

## I. The Regression Approach to Portfolio Analysis

In this paper a riskless asset is assumed available for both borrowing and lending in each period. *Excess returns* are calculated by subtracting the return of this riskless asset from the total return.<sup>6</sup> There are  $K$  risky assets indexed by  $k = 1, \dots, K$ . The excess returns on the  $K$  assets in some period  $t$  in  $(1, \dots, T)$  are denoted by the  $K$  elements of the vector  $\mathbf{x}_t$ :

$$\mathbf{x}'_t = [x_{1t}, \dots, x_{kt}, \dots, x_{Kt}]. \quad (1)$$

The  $T$  observations of excess returns are contained in the  $T \times K$  matrix  $\mathbf{X}$ :

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}'_1 \\ \vdots \\ \mathbf{x}'_T \end{bmatrix}. \quad (2)$$

Note that a portfolio of risky assets and a riskless asset has an excess return that is determined solely by the weights and excess returns of the risky assets. Thus, given a  $K$ -vector of risky asset weights  $\mathbf{b}$ , the excess return of this portfolio in period  $t$  is simply  $\mathbf{x}'_t \mathbf{b}$ , where the weights in  $\mathbf{b}$  need not sum to one.

Let  $\mathbf{1}$  represent a vector of ones with length conforming to the rules of matrix algebra. Viewed as a portfolio excess return, the  $T$ -vector of ones  $\mathbf{1}$  is highly desirable as it has positive excess return with zero sample standard deviation. The regression approach to portfolio selection<sup>7</sup> is based on minimizing the squared deviations between the excess returns on a constructed portfolio and the excess returns in  $\mathbf{1}$ . This minimization problem can be per-

formed using an artificial ordinary least squares (OLS) regression and the following proposition states that such a regression recovers the weights of a sample efficient portfolio.

**THEOREM 1:** *OLS regression of a constant  $\mathbf{1}$  onto a set of asset's excess returns  $\mathbf{X}$ , without an intercept term,*

$$\begin{matrix} \mathbf{1} & = & \mathbf{X}\mathbf{b} & + & \mathbf{u}, \\ (T \times 1) & & (T \times k) & (k \times 1) & (T \times 1) \end{matrix} \quad (3)$$

*results in an estimated coefficient vector*

$$\hat{\mathbf{b}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{1}, \quad (4)$$

*that is a set of risky-asset-only portfolio weights for a sample efficient portfolio. The scaled (so that weights sum to one) coefficient vector  $\hat{\mathbf{b}}/\mathbf{1}'\hat{\mathbf{b}}$  is thus the familiar tangency portfolio*

$$\frac{\bar{\Sigma}^{-1}\bar{\mathbf{x}}}{\mathbf{1}'\bar{\Sigma}^{-1}\bar{\mathbf{x}}}, \quad (5)$$

*derived from quadratic programming, where the sample mean  $\bar{\mathbf{x}} = \mathbf{X}'\mathbf{1}/T$ , and the (maximum likelihood) sample covariance  $\bar{\Sigma} = (\mathbf{X} - \mathbf{1}\bar{\mathbf{x}})'(\mathbf{X} - \mathbf{1}\bar{\mathbf{x}})/T$ , are used as parameters.*

*Proof:* Using the updating formula for an inverse matrix,<sup>8</sup> express the coefficient vector  $\hat{\mathbf{b}}$  from the regression in equation (3) in terms of the sample mean  $\bar{\mathbf{x}}$  and sample covariance  $\bar{\Sigma}$ :

$$\begin{aligned} \hat{\mathbf{b}} &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{1} \\ &= (\bar{\Sigma} + \bar{\mathbf{x}}\bar{\mathbf{x}}')^{-1}\bar{\mathbf{x}} \\ &= \left( \bar{\Sigma}^{-1} - \frac{\bar{\Sigma}^{-1}\bar{\mathbf{x}}\bar{\mathbf{x}}'\bar{\Sigma}^{-1}}{1 + \bar{\mathbf{x}}'\bar{\Sigma}^{-1}\bar{\mathbf{x}}} \right) \bar{\mathbf{x}} \\ &= \frac{\bar{\Sigma}^{-1}\bar{\mathbf{x}}}{1 + \bar{\mathbf{x}}'\bar{\Sigma}^{-1}\bar{\mathbf{x}}}. \end{aligned} \quad (6)$$

Scaling  $\hat{\mathbf{b}}$  so that the coefficients sum to one results in the tangency portfolio

$$\frac{\hat{\mathbf{b}}}{\mathbf{1}'\hat{\mathbf{b}}} = \frac{\bar{\Sigma}^{-1}\bar{\mathbf{x}}}{\mathbf{1}'\bar{\Sigma}^{-1}\bar{\mathbf{x}}} \quad (7)$$

when sample means and covariances are used as parameters. Q.E.D.

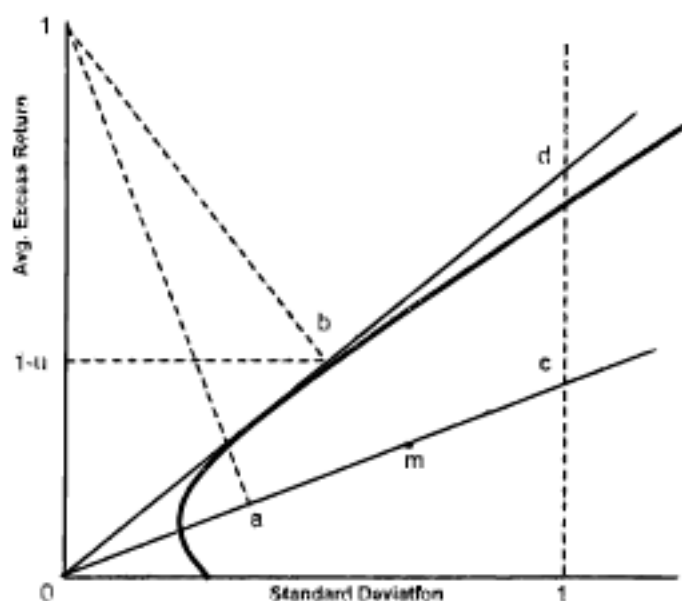


Figure 1. Sample mean standard deviation diagram. The point  $b$  is the point on the line  $Od$  that is closest to the point  $(0,1)$  and the point  $a$  is the point on the line  $Om$  that is closest to  $(0,1)$ .

The regression in equation (3) is unusual. There is no intercept, the dependent variable is nonstochastic, and the residual vector  $u$  is correlated with the regressors, which are stochastic. However, the regression has a simple interpretation: The dependent variable  $l$  is a sample counterpart to arbitrage profits—positive excess return with zero standard deviation; the coefficients  $b$  represent the weights on risky assets in the portfolio;  $Xb$  represents excess returns on this portfolio; and the residual vector  $u$  shows deviations in this portfolio's return from  $l$ .

The estimated portfolio weights  $\hat{b}$  produce a portfolio return vector that is closest in terms of least squares distance to the arbitrage return vector  $l$ . This least squares distance can be illustrated using the familiar mean-standard deviation diagram. The feasible set, constructed from the sample mean and (maximum-likelihood) sample covariance, has an efficient boundary shown by the line  $Od$  from the origin passing through the tangency portfolio (Figure 1). The arbitrage return vector  $l$  is located at the point  $(0,1)$ .