

TEST #2

STA 4853

Name: \_\_\_\_\_

May 4, 2023

Please read the following directions.

**DO NOT TURN THE PAGE UNTIL INSTRUCTED TO DO SO**

## Directions

- This exam is **closed book** and **closed notes**.
- Circle the **single best** answer for each multiple choice question. Your choice should be made clearly.
- Always **circle the correct response**. (Sometimes the question has an empty blank or a box, but this is **NOT** where the answer goes.)
- Each question is worth equal credit.
- There is no penalty for guessing.
- There are **33** multiple choice questions.
- The exam has **12** pages.

**Problem 1.** Suppose  $\{y_t\}$ ,  $\{x_{1,t}\}$ ,  $\{x_{2,t}\}$  are time series stored in variables named Y, X1, X2 in the SAS Dataset STUFF. Consider the SAS code given below.

```
PROC ARIMA DATA=STUFF;
IDENTIFY VAR=Y CROSSCOR=(X1 X2) NOPRINT;
ESTIMATE P=2 INPUT=(X1 X2) METHOD=ML;
RUN;
```

This code fits which of the following models?

- a)  $(1 - \phi_1 B - \phi_2 B^2)y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + a_t$
- b)  $\frac{1}{1 - \phi_1 B - \phi_2 B^2} y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + a_t$
- c)  $y_t = C + \phi_1 x_{1,t-1} + \phi_2 x_{2,t-2} + a_t$
- d)  $y_t = C + \phi_1 x_{1,t-1} + \phi_2 x_{1,t-2} + \phi_1 x_{2,t-2} + \phi_2 x_{2,t-2} + a_t$
- e)  $y_t = C + \phi_1 x_{1,t-1} + \phi_2 x_{2,t-2} + a_t + \phi_1 a_{t-1} + \phi_2 a_{t-2}$
- f)  $y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \frac{1}{1 - \phi_1 B - \phi_2 B^2} a_t$
- g)  $y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + (1 - \phi_1 B - \phi_2 B^2) a_t$
- h)  $y_t = C + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \beta_1 x_{1,t} + \beta_2 x_{2,t} + a_t$

**Problem 2.** Differencing an ARIMA(5,3,7) process 3 times produces a \_\_\_\_\_ process.

- a) ARMA(5,7)      b) ARMA(5,4)      c) ARMA(2,7)      d) ARIMA(2,3,7)
- e) ARIMA(5,6,7)      f) ARIMA(5,3,10)      g) ARIMA(8,3,7)      h) ARIMA(8,6,10)

**Problem 3.** Suppose you wish to forecast a time series  $x_t$ . You decide to use a square root transformation  $y_t = \sqrt{x_t}$ , and you model the series  $y_t$  and obtain forecasts  $\hat{y}_t$  for the series  $y_t$ . The forecasts for the original series  $x_t$  are then given by  $\hat{x}_t = \underline{\hspace{2cm}}$ .

