

Name Mr. Key
ID# 7777777

ECO 5375
Eco. & Bus. Forecasting

Prof. Tom Fomby
Fall 2015

MID-TERM EXAM

Instructions: Write in your name and student ID above. You have 1 hour and 30 minutes to complete this exam. This exam is worth a total of 97 points. The points for the separate question are broken out as follows:

- Q1 – Q7 = 2 points each.
- Q8 = 4 points
- Q9 = 5 points
- Q10 = 3 points
- Q11 – Q13 = 2 points each
- Q14 = (2, 2, 2) = 6 points
- Q15 = 2 points
- Q16 = 6 points
- Q17 = 4 points
- Q18 = (6, 2) = 8 points
- Q19 = (5, 2) = 7 points
- Q20 – Q28 = 2 points each
- Q29 = (2, 2, 2) = 6 points
- Q30 = 4 points
- Q31 = 4 points

- ② 1. In an additive decomposition of time series we assume that any time series potentially consists of four components. These components are Trend, season, cycle, Irregular
- ② 2. SAS programs have two basic steps. They are the Data step and the Proc step.
- ② 3. The basic punctuation following each executable statement in SAS is
- Quotation mark (“”)
 - Period (“.”)
 - c.** Semicolon (“;”)
 - Dash (“-“)
- ② 4. To put comments in a SAS program
- Enclose the comments between quotation marks as in: “content”
 - b.** Enclose the comments between /* and */ as in /*content*/
 - Enclose the comments between (and) as in (content)
 - Enclose the comments between # and # as in #content#
- ② 5. **True** or False. If a time series is slow-turning around a mean, it is probably a nonstationary time series and needs to be differenced before analyzing it.
- ② 6. If a time series y_t exhibits an exponential growth pattern, it can be transformed to stationarity by the transformation
- Δy_t
 - b.** $\Delta \log_e(y_t)$
 - $\exp(y_t)$
 - $\tan^{-1}(y_t)$
- ② 7. **True** or False. If some time series data, say x , data needs to be differenced to be made stationary, then the identify statement in the SAS Procedure ARIMA should read “identify var = x(1);”

Consider the AR(1) Box-Jenkins Model $y_t = \phi_1 y_{t-1} + a_t$ (Model (1))

8. The four properties that we assume for the error term a_t in Model (1) are

④

$$\begin{aligned} E(a_t) &= 0 \quad \forall t \\ \text{Var}(a_t) &= \sigma_a^2 \quad \forall t \\ \text{Cov}(a_t, a_s) &= 0 \quad \forall s \neq t \\ a_t &\sim N(0, \sigma_a^2) \quad \forall t \end{aligned}$$

9. Fill in the following blanks as they relate to the above Model (1) with $|\phi_1| < 1$.

⑤

$$\begin{aligned} E(y_t) &= 0 \\ \text{Var}(y_t) &= \frac{\sigma_a^2}{(1-\phi_1^2)} \\ \text{Corr}(y_t, y_{t-j}) &= \phi_1^j \\ \hat{y}_{t+h} &= \phi_1^h y_t \\ \text{se}(e_{t+h}) &= \frac{\sigma_a \sqrt{1 + \phi_1^2 + \phi_1^4 + \dots + \phi_1^{2(h-1)}}}{\sqrt{1 - \phi_1^2}} \end{aligned}$$

3

10. Suppose that the last available observation we have available on some time series data described by Model (1), $y_t = 4$. Assume that by the method of least squares we determine that a reasonable model for the data is $y_t = 0.5y_{t-1} + \hat{a}_t$ with $sd(a_t) = 1.0$ or equivalently, $Var(a_t) = 1.0$. Then the one-step-ahead forecast for y is $\hat{y}_{t+1} =$ 2. The 95% prediction interval for this forecast is (0.04, 3.96). Show your work below to receive full credit.

$\hat{y}_{t+1} = \hat{\phi}_1 y_t = 0.5(4) = 2$
 $se(e_{t+1}) = \sqrt{\sigma_a^2(1)} = \sqrt{1} = 1$
 $2 \pm 1.96 se(e_{t+1}) = 2 \pm 1.96(1)$

2

11. In the Unit Root case of Model (1), suppose that the last available observation in our time series is $y_t = 4$ and $\sigma_a^2 = 1$. Then $\hat{y}_{t+2} =$ 4 and $se(e_{t+2}) =$ $\sqrt{2}$.

$\hat{y}_{t+h} = y_t$ $se(e_{t+h}) = \sqrt{h\sigma_a^2}$

2

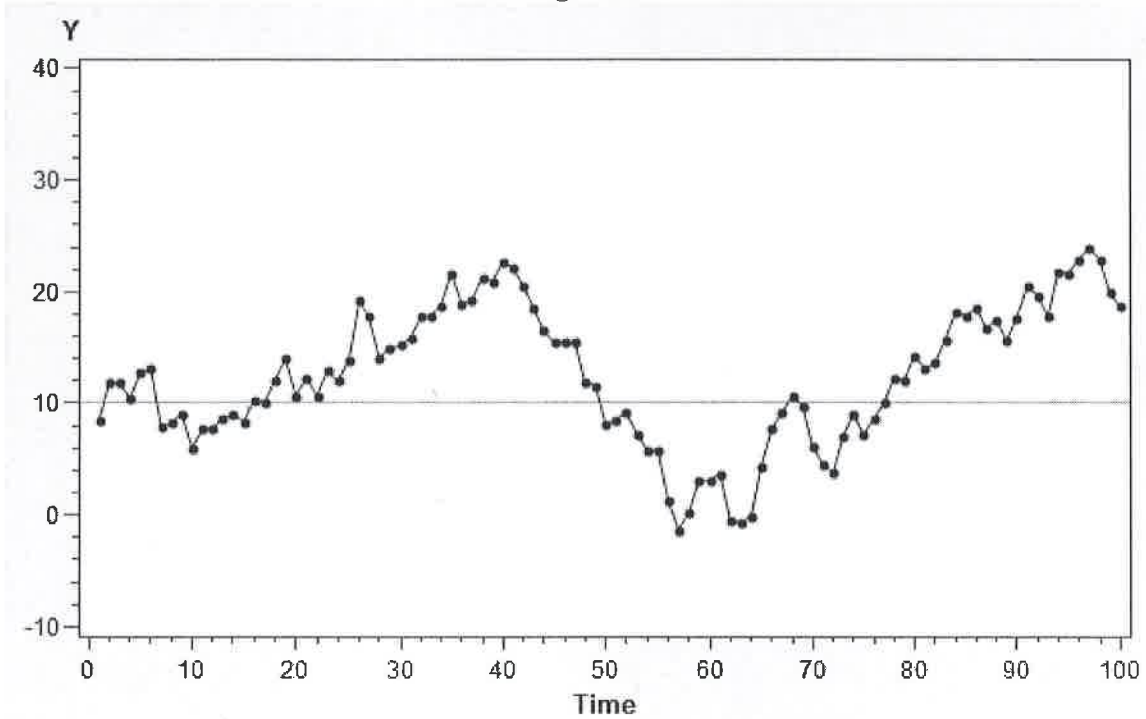
12. True or False. The "Damping" and "Cutting Off" patterns of the ACF and PACF of the stationary form of a time series provide a way to identify the orders of pure Box-Jenkins processes.

2

13. If the ACF has 3 spikes in it and then cuts off and if the PACF tails off, the ARMA model that is appropriate for the data is ARMA(0, 3).

14. Consider the time series plotted in **Figure 1** below.

Figure 1



②

(a) Does this time series look stationary to you? Explain your answer.

no. It is slow-trending and looks like a random walk without drift.

②

(b) Is it all right to apply the Box-Jenkins modeling approach to this data directly or should you transform the data first and, if so, how? Explain your answer.

As the data is similar to the process $y_t = y_{t-1} + a_t$ with $y_0 = 10$, we should difference the data to make it stationary

②

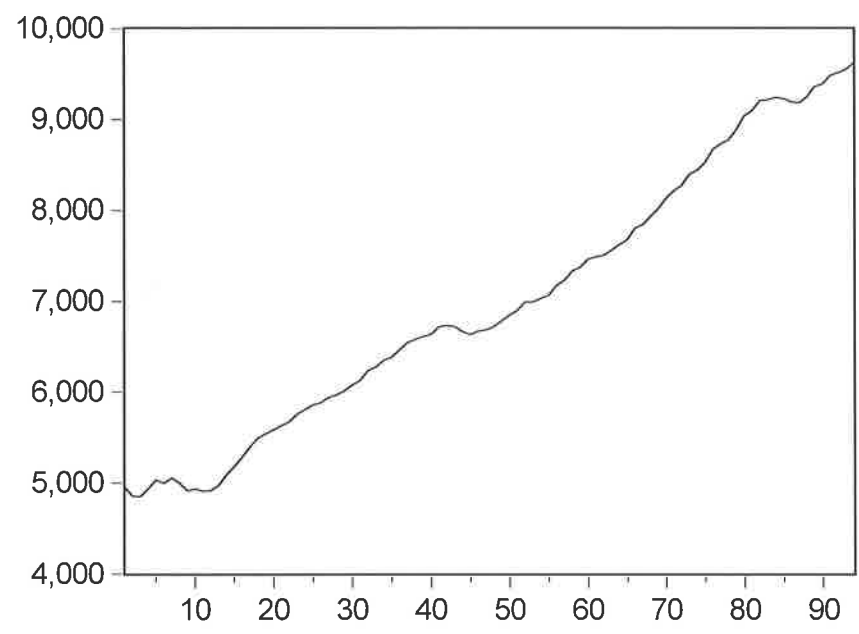
(c) Formally, state the conditions for a time series y_t to be stationary.

