

TEST #2

STA 4853

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

April 28, 2016

Please read the following directions.

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

## Directions

- This exam is **closed book** and **closed notes**.
- There are 30 multiple choice questions.
- 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.)
- There is no penalty for guessing.
- The exam has **11** pages.
- Each question is worth equal credit.

**Problem 1.** One general approach to modeling a series with a non-stationary mean which exhibits seasonal patterns or seasonal variation is to \_\_\_\_\_.

- a) make the series stationary by ordinary and/or seasonal differencing, and then choose an appropriate  $\text{ARIMA}(p, 0, q)(P, 0, Q)_s$  process to model the differenced series
- b) choose an appropriate  $\text{ARIMA}(p, 0, q)(P, 0, Q)_s$  process to eliminate the seasonal effects, and then transform the resulting series (for example, by using a log or square root transformation) to eliminate the non-stationarity
- c) choose an appropriate  $\text{ARIMA}(p, 0, q)(P, 0, Q)_s$  process to eliminate the seasonal effects, and then difference the resulting series (using ordinary and/or seasonal differencing) to eliminate the non-stationarity
- d) transform the series (for example, by using a log or square root transformation), and then choose an appropriate  $\text{ARIMA}(p, 0, q)(P, 0, Q)_s$  process to model the transformed series

**Problem 2.** Transforming a series  $z_t$  (that is, modeling  $y_t = f(z_t)$  instead of  $z_t$  for some appropriately chosen function  $f$  such as log or square root) is useful when \_\_\_\_\_

- a) the level of the series changes systematically with time.
- b) the level of the series  $z_t$  changes periodically with time.
- c) the level of the series  $z_t$  changes repeatedly over time.
- d) the variability of the series  $z_t$  changes systematically with time.
- e) the variability of the series  $z_t$  changes systematically with the level of the series.
- f) the variability of the series  $z_t$  changes periodically with time.

**Problem 3.** A series which approximately repeats a consistent seasonal pattern is \_\_\_\_\_.

- a) stationary    b) non-stationary    c) invertible    d) non-invertible    e) multiplicative
- f) non-multiplicative    g) integrated    h) differenced    i) over-differenced    j) autoregressive

**Problem 4.** If you model a time series  $z_t$  using a **stationary ARMA process with a non-zero constant** ( $C \neq 0$ ) and use it to forecast future values of  $z_t$ , then as you forecast further and further into the future, the **confidence interval widths** for your forecasts will \_\_\_\_\_

- a) continue to increase and eventually reach arbitrarily large values
- b) follow a straight line with a non-zero slope
- c) gradually decay to zero
- d) cutoff to zero after some lag
- e) converge to a non-zero limiting value
- f) converge to a repeating pattern with period  $C$

**Problem 5.** The sample IACF of an invertible process will \_\_\_\_\_.

- a) have all of its roots strictly inside the unit circle
- b) have all of its roots strictly outside the unit circle
- c) decay to zero at a reasonable rate
- d) decay to zero very slowly
- e) indicate there has been overdifferencing
- f) be the same as the PACF of the dual process
- g) depend only on the MA coefficients

**Problem 6.** Which one of the following choices for  $v(B)$  will produce a transfer function  $v(B)X_t$  with  $v$ -weights which decay sinusoidally? (Note: alternating exponential decay is **not** considered to be sinusoidal.)

- a)  $v(B) = \frac{B(1 - 0.8B)}{1 - 1.6B - (-0.8)B^2}$
- b)  $v(B) = \frac{1 - 1.6B - (-0.8)B^2}{1 - 0.8B}$
- c)  $v(B) = \frac{1 - 1.6B - (-0.8)B^2}{1 - (-0.8)B}$
- d)  $v(B) = \frac{B^2(1 - 1.6B - (-0.8)B^2)}{1 - 0.8B}$
- e)  $v(B) = \frac{B^2}{1 - (-0.8)B}$
- f)  $v(B) = B(1 - 1.6B - (-0.8)B^2)$

