

**Q1**

2 Points

Let  $Z_0, Z_1, \dots$ , be independent standard normal random variables, and  $X_t = Z_0 + Z_t, t \geq 1$ .

**Q1.1**

1 Point

Compute the mean and autocovariances of the series  $X = \{X_1, X_2, \dots, X_t, \dots\}$  for all possible lags.

$$\gamma(0) = 2, \gamma(h) = 1 \text{ for } h >= 1.$$

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**Q1**

2 Points

Let  $Z_0, Z_1, \dots$ , be independent standard normal random variables, and  $X_t = Z_0 + Z_t, t \geq 1$ .

**Q1.1**

1 Point

Compute the mean and autocovariances of the series  $X = \{X_1, X_2, \dots, X_t, \dots\}$  for all possible lags.

$$Z_0, Z_1, \dots \sim N(0, 1)$$

$$X_1 = Z_0 + Z_1$$

$$X_2 = Z_0 + Z_2$$

⋮

$$\underline{X_t = Z_0 + Z_t}$$

$$\mathbb{E}(X_t) = \mathbb{E}(Z_0) + \mathbb{E}(Z_t) = 0$$

$$\gamma(0) = \text{Var}(X_1) = \text{Var}(Z_0 + Z_1), \text{ since } Z_0, Z_1 \text{ is iid.}$$

$$\begin{aligned} &\Rightarrow \text{Var}(Z_0) + \text{Var}(Z_1) + \text{Cov}(Z_0, Z_1) \xrightarrow{\text{IID}} \\ &= | + | = \sigma^2 \end{aligned}$$

$$\begin{aligned} \gamma(1) &= \text{Cov}(X_1, X_2) = \mathbb{E}[(X_1 - \mathbb{E}(X))(X_2 - \mathbb{E}(X))] \\ &= \mathbb{E}(X_1 X_2) = \mathbb{E}[(Z_0 + Z_1)(Z_0 + Z_2)] \\ &= \mathbb{E}[Z_0^2 + Z_0 Z_2 + Z_0 Z_1 + Z_1 Z_2] \end{aligned}$$

$$\begin{aligned} &= E(\hat{z}_0) = 1 \\ \text{or } \text{Var}(\hat{z}_0) &= 1 = E(\hat{z}_0^2) - E(\hat{z}_0)^2 \Rightarrow E(\hat{z}_0^2) \end{aligned}$$

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$$\begin{aligned}
 \gamma(r) &= \text{Cov}(X_1, X_3) = E[(X_1 X_3)] \\
 &= E[(z_0 + z_1)(z_0 + z_3)] \\
 &= E[z_0^2] = 1
 \end{aligned}$$

$$\Rightarrow \gamma(0) = 2, \quad \gamma(h) = 1, \quad h \neq 0$$

$A = \text{mean} = 0, \quad \text{Autocov} \left\{ \begin{array}{l} \gamma(0) = 2 \\ \gamma(h) = 1, \quad h \neq 0 \end{array} \right.$

## **Q1.2**

1 Point

Is  $X$  weakly stationary? Why? Is  $X$  a white noise? Why?

Yes. It is weakly stationary process. As I have shown below:

- (1)  $E(X_t)$  regardless of time  $t$ , always is 0.
- (2) Covariance depends on  $lag - h$  only.

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No. It is not white noise. Since  $cov(X_s, X_t) = 1$ , not 0.

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**Q1.2**

1 Point

Is  $X$  weakly stationary? Why? Is  $X$  a white noise? Why?

$$\textcircled{1} \quad \mathbb{E}(X_t) = \mathbb{E}(z_0 + z_t) = \underbrace{\mathbb{E}(z_0)}_{z_i's \text{ iid}} + \mathbb{E}(z_t) = 0$$

$$\begin{aligned}\textcircled{2} \quad \gamma(0) &= \text{Var}(X_t) = \text{Var}(z_0 + z_t) \\ &= \text{Var}(z_0) + \text{Var}(z_t) + 2\text{Cov}(z_0, z_t) \quad \text{z's iid} \\ &= \text{Var}(z_0) + \text{Var}(z_t) \\ &= [\mathbb{E}(z_0^2) - \mathbb{E}(z_0)^2] + [\mathbb{E}(z_t^2) - \mathbb{E}(z_t)^2] \\ &= \gamma\end{aligned}$$

