Allocations as Decisions

MFM Practitioner Module: Risk & Asset Allocation

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Recall that we denote by $\theta$ the parameters that we have chosen to characterize the market vector random variable $M \sim \cdot (\theta)$. Since the investor satisfaction $S_\theta(\alpha)$ and the feasible set $C_\theta$ associated with an portfolio $\alpha \in C_\theta$ are estimable, the optimal portfolio

$$\alpha^* = \arg \max_{\alpha \in C_\theta} S_\theta(\alpha)$$

also depends in an estimable (non-random) way on $\theta$.

**Estimation Risk**

- But we can only estimate $\theta$; and
- we may have doubts about the characterization of $M$.

These are two varieties of estimation risk. How can we express our “risk aversion” to estimation risk in our allocation decision?
Estimation Risk

This is not a theoretical or academic issue. The procedures we have outlined so far effectively seek out and try to exploit fine-grained details in the markets in their attempt to optimize satisfaction.

Robust Decisions
We would be ill-advised to incur transaction costs and undue risks if these details are artificial. We need our portfolio allocation procedure to be robust. In analogy to the concept of estimator loss that was introduced in chapter 4, Meucci introduces here the concept of opportunity cost,

\[ \mathcal{OC}_\theta(\alpha) = S_\theta(\alpha^*) - S_\theta(\alpha) \geq 0 \]

where \( \alpha \) plays the rôle of the estimator and \( \theta \) plays the rôle of the random sample.
In contrast to the situation in classical estimation theory with quadratic loss, we do not have a direct decomposition of expected loss into contributions from bias and inefficiency.

**Decision Strategies**

But Meucci shows us two examples of extreme allocation decision strategies that attempt to illustrate this trade-off.

- prior allocation strategy
- sample-based allocation strategy

Ultimately he will argue in the last chapter for a *minimax* decision strategy, which we will explore in the exercise this week.