IBM SPSS Forecasting 21

Note: Before using this information and the product it supports, read the general information under Notices on p. 107.

This edition applies to IBM® SPSS® Statistics 21 and to all subsequent releases and modifications until otherwise indicated in new editions.

Preface

IBM® SPSS® Statistics is a comprehensive system for analyzing data. The Forecasting optional add-on module provides the additional analytic techniques described in this manual. The Forecasting add-on module must be used with the SPSS Statistics Core system and is completely integrated into that system.

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Part I: User's Guide

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Introduction to Time Series

A **time series** is a set of observations obtained by measuring a single variable regularly over a period of time. In a series of inventory data, for example, the observations might represent daily inventory levels for several months. A series showing the market share of a product might consist of weekly market share taken over a few years. A series of total sales figures might consist of one observation per month for many years. What each of these examples has in common is that some variable was observed at regular, known intervals over a certain length of time. Thus, the form of the data for a typical time series is a single sequence or list of observations representing measurements taken at regular intervals.

Table 1-1
Daily inventory time series

Time	Week	Day	Inventory level
t_1	1	Monday	160
t_2	1	Tuesday	135
t_3	1	Wednesday	129
t_4	1	Thursday	122
t_5	1	Friday	108
t_6	2	Monday	150
		...	
t_{60}	12	Friday	120

One of the most important reasons for doing time series analysis is to try to forecast future values of the series. A model of the series that explained the past values may also predict whether and how much the next few values will increase or decrease. The ability to make such predictions successfully is obviously important to any business or scientific field.

Time Series Data

When you define time series data for use with the Forecasting add-on module, each series corresponds to a separate variable. For example, to define a time series in the Data Editor, click the Variable View tab and enter a variable name in any blank row. Each observation in a time series corresponds to a case (a row in the Data Editor).

If you open a spreadsheet containing time series data, each series should be arranged in a column in the spreadsheet. If you already have a spreadsheet with time series arranged in rows, you can open it anyway and use Transpose on the Data menu to flip the rows into columns.

Data Transformations

A number of data transformation procedures provided in the Core system are useful in time series analysis.

- The Define Dates procedure (on the Data menu) generates date variables used to establish periodicity and to distinguish between historical, validation, and forecasting periods. Forecasting is designed to work with the variables created by the Define Dates procedure.
- The Create Time Series procedure (on the Transform menu) creates new time series variables as functions of existing time series variables. It includes functions that use neighboring observations for smoothing, averaging, and differencing.
- The Replace Missing Values procedure (on the Transform menu) replaces system- and user-missing values with estimates based on one of several methods. Missing data at the beginning or end of a series pose no particular problem; they simply shorten the useful length of the series. Gaps in the middle of a series (*embedded* missing data) can be a much more serious problem.

See the *Core System User's Guide* for detailed information concerning data transformations for time series.

Estimation and Validation Periods

It is often useful to divide your time series into an *estimation*, or *historical*, period and a *validation* period. You develop a model on the basis of the observations in the estimation (historical) period and then test it to see how well it works in the validation period. By forcing the model to make predictions for points you already know (the points in the validation period), you get an idea of how well the model does at forecasting.

The cases in the validation period are typically referred to as holdout cases because they are held-back from the model-building process. The estimation period consists of the currently selected cases in the active dataset. Any remaining cases following the last selected case can be used as holdouts. Once you're satisfied that the model does an adequate job of forecasting, you can redefine the estimation period to include the holdout cases, and then build your final model.

Building Models and Producing Forecasts

The Forecasting add-on module provides two procedures for accomplishing the tasks of creating models and producing forecasts.

- The Time Series Modeler procedure creates models for time series, and produces forecasts. It includes an Expert Modeler that automatically determines the best model for each of your time series. For experienced analysts who desire a greater degree of control, it also provides tools for custom model building.
- The Apply Time Series Models procedure applies existing time series models—created by the Time Series Modeler—to the active dataset. This allows you to obtain forecasts for series for which new or revised data are available, without rebuilding your models. If there's reason to think that a model has changed, it can be rebuilt using the Time Series Modeler.

Chapter
2

Time Series Modeler

The Time Series Modeler procedure estimates exponential smoothing, univariate Autoregressive Integrated Moving Average (ARIMA), and multivariate ARIMA (or transfer function models) models for time series, and produces forecasts. The procedure includes an Expert Modeler that automatically identifies and estimates the best-fitting ARIMA or exponential smoothing model for one or more dependent variable series, thus eliminating the need to identify an appropriate model through trial and error. Alternatively, you can specify a custom ARIMA or exponential smoothing model.

Example. You are a product manager responsible for forecasting next month's unit sales and revenue for each of 100 separate products, and have little or no experience in modeling time series. Your historical unit sales data for all 100 products is stored in a single Excel spreadsheet. After opening your spreadsheet in IBM® SPSS® Statistics, you use the Expert Modeler and request forecasts one month into the future. The Expert Modeler finds the best model of unit sales for each of your products, and uses those models to produce the forecasts. Since the Expert Modeler can handle multiple input series, you only have to run the procedure once to obtain forecasts for all of your products. Choosing to save the forecasts to the active dataset, you can easily export the results back to Excel.

Statistics. Goodness-of-fit measures: stationary *R*-square, *R*-square (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), maximum absolute error (MaxAE), maximum absolute percentage error (MaxAPE), normalized Bayesian information criterion (BIC). Residuals: autocorrelation function, partial autocorrelation function, Ljung-Box *Q*. For ARIMA models: ARIMA orders for dependent variables, transfer function orders for independent variables, and outlier estimates. Also, smoothing parameter estimates for exponential smoothing models.

Plots. Summary plots across all models: histograms of stationary *R*-square, *R*-square (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), maximum absolute error (MaxAE), maximum absolute percentage error (MaxAPE), normalized Bayesian information criterion (BIC); box plots of residual autocorrelations and partial autocorrelations. Results for individual models: forecast values, fit values, observed values, upper and lower confidence limits, residual autocorrelations and partial autocorrelations.

Time Series Modeler Data Considerations

Data. The dependent variable and any independent variables should be numeric.

Assumptions. The dependent variable and any independent variables are treated as time series, meaning that each case represents a time point, with successive cases separated by a constant time interval.

- **Stationarity.** For custom ARIMA models, the time series to be modeled should be stationary. The most effective way to transform a nonstationary series into a stationary one is through a difference transformation—available from the Create Time Series dialog box.
- **Forecasts.** For producing forecasts using models with independent (predictor) variables, the active dataset should contain values of these variables for all cases in the forecast period. Additionally, independent variables should not contain any missing values in the estimation period.