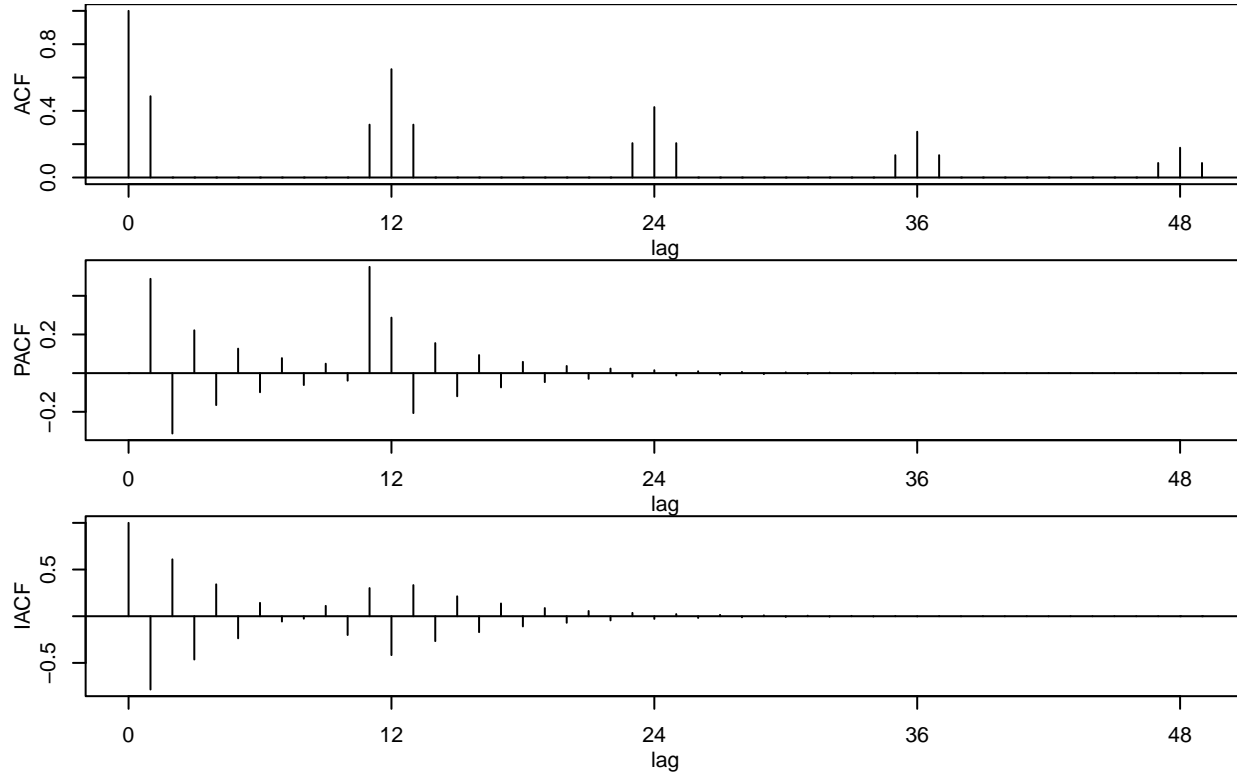
- a)  $\frac{1}{\sqrt{\hat{y}_t}}$       b)  $\frac{1}{\log \hat{y}_t}$       c)  $\frac{1}{\exp \hat{y}_t}$       d)  $\frac{1}{\hat{y}_t^2}$
- e)  $\sqrt{\hat{y}_t}$       f)  $\log \hat{y}_t$       g)  $\exp \hat{y}_t$       h)  $\hat{y}_t^2$

**Problem 4.** Suppose  $\{z_t\}$  is a stationary AR(2) process and we compute  $w_t = \nabla z_t$ . Then  $\{w_t\}$  is \_\_\_\_\_.

- a) an AR(3) process      b) an ARMA(1,2) process      c) an ARMA(1,1) process
- d) non-invertible      e) non-stationary      f) invertible

**Problem 5.** The following plots give the theoretical ACF, PACF, and IACF of a seasonal ARMA process with seasonality  $s = 12$  up to lag 49. What is this process?

- |                                 |                                 |                                 |
|---------------------------------|---------------------------------|---------------------------------|
| a) ARMA(1,0)(0,1) <sub>12</sub> | b) ARMA(3,0)(4,0) <sub>12</sub> | c) ARMA(3,0)(0,4) <sub>12</sub> |
| d) ARMA(0,1)(0,1) <sub>12</sub> | e) ARMA(1,0)(1,0) <sub>12</sub> | f) ARMA(0,1)(1,0) <sub>12</sub> |
| g) ARMA(0,3)(4,0) <sub>12</sub> | h) ARMA(0,3)(0,4) <sub>12</sub> | i) ARMA(1,0)(0,4) <sub>12</sub> |



**Problem 6.** A seasonal ARIMA process  $\text{ARIMA}(p, d, q)(P, D, Q)_s$  will be **non**-stationary if \_\_\_\_\_. (Select the best answer.)

- a) the roots of  $\theta(B) = 0$  are **not** all strictly outside the unit circle
- b) the sample IACF is decaying very slowly
- c) the  $\pi$ -weights  $\pi_k$  do **not** decay to zero as  $k \rightarrow \infty$
- d) any of (a) or (b) or (c) is true
- e)  $d > 0$
- f)  $D > 0$
- g) the AR coefficients violate the stationarity conditions
- h) any of (e) or (f) or (g) is true

**Problem 7.** An ARMA(1,1) process is invertible if \_\_\_\_\_.

- |                            |                            |                                |                              |
|----------------------------|----------------------------|--------------------------------|------------------------------|
| a) $ \phi_1  < 1$          | b) $ \phi_1  > 1$          | c) $ \theta_1  < 1$            | d) $ \theta_1  > 1$          |
| e) $\phi_1 + \theta_1 < 1$ | f) $\phi_1 - \theta_1 < 1$ | g) $ \phi_1  +  \theta_1  < 1$ | h) $ \phi_1 + \theta_1  < 1$ |

**Problem 8.** Suppose  $z_t$  is a **quarterly** series with a **nonstationary** mean. You wish to find a reasonable ARIMA model (possibly seasonal) for this series. If the first differences  $\nabla z_t$  appear stationary but have substantial autocorrelations at lags 1, 4, and 8, which of the following options might you wish to pursue? (More than one may be reasonable.)