$$\begin{aligned}\gamma(h) &= \text{Cov}(X_t, X_{t+h}) \\ &= \mathbb{E}[(X_t - \mathbb{E}(X_t))(X_{t+h} - \mathbb{E}(X_{t+h}))] \\ &= \mathbb{E}[X_t \cdot X_{t+h}] \\ &= \mathbb{E}[(z_0 + z_t)(z_0 + z_{t+h})] \\ &= \mathbb{E}[z_0^2 + z_0 z_{t+h} + z_0 z_t + z_t z_{t+h}] \\ &= \mathbb{E}[z_0^2] = 1\end{aligned}$$

## **Q2**

4 Points

In the following,  $\{\epsilon_t\}$  is a white noise with variance  $\sigma_\epsilon^2 = 1$ . Consider a MA(3) process  $Y_t = \mu + \epsilon_t + 2\epsilon_{t-1} + 3\epsilon_{t-2} + 4\epsilon_{t-3}$ .

### **Q2.1**

1 Point

Is  $Y_t$  stationary (here stationarity refers to weak stationarity)?

Yes, as I shown below,

- (1) the mean of  $Y_t$  is  $\mu$ , which is indepent with  $t$ ,
- (2) and the  $\gamma$  (covariance) will die out when  $h >= 4$ .

Thus,  $Y_t$  process is stationary. (The description itself confirms that  $Y_t$  process is *MA3* model, which already confirms that it is stationary by itself. )

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$$\frac{Y_t = M + \varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3}}{\Rightarrow E(Y_t) = E(M) + E(\varepsilon_t) + 2E(\varepsilon_{t-1}) + 3E(\varepsilon_{t-2}) + 4E(\varepsilon_{t-3}) \\ = M}$$

$$\begin{aligned} \text{Cov}(Y_t, Y_{t+4}) &= \gamma(4) \\ &= E[(\varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3}) \times \\ &\quad (\varepsilon_{t+4} + 2\varepsilon_{t+3} + 3\varepsilon_{t+2} + 4\varepsilon_{t+1})] \\ &= 0 \end{aligned}$$

2. If  $X$  and  $Y$  are independent, then  $E(XY) = E(X)E(Y)$ .

$$\begin{aligned} \text{Cov}(Y_t, Y_{t+3}) &= \gamma(3) \\ &= E[(\varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3}) \\ &\quad (\varepsilon_{t+3} + 2\varepsilon_{t+2} + 3\varepsilon_{t+1} + 4\varepsilon_t)] = 4E(\varepsilon_t^2) \\ &\stackrel{?}{=} 4 \\ \text{Var}(\varepsilon_t) &= 1 = E(\varepsilon_t^2) - E(\varepsilon_t)^2 = E(\varepsilon_t^2) \end{aligned}$$

$$\begin{aligned} \gamma(2) &= \text{Cov}(Y_t, Y_{t+2}) \\ &= E[(\varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3}) \\ &\quad (\varepsilon_{t+2} + 2\varepsilon_{t+1} + 3\varepsilon_t + 4\varepsilon_{t-1})] \\ &= 3E(\varepsilon_t^2) + 8E(\varepsilon_t^2) = 11 \end{aligned}$$

$$\begin{aligned} \gamma(1) &= \text{Cov}(Y_t, Y_{t+1}) \\ &= E[(\varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3}) \end{aligned}$$

$$\begin{aligned} & (\varepsilon_{t+1} + 2\varepsilon_t + 3\varepsilon_{t-1} + 4\varepsilon_{t-2}) \\ & = 2\varepsilon_t(\varepsilon_t^2) + 6\varepsilon_t(\varepsilon_{t-1}^2) + 12\varepsilon_t(\varepsilon_{t-2}^2) = 20 \end{aligned}$$

## Q2.2

1 Point

What's the variance of  $Y_t$ ?