The time series y_t is stationary if
(i) $E(y_t) = \mu$ $\forall t$ (constant mean)
(ii) $Var(y_t) = \sigma^2$ $\forall t$ (constant variance)
(iii) $cov(y_t, y_{t-j}) = \gamma_j$ $\forall t$ and arbitrary integer $j > 0$ (constant covariance)
(iv) y_t is normally distributed

weak stationarity
If you add condition (iv) you have strong stationarity.

Now let us conduct a unit root test on the data in Figure 2. In the EViews Computer Output # 1 there is some information that should allow you to answer the following 2 questions.

Figure 2



— Y

②

15. The null hypothesis of the Dickey-Fuller test for the data in Figure 2 is data has stochastic trend. The alternative hypothesis is the data follows a deterministic trend and should be modeled as $y_t = a + bt + a_t$.

and needs to be differenced to make it stationary (i.e. the time series has a unit root)

16. Using **EVIIEWS Computer Output # 1** and the correct Dickey-Fuller case for this data (Y), report the following information:

⑥

(a) The appropriate case for the Dickey-Fuller test is Zero Mean / Single Mean / Trend (circle a choice)

(b) The number of augmenting terms chosen for the test is = 2

$D(Y(-1))$
 $D(Y(-2))$

(c) Dickey-Fuller t-statistic (tau) = -1.983249

(d) Probability Value of DF t-statistic = 0.023

(e) This test result indicates that the time series Y (is/is not) stationary and does (circle) need to be differenced to make the series stationary.

Now consider the **SAS Computer Output # 2**. Use this output to determine a best Box-Jenkins model for the data plotted in **Figure 2**. Assume that the time series is observed **monthly**.

17. Using the sample ACF and sample PACF that is provided by **SAS Computer Output # 2**, give me a tentative identification of the p and q values for the Y series. Explain your answer.

②

p = 1, q = 0.

②

Explanation: The PACF has one spike and then cuts off while the ACF damps out.

18. Using **Computer Output # 2**, fill in the following P-Q box. Be sure to tell me what the entries of the cells of your box are. Which model is indicated to be the best model in the P-Q box? Explain your reasoning.

⑥

		Q		
		0	1	2
P	0	985.1017 987.6342 30.39 (0.1723)	977.6966 982.7618 18.01 (0.7568)	976.0719 983.6697 15.89 (0.5214)
	1	974.0883 979.1535 16.23 (0.8452)	974.1618 981.7596 14.96 (0.8641)	
	2	973.9127 981.5105 15.05 (0.8602)		

Legend: AIC
in cells SBC
Q₂₄
(p-value) of Q₂₄

2

Reasoning: The AIC chooses the AR(2) model, while the SBC chooses the AR(1) model. The ACF and PACF favor the AR(1) model. The overfitting exercise below will support the AR(1) model over the AR(2) model. The residuals of both models are i.i.d.
19. Use **Computer Output #2** to conduct an overfitting exercise on the model you chose from the P-Q box. Below, report the overfitting coefficient of each overfitting model and its corresponding t-statistic. What conclusion do you draw from the overfitting exercise? Explain your answer.

2.5

Overfitting Model 1 is ARMA(2, 0).
The overfitting coefficient is 0.15330. AR(1, 2) coefficient
The T-statistic of the overfitting coefficient is 1.47.
Therefore the overfitting coefficient from this model is statistically (significant/insignificant). Circle one alternative.

2.5

Overfitting Model 2 is ARMA(1, 1).
The overfitting coefficient is 0.32538. MA(1, 1) coefficient
The T-statistic of the overfitting coefficient is 1.32.
Therefore the overfitting coefficient from this model is statistically (significant/insignificant). Circle one alternative.

2

My conclusion is From the overfitting exercises we see that the extra coefficients added to the AR(1) model are statistically insignificant therefore we choose the AR(1) model as our final model.

2

20. In the below space write out the final model that you have chosen for the Y time series in **Computer Output #2** with accompanying t-statistics, standard errors, goodness-of-fit measures, and a test statistic for white noise residuals with accompanying p-value. (You can report your estimated model either in the intercept-form or the deviation-from-mean form.)

Intercept form:
$$\Delta y_t = 31.15467 + 0.36274 \Delta y_{t-1} + \hat{a}_t \quad (\Delta y_t - 45.88861) = 0.36274 \cdot (\Delta y_{t-1} - 45.88861) + \hat{a}_t$$

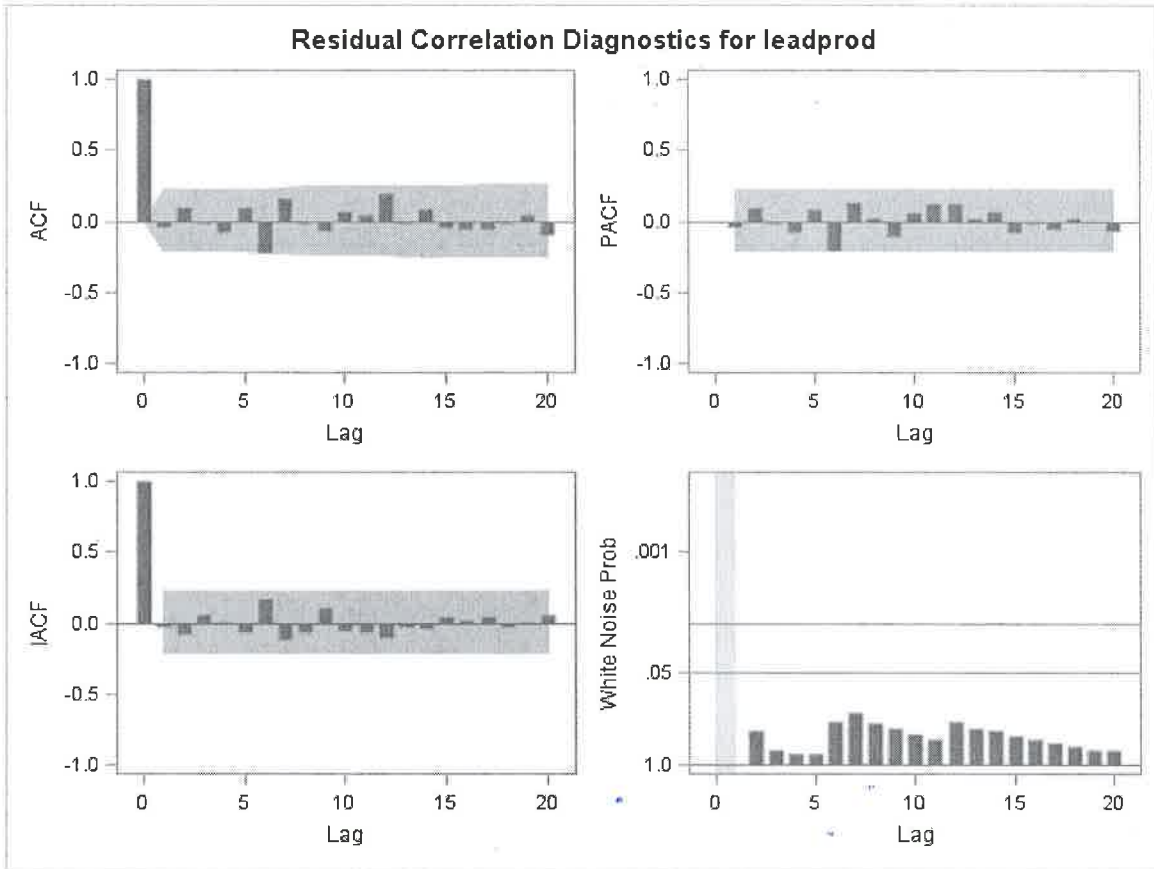
(0.09757)

2

21. One reason we use Information Criteria, tests for white noise residuals, and overfitting exercises to pick "best" Box-Jenkins models is because
- a. Choosing the wrong Box-Jenkins model can lead to poor forecasting accuracy.
 - b. Sometimes the sample ACF and PACF functions are not pristine in the sense that they don't sharply distinguish between competing Box-Jenkins models.
 - c. Box-Jenkins models whose residuals are not white noise are incomplete in that they have not explained all of the variation in the times series and, therefore, more parameters need to be added to the B-J model to produce more accurate forecasts.
 - d. All of the above statements are true.

AIC = 974.0883
SBC = 979.15
Q₂₄ = 16.23
p = 0.854

22. Consider the following graph:



Are the residuals of this fitted Box-Jenkins model white noise? Explain:

② Yes, the residuals of this model are white noise. The ACF and PACF do not have any significant spikes in them and the Q-statistics at the various 2-20 lags all have p-values greater than 0.05. All of these items indicate white noise residuals.

② 23. When forecasting aggregate sales by summing up individual product sales forecasts, we are utilizing the bottom-up approach to forecasting aggregate sales.

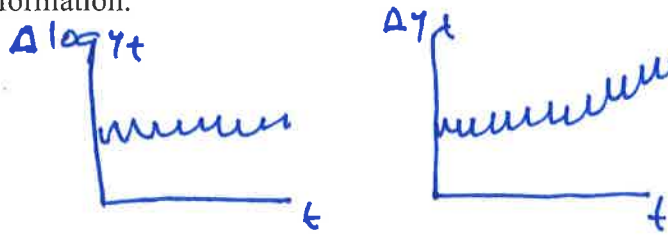
② 24. When forecasting individual product sales from the aggregate sales forecast, we are utilizing the top-down approach to producing individual product sales forecasts.

