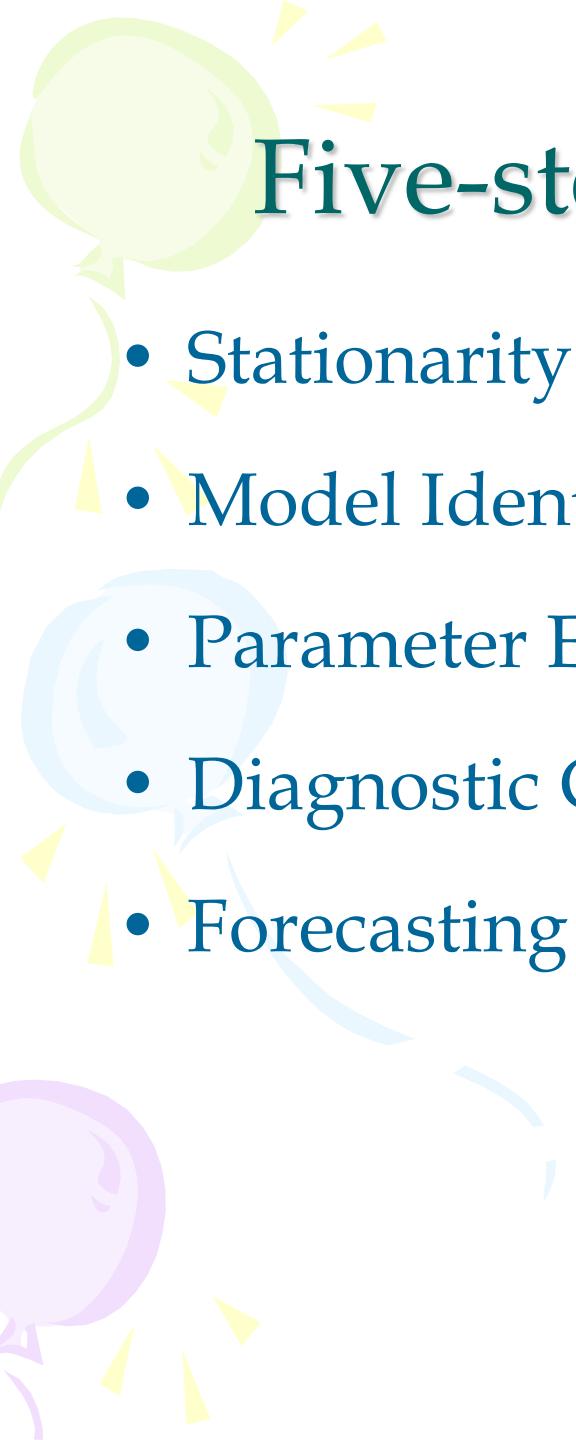


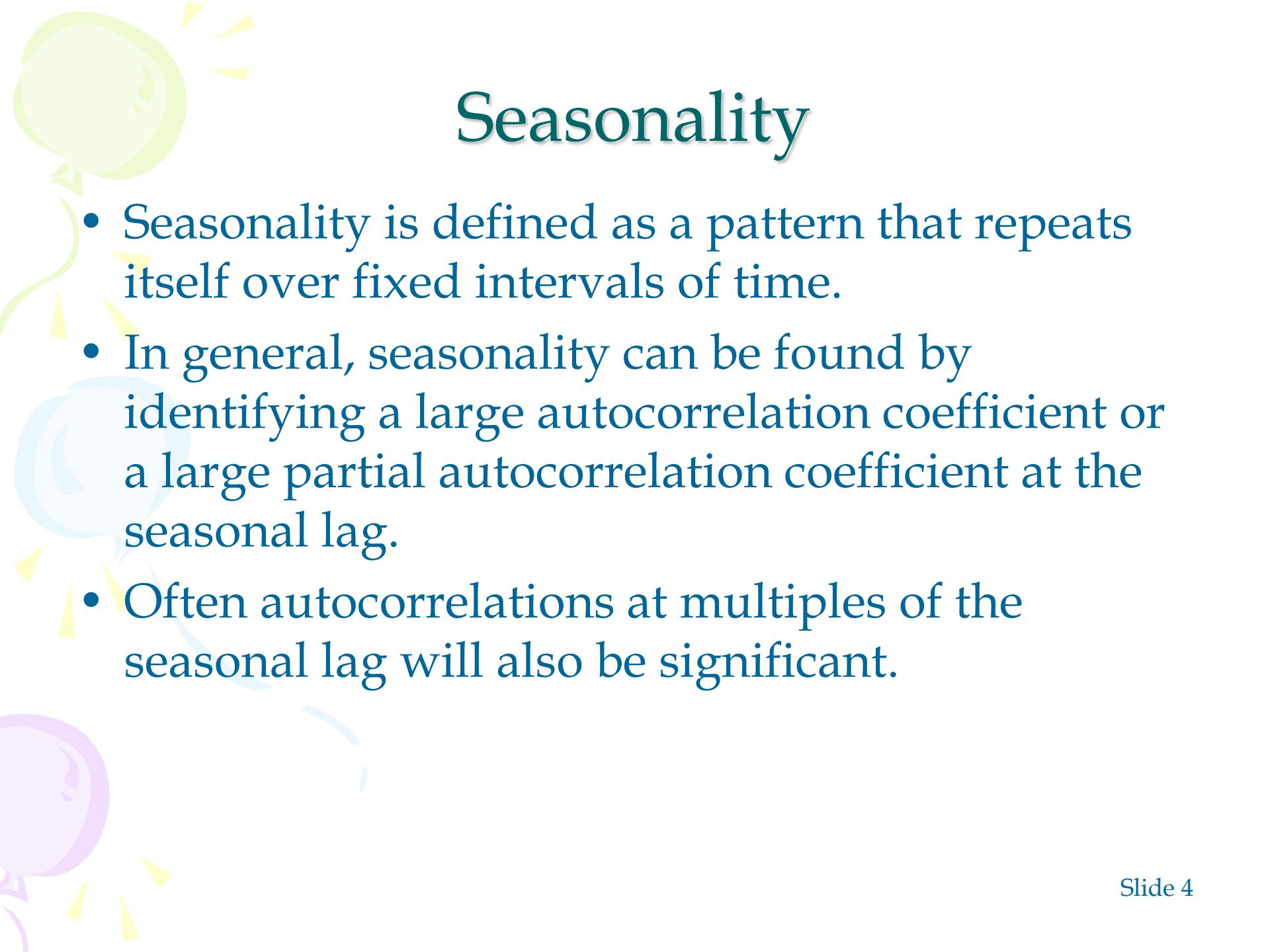
# **Box-Jenkins Seasonal Modeling**



# Five-step Iterative Procedures

- Stationarity Checking and Differencing
- Model Identification
- Parameter Estimation
- Diagnostic Checking
- Forecasting

# **Step One: Stationarity Checking and Differencing**



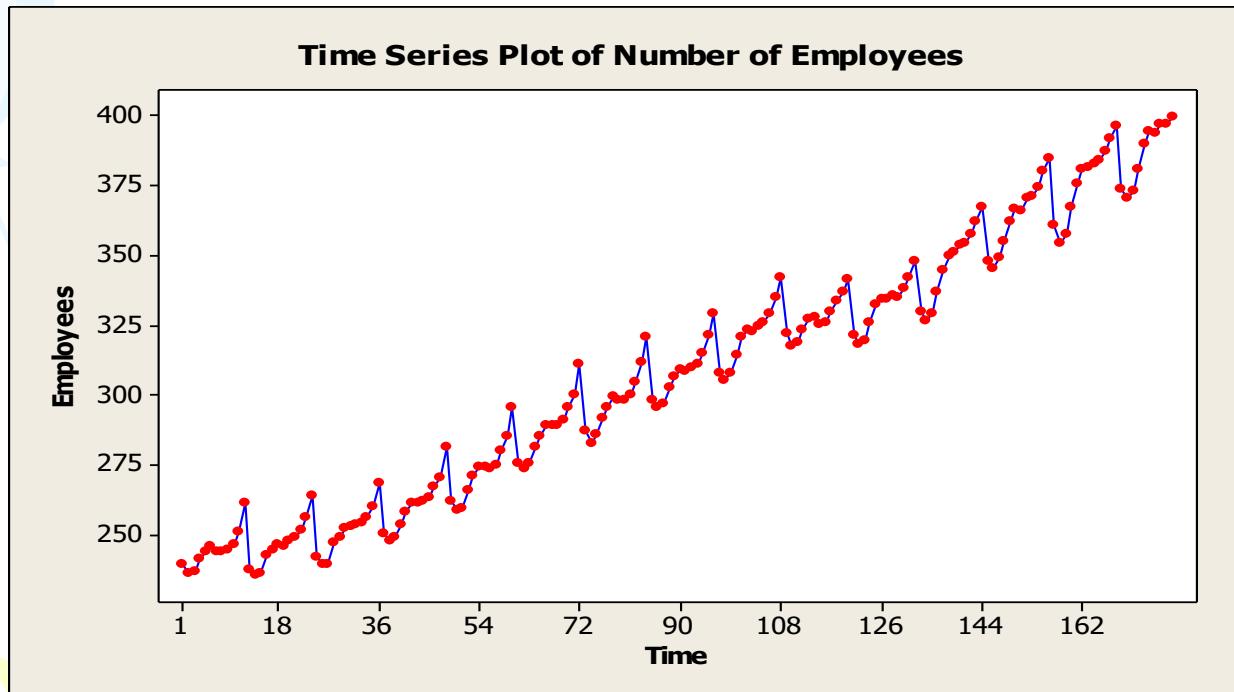
# Seasonality

- Seasonality is defined as a pattern that repeats itself over fixed intervals of time.
- In general, seasonality can be found by identifying a large autocorrelation coefficient or a large partial autocorrelation coefficient at the seasonal lag.
- Often autocorrelations at multiples of the seasonal lag will also be significant.

# Example: Employees

178 monthly values of the number of people in Wisconsin employed in “trade” are reported from 1961 to 1975.

- Dataset: employees.txt
- SAS program: ARIMA\_employees.sas



# Example: Employees

Lag	Covariance	Correlation	Autocorrelations													Std Error						
			-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9
0	2174.219	1.00000	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0
1	2111.301	0.97106	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.074953
2	2046.143	0.94109	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.127330
3	1990.467	0.91549	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.161754
4	1953.651	0.89855	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.188630
5	1923.082	0.88449	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.211313
6	1894.387	0.87130	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.231178
7	1857.165	0.85418	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.248944
8	1822.990	0.83846	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.264898
9	1795.368	0.82575	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.279410
10	1781.604	0.81942	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.292800
11	1766.588	0.81252	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.305411
12	1754.960	0.80717	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.317323
13	1689.253	0.77695	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.328655
14	1622.604	0.74629	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.338817
15	1565.605	0.72008	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.347929
16	1526.444	0.70207	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.356203
17	1493.548	0.68694	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.363894
18	1462.579	0.67269	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.371108
19	1424.437	0.65515	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.377896
20	1390.875	0.63971	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.384224
21	1363.633	0.62718	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.390162
22	1347.737	0.61987	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.395785
23	1328.662	0.61110	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.401202
24	1312.463	0.60365	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.406398
25	1248.092	0.57404	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.411404
26	1183.569	0.54437	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.415880
27	1127.791	0.51871	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.419864
28	1090.018	0.50134	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.423448
29	1058.246	0.48672	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.426770
30	1027.732	0.47269	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.429877
31	990.402	0.45552	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.432787
32	955.643	0.43953	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.435473
33	926.976	0.42635	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.437958
34	910.295	0.41868	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.440283
35	891.731	0.41014	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.442514
36	876.729	0.40324	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.444645

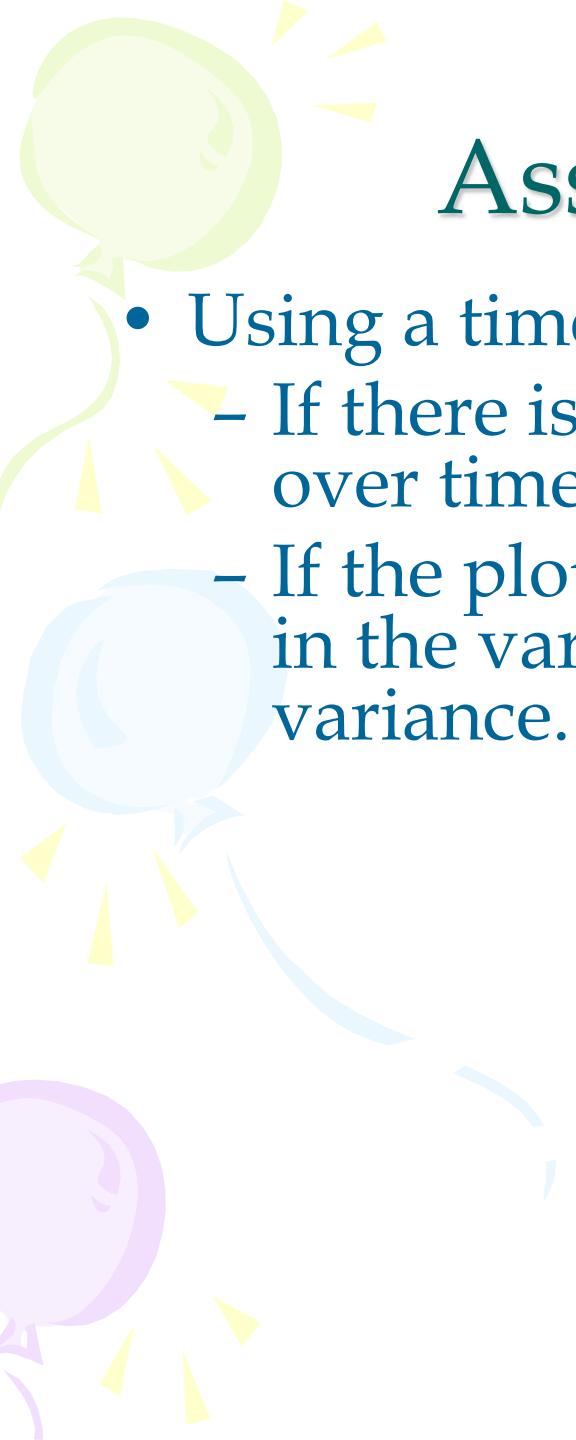
"." marks two standard errors

# Example: Employees

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	0.97106												*									
2	-0.03275												*	.								
3	0.06141												*	.								
4	0.13652												***	.								
5	0.04323												*	.								
6	0.02889												*	.								
7	-0.04794												*	.								
8	0.03610												*	.								
9	0.04774												*	.								
10	0.09973												**	.								
11	-0.00141												*	.								
12	0.05761												*	.								
13	-0.41758												*****	.								
14	0.00616												.									
15	0.01128												.									
16	0.03402												.									
17	0.02505												.									
18	0.01620												.									
19	-0.00012												.									
20	0.03095												.									
21	0.02301												.									
22	0.02393												.									
23	0.00786												.									
24	0.01425												.									
25	-0.24382												*****	.								
26	0.01064												.									
27	-0.01865												.									
28	0.01931												.									
29	0.01201												.									
30	0.00269												.									
31	0.00312												.									
32	-0.00752												.									
33	0.01229												.									
34	0.02577												.									
35	0.03366												.									
36	0.01177												.									

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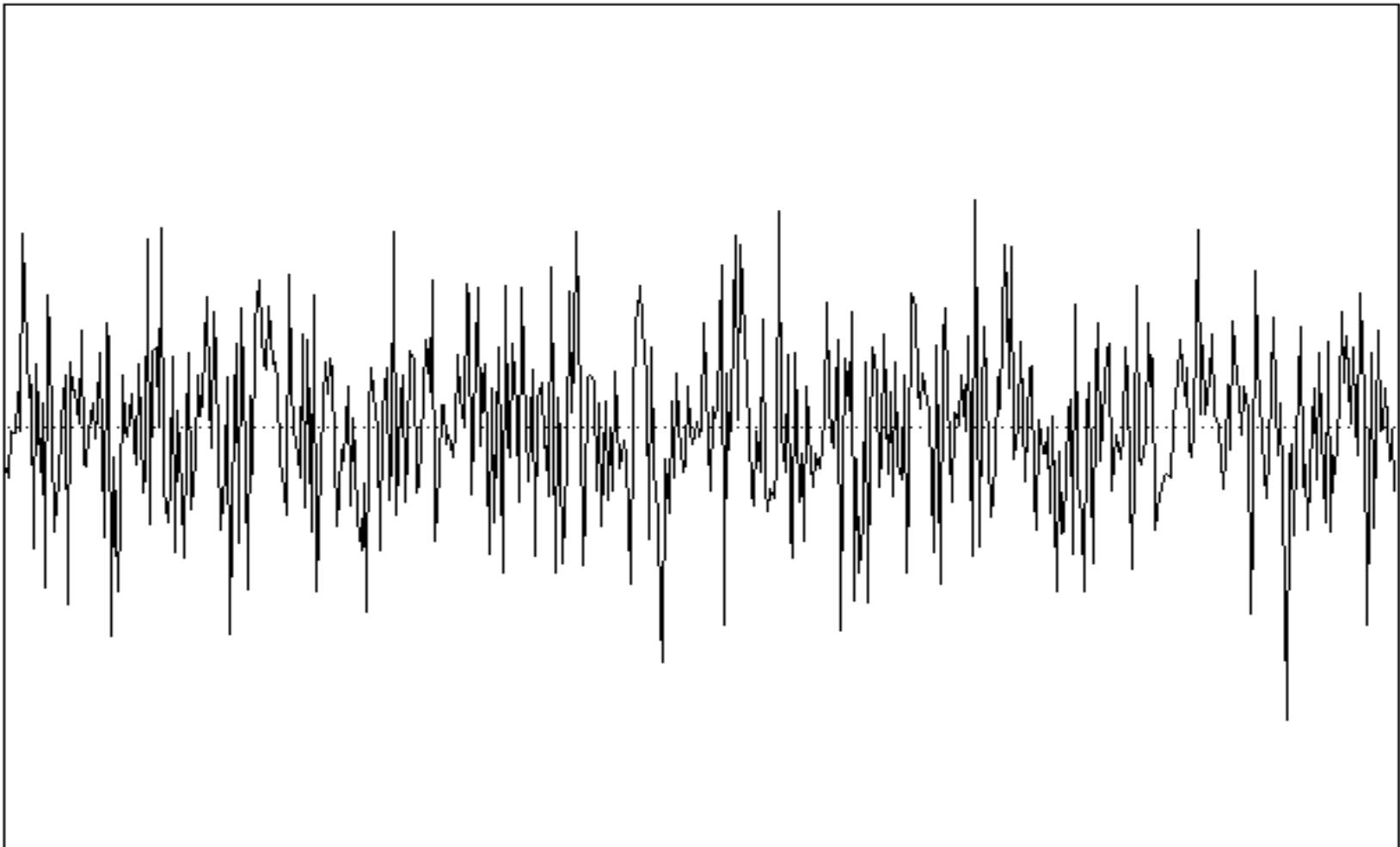
[Continue](#)



# Assessing Stationarity

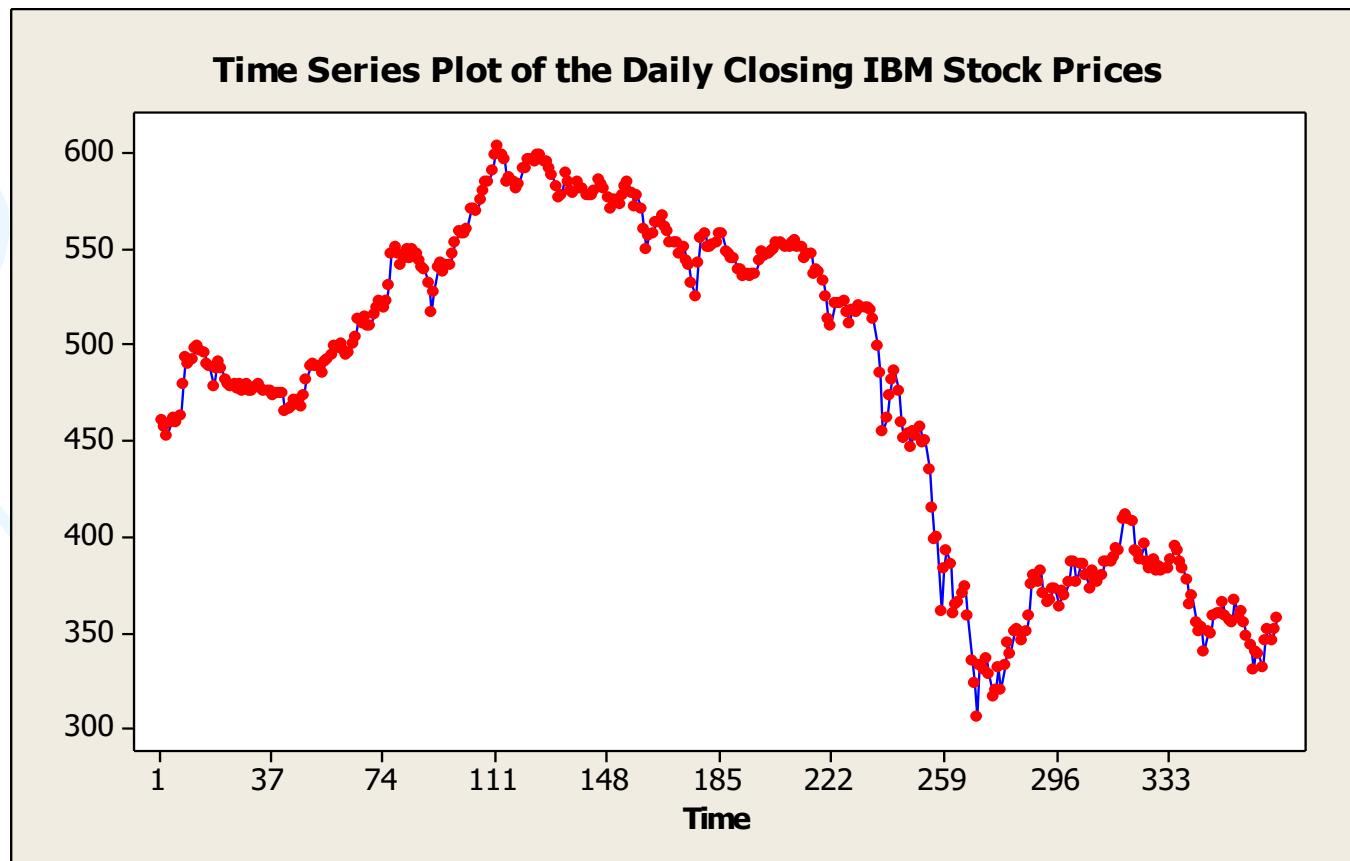
- Using a time series plot
  - If there is no evidence of a change in the mean over time, the series is stationary in the mean.
  - If the plotted series shows no obvious change in the variance over time, it is stationary in the variance.

