

Note on the Upper Tangency Condition

We first derive a test of the upper tangency condition for the mimicking-portfolio case. We then specialize the resulting expression to the case of traded factors only. Suppose that the K -vector f_t consists of some traded and some nontraded factors. Let R_t be an N -vector of excess returns (return spreads) on the basis assets. For a traded factor, the mimicking portfolio is, of course, simply the factor itself.

We define $Y_t = [f_t', R_t']'$ and its population mean and covariance matrix as

$$\mu = E[Y_t] \equiv \begin{bmatrix} \mu_f \\ \mu_R \end{bmatrix}, \quad (1)$$

$$V = \text{Var}[Y_t] \equiv \begin{bmatrix} V_f & V_{fR} \\ V_{Rf} & V_R \end{bmatrix}. \quad (2)$$

In the following analysis, we assume that V_f and V_R are invertible and that V_{Rf} is of full column rank. Consider the projection of f_t on R_t and a constant and denote the resulting mimicking-portfolio returns by $f_t^* = V_{fR}V_R^{-1}R_t \equiv AR_t$ with $\mu^* = E[f_t^*] = A\mu_R$ and $V^* = \text{Var}[f_t^*] = AV_R A' = V_{fR}V_R^{-1}V_{Rf}$. The initial costs of the mimicking portfolios are Ae , where $e_i = 1$ for basis asset returns in excess of the risk-free rate and $e_i = 0$ for differences in returns on two basis assets.*

A model's tangency portfolio is on the upper half of the minimum-variance frontier when

$$b = e' A' (AV_R A')^{-1} A \mu_R \geq 0.$$

Denote with hats the sample equivalents of the quantities above. Then, the upper tangency condition can be tested by considering $\hat{b} = e' \hat{A}' (\hat{A} \hat{V}_R \hat{A}')^{-1} \hat{A} \hat{\mu}_R$ and its associated t -statistic. We now derive the asymptotic distribution of \hat{b} .

*Alternatively, one could set the e vector equal to a vector of ones. This requires assuming that return spreads, such as HML, can be viewed as long \$1 in the risk-free asset and \$1 on each side of the spread. Then, HML is the excess return on that unit investment factor.

Note that

$$\begin{aligned}
b &= e' A' (A V_R A')^{-1} A \mu_R \\
&= e' A' V^{*-1} \mu^* \\
&= e' V_R^{-1} \beta^* \mu^*,
\end{aligned} \tag{3}$$

where $\beta^* = V_R f V^{*-1}$.

It is easy to show that

$$\frac{\partial b}{\partial \mu'_f} = 0'_K, \tag{4}$$

$$\frac{\partial b}{\partial \mu'_R} = e' A' V^{*-1} A. \tag{5}$$

Moreover,

$$\frac{\partial b}{\partial \text{vec}(V)'} = (\mu^{*'} \otimes e' V_R^{-1}) \frac{\partial \text{vec}(\beta^*)}{\partial \text{vec}(V)'} + (\mu^{*'} \beta^{*'} \otimes e') \frac{\partial \text{vec}(V_R^{-1})}{\partial \text{vec}(V)'} + e' V_R^{-1} \beta^* \frac{\partial \mu^*}{\partial \text{vec}(V)'}. \tag{6}$$

After some algebra, we obtain

$$\frac{\partial \text{vec}(\beta^*)}{\partial \text{vec}(V)'} = [0_{K \times K}, V^{*-1} A] \otimes [-\beta^*, \beta^* A] + [V^{*-1}, 0_{K \times N}] \otimes [0_{N \times K}, I_N - \beta^* A], \tag{7}$$

$$\frac{\partial \text{vec}(V_R^{-1})}{\partial \text{vec}(V)'} = [0_{N \times K}, V_R^{-1}] \otimes [0_{N \times K}, -V_R^{-1}], \tag{8}$$

$$\frac{\partial (\mu^*)}{\partial \text{vec}(V)'} = [I_K, 0_{K \times N}] \otimes [0'_K, \mu'_R V_R^{-1}] - [0'_K, \mu'_R V_R^{-1}] \otimes [0_{K \times K}, A]. \tag{9}$$