② 25. The purpose of looking at the SAS programs MCARLO_Det_Trend_Pred_Intervals.sas and MCARLO_RW_Pred_Intervals.sas during our class was to compare the prediction intervals of stochastic trends versus deterministic trends.

When the data contains a stochastic trend the deterministic trend prediction intervals are too narrow and thus too optimistic. When the data contains a deterministic trend the stochastic trend prediction intervals are too wide and thus are too pessimistic.

2

26. Suppose that $\Delta \log y_t$ is the correct transformation of a time series to stationarity. Draw a diagram below that has Δy_t on the y-axis and time (t) on the x-axis and then in the graph draw the Δy_t time series that shows that the level transformation is the incorrect transformation.



The incorrect transform Δy_t is slowly trending up and becoming more variable.

2

27. Consider the following output produced by the SAS Macro %logtest:

TRANS	LOGLIK	RMSE	AIC	SBC
NONE	-252.221	53.0128	516.442	530.267
LOG	-219.245	46.2693	450.490	464.314

In this case which transformation of the data is preferred? Explain your answer.

The log transformation is to be preferred. The %log test macro produces the smallest RMSE, AIC, and SBC for the log transform and the largest log likelihood value.

2

28. Suppose that the last available observation on y is $y_T = 100$. Further suppose that the y_t series has a unit root in it and that we have built a good Box-Jenkins model that produced the two forecasts $\widehat{\Delta y_{T+1}} = 20$ and $\widehat{\Delta y_{T+2}} = 10$. Then we know that $\widehat{y_{T+2}} =$

130

$$\widehat{y_{T+2}} = 100 + 20 + 10 = y_T + \widehat{\Delta y_{T+1}} + \widehat{\Delta y_{T+2}}$$

29. Suppose you have applied ordinary least squares model to a DTDS model that produces the following table.

OLS regression to get the DW statistic

The REG Procedure
Model: MODEL1
Dependent Variable: TOT

Durbin-Watson D	0.432
Pr < DW	<.0001
Pr > DW	1.0000
Number of Observations	312
1st Order Autocorrelation	0.783

Note: Pr<DW is the p-value for testing positive autocorrelation, and Pr>DW is the p-value for testing negative autocorrelation

2

(a) What are the null and alternative hypotheses of this test?

H_0 : The errors of the model are uncorrelated
 H_1 : The errors of the model are autocorrelated

2

(b) Given the above result, what is the conclusion of this test?

Since the DW is $< .0001$ and thus we reject H_0 and accept H_1 that the errors of the model are autocorrelated.

2

(c) In further testing of the DTDS model that you are investigating, would you be inclined to use Ordinary Least Squares Output (Proc Reg) or Generalized Least Squares Output (Proc Autoreg)? Explain your answer.

Since the errors of the model are autocorrelated we should use the Generalized Least Squares method for estimation and inference (i.e. Proc Autoreg)

30. Given the computer output below, does it look like there is significant seasonality in the data? (It is assumed that the proper choice of OLS and GLS has been chosen for the DTDS model.) Explain your reasoning. What are the null and alternative hypotheses of the test result reported in this output?

4

The below F-test is testing the joint significance of the dummy variable coefficients in the DTDS model. The null hypothesis is H_0 : no seasonality in data while H_1 : seasonality is present in the data. Since the probability of the F-statistic is less than 0.05 we reject H_0 and accept H_1 . There is seasonality in the data.

		Test		
Source	DF	Mean Square	F Value	Pr > F
Numerator	11	29317586854	24.37	<.0001
Denominator	298	1202946247		

31. Consider the computer output below. Suppose that the DTDS model has produced the following output. Which months of the year are weak? Which months are strong? Which is the weakest month? Which is the strongest month? Thoroughly explain your answer.

4

Obs	sum	d1a	d2a	d3a	d4a	d5a	d6a
1	1.97E-15	-0.0231	-0.146	0.21651	-0.1997	-0.2707	0.19076
	d7a	d8a	d9a	d10a	d11a	d12a	
	0.42398	0.59343	-0.37016	-0.22391	-0.27397	0.082865	

The strongest month is the 8th month (August). This month has the largest positive coefficient (0.59343)
The weakest month is the 9th month (September). This month has the most negative coefficient (-0.37016)
The weak months are those with negative signs {Jan., Feb., Apr., May, Sept., Oct., Nov.}

The strong months have positive coefficients {Mar., June, July, Aug., Dec.}

Computer Output #1

Null Hypothesis: Y has a unit root
 Exogenous: None
 Lag Length: 1 (Automatic - based on SIC, maxlag=11)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	5.312408	1.0000
Test critical values:		
1% level	-2.590340	
5% level	-1.944364	
10% level	-1.614441	

*Mackinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
 Dependent Variable: D(Y)
 Method: Least Squares
 Date: 10/19/13 Time: 11:52
 Sample (adjusted): 3 94
 Included observations: 92 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Y(-1)	0.004872	0.000917	5.312408	0.0000
D(Y(-1))	0.342754	0.094485	3.627604	0.0005
R-squared	0.147427	Mean dependent var		51.82283
Adjusted R-squared	0.137954	S.D. dependent var		45.59209
S.E. of regression	42.33063	Akaike info criterion		10.35040
Sum squared resid	161269.4	Schwarz criterion		10.40522
Log likelihood	-474.1183	Hannan-Quinn criter.		10.37252
Durbin-Watson stat	2.096705			

Null Hypothesis: Y has a unit root
 Exogenous: Constant
 Lag Length: 1 (Automatic - based on SIC, maxlag=11)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	0.820061	0.9939
Test critical values:		
1% level	-3.503049	
5% level	-2.893230	
10% level	-2.583740	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
 Dependent Variable: D(Y)
 Method: Least Squares
 Date: 10/19/13 Time: 11:53
 Sample (adjusted): 3 94
 Included observations: 92 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Y(-1)	0.002599	0.003170	0.820061	0.4144
D(Y(-1))	0.343837	0.094727	3.629753	0.0005
C	16.49044	22.01721	0.748979	0.4558
R-squared	0.152767	Mean dependent var		51.82283
Adjusted R-squared	0.133728	S.D. dependent var		45.59209
S.E. of regression	42.43425	Akaike info criterion		10.36585
Sum squared resid	160259.3	Schwarz criterion		10.44809
Log likelihood	-473.8293	Hannan-Quinn criter.		10.39904
F-statistic	8.023939	Durbin-Watson stat		2.107897
Prob(F-statistic)	0.000625			

Null Hypothesis: Y has a unit root
 Exogenous: Constant, Linear Trend
 Lag Length: 2 (Automatic - based on SIC, maxlag=11)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.983249	0.6023
Test critical values:		
1% level	-4.062040	
5% level	-3.459950	
10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
 Dependent Variable: D(Y)
 Method: Least Squares
 Date: 10/19/13 Time: 11:55
 Sample (adjusted): 4 94
 Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Y(-1)	-0.047957	0.024181	-1.983249	0.0505
D(Y(-1))	0.293021	0.104490	2.804304	0.0062
D(Y(-2))	0.157670	0.100263	1.572572	0.1195
C	235.8543	107.2270	2.199580	0.0305
@TREND("1")	2.705673	1.306515	2.070909	0.0414
R-squared	0.196223	Mean dependent var		52.47473
Adjusted R-squared	0.158838	S.D. dependent var		45.41148
S.E. of regression	41.64909	Akaike info criterion		10.34981
Sum squared resid	149179.6	Schwarz criterion		10.48777
Log likelihood	-465.9165	Hannan-Quinn criter.		10.40547
F-statistic	5.248705	Durbin-Watson stat		1.958721
Prob(F-statistic)	0.000786			

CODE FOR COMPUTER OUTPUT # 2

```
data MT;
input y;
datalines;
4958.900
4857.800
4850.300
4936.600
5032.500
4997.300
.
.
.
9485.600
9518.200
9552.000
9625.500
;

proc arima data = MT;
  identify var = y(1);
  e p = 0 q = 0;
  e p = 1 q = 0;
  e p = 2 q = 0;
  e p = 0 q = 1;
  e p = 0 q = 2;
  e p = 1 q = 1;
run;
```