**Problem 7.** An MA(1) process with  $|\theta_1| < 1$  can be re-written in the form \_\_\_\_\_.

- a)  $\tilde{z}_t = a_t + \theta_1\tilde{z}_{t-1} + \theta_2\tilde{z}_{t-2} + \theta_3\tilde{z}_{t-3} + \dots$
- b)  $\tilde{z}_t = a_t + \theta_1a_{t-1} + \theta_1^2a_{t-2} + \theta_1^3a_{t-3} + \dots$
- c)  $\tilde{z}_t = a_t - \theta_1a_{t-1} - \theta_1^2a_{t-2} - \theta_1^3a_{t-3} - \dots$
- d)  $\tilde{z}_t = a_t - \theta_1a_{t-1} - \theta_2a_{t-2} - \theta_3a_{t-3} - \dots$
- e)  $\tilde{z}_t = a_t - \theta_1\tilde{z}_{t-1} - \theta_1^2\tilde{z}_{t-2} - \theta_1^3\tilde{z}_{t-3} - \dots$
- f)  $\tilde{z}_t = a_t + \theta_1\tilde{z}_{t-1} + \theta_1^2\tilde{z}_{t-2} + \theta_1^3\tilde{z}_{t-3} + \dots$

**Problem 8.** Suppose that  $Y$  has a Normal distribution with mean  $\mu$  and variance  $\sigma^2$  (that is,  $Y \sim N(\mu, \sigma^2)$ ). Then  $X = e^Y$  has a log-normal distribution with **median** equal to \_\_\_\_\_.

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

**Problem 9.** If you have a transfer function model

$$Y_t = C + v(B)X_t + N_t$$

where the noise process  $N_t$  is an  $\text{ARIMA}(p, d, q)(P, D, Q)_s$  process, then you can write the noise process as \_\_\_\_\_, where as usual  $a_t$  denotes a random shock process, and  $\phi(B)$  and  $\theta(B)$  are the AR and MA polynomials, respectively.

- a)  $N_t = \frac{(1-B)^d(1-B^s)^D\phi(B)}{\theta(B)}a_t$
- b)  $N_t = \frac{(1-B^d)(1-B^D)^s\phi(B)}{\theta(B)}a_t$
- c)  $N_t = \frac{\phi(B)}{(1-B)^d(1-B^s)^D\theta(B)}a_t$
- d)  $N_t = \frac{\theta(B)}{(1-B)^d(1-B^s)^D\phi(B)}a_t$
- e)  $N_t = \frac{\phi(B)}{(1-B^d)(1-B^D)^s\theta(B)}a_t$
- f)  $N_t = \frac{(1-B^d)(1-B^D)^s\theta(B)}{\phi(B)}a_t$

**Problem 10.** The SAS code given below \_\_\_\_\_

```
PROC ARIMA DATA=STUFF;
  IDENTIFY VAR=Y CROSSCOR=(X1 X2 X3) NOPRINT;
  ESTIMATE INPUT=(X1 X2 X3) METHOD=ML;
  QUIT;
```

- a) fits a transfer function model for  $Y_t$  on  $X_{t-1}, X_{t-2}, X_{t-3}$ .
- b) fits a transfer function model for  $Y_t$  on  $X_{1,t}, X_{2,t}, X_{3,t}$ .
- c) fits a multiple regression model for  $Y_t$  on the regressors  $X_{1,t}, X_{2,t}, X_{3,t}$ .
- d) fits a multiple regression model for  $Y_t$  on the regressors  $X_{t-1}, X_{t-2}, X_{t-3}$ .
- e) uses pre-whitening to identify a transfer function for  $Y_t$  on  $X_{1,t}, X_{2,t}, X_{3,t}$ .
- f) uses pre-whitening to identify a transfer function for  $Y_t$  on  $X_{t-1}, X_{t-2}, X_{t-3}$ .
- g) fits a transfer function model for  $Y_t$  on  $X_{t-1}, X_{t-2}, X_{t-3}$  using a proxy AR(2) model for the noise.
- h) fits a transfer function model for  $Y_t$  on  $X_{1,t}, X_{2,t}, X_{3,t}$  using a proxy AR(2) model for the noise.