30

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$$\begin{aligned}
\text{Var}(Y_t) &= \text{Cov}(Y_t, Y_t) = E((Y_t - M_Y)^2) \\
&= E[(\varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3})^2] \\
&= E[\varepsilon_t^2 + 2\varepsilon_{t-1}\varepsilon_t + 3\varepsilon_t\varepsilon_{t-2} + 4\varepsilon_t\varepsilon_{t-3} \\
&\quad + 2\varepsilon_t\varepsilon_{t-1} + 4\varepsilon_{t-1}^2 + 6\varepsilon_{t-1}\varepsilon_{t-2} + 8\varepsilon_{t-1}\varepsilon_{t-3} \\
&\quad + 3\varepsilon_t\varepsilon_{t-2} + 6\varepsilon_{t-1}\varepsilon_{t-2} + 9\varepsilon_{t-2}^2 + 12\varepsilon_{t-2}\varepsilon_{t-3} \\
&\quad + 4\varepsilon_t\varepsilon_{t-3} + 8\varepsilon_{t-1}\varepsilon_{t-3} + 12\varepsilon_{t-2}\varepsilon_{t-3} + 16\varepsilon_{t-3}^2] \\
&= E(\varepsilon_t^2) + 4E[\varepsilon_t\varepsilon_{t-1}] + 6E[\varepsilon_t\varepsilon_{t-2}] + 8E[\varepsilon_t\varepsilon_{t-3}] \\
&\quad + 4(E_{t-1}^2) + 12E[\varepsilon_{t-1}\varepsilon_{t-2}] + 16E[\varepsilon_{t-1}\varepsilon_{t-3}] \\
&\quad + 9(E_{t-2}^2) + 24E[\varepsilon_{t-2}\varepsilon_{t-3}] + 16E(\varepsilon_{t-3}^2) \\
&= E(\varepsilon_t^2) + 4(E_{t-1}^2) + 9(E_{t-2}^2) + 16E(\varepsilon_{t-3}^2) \\
&= 1 + 4 + 9 + 16 = 30
\end{aligned}$$

↑

$$\Rightarrow \text{Var}(\varepsilon_t) = 1 = E(\varepsilon_t^2) - E(\varepsilon_t)^2 = E(\varepsilon_t^2)$$

**Q2.3**

1 Point

What's the lag-1 autocorrelation?

2/3

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$$\begin{aligned}
r(1) &= \text{Cov}(Y_t, Y_{t+1}) \\
&= E[(\underbrace{\varepsilon_t}_{\varepsilon_{t+1}} + \underbrace{2\varepsilon_{t-1}}_{\varepsilon_t} + \underbrace{3\varepsilon_{t-2}}_{\varepsilon_{t-1}} + \underbrace{4\varepsilon_{t-3}}_{\varepsilon_{t-2}}) \\
&\quad (\underbrace{\varepsilon_{t+1}}_{\varepsilon_t} + \underbrace{2\varepsilon_t}_{\varepsilon_{t+1}} + \underbrace{3\varepsilon_{t-1}}_{\varepsilon_t} + \underbrace{4\varepsilon_{t-2}}_{\varepsilon_{t-1}})] \\
&= \underbrace{2\varepsilon_t(\varepsilon_t^2)}_{-} + 6E(\varepsilon_{t-1}\varepsilon_t) + 12E(\varepsilon_{t-2}\varepsilon_t) \\
&= 20
\end{aligned}$$