# Example: Stationary Series



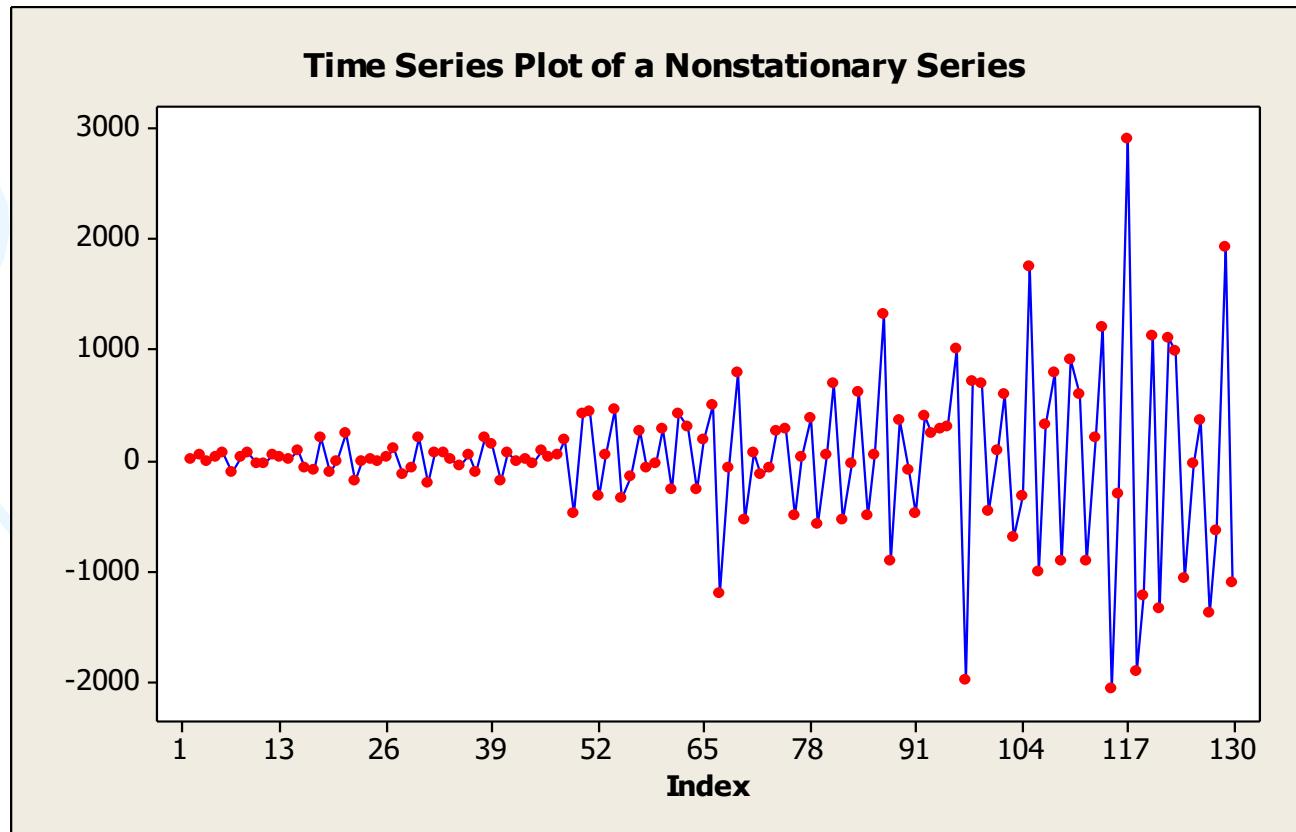
# Example: Non-stationary Series

- Non-stationary in the mean



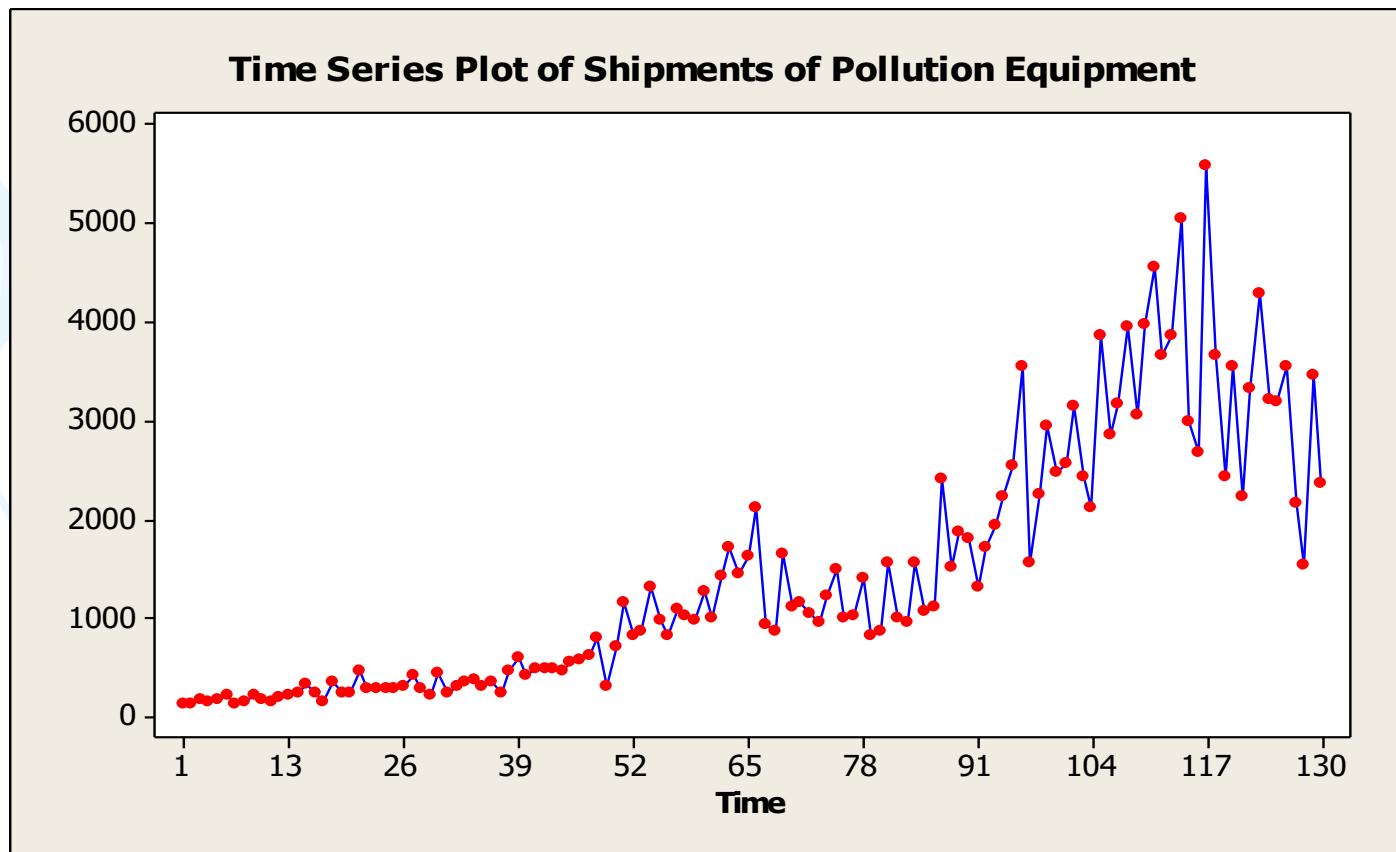
# Example: Non-stationary Series

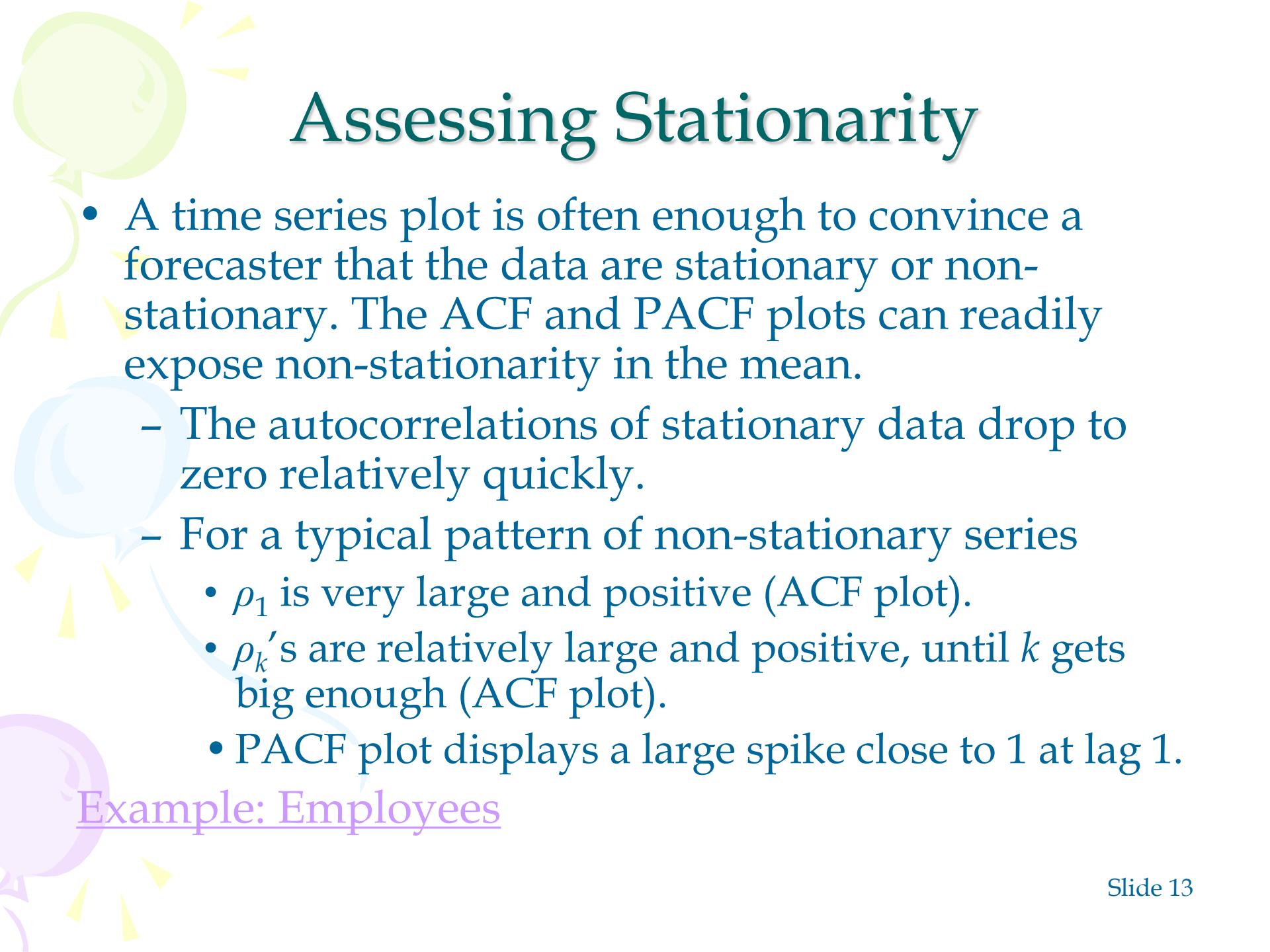
- Non-stationary in the variance



# Example: Non-stationary Series

- Non-stationary in both the mean and the variance

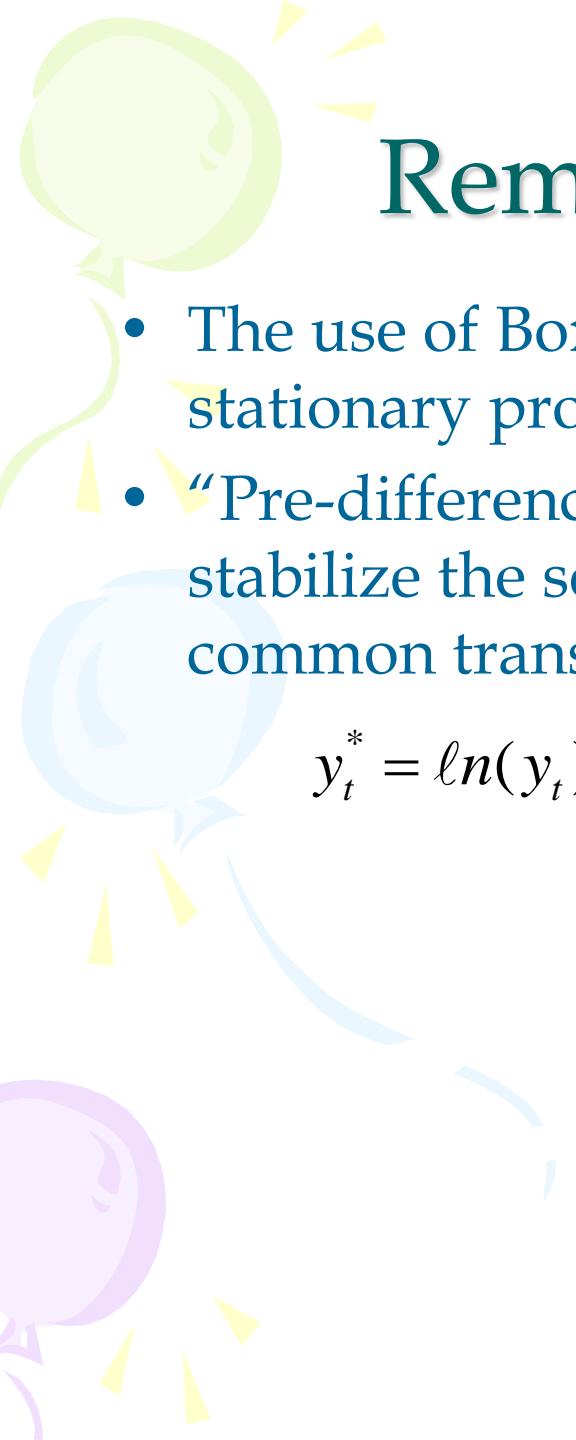




# Assessing Stationarity

- A time series plot is often enough to convince a forecaster that the data are stationary or non-stationary. The ACF and PACF plots can readily expose non-stationarity in the mean.
  - The autocorrelations of stationary data drop to zero relatively quickly.
  - For a typical pattern of non-stationary series
    - $\rho_1$  is very large and positive (ACF plot).
    - $\rho_k$ 's are relatively large and positive, until  $k$  gets big enough (ACF plot).
    - PACF plot displays a large spike close to 1 at lag 1.

Example: Employees



# Remove Nonstationarity

- The use of Box-Jenkins modeling techniques requires a stationary process.
- “Pre-differencing transformation” is often used to stabilize the seasonal variation of the time series. A common transformation is of the form:

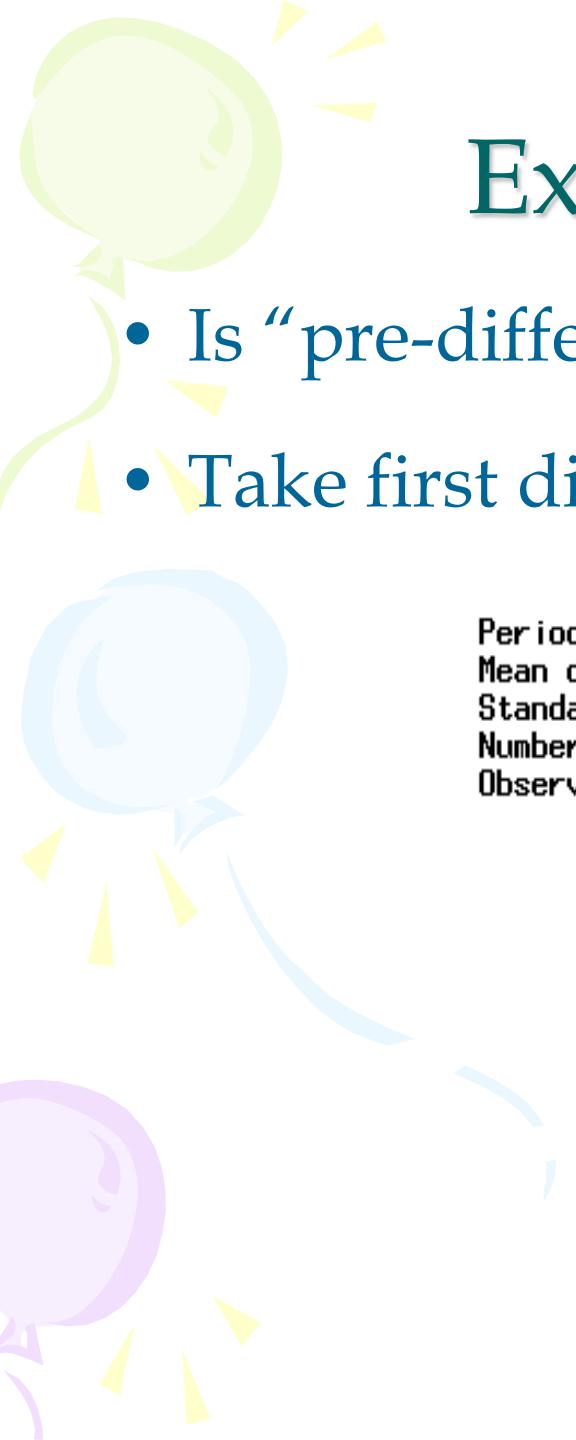
$$y_t^* = \ln(y_t)$$

# Remove Nonstationarity

- Regular differencing
  - Let  $y_t^*$  represent an appropriate predifferencing transformation.
  - If  $y_t^*$  exhibits the pattern of nonstationarity, “first regular differencing” can be applied.

$$z_t = y_t^* - y_{t-1}^*$$

Example: Employees



# Example: Employees

- Is “pre-differencing transformation” necessary?
- Take first differences

Period(s) of Differencing	1
Mean of Working Series	0.902825
Standard Deviation	7.210001
Number of Observations	177
Observation(s) eliminated by differencing	1

# Example: Employees

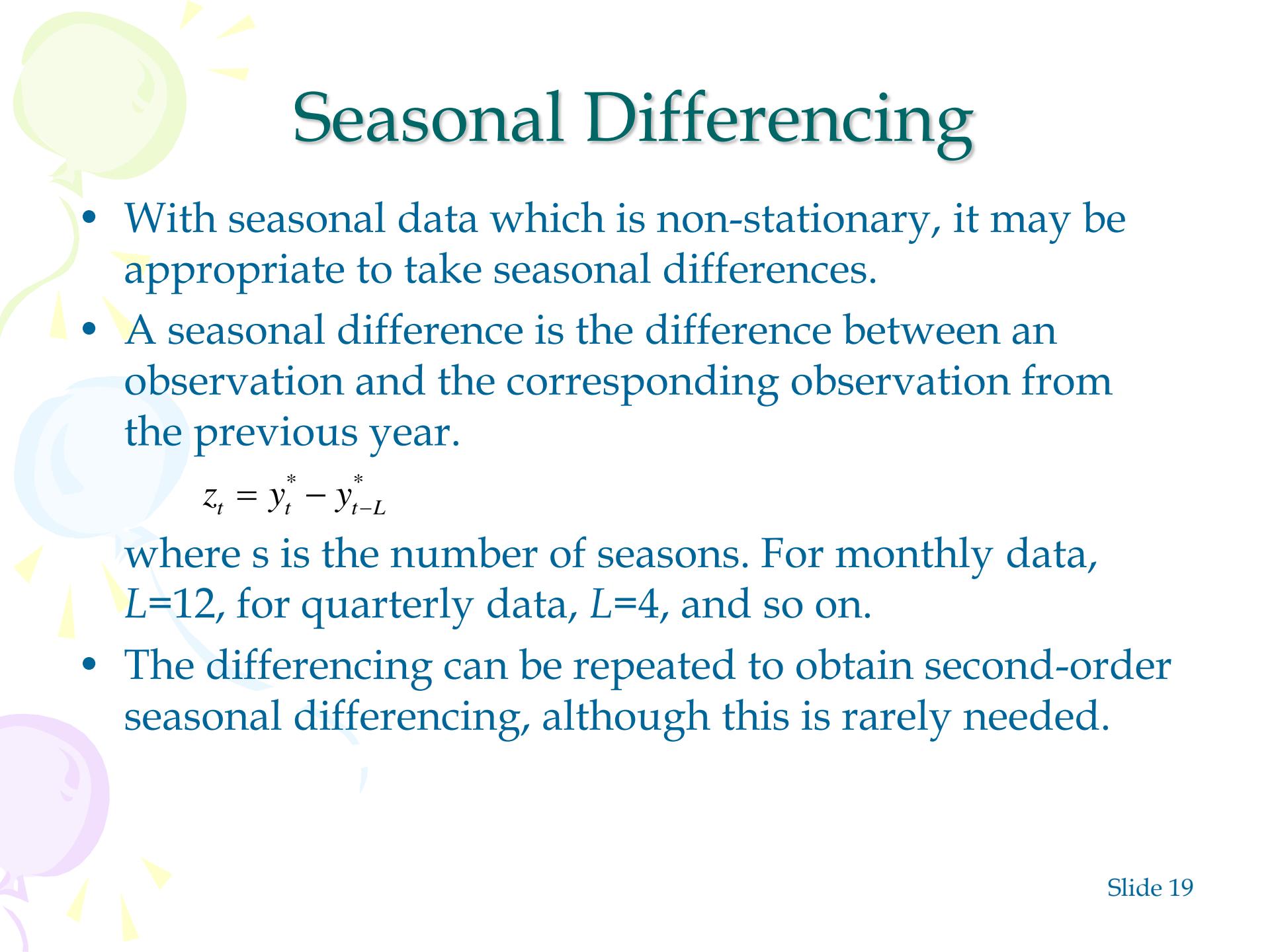
Autocorrelations

Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	51.984116	1.00000	.										*											0
1	1.341360	0.02580	.										.											0.075165
2	-10.104648	-.19438	.										****	.										0.075215
3	-16.397040	-.31542	.										****	.										0.078001
4	-6.537721	-.12576	.										***	.										0.084902
5	0.720104	0.01385	.										.											0.085948
6	11.646511	0.22404	.										.	***										0.085961
7	0.382655	0.00736	.										.											0.089199
8	-5.583873	-.10741	.										.	**	.									0.089202
9	-15.804044	-.30402	.										****	.										0.089930
10	-9.291756	-.17874	.										***	.										0.095560
11	2.139864	0.04116	.										.	*										0.097431
12	46.868231	0.90159	.										.	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****	0.097529
13	0.801322	0.01541	.										.											0.136736
14	-9.690318	-.18641	.										****	.										0.136746
15	-15.285807	-.29405	.										****	.										0.138174
16	-6.236594	-.11997	.										.	**	.									0.141665
17	0.881801	0.01696	.										.											0.142238
18	10.680823	0.20546	.										.	***	.									0.142250
19	0.496121	0.00954	.										.											0.143917
20	-4.968756	-.09558	.										.	**	.									0.143920
21	-14.320935	-.27549	.										****	.										0.144278
22	-8.286359	-.15940	.										***	.										0.147220
23	1.685671	0.03243	.										.	*	.									0.148192
24	42.361435	0.81489	.										.	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****	0.148232
25	0.121192	0.00233	.										.											0.171686
26	-9.063339	-.17435	.										.	***	.									0.171686
27	-13.777984	-.26504	.										****	.										0.172684
28	-6.266858	-.12055	.										.	**	.									0.174967
29	1.370233	0.02636	.										.	*	.									0.175436
30	10.070043	0.19371	.										.	***	.									0.175458
31	0.413689	0.00796	.										.											0.176662
32	-4.482652	-.08623	.										.	**	.									0.176664
33	-13.450155	-.25874	.										****	.										0.176902
34	-7.366474	-.14171	.										.	***	.									0.179027
35	1.845753	0.03551	.										.	*	.									0.179660
36	39.150698	0.75313	.										.	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****	0.179699

"." marks two standard errors

# Example: Employees

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	0.02580												*									
2	-0.19518																					
3	-0.31666																					
4	-0.18893																					
5	-0.14977																					
6	0.05427																					
7	-0.11691																					
8	-0.14022																					
9	-0.34980																					
10	-0.42848																					
11	-0.53214																					
12	0.75935																					
13	-0.05378																					
14	0.03904																					
15	0.11033																					
16	0.08907																					
17	0.00483																					
18	-0.06527																					
19	0.04622																					
20	-0.04072																					
21	0.06118																					
22	0.01489																					
23	-0.11010																					
24	0.01351																					
25	-0.05537																					
26	-0.02404																					
27	-0.01628																					
28	-0.06433																					
29	0.02361																					
30	-0.00076																					
31	-0.01543																					
32	-0.04057																					
33	-0.06671																					
34	-0.01294																					
35	-0.00254																					
36	0.07857																					



# Seasonal Differencing

- With seasonal data which is non-stationary, it may be appropriate to take seasonal differences.
- A seasonal difference is the difference between an observation and the corresponding observation from the previous year.

$$z_t = y_t^* - y_{t-L}^*$$

where  $s$  is the number of seasons. For monthly data,  $L=12$ , for quarterly data,  $L=4$ , and so on.

- The differencing can be repeated to obtain second-order seasonal differencing, although this is rarely needed.

# Example: Employees

- Non-stationarity in the mean remains in the seasonal level. Try to remove it with a further first seasonal difference.

$$z_t = (y_t^* - y_{t-1}^*) - (y_{t-L}^* - y_{t-1-L}^*) = (y_t^* - y_{t-1}^*) - (y_{t-12}^* - y_{t-13}^*)$$

# Example: Employees

Period(s) of Differencing	1,12
Mean of Working Series	0.087273
Standard Deviation	1.438735
Number of Observations	165
Observation(s) eliminated by differencing	13

Autocorrelations																								
Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Er
0	2.069959	1.00000																						
1	0.380397	0.18377	.									*												0.077
2	-0.056837	-.02746	.									.												0.080
3	-0.021478	-.01038	.									.												0.080
4	-0.290834	-.14050	.									***	.											0.080
5	-0.0045074	-.00218	.									.												0.081
6	0.200142	0.09669	.									.	**	.										0.081
7	0.041474	0.02004	.									.												0.082
8	0.187094	0.09039	.									.	**	.										0.082
9	0.197702	0.09551	.									.	**	.										0.083
10	0.00045630	0.00022	.									.	.	.										0.083
11	-0.144889	-.07000	.									*	.											0.083
12	-0.572732	-.27669	.									*****	.											0.084
13	-0.200208	-.09672	.									.	**	.										0.089
14	0.056730	0.02741	.									.	*	.										0.090
15	0.0061858	0.00299	.									.	.	.										0.090
16	0.287759	0.13902	.									.	***	.										0.090
17	0.049923	0.02412	.									.	.	.										0.091
18	-0.209991	-.10145	.									*	.	.										0.091
19	-0.198252	-.09578	.									**	.	.										0.092
20	-0.113819	-.05499	.									*	.	.										0.092
21	-0.039443	-.01906	.									.	.	.										0.093
22	-0.039793	-.01922	.									.	*	.										0.093
23	0.106062	0.05124	.									.	*	.										0.093
24	-0.165247	-.07983	.									*	.	.										0.093

"." marks two standard errors

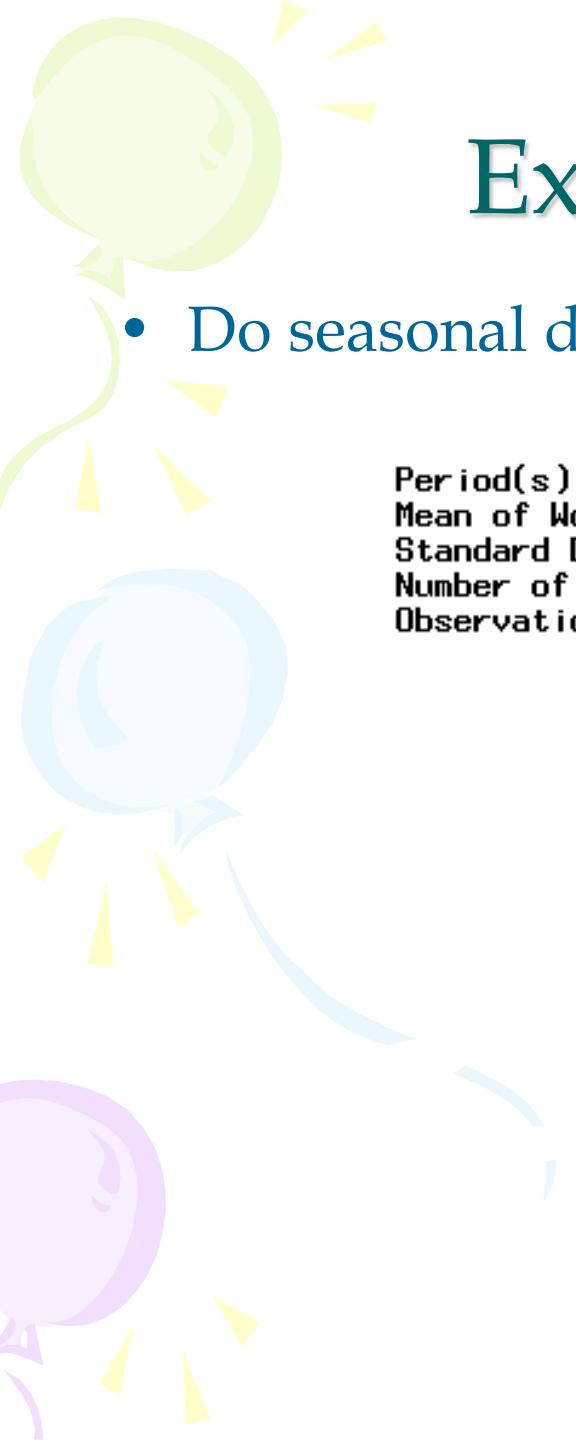
# Example: Employees

Lag	Correlation	Partial Autocorrelations																				
		-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	0.18377	.										****										
2	-0.06337	.									*	.	.									
3	0.00689	.									.	.	.	.								
4	-0.14706	.									***	.	.	.								
5	0.05599	.									.	*	.	.								
6	0.07694	.									.	**	.	.								
7	-0.00961	.									.	.	.	.								
8	0.08102	.									.	**	.	.								
9	0.07084	.									.	*	.	.								
10	0.00110	.									.	.	.	.								
11	-0.07361	.									.	*	.	.								
12	-0.25948	.									*****	.	.	.								
13	0.01555	.									.	.	.	.								
14	0.00615	.									.	*	.	.								
15	-0.03042	.									.	*	.	.								
16	0.09184	.									.	**	.	.								
17	-0.01900	.									.	.	.	.								
18	-0.04354	.									.	*	.	.								
19	-0.08056	.									.	**	.	.								
20	0.03107	.									.	*	.	.								
21	0.03687	.									.	*	.	.								
22	-0.06723	.									.	*	.	.								
23	0.03476	.									.	*	.	.								
24	-0.18999	.									****	.	.	.								

Back

# Remarks for Removing Nonstationarity

- When both seasonal and first differences are applied, it makes no difference which is done first – the result will be the same.
- If differencing is used, the differences should be interpretable. First differences are the change between one observation and next. Seasonal differences are the change from one year to the next.



# Example: Employees

- Do seasonal differencing:  $Z_t = y_t - y_{t-12}$

Period(s) of Differencing	12
Mean of Working Series	10.3759
Standard Deviation	5.005722
Number of Observations	166
Observation(s) eliminated by differencing	12

# Example: Employees

Lag	Covariance	Correlation	Autocorrelations													Std Error						
			-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9
0	25.057251	1.00000	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0
1	23.551046	0.93989	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.077615
2	21.750363	0.86803	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.129102
3	19.984942	0.79757	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.160454
4	18.383410	0.73366	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.182782
5	17.031926	0.67972	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.199736
6	15.647808	0.62448	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.213216
7	14.141135	0.56435	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.223963
8	12.707374	0.50713	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.232372
9	11.123315	0.44392	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.238946
10	9.421701	0.37601	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.243864
11	7.755107	0.30950	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.247332
12	6.024674	0.24044	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.249654
13	5.018099	0.20027	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.251045
14	4.119250	0.16439	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.252005
15	3.165849	0.12634	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.252651
16	2.245328	0.08961	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.253031
17	1.057665	0.04221	.	.	.	.	.	.	.	.	.	.	.	.	*	.	.	.	.	.	.	0.253222
18	-0.103884	-.00415	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.253264
19	-0.936067	-.03736	.	.	.	.	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	0.253265
20	-1.623877	-.06481	.	.	.	.	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	0.253298
21	-2.257332	-.09009	.	.	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	0.253398
22	-2.941722	-.11740	.	.	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	0.253591
23	-3.670260	-.14647	.	.	.	.	.	.	.	.	.	.	.	***	.	.	.	.	.	.	.	0.253918
24	-4.472118	-.17848	.	.	.	.	.	.	.	.	.	.	.	***	.	.	.	.	.	.	.	0.254426

"." marks two standard errors

# Example: Employees

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	0.93989											.	*****	*****	*****	*****	*****	*****	*****	*****	*****	*****
2	-0.13177											***	.	.	.	.	.	.	.	.	.	.
3	-0.01687											.	.	.	.	.	.	.	.	.	.	.
4	0.01467											.	.	.	.	.	.	.	.	.	.	.
5	0.03995											.	*	.	.	.	.	.	.	.	.	.
6	-0.05817											*	.	.	.	.	.	.	.	.	.	.
7	-0.06967											*	.	.	.	.	.	.	.	.	.	.
8	0.00167											.	*	.	.	.	.	.	.	.	.	.
9	-0.09306											.	**	.	.	.	.	.	.	.	.	.
10	-0.08076											.	**	.	.	.	.	.	.	.	.	.
11	-0.03285											.	*	.	.	.	.	.	.	.	.	.
12	-0.07481											.	*	.	.	.	.	.	.	.	.	.
13	0.19780											.	***	.	.	.	.	.	.	.	.	.
14	-0.05541											.	*	.	.	.	.	.	.	.	.	.
15	-0.04737											.	*	.	.	.	.	.	.	.	.	.
16	-0.00425											.	.	.	.	.	.	.	.	.	.	.
17	-0.10667											.	**	.	.	.	.	.	.	.	.	.
18	-0.01782											.	.	.	.	.	.	.	.	.	.	.
19	0.04612											.	*	.	.	.	.	.	.	.	.	.
20	0.00470											.	.	.	.	.	.	.	.	.	.	.
21	-0.05160											.	*	.	.	.	.	.	.	.	.	.
22	-0.06924											.	*	.	.	.	.	.	.	.	.	.
23	-0.01942											.	.	.	.	.	.	.	.	.	.	.
24	-0.09627											.	**	.	.	.	.	.	.	.	.	.

