

# Some Takeaways - Tangency Portfolio Factor Model: Derivation of In-Sample $R^2 = 1$ in the Cross-Sectional Regression

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When we use the tangency portfolio for a given set of assets as the factor model for the same assets, the tangency portfolio explains 100% of the variability in the cross-section. Meaning that, in-sample, it is the perfect pricing model ( $R^2 = 1$ ).

Why is that the case?

## 1 Reminders

Weights in the tangency portfolio:

$$\mathbf{w}_p = \frac{\Sigma^{-1}\boldsymbol{\mu}}{\mathbf{1}^\top \Sigma^{-1}\boldsymbol{\mu}}$$

The denominator,  $\mathbf{1}^\top \Sigma^{-1}\boldsymbol{\mu}$ , serves as a scaling factor to normalize the portfolio weights.

The  $\beta$  value in a regression with a single feature:

$$\beta = \frac{\text{Cov}(y, x)}{\text{Var}(y)}$$

In our case:

$$\beta = \frac{\text{Cov}(r_i, r_p)}{\text{Var}(r_p)}$$

Where:

- $r_p$  is the time-series of returns of the tangency portfolio.
- $r_i$  is the time-series of returns of the asset  $i$ .

## 2 Covariance between $r_i$ and Tangency Portfolio

The covariance between the return of asset  $i$  and the tangency portfolio  $r_p$  is:

$$\text{Cov}(r_i, r_p) = \text{Cov}(r_i, \mathbf{w}_p^\top \mathbf{r}) = \mathbf{w}_p^\top \text{Cov}(r_i, \mathbf{r}) = \mathbf{w}_p^\top \Sigma_{\cdot i}$$

where  $\mathbf{w}_p^\top \Sigma_{\cdot i}$  represents the  $i$  column of  $\Sigma$  or the  $i$  value of the vector  $\mathbf{w}_p^\top \Sigma$ .

Since:

$$\Sigma \mathbf{w}_p = \frac{\boldsymbol{\mu}}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}},$$

we have:

$$\text{Cov}(r_i, r_p) = \frac{\mu_i}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}}.$$

## 3 Variance of the Tangency Portfolio

The variance of the tangency portfolio  $r_p$  is:

$$\text{Var}(r_p) = \mathbf{w}_p^\top \Sigma \mathbf{w}_p = \left( \frac{\Sigma^{-1} \boldsymbol{\mu}}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}} \right)^\top \Sigma \left( \frac{\Sigma^{-1} \boldsymbol{\mu}}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}} \right).$$

Which simplifies to:

$$\text{Var}(r_p) = \frac{\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu}}{(\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu})^2}.$$

## 4 Beta of $r_i$ to the Tangency Portfolio

The beta of asset  $i$  relative to the tangency portfolio is:

$$\beta_i = \frac{\text{Cov}(r_i, r_p)}{\text{Var}(r_p)} = \frac{\frac{\mu_i}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}}}{\frac{\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu}}{(\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu})^2}}$$

Simplifying:

$$\beta_i = \frac{\mu_i \cdot \mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}}{\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu}}.$$

## 5 Expected Returns as a Function of Beta

Rearranging the expression for  $\beta_i$ , we find:

$$\mu_i = \beta_i \cdot \frac{\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu}}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}}.$$

This shows a perfect linear relationship between  $\mu_i$  and  $\beta_i$ , with the slope given by:

$$\frac{\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu}}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}}$$

Thus, the relationship between the asset and its  $\beta$ , for any asset  $i$ , is given by this **same** slope.

## 6 Cross-Sectional Regression

When performing a cross-sectional regression:

$$\mu_i = \eta + \lambda \beta_i + \nu_i$$

From the relationship  $\mu_i = \beta_i \cdot \frac{\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu}}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}}$ , we find:

$$\hat{\lambda} = \frac{\boldsymbol{\mu}^\top \Sigma^{-1} \boldsymbol{\mu}}{\mathbf{1}^\top \Sigma^{-1} \boldsymbol{\mu}}$$

$$\hat{\eta} = 0$$

Which connects perfectly all the  $\mu_i$ , leading to  $\nu_i = 0 \quad \forall \quad i$ . Consequently:

$$R^2 = 1.$$

Thus, in-sample the tangency portfolio is the perfect factor pricing model.