

$$Q5 a) y_t = \mu + \phi(y_{t-1} - \mu) + \epsilon_t$$

$$y_{t+1} = \mu + \phi(y_t - \mu) + \epsilon_{t+1}$$

$$y_{t+2} = \mu + \phi(y_{t+1} - \mu) + \epsilon_{t+2}$$

$$y_{t+2} = \mu + \phi(\mu + \phi(y_t - \mu) + \epsilon_{t+1} - \mu) + \epsilon_{t+2}$$

$$y_{t+2} = \mu + \phi(\mu + \phi y_t - \phi \mu + \epsilon_{t+1} - \mu) + \epsilon_{t+2}$$

$$y_{t+2} = \mu + \phi^2 y_t - \phi^2 \mu + \phi \epsilon_{t+1} + \epsilon_{t+2}$$

$$\begin{matrix} \downarrow & \downarrow \\ E(\epsilon_t) = 0 & E(\epsilon_t) = 0 \end{matrix}$$

$$E(y_{t+2} | I_{t-1}) = \mu + \phi^2 E(y_t) - \phi^2 \mu$$

$$= \mu + \phi^2 \mu - \phi^2 \mu$$

$$E(y_{t+2} | I_{t-1}) = \mu$$

The $E(y_{t+2} | I_{t-1})$ is equal to the mean of the series.

This makes sense as it is a mean reverting process.

$$b) L(y_{t+2} - \hat{y}_{t+2}) = (y_{t+2} - \hat{y}_{t+2})^2$$

$$E(y_{t+2} - \hat{y}_{t+2})^2 = E(y_{t+2}^2) + \hat{y}_{t+2}^2 - 2\hat{y}_{t+2} E(y_{t+2})$$

$$\text{Taking the FOC w.r.t } \hat{y}_{t+2} \Rightarrow 2\hat{y}_{t+2} - 2E(y_{t+2}) = 0$$

$$\hat{y}_{t+2} = E(y_{t+2})$$

$\therefore \hat{y}_{t+2}$ minimizes the ~~exp~~ ^{expected} loss function.

$$c) f(y_{t+2} | I_{t-1}, \theta)$$

$$\cancel{E(y_{t+2}) = \mu}, \quad \epsilon_t \sim N(0, \sigma^2) \quad y_{t+2} = \mu + \phi^2 y_t - \phi^2 \mu + \phi \epsilon_{t+1} + \epsilon_{t+2}$$

$$\cancel{y_{t+2} \sim N(\mu, \sigma^2)}$$

$$\text{var}(y_{t+2}) = \phi^2 \sigma^2 + \sigma^2 = \sigma^2(\phi^2 + 1)$$

$$\cancel{y_{t+2} \sim N(\mu, \sigma^2)}$$

$$f(y_{t+2} | I_{t-1}, \theta) \sim \cancel{N} N(\mu, \sigma^2(\phi^2 + 1))$$

d) As θ is unknown, ϕ and μ are unknown. A way to still estimate this equation is to provide sample estimates for ϕ and μ with the current samples.

$$\text{As } E(\hat{\phi}) = \phi \text{ and } E(\hat{\mu}) = \mu$$