# Example: Employees

- Is stationarity achieved after first seasonal differencing?





# Stationarity

- In general, if ACF does both of the following, the series should be considered stationary.
  - Cuts off fairly quickly or dies down fairly quickly at the nonseasonal level
    - Arbitrarily define the “nonseasonal level” as lags 1 through  $L-3$ .
      - For monthly data, lags 1 through 9
      - For quarterly data, lags 1, 2, and possibly 3
    - Cuts off fairly quickly or dies down fairly quickly at the seasonal level
      - Define the “seasonal level” as lags equal to (or nearly equal to)  $L$ ,  $2L$ ,  $3L$ , and  $4L$ .
        - Define the lags  $L$ ,  $2L$ ,  $3L$ , and  $4L$  to be “exact seasonal lags”
        - Define the lags  $L - 2$ ,  $L - 1$ ,  $L + 1$ ,  $L + 2$ ,  $2L - 2$ ,  $2L - 1$ ,  $2L + 1$ ,  $2L + 2$ ,  $3L - 2$ ,  $3L - 1$ ,  $3L + 1$ ,  $3L + 2$ ,  $4L - 2$ ,  $4L - 1$ ,  $4L + 1$ , and  $4L + 2$  to be “near seasonal lags”

Example: Employees

# Summary of Removing Nonstationarity

- “Pre-differencing transformation” is often used to stabilize the seasonal variation of the time series. A common transformation is of the form:

$$y_t^* = \ln(y_t)$$

# Summary of Removing Nonstationarity

- First regular difference

$$z_t = y_t^* - y_{t-1}^*$$

- First seasonal difference, where  $L$  is the number of seasons in a year

$$z_t = y_t^* - y_{t-L}^*$$

- First seasonal and first regular difference

$$z_t = (y_t^* - y_{t-1}^*) - (y_{t-L}^* - y_{t-L-1}^*)$$

- One can also obtain second and higher order differences by simply applying the same rule.
- For most practical purposes, a maximum of two differences (including both regular and seasonal differences) will transform the data into a stationary series.

# Backshift Notation

- Backward shift operator,  $B$

$$By_t = y_{t-1}$$

- $B$ , operating on  $y_t$ , has the effect of shifting the data back one period.
- Two applications of  $B$  to  $y_t$  shifts the data back two periods.

$$B(By_t) = B^2 y_t = y_{t-2}$$

- $m$  applications of  $B$  to  $y_t$  shifts the data back  $m$  periods.

$$B^m y_t = y_{t-m}$$

# Backshift Notation

- The backward shift operator is convenient for describing the process of differencing.

$$\Delta y_t = y_t - y_{t-1} = y_t - B y_t = (1 - B) y_t$$

$$\Delta^2 y_t = y_t - 2y_{t-1} + y_{t-2} = (1 - 2B + B^2) y_t = (1 - B)^2 y_t$$

- In general, a  $d$ th-order can be written as

$$\Delta^d y_t = (1 - B)^d y_t$$

- An  $s$ th difference

$$(1 - B^s) y_t$$

- The backshift notation is convenient because the terms can be multiplied together to see the combined effect.

$$(1 - B)(1 - B^s) y_t = (1 - B - B^s + B^{s+1}) y_t = y_t - y_{t-1} - y_{t-s} + y_{t-s-1}$$

## **Step Two: Model Identification**

# ARIMA models for time series data

- Three basic Box-Jenkins models for a stationary time series  $\{y_t\}$ 
  - Autoregressive models (AR)
  - Moving Average models (MA)
  - Autoregressive Moving Average models (ARMA)
- Autoregressive Integrated Moving Average models (ARIMA)
  - ARMA models extended to nonstationary series by allowing differencing of the data series

# Autoregressive Models (AR)

- Autoregressive model of order  $p$  (AR( $p$ ))

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

i.e.,  $y_t$  depends on its  $p$  previous values

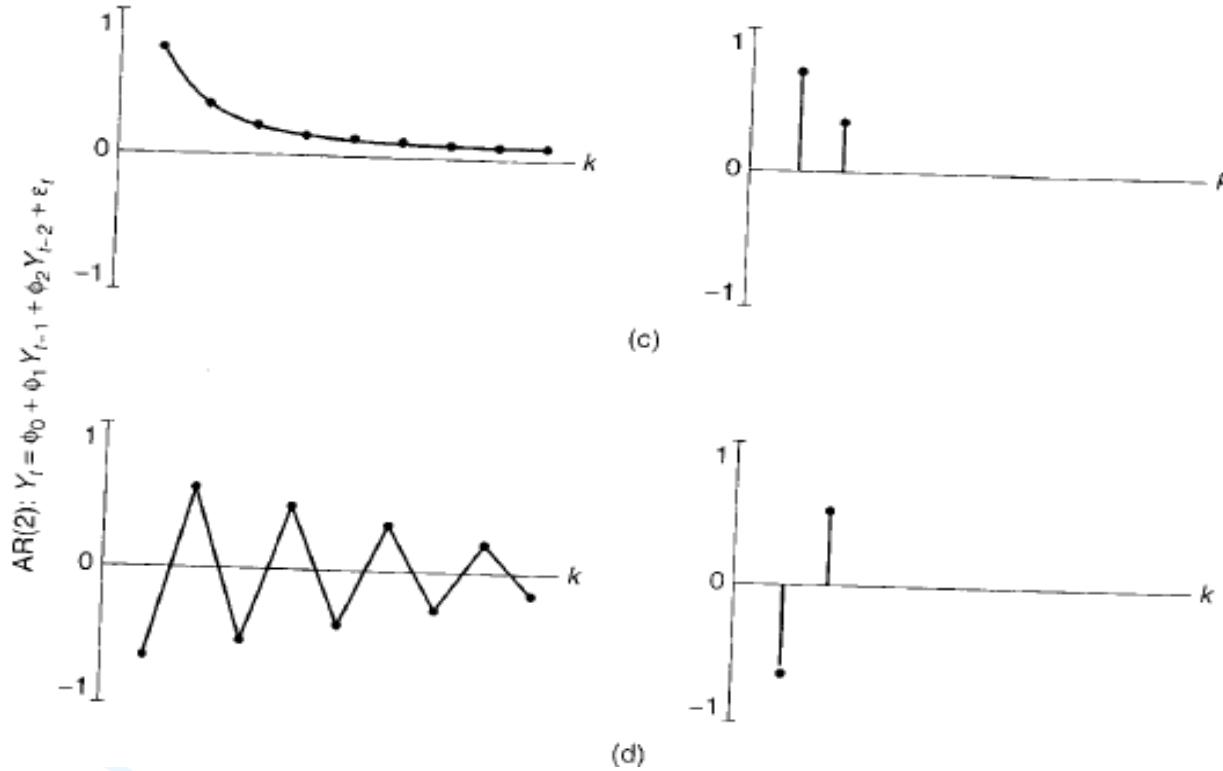
- Using backshift notation

$$\phi_p(B)y_t = \delta + \varepsilon_t$$

where

$$\phi_p(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$$

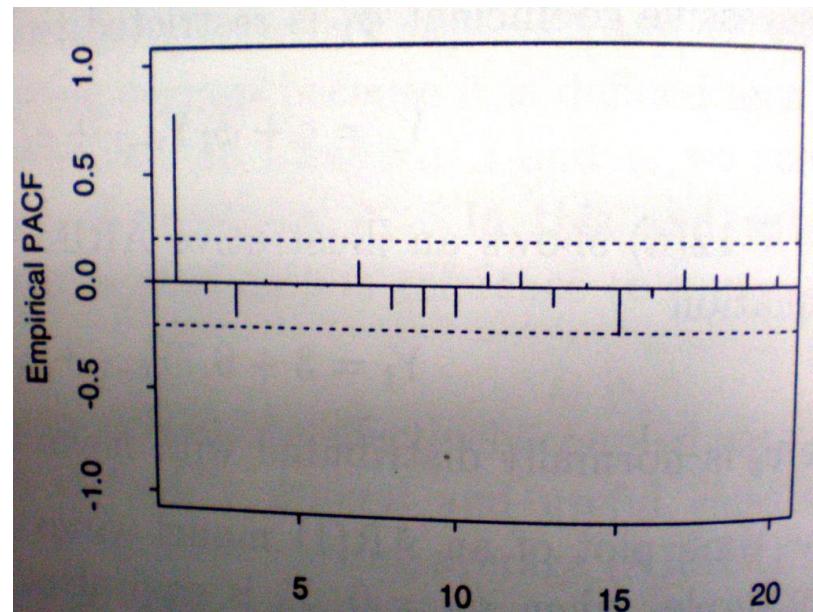
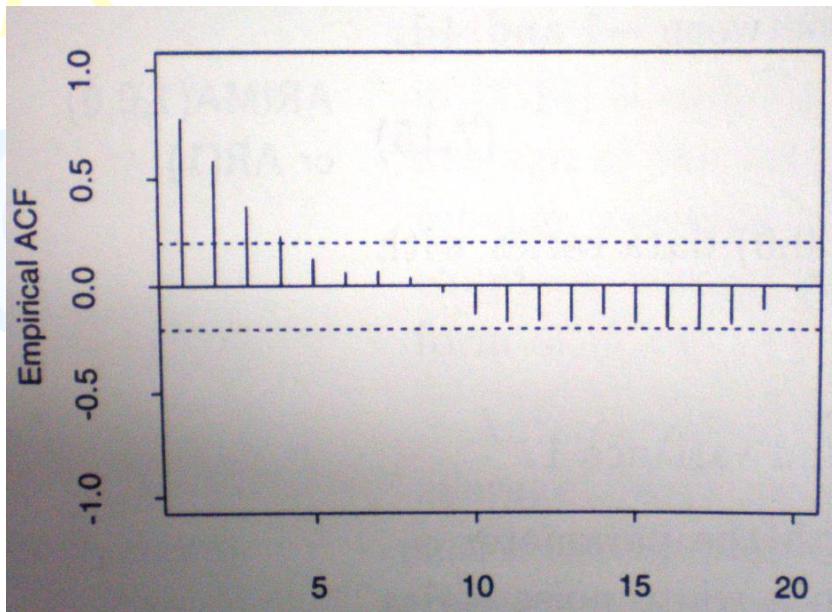
# Theoretical ACF and PACF for AR( $p$ )



- Characteristics:
  - ACF dies down.
  - PACF cuts off after lag  $p$ .

# Example for AR(1)

- Empirical ACF and PACF



$$y_t = 3 + 0.7 y_{t-1} + \varepsilon_t$$

# Moving Average Models (MA)

- Moving Average model of order  $q$  (MA( $q$ ))

$$y_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

i.e.,  $y_t$  depends on  $q$  previous random error terms.

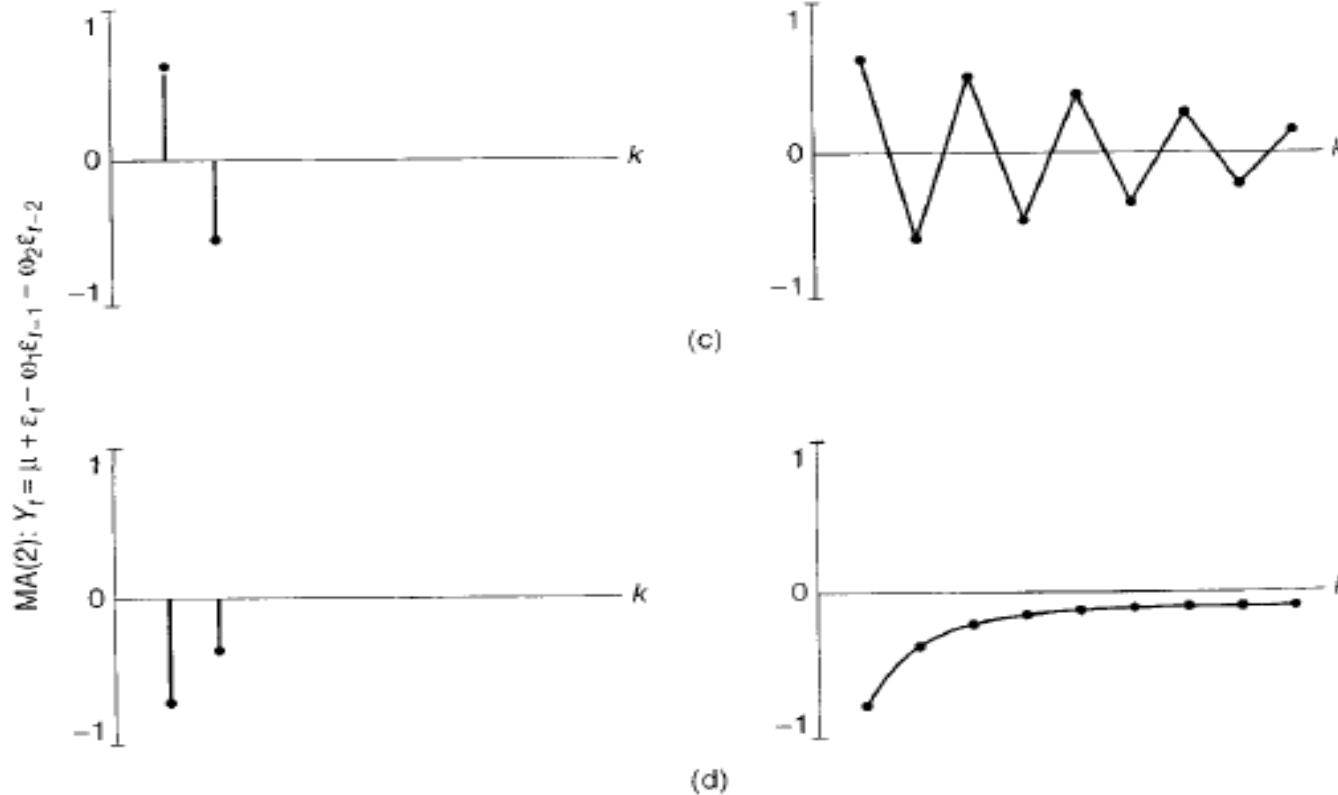
- Using backshift notation

$$y_t = \mu + \theta_q(B) \varepsilon_t$$

where

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$$

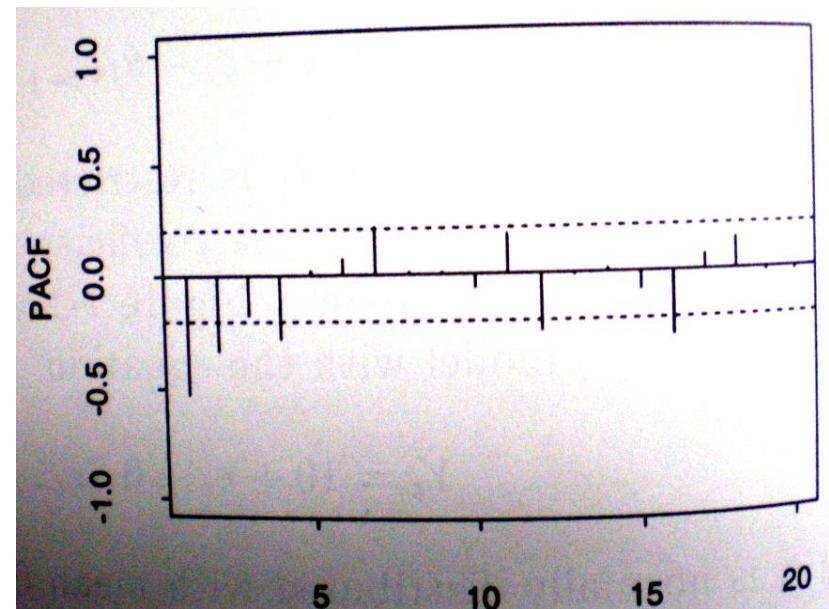
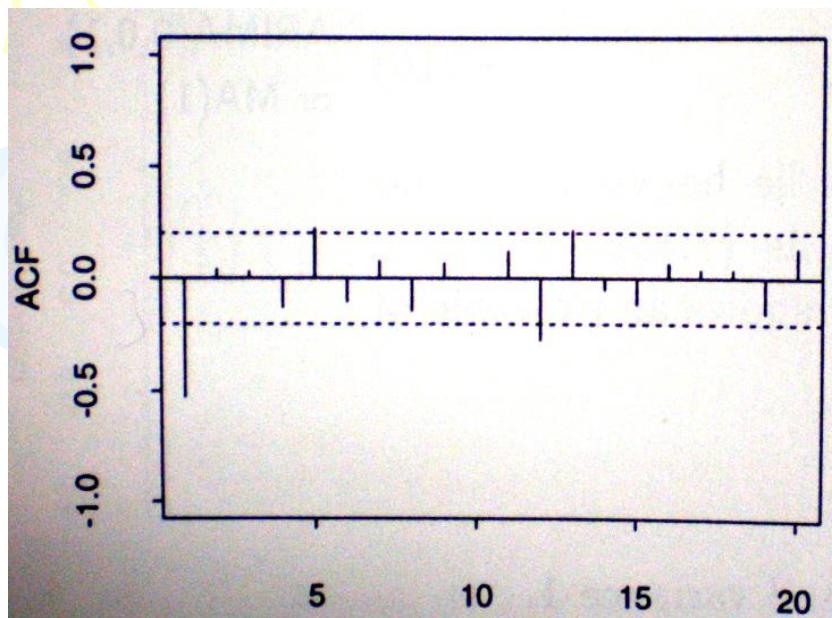
# Theoretical ACF and PACF for MA( $q$ )



- Characteristics:
  - ACF cuts off after lag  $q$ .
  - PACF dies down.

# Example for MA(1)

- Empirical ACF and PACF



$$y_t = 10 + \varepsilon_t - 0.7\varepsilon_{t-1}$$

# Autoregressive Moving Average Models (ARMA)

- Autoregressive-moving average model of order  $p$  and  $q$  (ARMA( $p,q$ ))

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

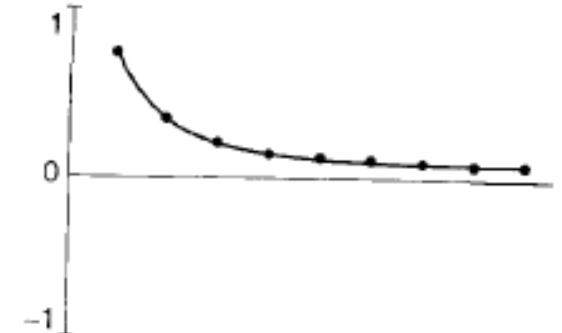
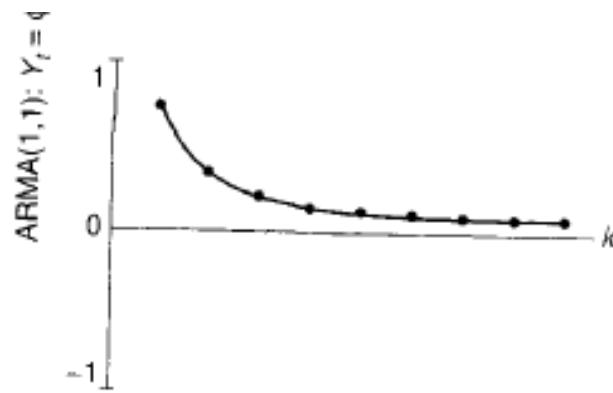
i.e.,  $y_t$  depends on its  $p$  previous values and  $q$  previous random error terms

- Using backshift notation

$$\phi_p(B)y_t = \delta + \theta_q(B)\varepsilon_t$$

- When  $q = 0$ , the ARMA( $p,0$ ) model reduces to AR( $p$ ); when  $p = 0$ , the ARMA( $0,q$ ) model reduces to MA( $q$ ).

# Theoretical ACF and PACF for ARMA( $p,q$ )



(c)



(d)

- Characteristics:
  - Both ACF and PACF die down.

# Summary of the Behaviors of ACF and PACF

Behaviors of ACF and PACF for general non-seasonal models

Process	ACF	PACF
AR( $p$ )	Dies down.	Cuts off after lag $p$ .
MA( $q$ )	Cuts off after lag $q$ .	Dies down.
ARMA( $p,q$ )	Dies down.	Dies down.

# Non-seasonal Autoregressive Integrated Moving Average models (ARIMA)

- ARMA models can only be used for stationary data. This class of models can be extended to non-stationary series by allowing differencing the data series.  $\Rightarrow$  ARIMA models
- Backshift notation

$$\phi_p(B)(1-B)^d y_t = \delta + \theta_q(B)\varepsilon_t$$

and  $\delta = \mu\phi_p(B)$

e.g. ARIMA(1,1,1)

$$(1-\phi_1 B)(1-B)y_t = \delta + (1-\theta_1 B)\varepsilon_t$$

- The general non-seasonal model: ARIMA( $p,d,q$ )
  - AR:  $p$  = order of the autoregressive part
  - I:  $d$  = order of integration
  - MA:  $q$  = order of the moving average part

# Seasonality and ARIMA Models

- One final complexity to add to ARIMA models is seasonality.
- ARIMA notation:  $\text{ARIMA}(p,d,q)(P,D,Q)_L$   
where  $L = \text{number of periods per season.}$

$$\text{ARIMA } \underbrace{(p,d,q)}_{\begin{pmatrix} \text{Non-seasoaal} \\ \text{part of the} \\ \text{model} \end{pmatrix}} \underbrace{(P,D,Q)}_{\begin{pmatrix} \text{Seasoal} \\ \text{part of} \\ \text{the model} \end{pmatrix}}_L$$

- Suppose  $y_t^*$  is a pre-differencing transformed series. The general stationarity transformation is

$$z_t = \Delta_L^D \Delta^d y_t^* = (1 - B^L)^D (1 - B)^d y_t^*$$

where  $D$  is the order of seasonal differencing and  $d$  is the order of non-seasonal differencing.

# Seasonality and ARIMA Models

- Using backshift notation

$$\phi_p(B)\Phi_p(B^L)z_t = \delta + \theta_q(B)\Theta_Q(B^L)\varepsilon_t$$

where

$$\phi_p(B) = (1 - \phi_1B - \phi_2B^2 - \dots - \phi_pB^p)$$

is the non-seasonal autoregressive operator of order  $p$ ,

$$\Phi_P(B^L) = (1 - \Phi_1B^L - \Phi_2B^{2L} - \dots - \Phi_PB^{PL})$$

is the seasonal autoregressive operator of order  $P$ ,

$$\theta_q(B) = (1 - \theta_1B - \theta_2B^2 - \dots - \theta_qB^q)$$

is the non-seasonal moving average operator of order  $q$ ,

$$\Theta_Q(B^L) = (1 - \Theta_1B^L - \Theta_2B^{2L} - \dots - \Theta_QB^{QL})$$

is the seasonal moving average operator of order  $Q$ ,

and

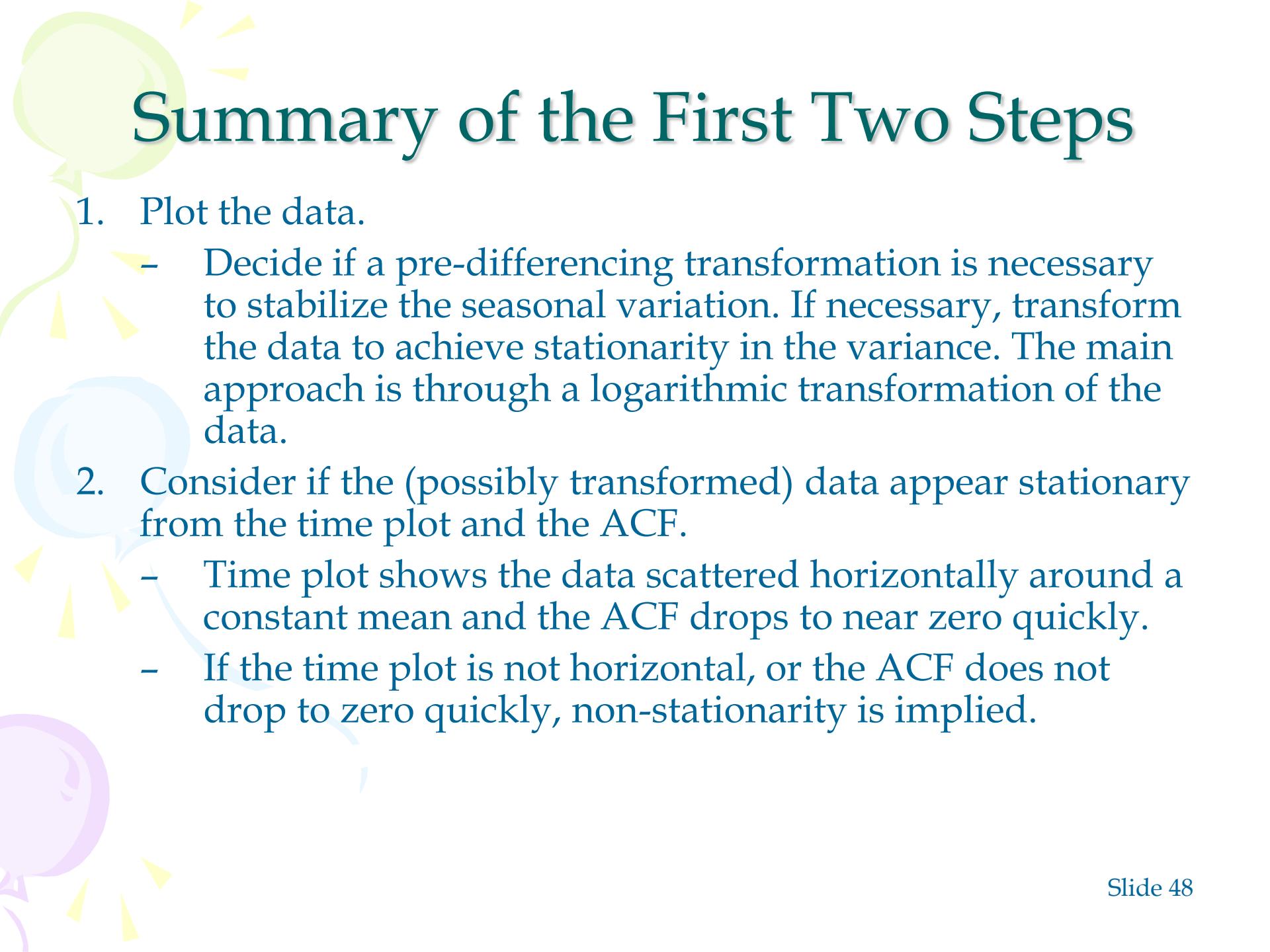
$$\delta = \mu\phi_p(B)\Phi_P(B^L)$$

- For example, ARIMA(1,1,1)(1,1,1)<sub>4</sub> model:

$$(1 - \phi_1B)(1 - \Phi_1B^4)(1 - B)(1 - B^4)y_t = \delta + (1 - \theta_1B)(1 - \Theta_1B^4)\varepsilon_t$$

# Seasonality and ARIMA Models

- The seasonal part of an AR or MA model will be seen in the seasonal lags of the ACF and PACF.
  - For example,  $\text{ARIMA}(0,0,0)(0,0,1)_{12}$  will show a spike at lag 12 in the ACF but no other significant spikes. The PACF will show exponential decay in the seasonal lags, i.e., lags 12, 24, 36,...
  - Similarly,  $\text{ARIMA}(0,0,0)(1,0,0)_4$  will show exponential decay in the seasonal lags of the ACF, and a single significant spike at lag 4 in the PACF.



