

$$1 (a) E(r_t) = E(\varepsilon_t + a\varepsilon_{t-1} + b) = b + E(\varepsilon_t) + aE(\varepsilon_{t-1}) = b$$

$$(b) \text{var}(r_t) = E[(r_t - b)^2] = E[(\varepsilon_t + a\varepsilon_{t-1})^2]$$

$$= E[\varepsilon_t^2] + a^2 E[\varepsilon_{t-1}^2] = (a^2 + 1)\sigma^2$$

$$\sigma_{r_t} = \sigma \sqrt{a^2 + 1}$$

$$(c) V_0 = \text{cov}(r_t, r_t) = \text{var}(r_t) = (a^2 + 1)\sigma^2$$

$$V_1 = \text{cov}(r_{t+1}, r_t) = E[(r_{t+1} - b)(r_t - b)]$$

$$= E[(\varepsilon_{t+1} + a\varepsilon_t)(\varepsilon_t + a\varepsilon_{t-1})]$$

$$= E(\varepsilon_{t+1}\varepsilon_t) + aE(\varepsilon_t^2) + a^2E(\varepsilon_t\varepsilon_{t-1}) + aE(\varepsilon_{t+1}\varepsilon_{t-1})$$

$$= a\sigma^2$$

$$\text{for } k > 1, V_k = \text{cov}(r_{t+k}, r_t) = E[(r_{t+k} - b)(r_t - b)]$$

$$= E[(\varepsilon_{t+k} + a\varepsilon_{t+k-1})(\varepsilon_t + a\varepsilon_{t-1})]$$

$$= E(\varepsilon_{t+k}\varepsilon_t) + aE(\varepsilon_{t+k}\varepsilon_{t-1}) + aE(\varepsilon_{t+k-1}\varepsilon_t)$$

$$+ a^2E[\varepsilon_{t+k-1}\varepsilon_{t-1}] = 0$$

(d) $b > 0$ since on average (in expectation) stock price is going up overtime (risk-free rate, inflation...)

$a = 0$: random walk model with drift b

$a \neq 0$: MAC(1) model

$$2. (a) \quad X_t = \lambda Y_{t-1} + \epsilon Z_{t-1} = \lambda (\lambda X_{t-2} + \epsilon W_{t-2}) + \epsilon Z_{t-1} \\ = \lambda^2 X_{t-2} + \lambda \epsilon W_{t-2} + \epsilon Z_{t-1}$$

$$E(X_t) = E(\lambda^2 X_{t-2} + \lambda \epsilon W_{t-2} + \epsilon Z_{t-1}) = \lambda^2 E(X_{t-2})$$

$$\text{given } E(X_t) = E(X_{t-2}) = \mu_X \quad (\text{stationary}) \Rightarrow$$

$$E \mu_X = 0 \quad \text{similarly, } \mu_Y = 0$$

$$\sigma_X^2 = E[X_t^2] = E[(\lambda X_{t-2} + \lambda \epsilon W_{t-2} + \epsilon Z_{t-1})^2] = \lambda^4 E[X_{t-2}^2] + \lambda^2 \epsilon^2 + \epsilon^2$$

$$= \lambda^4 \sigma_X^2 + (\lambda^2 + 1) \epsilon^2 \Rightarrow \sigma_X^2 = \frac{\epsilon^2}{1 - \lambda^2}$$

$$\text{similarly, } \sigma_Y^2 = \frac{\epsilon^2}{1 - \lambda^2}$$

$$(b) \quad \text{cov}(X_t, X_{t+1}) = E[X_t X_{t+1}] = E[X_t (\lambda Y_t + \epsilon Z_t)] = \lambda E[X_t Y_t]$$

$$E(X_0 Y_0) = E(\epsilon Z_0 \epsilon W_0) = 0; \quad E(X_1 Y_1) = E[(\lambda X_0 + \epsilon Z_1)(\lambda Y_0 + \epsilon W_1)] \\ = \lambda^2 E(X_0 Y_0) = 0 \dots$$

$$\Rightarrow E(X_t Y_t) = 0 \Rightarrow \text{cov}(X_t, X_{t+1}) = 0 \quad \text{similarly, } \text{cov}(Y_t, Y_{t+1}) = 0$$

$$\text{cov}(X_t, X_{t+2}) = E[X_t (\lambda^2 X_{t-2} + \lambda \epsilon W_{t-2} + \epsilon Z_{t-1})] = \lambda^2 E[X_t^2] = \frac{\lambda^2 \epsilon^2}{1 - \lambda^2}$$

