

Advanced Financial and Macro Econometrics

Comments on Solution

1 CO-INTEGRATION AND PRICING

[1] Both systems have $p = 3$.

Model (1.1) has $r = 2$ and therefore $p - r = 1$ stochastic trend. We can choose

$$\beta = \begin{pmatrix} 1 & 0 \\ -\frac{1}{4} & 1 \\ 0 & \frac{3}{4} \end{pmatrix} \quad \text{and} \quad \beta_{\perp} = \begin{pmatrix} 1 \\ 4 \\ -\frac{16}{3} \end{pmatrix}.$$

Model (1.2) has $r = 1$ and therefore $p - r = 2$ stochastic trends. We can choose

$$b = \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix} \quad \text{and} \quad b_{\perp} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 0 \end{pmatrix}.$$

[2] Following the arguments in the lecture note, the solution should find the MA-solution for the stationary process $\beta'X_t$, i.e.

$$\varrho_t = \alpha (\beta' \alpha)^{-1} \left(\sum_{i=0}^{t-1} (I_r + \beta' \alpha)^i \beta' \epsilon_{t-i} + (I_r + \beta' \alpha)^t \beta' X_0 \right).$$

Similarly for S_t .

[3] The two systems have three co-integrating relationships. Following the lecture note, the solution should argue that they are candidates for trading pairs. Whenever the deviation from equilibrium is non-zero (or significantly non-zero) the agent could buy the underpriced stock and sell the overpriced stock and wait for reversal to equilibrium. More details could be given.

[4] Now a system of $p = 4$ variables, $Z_t = (x_{1,t}, x_{3,t}, y_{1,t}, y_{3,t})'$, is considered.

[4.1] In this case $r = 2$. We can choose

$$\beta^* = \begin{pmatrix} 1 & 0 \\ \frac{3}{16} & 0 \\ 0 & 1 \\ 0 & -1 \end{pmatrix} \quad \text{and} \quad \beta_{\perp}^* = \begin{pmatrix} 1 & 0 \\ -\frac{16}{3} & 0 \\ 0 & 1 \\ 0 & 1 \end{pmatrix}.$$

[4.2] Next, we are informed that $x_{1,t} - y_{3,t}$ is also stationary. We can choose

$$\beta^* = \begin{pmatrix} 1 & 0 & 1 \\ \frac{3}{16} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & -1 & -1 \end{pmatrix} \quad \text{and} \quad \beta_{\perp}^* = \begin{pmatrix} 1 \\ -\frac{16}{3} \\ 1 \\ 1 \end{pmatrix}.$$

[5] Let $y_{3,t}$ denote the market portfolio and consider the system for $Y_t = (y_{1,t}, y_{2,t}, y_{3,t})'$:

$$\begin{pmatrix} \Delta y_{1,t} \\ \Delta y_{2,t} \\ \Delta y_{3,t} \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}' \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{pmatrix}, \quad \text{and} \quad O = \begin{pmatrix} O_{11} & O_{12} & O_{13} \\ O_{21} & O_{22} & O_{23} \\ O_{31} & O_{32} & O_{33} \end{pmatrix}.$$

[5.1] The short-run conditional pricing beta for the first asset is

$$B_t^1 = \frac{\text{cov}_{t-1}(\Delta y_{1,t}, \Delta y_{3,t})}{V_{t-1}(\Delta y_{3,t})} = \frac{\text{cov}_{t-1}(e_{1,t}, e_{3,t})}{V_{t-1}(e_{3,t})} = \frac{O_{13}}{O_{33}}.$$

In this case the conditional variance is constant and B_t^1 is not time-varying. By conditioning in the Gaussian distribution, the model $y_{1,t}, y_{2,t} \mid y_{3,t}$ is

$$\begin{pmatrix} \Delta y_{1,t} \\ \Delta y_{2,t} \end{pmatrix} = \omega \Delta y_{3,t} + \begin{pmatrix} a_1 - \omega a_3 \\ a_2 - \omega a_3 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}' \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{pmatrix} + \begin{pmatrix} e_{1,t}^* \\ e_{2,t}^* \end{pmatrix},$$

where $\omega = O_{13}/O_{33} = B_t^1$ can be easily estimated.