# Summary of the First Two Steps

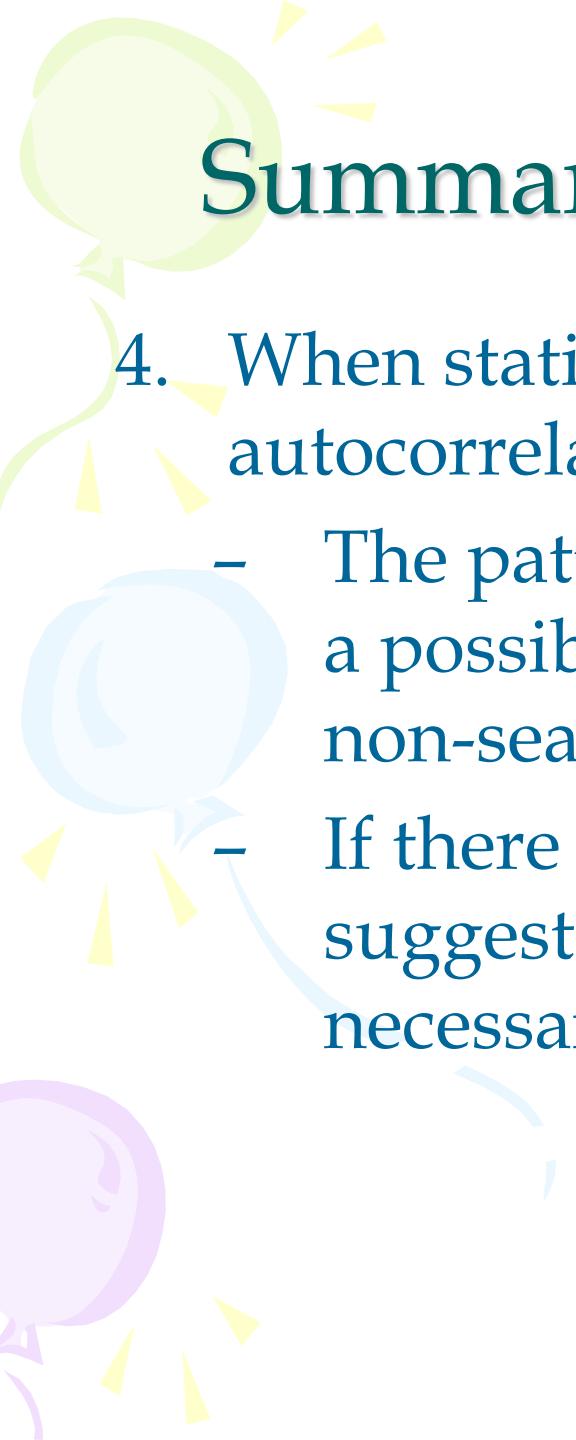
1. Plot the data.
  - Decide if a pre-differencing transformation is necessary to stabilize the seasonal variation. If necessary, transform the data to achieve stationarity in the variance. The main approach is through a logarithmic transformation of the data.
2. Consider if the (possibly transformed) data appear stationary from the time plot and the ACF.
  - Time plot shows the data scattered horizontally around a constant mean and the ACF drops to near zero quickly.
  - If the time plot is not horizontal, or the ACF does not drop to zero quickly, non-stationarity is implied.



# Summary of the First Two Steps

(continued)

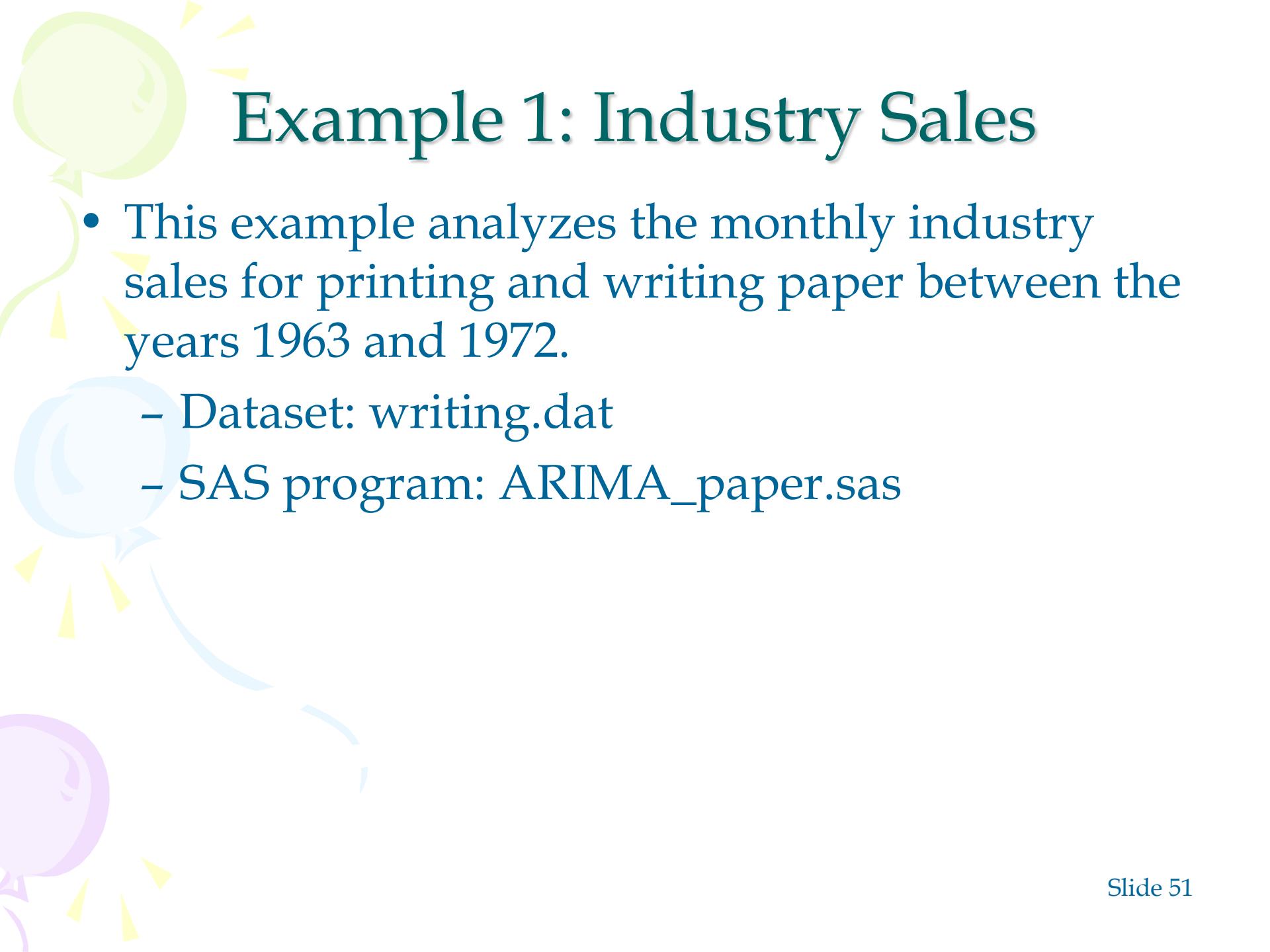
3. When the data appear non-stationary, remove nonstationarity by differencing.
  - Check whether the data appear stationary in the non-seasonal level. If not, take the first differences of the data.
  - Check whether the data appear stationary in the seasonal level. If not, take the seasonal differences of the data.
  - For most practical purposes, a maximum of two differences will transform the data into a stationary series.



# Summary of the First Two Steps

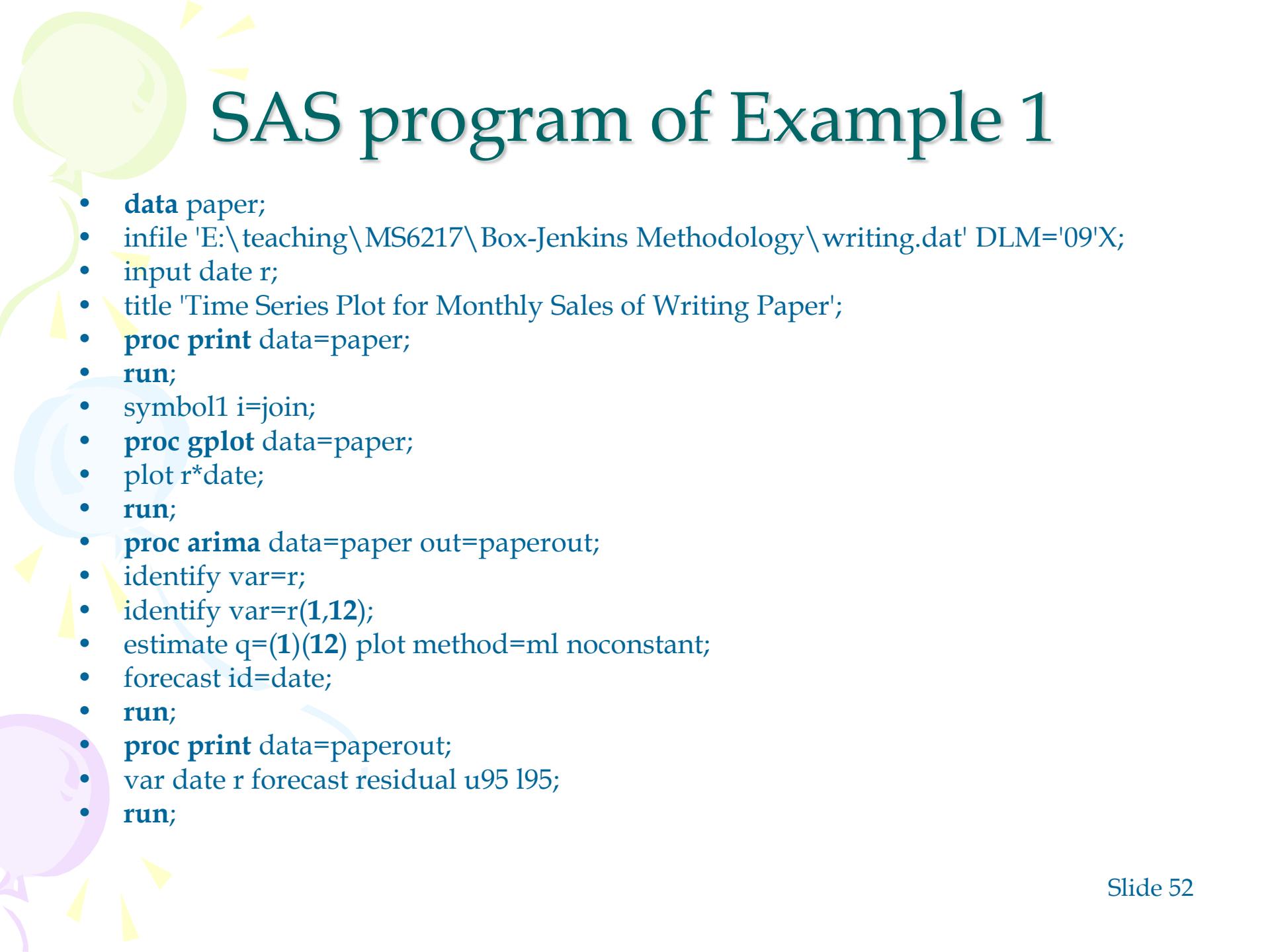
(continued)

4. When stationarity is achieved, examine the autocorrelation to see if any pattern remains.
  - The patterns of ACF and PACF may suggest a possible model at both seasonal level and non-seasonal level.
  - If there is no clear MA or AR model suggested, a mixture model may be necessary.



# Example 1: Industry Sales

- This example analyzes the monthly industry sales for printing and writing paper between the years 1963 and 1972.
  - Dataset: writing.dat
  - SAS program: ARIMA\_paper.sas

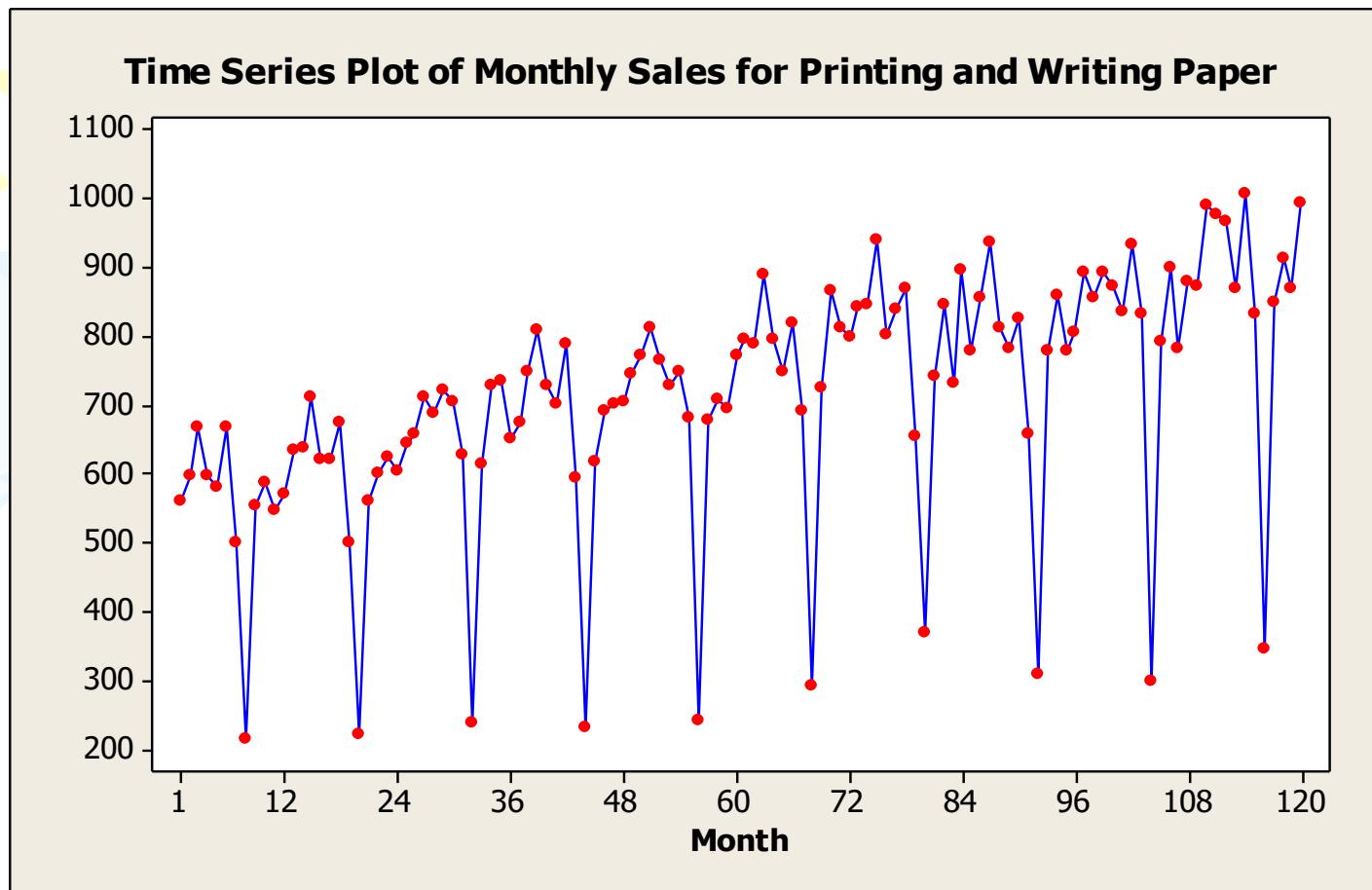


# SAS program of Example 1

- **data paper;**
- infile 'E:\teaching\MS6217\Box-Jenkins Methodology\writing.dat' DLM='09'X;
- input date r;
- title 'Time Series Plot for Monthly Sales of Writing Paper';
- **proc print data=paper;**
- **run;**
- symbol1 i=join;
- **proc gplot data=paper;**
- plot r\*date;
- **run;**
- **proc arima data=paper out=paperout;**
- identify var=r;
- identify var=r(1,12);
- estimate q=(1)(12) plot method=ml noconstant;
- forecast id=date;
- **run;**
- **proc print data=paperout;**
- var date r forecast residual u95 l95;
- **run;**

# Example 1: Industry Sales

(continued)



# Example 1: Industry Sales

(continued)

Lag	Covariance	Correlation	Autocorrelations													Std Error							
			-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
0	30041.142	1.00000																					0
1	13128.669	0.43702	.	.	.	.	.	.	.	*	*****	.	.	.	.	.	.	.	.	.	.	0.091287	
2	5032.062	0.16751	.	.	.	.	.	.	.	***	.	.	.	.	.	.	.	.	.	.	.	0.107315	
3	7980.640	0.26566	.	.	.	.	.	.	.	****	.	.	.	.	.	.	.	.	.	.	.	0.109472	
4	4744.480	0.15793	.	.	.	.	.	.	.	***	.	.	.	.	.	.	.	.	.	.	.	0.114719	
5	2004.329	0.06672	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.116516	
6	2946.138	0.09807	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.	0.116834	
7	2002.376	0.06665	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.117518	
8	4628.363	0.15407	.	.	.	.	.	.	.	***	.	.	.	.	.	.	.	.	.	.	.	0.117833	
9	6745.155	0.22453	.	.	.	.	.	.	.	****	.	.	.	.	.	.	.	.	.	.	.	0.119500	
10	3566.337	0.11872	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.	0.122965	
11	10204.192	0.33967	.	.	.	.	.	.	.	*****	.	.	.	.	.	.	.	.	.	.	.	0.123917	
12	23673.899	0.78805	.	.	.	.	.	.	.	*****	.	.	.	.	.	.	.	.	.	.	.	0.131447	
13	9811.962	0.32662	.	.	.	.	.	.	.	*****	.	.	.	.	.	.	.	.	.	.	.	0.166219	
14	2363.778	0.07868	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.	0.171484	
15	4643.380	0.15457	.	.	.	.	.	.	.	***	.	.	.	.	.	.	.	.	.	.	.	0.171784	
16	2062.207	0.06865	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.172939	
17	-181.901	-.00606	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.173166	
18	644.661	0.02146	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.173168	
19	-418.796	-.01394	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.173190	
20	1761.975	0.05865	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.173200	
21	3521.549	0.11722	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.	0.173365	
22	1072.664	0.03571	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.174024	
23	6982.004	0.23241	.	.	.	.	.	.	.	****	.	.	.	.	.	.	.	.	.	.	.	0.174085	
24	18887.134	0.62871	.	.	.	.	.	.	.	*****	.	.	.	.	.	.	.	.	.	.	.	0.176652	
25	7105.623	0.23653	.	.	.	.	.	.	.	***	.	.	.	.	.	.	.	.	.	.	.	0.194406	
26	139.948	0.00466	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.196790	
27	2071.211	0.06895	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.196791	
28	-116.533	-.00388	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.	0.196992	
29	-2561.166	-.08526	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.196993	
30	-1148.110	-.03822	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.197300	
31	-1494.620	-.04975	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.197362	
32	345.171	0.01149	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.197466	
33	2108.430	0.07018	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	0.197472	
34	-185.315	-.00617	.	.	.	.	.	.	.	***	.	.	.	.	.	.	.	.	.	.	.	0.197680	
35	5193.412	0.17288	.	.	.	.	.	.	.	*****	.	.	.	.	.	.	.	.	.	.	.	0.197681	
36	15559.649	0.51794	.	.	.	.	.	.	.	*****	.	.	.	.	.	.	.	.	.	.	.	0.198937	

# Example 1: Industry Sales

(continued)

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	0.43702										.	*	*****									
2	-0.02903										.	*	****									
3	0.25115										.	*	.									
4	-0.06529										.	*	.									
5	0.01804										.	*	.									
6	0.02680										.	*	.									
7	-0.00963										.	*	.									
8	0.16955										.	***	.									
9	0.09715										.	**	.									
10	-0.02731										.	*	.									
11	0.35138										.	*****	.									
12	0.68864										.	*****	*****	.								
13	-0.38726										.	*****	.									
14	-0.13079										.	***	.									
15	-0.19058										.	***	.									
16	0.01961										.	*	.									
17	-0.02804										.	*	.									
18	-0.03943										.	*	.									
19	-0.09296										.	**	.									
20	-0.09448										.	**	.									
21	-0.00628										.	*	.									
22	0.05835										.	*	.									
23	0.05340										.	*	.									
24	0.12646										.	***	.									
25	-0.06074										.	*	.									
26	-0.01692										.	*	.									
27	-0.02145										.	*	.									
28	0.01062										.	*	.									
29	-0.07732										.	**	.									
30	0.04128										.	*	.									
31	0.04507										.	*	.									
32	0.01637										.	*	.									
33	0.02704										.	*	.									
34	-0.05001										.	*	.									
35	0.03071										.	*	.									
36	-0.00168										.	*	.									

# Example 1: Industry Sales

(continued)

- What patterns can you see from the plots?
- How should you deal with the data?



# Example 1: Industry Sales

(continued)

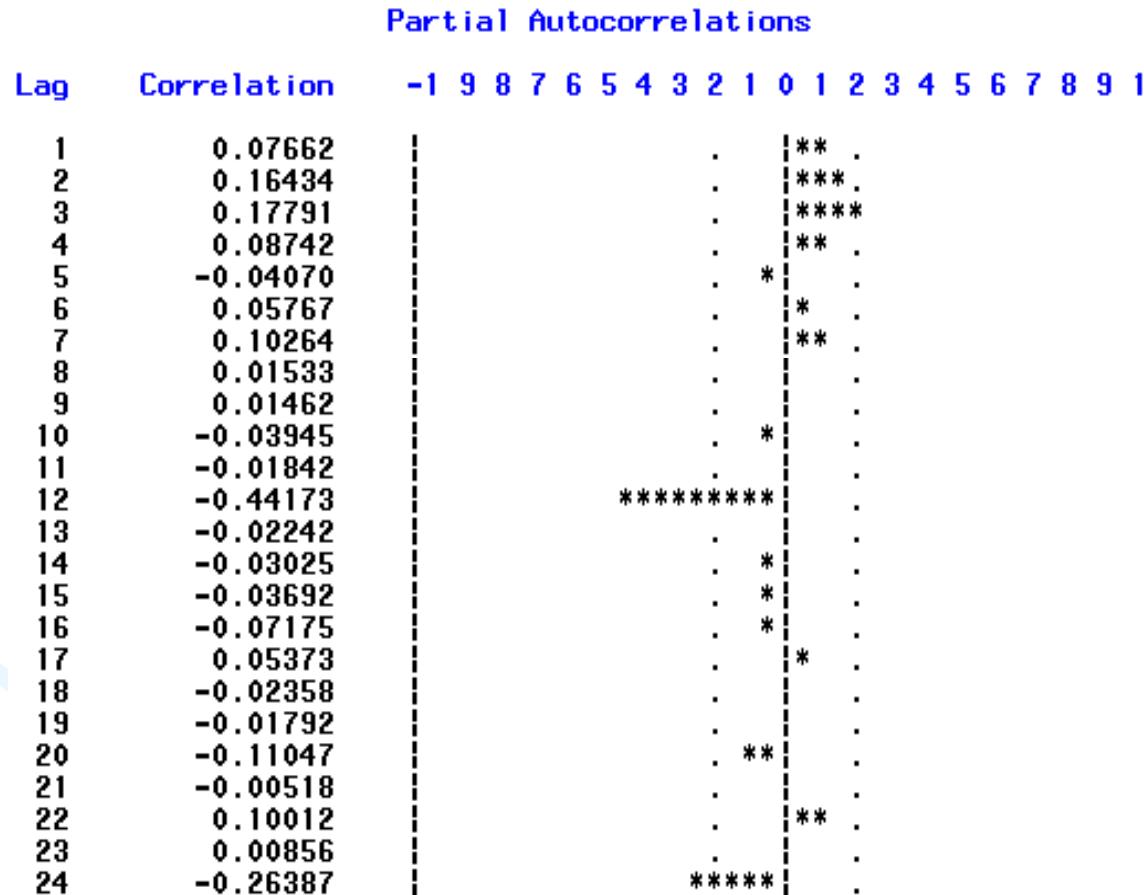
Period(s) of Differencing	12
Mean of Working Series	35.60183
Standard Deviation	50.5778
Number of Observations	108
Observation(s) eliminated by differencing	12

Lag	Covariance	Correlation	Autocorrelations												Std Error								
			-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
0	2558.114	1.00000																					0
1	195.992	0.07662																					0.096225
2	432.944	0.16924																					0.096788
3	500.149	0.19551																					0.099491
4	327.943	0.12820																					0.102987
5	72.191703	0.02822																					0.104454
6	307.173	0.12008																					0.104525
7	349.566	0.13665																					0.105794
8	135.242	0.05287																					0.107416
9	196.161	0.07668																					0.107657
10	78.023328	0.03050																					0.108161
11	60.459291	0.02363																					0.108241
12	-979.276	-.38281																					0.108289
13	-10.801001	-.00422																					0.120167
14	-294.950	-.11530																					0.120169
15	-395.715	-.15469																					0.121189
16	-343.554	-.13430																					0.123003
17	-3.463499	-.00135																					0.124354
18	-393.085	-.15366																					0.124354
19	-365.626	-.14293																					0.126100
20	-420.682	-.16445																					0.127591
21	-379.630	-.14840																					0.129539
22	-156.619	-.06122																					0.131103
23	-281.543	-.11006																					0.131368
24	-266.424	-.10415																					0.132219

"\*\*" marks two standard errors

# Example 1: Industry Sales

(continued)



# Example 1: Industry Sales

(continued)

Period(s) of Differencing	1,12
Mean of Working Series	0.389673
Standard Deviation	68.54769
Number of Observations	107
Observation(s) eliminated by differencing	13

## Autocorrelations

Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	4698.785	1.00000																						0
1	-2593.215	-.55189																						0.096674
2	223.699	0.04761													*	.	.	.	.	.	.	.	.	0.122633
3	216.012	0.04597													*	.	.	.	.	.	.	.	.	0.122806
4	87.521220	0.01863													.	.	.	.	.	.	.	.	.	0.122967
5	-450.312	-.09584													**	.	.	.	.	.	.	.	.	0.122993
6	142.953	0.03042													*	.	.	.	.	.	.	.	.	0.123689
7	284.013	0.06044													*	.	.	.	.	.	.	.	.	0.123759
8	-319.788	-.06806													*	.	.	.	.	.	.	.	.	0.124034
9	184.252	0.03921													*	.	.	.	.	.	.	.	.	0.124383
10	-162.709	-.03463													*	.	.	.	.	.	.	.	.	0.124498
11	1162.223	0.24735													*****	.	.	.	.	.	.	.	.	0.124588
12	-2086.936	-.44414													*****	.	.	.	.	.	.	.	.	0.129096
13	1313.279	0.27949													.	*****	.	.	.	.	.	.	.	0.142664
14	-206.928	-.04404													.	*	.	.	.	.	.	.	.	0.147693
15	-155.607	-.03312													*	.	.	.	.	.	.	.	.	0.147815
16	-287.067	-.06109													*	.	.	.	.	.	.	.	.	0.147885
17	625.158	0.13305													***	.	.	.	.	.	.	.	.	0.148120
18	-403.615	-.08590													**	.	.	.	.	.	.	.	.	0.149233
19	160.764	0.03421													*	.	.	.	.	.	.	.	.	0.149694
20	-116.622	-.02482													*	.	.	.	.	.	.	.	.	0.149767
21	-130.188	-.02771													*	.	.	.	.	.	.	.	.	0.149806
22	324.875	0.06914													*	.	.	.	.	.	.	.	.	0.149854
23	-205.937	-.04383													*	.	.	.	.	.	.	.	.	0.150152
24	184.075	0.03918													*	.	.	.	.	.	.	.	.	0.150271

"." marks two standard errors

# Example 1: Industry Sales

(continued)

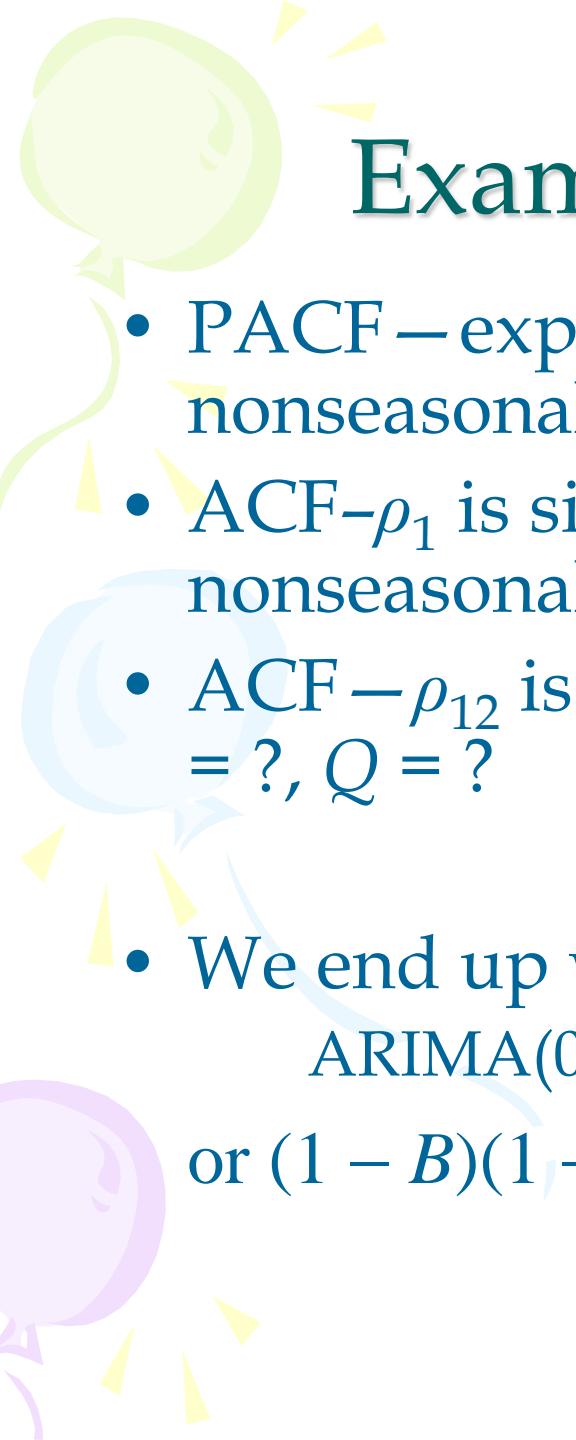
Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	-0.55189																					
2	-0.36953																					
3	-0.20315																					
4	-0.05279																					
5	-0.12580																					
6	-0.15464																					
7	-0.04740																					
8	-0.05675																					
9	-0.01424																					
10	-0.06486																					
11	0.35398																					
12	-0.13429																					
13	-0.08475																					
14	-0.05507																					
15	-0.01514																					
16	-0.12420																					
17	-0.05478																					
18	-0.09415																					
19	0.02577																					
20	-0.09031																					
21	-0.14458																					
22	-0.06127																					
23	0.18887																					
24	-0.02287																					

# Example 1: Industry Sales

(continued)

- The model is identified to be ARIMA( $p, 1, q$ )( $P, 1, Q$ )<sub>12</sub>.
- What are the values of  $p$ ,  $q$ ,  $P$ , and  $Q$ ?