1. Try a model without any differencing.
2. Try differencing at lag 1 a second time.
3. Try replacing differencing at lag 1 by differencing at lag 4.
4. Try a seasonal model which includes a seasonal term at lag 4.
5. Try an MA(1) model on  $\nabla z_t$ .
6. Try an AR(1) model on  $\nabla z_t$ .

Select the pair of options which seem most reasonable and circle your choice **below**. (Do NOT circle items on the list above!)

- |           |           |           |           |
|-----------|-----------|-----------|-----------|
| a) 2 or 5 | b) 2 or 6 | c) 3 or 4 | d) 3 or 5 |
| e) 1 or 2 | f) 1 or 5 | g) 1 or 6 | h) 5 or 6 |

**Problem 9.** The standard error for  $k$ -step-ahead forecasts is  $\sigma[e_n(k)] = \underline{\hspace{2cm}}$ .

- |  |  |
|--|--|
| a) $\left(1 + 2 \sum_{j=1}^{k-1} r_j^2\right)^{1/2} n^{-1/2}$    | b) $\left(1 + 2 \sum_{j=1}^k r_j^2\right)^{1/2} n^{-1/2}$            |
| c) $n^{-1/2}$  | d) $n^{1/2}$   |
| e) $\frac{\sigma_a^2}{1 - \phi_1^2}$                             | f) $\frac{\sigma_a^2}{1 + \phi_1^2}$                                 |
| g) $\sigma_a \sqrt{1 + \psi_1^2 + \psi_2^2 + \cdots + \psi_k^2}$ | h) $\sigma_a \sqrt{1 + \psi_1^2 + \psi_2^2 + \cdots + \psi_{k-1}^2}$ |

**Problem 10.** If the correct model for a time series is an ARIMA model with normally distributed random shocks, then  $\underline{\hspace{2cm}}$ .

- a) the best prediction of a future value will depend on whether we use the squared error or absolute error loss function
- b) the absolute error loss function is preferable to the squared error loss function
- c) the conditional distribution of a future value is a normal distribution
- d) the conditional distribution of a future value is skewed
- e) the conditional distribution of a future value is bimodal

**Problem 11.** Suppose  $Y \sim N(\mu, \sigma^2)$  where  $\mu$  and  $\sigma^2$  are known values. You wish to forecast the quantity  $X = e^Y$ , which has a **log**-normal distribution. If your loss function is “squared error loss”, then the best forecast for  $X = e^Y$  is equal to  $\underline{\hspace{2cm}}$ .

- |                |                           |               |                               |
|----------------|---------------------------|---------------|-------------------------------|
| a) $e^\mu$     | b) $e^{\mu - \sigma^2}$   | c) $\mu$      | d) $e^{\mu + (\sigma^2/2)}$   |
| e) $\log(\mu)$ | f) $\log(\mu - \sigma^2)$ | g) $\sigma^2$ | h) $\log(\mu + (\sigma^2/2))$ |

**Problem 12.** When choosing (identifying) an appropriate  $\text{ARIMA}(p, d, q)$  model for a time series, it is best to \_\_\_\_\_.

- a) first choose  $p$  and  $q$  and then choose  $d$
- b) first choose  $d$  and then choose  $p$  and  $q$
- c) choose  $p$ , then  $d$ , and finally  $q$
- d) choose  $q$ , then  $d$ , and finally  $p$
- e) use the MINIC option to simultaneously choose  $p$ ,  $d$ , and  $q$

**Problem 13.** If you wish to model a time series in which the variability of the series increases systematically with the level of the series, then you should consider \_\_\_\_\_.

- a) using a seasonal ARIMA model
- b) differencing the series at the seasonal lag
- c) dividing the series into parts
- d) transforming the series
- e) differencing the series at lag 1
- f) modeling the series as (Trend) + (stationary ARMA process)

**Problem 14.** A time series with an approximately repeating seasonal pattern or tendency has/is \_\_\_\_\_.

- a) weakly stationary
- b) strictly stationary
- c) a funnel shape in the residuals versus forecast plot
- d) a bend in the residuals versus forecast plot
- e) a nonstationary mean
- f) a nonstationary variance
- g) a nonstationary ACF

**Problem 15.** Suppose we are given a series  $x_1, x_2, \dots, x_n$  and we **integrate** this series to obtain the series  $w_1, w_2, \dots, w_n$ . This means that \_\_\_\_\_.