**Problem 11.** Suppose we wish to forecast an AR(1) process  $z_t = C + \phi_1 z_{t-1} + a_t$  and we know all the values of  $z_t$  and  $a_t$  up to time  $n$ . What is the best forecast for  $z_{n+2}$ ?

- a)  $\mu_z$
- b)  $z_n$
- c)  $\mu_z + \phi_1^2 z_n$
- d)  $z_n + \phi_1^2 a_n$
- e)  $C + \phi_1 C + \phi_1^2 z_n$
- f)  $C + \phi_1 C + \phi_1^2 a_n$
- g)  $z_n + \phi_1 z_n + \phi_1^2 a_n$
- h)  $z_n + \phi_1 C + \phi_1^2 a_n$

**Problem 12.** The model

$$(1 - \phi_1 B - \phi_2 B^2)(1 - \Phi_1 B^s)z_t = C + a_t$$

may be re-written as \_\_\_\_\_.

- a)  $z_t = C - \phi_1 z_{t-1} - \phi_2 z_{t-2} - \Phi_1 z_{t-s} - \phi_1 \Phi_1 z_{t-s-1} - \phi_2 \Phi_1 z_{t-s-2} + a_t$
- b)  $z_t = C + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \Phi_1 z_{t-s} + \phi_1 \Phi_1 z_{t-s-1} + \phi_2 \Phi_1 z_{t-s-2} + a_t$
- c)  $z_t = C + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \Phi_1 z_{t-s} - \phi_1 \Phi_1 z_{t-s-1} - \phi_2 \Phi_1 z_{t-s-2} + a_t$
- d)  $z_t = C - \phi_1 z_{t-1} - \phi_2 z_{t-2} - \Phi_1 z_{t-s} + \phi_1 \Phi_1 z_{t-s-1} + \phi_2 \Phi_1 z_{t-s-2} + a_t$
- e)  $z_t = C + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \Phi_1 z_{t-s} - \phi_1 \Phi_1 z_{t-1} z_{t-s} - \phi_2 \Phi_1 z_{t-2} z_{t-s} + a_t$
- f)  $z_t = C - \phi_1 z_{t-1} - \phi_2 z_{t-2} - \Phi_1 z_{t-s} - \phi_1 \Phi_1 z_{t-1} z_{t-s} - \phi_2 \Phi_1 z_{t-2} z_{t-s} + a_t$
- g)  $z_t = C + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \Phi_1 z_{t-s} + \phi_1 \Phi_1 z_{t-1} z_{t-s} + \phi_2 \Phi_1 z_{t-2} z_{t-s} + a_t$
- h)  $z_t = C - \phi_1 z_{t-1} - \phi_2 z_{t-2} - \Phi_1 z_{t-s} + \phi_1 \Phi_1 z_{t-1} z_{t-s} + \phi_2 \Phi_1 z_{t-2} z_{t-s} + a_t$

**Problem 13.** If you difference a series and then observe that the sample ACF of the differenced series decays very slowly, what should you do?

- a) Conclude that the series has been over-differenced.
- b) Try a transformation, perhaps a log or square root.
- c) Use a mixed model with both  $p > 0$  and  $q > 0$ .
- d) Conclude that the series is non-invertible.
- e) Try differencing the series again.
- f) Use an MA( $q$ ) model with a large value of  $q$ .

**Problem 14.** Suppose the conditional distribution of  $X$  given the information  $\mathcal{I}$  is

Normal with mean  $= E(X | \mathcal{I})$  and variance  $= \text{Var}(X | \mathcal{I})$ ,

and we are using the squared error loss function. Then our best forecast of  $X$  is \_\_\_\_\_

- a)  $E(X | \mathcal{I})$
- b)  $\text{Var}(X | \mathcal{I})$
- c)  $X - \hat{X}$
- d)  $E[(X - \hat{X})^2 | \mathcal{I}]$
- e)  $E(|X - \hat{X}| | \mathcal{I})$
- f)  $\sqrt{\text{Var}(X | \mathcal{I})}$
- g)  $(\hat{X} - 1.96 \text{ SE}, \hat{X} + 1.96 \text{ SE})$

**Problem 15.** The theoretical IACF of an AR( $p$ ) process \_\_\_\_\_

- a) is the same as the PACF of an MA( $p$ ) process.
- b) is the same as the ACF of an MA( $p$ ) process.
- c) is the same as the ACF of an AR( $p$ ) process.
- d) eventually decays to zero (perhaps in a complicated way).
- e) decays to zero very slowly.
- f) gets closer and closer to a non-zero limiting value for large lags.
- g) converges to a value depending mainly on the last few observed values.