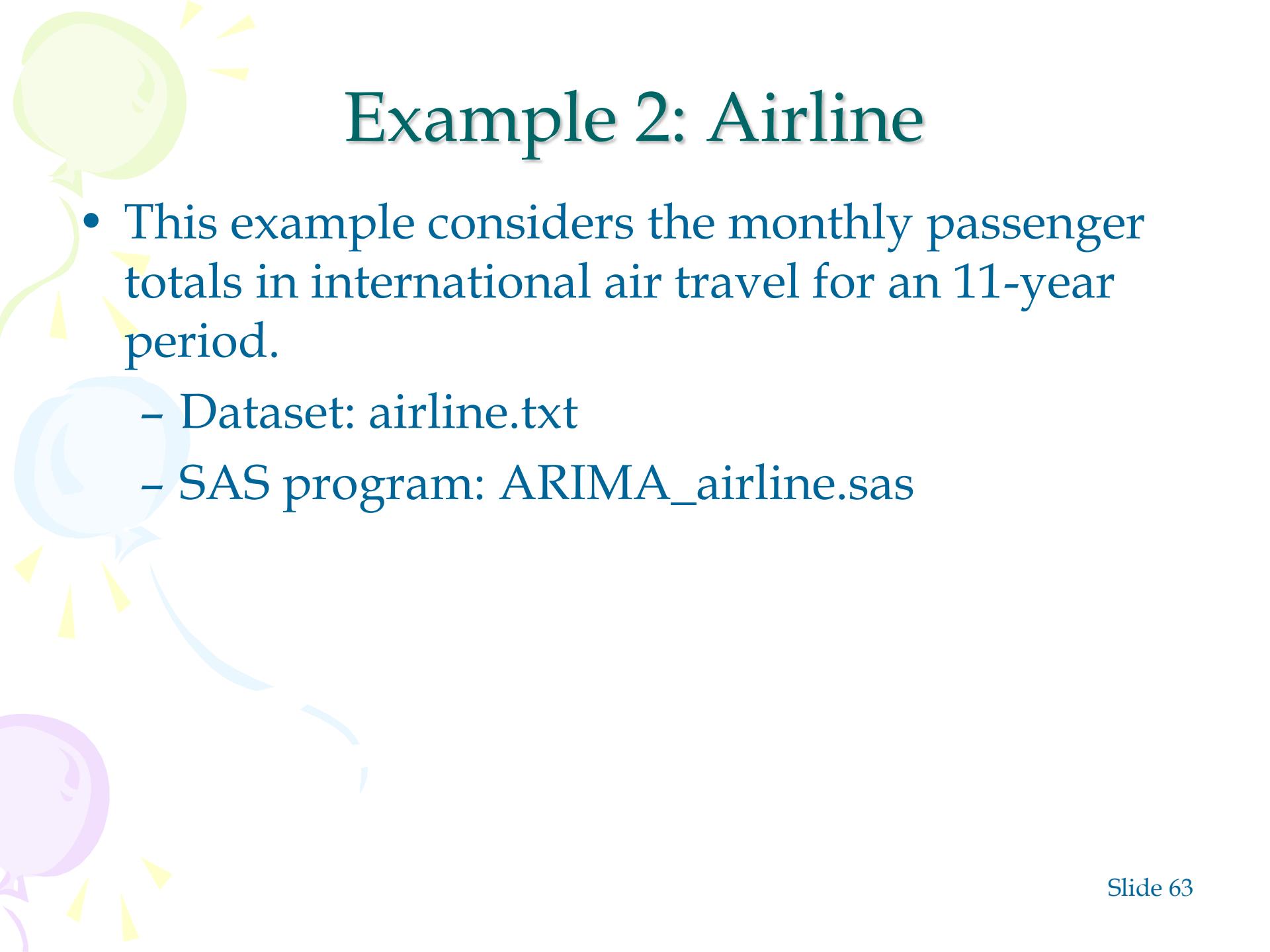




# Example 1: Industry Sales

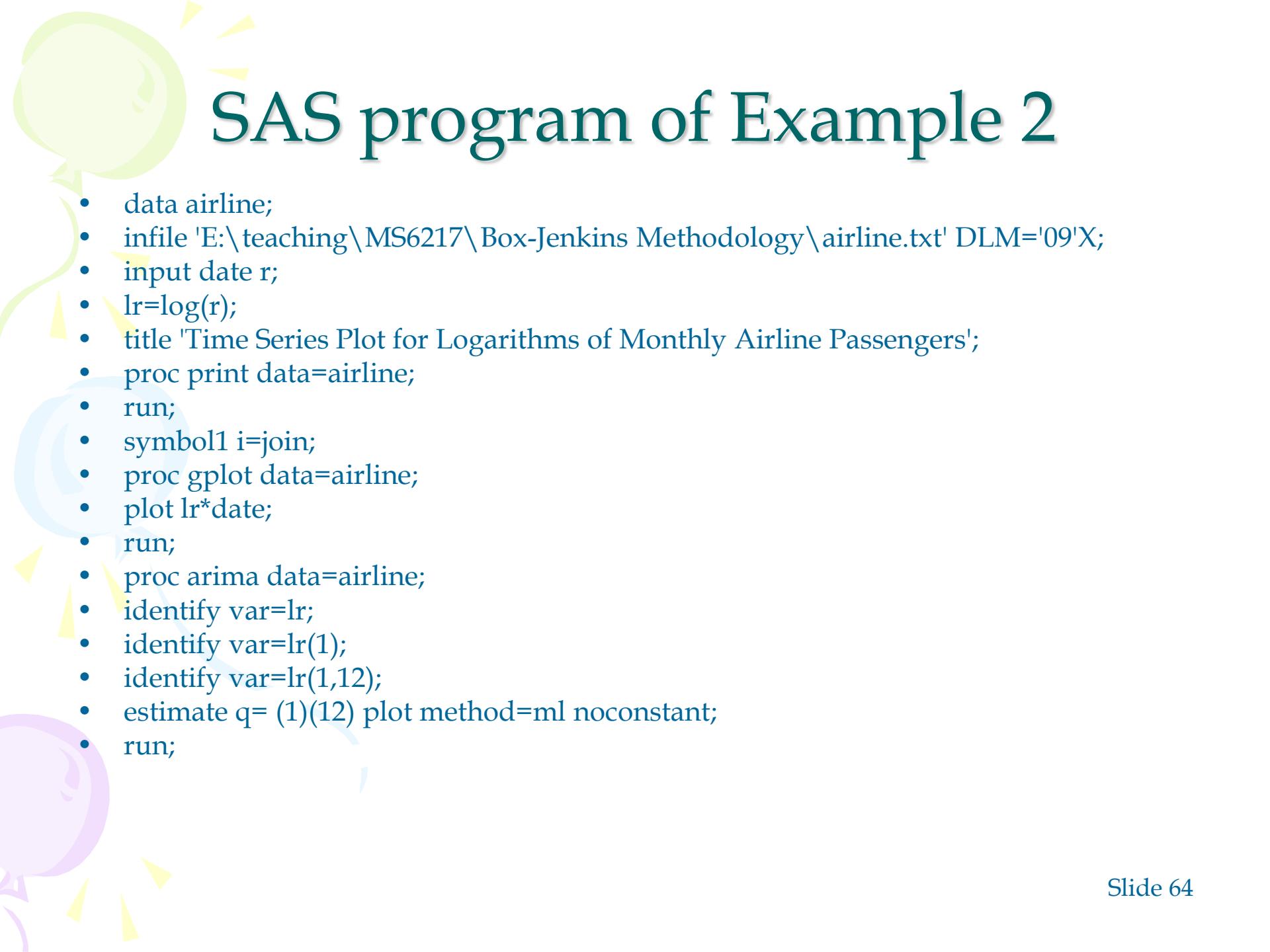
(continued)

- PACF – exponential decay of the first few lags  $\Rightarrow$  nonseasonal MA(1)  $\Rightarrow p = ?, q = ?$
- ACF  $-\rho_1$  is significant  $\Rightarrow$  reinforcing the nonseasonal MA(1)
- ACF  $-\rho_{12}$  is significant  $\Rightarrow$  seasonal MA(1)  $\Rightarrow P = ?, Q = ?$
- We end up with the tentative identification:  
$$\text{ARIMA}(0,1,1)(0,1,1)_{12}$$
  
or 
$$(1 - B)(1 - B^{12})y_t = \delta + (1 - \theta_1 B)(1 - \Theta_1 B^{12})\varepsilon_t$$



## Example 2: Airline

- This example considers the monthly passenger totals in international air travel for an 11-year period.
  - Dataset: `airline.txt`
  - SAS program: `ARIMA_airline.sas`

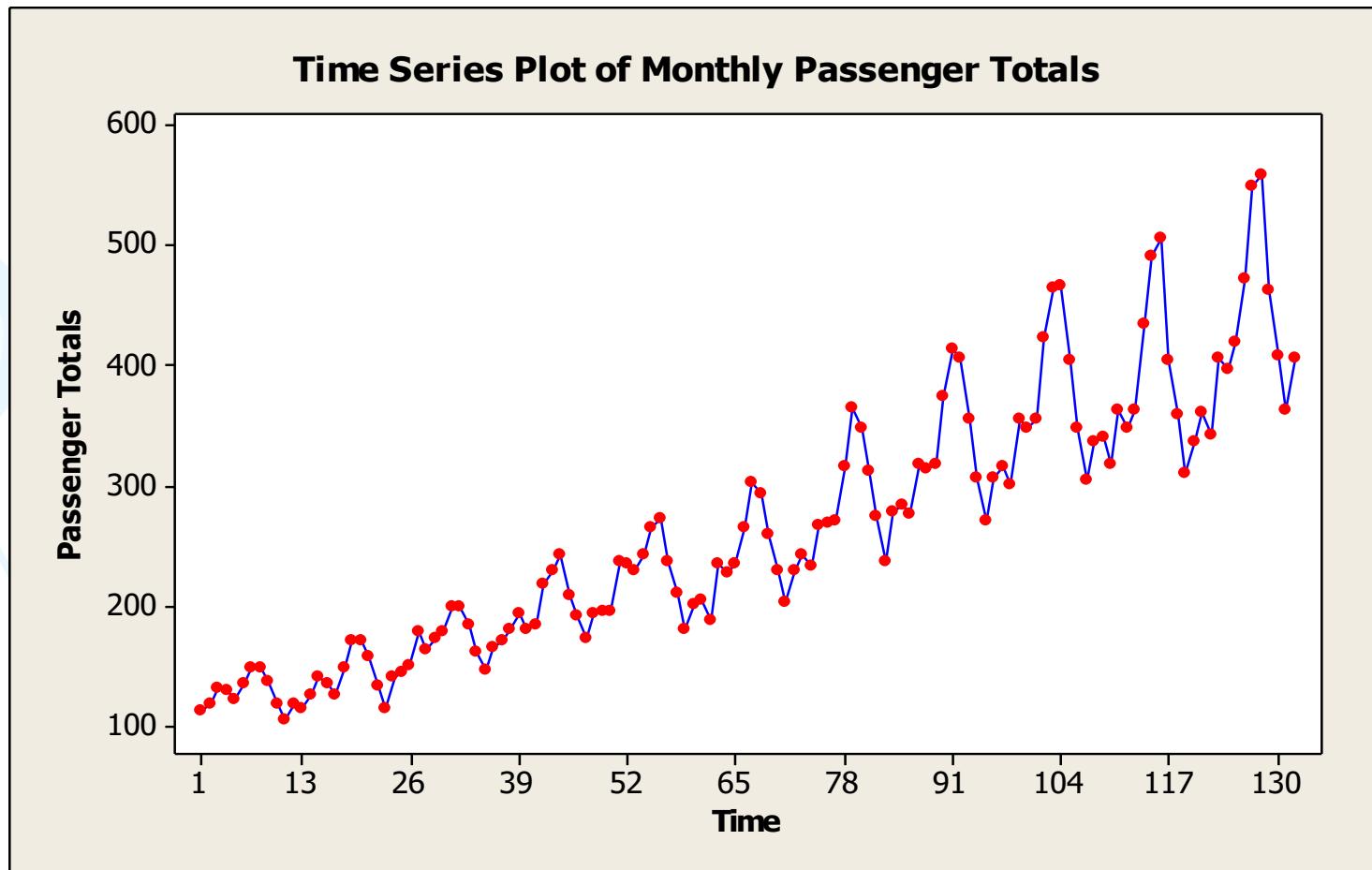


# SAS program of Example 2

- data airline;
- infile 'E:\teaching\MS6217\Box-Jenkins Methodology\airline.txt' DLM='09'X;
- input date r;
- lr=log(r);
- title 'Time Series Plot for Logarithms of Monthly Airline Passengers';
- proc print data=airline;
- run;
- symbol1 i=join;
- proc gplot data=airline;
- plot lr\*date;
- run;
- proc arima data=airline;
- identify var=lr;
- identify var=lr(1);
- identify var=lr(1,12);
- estimate q= (1)(12) plot method=ml noconstant;
- run;

# Example 2: Airline

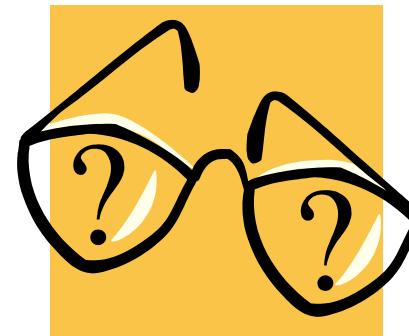
(continued)



## Example 2: Airline

(continued)

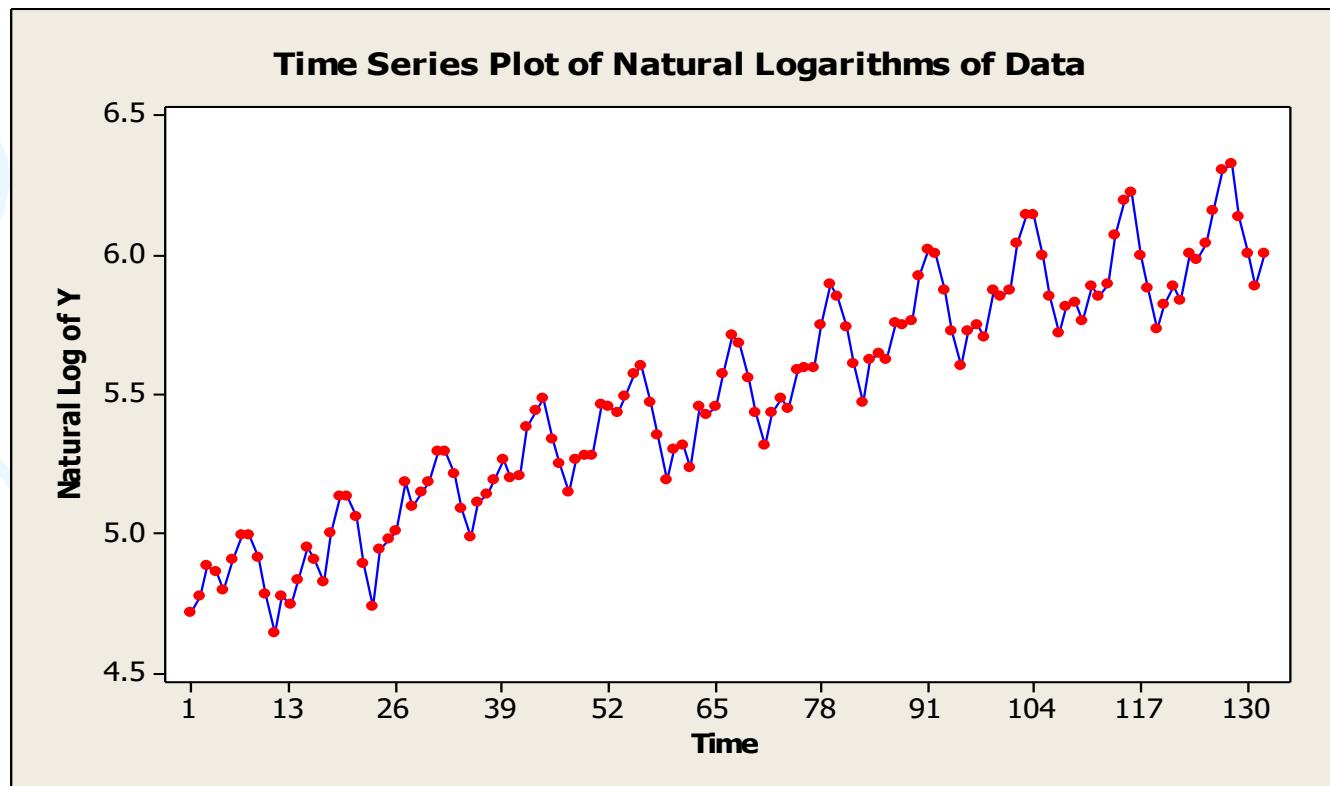
- What pattern can you see from this plot?
- How should we deal with the data?

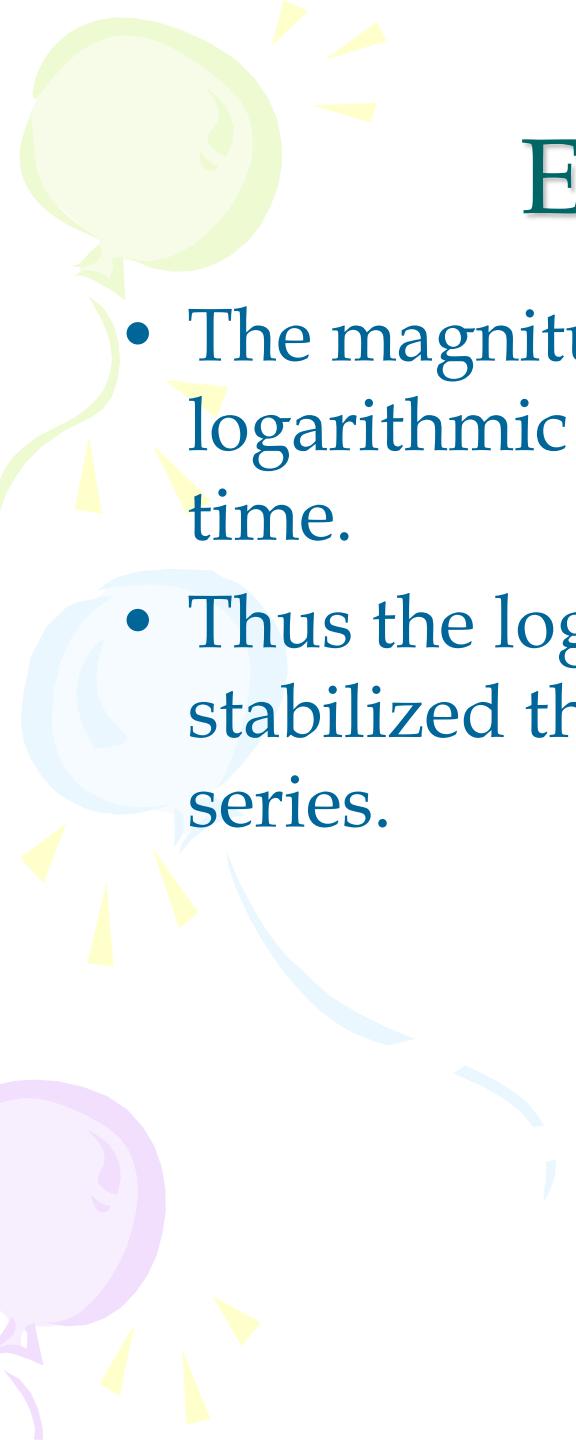


# Example 2: Airline

(continued)

- The main approach for achieving stationarity in variance is through a logarithmic transformation of the data.





## Example 2: Airline

(continued)

- The magnitude of the fluctuations in the logarithmic transformed data does not vary with time.
- Thus the logarithmic transformation has stabilized the seasonal variation of the time series.

# Example 2: Airline

(continued)

Lag	Covariance	Correlation	Autocorrelations													Std Error								
			-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
0	0.171929	1.00000	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0
1	0.163046	0.94833	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.087039
2	0.152719	0.88827	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.145609
3	0.143920	0.83709	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.182090
4	0.136109	0.79165	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.209222
5	0.130713	0.76027	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.230802
6	0.126663	0.73671	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.249053
7	0.123189	0.71651	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.265049
8	0.121189	0.70487	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.279337
9	0.122678	0.71354	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.292502
10	0.124408	0.72360	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.305404
11	0.127268	0.74023	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.318127
12	0.128345	0.74650	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.330918
13	0.120137	0.69876	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.343439
14	0.110500	0.64271	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.354046
15	0.102461	0.59595	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.362777
16	0.094839	0.55162	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.370119
17	0.089001	0.51766	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.376296
18	0.084712	0.49271	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.381652
19	0.081181	0.47218	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.386441
20	0.079455	0.46214	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.390788
21	0.080889	0.47048	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.394906
22	0.082262	0.47847	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.399130
23	0.084101	0.48916	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.403452
24	0.084720	0.49276	.	.	.	.	.	.	.	.	.	*	*	*	*	*	*	*	*	*	*	*	*	0.407920

"." marks two standard errors

# Example 2: Airline

(continued)

Name of Variable = lr

Period(s) of Differencing	1
Mean of Working Series	0.009812
Standard Deviation	0.106108
Number of Observations	131
Observation(s) eliminated by differencing	1

## Autocorrelations

Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	0.011259	1.00000																						0
1	0.0021204	0.18833																						0.087370
2	-0.0014316	-.12715																						0.090416
3	-0.0017371	-.15428																						0.091771
4	-0.0036710	-.32605																						0.093730
5	-0.0007441	-.06609																						0.102022
6	0.00045622	0.04052																						0.102348
7	-0.0011062	-.09826																						0.102470
8	-0.0038662	-.34339																						0.103187
9	-0.0012221	-.10855																						0.111570
10	-0.0013476	-.11969																						0.112373
11	0.0022423	0.19916																						0.113342
12	0.0093768	0.83283																						0.115983
13	0.0022286	0.19794																						0.155053
14	-0.0016113	-.14311																						0.156970
15	-0.0012339	-.10959																						0.157963
16	-0.0032466	-.28836																						0.158542
17	-0.0005219	-.04636																						0.162497
18	0.00040322	0.03581																						0.162598
19	-0.0011741	-.10428																						0.162658
20	-0.0035209	-.31272																						0.163167
21	-0.0011947	-.10612																						0.167680
22	-0.0009539	-.08473																						0.168192
23	0.0020862	0.18530																						0.168518
24	0.0080362	0.71376																						0.170066

"." marks two standard errors

# Example 2: Airline

(continued)

Name of Variable = Ir

Period(s) of Differencing	1,12
Mean of Working Series	0.001322
Standard Deviation	0.044849
Number of Observations	119
Observation(s) eliminated by differencing	13

## Autocorrelations

Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error	
0	0.0020114	1.00000												*****	*****	*****	*****	*****	*****	*****	*****	*****	*****	0	
1	-0.0006378	-.31710												.	**	.									0.091670
2	0.00021914	0.10895												.	*	.									0.100466
3	-0.0004343	-.21592												***	.	.									0.101454
4	0.00008998	0.04474												.	*	.									0.105244
5	0.00006247	0.03106												.	*	.									0.105404
6	0.00008597	0.04274												.	*	.									0.105481
7	-0.0001303	-.06478												.	*	.									0.105626
8	0.00002510	0.01248												.	.	.									0.105960
9	0.00032664	0.16239												.	***	.								0.105972	
10	-0.0001042	-.05179												.	*	.									0.108043
11	0.00014860	0.07388												.	*	.									0.108251
12	-0.0008254	-.41035												*****	.	*	.								0.108674
13	0.00032666	0.16240												.	***	.									0.120996
14	-0.0001072	-.05329												.	*	.									0.122814
15	0.00029374	0.14604												.	***	.									0.123008
16	-0.0002927	-.14552												.	***	.									0.124457
17	0.00018639	0.09267												.	**	.									0.125879
18	-0.0000602	-.02992												.	*	.									0.126451
19	0.00010879	0.05409												.	*	.									0.126510
20	-0.0002837	-.14102												.	***	.									0.126704
21	0.00007227	0.03593												.	*	.									0.128016
22	-0.0001621	-.08061												.	**	.									0.128101
23	0.00043582	0.21667												.	****	.									0.128527
24	-0.0000607	-.03017												.	*	.									0.131560

... marks two standard errors

# Example 2: Airline

(continued)

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	-0.31710																					
2	0.00934																					
3	-0.19873																					
4	-0.09252																					
5	0.03361																					
6	0.03035																					
7	-0.06064																					
8	-0.00849																					
9	0.21218																					
10	0.04408																					
11	0.07212																					
12	-0.35474																					
13	-0.08283																					
14	-0.02168																					
15	-0.01661																					
16	-0.13096																					
17	0.05560																					
18	0.07705																					
19	-0.00278																					
20	-0.14277																					
21	0.11704																					
22	-0.04138																					
23	0.18134																					
24	-0.10472																					

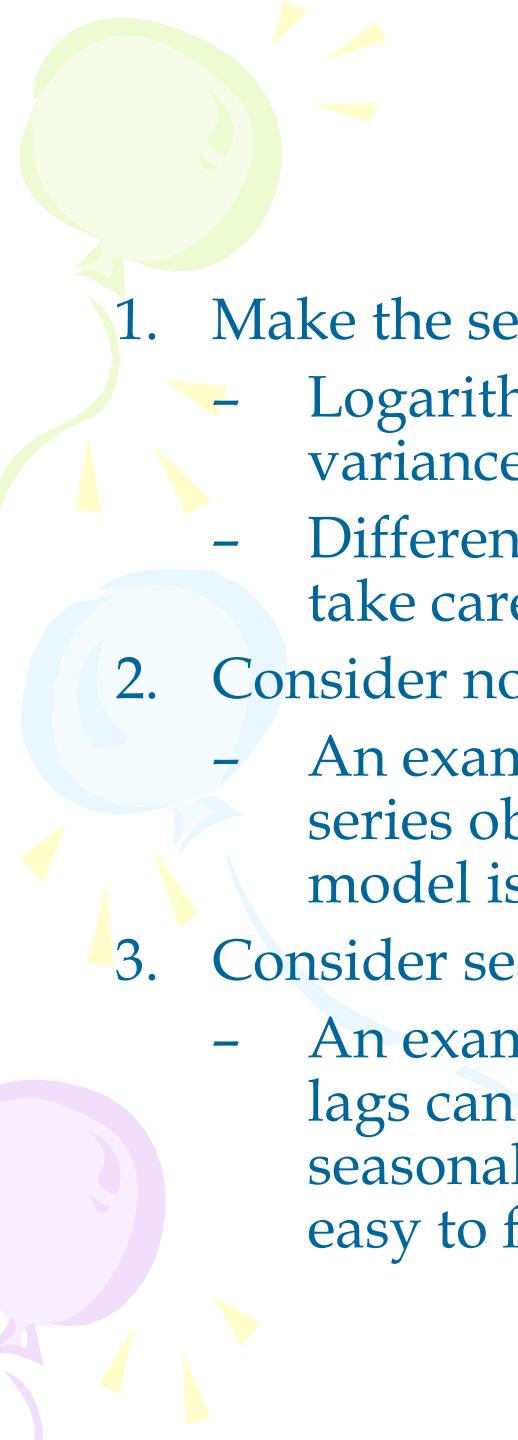
# Example 2: Airline

(continued)