$$\begin{aligned}
\text{Var}(Y_t) &= \text{Cov}(Y_t, Y_t) = E((Y_t - M_0)^2) \\
&= E[(\varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3})^2] \\
&= E[\varepsilon_t^2 + 2\varepsilon_{t-1}\varepsilon_t + 3\varepsilon_t\varepsilon_{t-2} + 4\varepsilon_t\varepsilon_{t-3} \\
&\quad + 2\varepsilon_t\varepsilon_{t-1} + 4\varepsilon_{t-1}^2 + 6\varepsilon_{t-1}\varepsilon_{t-2} + 8\varepsilon_{t-1}\varepsilon_{t-3} \\
&\quad + 3\varepsilon_t\varepsilon_{t-2} + 6\varepsilon_{t-1}\varepsilon_{t-2} + 9\varepsilon_{t-2}^2 + 12\varepsilon_{t-2}\varepsilon_{t-3} \\
&\quad + 4\varepsilon_t\varepsilon_{t-3} + 8\varepsilon_{t-1}\varepsilon_{t-3} + 12\varepsilon_{t-2}\varepsilon_{t-3} + 16\varepsilon_{t-3}^2] \\
&= E(\varepsilon_t^2) + 4E[\varepsilon_t\varepsilon_{t-1}] + 6E[\varepsilon_t\varepsilon_{t-2}] + 8E[\varepsilon_t\varepsilon_{t-3}] \\
&\quad + 4(\varepsilon_{t-1}^2) + 12E[\varepsilon_{t-1}\varepsilon_{t-2}] + 16E[\varepsilon_{t-1}\varepsilon_{t-3}] \\
&\quad + 9(\varepsilon_{t-2}^2) + 24E[\varepsilon_{t-2}\varepsilon_{t-3}] + 16E(\varepsilon_{t-3}^2) \\
&= E(\varepsilon_t^2) + 4(E\varepsilon_{t-1}^2) + 9(E\varepsilon_{t-2}^2) + 16E(\varepsilon_{t-3}^2) \\
&= 1 + 4 + 9 + 16 = 30 = V(0)
\end{aligned}$$

$$\Rightarrow r(0) = 30, r(1) = 20, \rho(1) = \frac{r(1)}{r(0)} = \frac{2}{3}.$$

**Q2.4**

1 Point

What are lag- $h$  autocorrelations for  $h \geq 4$ ?

0

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$$\begin{aligned}
\text{Var}(Y_t) &= \text{Cov}(Y_t, Y_t) = E((Y_t - M_Y)^2) \\
&= E[(\varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3})^2] \\
&= E[\varepsilon_t^2 + 2\varepsilon_{t-1}\varepsilon_t + 3\varepsilon_t\varepsilon_{t-2} + 4\varepsilon_t\varepsilon_{t-3} \\
&\quad + 2\varepsilon_t\varepsilon_{t-1} + 4\varepsilon_{t-1}^2 + 6\varepsilon_{t-1}\varepsilon_{t-2} + 8\varepsilon_{t-1}\varepsilon_{t-3} \\
&\quad + 3\varepsilon_t\varepsilon_{t-2} + 6\varepsilon_{t-1}\varepsilon_{t-2} + 9\varepsilon_{t-2}^2 + 12\varepsilon_{t-2}\varepsilon_{t-3} \\
&\quad + 4\varepsilon_t\varepsilon_{t-3} + 8\varepsilon_{t-1}\varepsilon_{t-3} + 12\varepsilon_{t-2}\varepsilon_{t-3} + 16\varepsilon_{t-3}^2] \\
&= E(\varepsilon_t^2) + 4E[\varepsilon_t\varepsilon_{t-1}] + 6E[\varepsilon_t\varepsilon_{t-2}] + 8E[\varepsilon_t\varepsilon_{t-3}] \\
&\quad + 4E(\varepsilon_{t-1}^2) + 12E[\varepsilon_{t-1}\varepsilon_{t-2}] + 16E[\varepsilon_{t-1}\varepsilon_{t-3}] \\
&\quad + 9E(\varepsilon_{t-2}^2) + 24E[\varepsilon_{t-2}\varepsilon_{t-3}] + 16E(\varepsilon_{t-3}^2) \\
&= E(\varepsilon_t^2) + 4(E\varepsilon_{t-1}^2) + 9(E\varepsilon_{t-2}^2) + 16E(\varepsilon_{t-3}^2) \\
&= 1 + 4 + 9 + 16 = 30
\end{aligned}$$

$$\begin{aligned}
\text{Cov}(Y_t, Y_{t+4}) &= r(4) \\
&= E[(\varepsilon_t + 2\varepsilon_{t-1} + 3\varepsilon_{t-2} + 4\varepsilon_{t-3}) \times \\
&\quad (\varepsilon_{t+4} + 2\varepsilon_{t+3} + 3\varepsilon_{t+2} + 4\varepsilon_{t+1})] \\
&= 0 \quad \Rightarrow \quad r(h) \rightarrow 0 \text{ for } h \geq 4
\end{aligned}$$

$$r(h) \approx 0, \quad r(0) = 30. \quad p(h) = \frac{r(h)}{r(0)} = 0, \quad h \geq 4$$

## **Q3**

4 Points

Let  $\phi(L) = 1 + \frac{1}{2}L$ .

