

* Lecture 8: pp. 18-21

$$\left. \begin{array}{l} Y_{10} = Y_9 + \varepsilon_{10} \\ Y_9 = Y_8 + \varepsilon_9 \\ \vdots \\ Y_3 = Y_2 + \varepsilon_3 \\ Y_2 = \underbrace{Y_1}_{=0} + \varepsilon_2 \end{array} \right\}$$

$$\overset{\text{iid}}{\varepsilon_t} \sim N(0, \sigma^2)$$

$$\text{Thus } Y_{10} = \sum_{t=2}^{10} \varepsilon_t$$

$$\begin{aligned} 1. \text{Var}(Y_{10}) &= \text{Var}\left(\sum_{t=2}^{10} \varepsilon_t\right) \\ &= \sum_{t=2}^{10} \text{var}(\varepsilon_t) \\ &= \sum_{t=2}^{10} \sigma^2 = \underbrace{\sigma^2 + \dots + \sigma^2}_{9 \text{ times}} \\ &= 9\sigma^2 \end{aligned}$$

$$2. \mathbb{E}\{Y_{10}\} = \mathbb{E}\left\{\sum_{t=2}^{10} \varepsilon_t\right\} = \sum_{t=2}^{10} \mathbb{E}\{\varepsilon_t\} = 0 + \dots + 0 = 0$$

$$Y_{10} \sim N(0, 9\sigma^2)$$

Conditional distribution

$$\begin{aligned} 1. \mathbb{E}\{Y_{10} | Y_1, \dots, Y_g\} &= \mathbb{E}\{Y_g | Y_1, \dots, Y_g\} + \mathbb{E}\{\varepsilon_{10} | Y_1, \dots, Y_g\} \\ &= Y_g + \mathbb{E}\{\varepsilon_{10}\} \quad \swarrow \text{by independence of } \varepsilon_{10} \text{ and } Y_1, \dots, Y_g \\ &= Y_g + 0 \\ &= Y_g \end{aligned}$$

$$\begin{aligned} 2. \text{Var}(Y_{10} | Y_1, \dots, Y_g) &= \text{Var}(Y_g | Y_1, \dots, Y_g) + \text{Var}(\varepsilon_{10} | Y_1, \dots, Y_g) \\ &= 0 + \text{Var}(\varepsilon_{10}) \quad \updownarrow \text{by independence} \\ &= \sigma^2 \end{aligned}$$

Thus $Y_{10} | Y_1, \dots, Y_g \sim N(Y_g, \sigma^2)$

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To understand how the model works, a definition of the conditional variance of a r.v. u_t is required.

$$\begin{aligned}\sigma_t^2 &= \text{Var}(u_t | u_{t-1}, u_{t-2}, \dots) \\ &= \mathbb{E}\{(u_t - \mathbb{E}(u_t))^2 | u_{t-1}, u_{t-2}, \dots\} \\ &= \mathbb{E}\{u_t^2 | u_{t-1}, u_{t-2}, \dots\} \\ &= \omega + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_p u_{t-p}^2\end{aligned}$$

* GARCH(1,1) as an ARMA(1,1)

Note that u_t^2 and σ_t^2 at time t are not the same:

$$\begin{aligned}u_t^2 - \sigma_t^2 &= v_t \\ \text{or} \\ \sigma_t^2 &= u_t^2 - v_t\end{aligned}$$

substitute in $\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

$$u_t^2 - v_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 (u_{t-1}^2 - v_{t-1})$$

$$u_t^2 = \omega + (\alpha_1 + \beta_1) u_{t-1}^2 + v_t - \beta_1 v_{t-1}$$

* GARCH(1,1) as ARCH(∞) p. 47

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$\sigma_{t-1}^2 = \omega + \alpha_1 u_{t-2}^2 + \beta_1 \sigma_{t-2}^2$$

$$\sigma_{t-2}^2 = \omega + \alpha_1 u_{t-3}^2 + \beta_1 \sigma_{t-3}^2$$

Substituting

$$\begin{aligned}\sigma_t^2 &= \omega + \alpha_1 u_{t-1}^2 + \beta_1 (\omega + \alpha_1 u_{t-2}^2 + \beta_1 (\omega + \alpha_1 u_{t-3}^2 + \beta_1 \sigma_{t-3}^2)) \\ &= \omega + \alpha_1 u_{t-1}^2 + \beta_1 \omega + \beta_1 \alpha_1 u_{t-2}^2 + \beta_1^2 \omega + \beta_1^2 \alpha_1 u_{t-3}^2 + \beta_1^3 \sigma_{t-3}^2\end{aligned}$$

After an infinite amount of successive substitutions

$$\sigma_t^2 = \underbrace{\omega(1 + \beta_1 + \beta_1^2 + \dots)}_{\text{let } \gamma = \frac{\omega}{1-\beta_1}} + \alpha_1 u_{t-1}^2 (1 + \beta_1 + \beta_1^2 + \dots) + \underbrace{\beta_1^\infty \sigma_0^2}_{\beta_1^\infty \rightarrow 0}$$

Hence

$$\begin{aligned}\sigma_t^2 &= \gamma + \underbrace{\alpha_1}_{\text{let } \alpha = \gamma_1} u_{t-1}^2 (1 + \beta_1 + \beta_1^2 + \dots) \\ &= \gamma + \gamma_1 u_{t-1}^2 + \underbrace{\gamma_2}_{=\alpha_1 \beta_1} u_{t-2}^2 + \gamma_3 u_{t-3}^2 + \dots\end{aligned}$$

Thus, GARCH(1,1) containing only 3 parameters in the conditional variance equation is a very parsimonious model that allows ARCH(∞)