- |   |   |
|---|---|
| a) $w_t = x_t - x_{t-1}$                | b) $w_t = x_{t+1} - x_t$                |
| c) $w_t = \frac{\theta(B)}{\phi(B)}x_t$ | d) $x_t = \frac{\theta(B)}{\phi(B)}w_t$ |
| e) $w_t = x_1 + x_2 + \dots + x_t$      | f) $x_t = w_1 + w_2 + \dots + w_t$      |

**Problem 16.** If you take a realization from an already stationary ARMA process and difference it, the sample IACF of the resulting differences will usually \_\_\_\_\_.

- a) decay to zero very slowly
- b) decay to zero fairly rapidly
- c) have a large spike at lag1 followed by much smaller spikes
- d) decays with a damped sine wave pattern
- e) exhibit alternating exponential decay
- f) have all of the spikes within the two standard error band

**Problem 17.** The theoretical IACF of the process

$$z_t = C + \phi_1 z_{t-1} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \theta_3 a_{t-3}$$

is equal to the theoretical ACF of the process \_\_\_\_\_.

- a)  $z_t = C + \theta_1 z_{t-1} + \theta_2 z_{t-2} + \theta_3 z_{t-3} + a_t - \phi_1 a_{t-1}$
- b)  $z_t = C + \phi_1 z_{t-1} + \theta_3 z_{t-2} + \theta_2 z_{t-3} + a_t - \theta_1 a_{t-1}$
- c)  $z_t = C + \theta_2 z_{t-1} + \theta_1 z_{t-2} + \phi_1 z_{t-3} + a_t - \theta_3 a_{t-1}$
- d)  $z_t = C + \theta_1 z_{t-1} + a_t - \phi_1 a_{t-1} - \theta_2 a_{t-2} - \theta_3 a_{t-3}$
- e)  $z_t = C + \phi_1 z_{t-1} + \phi_2 z_{t-2} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2}$
- f)  $z_t = C + \phi_1 z_{t-1} + \theta_2 z_{t-2} + a_t - \theta_1 a_{t-1} - \phi_2 a_{t-2}$

**Problem 18.** A realization from a process with a NON-stationary mean will typically have \_\_\_\_\_.

- a) a residuals versus forecasts plot which does NOT remain centered about zero
- b) a residuals versus forecasts plot which does NOT have constant width
- c) a normal probability plot which does not follow a straight line
- d) a sample ACF which decays very slowly to zero
- e) a sample PACF which decays very slowly to zero
- f) a sample IACF which decays very slowly to zero

**Problem 19.** An ARMA(1,1) process with  $\phi_1 = \theta_1 = 0.8$  has a theoretical ACF which \_\_\_\_\_.

- a) approaches zero at an eventually exponential rate
- b) has a cutoff to zero after lag 1
- c) has alternating exponential decay
- d) decays with a damped sine wave pattern
- e) has  $\rho_k = 0$  for all  $k > 0$
- f) has  $\rho_k = \phi_1^k$  for all  $k > 0$

The next two questions concern the long-run behavior of the forecasts and their associated confidence interval widths for the model specified in the following lines of code. The time series `xsine1`, `xcos1`, and `xsine2` appearing in this code are periodic functions of time with period 12 defined in terms of sine and cosine functions.

```
identify var=z crosscor=(xsine1 xcos1 xsine2) noprint;
estimate p=1 input=(xsine1 xcos1 xsine2) method=ml;
```

**Problem 20.** Describe the long-run behavior of the forecasts.

- a) The forecasts converge to a repetitive pattern which repeats with a period of 12.
- b) The forecasts converge to the estimated mean  $\hat{\mu}_z$  of the process.
- c) The forecasts converge to a value which depends mainly on the last few observed values of the time series.
- d) The time series plot of the forecasts converges to a straight line with a nonzero slope.
- e) The time series plot of the forecasts converges to a repetitive pattern added to a straight line with nonzero slope.

**Problem 21.** Describe the long-run behavior of the confidence interval widths.

- a) The widths converge to a repetitive pattern which repeats with a period of 12.
- b) The widths converge to a limiting value.
- c) The widths continue to gradually increase and will eventually reach arbitrarily large values.

**Problem 22.** If you write an  $\text{ARIMA}(0, 0, 1)(0, 0, 2)_s$  model in backshift notation, expand the product, and then eliminate the backshift notation, you see it is a special case of a \_\_\_\_\_ process.

