

3.

Consider the $AR(1)$ model with a linear drift and let

$$\hat{\epsilon}_t = X_t - \beta X_{t-1} - \alpha - \delta t$$

for $t = 1, 2, \dots, T$ be the disturbances implied from the data. According to the model specification, each $\hat{\epsilon}_t$ is independently drawn from $N(0, \sigma^2)$, and thus

$$p(x_1, \dots, x_T | x_0, \theta) = \frac{1}{(2\pi\sigma^2)^{T/2}} \exp\left(-\frac{1}{2\sigma^2} \sum_{t=1}^T \epsilon_t^2\right)$$

$$\mathcal{L}(\theta | x_0, x_1, \dots, x_T) = \frac{1}{(2\pi\sigma^2)^{T/2}} \exp\left(-\frac{1}{2\sigma^2} \sum_{t=0}^{T-1} (X_{t+1} - \beta X_t - \alpha - \delta t)^2\right)$$

The log-likelihood function is given as

$$-\log \mathcal{L}(\theta | x_0, x_1, \dots, x_T) = \frac{T}{2} \log \sigma^2 + \frac{1}{2\sigma^2} \sum_{t=0}^{T-1} (X_{t+1} - \beta X_t - \alpha - \delta t)^2 + \text{const.}$$

Taking derivative of σ and set it to 0

$$\hat{\sigma}^2 = \frac{1}{T} \sum_{t=0}^{T-1} \left(X_{t+1} - \hat{\beta} X_t - \hat{\alpha} - \hat{\delta} t\right)^2$$

To figure out $\hat{\alpha}, \hat{\beta}, \hat{\delta}$, we need minimize $-\log \mathcal{L}(\theta | x_0, x_1, \dots, x_T)$. It could be written as

$$-\log \mathcal{L}(\theta | x_0, x_1, \dots, x_T) = \frac{T}{2} \log \sigma^2 + \frac{1}{2\sigma^2} \sum_{t=0}^{T-1} (X_{t+1} - \beta X_t - \alpha - \delta t)^2 + \text{const}$$

$$= \frac{T}{2} \log \sigma^2 + \frac{1}{2\sigma^2} (X - Yv)^T (X - Yv) + \text{const}$$

where $X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_T \end{bmatrix}$, $v = \begin{bmatrix} \alpha \\ \beta \\ \delta \end{bmatrix}$, $Y = \begin{bmatrix} 1 & X_0 & 0 \\ 1 & X_1 & 1 \\ \vdots & \vdots & \vdots \\ 1 & X_{T-1} & T-1 \end{bmatrix}$.

Take derivatives of v ,

$$f'(v) = CY^T(X - Yv) = 0 \quad \text{C is a constant}$$

$$v = (Y^T Y)^{-1} Y^T X$$

$$\begin{pmatrix} \hat{\alpha} \\ \hat{\beta} \\ \hat{\delta} \end{pmatrix} = \begin{pmatrix} T & \sum_{t=0}^{T-1} X_t & \frac{T(T-1)}{2} \\ \sum_{t=0}^{T-1} X_t & \sum_{t=0}^{T-1} X_t^2 & \sum_{t=0}^{T-1} t X_t \\ \frac{T(T-1)}{2} & \sum_{t=0}^{T-1} t X_t & \frac{T(T-1)(2T-1)}{6} \end{pmatrix}^{-1} \begin{pmatrix} \sum_{t=0}^{T-1} X_{t+1} \\ \sum_{t=0}^{T-1} X_t X_{t+1} \\ \sum_{t=0}^{T-1} t X_{t+1} \end{pmatrix}$$

and

$$\hat{\sigma}^2 = \frac{1}{T} \sum_{t=0}^{T-1} \left(X_{t+1} - \hat{\beta} X_t - \hat{\alpha} - \hat{\delta} t\right)^2$$

4.

$E(\epsilon_t^4) = E(\sigma_t^4) E(z_t^4) = 3E(\sigma_t^4)$, since we know $E(z_t^4) = 3$.

Then,

$$\begin{aligned}
E(\sigma_t^4) &= \kappa^2 + \eta^2 E(\sigma_{t-1}^4) + \zeta^2 E(\epsilon_{t-1}^4) + 2\kappa\eta E(\sigma_{t-1}^2) + 2\kappa\zeta E(\epsilon_{t-1}^2) + 2\eta\zeta E(\sigma_{t-1}^2 \epsilon_{t-1}^2) \\
&= \kappa^2 + \eta^2 E(\sigma_t^4) + 3\zeta^2 E(\sigma_{t-1}^4) + 2\kappa\eta\sigma^2 + 2\kappa\zeta E(\sigma_{t-1}^2) + 2\eta\zeta E(z_{t-1}^2) E(\sigma_{t-1}^4) \\
&= \kappa^2 + \eta^2 E(\sigma_t^4) + 3\zeta^2 E(\sigma_t^4) + 2\kappa\eta\sigma^2 + 2\kappa\zeta\sigma^2 + 2\eta\zeta E(\sigma_t^4) \\
E(\sigma_t^4) &= \frac{\kappa^2 + 2\kappa(\eta + \zeta) \frac{\kappa}{1-\eta-\zeta}}{1 - \eta^2 - 3\zeta^2 - 2\eta\zeta}
\end{aligned}$$

Also

$$\begin{aligned}
E(\epsilon_t^2)^2 &= (E(\sigma_t^2) E(z_t^2))^2 \\
&= (\sigma^2)^2 \\
&= \frac{\kappa^2}{(1 - \eta - \zeta)^2}
\end{aligned}$$

The kurtosis in the GARCH(1,1) model is

$$\begin{aligned}
\frac{E(\epsilon_t^4)}{E(\epsilon_t^2)^2} &= \frac{3 \frac{\kappa^2 + 2\kappa(\eta + \zeta) \frac{\kappa}{1-\eta-\zeta}}{1 - \eta^2 - 3\zeta^2 - 2\eta\zeta}}{\frac{\kappa^2}{(1-\eta-\zeta)^2}} \\
&= 3 \frac{(1 - \eta - \zeta)^2 + 2(1 - \eta - \zeta)(\eta + \zeta)}{1 - \eta^2 - 3\zeta^2 - 2\eta\zeta} \\
&= 3 \frac{(1 - \eta - \zeta)(1 - \eta - \zeta + 2(\eta + \zeta))}{1 - (\zeta + \eta)^2 - 2\zeta^2} \\
&= 3 \frac{(1 - \eta - \zeta)(1 + \eta + \zeta)}{1 - (\zeta + \eta)^2 - 2\zeta^2} \\
&= 3 \frac{1 - (\eta + \zeta)^2}{1 - (\zeta + \eta)^2 - 2\zeta^2}
\end{aligned}$$