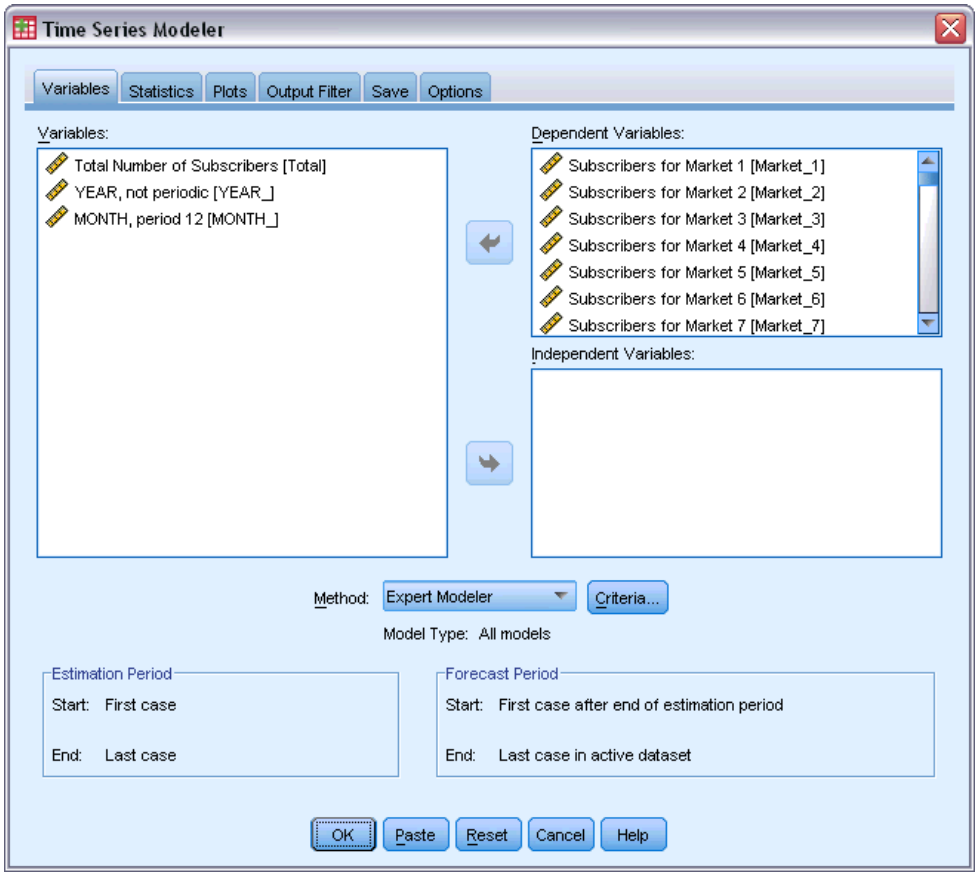
Defining Dates

Although not required, it's recommended to use the Define Dates dialog box to specify the date associated with the first case and the time interval between successive cases. This is done prior to using the Time Series Modeler and results in a set of variables that label the date associated with each case. It also sets an assumed periodicity of the data—for example, a periodicity of 12 if the time interval between successive cases is one month. This periodicity is required if you're interested in creating seasonal models. If you're not interested in seasonal models and don't require date labels on your output, you can skip the Define Dates dialog box. The label associated with each case is then simply the case number.

To Use the Time Series Modeler

▶ From the menus choose:
Analyze > Forecasting > Create Models...

Figure 2-1
Time Series Modeler, Variables tab



- On the Variables tab, select one or more dependent variables to be modeled.
- From the Method drop-down box, select a modeling method. For automatic modeling, leave the default method of Expert Modeler. This will invoke the Expert Modeler to determine the best-fitting model for each of the dependent variables.

  To produce forecasts:

- Click the Options tab.
- Specify the forecast period. This will produce a chart that includes forecasts and observed values.

  Optionally, you can:

  - Select one or more independent variables. Independent variables are treated much like predictor variables in regression analysis but are optional. They can be included in ARIMA models but not exponential smoothing models. If you specify Expert Modeler as the modeling method and include independent variables, only ARIMA models will be considered.
  - Click Criteria to specify modeling details.
  - Save predictions, confidence intervals, and noise residuals.

- Save the estimated models in XML format. Saved models can be applied to new or revised data to obtain updated forecasts without rebuilding models. This is accomplished with the Apply Time Series Models procedure.
- Obtain summary statistics across all estimated models.
- Specify transfer functions for independent variables in custom ARIMA models.
- Enable automatic detection of outliers.
- Model specific time points as outliers for custom ARIMA models.

Modeling Methods

The available modeling methods are:

Expert Modeler. The Expert Modeler automatically finds the best-fitting model for each dependent series. If independent (predictor) variables are specified, the Expert Modeler selects, for inclusion in ARIMA models, those that have a statistically significant relationship with the dependent series. Model variables are transformed where appropriate using differencing and/or a square root or natural log transformation. By default, the Expert Modeler considers both exponential smoothing and ARIMA models. You can, however, limit the Expert Modeler to only search for ARIMA models or to only search for exponential smoothing models. You can also specify automatic detection of outliers.

Exponential Smoothing. Use this option to specify a custom exponential smoothing model. You can choose from a variety of exponential smoothing models that differ in their treatment of trend and seasonality.

ARIMA. Use this option to specify a custom ARIMA model. This involves explicitly specifying autoregressive and moving average orders, as well as the degree of differencing. You can include independent (predictor) variables and define transfer functions for any or all of them. You can also specify automatic detection of outliers or specify an explicit set of outliers.

Estimation and Forecast Periods

Estimation Period. The estimation period defines the set of cases used to determine the model. By default, the estimation period includes all cases in the active dataset. To set the estimation period, select Based on time or case range in the Select Cases dialog box. Depending on available data, the estimation period used by the procedure may vary by dependent variable and thus differ from the displayed value. For a given dependent variable, the true estimation period is the period left after eliminating any contiguous missing values of the variable occurring at the beginning or end of the specified estimation period.

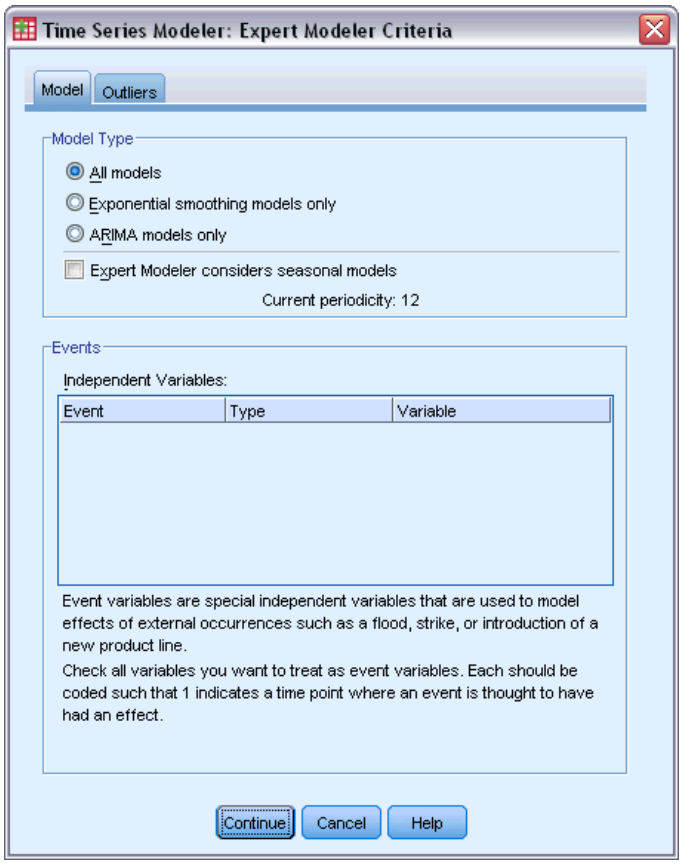
Forecast Period. The forecast period begins at the first case after the estimation period, and by default goes through to the last case in the active dataset. You can set the end of the forecast period from the Options tab.

Specifying Options for the Expert Modeler

The Expert Modeler provides options for constraining the set of candidate models, specifying the handling of outliers, and including event variables.

Model Selection and Event Specification

Figure 2-2
Expert Modeler Criteria dialog box, Model tab



The Model tab allows you to specify the types of models considered by the Expert Modeler and to specify event variables.

Model Type. The following options are available:

- **All models.** The Expert Modeler considers both ARIMA and exponential smoothing models.
- **Exponential smoothing models only.** The Expert Modeler only considers exponential smoothing models.
- **ARIMA models only.** The Expert Modeler only considers ARIMA models.

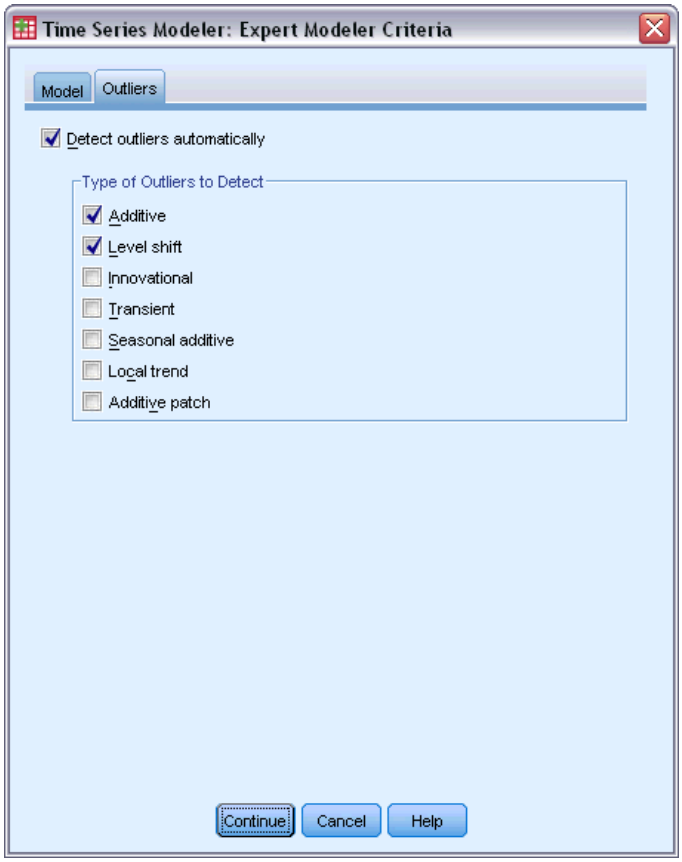
Expert Modeler considers seasonal models. This option is only enabled if a periodicity has been defined for the active dataset. When this option is selected (checked), the Expert Modeler considers both seasonal and nonseasonal models. If this option is not selected, the Expert Modeler only considers nonseasonal models.