COMPUTER OUTPUT # 2

The ARIMA Procedure

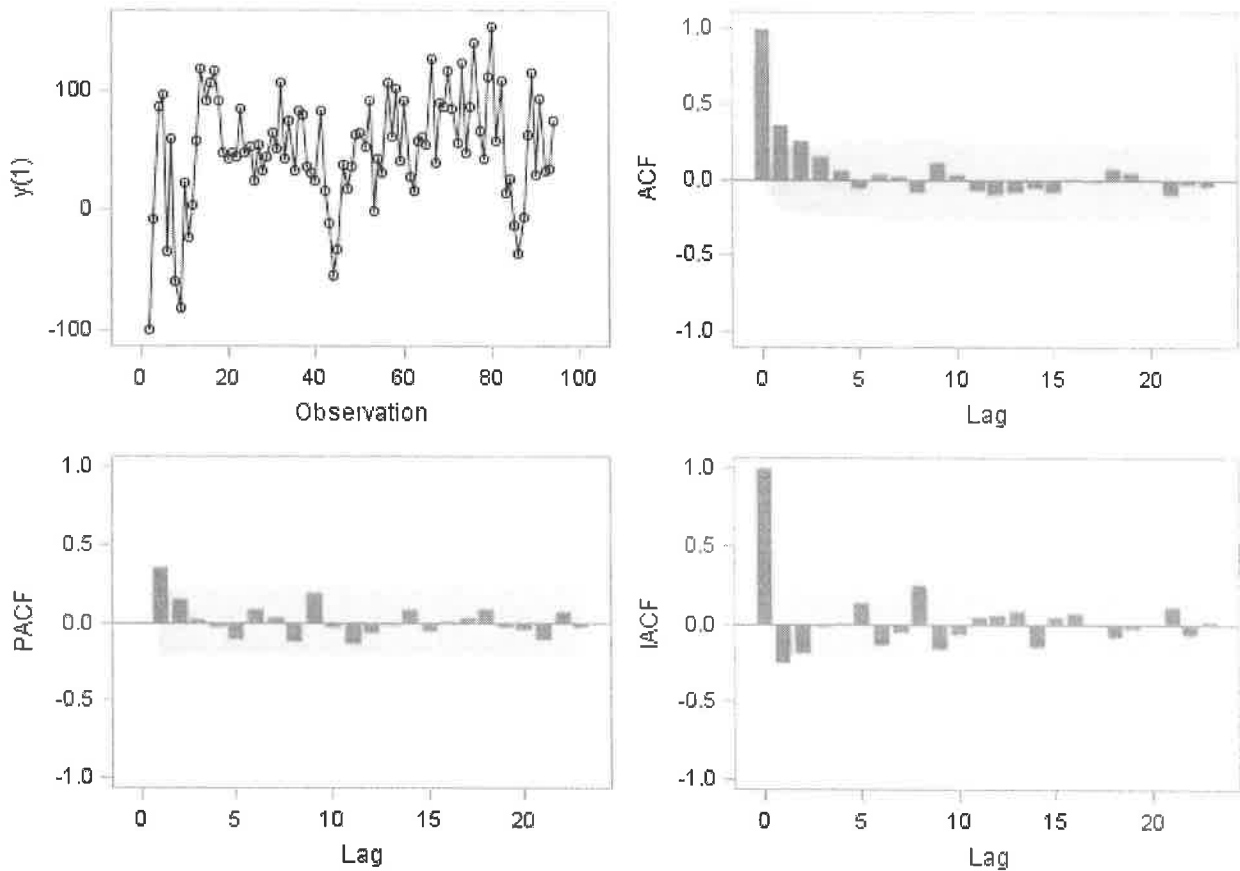
Name of Variable = y

Period(s) of Differencing	1
Mean of Working Series	50.17849
Standard Deviation	47.77749
Number of Observations	93
Observation(s) eliminated by differencing	1

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations						
6	22.15	6	0.0011	0.360	0.261	0.153	0.061	-0.053	0.029	
12	26.08	12	0.0105	0.027	-0.082	0.112	0.038	-0.069	-0.103	
18	28.50	18	0.0548	-0.079	-0.055	-0.078	0.004	-0.019	0.075	

Trend and Correlation Analysis for y(1)



Conditional Least Squares Estimation

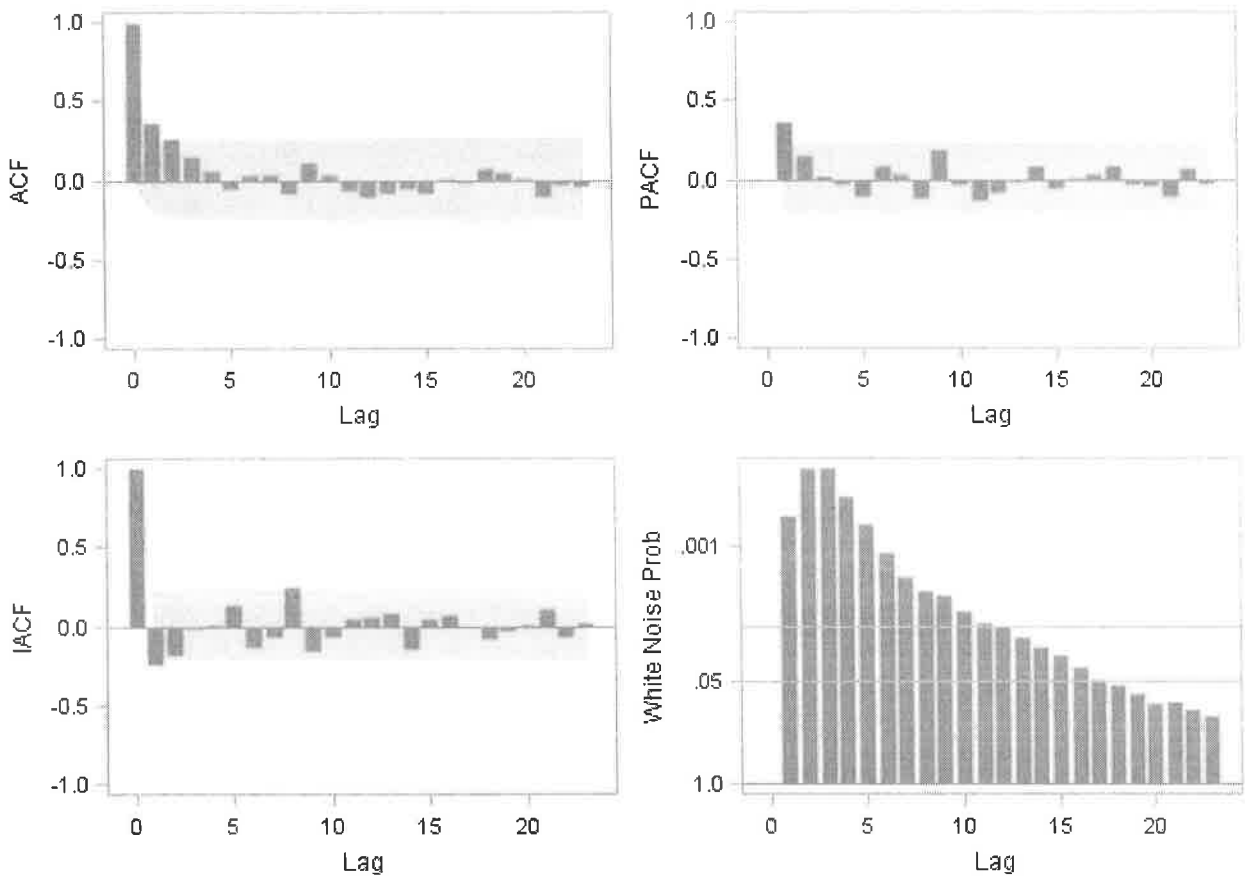
Parameter	Estimate	Standard Error	t Value	Approx Pr > t	Lag
MU	50.17849	4.98115	10.07	<.0001	0
Constant Estimate	50.17849				
Variance Estimate	2307.501				
Std Error Estimate	48.03645				
AIC	985.1017				
SBC	987.6343				
Number of Residuals	93				

* AIC and SBC do not include log determinant.

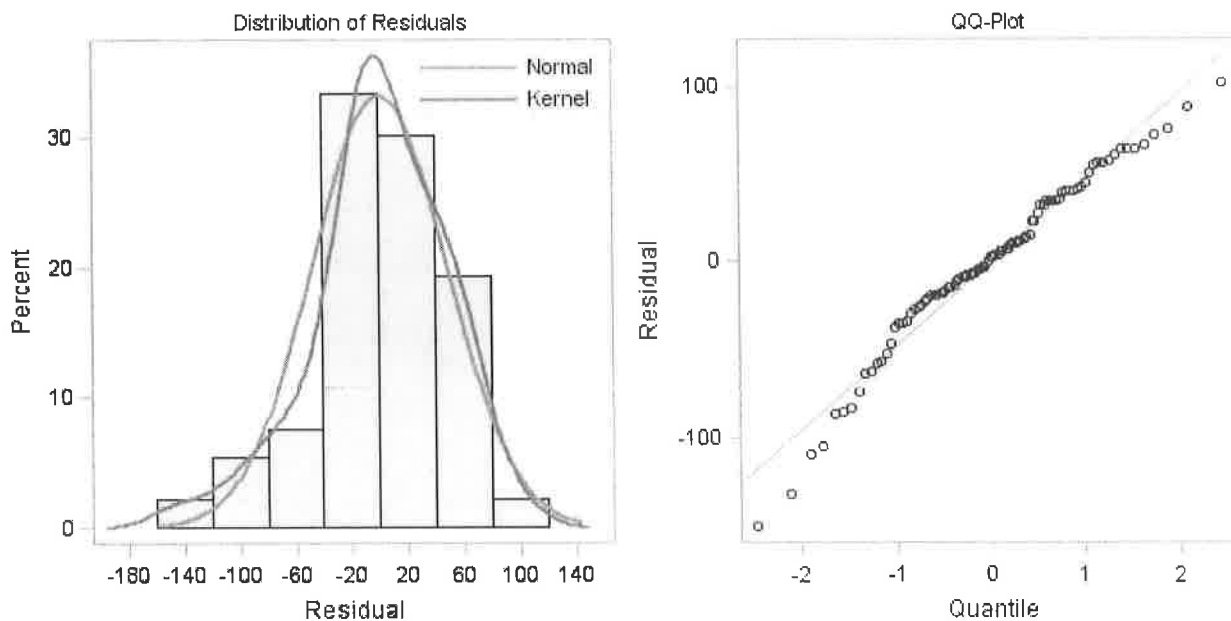
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	22.15	6	0.0011	0.360	0.261	0.153	0.061	-0.053	0.029
12	26.08	12	0.0105	0.027	-0.082	0.112	0.038	-0.069	-0.103
18	28.50	18	0.0548	-0.079	-0.055	-0.078	0.004	-0.019	0.075
24	30.39	24	0.1723	0.045	0.012	-0.102	-0.028	-0.045	0.002

Residual Correlation Diagnostics for y(1)



Residual Normality Diagnostics for $y(1)$



Model for variable y

Estimated Mean 50.17849

Period(s) of Differencing 1

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > t	Lag
MU	48.88861	7.27282	6.72	<.0001	0
AR1,1	0.36274	0.09787	3.71	0.0004	1

Constant Estimate 31.15467

Variance Estimate 2028.233

Std Error Estimate 45.03591

AIC 974.0883

SBC 979.1535

Number of Residuals 93

* AIC and SBC do not include log determinant.

