A. Static (Marginal) Analysis A.I. Descriptive Statistics

Olivier Scaillet

University of Geneva and Swiss Finance Institute



Outline

- Introduction
- 2 Mean and Covariance
- Shape Parameters
- 4 Issues



Introduction

To conduct data analysis, we need summary statistics.

They will be an *average* of the observations or their functions in a given period of time.

Here dynamic aspects are not taken into account.

This means that the fact that available information evolves through time is not taken into account.

⇒ This is essentially a *static* or marginal analysis.



Preliminaries

We consider n financial assets with prices $p_{i,t}$ at date t.

The returns of asset i is computed as

$$y_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}}$$
 or $y_{i,t} = \ln \frac{p_{i,t}}{p_{i,t-1}}$.

The time horizon is one period, say one day.

In a vectorial notation, we get

$$y_t = \left(egin{array}{c} y_{1,t} \ dots \ y_{i,t} \ dots \ y_{n,t} \end{array}
ight) = \left(y_{1,t},...,y_{i,t},...y_{n,t}
ight)'.$$



The *mean* is defined by $m = E[Y_t]$.

It is a vector of size $n \times 1$ with components equal to asset mean return: $m_i = E[Y_{i,t}]$.

It measures the average location of the random vector.

The covariance matrix is defined by

$$\Sigma = V[Y_t] = E[(Y_t - E[Y_t])(Y_t - E[Y_t])'].$$

It is a matrix of size $n \times n$ with diagonal elements equal to the variances

$$\sigma_i^2 = E[Y_{i,t}^2] - E[Y_{i,t}]^2,$$

and off-diagonal elements equal to the covariances

$$\sigma_{ij} = E[Y_{i,t}Y_{j,t}] - E[Y_{i,t}]E[Y_{j,t}].$$



Issues

Estimation of the Mean

The mean and covariance measure the dispersion and the linear dependence between the components of the random vector.

To estimate an expectation we only need to replace E by an empirical average. Hence we get the empirical mean

$$\hat{m} = \frac{1}{T} \sum_{t=1}^{T} y_t,$$

which is a vector of size $n \times 1$ with components equal to the average returns

$$\hat{m}_i = \frac{1}{T} \sum_{t=1}^T y_{i,t},$$

Estimation of the Covariance

and the *empirical* covariance matrix

$$\hat{\Sigma} = \frac{1}{T} \sum_{t=1}^{T} \left[(y_t - \hat{m}) (y_t - \hat{m})' \right]$$

which is a matrix of size $n \times n$ with diagonal elements equal to the empirical variances

$$\hat{\sigma}_i^2 = \frac{1}{T} \sum_{t=1}^I y_{i,t}^2 - \hat{m}_i^2,$$

and off-diagonal elements equal to empirical covariances

$$\hat{\sigma}_{ij} = \frac{1}{T} \sum_{t=1}^{T} y_{i,t} y_{j,t} - \hat{m}_i \hat{m}_j.$$

Shape Parameters - Skewness

Other summaries are also available. They are called the skewness and the kurtosis and are shape parameters.

The *skewness* summarizes asymmetry:

$$g_{i1} = \frac{E[(Y_{it} - m_i)^3]}{\sigma_i^3}$$
 (Fischer coefficient)

```
if > 0,
    then we get positive (or left) asymmetry.
if = 0,
    then we get symmetry.
if < 0,
    then we get negative (or right) asymmetry.</pre>
```



Shape Parameters - Kurtosis

The *kurtosis* summarizes the thickness of tails:

$$b_i = \frac{E[(Y_{it} - m_i)^4]}{\sigma_i^4}$$
 (Pearson coefficient)

if > 3. then fatter tails than normal distribution (leptokurtic) if = 3. then normal tails (mesokurtic) if < 3. then thinner tails than normal distribution (platykurtic)

We often work with excess kurtosis:

$$g_{i2} = \frac{E[(Y_{it} - m_i)^4]}{\sigma_i^4} - 3$$
 (Fischer coefficient)

Empirical Estimators

Again estimators are obtained by substituting an empirical average for the expectation.

Skewness

$$\hat{g}_{i1} = \frac{\frac{1}{T} \sum_{t=1}^{T} (y_{it} - \hat{m}_i)^3}{\hat{\sigma}_i^3}$$

Kurtosis

$$\hat{b}_{i} = \frac{\frac{1}{T} \sum_{t=1}^{T} (y_{it} - \hat{m}_{i})^{4}}{\hat{\sigma}_{i}^{4}}$$
$$\hat{g}_{i2} = \hat{b}_{i} - 3$$

Issues

If the sample is too short, then the bias may be large.

It is preferable to use instead the following estimators

$$\hat{\Sigma} = \frac{1}{T-1} \sum_{t=1}^{T} \left[(y_t - \hat{m}) (y_t - \hat{m})' \right]$$

$$\hat{g}_{i1} = \frac{\frac{T}{(T-1)(T-2)} \sum_{t=1}^{T} (y_{it} - \hat{m}_i)^3}{\hat{\sigma}_i^3}$$

$$\hat{g}_{i2} = \frac{\frac{T(T+1)}{(T-1)(T-2)(T-3)} \sum_{t=1}^{T} (y_{it} - \hat{m}_i)^4}{\hat{\sigma}_i^4} - 3 \frac{(T-1)^2}{(T-2)(T-3)}$$