$$\text{similarly, } \text{cov}(Y_t, Y_{t+2}) = \frac{\lambda^2 \epsilon^2}{1 - \lambda^2}$$

$$\text{if } l \geq 3, \quad \text{cov}(X_t, X_{t+l}) = E[X_t (\lambda^2 X_{t+l-2} + \lambda \epsilon W_{t+l-2} + \epsilon Z_{t-1})]$$

$$= \lambda^2 E(X_t + X_{t+l-2})$$

$$\text{if } l = 2k, k \in \mathbb{N}, \quad \text{cov}(X_t, X_{t+l}) = \lambda^k \frac{\epsilon^2}{1 - \lambda^2}$$

$$\text{if } l = 2k+1, k \in \mathbb{N}, \quad \text{cov}(X_t, X_{t+l}) = \lambda^{2k+1} E(X_t X_{t+1}) = 0$$

$$\text{similarly, if } l = 2k, k \in \mathbb{N}, \quad \text{cov}(Y_t, Y_{t+l}) = \lambda^k \frac{\epsilon^2}{1 - \lambda^2}$$

$$l = 2k+1, k \in \mathbb{N}, \quad \text{cov}(Y_t, Y_{t+l}) = 0$$

$$2(c) \text{cov}(x_t, y_{t-1}) = E[x_t y_{t-1}] = E[(\lambda y_{t-1} + \epsilon_t) y_{t-1}]$$

$$= \lambda E[y_{t-1}^2]$$

$$\text{if } t=2k, k \in \mathbb{N}, \text{cov}(x_t, y_{t-1}) = \lambda \text{cov}(y_{t-1}, y_{t-1}) = 0$$

$$\text{if } t=2k+1, k \in \mathbb{N}, \text{cov}(x_t, y_{t-1}) = \lambda \cdot \lambda^{t-1} \frac{\sigma^2}{1-\lambda^2} = \frac{\lambda^t \sigma^2}{1-\lambda^2}$$

$$3(a) R_t = \mu - \lambda(R_{t-1} - \mu) + \epsilon_t$$

$$E[R_t] = \mu - \lambda E[R_{t-1}] + \lambda \mu \Rightarrow (\lambda+1) E[R_t] = (\lambda+1) \mu$$

$$\text{since } \lambda+1 \neq 0, E[R_t] = \mu$$

$$E[(R_t - \mu)^2] = \lambda^2 E[(R_{t-1} - \mu)^2] + \sigma^2 \Rightarrow \text{var}(R_t) = \frac{\sigma^2}{1-\lambda^2}, 0 < \lambda < 1$$

$$E[\lambda_t] = E[-c R_{t-1} R_t] = -c E[R_{t-1} R_t]$$

$$= -c E[(1 - \lambda(R_{t-1} - \mu) + \epsilon_t + \mu) R_{t-1}]$$

$$= c \lambda E[R_{t-1}^2] - c \lambda \mu E[R_{t-1}] - c E[\epsilon_t R_{t-1}] - c \mu E[R_{t-1}]$$

$$= c \left(\frac{\lambda \sigma^2}{1-\lambda^2} - \mu^2 \right) > 0 \text{ to be positive}$$

$$(b) E[\lambda_t] = E[-c R_{t-1} R_t] = -c E[R_{t-1} R_t]$$

$$= -c E[(\mu + \epsilon_{t-1} + \phi \epsilon_{t-2})(\mu + \epsilon_{t-1} + \phi \epsilon_{t-2})]$$

$$= -c [\mu^2 + \phi^2 E[\epsilon_{t-2}^2]] = -c (\mu^2 + \phi^2)$$

so if $\phi, \sigma > 0$, if we set $c < 0$ we can generate positive expected return without further requirement, which is more attractive

A better way could be: since $R_t = \mu + \epsilon_t + \phi \epsilon_{t-1}$,

$$E_{t-1}(R_t) = E(\mu + \epsilon_t + \phi \epsilon_{t-1} | \mathcal{F}_{t-1})$$

$$= \mu + \phi \epsilon_{t-1} + \phi E_{t-1}(\epsilon_t) = \mu + \phi \epsilon_{t-1}$$

so essentially we can set $I_t = c(\mu + \phi \epsilon_t)$ after

observing ϵ_t , $E[\lambda_t] = E(I_t | R_t) = E[c(\mu + \phi \epsilon_t) | \mu + \epsilon_t + \phi \epsilon_{t-1}] = c(\mu + \phi^2)$

we can loose the requirement that $\mu > 0$