Putting everything together, Equation (6) becomes

$$\begin{aligned}
\frac{\partial b}{\partial \text{vec}(V)'} &= [0'_K, \mu^{*'} V^{*-1} A] \otimes [-e' A' V^{*-1}, e' A' V^{*-1} A] \\
&\quad + [\mu^{*'} V^{*-1}, -\mu^{*'} V^{*-1} A] \otimes [0'_K, e' V_R^{-1}] \\
&\quad - [\mu^{*'} V^{*-1}, \mu'_R V_R^{-1}] \otimes [0'_K, e' A' V^{*-1} A] \\
&\quad + [e' A' V^{*-1}, 0'_N] \otimes [0'_K, \mu'_R V_R^{-1}].
\end{aligned} \tag{10}$$

The proof relies on the fact that \hat{b} is a smooth function of $\hat{\mu}$ and \hat{V} . Therefore, once we have the asymptotic distribution of $\hat{\mu}$ and \hat{V} , we can use the delta method to obtain the asymptotic distribution of \hat{b} . Let

$$\varphi = \begin{bmatrix} \mu \\ \text{vec}(V) \end{bmatrix}, \quad \hat{\varphi} = \begin{bmatrix} \hat{\mu} \\ \text{vec}(\hat{V}) \end{bmatrix}. \quad (11)$$

We first note that $\hat{\mu}$ and \hat{V} can be written as the GMM estimator that uses the moment conditions $E[r_t(\varphi)] = 0_{(N+K)(N+K+1)}$, where

$$r_t(\varphi) = \begin{bmatrix} Y_t - \mu \\ \text{vec}((Y_t - \mu)(Y_t - \mu)' - V) \end{bmatrix}. \quad (12)$$

Since this is an exactly identified system of moment conditions, it is straightforward to verify that under the assumption that Y_t is stationary and ergodic with finite fourth moment, we have

$$\sqrt{T}(\hat{\varphi} - \varphi) \overset{A}{\rightsquigarrow} N(0_{(N+K)(N+K+1)}, S_0), \quad (13)$$

where

$$S_0 = \sum_{j=-\infty}^{\infty} E[r_t(\varphi)r_{t+j}(\varphi)']. \quad (14)$$

Note that S_0 is a singular matrix as \hat{V} is symmetric, so there are redundant elements in $\hat{\varphi}$. We could have written $\hat{\varphi}$ as $[\hat{\mu}', \text{vech}(\hat{V})']'$, but the results are the same under both specifications.

Using the delta method, the asymptotic distribution of \hat{b} is given by

$$\begin{aligned} \sqrt{T}(\hat{b} - b) &\overset{A}{\rightsquigarrow} N\left(0, \begin{bmatrix} \frac{\partial b}{\partial \varphi'} \end{bmatrix} S_0 \begin{bmatrix} \frac{\partial b}{\partial \varphi'} \end{bmatrix}'\right) \\ &\overset{A}{\rightsquigarrow} N(0, E[g_t^2]), \end{aligned} \quad (15)$$

where

$$g_t = e' A' V^{*-1} (f_t^* - \mu^*) [1 - y_t - u_t] + e' A' V^{*-1} (v_t - u_t) \eta_t + e' V_R^{-1} (R_t - \mu_R) y_t + b, \quad (16)$$

where $v_t = \mu'_R V_R^{-1} (R_t - \mu_R)$, $u_t = \mu^{*'} V^{*-1} (f_t^* - \mu^*)$, $y_t = \mu^{*'} V^{*-1} \eta_t$, and $\eta_t = (f_t - \mu_f) - A(R_t - \mu_R)$.

When all the factors are traded, the expression above simplifies by noting that $f_t^* = f_t$, $\mu^* = \mu_f$, $V^* = V_f$, $\eta_t = 0_K$, $y_t = 0$, and $Ae = q$, where q are the initial costs of the K factors. We then have

$$b = q'V_f^{-1}\mu_f$$

and

$$g_t = q'V_f^{-1}(f_t - \mu_f)[1 - \mu_f'V_f^{-1}(f_t - \mu_f)] + b. \quad (17)$$