risk (variance), but also return or P&L. In particular, the portfolio's one-period P&L is given by

$$h'R = h'\epsilon + \mathbf{x}'f = h'\epsilon + \sum_i x_i f_i, \qquad \mathbf{x} := h'X. \tag{4.7}$$

Schematically, (4.7) means that

$$\text{PL} = [\text{idiosyncratic PL}] + \sum_i [\text{PL contribution from } i\text{-th factor}]$$

Eq.(4.7) is called a *performance attribution.*

Three of the most common measures of risk are volatility, value-at-risk, and expected shortfall. Since you're already quite familiar with volatility, we now discuss the latter two.

Imagine you are at a large investment bank before the Volcker rule, and upper management gets nervous if the trading division loses more than \$50mm in a single day. If π is a random variable representing the profit in a day, then $\ell = -\pi$ is known as the *loss.* Suppose the strategists analyze the density $p(\ell)$ and find out that

$$\int_{5\times 10^7}^{\infty} p(\ell) d\ell \approx 0.01,$$

so the strategy will only make management nervous about once in every 100 days. In this situation, the number \$50mm equals the 99% VaR.

Supposing that

$$F_\ell(x) = \int_{-\infty}^{x} p(\ell) d\ell,$$

the c.d.f. of the loss distribution, is a one-to-one function and hence invertible, the 99% VaR is $F_\ell^{-1}(0.99)$. More generally, F_ℓ may not be invertible and there is nothing magical about the number 0.99. For any $\alpha \in (0, 1)$, we define VaR_α to be

$$\mathrm{VaR}_\alpha = \inf \{x \in \mathbb{R} : \alpha \leq F_\ell(x)\}.$$

The statistically-minded will recognize this as the definition of the *quantile function* and is thus an old idea.

The problem with VaR is that it has nothing to say about the *size of the loss*, when it does occur. For illustrative purposes consider a hypothetical strategy whose profit distribution takes the form of a mixture of two distributions. The first is a normal distribution with daily sigma of \$1m and mean annual profit of \$80m (hence a Sharpe ratio of 5). The second is a distribution which is usually zero, but once in 1000 trading days (about four years) there is a “catastrophe” which causes the strategy to lose \$1,000m. This example, although stylized, illustrates the problem with relying too heavily on VaR. For this reason, VaR has amusingly been compared to “an air bag which works all of the time, except when you have a car accident.” (Einhorn and Brown, 2008).

Suppose all risk-management were done by means of VaR and that all traders were compensated with an annual performance bonus, without too much visibility into what the individual traders were doing. Unscrupulous or nescient traders might be drawn to strategies of the type considered above. Moreover, it wouldn’t be surprising to find such strategies readily available in the marketplace, since the expected gain of taking the other side or “selling the strategy” is \$680m every four years. VaR isn’t the ultimate panacea we might have hoped for.

Attempts have been made to formulate risk measures which address some of the shortcomings of VaR. One of the more promising ones is *expected* *shortfall*, defined as the conditional expected loss, conditional on the event that the loss is greater than the VaR. Expected shortfall is also called Conditional Value at Risk (CVaR), and expected tail loss (ETL).

Mathematically, if the underlying distribution for X is a continuous distribution then the expected shortfall is equivalent to the tail conditional expectation defined by

$$\mathrm{TCE}_\alpha(X) = \mathbb{E}[-X \mid X \leq -\mathrm{VaR}_\alpha(X)].$$

This is a nice measure theoretically. The main problem is that it's very hard to measure empirically, because you never have very many real historical events where $X \leq -\mathrm{VaR}_\alpha(X)$.