The OLS estimator in the linear regression

$$\Delta y_{1,t} = \lambda \Delta y_{3,t} + \nu_t,$$

is given by

$$\hat{\lambda} = \frac{\frac{1}{T} \sum_{t=1}^T \Delta y_{1,t} \Delta y_{3,t}}{\frac{1}{T} \sum_{t=1}^T (\Delta y_{3,t})^2} = \frac{\frac{1}{T} \sum_{t=1}^T (a_1 b' Y_{t-1} + e_{1,t})(a_3 b' Y_{t-1} + e_{3,t})}{\frac{1}{T} \sum_{t=1}^T (a_3 b' Y_{t-1} + e_{3,t})^2}.$$

The probability limit is given by

$$\hat{\lambda} \rightarrow_P \lambda = \frac{E(a_1 b' Y_{t-1} + e_{1,t})(a_3 b' Y_{t-1} + e_{3,t})}{E(a_3 b' Y_{t-1} + e_{3,t})^2} = \frac{a_1 a_3 \Sigma_{bb} + O_{13}}{a_3^2 \Sigma_{bb} + O_{33}},$$

where Σ_{bb} is the variance of $b' Y_t$. For $\hat{\lambda}$ to be a consistent estimator of $B_{1,t}$, the requirement is that $a_3 = 0$, such that the omitted variable, $b' Y_{t-1}$, is uncorrelated with the regressor, $\Delta y_{3,t}$.

[5.2] The solution should explain that according to the CAPM model the pricing beta, B_t^1 , is the relevant measure of risk in a well-diversified portfolio. The investor is compensated for this systematic risk, while the idiosyncratic risk can be diversified away and is therefore not priced according to the CAPM.

[5.3] Because it is market neutral, a pairs-trading portfolio has a zero beta, and in terms of CAPM it should therefore pay the risk-free rate. One main difference between CAPM and the pairs-trading strategy is that CAPM is an equilibrium pricing theory, while pairs-trading strategies tries to identify prices out of equilibrium.

[6] In the extended case

$$\begin{aligned}
O_t &= \begin{pmatrix} O_{11,t} & O_{12,t} & O_{13,t} \\ O_{21,t} & O_{22,t} & O_{23,t} \\ O_{31,t} & O_{32,t} & O_{33,t} \end{pmatrix} \\
&= \begin{pmatrix} \sigma_{1,t} & 0 & 0 \\ 0 & \sigma_{2,t} & 0 \\ 0 & 0 & \sigma_{3,t} \end{pmatrix} \begin{pmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{pmatrix} \begin{pmatrix} \sigma_{1,t} & 0 & 0 \\ 0 & \sigma_{2,t} & 0 \\ 0 & 0 & \sigma_{3,t} \end{pmatrix} \\
&= \begin{pmatrix} \sigma_{1,t}^2 & \rho_{12}\sigma_{1,t}\sigma_{2,t} & \rho_{13}\sigma_{1,t}\sigma_{3,t} \\ \rho_{12}\sigma_{1,t}\sigma_{2,t} & \sigma_{2,t}^2 & \rho_{23}\sigma_{2,t}\sigma_{3,t} \\ \rho_{13}\sigma_{1,t}\sigma_{3,t} & \rho_{23}\sigma_{2,t}\sigma_{3,t} & \sigma_{3,t}^2 \end{pmatrix}.
\end{aligned}$$

Here the conditional pricing beta is

$$B_t^1 = \frac{O_{13,t}}{O_{33,t}} = \rho_{13} \frac{\sigma_{1,t}}{\sigma_{3,t}},$$

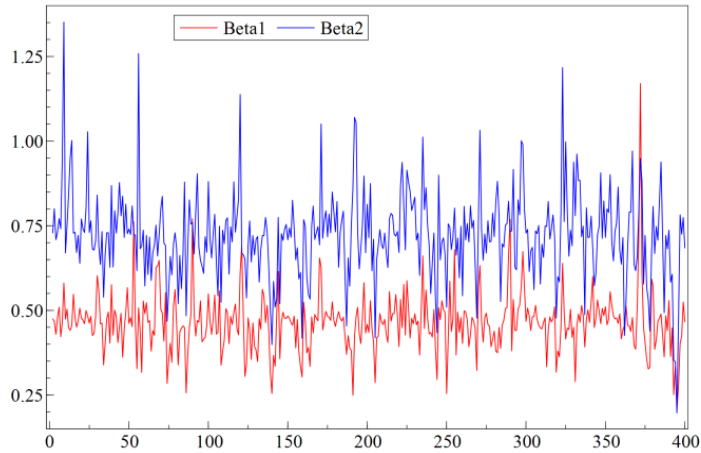
which is time varying.

