

Problem Set 4

1. GARCH(1,1)

$$\begin{aligned}
 h_t &= a_0 + a_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \\
 &= a_0 + a_1 \varepsilon_{t-1}^2 + \beta_1 (a_0 + a_1 \varepsilon_{t-2}^2 + \beta_1 h_{t-2}) \\
 &= a_0 (1 + \beta_1) + a_1 (\varepsilon_{t-1}^2 + \beta_1 \varepsilon_{t-2}^2) + \beta_1^2 h_{t-2} \\
 &= a_0 (1 + \beta_1 + \beta_1^2) + a_1 (\varepsilon_{t-1}^2 + \beta_1 \varepsilon_{t-2}^2 + \beta_1^2 \varepsilon_{t-3}^2) + \beta_1^3 h_{t-3} \\
 &\vdots \\
 &= \frac{a_0}{1 - \beta_1} + a_1 \sum_{i=0}^{\infty} \beta_1^i \varepsilon_{t-1-i}^2
 \end{aligned}$$

Therefore the GARCH(1,1) model can be expressed as a GARCH(0,∞) model, which is equivalent to the ARCH(∞) model.

$$2. y_t = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t$$

$$\varepsilon_t = \sqrt{h_t} v_t, \quad v_t \sim \text{IID}(0,1)$$

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2$$

$$|\phi_1| < 1, \quad a_0 > 1, \quad a_i \geq 0, \quad a_1 + a_2 < 1$$

$$(a) \mathcal{L}_{t-1} = \{y_{t-1}, y_{t-2}, \dots\}$$

Conditional mean:

$$\begin{aligned}
 \hat{y}_{t|t-1} &= E_{t-1} y_t = E(\phi_0 + \phi_1 y_{t-1} | \mathcal{L}_{t-1}) \\
 &= \phi_0 + \phi_1 y_{t-1}
 \end{aligned}$$

Conditional variance:

$$\begin{aligned}
 \text{var}(y_t | \mathcal{L}_{t-1}) &= E_{t-1} (y_t - E_{t-1} y_t)^2 \\
 &= E_{t-1} (y_t - \phi_0 - \phi_1 y_{t-1})^2 \\
 &= E_{t-1} (\varepsilon_t^2) \\
 &= h_t \\
 &= a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2
 \end{aligned}$$

} ARCH(2) model

(b) Unconditional mean:

$$\begin{aligned}\mu &= E(y_t) = E(\Phi_0 + \Phi_1 y_{t-1} + \varepsilon_t) \\ &= \Phi_0 + \Phi_1 \mu + 0\end{aligned}$$

$$\Rightarrow \mu = E(y_t) = \frac{\Phi_0}{1 - \Phi_1}$$

Unconditional Variance:

Let $x_t = y_t - \mu$ be the mean adjusted series.

$$\begin{aligned}\Rightarrow x_t &= \cancel{\Phi_0} + \Phi_1 y_{t-1} + \varepsilon_t - \cancel{\Phi_0} - \Phi_1 \mu \\ &= \varepsilon_t + \Phi_1 (y_{t-1} - \mu) \\ &= \varepsilon_t + \Phi_1 (\cancel{\Phi_0} + \Phi_1 y_{t-2} + \varepsilon_{t-1} - \cancel{\Phi_0} - \Phi_1 \mu) \\ &= \varepsilon_t + \Phi_1 \varepsilon_{t-1} + \Phi_1^2 (y_{t-2} - \mu) \\ &\vdots \\ &= \sum_{i=0}^{\infty} \Phi_1^i \varepsilon_{t-i}\end{aligned}$$

$$\begin{aligned}\text{So } \text{var}(x_t) &= \text{var}(y_t - \mu) \\ &= \text{var}(y_t) + \text{var}(\mu) - 2 \text{cov}(y_t, \mu) \\ &= \text{var}(y_t)\end{aligned}$$

$$\text{and } \text{var}(x_t) = \text{var}\left(\sum_{i=0}^{\infty} \Phi_1^i \varepsilon_{t-i}\right)$$

$$= \underbrace{\sum_{i=0}^{\infty} \Phi_1^{2i}}_{\downarrow} \underbrace{\text{var}(\varepsilon_{t-i})}_{\downarrow}$$

$$= \left(\frac{1}{1 - \Phi_1^2} \right) \left(\frac{a_0}{1 - a_1 - a_2} \right) \quad \nwarrow$$