Current Periodicity. Indicates the periodicity (if any) currently defined for the active dataset. The current periodicity is given as an integer—for example, 12 for annual periodicity, with each case representing a month. The value *None* is displayed if no periodicity has been set. Seasonal models require a periodicity. You can set the periodicity from the Define Dates dialog box.

Events. Select any independent variables that are to be treated as event variables. For event variables, cases with a value of 1 indicate times at which the dependent series are expected to be affected by the event. Values other than 1 indicate no effect.

Handling Outliers with the Expert Modeler

Figure 2-3
Expert Modeler Criteria dialog box, Outliers tab



The Outliers tab allows you to choose automatic detection of outliers as well as the type of outliers to detect.

Detect outliers automatically. By default, automatic detection of outliers is not performed. Select (check) this option to perform automatic detection of outliers, then select one or more of the following outlier types:

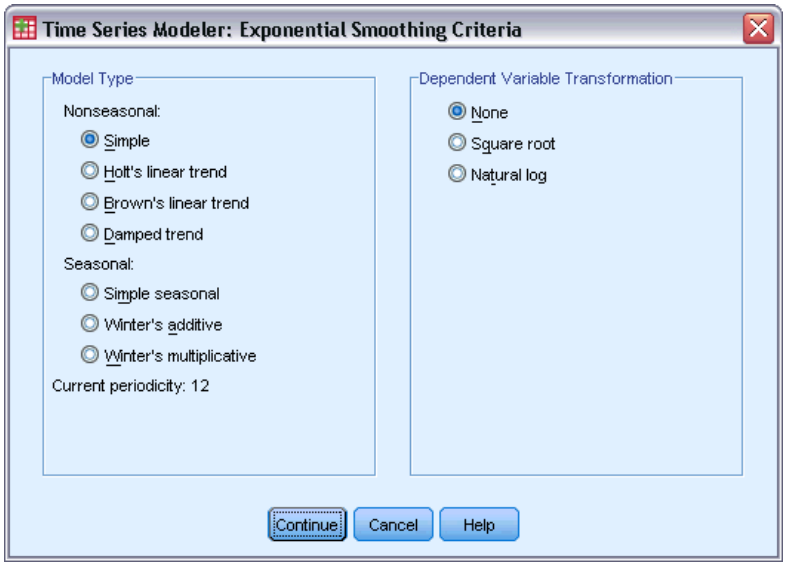
- Additive
- Level shift
- Innovational
- Transient
- Seasonal additive

- Local trend
- Additive patch

For more information, see the topic Outlier Types in Appendix B on p. 93.

Custom Exponential Smoothing Models

Figure 2-4
Exponential Smoothing Criteria dialog box



Model Type. Exponential smoothing models (Gardner, 1985) are classified as either seasonal or nonseasonal. Seasonal models are only available if a periodicity has been defined for the active dataset (see "Current Periodicity" below).

- **Simple.** This model is appropriate for series in which there is no trend or seasonality. Its only smoothing parameter is level. Simple exponential smoothing is most similar to an ARIMA model with zero orders of autoregression, one order of differencing, one order of moving average, and no constant.
- **Holt's linear trend.** This model is appropriate for series in which there is a linear trend and no seasonality. Its smoothing parameters are level and trend, which are not constrained by each other's values. Holt's model is more general than Brown's model but may take longer to compute for large series. Holt's exponential smoothing is most similar to an ARIMA model with zero orders of autoregression, two orders of differencing, and two orders of moving average.
- **Brown's linear trend.** This model is appropriate for series in which there is a linear trend and no seasonality. Its smoothing parameters are level and trend, which are assumed to be equal. Brown's model is therefore a special case of Holt's model. Brown's exponential smoothing is most similar to an ARIMA model with zero orders of autoregression, two orders of differencing, and two orders of moving average, with the coefficient for the second order of moving average equal to the square of one-half of the coefficient for the first order.

- **Damped trend.** This model is appropriate for series with a linear trend that is dying out and with no seasonality. Its smoothing parameters are level, trend, and damping trend. Damped exponential smoothing is most similar to an ARIMA model with 1 order of autoregression, 1 order of differencing, and 2 orders of moving average.
- **Simple seasonal.** This model is appropriate for series with no trend and a seasonal effect that is constant over time. Its smoothing parameters are level and season. Simple seasonal exponential smoothing is most similar to an ARIMA model with zero orders of autoregression, one order of differencing, one order of seasonal differencing, and orders 1, p, and p + 1 of moving average, where p is the number of periods in a seasonal interval (for monthly data, p = 12).
- **Winters' additive.** This model is appropriate for series with a linear trend and a seasonal effect that does not depend on the level of the series. Its smoothing parameters are level, trend, and season. Winters' additive exponential smoothing is most similar to an ARIMA model with zero orders of autoregression, one order of differencing, one order of seasonal differencing, and p + 1 orders of moving average, where p is the number of periods in a seasonal interval (for monthly data, p = 12).
- **Winters' multiplicative.** This model is appropriate for series with a linear trend and a seasonal effect that depends on the level of the series. Its smoothing parameters are level, trend, and season. Winters' multiplicative exponential smoothing is not similar to any ARIMA model.

Current Periodicity. Indicates the periodicity (if any) currently defined for the active dataset. The current periodicity is given as an integer—for example, 12 for annual periodicity, with each case representing a month. The value *None* is displayed if no periodicity has been set. Seasonal models require a periodicity. You can set the periodicity from the Define Dates dialog box.

Dependent Variable Transformation. You can specify a transformation performed on each dependent variable before it is modeled.

- **None.** No transformation is performed.
- **Square root.** Square root transformation.
- **Natural log.** Natural log transformation.

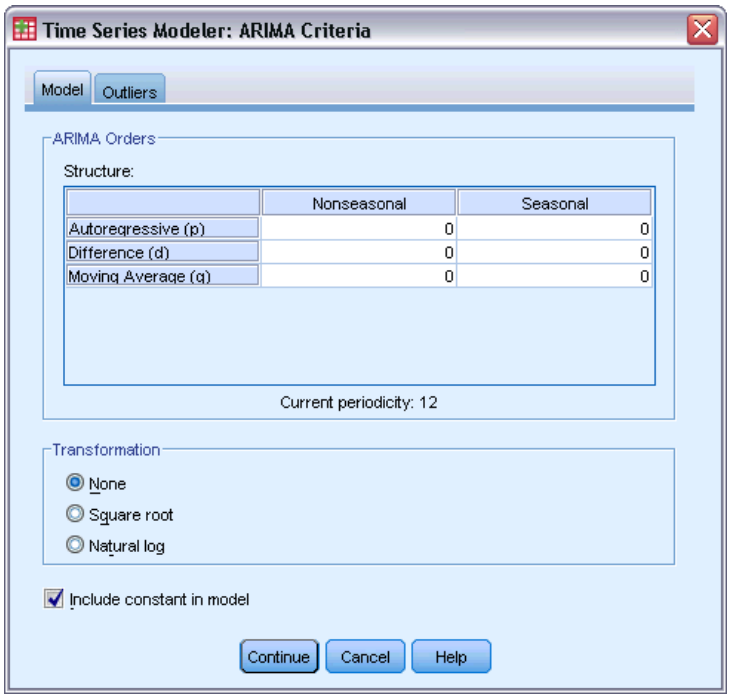
Custom ARIMA Models

The Time Series Modeler allows you to build custom nonseasonal or seasonal ARIMA (Autoregressive Integrated Moving Average) models—also known as Box-Jenkins (Box, Jenkins, and Reinsel, 1994) models—with or without a fixed set of predictor variables. You can define transfer functions for any or all of the predictor variables, and specify automatic detection of outliers, or specify an explicit set of outliers.