The next three problems involve this situation: Suppose

$$v(B) = \frac{B^b \omega(B)}{\delta(B)} \quad \text{with}$$

$$\omega(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_h B^h \quad \text{and}$$

$$\delta(B) = \delta_0 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r.$$

**Problem 16.** If  $r = 1$ , then the **first** non-zero  $v$ -weight is at lag \_\_\_\_\_.

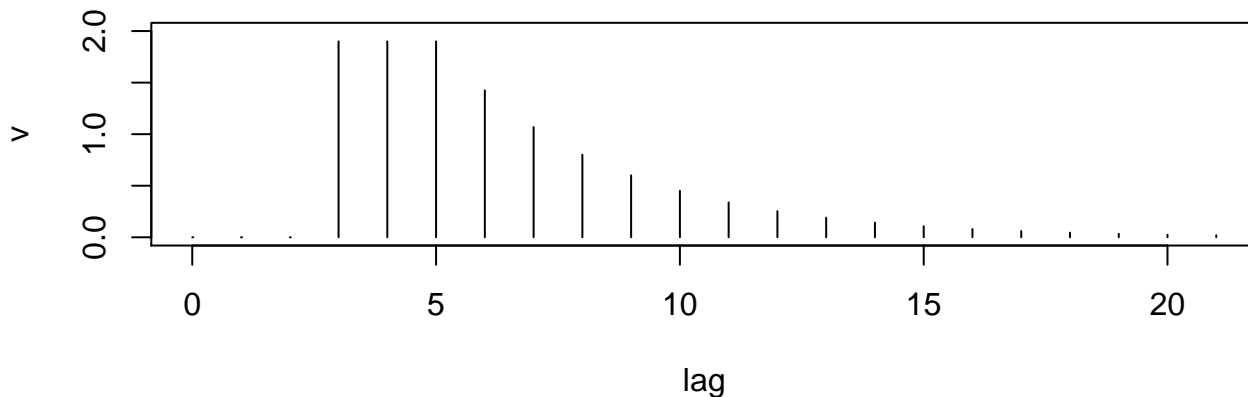
- a)  $b + 1$       b)  $b + h$       c)  $b + h + 1$       d)  $b - 1$       e)  $b$   
f)  $b + h - 1$       g)  $h$       h)  $h - 1$       i)  $h + 1$       j)  $b - h + 1$

**Problem 17.** If  $r = 0$ , then the **last** non-zero  $v$ -weight is at lag \_\_\_\_\_.

- a)  $b$       b)  $h$       c)  $b - h$       d)  $b + h$       e)  $h - b$       f)  $bh$       g)  $b/h$       h)  $h/b$

**Problem 18.** What is the value of  $h$  for the transfer function with  $v$ -weights given in the plot below?

- a) 0      b) 1      c) 2      d) 3      e) 4      f) 5      g) 6



**Problem 19.** Suppose  $w_t = \nabla^2 z_t$ . If  $w_t$  appears to be stationary, and the sample ACF of  $w_t$  has a single large spike at lag 1 followed by much smaller non-significant spikes, then a reasonable model for the original series  $z_t$  is \_\_\_\_\_

- a) ARIMA(1,1,0)      b) ARIMA(0,1,1)      c) ARIMA(0,0,1)<sub>2</sub>      d) ARIMA(1,0,0)<sub>2</sub>  
e) ARIMA(1,2,0)      f) ARIMA(0,2,1)      g) ARIMA(0,1,2)      h) ARIMA(2,1,0)

**Problem 20.** For a time series with a non-stationary mean, it is common for the **PACF** to

- a) decay very slowly.
- b) have a single large spike at lag 1 with  $\hat{\phi}_{11}$  close to 1.
- c) have several large spikes followed by an approximate cutoff to zero.
- d) display strong sinusoidal oscillations.
- e) decay exponentially.
- f) exhibit alternating exponential decay.
- g) exhibit variability which changes with the level.