### **Q3.1**

1 Point

What's  $\phi(L)^{-1}$ ?

(shown below)

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**Q3**

4 Points

Let  $\phi(L) = 1 + \frac{1}{2}L$ .

**Q3.1**

1 Point

What's  $\phi(L)^{-1}$ ?

$$\begin{aligned}\phi(L) &= 1 + \frac{1}{2}L, \Rightarrow \phi_1 = -\frac{1}{2}, \\ \phi^{-1}(L) &= 1 + \phi_1 L + \phi_1^2 L^2 + \phi_1^3 L^3 + \dots \\ &= 1 - \frac{1}{2}L + \frac{1}{4}L^2 - \frac{1}{8}L^3 + \dots\end{aligned}$$

### **Q3.2**

1 Point

Is  $\phi(L)^{-1}$  absolutely summable? Is  $\phi(L)^{-1}\epsilon_t$  stationary? Here  $\epsilon_t$  is a white noise.

Yes. (reason shown below)

Yes. (reason shown below)

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**Q3.2**

1 Point

Is  $\phi(L)^{-1}$  absolutely summable? Is  $\phi(L)^{-1}\epsilon_t$  stationary? Here  $\epsilon_t$  is a white noise.

$$\begin{aligned} \textcircled{1} \quad \phi(L)^{-1} &= 1 - \frac{1}{2}L + \frac{1}{4}L^2 - \frac{1}{8}L^3 + \dots \\ \Rightarrow \psi(L) &= \psi_0 + \psi_1 L + \psi_2 L^2 + \psi_3 L^3 \end{aligned}$$

$$\begin{aligned} \psi_0 &= 1, \quad \psi_1 = -\frac{1}{2}, \quad \psi_2 = \frac{1}{4}, \quad \psi_3 = -\frac{1}{8}, \dots \\ \Rightarrow \psi_t &= \left(-\frac{1}{2}\right)^t \\ \downarrow \\ \sum_{j=0}^{\infty} |\psi_j| &= \sum_{j=0}^{\infty} \left| \left(-\frac{1}{2}\right)^j \right| = \sum_{j=0}^{\infty} \left(\frac{1}{2}\right)^j = \frac{1}{1-\frac{1}{2}} = 2 < \infty \end{aligned}$$

$\Rightarrow$  Absolutely summable (converging)

- $$\begin{aligned} \textcircled{2} \quad (\text{if } \{x_t\} \text{ is stationary} \quad \& \quad \psi_j \text{'s is absolutely summable}) \\ \rightarrow Y_t &= \psi(L)x_t \text{ is stationary} \\ \Rightarrow \epsilon_t &\text{ is stationary (since it is weakly stationary process)} \\ \phi(L)^{-1} &\text{ is absolutely summable (as shown above)} \\ \rightarrow \phi(L)^{-1}\epsilon_t &\text{ is stationary! *} \end{aligned}$$

### **Q3.3**

1 Point

Consider an AR(1) process  $Y_t = 3 - \frac{1}{2}Y_{t-1} + \epsilon_t$ . Find  $\mu$  so that  $Y_t - \mu = -\frac{1}{2}(Y_{t-1} - \mu) + \epsilon_t$ . Provide the MA( $\infty$ ) representation for  $Y_t$ .

$$\mu = 2$$

(shown below)

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**Q3.3**

1 Point

Consider an AR(1) process  $Y_t = 3 - \frac{1}{2}Y_{t-1} + \epsilon_t$ . Find  $\mu$  so that  $Y_t - \mu = -\frac{1}{2}(Y_{t-1} - \mu) + \epsilon_t$ . Provide the MA( $\infty$ ) representation for  $Y_t$ .