- |                        |                        |                       |                       |
|------------------------|------------------------|-----------------------|-----------------------|
| a) $\text{MA}(2s - 1)$ | b) $\text{MA}(2s + 1)$ | c) $\text{MA}(s + 1)$ | d) $\text{MA}(s + 2)$ |
| e) $\text{MA}(s + 3)$  | f) $\text{MA}(3)$      | g) $\text{MA}(4)$     | h) $\text{MA}(5)$     |
| i) $\text{AR}(2s - 1)$ | j) $\text{AR}(2s + 1)$ | k) $\text{AR}(s + 1)$ | l) $\text{AR}(s + 2)$ |
| m) $\text{AR}(s + 3)$  | n) $\text{AR}(3)$      | o) $\text{AR}(4)$     | p) $\text{AR}(5)$     |

**Problem 23.**  $\nabla_s z_t =$  \_\_\_\_\_

- |                          |                    |                          |                    |
|--------------------------|--------------------|--------------------------|--------------------|
| a) $(1 - B)^s z_t$       | b) $(B - 1)^s z_t$ | c) $(1 - B)^t z_s$       | d) $z_t - z_{t-s}$ |
| e) $z_{t+s} - z_{t+s-1}$ | f) $z_{t+s} - z_t$ | g) $z_{t-s} - z_{t-s-1}$ |                    |

**Problem 24.**  $(1 + 2B^2)(1 + 3B^{12}) =$  \_\_\_\_\_

- |                                   |                                   |                                   |
|-----------------------------------|-----------------------------------|-----------------------------------|
| a) $2 + 3B^2 + 4B^{12} + 5B^{14}$ | b) $1 + 2B^2 + 3B^{12} + 6B^{14}$ | c) $1 + 6B^{24}$                  |
| d) $2 + 2B^2 + 3B^{12} + 6B^{24}$ | e) $2 + 2B^2 + 3B^{12}$           | f) $1 + 3B^2 + 4B^{12} + 5B^{24}$ |

**Problem 25.** The AR(1) process in mean-centered form

$$\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + a_t$$

may be written in backshift notation as

$$\phi(B)\tilde{z}_t = a_t$$

where  $\phi(B)$  is the AR polynomial. This AR polynomial has a single zero (or root) which is equal to \_\_\_\_\_.

- |                         |                  |                   |                       |                          |
|-------------------------|------------------|-------------------|-----------------------|--------------------------|
| a) $\frac{1}{\phi_1 B}$ | b) $-\phi_1 B$   | c) $\frac{-1}{B}$ | d) $\frac{1}{\phi_1}$ | e) $\frac{-1}{\phi_1 B}$ |
| f) $\phi_1$             | g) $\frac{1}{B}$ | h) 1              | i) $B$                | j) $\phi_1 B$            |

**Problem 26.** How would the ARIMA(2, 0, 0)(1, 0, 0)<sub>12</sub> model be written in backshift notation?

- a)  $(1 - \phi_2 B^2)(1 - \Phi_1 B^{12})z_t = C + a_t$
- b)  $(1 - \phi_1 B - \phi_2 B^2)(1 - \Phi_1 B^{12})z_t = C + a_t$
- c)  $(1 - \phi_2 B^2)(1 - \Phi_1 B)z_{t-12} = C + a_t$
- d)  $(1 - \phi_2 B^2)z_t = C + (1 - \Theta_1 B^{12})a_t$
- e)  $(1 - \phi_2 B^2)z_t = C + (1 - \Theta_1 B)a_{t-12}$
- f)  $(1 - \phi_2 B^2)z_{t-12} = C + (1 - \Theta_1 B)a_{t-12}$
- g)  $z_t = C + (1 - \theta_1 B - \theta_2 B^2)(1 - \Theta_1 B^{12})a_t$
- h)  $z_t = C + (1 - \theta_2 B^2)(1 - \Theta_1 B^{12})a_t$
- i)  $z_t = C + (1 - \theta_2 B^2)(1 - \Theta_1 B)a_{t-12}$

**Problem 27.** An AR(2)<sub>12</sub> or ARIMA(2, 0, 0)<sub>12</sub> is a purely seasonal model. It may be written as \_\_\_\_\_.

- |  |   |
|--|---|
| a) $z_t = C + \Phi_1 z_{t-1} + \Phi_2 z_{t-12} + a_t$      | b) $z_t = C + \Phi_1 z_{t-12} + \Phi_2 z_{t-13} + a_t$      |
| c) $z_t = C + \Phi_1 z_{t-12} + \Phi_2 z_{t-24} + a_t$     | d) $z_t = C + \Phi_1 z_{t-12} + \Phi_2 z_{t-24} + a_{t-24}$ |
| e) $z_t = C + \Phi_1 z_{t-1} + \Phi_2 z_{t-12} + a_{t-12}$ | f) $z_t = C + \Phi_1 z_{t-12} + \Phi_2 z_{t-13} + a_{t-12}$ |



**Problem 28.** Suppose you wish to explain a response series  $\{y_t\}$  by a regression with ARMA errors using  $k$  input series  $\{x_{1,t}\}, \{x_{2,t}\}, \dots, \{x_{k,t}\}$ . That is, you plan to use a multiple regression model