**Problem 21.** To estimate the transfer function model

$$Y_t = C + \frac{B^3 \omega_0}{1 - \delta_1 B} X_t + \frac{1}{(1 - \phi_{1,1} B)(1 - \phi_{2,1} B^{12})} a_t,$$

you use the SAS code \_\_\_\_\_.

- a) ESTIMATE INPUT=(3\$(1)X) P=(1)(12) ;
- b) ESTIMATE INPUT=(3\$(1)X) P=(1,12) ;
- c) ESTIMATE INPUT=(3\$(0)/(0,1)X) P=(1)(12) ;
- d) ESTIMATE INPUT=(3\$(0)/(0,1)X) P=(1,12) ;
- e) ESTIMATE INPUT=(3\$(0)/(0,1)X) Q=(1,12) ;
- f) ESTIMATE INPUT=(\$3)/(0,1)X) Q=(1)(12) ;
- g) ESTIMATE INPUT=(\$3)/(1)X) Q=(1,12) ;
- h) ESTIMATE INPUT=(\$3)/(1)X) P=(1)(12) ;

**Problem 22.** Suppose  $z_t$  is a stationary ARMA process with psi-weights  $\psi_1, \psi_2, \psi_3, \dots$ . Let  $e_n(3) = z_{n+3} - \hat{z}_{n+3}$  be the 3-step-ahead forecast error based on information about the series up to time  $n$ . The forecast error  $e_n(3)$  is equal to \_\_\_\_\_.

- a)  $\sigma_a^2(1 + \psi_1^2 + \psi_2^2)$
- b)  $\sigma_a^2(1 + \psi_1^2 + \psi_2^2 + \psi_3^2)$
- c)  $\sigma_a \sqrt{1 + \psi_1^2 + \psi_2^2}$
- d)  $\sigma_a \sqrt{1 + \psi_1^2 + \psi_2^2 + \psi_3^2}$
- e)  $a_n + \psi_1 a_{n-1} + \psi_2 a_{n-2}$
- f)  $a_{n+3} + \psi_1 a_{n+2} + \psi_2 a_{n+1}$
- g)  $a_{n+3} + \psi_1 a_{n+2} + \psi_2 a_{n+1} + \psi_3 a_n$
- h)  $a_n + \psi_1 a_{n-1} + \psi_2 a_{n-2} + \psi_3 a_{n-3}$

**Problem 23.** Suppose we start with the series  $x_t$ , then calculate  $y_t = \nabla x_t$ , and then  $z_t = \nabla_s y_t$ . We find that  $z_t =$  \_\_\_\_\_.

- a)  $x_{t-1} - x_t - x_{t-s-1} + x_{t-s}$
- b)  $x_t + x_{t-1} - x_{t-s} - x_{t-s-1}$
- c)  $x_t - x_{t-1} - x_{t-s} + x_{t-s-1}$
- d)  $x_t - x_{t+1} - x_{t+s} + x_{t+s+1}$
- e)  $x_{t-1} + x_t - x_{t+s+1} + x_{t+s}$
- f)  $x_t + x_{t+1} - x_{t+s} - x_{t+s+1}$

**Problem 24.** A stationary ARMA process  $z_t$  with psi-weights  $\psi_1, \psi_2, \psi_3, \dots$  can be written as \_\_\_\_\_.