- All independent (predictor) variables specified on the Variables tab are explicitly included in the model. This is in contrast to using the Expert Modeler where independent variables are only included if they have a statistically significant relationship with the dependent variable.

Model Specification for Custom ARIMA Models

Figure 2-5
ARIMA Criteria dialog box, Model tab



The Model tab allows you to specify the structure of a custom ARIMA model.

ARIMA Orders. Enter values for the various ARIMA components of your model into the corresponding cells of the Structure grid. All values must be non-negative integers. For autoregressive and moving average components, the value represents the maximum order. All positive lower orders will be included in the model. For example, if you specify 2, the model includes orders 2 and 1. Cells in the Seasonal column are only enabled if a periodicity has been defined for the active dataset (see "Current Periodicity" below).

- **Autoregressive (p).** The number of autoregressive orders in the model. Autoregressive orders specify which previous values from the series are used to predict current values. For example, an autoregressive order of 2 specifies that the value of the series two time periods in the past be used to predict the current value.
- **Difference (d).** Specifies the order of differencing applied to the series before estimating models. Differencing is necessary when trends are present (series with trends are typically nonstationary and ARIMA modeling assumes stationarity) and is used to remove their effect. The order of differencing corresponds to the degree of series trend—first-order differencing accounts for linear trends, second-order differencing accounts for quadratic trends, and so on.
- **Moving Average (q).** The number of moving average orders in the model. Moving average orders specify how deviations from the series mean for previous values are used to predict current values. For example, moving-average orders of 1 and 2 specify that deviations from the mean value of the series from each of the last two time periods be considered when predicting current values of the series.

Seasonal Orders. Seasonal autoregressive, moving average, and differencing components play the same roles as their nonseasonal counterparts. For seasonal orders, however, current series values are affected by previous series values separated by one or more seasonal periods. For example, for monthly data (seasonal period of 12), a seasonal order of 1 means that the current series value is affected by the series value 12 periods prior to the current one. A seasonal order of 1, for monthly data, is then the same as specifying a nonseasonal order of 12.

Current Periodicity. Indicates the periodicity (if any) currently defined for the active dataset. The current periodicity is given as an integer—for example, 12 for annual periodicity, with each case representing a month. The value *None* is displayed if no periodicity has been set. Seasonal models require a periodicity. You can set the periodicity from the Define Dates dialog box.

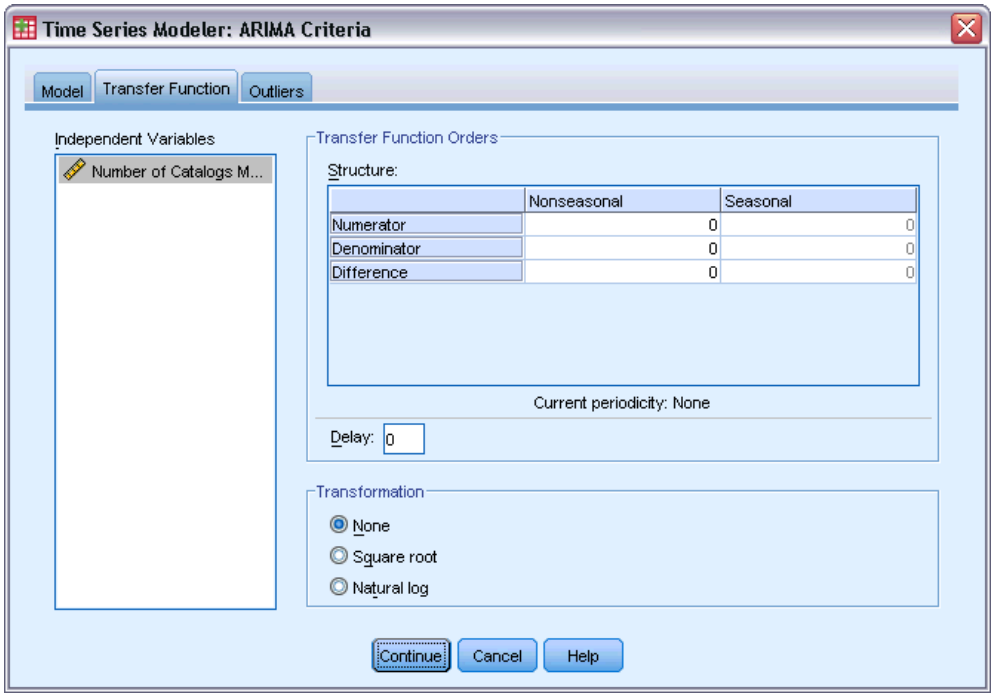
Dependent Variable Transformation. You can specify a transformation performed on each dependent variable before it is modeled.

- **None.** No transformation is performed.
- **Square root.** Square root transformation.
- **Natural log.** Natural log transformation.

Include constant in model. Inclusion of a constant is standard unless you are sure that the overall mean series value is 0. Excluding the constant is recommended when differencing is applied.

Transfer Functions in Custom ARIMA Models

Figure 2-6
ARIMA Criteria dialog box, Transfer Function tab



The Transfer Function tab (only present if independent variables are specified) allows you to define transfer functions for any or all of the independent variables specified on the Variables tab. Transfer functions allow you to specify the manner in which past values of independent (predictor) variables are used to forecast future values of the dependent series.

Transfer Function Orders. Enter values for the various components of the transfer function into the corresponding cells of the Structure grid. All values must be non-negative integers. For numerator and denominator components, the value represents the maximum order. All positive lower orders will be included in the model. In addition, order 0 is always included for numerator components. For example, if you specify 2 for numerator, the model includes orders 2, 1, and 0. If you specify 3 for denominator, the model includes orders 3, 2, and 1. Cells in the Seasonal column are only enabled if a periodicity has been defined for the active dataset (see "Current Periodicity" below).

- **Numerator.** The numerator order of the transfer function. Specifies which previous values from the selected independent (predictor) series are used to predict current values of the dependent series. For example, a numerator order of 1 specifies that the value of an independent series one time period in the past—as well as the current value of the independent series—is used to predict the current value of each dependent series.
- **Denominator.** The denominator order of the transfer function. Specifies how deviations from the series mean, for previous values of the selected independent (predictor) series, are used to predict current values of the dependent series. For example, a denominator order of 1 specifies that deviations from the mean value of an independent series one time period in the past be considered when predicting the current value of each dependent series.
- **Difference.** Specifies the order of differencing applied to the selected independent (predictor) series before estimating models. Differencing is necessary when trends are present and is used to remove their effect.

Seasonal Orders. Seasonal numerator, denominator, and differencing components play the same roles as their nonseasonal counterparts. For seasonal orders, however, current series values are affected by previous series values separated by one or more seasonal periods. For example, for monthly data (seasonal period of 12), a seasonal order of 1 means that the current series value is affected by the series value 12 periods prior to the current one. A seasonal order of 1, for monthly data, is then the same as specifying a nonseasonal order of 12.

Current Periodicity. Indicates the periodicity (if any) currently defined for the active dataset. The current periodicity is given as an integer—for example, 12 for annual periodicity, with each case representing a month. The value *None* is displayed if no periodicity has been set. Seasonal models require a periodicity. You can set the periodicity from the Define Dates dialog box.