$|\Phi_1| < 1 \rightarrow$

Since $\text{var}(\varepsilon_t) = \frac{a_0}{1 - a_1 - \dots - a_q}$
for an ARCH(q) model

3. GARCH(1,2)

$$\varepsilon_t \sim \sqrt{h_t} v_t, v_t \sim \text{IID}(0,1)$$

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \beta_1 h_{t-1}$$

$| \Phi, | < 1, a_0 > 0, a_i \geq 0 \text{ for } i=1,2, \beta_1 \geq 0, a_1 + a_2 + \beta_1 < 1$

$$\begin{aligned} (a) E(\varepsilon_t^2 | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots) &= E(h_t v_t^2 | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots) \\ &= h_t E(v_t^2 | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots) \\ &= h_t E(v_t^2) \leftarrow \sigma^2 \text{ (second moment)} \\ &= h_t(1) \\ &= h_t = \text{var}(\varepsilon_t | \mathcal{L}_{t-1}) \end{aligned}$$

(b) Unconditional Variance:

Since $a_1 + a_2 + \beta_1 < 1$, the process is weakly stationary.

Therefore $E(h_t) = E(\varepsilon_t^2) = \sigma_t^2$ and we can write

$$\begin{aligned} \sigma_t^2 &= \text{var}(\varepsilon_t) = E(\text{var}(\varepsilon_t | \mathcal{L}_{t-1})) + \text{var}(E(\varepsilon_t | \mathcal{L}_{t-1})) \\ &= E(h_t) \\ &= E(a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \beta_1 h_{t-1}) \\ &= a_0 + a_1 \sigma_{t-1}^2 + a_2 \sigma_{t-2}^2 + \beta_1 \sigma_{t-1}^2 \\ \Rightarrow \sigma_t^2 &= \text{var}(\varepsilon_t) = \frac{a_0}{1 - a_1 - a_2 - \beta_1} \end{aligned}$$

(c) h -step ahead forecasts of h_{t+h} at forecast origin t , for $h \geq 1$

$$\begin{aligned} h_{t+1} &= a_0 + a_1 \varepsilon_t^2 + a_2 \varepsilon_{t-1}^2 + \beta_1 h_t \\ \Rightarrow \hat{h}_{t+1|t} &= a_0 + a_1 \varepsilon_t^2 + a_2 \varepsilon_{t-1}^2 + \beta_1 h_t \\ h_{t+2} &= a_0 + a_1 \varepsilon_{t+1}^2 + a_2 \varepsilon_t^2 + \beta_1 h_{t+1} \\ \Rightarrow \hat{h}_{t+2|t} &= a_0 + a_1 E(\varepsilon_{t+1}^2 | \mathcal{L}_t) + a_2 \varepsilon_t^2 + \beta_1 E(h_{t+1} | \mathcal{L}_t) \\ &= a_0 + (a_1 + \beta_1) \hat{h}_{t+1|t} + a_2 \varepsilon_t^2 \\ h_{t+3} &= a_0 + a_1 \varepsilon_{t+2}^2 + a_2 \varepsilon_{t+1}^2 + \beta_1 h_{t+2} \\ \Rightarrow \hat{h}_{t+3|t} &= a_0 + (a_1 + \beta_1) \hat{h}_{t+2|t} + a_2 \hat{h}_{t+1|t} \\ \therefore \hat{h}_{t+h|t} &= a_0 + (a_1 + \beta_1) \hat{h}_{t+h-1|t} + a_2 \hat{h}_{t+h-2|t} \end{aligned}$$

$$4. \vec{y}_t = (y_{1t}, y_{2t})^\top \quad y_t = \Phi_0 + \Phi y_{t-1} + \varepsilon_t$$