- At the nonseasonal level ACF has a significant spike at lag 1 and cuts off after lag 1 (with the exception of a spike at lag 3), and the PACF dies down  $\Rightarrow$  nonseasonal MA(1) component
- At the seasonal level both ACF and PACF appear to cut off after lag 12. However, autocorrelation at lag 24 in ACF is smaller than the partial autocorrelation at lag 24 in PACF.  $\Rightarrow$  ACF cuts off after lag 12 and PACF dies down.  $\Rightarrow$  seasonal MA(1) component
- For the logged data, a tentative model would be:

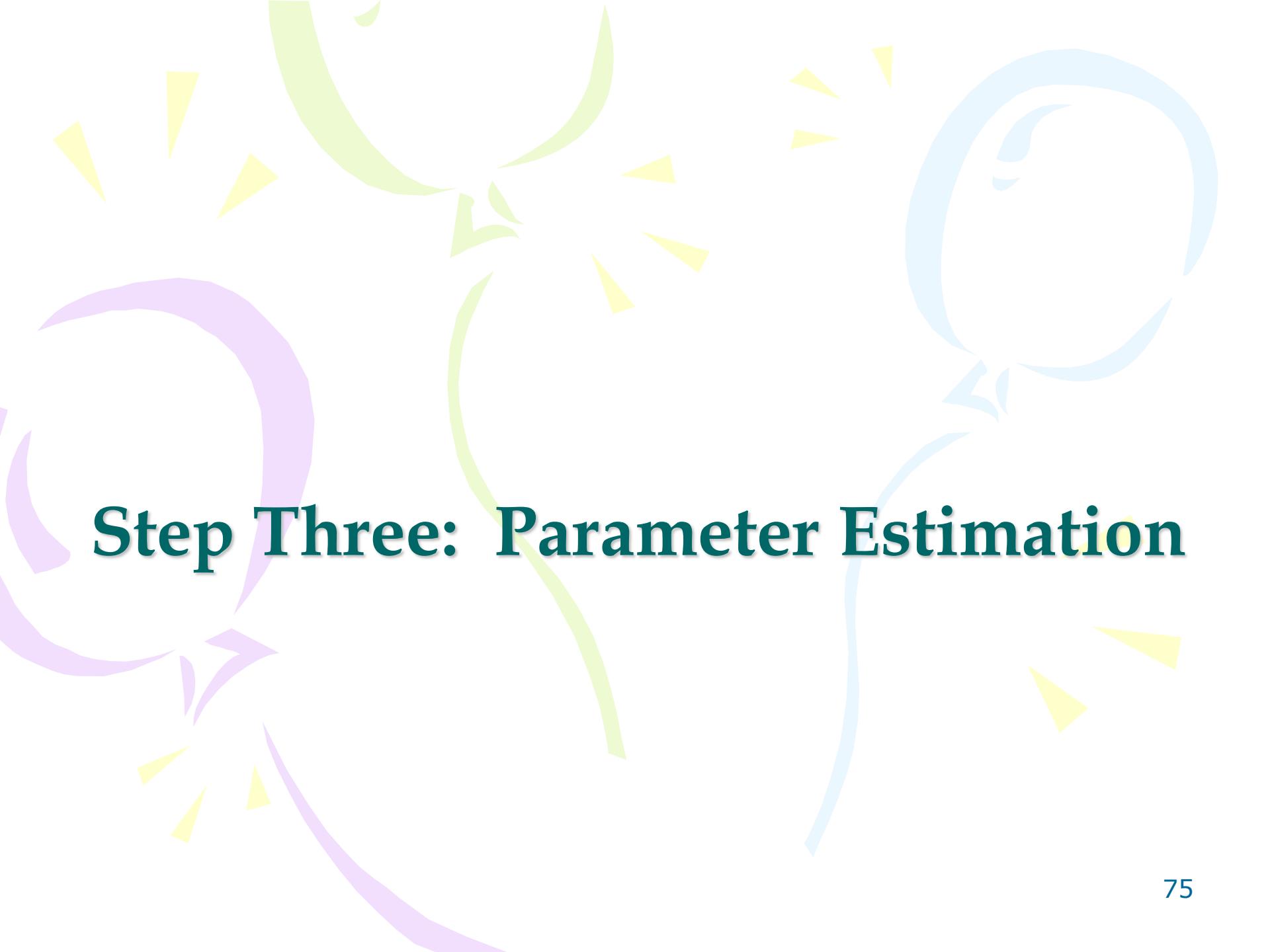
$$\text{ARIMA}(0,1,1)(0,1,1)_{12}$$

$$\text{or } (1 - B)(1 - B^{12})(\ln y_t) = \delta + (1 - \theta_1 B)(1 - \Theta_1 B^{12})\varepsilon_t$$

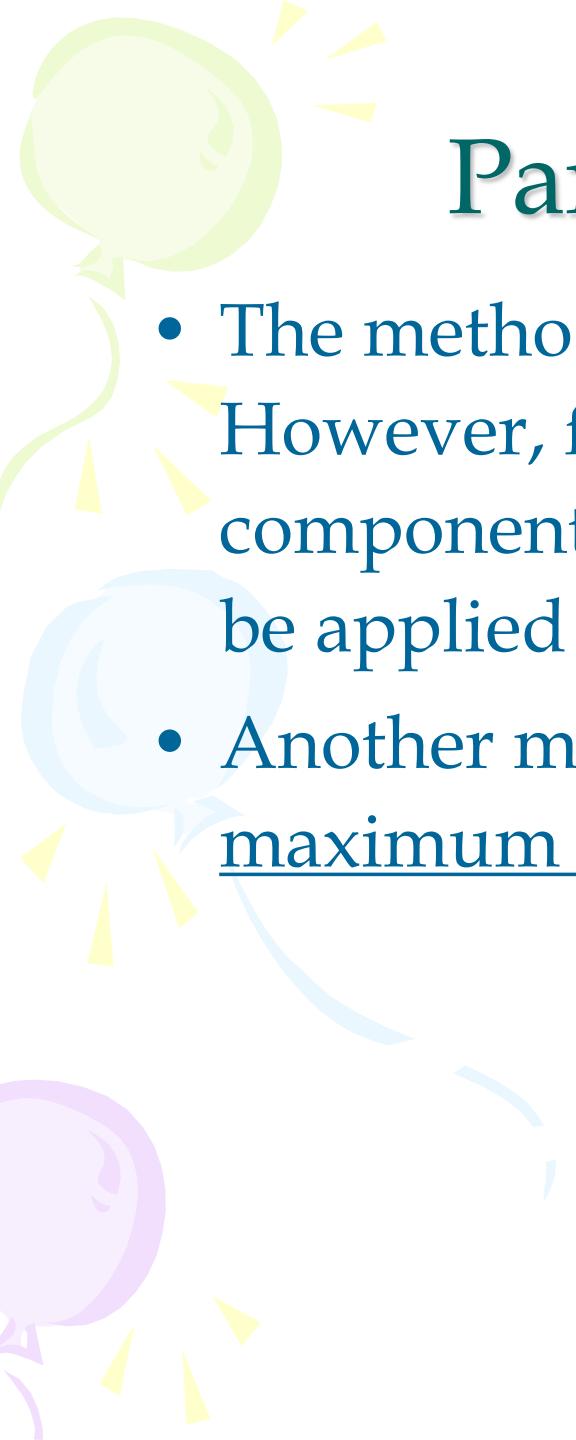


# Recapitulation

1. Make the series stationary.
  - Logarithmic will often take care of nonstationary variance (pre-differencing transformation).
  - Differencing (nonseasonal and/or seasonal) will usually take care of nonstationarity in the mean.
2. Consider nonseasonal aspects.
  - An examination of the ACF and PACF of the stationary series obtained in Step 1 can reveal whether a MA or AR model is feasible.
3. Consider seasonal aspects.
  - An examination of the ACF and PACF at the seasonal lags can help identify MA and AR models for the seasonal aspects of the data, but the indications are not as easy to find as in the case of the nonseasonal aspects.

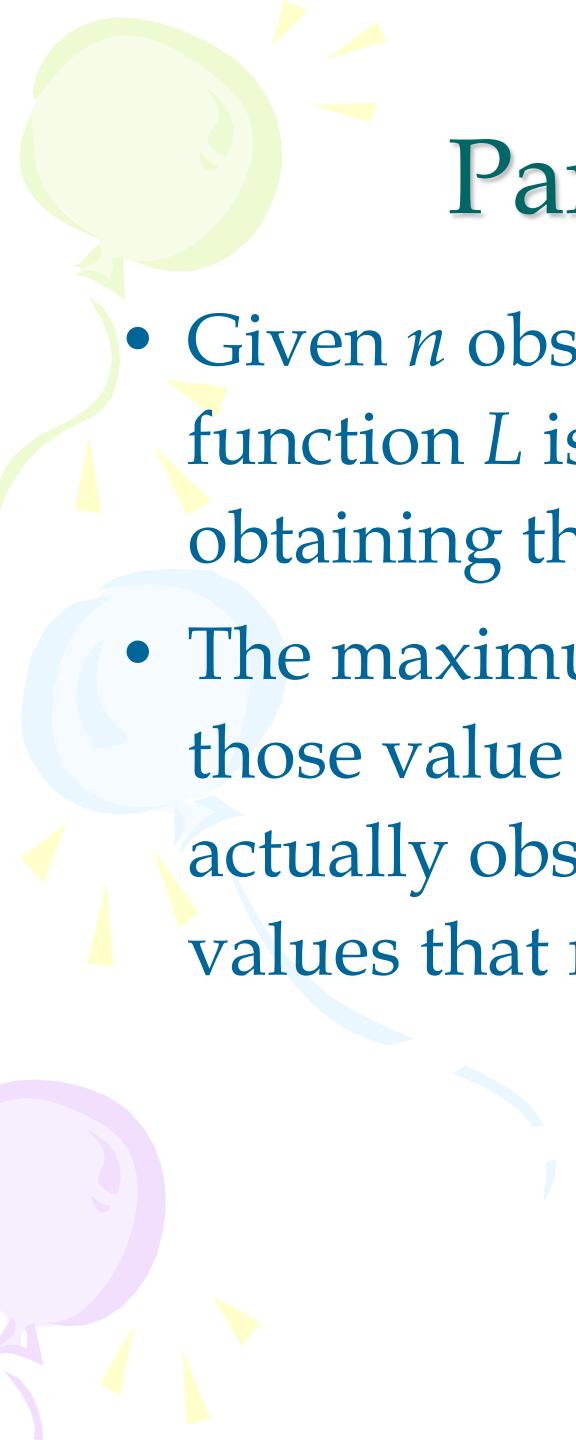


## **Step Three: Parameter Estimation**



# Parameter Estimation

- The method of least squares can be used. However, for models involving an MA component, there is no simple formula that can be applied to obtain the estimates.
- Another method which is frequently used is maximum likelihood.



# Parameter Estimation

(continued)

- Given  $n$  observations  $y_1, y_2, \dots, y_n$ , the likelihood function  $L$  is defined to be the probability of obtaining the data actually observed.
- The maximum likelihood estimators (m.l.e.) are those value of the parameters for which the data actually observed are most likely, that is, the values that maximize the likelihood function  $L$ .

# Parameter Estimation

- Estimate parameters once a tentative model has been selected.
  - Determine whether the parameters are significantly different from zero.
    - t – values
$$t = \frac{\hat{\theta}}{s_{\hat{\theta}}}$$
where  $\hat{\theta}$  is the estimated coefficient and  $s_{\hat{\theta}}$  is the standard error of the estimated coefficient. Reject  $H_0: \theta = 0$  if  $|t| > t_{\alpha/2, n-r}$
    - p-value: Reject  $H_0: \theta = 0$  if p-value <  $\alpha$ .
  - If these parameters are not significant, we may have been able to improve the model by dropping the corresponding terms from the model.

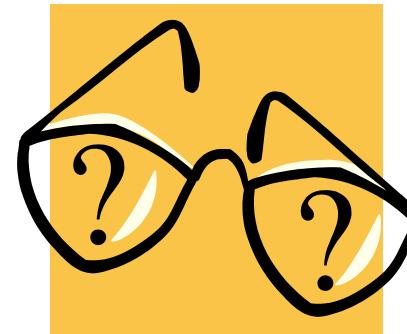
# Parameter Estimation

- In most Box-Jenkins models, the sample size after differencing is at least 30. Therefore, as a practical rule, it is reasonable to compare the absolute value of a parameter estimate with 2 for the testing.
- To test whether the constant term should be included in the model, i.e.,  $H_0: \delta = 0$  vs  $H_a: \delta \neq 0$ 
  - If  $\left| \frac{\bar{z}}{s_z / \sqrt{n'}} \right| > 2$ , reject  $H_0$ , where  $\bar{z}$  is the mean of the working series,  $s_z$  is the standard deviation, and  $n'$  is the sample size of the working series.

# Example 1: Industry Sales

Period(s) of Differencing	1,12
Mean of Working Series	0.389673
Standard Deviation	68.54769
Number of Observations	107
Observation(s) eliminated by differencing	13

Should the constant be included in the model?



# Example 1: Industry Sales

(continued)

- An ARIMA(0,1,1)(0,1,1)<sub>12</sub> model was identified

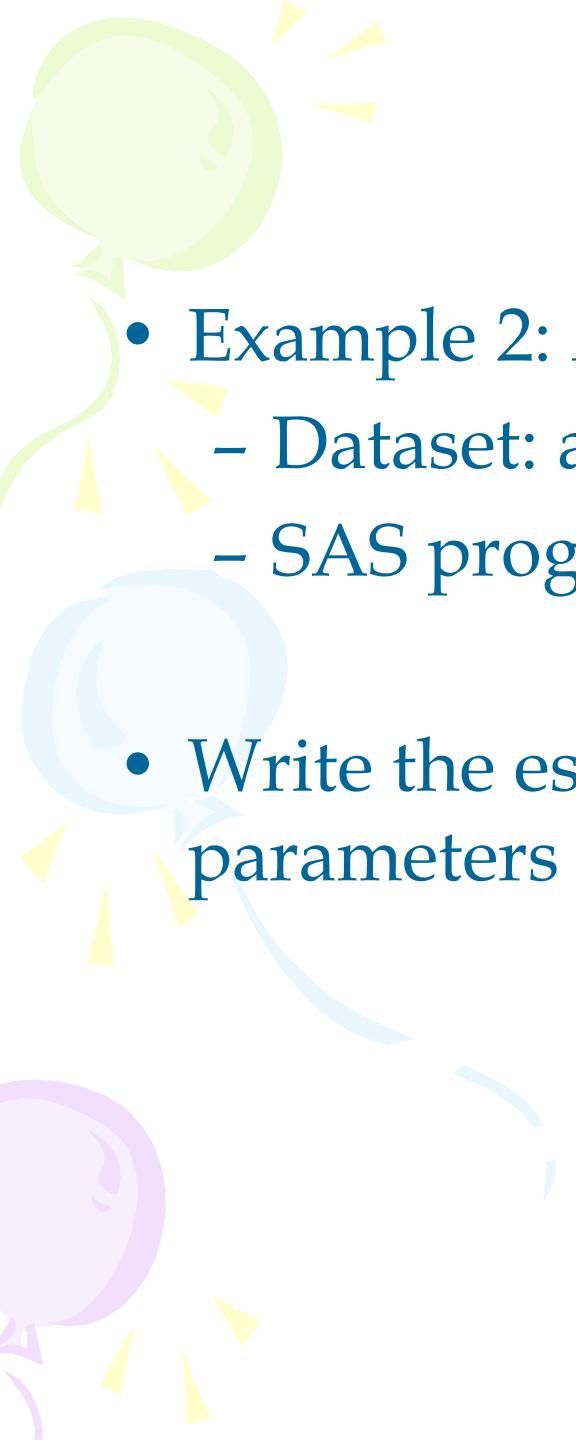
The ARIMA Procedure					
Maximum Likelihood Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr >  t	Lag
MA1,1	0.84028	0.05527	15.20	<.0001	1
MA2,1	0.63569	0.10202	6.23	<.0001	12

- The estimated model is

$$(1 - B)(1 - B^{12})y_t = (1 - 0.840B)(1 - 0.636B^{12})\varepsilon_t$$

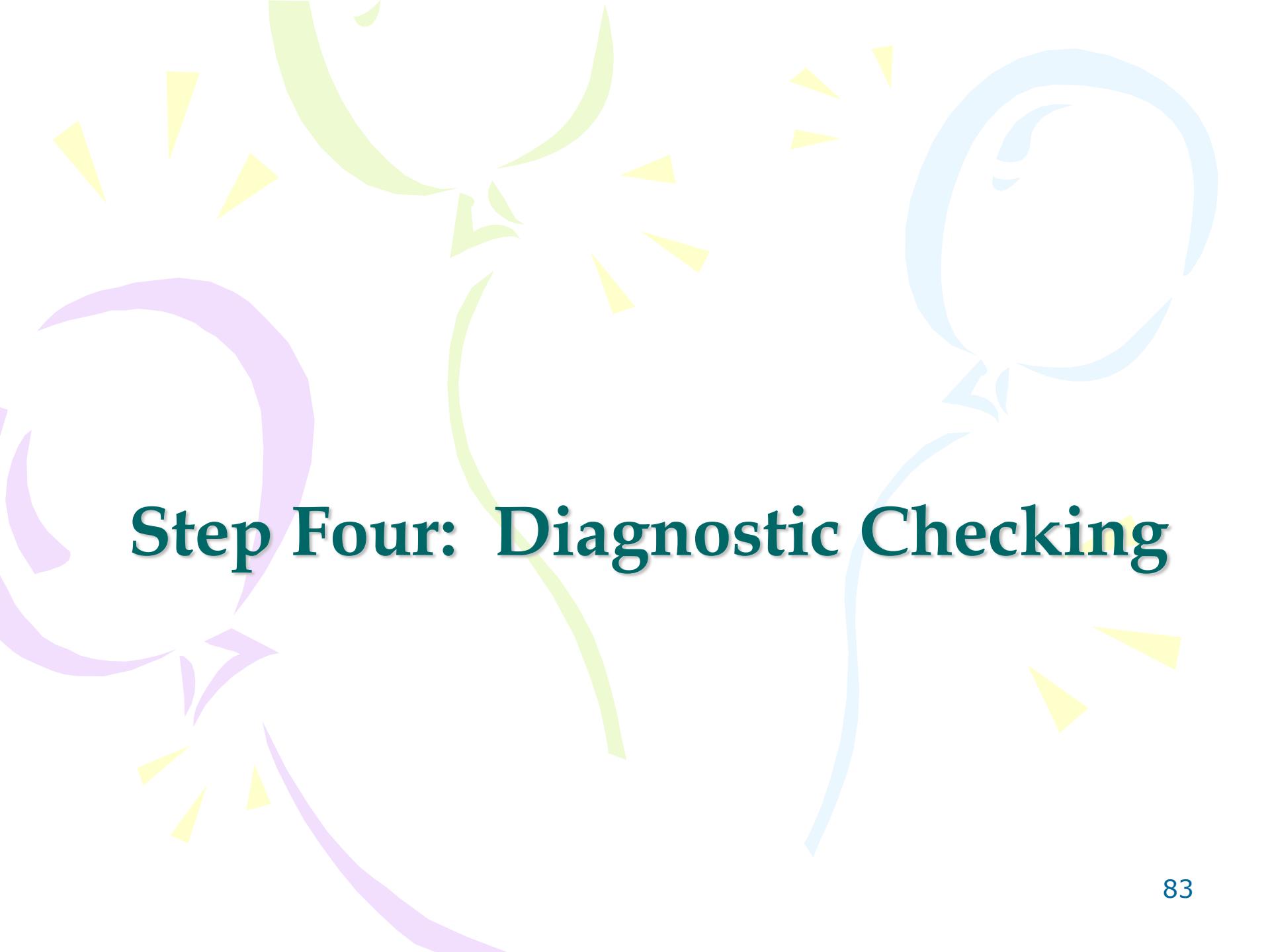
i.e.,

$$y_t = y_{t-1} + y_{t-12} - y_{t-13} + \varepsilon_t - 0.840\varepsilon_{t-1} - 0.636\varepsilon_{t-12} + 0.534\varepsilon_{t-13}$$

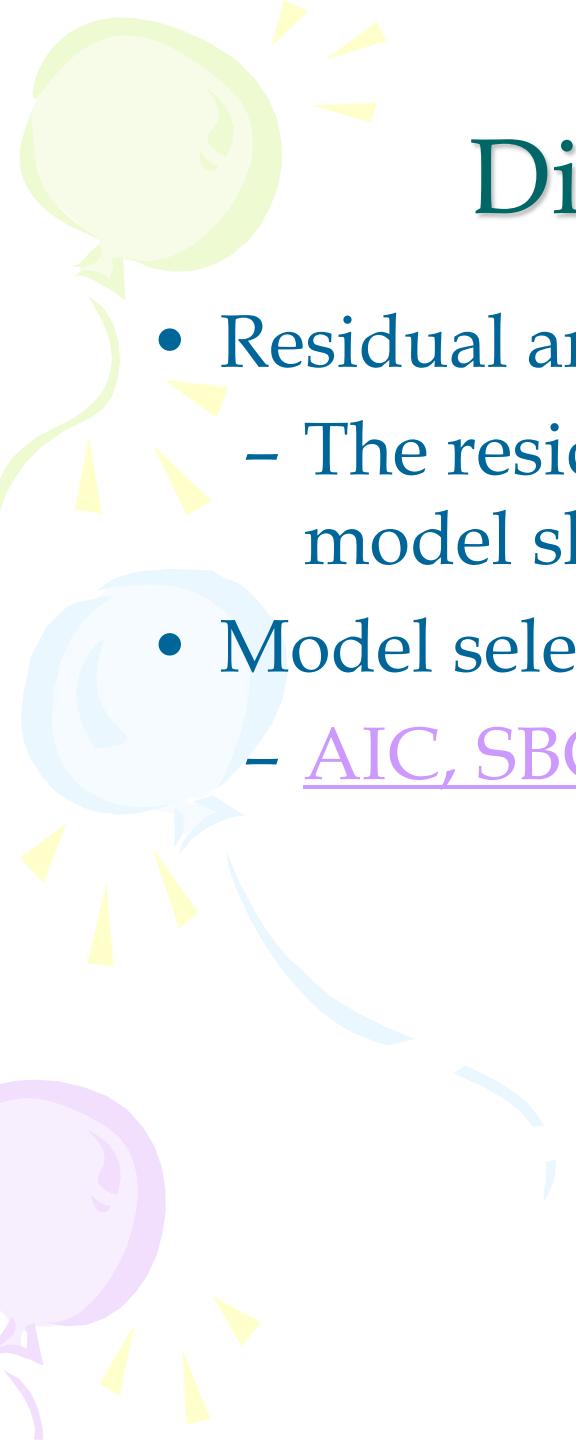


# Exercise

- Example 2: Airline
  - Dataset: airline.dat
  - SAS program: ARIMA\_airline.sas
- Write the estimated model. Are all the parameters significant?

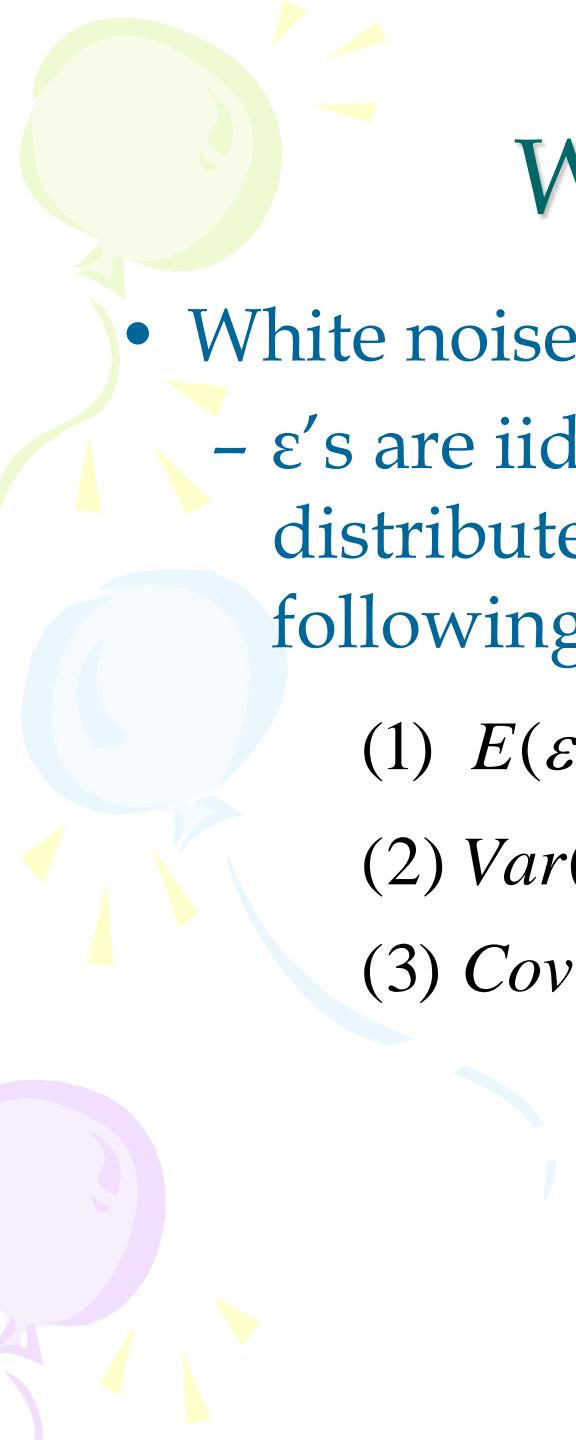


## **Step Four: Diagnostic Checking**



# Diagnostic Checking

- Residual analysis
  - The residuals left over after fitting the model should be white noise.
- Model selection criteria.
  - AIC, SBC



# White Noise Series

- White noise series  $\{\varepsilon_t\}$ 
  - $\varepsilon$ 's are iid (independent and identically distributed) random variables with the following properties.
    - (1)  $E(\varepsilon_t) = 0 \quad \text{for all } t.$
    - (2)  $\text{Var}(\varepsilon_t) = \sigma^2 \quad \text{for all } t.$
    - (3)  $\text{Cov}(\varepsilon_t, \varepsilon_{t+s}) = 0 \quad \text{for all } t, s \neq t.$