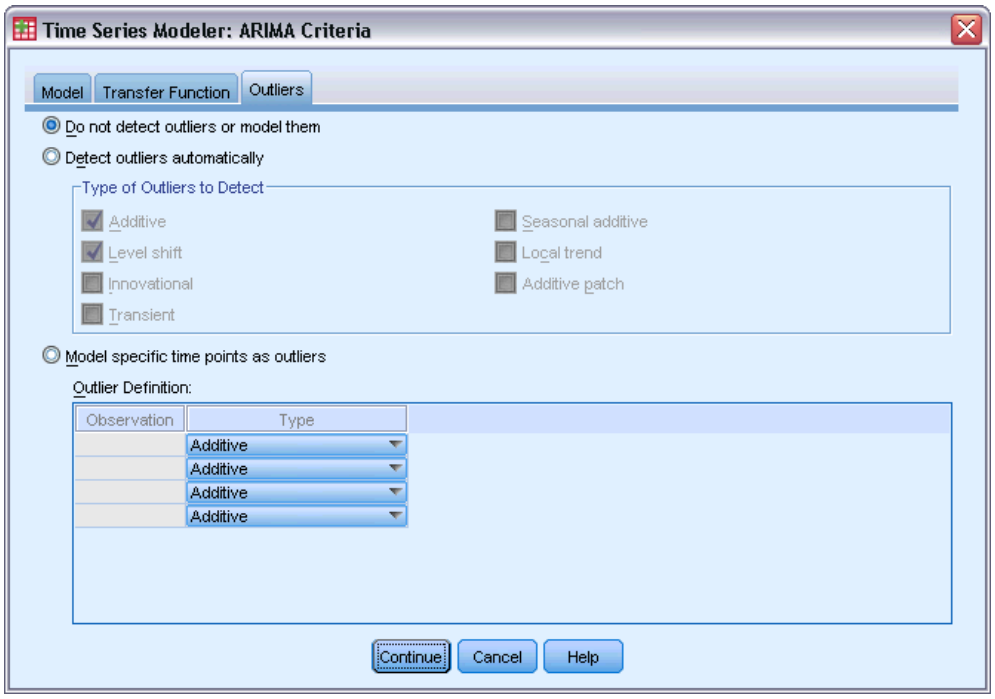
Delay. Setting a delay causes the independent variable's influence to be delayed by the number of intervals specified. For example, if the delay is set to 5, the value of the independent variable at time t doesn't affect forecasts until five periods have elapsed ($t + 5$).

Transformation. Specification of a transfer function, for a set of independent variables, also includes an optional transformation to be performed on those variables.

- **None.** No transformation is performed.
- **Square root.** Square root transformation.
- **Natural log.** Natural log transformation.

Outliers in Custom ARIMA Models

Figure 2-7
ARIMA Criteria dialog box, Outliers tab



The Outliers tab provides the following choices for the handling of outliers (Pena, Tiao, and Tsay, 2001): detect them automatically, specify particular points as outliers, or do not detect or model them.

Do not detect outliers or model them. By default, outliers are neither detected nor modeled. Select this option to disable any detection or modeling of outliers.

Detect outliers automatically. Select this option to perform automatic detection of outliers, and select one or more of the following outlier types:

- Additive
- Level shift
- Innovational
- Transient
- Seasonal additive
- Local trend
- Additive patch

For more information, see the topic Outlier Types in Appendix B on p. 93.

Model specific time points as outliers. Select this option to specify particular time points as outliers. Use a separate row of the Outlier Definition grid for each outlier. Enter values for all of the cells in a given row.

- **Type.** The outlier type. The supported types are: additive (default), level shift, innovational, transient, seasonal additive, and local trend.

Note 1: If no date specification has been defined for the active dataset, the Outlier Definition grid shows the single column *Observation*. To specify an outlier, enter the row number (as displayed in the Data Editor) of the relevant case.

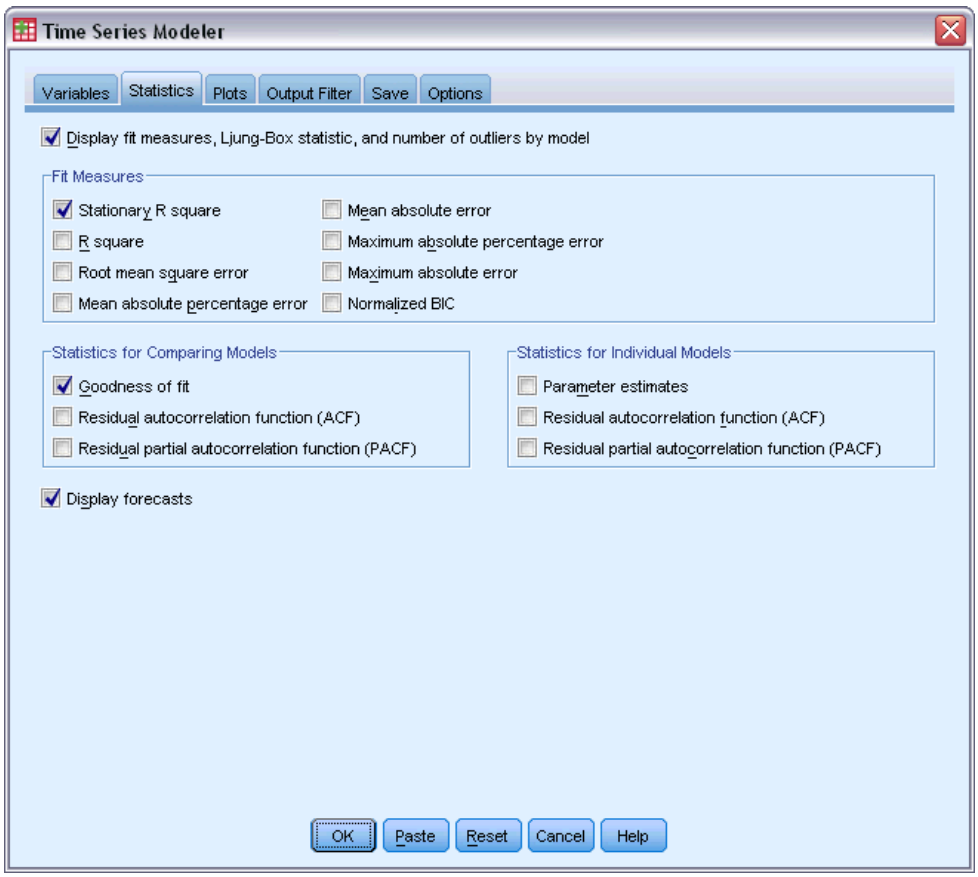
Note 2: The *Cycle* column (if present) in the Outlier Definition grid refers to the value of the *CYCLE_* variable in the active dataset.

Output

Available output includes results for individual models as well as results calculated across all models. Results for individual models can be limited to a set of best- or poorest-fitting models based on user-specified criteria.

Statistics and Forecast Tables

Figure 2-8
Time Series Modeler, Statistics tab



The Statistics tab provides options for displaying tables of the modeling results.

Display fit measures, Ljung-Box statistic, and number of outliers by model. Select (check) this option to display a table containing selected fit measures, Ljung-Box value, and the number of outliers for each estimated model.

Fit Measures. You can select one or more of the following for inclusion in the table containing fit measures for each estimated model:

- Stationary *R*-square
- *R*-square
- Root mean square error
- Mean absolute percentage error
- Mean absolute error
- Maximum absolute percentage error
- Maximum absolute error
- Normalized BIC

For more information, see the topic Goodness-of-Fit Measures in Appendix A on p. 92.

Statistics for Comparing Models. This group of options controls display of tables containing statistics calculated across all estimated models. Each option generates a separate table. You can select one or more of the following options:

- **Goodness of fit.** Table of summary statistics and percentiles for stationary *R*-square, *R*-square, root mean square error, mean absolute percentage error, mean absolute error, maximum absolute percentage error, maximum absolute error, and normalized Bayesian Information Criterion.
- **Residual autocorrelation function (ACF).** Table of summary statistics and percentiles for autocorrelations of the residuals across all estimated models.
- **Residual partial autocorrelation function (PACF).** Table of summary statistics and percentiles for partial autocorrelations of the residuals across all estimated models.