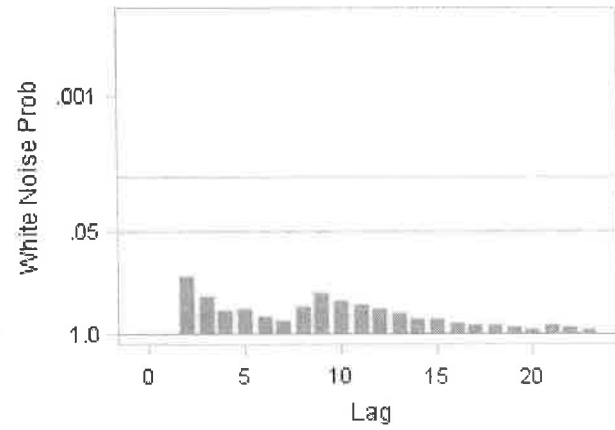
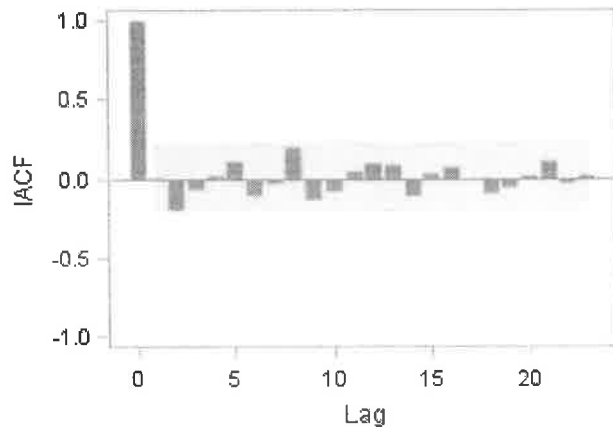
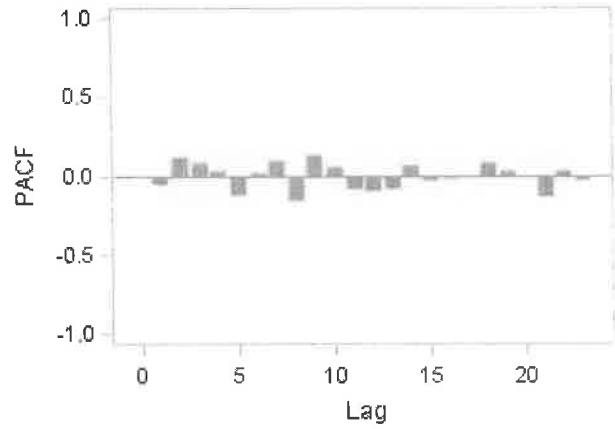
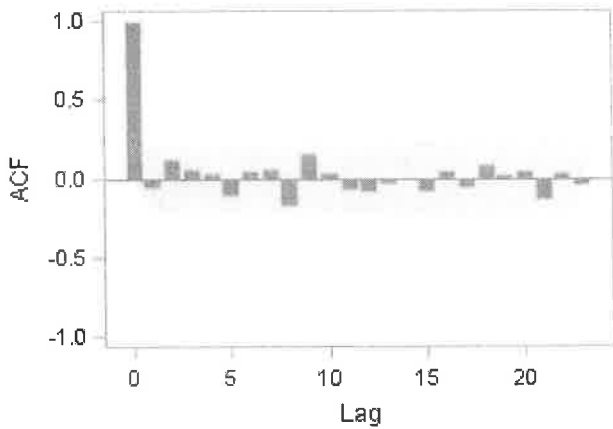
Correlations of Parameter Estimates

Parameter	MU	AR1,1
MU	1.000	-0.021
AR1,1	-0.021	1.000

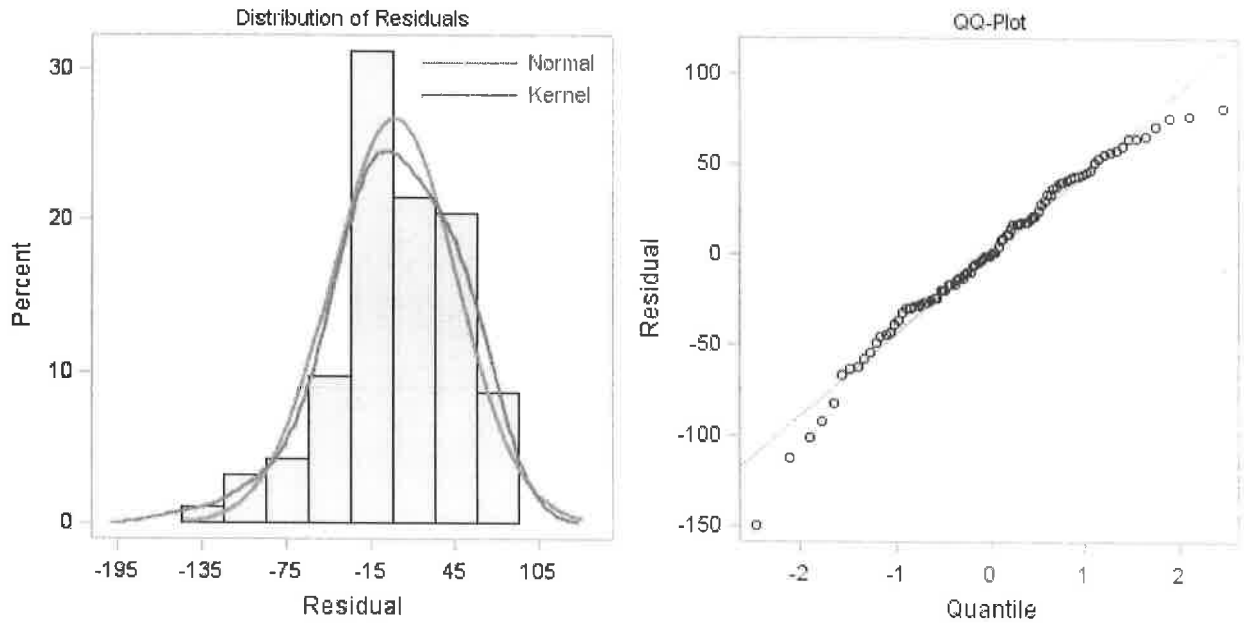
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	3.83	5	0.5741	-0.055	0.126	0.064	0.040	-0.107	0.052
12	10.88	11	0.4532	0.060	-0.164	0.163	0.032	-0.061	-0.072
18	13.21	17	0.7222	-0.032	-0.006	-0.075	0.050	-0.058	0.088
24	16.23	23	0.8452	0.026	0.041	-0.126	0.028	-0.047	0.056

Residual Correlation Diagnostics for y(1)



Residual Normality Diagnostics for y(1)



Model for variable y

Estimated Mean 48.88861
Period(s) of Differencing 1

Autoregressive Factors

Factor 1: $1 - 0.36274 B^{**}(1)$

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > t	Lag
MU	47.76943	8.49179	5.63	<.0001	0
AR1,1	0.30844	0.10446	2.95	0.0040	1
AR1,2	0.15330	0.10456	1.47	0.1461	2

Constant Estimate 25.71258

Variance Estimate 2003.35

Std Error Estimate 44.7588

AIC 973.9127

SBC 981.5105
Number of Residuals 93

* AIC and SBC do not include log determinant.