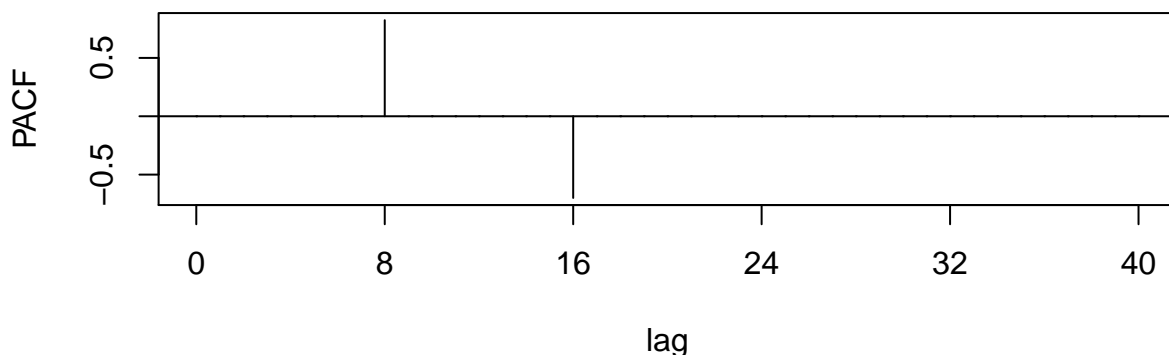
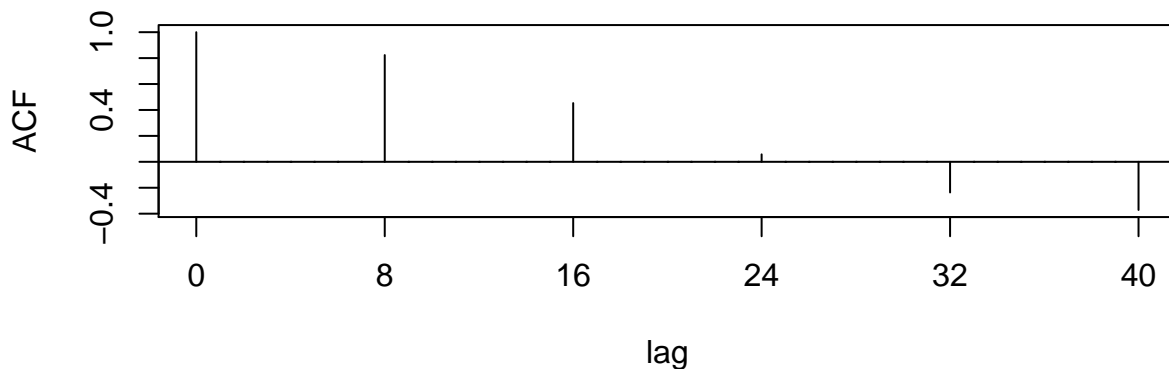
$$y_t = \beta_0 + \beta_1 x_{1,t} + \dots + \beta_k x_{k,t} + \varepsilon_t$$

in which you assume the error series  $\varepsilon_t$  is an ARMA( $p, q$ ) process. Which of the following is a reasonable way to make an initial choice of  $p$  and  $q$ ?

- a) Fit an ordinary multiple regression model and use the  $p$ -values from this to drop the non-significant terms.
- b) Fit an ordinary multiple regression model and then study the ACF and PACF of the residuals.
- c) Apply the MINIC method to the series  $y_t$ .
- d) Apply the MINIC method to the series  $x_{1,t}, x_{2,t}, \dots, x_{k,t}$ .
- e) Fit an AR(2) model to  $y_t$  and then use the residual ACF and PACF to select a better choice of  $p$  and  $q$ .
- f) Study the ACF and PACF of the series  $x_{1,t}, x_{2,t}, \dots, x_{k,t}$ .
- g) Study the ACF and PACF of the series  $y_t$ .

**Problem 29.** The plots below give the theoretical ACF and PACF of an ARMA process. What is this process?

- |                                   |                                   |                                   |
|-----------------------------------|-----------------------------------|-----------------------------------|
| a) ARMA(0, 0)(2, 0) <sub>16</sub> | b) ARMA(0, 0)(2, 0) <sub>8</sub>  | c) ARMA(0, 0)(0, 2) <sub>16</sub> |
| d) ARMA(0, 0)(0, 2) <sub>8</sub>  | e) ARMA(0, 0)(2, 2) <sub>8</sub>  | f) ARMA(0, 0)(2, 2) <sub>16</sub> |
| g) ARMA(2, 0)(0, 0) <sub>8</sub>  | h) ARMA(2, 0)(0, 0) <sub>16</sub> | i) ARMA(0, 2)(0, 0) <sub>8</sub>  |
| j) ARMA(0, 2)(0, 0) <sub>16</sub> | k) ARMA(2, 2)(0, 0) <sub>8</sub>  | l) ARMA(2, 2)(0, 0) <sub>16</sub> |



**Problem 30.** An ARMA( $p, q$ ) process is stationary if and only if all the solutions of \_\_\_\_\_ the unit circle in the complex plane.