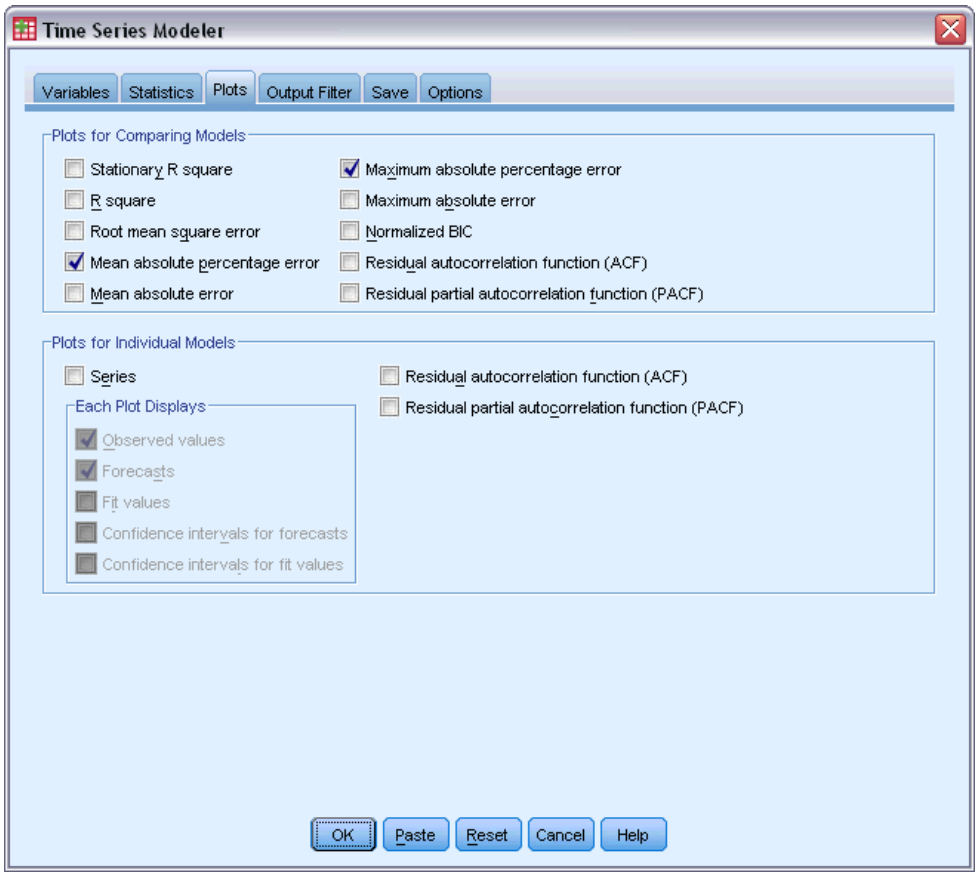
Statistics for Individual Models. This group of options controls display of tables containing detailed information for each estimated model. Each option generates a separate table. You can select one or more of the following options:

- **Parameter estimates.** Displays a table of parameter estimates for each estimated model. Separate tables are displayed for exponential smoothing and ARIMA models. If outliers exist, parameter estimates for them are also displayed in a separate table.
- **Residual autocorrelation function (ACF).** Displays a table of residual autocorrelations by lag for each estimated model. The table includes the confidence intervals for the autocorrelations.
- **Residual partial autocorrelation function (PACF).** Displays a table of residual partial autocorrelations by lag for each estimated model. The table includes the confidence intervals for the partial autocorrelations.

Display forecasts. Displays a table of model forecasts and confidence intervals for each estimated model. The forecast period is set from the Options tab.

Plots

Figure 2-9
Time Series Modeler, Plots tab



The Plots tab provides options for displaying plots of the modeling results.

Plots for Comparing Models

This group of options controls display of plots containing statistics calculated across all estimated models. Each option generates a separate plot. You can select one or more of the following options:

- Stationary *R*-square
- *R*-square
- Root mean square error
- Mean absolute percentage error
- Mean absolute error
- Maximum absolute percentage error
- Maximum absolute error
- Normalized BIC

- Residual autocorrelation function (ACF)
- Residual partial autocorrelation function (PACF)

For more information, see the topic Goodness-of-Fit Measures in Appendix A on p. 92.

Plots for Individual Models

Series. Select (check) this option to obtain plots of the predicted values for each estimated model. You can select one or more of the following for inclusion in the plot:

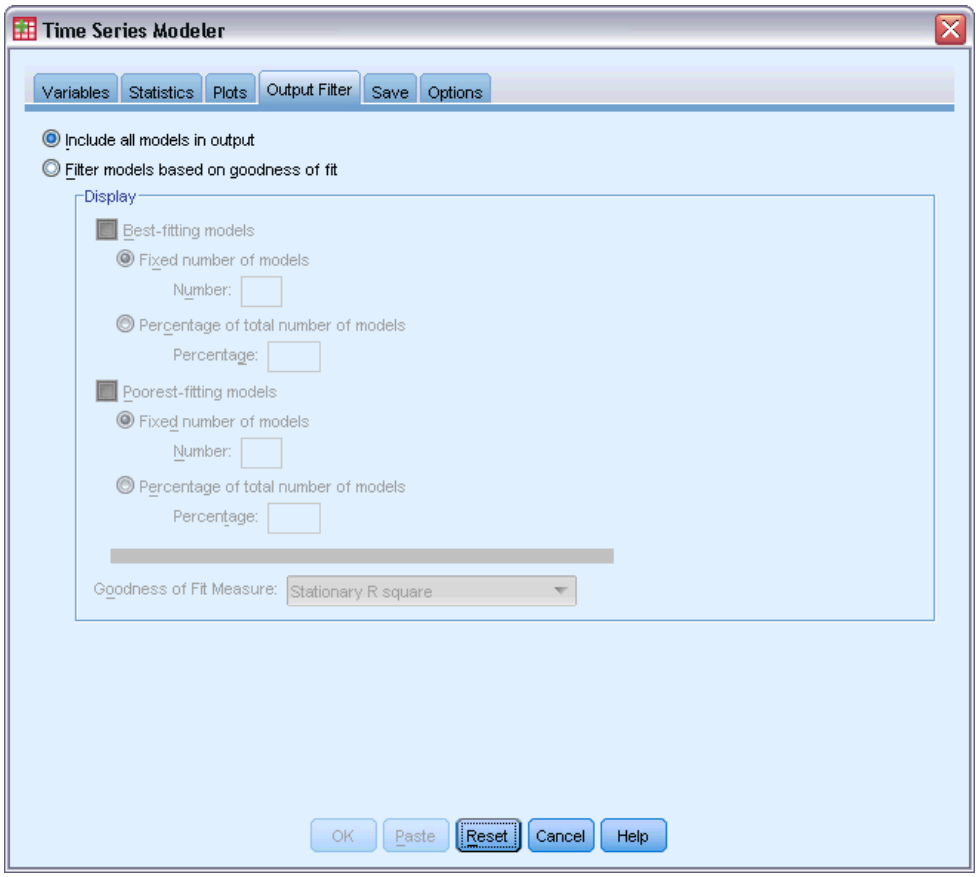
- **Observed values.** The observed values of the dependent series.
- **Forecasts.** The model predicted values for the forecast period.
- **Fit values.** The model predicted values for the estimation period.
- **Confidence intervals for forecasts.** The confidence intervals for the forecast period.
- **Confidence intervals for fit values.** The confidence intervals for the estimation period.

Residual autocorrelation function (ACF). Displays a plot of residual autocorrelations for each estimated model.

Residual partial autocorrelation function (PACF). Displays a plot of residual partial autocorrelations for each estimated model.

Limiting Output to the Best- or Poorest-Fitting Models

Figure 2-10
Time Series Modeler, Output Filter tab



The Output Filter tab provides options for restricting both tabular and chart output to a subset of the estimated models. You can choose to limit output to the best-fitting and/or the poorest-fitting models according to fit criteria you provide. By default, all estimated models are included in the output.

Best-fitting models. Select (check) this option to include the best-fitting models in the output. Select a goodness-of-fit measure and specify the number of models to include. Selecting this option does not preclude also selecting the poorest-fitting models. In that case, the output will consist of the poorest-fitting models as well as the best-fitting ones.

- **Fixed number of models.** Specifies that results are displayed for the *n* best-fitting models. If the number exceeds the number of estimated models, all models are displayed.
- **Percentage of total number of models.** Specifies that results are displayed for models with goodness-of-fit values in the top *n* percent across all estimated models.

Poorest-fitting models. Select (check) this option to include the poorest-fitting models in the output. Select a goodness-of-fit measure and specify the number of models to include. Selecting this option does not preclude also selecting the best-fitting models. In that case, the output will consist of the best-fitting models as well as the poorest-fitting ones.

- **Fixed number of models.** Specifies that results are displayed for the *n* poorest-fitting models. If the number exceeds the number of estimated models, all models are displayed.
- **Percentage of total number of models.** Specifies that results are displayed for models with goodness-of-fit values in the bottom *n* percent across all estimated models.

Goodness of Fit Measure. Select the goodness-of-fit measure to use for filtering models. The default is stationary *R* square.

Saving Model Predictions and Model Specifications

The Save tab allows you to save model predictions as new variables in the active dataset and save model specifications to an external file in XML format.