Let $\mathbf{x} = (x_1, \ldots, x_n) \in \mathbb{R}^n$. A function $f : \mathbb{R}^n \to \mathbb{R}$ is said to be *homogeneous of degree* k if

$$f(\lambda \mathbf{x}) = \lambda^k f(\mathbf{x}) \text{ for all } \lambda > 0.$$

Three of the most commonly-used risk measures are volatility, value-at-risk, and expected shortfall. They are all homogeneous of degree $k = 1$. For example, the volatility of a 2:1 levered portfolio is theoretically twice the volatility of the unlevered version. It is worth noting that, for a very large portfolio, if it had to be liquidated quickly then the losses could be magnified due to the market impact of the liquidation itself. This special case contradicts the homogeneity statement above, but nonetheless we shall continue to investigate the consequences of homogeneity.

Euler's homogeneous function theorem states that f is homogeneous of degree k if and only if

$$\mathbf{x} \cdot \nabla f = k f(\mathbf{x})\,. \tag{4.8}$$

This is typically applied with $k = 1$, as follows.

Quite generally, say some return denoted r (which could be our portfolio's return $h'R$) can be written

$$r = \sum_m x_m g_m \tag{4.9}$$

where x_m are non-random "exposures" known at the beginning of the period (known *ex ante*, in other words) and g_m are random return sources whose realizations become known *ex post*, or at the end of the period. Then by

Euler's theorem (4.8) one can write

$$\sigma(r) = \sum_m x_m \,\mathrm{MCR}_m, \quad \text{where} \quad \mathrm{MCR}_m := \frac{\partial \sigma(r)}{\partial x_m} \tag{4.10}$$

where MCR is for *marginal contribution to risk.*

Applying the definition of covariance one can also derive from (4.9) another variance decomposition,

$$\sigma^2(r) = \mathrm{var}(r) = \sum_m x_m \,\mathrm{cov}(g_m, r)$$

Dividing the last equation by $\sigma(r)$ yields the *x-sigma-rho attribution*

$$\sigma(r) = \sum_m x_m \sigma(g_m)\rho(g_m, r) \tag{4.11}$$

where $\rho(g_m, r)$ is the correlation of source m with the portfolio's return. By comparing (4.11) with (4.10) we see that

$$\mathrm{MCR}_m = \sigma(g_m)\rho(g_m, r)$$

Theorem 4.1. For an unconstrained optimal portfolio (i.e., maximum information ratio), the expected source returns are directly proportional to the source marginal contributions,

$$\mathbb{E}[g_m] = \mathrm{IR} \cdot \mathrm{MCR}_m$$

where IR is the portfolio information ratio.

Proof. If we are at optimal $\mathrm{IR} = \mathbb{E}[r]/\sigma(r)$, then

$$0 = \frac{\partial}{\partial x_i}\left[\frac{\mathbb{E}(r)}{\sigma(r)}\right] = \frac{\sigma(r)\mathbb{E}[g_i] - \mathbb{E}[r]\,\mathrm{MCR}_i}{\sigma(r)^2}$$

Hence $\sigma(r)\mathbb{E}[g_i] = \mathbb{E}[r]\,\mathrm{MCR}_i$, from which we get the desired relation by dividing by $\sigma(r)$ on both sides. □

Theorem 4.1 provides implied returns that serve as an important reality check on whether the actual portfolio is consistent with the manager's views. In any situation where we can calculate MCR's, we can then calculate $\mathrm{IR} \cdot \mathrm{MCR}_m$ for a few reasonable choices of IR. Sometimes non-quantitative portfolio managers are surprised by the results. The directions and signs line up to make sense: if $\mathrm{MCR}_m < 0$ for some m, it means you could reduce risk by having more exposure to it. This would happen, for example, if source m were uncorrelated to the other sources, and you were short (negative exposure), which would happen if $\mathbb{E}[g_m] < 0$.

4.2. **Optimization and APT.** The Markowitz (1952) mean-variance problem with moments (4.4) is

$$
\begin{aligned}
h^* &= \operatorname{argmax} f(h) \quad \text{where} &\quad (4.12)\\
f(h) &= h'X\mu_f - \frac{\kappa}{2}h'XFX'h - \frac{\kappa}{2}h'Dh &\quad (4.13)
\end{aligned}
$$

and where $\kappa > 0$ is the Arrow-Pratt constant absolute risk aversion.