- a)  $z_t = \mu_z + \frac{1}{1 - \psi_1 B - \psi_2 B^2 - \psi_3 B^3 - \dots} a_t$
- b)  $z_t = C + a_t + \frac{\omega_0 - \omega_1 B - \omega_2 B^2 - \omega_3 B^3 - \dots}{1 - \psi_1 B - \psi_2 B^2 - \psi_3 B^3 - \dots} z_t$
- c)  $z_t = C + \frac{1 - \psi_1 B - \psi_2 B^2 - \psi_3 B^3 - \dots}{1 - \delta_1 B - \delta_2 B^2 - \delta_3 B^3 - \dots} a_t$
- d)  $z_t = C + a_t + \psi_1 z_{t-1} + \psi_2 z_{t-2} + \psi_3 z_{t-3} + \dots$
- e)  $z_t = \mu_z + a_t + \psi_1 a_{t+1} + \psi_2 a_{t+2} + \psi_3 a_{t+3} + \dots$
- f)  $z_t = \mu_z + a_t + \psi_1 a_{t-1} + \psi_2 a_{t-2} + \psi_3 a_{t-3} + \dots$
- g)  $z_t = C + a_t + \psi_1 z_{t+1} + \psi_2 z_{t+2} + \psi_3 z_{t+3} + \dots$

**Problem 25.** If we form a new series  $w_t$  by differencing the series  $x_t$  3 times at lag 1 and then 4 times at lag 6, we may write  $w_t =$  \_\_\_\_\_.

- a)  $(1 - B^3)(1 - B^4)^6 x_t$
- b)  $(1 - B^3)(1 - B^6)^4 x_t$
- c)  $(1 - B)^4(1 - B^6)^3 x_t$
- d)  $(1 - B)^4(1 - B^3)^6 x_t$
- e)  $(1 - B^6)(1 - B^3)^4 x_t$
- f)  $(1 - B^6)(1 - B^4)^3 x_t$
- g)  $(1 - B)^3(1 - B^6)^4 x_t$
- h)  $(1 - B)^3(1 - B^4)^6 x_t$

**Problem 26.** The ACF and PACF of a stationary  $\text{ARIMA}(p, 0, q)(P, 0, Q)_8$  process is given on the next page. What is this process?

- |                                       |                                       |                                       |
|---------------------------------------|---------------------------------------|---------------------------------------|
| a) $\text{ARIMA}(2, 0, 0)(1, 0, 0)_8$ | b) $\text{ARIMA}(1, 0, 0)(0, 0, 2)_8$ | c) $\text{ARIMA}(1, 0, 0)(2, 0, 0)_8$ |
| d) $\text{ARIMA}(0, 0, 2)(0, 0, 1)_8$ | e) $\text{ARIMA}(2, 0, 0)(0, 0, 1)_8$ | f) $\text{ARIMA}(0, 0, 2)(1, 0, 0)_8$ |
| g) $\text{ARIMA}(0, 0, 1)(0, 0, 2)_8$ | h) $\text{ARIMA}(0, 0, 1)(2, 0, 0)_8$ | i) $\text{ARIMA}(0, 0, 2)(2, 0, 0)_8$ |



LAG	ACF	PACF	PSI	PI
1	-0.593939	-0.593939	-0.700000	-0.700000
2	0.242424	-0.170478	0.400000	-0.090000
3	0.0	0.107058	0.0	0.217000
4	0.0	0.139839	0.0	0.187900
5	0.0	0.056075	0.0	0.044730
6	0.145455	0.223094	0.0	-0.043849
7	-0.356364	-0.297598	0.0	-0.048586
8	0.600000	0.381590	0.600000	0.583529
9	-0.356364	0.340515	-0.420000	0.427905
10	0.145455	0.106021	0.240000	0.066122
11	0.0	-0.059646	0.0	-0.124877
12	0.0	-0.083460	0.0	-0.113862
13	0.0	-0.034765	0.0	-0.029753
14	0.087273	0.009001	0.0	0.024718
15	-0.213818	0.020196	0.0	0.029204
16	0.360000	0.010539	0.360000	0.010555
17	-0.213818	-0.000700	-0.252000	-0.004293
18	0.087273	-0.004706	0.144000	-0.007227
19	0.0	-0.003014	0.0	-0.003342
20	0.0	-0.000227	0.0	0.000552
21	0.0	0.001046	0.0	0.001723
22	0.052364	0.000823	0.0	0.000985
23	-0.128291	0.000158	0.0	0.000001
24	0.216000	-0.000219	0.216000	-0.000394
25	-0.128291	-0.000216	-0.151200	-0.000276
26	0.052364	-0.000064	0.086400	-0.000036
27	0.0	0.000042	0.0	0.000085
28	0.0	0.000055	0.0	0.000074
29	0.0	0.000022	0.0	0.000018
30	0.031418	-0.000007	0.0	-0.000017
31	-0.076975	-0.000013	0.0	-0.000019
32	0.129600	-0.000007	0.129600	-0.000006
33	-0.076975	0.000001	-0.090720	0.000003
34	0.031418	0.000003	0.051840	0.000005
35	0.0	0.000002	0.0	0.000002
36	0.0	0.0	0.0	0.0
37	0.0	-0.000001	0.0	-0.000001
38	0.018851	-0.000001	0.0	-0.000001
39	-0.046185	0.0	0.0	0.0
40	0.077760	0.0	0.077760	0.0