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} 4 \\ 2 \end{pmatrix} + \begin{pmatrix} 0.2 & 0.3 \\ -0.6 & 1.1 \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})^\top \sim WN(0, \Sigma)$ with

$$\Sigma = \begin{pmatrix} 1.0 & 0.7 \\ 0.7 & 0.5 \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{pmatrix}$$

$$(a) |\Phi - \lambda I_2| = \det \left[\begin{pmatrix} 0.2 & 0.3 \\ -0.6 & 1.1 \end{pmatrix} - \lambda \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right]$$

$$= \det \begin{pmatrix} 0.2 - \lambda & 0.3 \\ -0.6 & 1.1 - \lambda \end{pmatrix}$$

$$= (0.2 - \lambda)(1.1 - \lambda) - (-0.6)(0.3)$$

$$= (0.22 - 1.1\lambda - 0.2\lambda + \lambda^2) + 0.18$$

$$= \lambda^2 - 1.3\lambda + 0.40$$

$$= 0$$

$$\Rightarrow \lambda_{1,2} = \frac{1.3 \pm \sqrt{1.3^2 - 4(0.40)}}{2}$$

$$= \frac{1.3 \pm 0.3}{2}$$

$$\Rightarrow |\lambda_1| = |0.8| < 1, \quad |\lambda_2| = |0.5| < 1$$

\therefore The roots of the equation lie inside the unit circle,
meaning \vec{y}_t is weakly stationary.

(b) The mean vector of \vec{y}_t is

$$\begin{aligned}
 \vec{\mu} &= E(\vec{y}_t) = (I_2 - \Phi)^{-1} \vec{\phi}_0 \\
 &= \left[\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \begin{pmatrix} 0.2 & 0.3 \\ -0.6 & 1.1 \end{pmatrix} \right]^{-1} \begin{pmatrix} 4 \\ 2 \end{pmatrix} \\
 &= \begin{pmatrix} 0.8 & -0.3 \\ 0.6 & -0.1 \end{pmatrix}^{-1} \begin{pmatrix} 4 \\ 2 \end{pmatrix} \\
 &= \frac{1}{-0.08 + 0.18} \begin{pmatrix} -0.1 & 0.3 \\ -0.6 & 0.8 \end{pmatrix} \begin{pmatrix} 4 \\ 2 \end{pmatrix} \\
 &= \frac{1}{0.10} \begin{pmatrix} 0.2 \\ -0.8 \end{pmatrix} \\
 &= \begin{pmatrix} 2 \\ -8 \end{pmatrix}
 \end{aligned}$$

(c) $T = 100$, $y_{1,100} = 1$, $y_{2,100} = 0.5$

The forecasts of $y_{1,101}$ and $y_{2,101}$ are

$$\begin{aligned}
 \hat{y}_{101|100} &= \vec{\phi}_0 + \Phi y_{100} \\
 &= \begin{pmatrix} 4 \\ 2 \end{pmatrix} + \begin{pmatrix} 0.2 & 0.3 \\ -0.6 & 1.1 \end{pmatrix} \begin{pmatrix} 1 \\ 0.5 \end{pmatrix} \\
 &= \begin{pmatrix} 4 \\ 2 \end{pmatrix} + \begin{pmatrix} 0.35 \\ -0.05 \end{pmatrix} \\
 &= \begin{pmatrix} 4.35 \\ 1.95 \end{pmatrix} = \begin{pmatrix} y_{1,101} \\ y_{2,101} \end{pmatrix}
 \end{aligned}$$

and the associated standard errors are given by the matrix Σ , where

$$\sigma_1 = \sqrt{\sigma_1^2} = \sqrt{1.0} = 1.0$$

$$\sigma_2 = \sqrt{\sigma_2^2} = \sqrt{0.5} \approx 0.71$$

(d) coefficient matrices on...

$$\varepsilon_t \rightarrow \Phi^0 \equiv I_2$$

$$\varepsilon_{t-1} \rightarrow \Phi^1 = \begin{pmatrix} 0.2 & 0.3 \\ -0.6 & 1.1 \end{pmatrix}$$

$$\varepsilon_{t-2} \rightarrow \Phi^2 = \begin{pmatrix} 0.2 & 0.3 \\ -0.6 & 1.1 \end{pmatrix} \begin{pmatrix} 0.2 & 0.3 \\ -0.6 & 1.1 \end{pmatrix} = \begin{pmatrix} -0.14 & 0.39 \\ -0.58 & 1.03 \end{pmatrix}$$