$$\text{AR(1): } Y_t = \alpha + \phi_1 Y_{t-1} + \epsilon_t$$

$$\Rightarrow Y_t = 3 - \frac{1}{2}Y_{t-1} + \epsilon_t$$

$$\frac{3}{2}\mu = 3$$

$$\mu = 2,$$

$$Y_t - \mu = -\frac{1}{2}(Y_{t-1} - \mu) + \epsilon_t$$

$$Y_t - \mu = -\frac{1}{2}Y_{t-1} + \frac{1}{2}\mu + \epsilon_t$$

$$Y_t = \frac{3}{2}\mu - \frac{1}{2}Y_{t-1} + \epsilon_t$$

$$A: \mu = 2$$

$$Y_t - \mu = -\frac{1}{2}(Y_{t-1} - \mu) + \epsilon_t$$

$$Y_{t-1} - \mu = -\frac{1}{2}(Y_{t-2} - \mu) + \epsilon_{t-1}$$

$$\begin{aligned} Y_t - \mu &= -\frac{1}{2} \left( -\frac{1}{2}(Y_{t-2} - \mu) + \epsilon_{t-1} \right) + \epsilon_t \\ &= \frac{1}{4}(Y_{t-2} - \mu) - \frac{1}{2}\epsilon_{t-1} + \epsilon_t \end{aligned}$$

$$\begin{aligned} &= \frac{1}{4} \left( -\frac{1}{2}(Y_{t-3} - \mu) + \epsilon_{t-2} \right) - \frac{1}{2}\epsilon_{t-1} + \epsilon_t \\ &= -\frac{1}{8}(Y_{t-3} - \mu) + \frac{1}{4}\epsilon_{t-2} - \frac{1}{2}\epsilon_{t-1} + \epsilon_t \end{aligned}$$

↓

$$\begin{aligned} Y_t &= \mu + \epsilon_t - \frac{1}{2}\epsilon_{t-1} + \frac{1}{4}\epsilon_{t-2} - \frac{1}{8}\epsilon_{t-3} + \dots \\ &= \mu + \sum_{j=0}^{\infty} \phi_1^j \epsilon_{t-j} \end{aligned}$$

### **Q3.4**

1 Point

Is  $\{Y_t\}$  stationary? Why? What's the mean of  $Y_t$ ?

Yes. (reason shown below)

$$\text{mean} = \mu = 2.$$

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**Q3.4**

1 Point

Is  $\{Y_t\}$  stationary? Why? What's the mean of  $Y_t$ ?

$$Y_t = M + \varepsilon_t - \frac{1}{2}\varepsilon_{t-1} + \frac{1}{4}\varepsilon_{t-2} - \frac{1}{8}\varepsilon_{t-3} + \dots$$
$$\Rightarrow Y_t = M + \sum_{j=0}^{\infty} \phi_j \varepsilon_{t-j},$$
$$\phi_1 = -\frac{1}{2} \Rightarrow |\phi_1| = \left| -\frac{1}{2} \right| < 1$$

 $\Rightarrow \{Y_t\}$  is stationary, since it satisfied

$$|\phi_1| < 1 \text{ for } Y_t = M + \sum_{j=0}^{\infty} \phi_j \varepsilon_{t-j}.$$

$$\bar{E}(Y_t) = \bar{E}(M) + \cancel{\bar{E}(\varepsilon_t)} - \cancel{\frac{1}{2}\bar{E}(\varepsilon_{t-1})} + \dots = M$$

# IE 522 HW11

 UNGRADED

## STUDENT

Yu-Ching Liao

## TOTAL POINTS

- / 10 pts

## QUESTION 1

(no title)

2 pts

1.1 (no title)

1 pt

1.2 (no title)

1 pt

## QUESTION 2

(no title)

4 pts

2.1 (no title)

1 pt

2.2 (no title)

1 pt

2.3	(no title)	1 pt
2.4	(no title)	1 pt

**QUESTION 3**

(no title)	4 pts
3.1 (no title)	1 pt
3.2 (no title)	1 pt
3.3 (no title)	1 pt
3.4 (no title)	1 pt