[7] The estimates of the model are

Robust Standard Errors (Sandwich formula)				
	Coefficient	Std.Error	t-value	t-prob
Part: Dy1				
Cst(M)	0.017293	0.051552	0.3354	0.7375
lagspread (M)	-0.157069	0.025285	-6.212	0.0000
Cst(V)	0.928276	0.082704	11.22	0.0000
ARCH(Alpha1)	0.297931	0.060889	4.893	0.0000
Part: Dy2				
Cst(M)	-0.044709	0.075182	-0.5947	0.5524
lagspread (M)	0.020588	0.032302	0.6374	0.5243
Cst(V)	2.022310	0.15978	12.66	0.0000
ARCH(Alpha1)	0.322421	0.068444	4.711	0.0000
Part: Dy3				
Cst(M)	-0.020567	0.088355	-0.2328	0.8161
lagspread (M)	0.014188	0.039903	0.3556	0.7224
Cst(V)	2.376187	0.22266	10.67	0.0000
ARCH(Alpha1)	0.365069	0.067735	5.390	0.0000
Part: Correlation				
rho_21	0.791882	0.018362	43.13	0.0000
rho_31	0.760147	0.020258	37.52	0.0000
rho_32	0.790171	0.016995	46.49	0.0000
No. Observations :	399	No. Parameters :	15	
No. Series :	3	Log Likelihood :	-1767.467	

The solution should also report estimated conditional variances, covariances and correlations, noting that the latter are constant by construction.

The estimated time-varying betas are gives as



The simple multivariate ARCH allows estimation of the time varying betas. The solution could discuss that a model with constant conditional correlations and ARCH(1) specifications for the conditional variances may be too simple to model time-varying betas. With $B_t^1 = \rho_{13}\sigma_{1,t}/\sigma_{3,t}$, all time variation comes from the relative conditional standard deviations, and they will typically not show very persistent movements. As a result, fluctuations in betas implied by the model are rather transitory.

2 MULTIVARIATE GARCH-X

[8] Drift criterion:

[8.1] It holds, that

$$\begin{aligned}
 E(1 + v_t'v_t|v_{t-1} = v) &= 1 + E(Y_t'Y_t + x_t^2|v_{t-1} = v) \\
 &= 1 + \text{tr}(\Omega_t) + \sigma_x^2 \\
 &= (\omega_1^2 + \omega_2^2 + \alpha_2 y_2^2 + \alpha_1 y_1^2 + 2\gamma x^2) + \sigma_x^2 \\
 &= c + \alpha_2 y_2^2 + \alpha_1 y_1^2 + 2\gamma x^2 \\
 &= c + v'Av \leq c + \max(\alpha_1, \alpha_2, 2\gamma) v'v.
 \end{aligned}$$

[8.2] Hence $\max(\alpha_1, \alpha_2, 2\gamma) < 1$ is a sufficient condition.

[8.3] As $Y_t'Y_t + x_t^2 = y_{1t}^2 + y_{2t}^2 + x_t^2$ the covariance does not change this.

[9] Testing:

[9.1] It follows that

$$\ell_T(\theta) = -\frac{1}{2} \sum_{t=1}^T (\log \det(\Omega_t) + \text{tr}\{Y_t Y_t' \Omega_t^{-1}\})$$

with $\partial \ell_T(\theta) / \partial \gamma = \frac{1}{2} \sum_{t=1}^T \frac{x_{t-1}^2}{\sigma_{1t}^2} [y_{1t}^2 / \sigma_{1t}^2 - 1] + \frac{x_{t-1}^2}{\sigma_{2t}^2} [y_{2t}^2 / \sigma_{2t}^2 - 1]$, as

$$\begin{aligned} \partial [\log \det(\Omega_t)] / \partial \gamma &= \partial [\log \det(D_t^2)] / \partial \gamma = \partial [\log \sigma_{1t}^2 + \log \sigma_{2t}^2] / \partial \gamma \\ &= [1/\sigma_{1t}^2 + 1/\sigma_{2t}^2] x_{t-1}^2 \end{aligned}$$

$$\begin{aligned} \partial [\text{tr}\{Y_t Y_t' \Omega_t^{-1}\}] / \partial \gamma &= \partial [y_{1t}^2 / \sigma_{1t}^2 + y_{2t}^2 / \sigma_{2t}^2] / \partial \gamma \\ &= -[y_{1t}^2 / \sigma_{1t}^4 + y_{2t}^2 / \sigma_{2t}^4] x_{t-1}^2 \end{aligned}$$