# Portmanteau Test

- Rather than study the autocorrelation values one at a time, an alternative approach is to consider a whole set of autocorrelation values all at one time, and test to see whether the set is significantly different from a zero set.
- Ljung-Box test

$$Q = n(n+2) \sum_{k=1}^m \frac{r_k^2(e)}{n-k} \sim \chi^2_{m-r}$$

where  $r_k(e)$  = the residual autocorrelation at lag k

$n$  = number of residuals

$k$  = time lag

$m$  = number of time lags to be tested

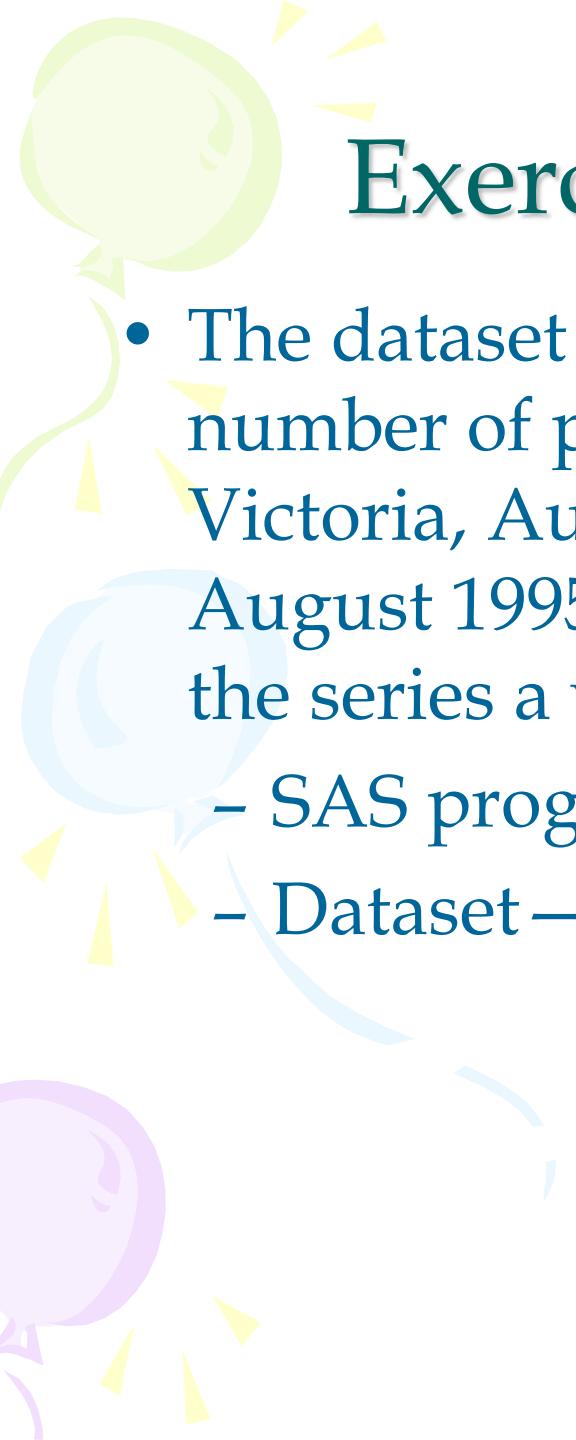
$r$  = number of parameters estimated in the model

# Example: Random Numbers (WNOISE.DAT)

## Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.44	6	0.8754	0.103	0.099	-0.043	-0.031	-0.183	0.025

$Q(6) = 2.44 < \chi^2_{0.05, 6} = 12.59 \Rightarrow$  White noise series



# Exercise: Pigs slaughtered

- The dataset `pigs.dat` lists the monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 1990 through August 1995. ACF and PACF plots are given. Is the series a white noise series?
  - SAS program – `ARIMA_pigs.sas`
  - Dataset – `pigs.dat`

# Exercise: Pigs slaughtered

(continued)

Lag	Covariance	Correlation	Autocorrelations													Std Error							
			-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
0	104001682	1.00000																					0
1	37233269	0.35801										.			*****								0.121268
2	29504608	0.28369									.			*****									0.135925
3	36875165	0.35456									.			*****									0.144370
4	6933036	0.06666									.	*		.									0.156653
5	19538193	0.18786									.	***	.										0.157070
6	19229857	0.18490									.	***	.										0.160340
7	9514415	0.09148									.	**	.										0.163445
8	2352843	0.02262									.	**	.										0.164197
9	3966057	0.03813									.	*	.										0.164243
10	-8420991	-.08097									.	**	.										0.164373
11	-754726	-.00726									.	***	.										0.164958
12	18206590	0.17506									.	***	.										0.164963
13	-2300270	-.02212									.	**	.										0.167673
14	-4904801	-.04716									.	*	.										0.167716
15	-4710970	-.04530									.	*	.										0.167911
16	-17556435	-.16881									.	***	.										0.168090
17	3678019	0.03536									.	**	.										0.170565

"." marks two standard errors

# Exercise: Pigs slaughtered

(continued)

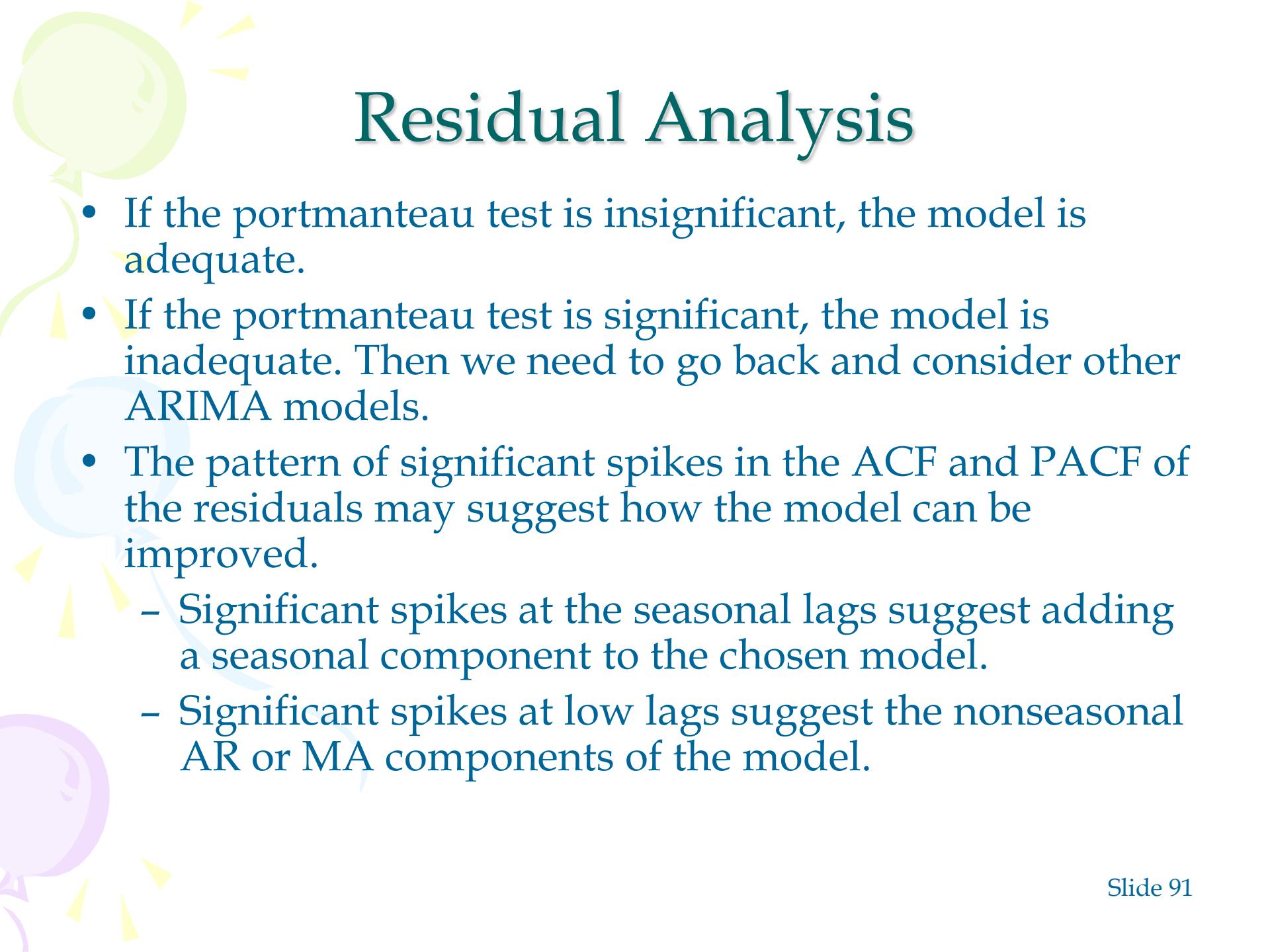
Partial Autocorrelations

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	0.35801	.										*****											
2	0.17839	.										****	.										
3	0.24553	.										****	.										
4	-0.17665	.										****	.										
5	0.13668	.										***	.										
6	0.04692	.										*	.										
7	0.03399	.										*	.										
8	-0.16238	.										***	.										
9	0.03352	.										*	.										
10	-0.13352	.										***	.										
11	0.10077	.										**	.										
12	0.18842	.										****	.										
13	-0.08236	.										**	.										
14	-0.15065	.										***	.										
15	-0.07418	.										*	.										
16	-0.03954	.										*	.										
17	0.18738	.										****	.										

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations								
6	29.74	6	<.0001	0.358	0.284	0.355	0.067	0.188	0.185			
12	33.70	12	0.0008	0.091	0.023	0.038	-0.081	-0.007	0.175			

Back to diagnostic checking

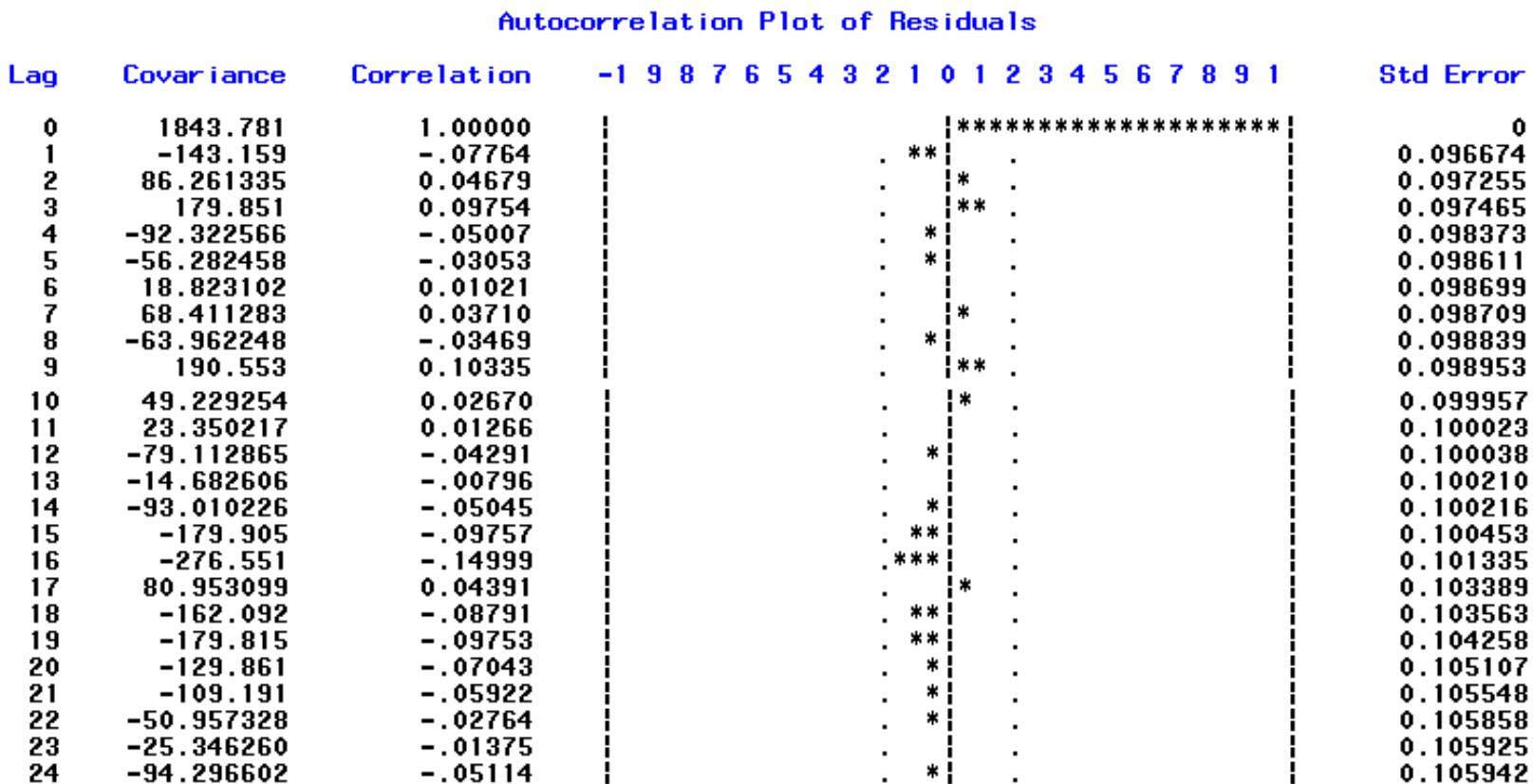


# Residual Analysis

- If the portmanteau test is insignificant, the model is adequate.
- If the portmanteau test is significant, the model is inadequate. Then we need to go back and consider other ARIMA models.
- The pattern of significant spikes in the ACF and PACF of the residuals may suggest how the model can be improved.
  - Significant spikes at the seasonal lags suggest adding a seasonal component to the chosen model.
  - Significant spikes at low lags suggest the nonseasonal AR or MA components of the model.

# Example 1: Industry Sales

- Fitted model: ARIMA(0,1,1)(0,1,1)<sub>12</sub>



# Example 1: Industry Sales

(continued)

		Partial Autocorrelations																					
Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	
1	-0.07764	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
2	0.04100	.	.	.	.	.	.	.	.	.	*	**	.	.	.	.	.	.	.	.	.	.	.
3	0.10502	.	.	.	.	.	.	.	.	.	**	*	**	.	.	.	.	.	.	.	.	.	.
4	-0.03721	.	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.
5	-0.04784	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.	.
6	-0.00138	.	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	.	.
7	0.05209	.	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	.	.
8	-0.02319	.	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.	.	.
9	0.09142	.	.	.	.	.	.	.	.	**	**	.	.	.	.	.	.	.	.	.	.	.	.
10	0.03570	.	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.
11	0.01743	.	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.
12	-0.06544	.	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.
13	-0.01789	.	.	.	.	.	.	.	.	**	**	.	.	.	.	.	.	.	.	.	.	.	.
14	-0.04222	.	.	.	.	.	.	.	.	**	**	.	.	.	.	.	.	.	.	.	.	.	.
15	-0.09073	.	.	.	.	.	.	.	.	****	****	.	.	.	.	.	.	.	.	.	.	.	.
16	-0.17890	.	.	.	.	.	.	.	.	****	****	.	.	.	.	.	.	.	.	.	.	.	.
17	0.03571	.	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.
18	-0.06427	.	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.
19	-0.10484	.	.	.	.	.	.	.	.	**	**	.	.	.	.	.	.	.	.	.	.	.	.
20	-0.12942	.	.	.	.	.	.	.	.	***	***	.	.	.	.	.	.	.	.	.	.	.	.
21	-0.05143	.	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.
22	-0.00946	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
23	0.00341	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
24	-0.05927	.	.	.	.	.	.	.	.	*	*	.	.	.	.	.	.	.	.	.	.	.	.

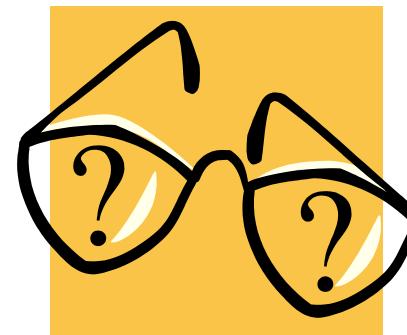
## Autocorrelation Check of Residuals

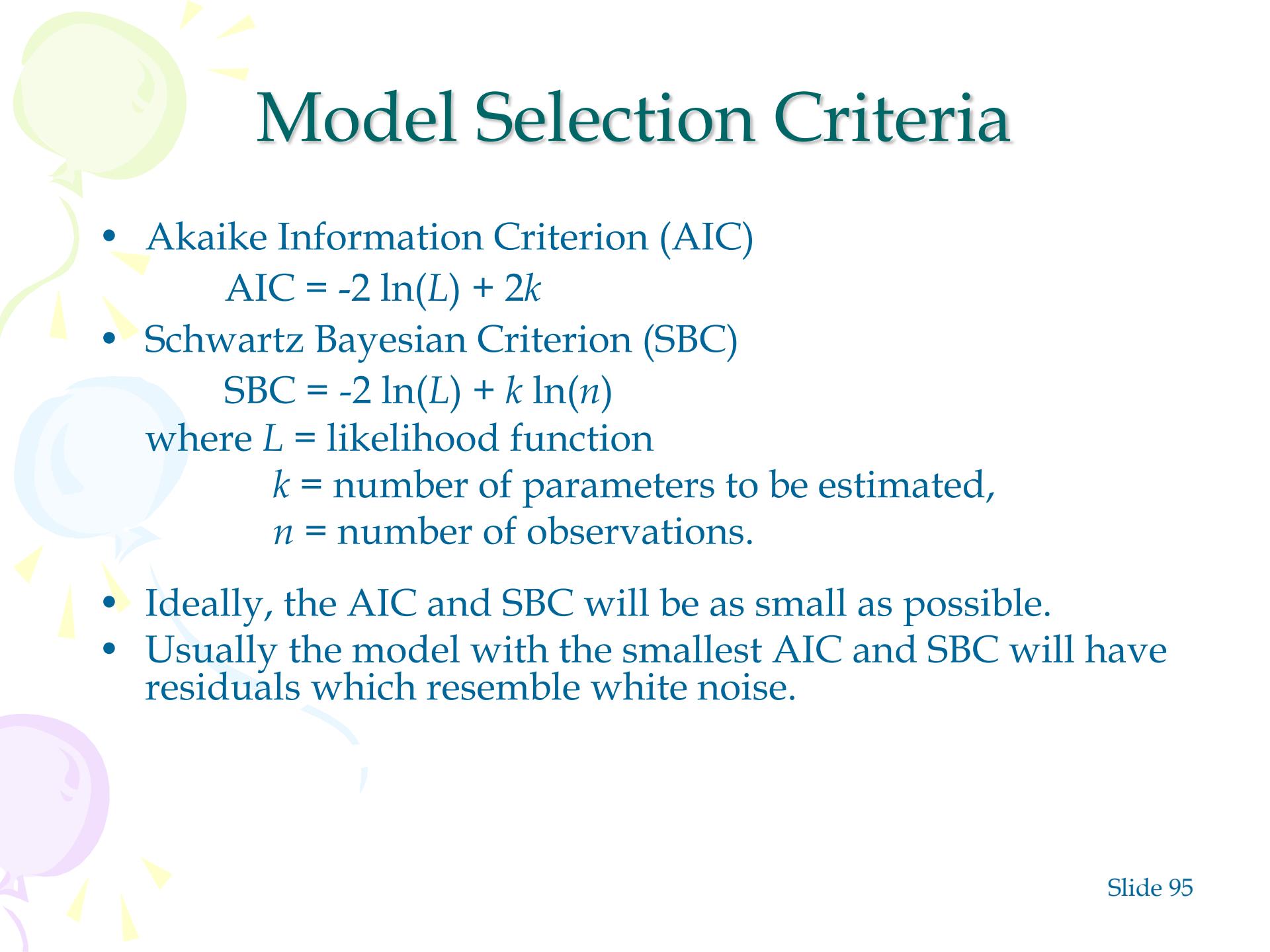
To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations									
6	2.38	4	0.6670	-0.078	0.047	0.098	-0.050	-0.031	0.010	.	.	.	.
12	4.28	10	0.9338	0.037	-0.035	0.103	0.027	0.013	-0.043	.	.	.	.
18	9.96	16	0.8687	-0.008	-0.050	-0.098	-0.150	0.044	-0.088	.	.	.	.
24	12.86	22	0.9370	-0.098	-0.070	-0.059	-0.028	-0.014	-0.051	.	.	.	.

# Example 1: Industry Sales

(continued)

- Is the residual series white noise? Why?
- Is the fitted model ARIMA(0,1,1)(0,1,1)<sub>12</sub> adequate? Why?





# Model Selection Criteria

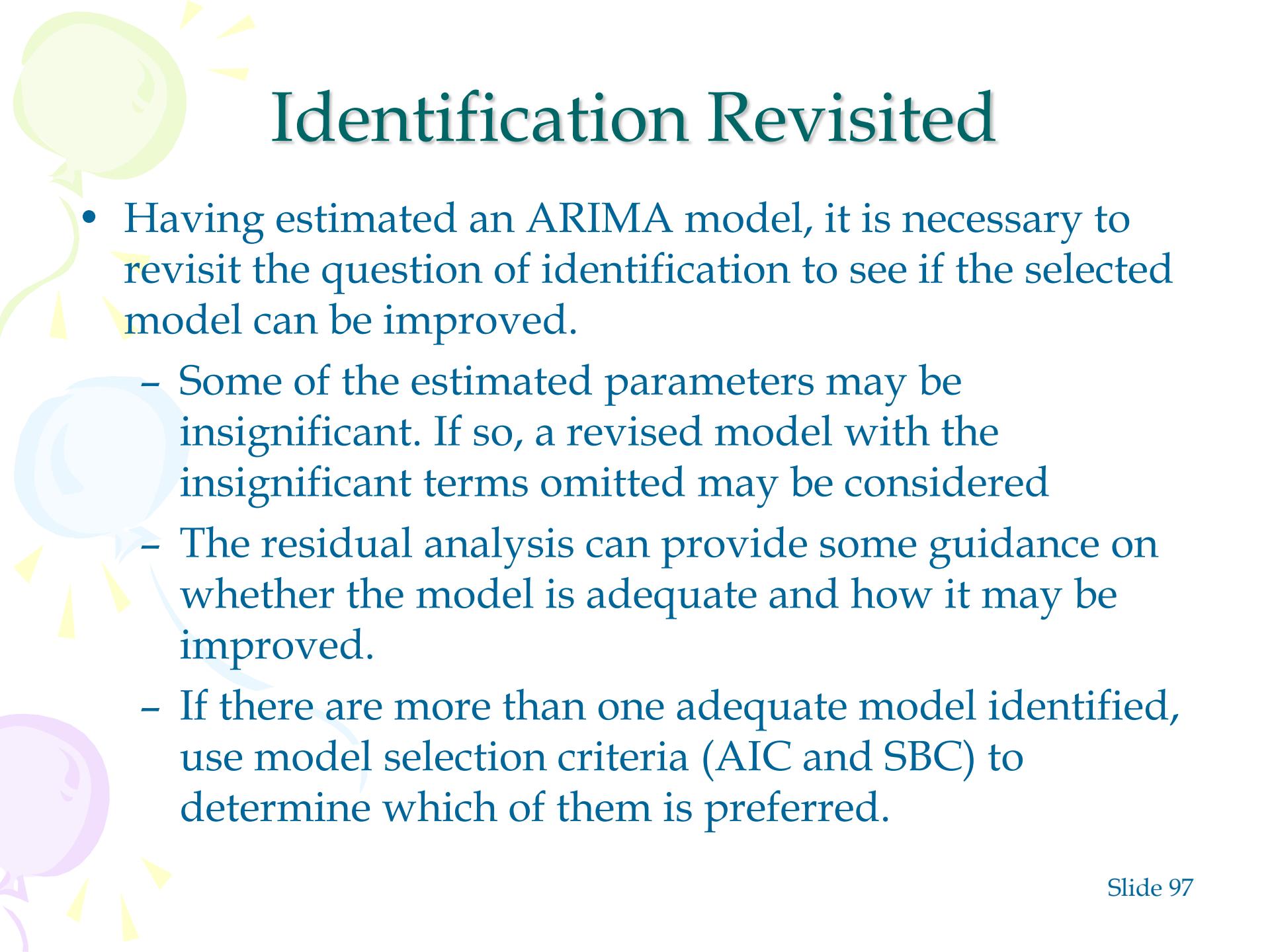
- Akaike Information Criterion (AIC)  
$$AIC = -2 \ln(L) + 2k$$
- Schwartz Bayesian Criterion (SBC)  
$$SBC = -2 \ln(L) + k \ln(n)$$

where  $L$  = likelihood function  
 $k$  = number of parameters to be estimated,  
 $n$  = number of observations.
- Ideally, the AIC and SBC will be as small as possible.
- Usually the model with the smallest AIC and SBC will have residuals which resemble white noise.

# Example 1: Industry Sales

- AIC and SBC values

The ARIMA Procedure					
Maximum Likelihood Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr >  t	Lag
MA1,1	0.84028	0.05527	15.20	<.0001	1
MA2,1	0.63569	0.10202	6.23	<.0001	12
Variance Estimate	1843.781				
Std Error Estimate	42.93927				
AIC	1117.827				
SBC	1123.173				
Number of Residuals	107				

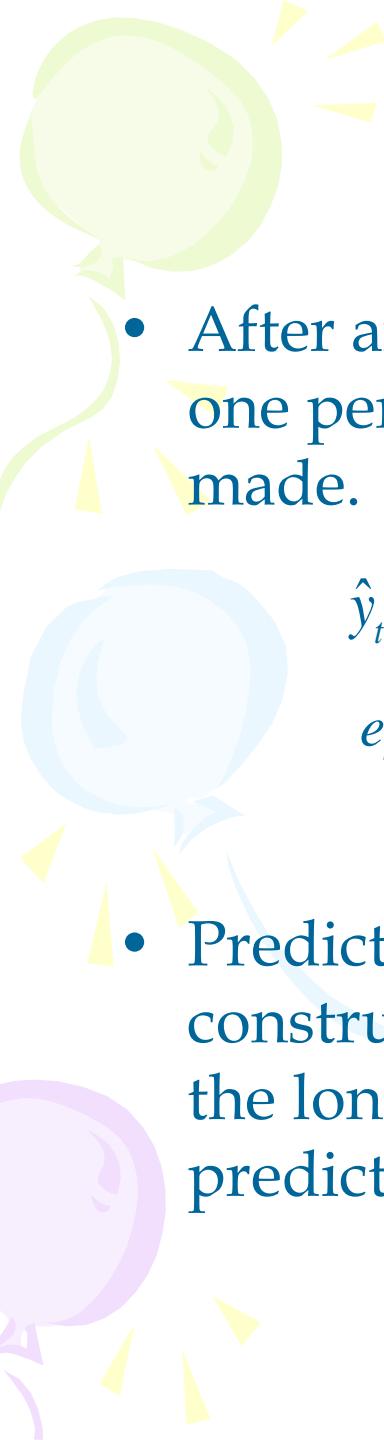


# Identification Revisited

- Having estimated an ARIMA model, it is necessary to revisit the question of identification to see if the selected model can be improved.
  - Some of the estimated parameters may be insignificant. If so, a revised model with the insignificant terms omitted may be considered
  - The residual analysis can provide some guidance on whether the model is adequate and how it may be improved.
  - If there are more than one adequate model identified, use model selection criteria (AIC and SBC) to determine which of them is preferred.



## Step Five: Forecasting



# Forecasting

- After an adequate model has been found, forecasts for one period or several periods into the future can be made.

$\hat{y}_{t+l}(t)$  =  $l$ -step-ahead forecast of  $y_{t+l}$  made at time  $t$

$e_{t+l}(t)$  =  $l$ -step-ahead forecast error

$$= y_{t+l} - \hat{y}_{t+l}(t)$$

- Prediction intervals based on the forecasts can also be constructed. In general, for a given confidence level, the longer the forecast lead time, the larger the prediction interval.

# Example 1: Industry Sales

- Fitted adequate model: ARIMA(0,1,1)(0,1,1)<sub>12</sub>

$$(1 - B)(1 - B^{12})y_t = (1 - 0.840B)(1 - 0.636B^{12})\varepsilon_t$$

or

$$y_t = y_{t-1} + y_{t-12} - y_{t-13} + \varepsilon_t - 0.840\varepsilon_{t-1} - 0.636\varepsilon_{t-12} + 0.534\varepsilon_{t-13}$$

- Therefore, the predicted value is expressed as

$$\hat{y}_t = y_{t-1} + y_{t-12} - y_{t-13} + e_t - 0.840e_{t-1} - 0.636e_{t-12} + 0.534e_{t-13}$$

where  $e_t$  = the residual at time  $t$ .

- As we forecast further ahead, there will be no empirical values for the  $e$  terms after a while, then their expected values will be zero.
- When there is no known past values for  $y$ , the forecasted values will be used instead.