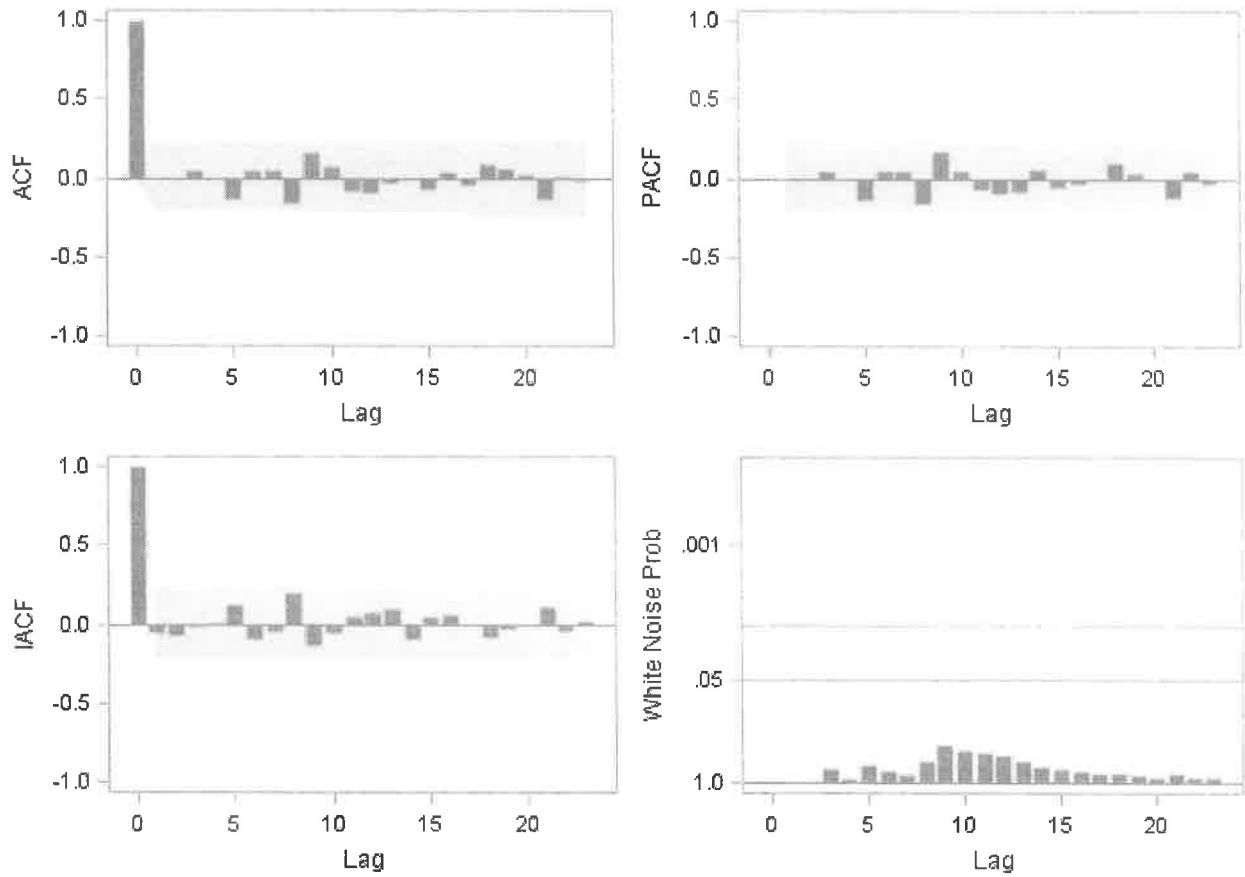
Correlations of Parameter Estimates

Parameter	MU	AR1,1	AR1,2
MU	1.000	-0.018	-0.036
AR1,1	-0.018	1.000	-0.365
AR1,2	-0.036	-0.365	1.000

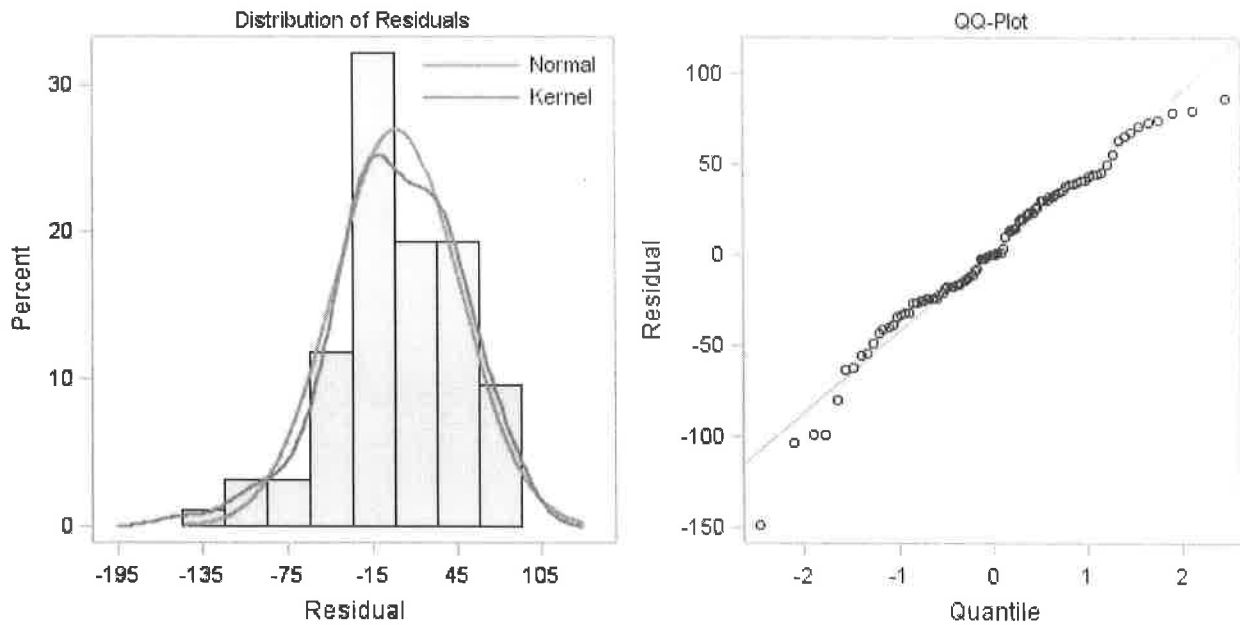
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.14	4	0.7095	-0.003	-0.003	0.048	-0.002	-0.128	0.052
12	9.96	10	0.4438	0.045	-0.160	0.169	0.072	-0.075	-0.085
18	11.81	16	0.7570	-0.025	-0.003	-0.065	0.037	-0.041	0.089
24	15.05	22	0.8602	0.057	0.028	-0.128	0.008	-0.016	0.075

Residual Correlation Diagnostics for $y(1)$



Residual Normality Diagnostics for $y(1)$



Model for variable y

Estimated Mean 47.76943

Period(s) of Differencing 1

Autoregressive Factors

Factor 1: 1 - 0.30844 B**(1) - 0.1533 B**(2)

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > t 	Lag
MU	49.71299	6.04443	8.22	<.0001	0
MA1,1	-0.27289	0.10104	-2.70	0.0082	1

Constant Estimate 49.71299

Variance Estimate 2108.473

Std Error Estimate 45.91811

AIC 977.6966

SBC 982.7618

Number of Residuals 93

* AIC and SBC do not include log determinant.

Correlations of Parameter Estimates

Parameter	MU	MA1,1
MU	1.000	0.005
MA1,1	0.005	1.000

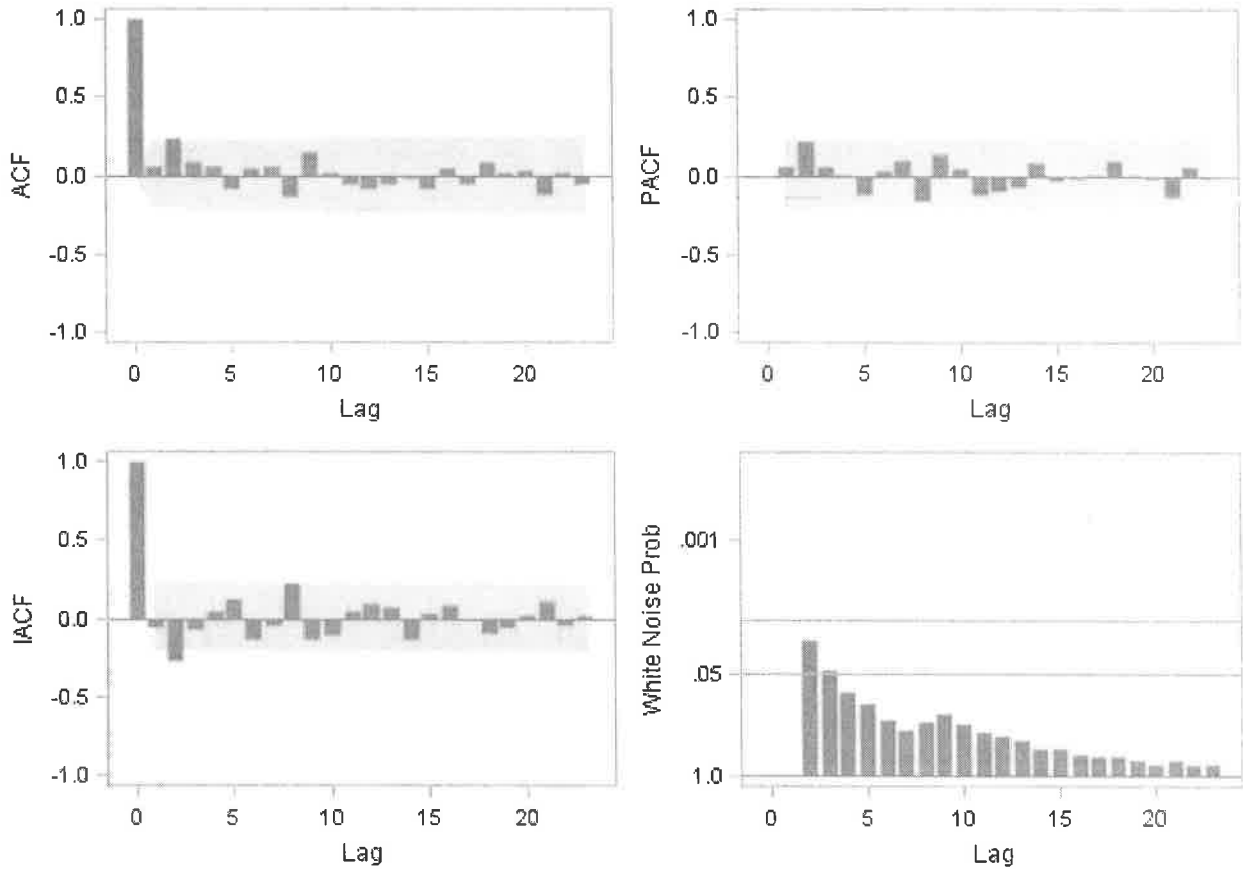
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.50	5	0.1859	0.059	0.233	0.082	0.064	-0.081	0.040
12	12.91	11	0.2991	0.053	-0.135	0.144	0.016	-0.055	-0.079
18	15.40	17	0.5665	-0.052	-0.021	-0.081	0.041	-0.052	0.087