The first two terms in (4.12) depend on h only through its exposures $\mathbf{x}$. In terms of $\mathbf{x}$ the first two terms in (4.12) can be written more simply as

$$\mathbf{x}'\mu_f - (\kappa/2)\mathbf{x}'F\mathbf{x}$$

A key insight is that at optimality, the third term can be written as a function of $\mathbf{x}$ as well:

Intuition 4.1. An optimal portfolio h for (4.12) must minimize idiosyncratic variance $h'Dh$ among all portfolios with the same exposures $\mathbf{x} = X'h$.

With this intuition in mind to clarify the proof, we can now proceed to the main result.

Theorem 4.2. The risk/alpha exposures of the portfolio optimizing (4.12) are x^* and the optimal holdings are h^*, where

$$
\begin{aligned}
x^* &= \kappa^{-1}[F + [X'D^{-1}X]^+]^{-1}\mu_f &\quad (4.14)\\
h^* &= \kappa^{-1}D^{-1/2}(X'D^{-1/2})^+\big[F + (X'D^{-1}X)^+\big]^{-1}\mu_f
\end{aligned}
$$

Proof. Let $h^*(x)$ be the solution to

$$h^*(x) = \underset{h}{\operatorname{argmin}}\, h'Dh \quad \text{subject to:} \quad X'h = x. \qquad (4.15)$$

Let

$$V(x) = h^*(x)'Dh^*(x)$$

be the minimum idiosyncratic variance (still subject to $X'h = x$).

Using Intuition 4.1, the mean-variance objective can then be written entirely in terms of x:

$$\max_x \left\{ x \cdot \mu_f - \frac{\kappa}{2}x'Fx - \frac{\kappa}{2}V(x) \right\}. \qquad (4.16)$$

Finding $V(x)$ will allow us to directly attack (4.16), hence we now devote ourselves to this task. We show in due course that $V(x)$ is quadratic and can be written down explicitly.

Changing variables to $\eta := D^{1/2}h$ the problem (4.15) is

$$\min_{\eta} \|\eta\|^2 \text{ subject to } X'D^{-1/2}\eta = x \tag{4.17}$$

Hence the solution to (4.17) is given by[1]

$$\eta^* = (X'D^{-1/2})^+ x \quad \Rightarrow \quad h^*(x) = D^{-1/2}(X'D^{-1/2})^+ x \tag{4.18}$$

and therefore

$$\begin{aligned} V(x) &= h^*(x)'Dh^*(x) \\ &= [D^{-1/2}(X'D^{-1/2})^+x]'D[D^{-1/2}(X'D^{-1/2})^+x] \\ &= x'[X'D^{-1}X]^+x \end{aligned}$$

The third term in (4.16) can thus be combined with the second term in (4.16) to form a single quadratic term. The optimal x is then given by

$$x^* = \kappa^{-1}[F + [X'D^{-1}X]^+]^{-1}\mu_f$$

and the optimal holdings h^* are found by plugging x^* into (4.18). This completes the proof. Theorem 4.2 and further discussion and examples can be found in: http://ssrn.com/abstract=2821360.

Theorem 4.3. Let the number of factors, p, be a fixed constant. The computational complexity of finding the optimal exposures and holdings, Eqns. (4.14) is linear-time in n, the number of assets.

Proof. Recall that if $X = USV'$ is the SVD of X, the Moore-Penrose pseudoinverse is given by

$$X^+ = VS^+U' \tag{4.19}$$

where S^+ is formed by replacing every non-zero diagonal entry by its reciprocal and transposing the resulting matrix. Let $p \ll n$; the "economical" SVD of an $n \times p$ matrix can be computed (Golub and Van Loan, 2012) in about

$$6np^2 + 20p^3 \ \text{ flops} \tag{4.20}$$

This bounds the complexity of the pseudoinverse and actual inverse required in (4.14), since the Moore-Penrose pseudoinverse is given in terms of the SVD by (4.19). But if p is constant then (4.20) is linear in n. This completes the proof.