# Example 1: Industry Sales

(continued)

Obs	date	r	FORECAST	RESIDUAL	U95	L95
101	101	835.09	826.79	8.295	910.97	742.613
102	102	934.60	872.73	61.860	956.91	788.556
103	103	832.50	719.64	112.861	803.82	635.460
104	104	300.00	388.63	-88.632	472.81	304.453
105	105	791.44	797.36	-5.914	881.54	713.179
106	106	900.00	885.21	14.792	969.39	801.030
107	107	781.73	822.38	-40.652	906.56	738.203
108	108	880.00	867.20	12.797	951.38	783.026
109	109	875.02	887.88	-12.856	972.05	803.709
110	110	992.97	894.94	98.033	979.11	810.765
111	111	976.80	975.80	1.000	1059.97	891.635
112	112	968.70	901.49	67.210	985.66	817.319
113	113	871.68	889.01	-17.337	973.18	804.844
114	114	1006.85	950.87	55.981	1035.04	866.704
115	115	832.04	819.03	13.005	903.20	734.864
116	116	345.59	405.19	-59.598	489.35	321.018
117	117	849.53	843.54	5.983	927.71	759.378
118	118	913.87	940.50	-26.629	1024.67	856.333
119	119	868.75	851.70	17.041	935.87	767.538
120	120	993.73	922.86	70.872	1007.03	838.695

# Example 1: Industry Sales

(continued)

- Forecast for period 121

$$\begin{aligned}\hat{y}_{121} &= y_{120} + y_{109} - y_{108} + \hat{e}_{121} - 0.840e_{120} - 0.636e_{109} + 0.534e_{108} \\ &= 993.73 + 875.02 - 880.00 + 0 - 0.840(70.87) - 0.636(-12.86) + 0.534(12.80) \\ &= 944.22\end{aligned}$$

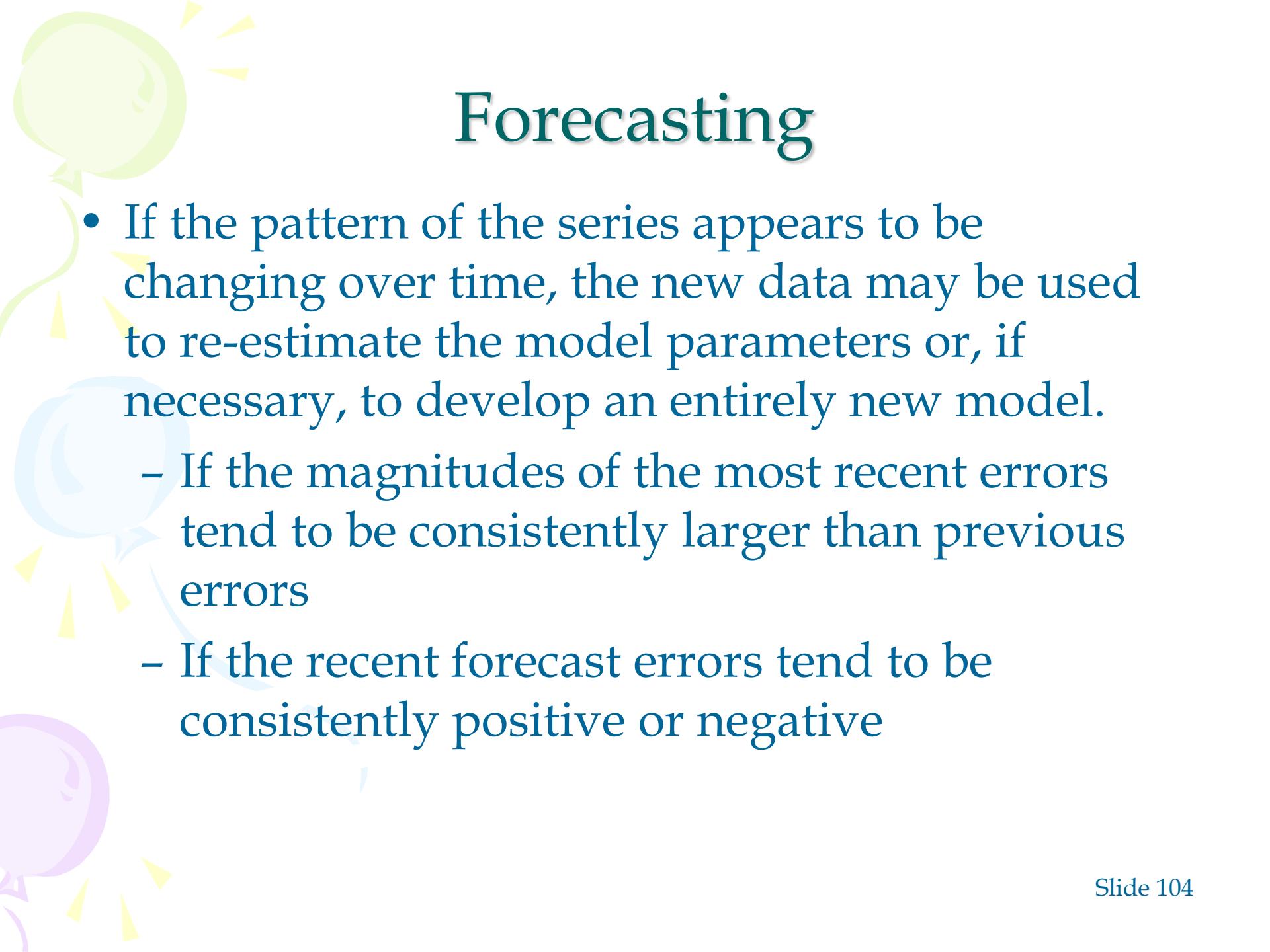
- Forecast for period 122

$$\begin{aligned}\hat{y}_{122} &= \hat{y}_{121} + y_{110} - y_{109} + \hat{e}_{122} - 0.840\hat{e}_{121} - 0.636e_{110} + 0.534e_{109} \\ &= 944.22 + 992.97 - 875.02 + 0 - 0.840(0) - 0.636(98.03) + 0.534(-12.86) \\ &= 992.99\end{aligned}$$

# Example 1: Industry Sales

*(continued)*

Obs	date	r	FORECAST	RESIDUAL	U95	L95
101	101	835.09	826.79	8.295	910.97	742.613
102	102	934.60	872.73	61.860	956.91	788.556
103	103	832.50	719.64	112.861	803.82	635.460
104	104	300.00	388.63	-88.632	472.81	304.453
105	105	791.44	797.36	-5.914	881.54	713.179
106	106	900.00	885.21	14.792	969.39	801.030
107	107	781.73	822.38	-40.652	906.56	738.203
108	108	880.00	867.20	12.797	951.38	783.026
109	109	875.02	887.88	-12.856	972.05	803.709
110	110	992.97	894.94	98.033	979.11	810.765
111	111	976.80	975.80	1.000	1059.97	891.635
112	112	968.70	901.49	67.210	985.66	817.319
113	113	871.68	889.01	-17.337	973.18	804.844
114	114	1006.85	950.87	55.981	1035.04	866.704
115	115	832.04	819.03	13.005	903.20	734.864
116	116	345.59	405.19	-59.598	489.35	321.018
117	117	849.53	843.54	5.983	927.71	759.378
118	118	913.87	940.50	-26.629	1024.67	856.333
119	119	868.75	851.70	17.041	935.87	767.538
120	120	993.73	922.86	70.872	1007.03	838.695
121	121	.	944.22	.	1028.38	860.056
122	122	.	992.99	.	1078.21	907.761
123	123	.	1028.54	.	1114.82	942.259
124	124	.	978.25	.	1065.57	890.929
125	125	.	928.14	.	1016.49	839.790
126	126	.	1018.48	.	1107.84	929.111
127	127	.	865.29	.	955.66	774.922
128	128	.	423.67	.	515.03	332.303
129	129	.	891.98	.	984.33	799.629
130	130	.	976.44	.	1069.76	883.119



# Forecasting

- If the pattern of the series appears to be changing over time, the new data may be used to re-estimate the model parameters or, if necessary, to develop an entirely new model.
  - If the magnitudes of the most recent errors tend to be consistently larger than previous errors
  - If the recent forecast errors tend to be consistently positive or negative

# Example: Electricity

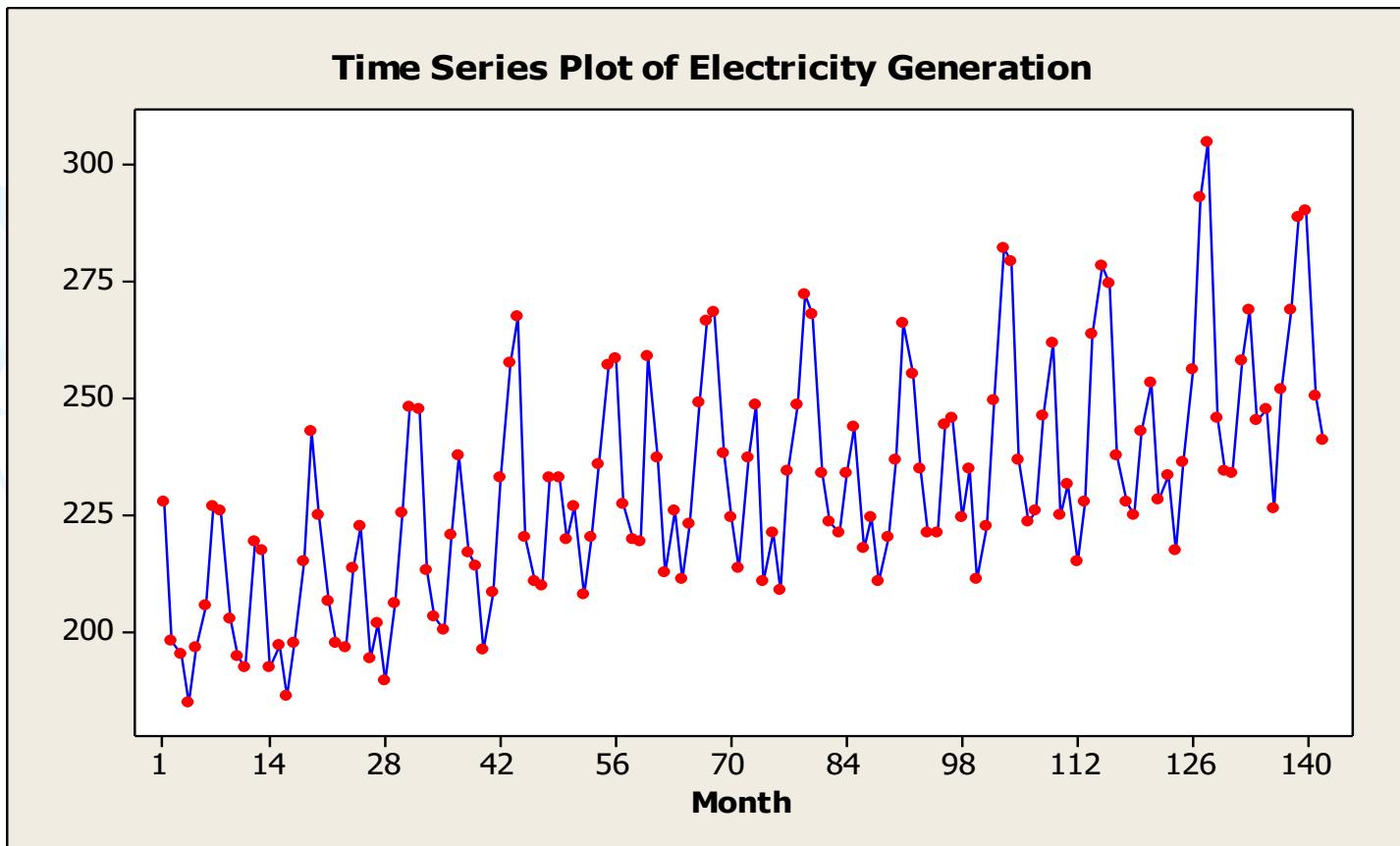
This example studies the total net generation of electricity by the US electric industry (monthly for the period 1985-1996). In general there are two peaks per year: in mid-summer and mid-winter.

- Dataset: elecnew.dat
- SAS program: ARIMA\_elec.sas

# Example: Electricity

(continued)

- Steps 1 and 2: Stationarity and Identification



# Questions

- Is the series stationary in the variance?
- Do the data need transformation?



# Example: Electricity

(continued)

- Steps 1 and 2: Stationarity and Identification

## The ARIMA Procedure

Name of Variable = r

Mean of Working Series	231.0894
Standard Deviation	24.28651
Number of Observations	142

## Autocorrelations

Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	589.835	1.00000																						0
1	397.900	0.67460	.																					0.083918
2	162.695	0.27583	.																					0.115982
3	13.410138	0.02274	.																					0.120513
4	60.179109	0.10203	.																					0.120543
5	226.535	0.38407	.																					0.121150
6	274.250	0.46496	.																					0.129441
7	231.566	0.39260	.																					0.140712
8	58.025227	0.09838	.																					0.148225
9	-4.049811	-0.00687	.																					0.148684
10	116.024	0.19671	.																					0.148686
11	314.046	0.53243	.																					0.150508
12	469.851	0.79658	.																					0.163234
13	310.204	0.52592	.																					0.188633
14	92.586524	0.15697	.																					0.198691
15	-50.421283	-0.08548	.																					0.199562
16	-11.409408	-0.01934	.																					0.199820
17	134.261	0.22762	.																					0.199833
18	185.093	0.31380	.																					0.201651
19	156.763	0.26577	.																					0.205061
20	4.533345	0.00769	.																					0.207473
21	-56.377598	-0.09558	.																					0.207475
22	47.541000	0.08060	.																					0.207785
23	227.166	0.38514	.																					0.208005
24	364.853	0.61857	.																					0.212967

"." marks two standard errors

# Example: Electricity

*(continued)*

- ## • Steps 1 and 2: Stationarity and Identification

## Partial Autocorrelations

# Questions

- What pattern can you see from the plots?
- Are the data stationary?
- If not, find an appropriate differencing which yields stationary data.



# Example: Electricity

(continued)

- Steps 1 and 2: Stationarity and Identification

Name of Variable = r																									
Period(s) of Differencing 12																									
Mean of Working Series 4.624538																									
Standard Deviation 8.460615																									
Number of Observations 130																									
Observation(s) eliminated by differencing 12																									
Autocorrelations																									
Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error	
0	71.582005	1.00000																							0
1	26.304756	0.36748																							0.087706
2	7.265402	0.10150																							0.098842
3	7.004010	0.09785																							0.099641
4	6.273813	0.08765																							0.100377
5	8.126128	0.11352																							0.100964
6	9.153861	0.12788																							0.101941
7	6.696492	0.09355																							0.103168
8	4.512418	0.06304																							0.103819
9	8.892881	0.12423																							0.104113
10	9.374951	0.13097																							0.105247
11	-8.022806	-.11208																							0.106493
12	-21.151168	-.29548																							0.107397
13	-1.095840	-.01531																							0.113478
14	-0.648280	-.00906																							0.113494
15	-2.745953	-.03836																							0.113499
16	2.438672	0.03407																							0.113599
17	-8.293145	-.11586																							0.113678
18	-3.462361	-.04837																							0.114582
19	1.602588	0.02239																							0.114739
20	2.210203	0.03088																							0.114773
21	1.457980	0.02037																							0.114837
22	-2.006987	-.02804																							0.114864
23	-0.707524	-.00988																							0.114917
24	-7.886328	-.11017																							0.114924

"." marks two standard errors



# Example: Electricity

*(continued)*

- ## • Steps 1 and 2: Stationarity and Identification

# Example: Electricity

(continued)

- Steps 1 and 2: Stationarity and Identification

Period(s) of Differencing	1,12
Mean of Working Series	0.130078
Standard Deviation	9.458743
Number of Observations	129
Observation(s) eliminated by differencing	13

Lag	Covariance	Correlation	Autocorrelations												Std Error								
			-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
0	89.467819	1.00000																					0
1	-25.912552	-.28963																					0.088045
2	-17.734845	-.19823																					0.095145
3	0.253296	0.00283																					0.098294
4	-2.920514	-.03264																					0.098295
5	1.853153	0.02071																					0.098379
6	4.338437	0.04849																					0.098412
7	-2.317332	-.02590																					0.098597
8	-6.085861	-.06802																					0.098650
9	3.793443	0.04240																					0.099013
10	18.131192	0.20266																					0.099154
11	-5.367522	-.05999																					0.102314
12	-32.125589	-.35907																					0.102587
13	19.313824	0.21587																					0.111906
14	2.622177	0.02931																					0.115089
15	-7.326501	-.08189																					0.115147
16	16.982155	0.18981																					0.115597
17	-15.698164	-.17546																					0.117989
18	-0.772249	-.00863																					0.119994
19	6.521073	0.07289																					0.119999
20	-0.522156	-.00584																					0.120342
21	2.782310	0.03110																					0.120344
22	-5.033370	-.05626																					0.120406
23	8.879535	0.09925																					0.120610
24	-15.200440	-.16990																					0.121242

"." marks two standard errors

# Example: Electricity

(continued)

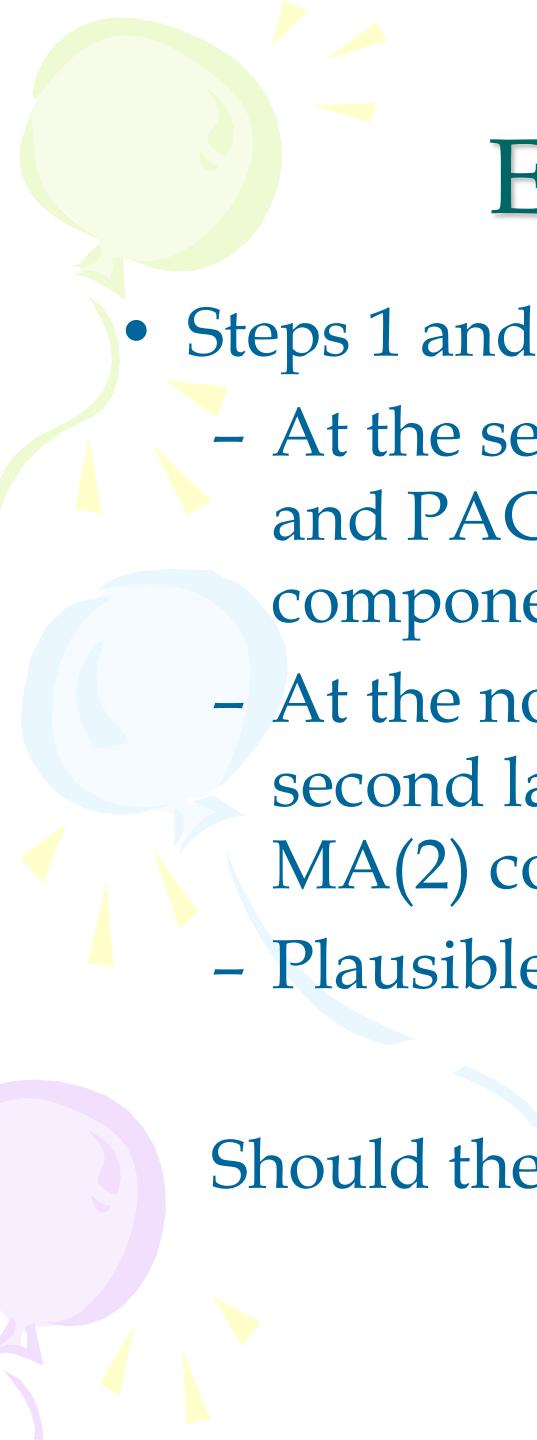
- Steps 1 and 2: Stationarity and Identification

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	-0.28963																					
2	-0.30794																					
3	-0.19470																					
4	-0.20488																					
5	-0.14309																					
6	-0.06941																					
7	-0.07629																					
8	-0.13707																					
9	-0.07819																					
10	0.19033																					
11	0.14969																					
12	-0.28764																					
13	-0.00810																					
14	-0.03952																					
15	-0.14995																					
16	0.08908																					
17	-0.12660																					
18	-0.03932																					
19	-0.02959																					
20	-0.10390																					
21	0.07577																					
22	0.10523																					
23	0.15359																					
24	-0.25199																					

# Question

- What model(s) do you think is(are) appropriate to fit the data?





# Example: Electricity

(continued)

- Steps 1 and 2: Stationarity and Identification
  - At the seasonal level, ACF cuts off after lag 12 and PACF dies down  $\Rightarrow$  seasonal MA(1) component
  - At the nonseasonal level, ACF cuts off after second lag and PACF dies down  $\Rightarrow$  nonseasonal MA(2) component
  - Plausible model: ARIMA(0,1,2)(0,1,1)<sub>12</sub>

Should the constant term be included?

# Example: Electricity

(continued)

- Step 3: Estimation
  - ARIMA(0,1,2)(0,1,1)<sub>12</sub>

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr >  t	Lag
MA1,1	0.57573	0.08309	6.93	<.0001	1
MA1,2	0.22962	0.08368	2.74	0.0061	2
MA2,1	0.80524	0.09450	8.52	<.0001	12

# Example: Electricity

(continued)

- Step 4: Diagnostic Checking
  - Residual analysis for ARIMA(0,1,2)(0,1,1)<sub>12</sub>

Autocorrelation Plot of Residuals

Lag	Covariance	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	41.755689	1.00000																						0
1	0.563880	0.01350	.									*	.											0.088045
2	0.844696	0.02023	.									*	.											0.088061
3	-1.380084	-.03305	.									*	.											0.088097
4	-0.509446	-.01220	.									*	.											0.088193
5	-1.073637	-.02571	.									*	.											0.088206
6	3.428447	0.08211	.									**	.											0.088264
7	-0.026933	-.00065	.									*	.											0.088855
8	-3.012537	-.07215	.									*	.											0.088855
9	2.614205	0.06261	.									*	.											0.089308
10	5.139207	0.12308	.									**	.											0.089647
11	-3.807877	-.09119	.									**	.											0.090948
12	3.123751	0.07481	.									*	.											0.091654
13	4.498787	0.10774	.									**	.											0.092126
14	1.030376	0.02468	.									*	.											0.093097
15	-3.953567	-.09468	.									**	.											0.093148
16	5.239907	0.12549	.									***	.											0.093891
17	-4.653677	-.11145	.									**	.											0.095183
18	-0.689724	-.01652	.									**	.											0.096189
19	2.483783	0.05948	.									*	.											0.096211
20	-2.139162	-.05123	.									*	.											0.096495
21	2.515779	0.06025	.									*	.											0.096706
22	-0.345529	-.00828	.									*	.											0.096997
23	3.292574	0.07885	.									**	.											0.097002
24	-3.576530	-.08565	.									**	.											0.097498

"." marks two standard errors

# Example: Electricity

(continued)

- Step 4: Diagnostic Checking
  - Residual analysis for ARIMA(0,1,2)(0,1,1)<sub>12</sub>

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	0.01350	.	.	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.
2	0.02005	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
3	-0.03361	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
4	-0.01172	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
5	-0.02407	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
6	0.08236	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
7	-0.00279	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
8	-0.07796	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
9	0.07061	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
10	0.12821	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
11	-0.10311	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
12	0.06908	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
13	0.12551	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
14	0.02721	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
15	-0.11616	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
16	0.12214	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
17	-0.07669	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
18	-0.03117	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
19	0.03104	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
20	-0.05387	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
21	0.10981	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
22	-0.07512	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
23	0.06219	.	.	.	.	.	.	.	.	.	**	.	.	.	.	.	.	.	.	.	.	.
24	-0.04060	.	.	.	.	.	.	.	.	.	*	.	.	.	.	.	.	.	.	.	.	.

# Example: Electricity

(continued)

- Step 4: Diagnostic Checking
  - Residual analysis for ARIMA(0,1,2)(0,1,1)<sub>12</sub>

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelation Check of Residuals						
				Autocorrelations						
6	1.26	3	0.7383	0.014	0.020	-0.033	-0.012	-0.026	0.082	
12	6.69	9	0.6693	-0.001	-0.072	0.063	0.123	-0.091	0.075	
18	14.07	15	0.5201	0.108	0.025	-0.095	0.125	-0.111	-0.017	
24	17.77	21	0.6633	0.059	-0.051	0.060	-0.008	0.079	-0.086	

Questions:

Is this model adequate? Why?



# Example: Electricity

(continued)

- Step 4: Diagnostic Checking

Fitted adequate model: ARIMA(0,1,2)(0,1,1)<sub>12</sub>

$$(1 - B)(1 - B^{12})y_t = (1 - 0.576B - 0.230B^2)(1 - 0.805B^{12})\varepsilon_t$$

or

$$y_t = y_{t-1} + y_{t-12} - y_{t-13} + \varepsilon_t - 0.576\varepsilon_{t-1} - 0.230\varepsilon_{t-2} - 0.805\varepsilon_{t-12} + 0.464\varepsilon_{t-13} + 0.185\varepsilon_{t-14}$$

Maximum Likelihood Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr >  t	Lag
MA1,1	0.57573	0.08309	6.93	<.0001	1
MA1,2	0.22962	0.08368	2.74	0.0061	2
MA2,1	0.80524	0.09450	8.52	<.0001	12

Variance Estimate	41.75569
Std Error Estimate	6.461864
AIC	864.0822
SBC	872.6616
Number of Residuals	129

# Example: Electricity

(continued)

- Step 5: Forecasting
  - Forecast the next 24 months of generation of electricity by the US electric industry.

Obs	Forecast	Std Error	95% Confidence Limits
143	240.3627	6.4619	227.6977 253.0277
144	262.6872	7.0194	248.9294 276.4449
145	270.3573	7.1312	256.3804 284.3342
146	244.0965	7.2413	229.9039 258.2892
147	249.9720	7.3497	235.5668 264.3771
148	232.8138	7.4566	218.1992 247.4284
149	249.4648	7.5619	234.6437 264.2859
150	270.8399	7.6658	255.8152 285.8646
151	295.6695	7.7683	280.4439 310.8951
152	295.8185	7.8695	280.3947 311.2424
153	257.2000	7.9694	241.5804 272.8197
154	246.5065	8.0680	230.6935 262.3195
155	245.1110	8.4513	228.5467 261.6752
156	267.2616	8.6392	250.3291 284.1940
157	274.9317	8.7689	257.7450 292.1184
158	248.6709	8.8967	231.2337 266.1082
159	254.5464	9.0228	236.8621 272.2307
160	237.3882	9.1470	219.4603 255.3161
161	254.0392	9.2697	235.8710 272.2074
162	275.4143	9.3907	257.0089 293.8197
163	300.2439	9.5102	281.6043 318.8836
164	300.3930	9.6282	281.5221 319.2639
165	261.7745	9.7448	242.6751 280.8738
166	251.0809	9.8600	231.7558 270.4061

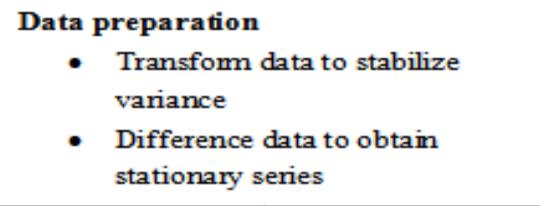
# Example: Electricity

(continued)

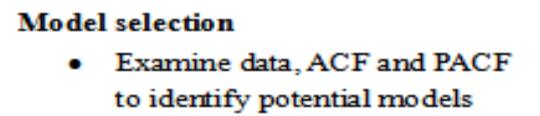
- Based on the following information, give forecast for period 143

date	r	FORECAST	RESIDUAL
120	242.91	249.752	-6.8422
121	253.08	253.866	-0.7856
122	228.13	227.621	0.5088
123	233.68	235.112	-1.4322
124	217.38	218.261	-0.8812
125	236.38	231.598	4.7823
126	256.08	256.924	-0.8439
127	292.83	278.779	14.0508
128	304.71	281.851	22.8589
129	245.57	255.050	-9.4805
130	234.41	234.955	-0.5450
131	234.12	234.937	-0.8175
132	258.17	256.343	1.8275
133	268.66	264.279	4.3815
134	245.31	238.745	6.5649
135	247.47	247.316	0.1544
136	226.25	229.714	-3.4637
137	251.67	242.705	8.9647
138	268.79	269.725	-0.9353
139	288.94	293.249	-4.3093
140	290.16	291.521	-1.3614
141	250.69	253.524	-2.8338
142	240.80	241.743	-0.9431

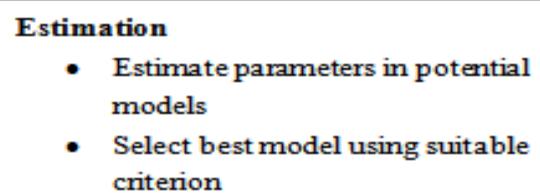
**Phase I**  
Identification



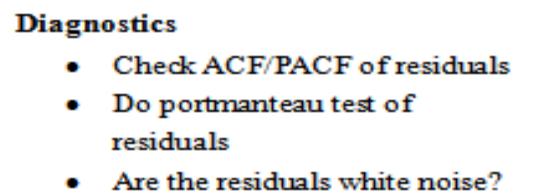
**Phase II**  
Estimation



**Phase III**  
Checking

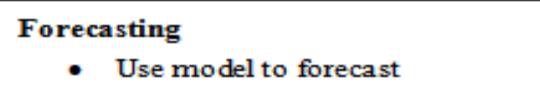


**Phase IV**  
Forecasting



No

Yes



Schematic representation of the Box-Jenkins methodology for time series modeling