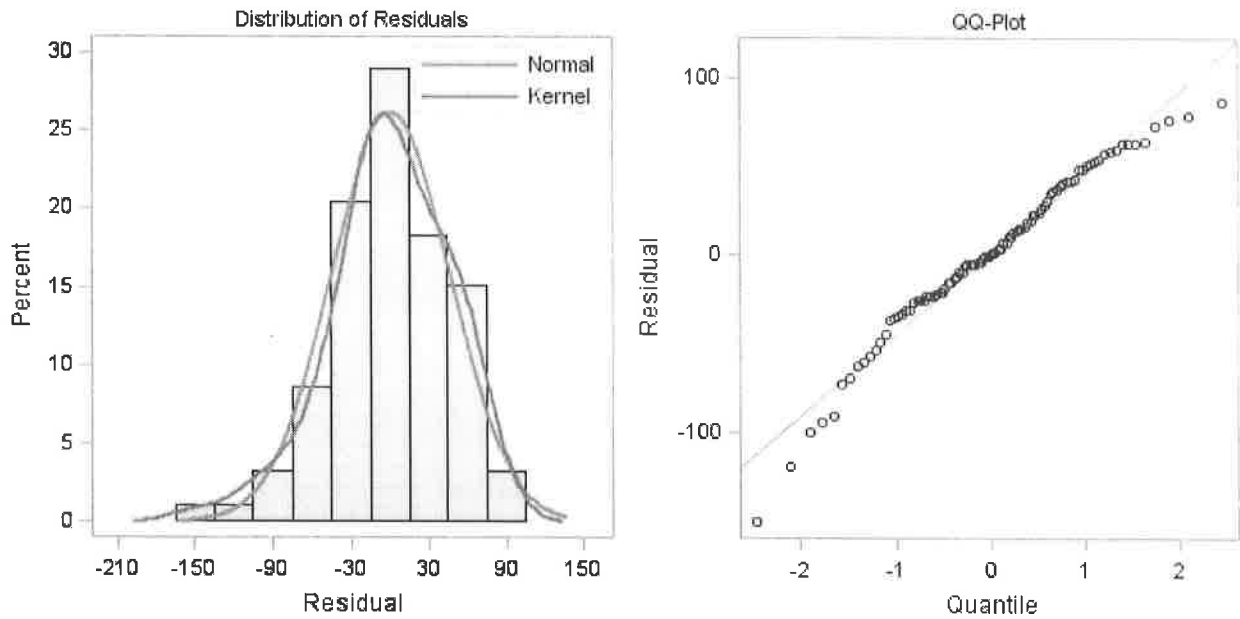
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
24	18.01	23	0.7568	0.017	0.040	-0.120	0.019	-0.059	0.034

Residual Correlation Diagnostics for y(1)



Residual Normality Diagnostics for y(1)



Model for variable y

Estimated Mean 49.71299

Period(s) of Differencing 1

Moving Average Factors

Factor 1: $1 + 0.27289 B^{**}(1)$

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > t	Lag
MU	49.09344	6.83021	7.19	<.0001	0
MA1,1	-0.28720	0.10419	-2.76	0.0071	1
MA1,2	-0.17595	0.10429	-1.69	0.0950	2

Constant Estimate 49.09344

Variance Estimate 2050.408

Std Error Estimate 45.28143

AIC 976.0719

SBC 983.6697
Number of Residuals 93

*** AIC and SBC do not include log determinant.**

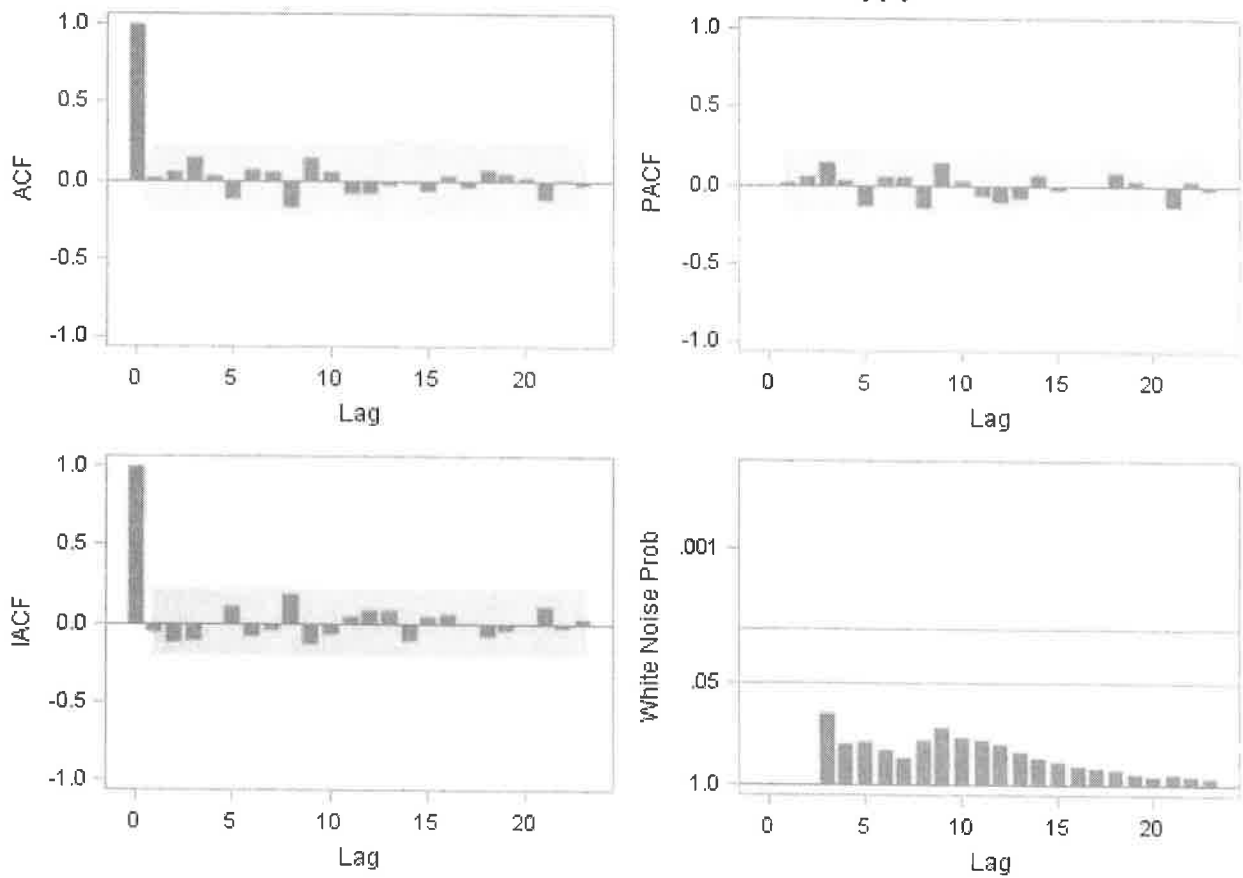
Correlations of Parameter Estimates

Parameter	MU	MA1,1	MA1,2
MU	1.000	0.007	0.014
MA1,1	0.007	1.000	0.240
MA1,2	0.014	0.240	1.000