[1]Under certain conditions on matrices A and B, one has $(AB)^+ = B^+A^+$ but none of those conditions apply here, so the right-hand side of (4.18) can't be simplified further.

We lose no generality in assuming that the outputs from m distinct alpha models are stored in the first m columns in X, and defining $k = p - m$ as the number of risk factors, one has

$$X = \begin{bmatrix} X_\alpha & X_\sigma \end{bmatrix} \in \mathbb{R}^{n\times(k+m)} \tag{4.21}$$

Several of the remarks below refer to the notation of (4.21).

As stated above we do not assume X is of full rank. This method deals gracefully with approximate or exact colinearities among the risk factors and alpha factors (or X_σ and X_α). This could arise if X_σ contains indicator variables for two classifications, such as sector and country, if two or more alpha models were closely related representations of the same model/dataset, or if some group of alpha factors were approximately spanned by the risk factors. Eqns. (4.14) remain valid if there *aren't* any collinearities of course, so this approach allows one formula to cover all cases.

The number of risk factors k, the number of alpha models m, and hence the overall number of factors $p = k + m$ is ultimately a modeling choice, but since the complexity scales as p^3 for fixed n, parsimonious models are more efficiently optimized. Parsimonious models are also preferred in statistical model selection procedures according to the Ockham's razor principle (Jefferys and Berger, 1992). Accordingly, one can select the number of factors (or model complexity) by splitting the full data into a training set, and a testing (or out-of-sample) set, and setting the model complexity via cross-validation within the training set. A full description of the procedure is beyond our current scope, but an excellent treatment can be found in Friedman, Hastie, and Tibshirani (2001, Chapter 7).

The technique above can be extended to include certain simple trading cost models. For example, if we have a starting portfolio h_0 and quadratic trading costs[2] given by

$$(h - h_0)'\Lambda(h - h_0) \quad \text{where} \quad \Lambda = \operatorname{diag}(\lambda_1, \ldots, \lambda_n).$$

then (4.12) becomes (with the shorthand $\alpha := X\mu_f$)

$$\begin{aligned} f(h) &= h'\alpha - \frac{\kappa}{2}h'XFX'h - \frac{\kappa}{2}h'Dh - (h - h_0)'\Lambda(h - h_0) \\ &= h'(\alpha + 2\Lambda h_0) - \frac{\kappa}{2}h'XFX'h - \frac{\kappa}{2}h'(D + \frac{2}{\kappa}\Lambda)h \end{aligned}$$

[2] This trading cost model is too simple to be used in practice because the quadratic structure tends to underestimate the cost of small trades.

The latter has the same mathematical structure as the original problem (4.12), so Theorem 4.2 applies.

If the alpha factors are statistically independent from the risk factors, then F must have a block structure with blocks F_α and F_σ. A portfolio *neutral* to all of the columns of X_σ (the risk factors), may be obtained as the limit of h^* as $[F_\sigma]_{i,i} \to +\infty$ for all $i = 1, \ldots, k$. This limit exists, and is equivalent to solving the optimization with the k linear constraints $h' X_\sigma = 0$. Under the independence assumption of alpha factors and risk factors, the constrained factor-neutral portfolio will usually be close to h^*, but not exactly the same since the constrained solution may have higher idiosyncratic variance than other unconstrained solutions.

References

Einhorn, David and Aaron Brown (2008). "Private profits and socialized risk". In: *Global Association of Risk Professionals* 42, pp. 10–26.

Friedman, Jerome, Trevor Hastie, and Robert Tibshirani (2001). *The elements of statistical learning*. Vol. 1. Springer series in statistics Springer, Berlin.

Golub, Gene H and Charles F Van Loan (2012). *Matrix computations*. Vol. 3. JHU Press.

Jefferys, William H and James O Berger (1992). "Ockham's razor and Bayesian analysis". In: *American Scientist* 80.1, pp. 64–72.

Markowitz, Harry (1952). "Portfolio selection*". In: *The Journal of Finance* 7.1, pp. 77–91.