- a)  $\theta(B)/\phi(B) = 0$  lie strictly inside
- b)  $\theta(B) = 0$  lie strictly inside
- c)  $\phi(B) = 0$  lie strictly inside
- d)  $\theta(B)/\phi(B) = 0$  lie on the boundary of
- e)  $\theta(B) = 0$  lie on the boundary of
- f)  $\phi(B) = 0$  lie on the boundary of
- g)  $\theta(B)/\phi(B) = 0$  lie strictly outside
- h)  $\theta(B) = 0$  lie strictly outside
- i)  $\phi(B) = 0$  lie strictly outside

**Problem 31.** The backshift expression  $B(C + \phi_1 z_{t-1} + a_t - \theta_1 a_{t-1})$  is equal to \_\_\_\_\_

- a)  $0 + \phi_1 z_{t-2} + a_{t-1} - \theta_1 a_{t-2}$
- b)  $0 + \phi_0 z_{t-2} + a_{t-1} - \theta_0 a_{t-2}$
- c)  $0 + \phi_2 z_{t+1} + a_{t+1} - \theta_2 a_{t+2}$
- d)  $C + \phi_2 z_{t-2} + a_{t-1} - \theta_2 a_{t-2}$
- e)  $C + \phi_1 z_{t-2} + a_{t-1} - \theta_1 a_{t-2}$
- f)  $C_{t+1} + \phi_2 z_t + a_{t+1} - \theta_2 a_t$
- g)  $C_{t-1} + \phi_0 z_{t-2} + a_{t-1} - \theta_0 a_{t-2}$

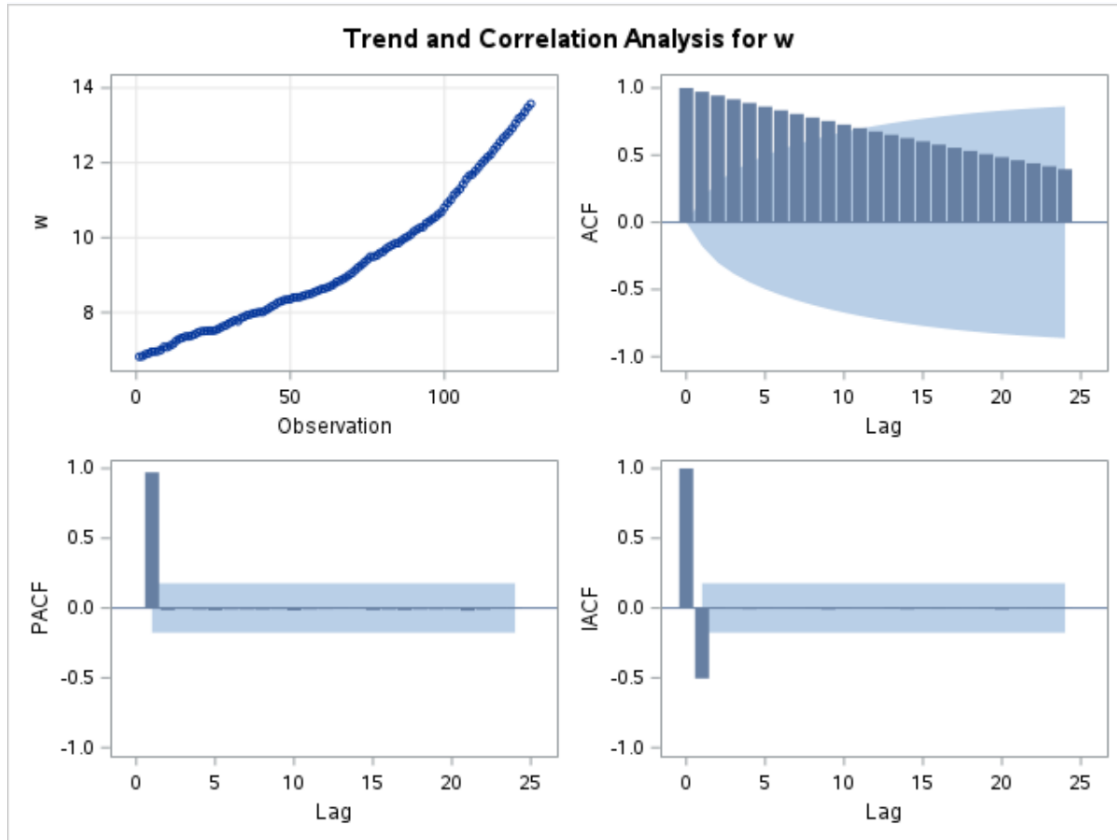
**Problem 32.** By very carefully reading the table given below, you can determine that the ESTIMATE statement which produced this table contained \_\_\_\_\_