Save Variables. You can save model predictions, confidence intervals, and residuals as new variables in the active dataset. Each dependent series gives rise to its own set of new variables, and each new variable contains values for both the estimation and forecast periods. New cases are added if the forecast period extends beyond the length of the dependent variable series. Choose to save new variables by selecting the associated Save check box for each. By default, no new variables are saved.

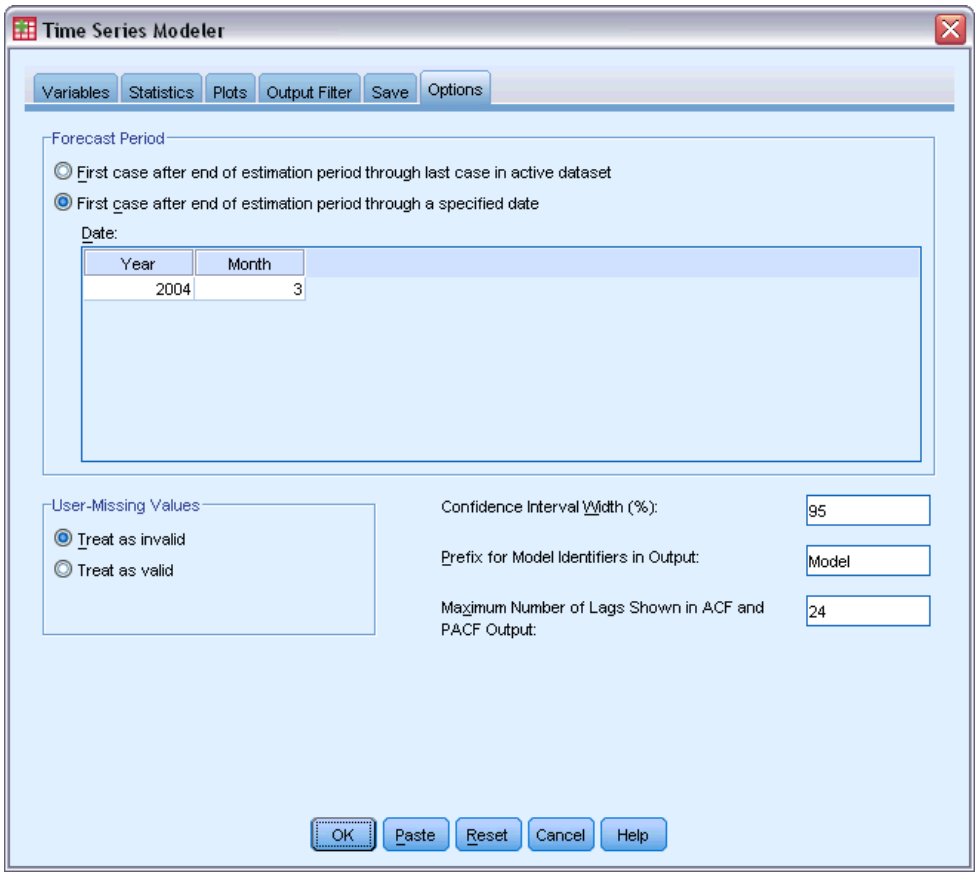
- **Predicted Values.** The model predicted values.
- **Lower Confidence Limits.** Lower confidence limits for the predicted values.
- **Upper Confidence Limits.** Upper confidence limits for the predicted values.
- **Noise Residuals.** The model residuals. When transformations of the dependent variable are performed (for example, natural log), these are the residuals for the transformed series.
- **Variable Name Prefix.** Specify prefixes to be used for new variable names, or leave the default prefixes. Variable names consist of the prefix, the name of the associated dependent variable, and a model identifier. The variable name is extended if necessary to avoid variable naming conflicts. The prefix must conform to the rules for valid variable names.

Export Model File. Model specifications for all estimated models are exported to the specified file in XML format. Saved models can be used to obtain updated forecasts, based on more current data, using the Apply Time Series Models procedure.

- **XML File.** Model specifications are saved in an XML file that can be used with IBM SPSS applications.
- **PMML File.** Model specifications are saved in a PMML-compliant XML file that can be used with PMML-compliant applications, including IBM SPSS applications.

Options

Figure 2-11
Time Series Modeler, Options tab



The Options tab allows you to set the forecast period, specify the handling of missing values, set the confidence interval width, specify a custom prefix for model identifiers, and set the number of lags shown for autocorrelations.

Forecast Period. The forecast period always begins with the first case after the end of the estimation period (the set of cases used to determine the model) and goes through either the last case in the active dataset or a user-specified date. By default, the end of the estimation period is the last case in the active dataset, but it can be changed from the Select Cases dialog box by selecting Based on time or case range.

- **First case after end of estimation period through last case in active dataset.** Select this option when the end of the estimation period is prior to the last case in the active dataset, and you want forecasts through the last case. This option is typically used to produce forecasts for a holdout period, allowing comparison of the model predictions with a subset of the actual values.
- **First case after end of estimation period through a specified date.** Select this option to explicitly specify the end of the forecast period. This option is typically used to produce forecasts beyond the end of the actual series. Enter values for all of the cells in the Date grid.

If no date specification has been defined for the active dataset, the Date grid shows the single column *Observation*. To specify the end of the forecast period, enter the row number (as displayed in the Data Editor) of the relevant case.

The *Cycle* column (if present) in the Date grid refers to the value of the *CYCLE_* variable in the active dataset.

User-Missing Values. These options control the handling of user-missing values.

- **Treat as invalid.** User-missing values are treated like system-missing values.
- **Treat as valid.** User-missing values are treated as valid data.

Missing Value Policy. The following rules apply to the treatment of missing values (includes system-missing values and user-missing values treated as invalid) during the modeling procedure:

- Cases with missing values of a dependent variable that occur within the estimation period are included in the model. The specific handling of the missing value depends on the estimation method.
- A warning is issued if an independent variable has missing values within the estimation period. For the Expert Modeler, models involving the independent variable are estimated without the variable. For custom ARIMA, models involving the independent variable are not estimated.
- If any independent variable has missing values within the forecast period, the procedure issues a warning and forecasts as far as it can.

Confidence Interval Width (%). Confidence intervals are computed for the model predictions and residual autocorrelations. You can specify any positive value less than 100. By default, a 95% confidence interval is used.

Prefix for Model Identifiers in Output. Each dependent variable specified on the Variables tab gives rise to a separate estimated model. Models are distinguished with unique names consisting of a customizable prefix along with an integer suffix. You can enter a prefix or leave the default of *Model*.

Maximum Number of Lags Shown in ACF and PACF Output. You can set the maximum number of lags shown in tables and plots of autocorrelations and partial autocorrelations.

TSMODEL Command Additional Features

You can customize your time series modeling if you paste your selections into a syntax window and edit the resulting `TSMODEL` command syntax. The command syntax language allows you to:

- Specify the seasonal period of the data (with the `SEASONLENGTH` keyword on the `AUXILIARY` subcommand). This overrides the current periodicity (if any) for the active dataset.
- Specify nonconsecutive lags for custom ARIMA and transfer function components (with the `ARIMA` and `TRANSFERFUNCTION` subcommands). For example, you can specify a custom ARIMA model with autoregressive lags of orders 1, 3, and 6; or a transfer function with numerator lags of orders 2, 5, and 8.
- Provide more than one set of modeling specifications (for example, modeling method, ARIMA orders, independent variables, and so on) for a single run of the Time Series Modeler procedure (with the `MODEL` subcommand).

See the *Command Syntax Reference* for complete syntax information.

Chapter
3

Apply Time Series Models

The Apply Time Series Models procedure loads existing time series models from an external file and applies them to the active dataset. You can use this procedure to obtain forecasts for series for which new or revised data are available, without rebuilding your models. Models are generated using the Time Series Modeler procedure.

Example. You are an inventory manager with a major retailer, and responsible for each of 5,000 products. You've used the Expert Modeler to create models that forecast sales for each product three months into the future. Your data warehouse is refreshed each month with actual sales data which you'd like to use to produce monthly updated forecasts. The Apply Time Series Models procedure allows you to accomplish this using the original models, and simply reestimating model parameters to account for the new data.

Statistics. Goodness-of-fit measures: stationary *R*-square, *R*-square (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), maximum absolute error (MaxAE), maximum absolute percentage error (MaxAPE), normalized Bayesian information criterion (BIC). Residuals: autocorrelation function, partial autocorrelation function, Ljung-Box *Q*.