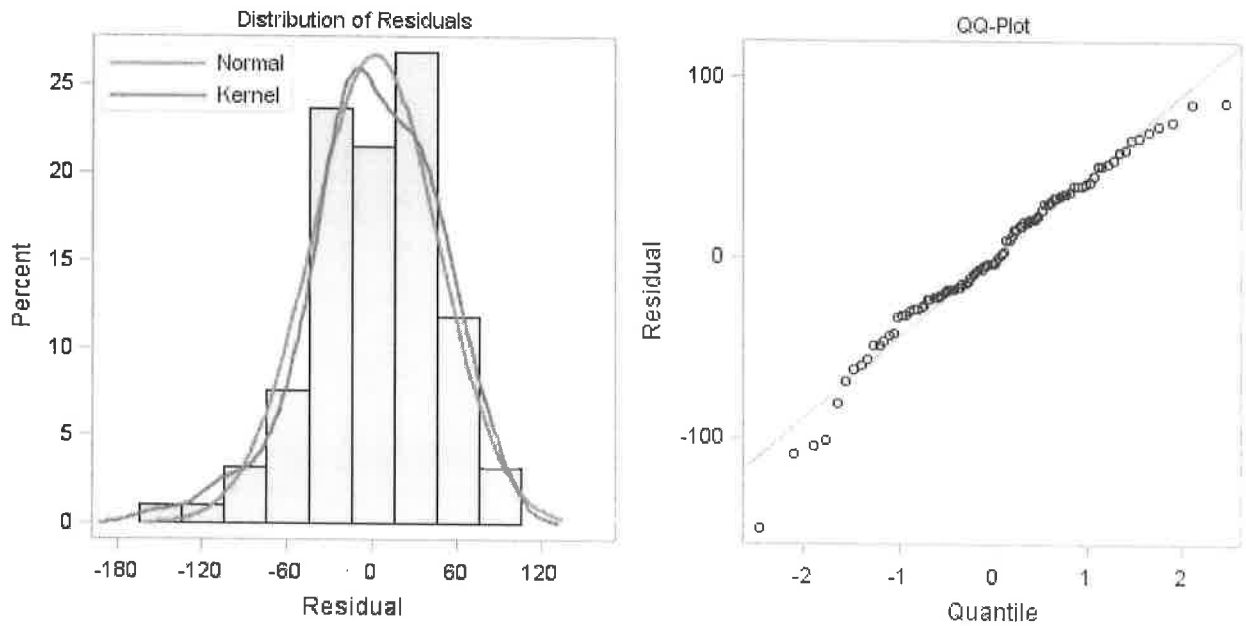
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	4.47	4	0.3459	0.027	0.056	0.145	0.036	-0.117	0.073
12	11.90	10	0.2920	0.055	-0.167	0.153	0.057	-0.084	-0.078
18	13.51	16	0.6351	-0.024	-0.017	-0.070	0.038	-0.045	0.069
24	15.89	22	0.8214	0.048	0.025	-0.116	0.008	-0.034	0.043

Residual Correlation Diagnostics for y(1)



Residual Normality Diagnostics for y(1)



Model for variable y

Estimated Mean 49.09344
Period(s) of Differencing 1

Moving Average Factors

Factor 1: $1 + 0.2872 B^{**}(1) + 0.17595 B^{**}(2)$

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > t	Lag
MU	47.70871	8.73031	5.46	<.0001	0
MA1,1	0.32538	0.24581	1.32	0.1890	1
AR1,1	0.64697	0.19839	3.26	0.0016	1

Constant Estimate 16.84271
Variance Estimate 2008.722
Std Error Estimate 44.81877
AIC 974.1618
SBC 981.7596
Number of Residuals 93

* AIC and SBC do not include log determinant.

Correlations of Parameter Estimates

Parameter	MU	MA1,1	AR1,1
MU	1.000	-0.043	-0.059
MA1,1	-0.043	1.000	0.914
AR1,1	-0.059	0.914	1.000

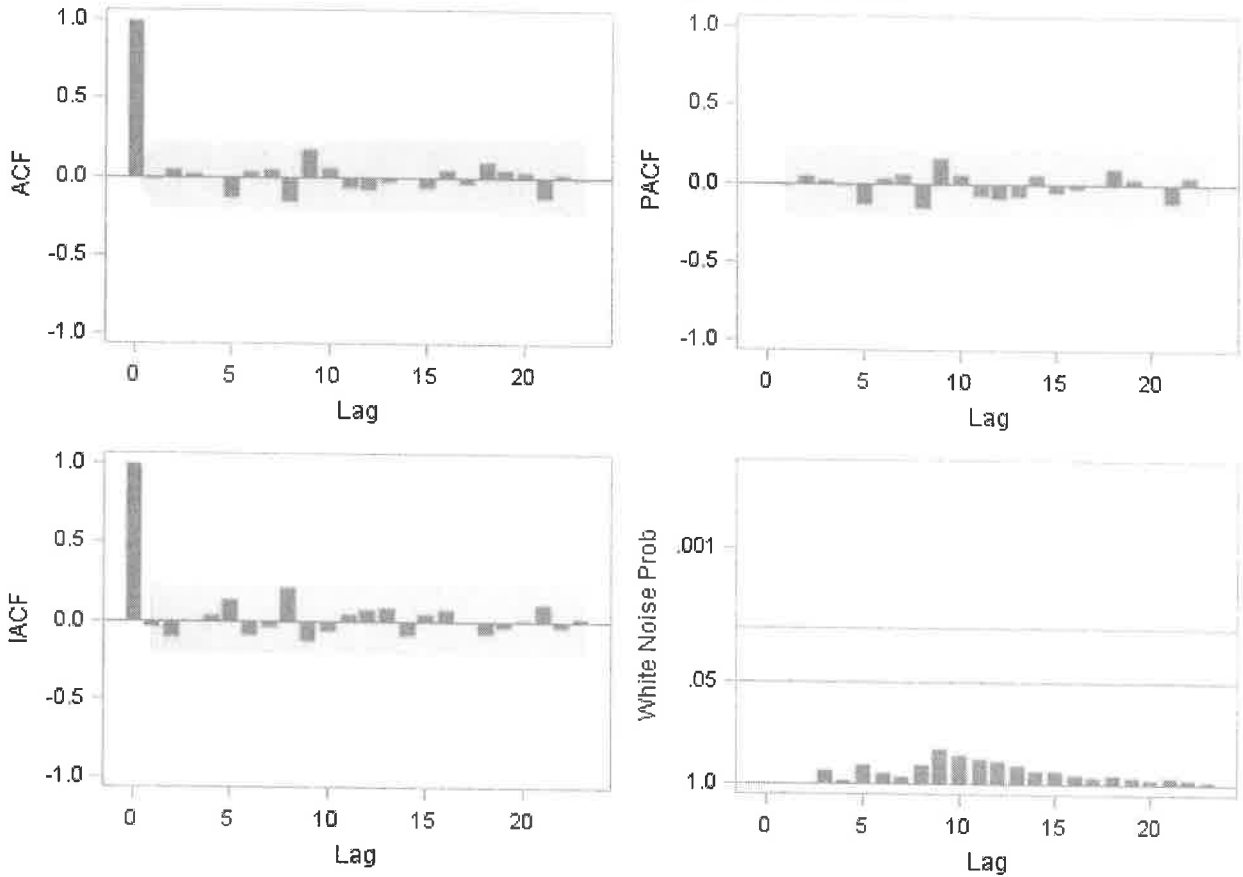
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.17	4	0.7036	-0.014	0.043	0.019	-0.010	-0.134	0.037
12	9.49	10	0.4866	0.044	-0.155	0.171	0.060	-0.065	-0.082

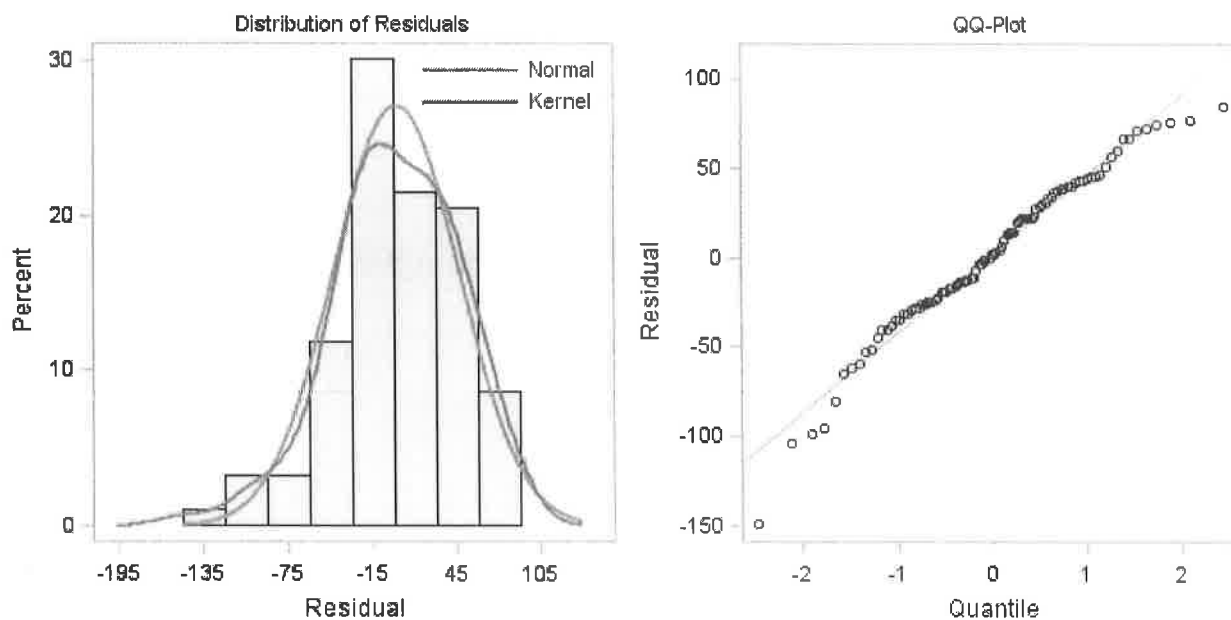
Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
18	11.68	16	0.7657	-0.033	-0.005	-0.068	0.043	-0.042	0.098
24	14.96	22	0.8641	0.049	0.035	-0.127	0.016	-0.022	0.077

Residual Correlation Diagnostics for y(1)



Residual Normality Diagnostics for y(1)



Model for variable y

Estimated Mean 47.70871

Period(s) of Differencing 1

Autoregressive Factors

Factor 1: $1 - 0.64697 B^{**}(1)$

Moving Average Factors

Factor 1: $1 - 0.32538 B^{**}(1)$