- a)  $q=(1)(2,12)$
- b)  $q=(1,2)(12)$
- c)  $q=(1,2,12)$
- d)  $q=(2)(12)$
- e)  $p=(1)(2,12)$
- f)  $p=(1,2)(12)$
- g)  $p=(1,2,12)$
- h)  $p=(2)(12)$

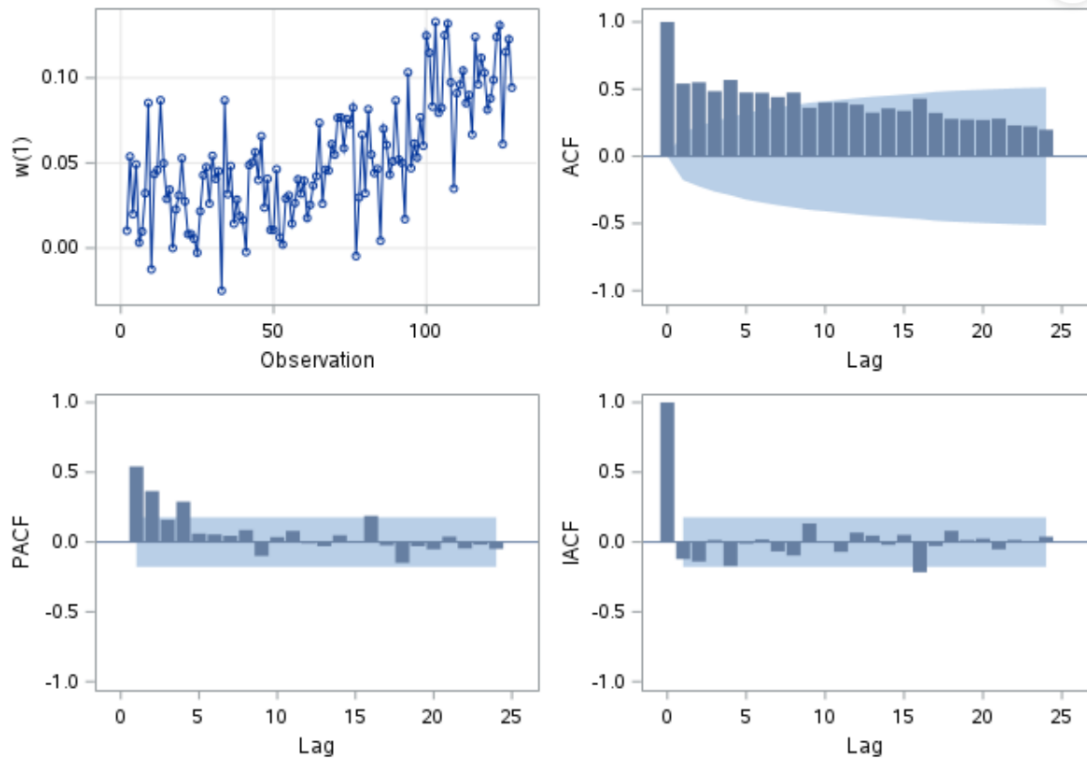
Maximum Likelihood Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr >  t	Lag
<b>MU</b>	0.28585	0.04178	6.84	<.0001	0
<b>AR1,1</b>	0.34024	0.11096	3.07	0.0022	1
<b>AR1,2</b>	0.31666	0.11044	2.87	0.0041	2
<b>AR1,3</b>	-0.18476	0.09540	-1.94	0.0528	12

**Problem 33.** The following output gives the ACF/PACF/IACF for a time series  $w_t$  and its first and second differences. On the basis of this output, choose a plausible initial model for this time series.

- |                 |                 |                 |
|-----------------|-----------------|-----------------|
| a) ARIMA(1,0,0) | b) ARIMA(0,0,1) | c) ARIMA(0,0,2) |
| d) ARIMA(0,2,1) | e) ARIMA(2,2,0) | f) ARIMA(0,2,3) |
| g) ARIMA(4,1,0) | h) ARIMA(0,1,4) | i) ARIMA(0,1,1) |



### Trend and Correlation Analysis for w(1)



### Trend and Correlation Analysis for w(1 1)