**Problem 27.** In addition to the ACF and PACF, the table on the previous page also has columns giving the  $\psi$ -weights and  $\pi$ -weights (PSI and PI). Is the ARMA process described in the table **invertible**? And why?

- a) Yes, because the  $\psi$ -weights are decaying to zero.
- b) Yes, because the  $\pi$ -weights are decaying to zero.
- c) Yes, because the ACF is decaying to zero.
- d) No, because the  $\psi$ -weights are decaying to zero.
- e) No, because the  $\pi$ -weights are decaying to zero.
- f) No, because the ACF is decaying to zero.

The last page of the exam contains some bits of PROC ARIMA output obtained from fitting a model to a time series  $y_t$  with 84 observations. Use this output to answer the following questions.

**Problem 28.** What is the estimated model?

- a)  $(1 - 0.34695B - 0.35167B^2)(1 - B^{12})y_t = (1 - 0.52048B^{12})a_t$
- b)  $(1 - 0.34695B - 0.35167B^2)(1 - B)y_t = (1 - 0.52048B)a_t$
- c)  $(1 - 0.34695B - 0.35167B^2)y_t = (1 - 0.52048B^{12})a_t$
- d)  $(1 - 0.34695B - 0.35167B^2)(1 - B^{12})y_t = 0.086079 + (1 - 0.52048B^{12})a_t$
- e)  $(1 - 0.34695B - 0.35167B^2)(1 - B)y_t = 0.086079 + (1 - 0.52048B)a_t$
- f)  $(1 - 0.34695B - 0.35167B^2)y_t = 0.086079 + (1 - 0.52048B^{12})a_t$
- g)  $(1 - 0.34695B - 0.35167B^2)(1 - B)^{12}y_t = 0.086079 + (1 - 0.52048B)a_t$

**Problem 29.** What is the standard error (that is, the square root of the variance) of the one-step-ahead prediction error?

- a) 0.17182    b) 0.221759    c) 0.03657    d) 0.13629    e) 0.11029    f) 0.11058    g) 0.1819

**Problem 30.** As you predict further and further into the future, the long-range forecasts from this model converge to \_\_\_\_\_.

- a) a straight line with a nonzero slope
- b) the estimated mean of the process
- c) a repeating pattern added to a straight line with nonzero slope
- d) a repeating pattern
- e) a value which depends mainly on the last few observed values

Name of Variable = y	
Period(s) of Differencing	12
Mean of Working Series	0.288627
Standard Deviation	0.221759
Number of Observations	72
Observation(s) eliminated by differencing	12

Maximum Likelihood Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr >  t	Lag
MU	0.28562	0.03657	7.81	<.0001	0
MA1,1	0.52048	0.13629	3.82	0.0001	12
AR1,1	0.34695	0.11029	3.15	0.0017	1
AR1,2	0.35167	0.11058	3.18	0.0015	2

Constant Estimate	0.086079
Variance Estimate	0.029522
Std Error Estimate	0.17182
AIC	-41.0894
SBC	-31.9828
Number of Residuals	72

Forecasts for variable y				
Obs	Forecast	Std Error	95% Confidence Limits	
85	9.5783	0.1718	9.2415	9.9150
86	9.7548	0.1819	9.3984	10.1113
87	10.2862	0.1991	9.8959	10.6765
88	10.0286	0.2051	9.6267	10.4306
89	9.9509	0.2101	9.5391	10.3627