Hence

$$\partial \ell_T(\theta) / \partial \gamma |_{\theta=\theta_0} = \frac{1}{2} \sum_{t=1}^T \frac{x_{t-1}^2}{\sigma_{1t}^2} [z_{1t}^2 - 1] + \frac{x_{t-1}^2}{\sigma_{2t}^2} [z_{2t}^2 - 1]$$

With $\xi_t = x_{t-1}^2 \left(\frac{1}{\sigma_{1t}^2}, \frac{1}{\sigma_{2t}^2} \right) \text{vec}(z_t z_t' - I_2)$, it follows that ξ_t is a MGD wrt. $\mathcal{F}_{t-1} = \{(x_{t-k}, Y_{t-k}), k \geq 1\}$ and

$$E \left(\left\{ \frac{x_{t-1}^2}{\sigma_{1t}^2} [z_{1t}^2 - 1] + \frac{x_{t-1}^2}{\sigma_{2t}^2} [z_{2t}^2 - 1] \right\}^2 | \mathcal{F}_{t-1} \right) = 2 \frac{x_{t-1}^4}{\sigma_{1t}^4} + 2 \frac{x_{t-1}^4}{\sigma_{2t}^4}.$$

And, moreover

$$T^{-1} \sum_{t=1}^T \left(\frac{x_{t-1}^4}{\sigma_{1t}^4} + 2 \frac{x_{t-1}^4}{\sigma_{2t}^4} \right) \rightarrow_P E \left(\frac{x_{t-1}^4}{\sigma_{1t}^4} + 2 \frac{x_{t-1}^4}{\sigma_{2t}^4} \right) = m$$

where $m < \infty$ if $\gamma_0 > 0$ since $(x_{t-1}^2 / \sigma_{it}^2)^2 \leq 1 / \gamma_0^2$. No moment restrictions needed. Hence just stationarity and ergodicity is sufficient.

[9.2] If the additional "usual" (to be included) reg. conditions hold on information and third derivatives - this implies that $\hat{\theta}$ can be reported with standard errors. However, this does not include the LR test for $\gamma = 0$ (and t-statistics).

[9.3] When $\gamma_0 = 0$, we need $E(x_{t-1}^4) < \infty$. This is not a further requirement as under Ass. eXo x_t is assumed Gaussian.

[9.4] The LR($\gamma = 0$) is asymptotically " $\frac{1}{2}\chi_1^2$ " distributed. Mention e.g.: (a) $\alpha_{i0} > 0$, (b) well-known implications (e.g. 5% quantile is the 10% quantile of the χ_1^2)

[10] Bootstrap:

[10.1] With $\hat{z}_t = \hat{\Omega}_t^{-1/2} Y_t$ the estimated residuals, set $\hat{z}_t^c = \hat{z}_t - T^{-1} \sum_{t=1}^T \hat{z}_t$ and empiricalV(\hat{z}_t^c) = $T^{-1} \sum_{t=1}^T \hat{z}_t^c \hat{z}_t^{c'}$. Define the standardized residuals (explain why this is needed)

$$\hat{z}_t^s = [\text{empiricalV}(\hat{z}_t^c)]^{-1/2} \hat{z}_t^c.$$

A bootstrap-sample $\{Y_t^*\}$ can then be constructed as e.g.

$$Y_t^* = (\Omega_t^*)^{1/2} \hat{z}_t^s$$

where z_t^* are sampled from \hat{z}_t^s (wild, with replacement etc.), and

$$\Omega_t^* = D_t^* \Gamma^* D_t^*.$$

Here, with $\tilde{\theta}$ denoting the restricted estimator (explain why),

$$\Gamma^* = \begin{pmatrix} 1 & \tilde{\rho} \\ \tilde{\rho} & 1 \end{pmatrix} \quad \text{and} \quad D_t^* = \text{diag}(\sigma_{it}^*)_{i=1,2} = \begin{pmatrix} \sigma_{1t}^* & 0 \\ 0 & \sigma_{2t}^* \end{pmatrix},$$

with

$$\sigma_{it}^{*2} = \tilde{\omega}_i + \tilde{\alpha}_i y_{it-1}^2$$

The LR^* statistic for $\gamma = 0$ is then computed. And as usual, this is repeated say $B = 399$ times - more text can be added.

[10.2] A main issue is if α_{10} and α_{20} equal zero or not (when $\gamma_0 = 0$) as this will affect the limiting distribution.