Plots. Summary plots across all models: histograms of stationary *R*-square, *R*-square (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), maximum absolute error (MaxAE), maximum absolute percentage error (MaxAPE), normalized Bayesian information criterion (BIC); box plots of residual autocorrelations and partial autocorrelations. Results for individual models: forecast values, fit values, observed values, upper and lower confidence limits, residual autocorrelations and partial autocorrelations.

Apply Time Series Models Data Considerations

Data. Variables (dependent and independent) to which models will be applied should be numeric.

Assumptions. Models are applied to variables in the active dataset with the same names as the variables specified in the model. All such variables are treated as time series, meaning that each case represents a time point, with successive cases separated by a constant time interval.

- **Forecasts.** For producing forecasts using models with independent (predictor) variables, the active dataset should contain values of these variables for all cases in the forecast period. If model parameters are reestimated, then independent variables should not contain any missing values in the estimation period.

Defining Dates

The Apply Time Series Models procedure requires that the periodicity, if any, of the active dataset matches the periodicity of the models to be applied. If you're simply forecasting using the same dataset (perhaps with new or revised data) as that used to the build the model, then this condition will be satisfied. If no periodicity exists for the active dataset, you will be given the opportunity

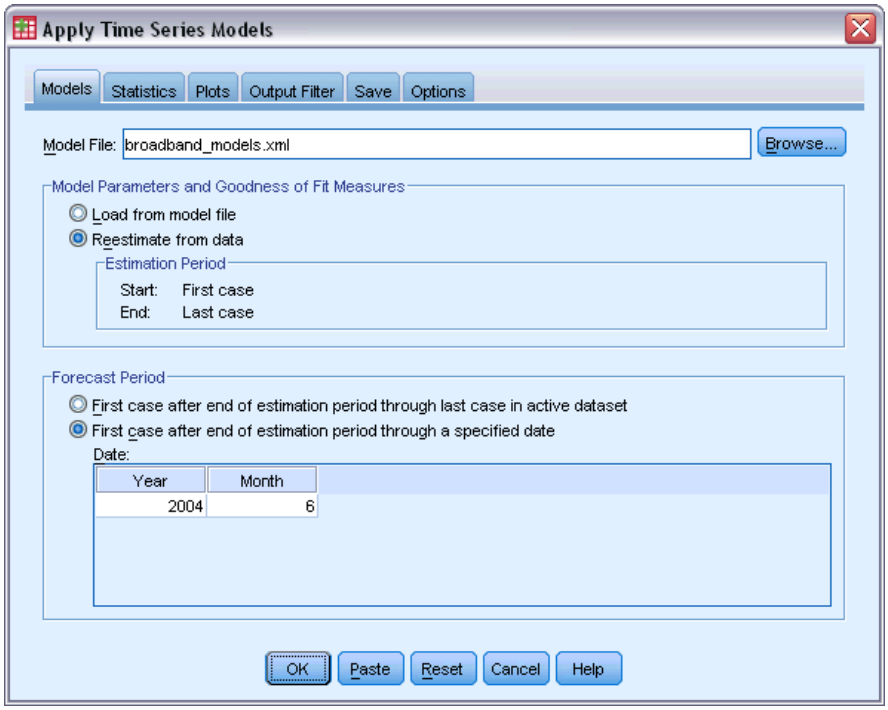
to navigate to the Define Dates dialog box to create one. If, however, the models were created without specifying a periodicity, then the active dataset should also be without one.

To Apply Models

- From the menus choose:

  Analyze > Forecasting > Apply Models...

Figure 3-1
Apply Time Series Models, Models tab



- Enter the file specification for a model file or click Browse and select a model file (model files are created with the Time Series Modeler procedure).

Optionally, you can:

- Reestimate model parameters using the data in the active dataset. Forecasts are created using the reestimated parameters.
- Save predictions, confidence intervals, and noise residuals.
- Save reestimated models in XML format.

Model Parameters and Goodness of Fit Measures

Load from model file. Forecasts are produced using the model parameters from the model file without reestimating those parameters. Goodness of fit measures displayed in output and used to filter models (best- or worst-fitting) are taken from the model file and reflect the data used when each model was developed (or last updated). With this option, forecasts do not take into account historical data—for either dependent or independent variables—in the active dataset. You must

choose Reestimate from data if you want historical data to impact the forecasts. In addition, forecasts do not take into account values of the dependent series in the forecast period—but they do take into account values of independent variables in the forecast period. If you have more current values of the dependent series and want them to be included in the forecasts, you need to reestimate, adjusting the estimation period to include these values.

Reestimate from data. Model parameters are reestimated using the data in the active dataset. Reestimation of model parameters has no effect on model structure. For example, an ARIMA(1,0,1) model will remain so, but the autoregressive and moving-average parameters will be reestimated. Reestimation does not result in the detection of new outliers. Outliers, if any, are always taken from the model file.

- **Estimation Period.** The estimation period defines the set of cases used to reestimate the model parameters. By default, the estimation period includes all cases in the active dataset. To set the estimation period, select Based on time or case range in the Select Cases dialog box. Depending on available data, the estimation period used by the procedure may vary by model and thus differ from the displayed value. For a given model, the true estimation period is the period left after eliminating any contiguous missing values, from the model's dependent variable, occurring at the beginning or end of the specified estimation period.

Forecast Period

The forecast period for each model always begins with the first case after the end of the estimation period and goes through either the last case in the active dataset or a user-specified date. If parameters are not reestimated (this is the default), then the estimation period for each model is the set of cases used when the model was developed (or last updated).

- **First case after end of estimation period through last case in active dataset.** Select this option when the end of the estimation period is prior to the last case in the active dataset, and you want forecasts through the last case.
- **First case after end of estimation period through a specified date.** Select this option to explicitly specify the end of the forecast period. Enter values for all of the cells in the Date grid.

  If no date specification has been defined for the active dataset, the Date grid shows the single column *Observation*. To specify the end of the forecast period, enter the row number (as displayed in the Data Editor) of the relevant case.

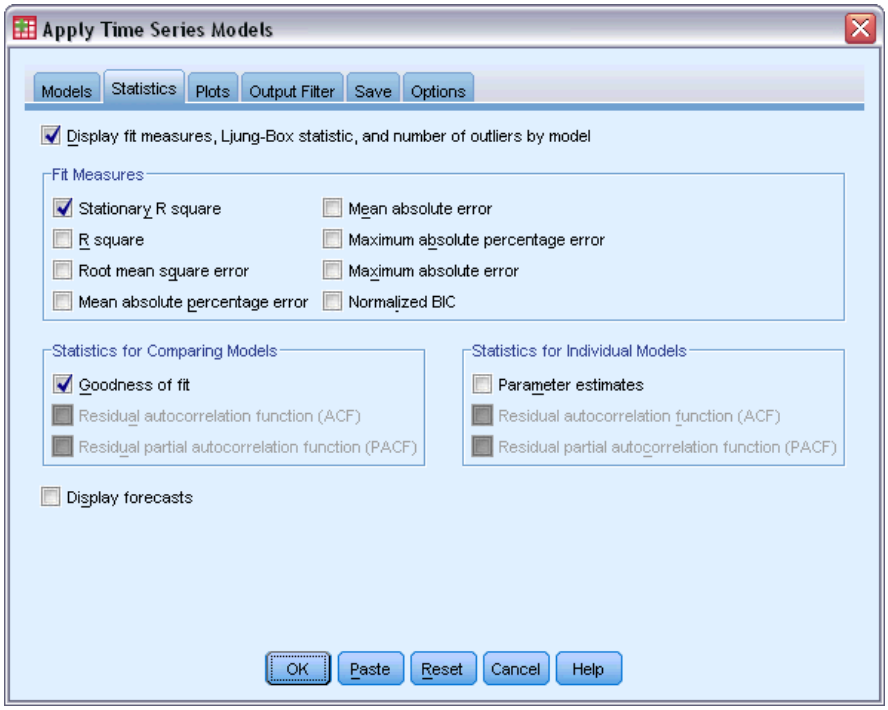
  The *Cycle* column (if present) in the Date grid refers to the value of the *CYCLE_* variable in the active dataset.

Output

Available output includes results for individual models as well as results across all models. Results for individual models can be limited to a set of best- or poorest-fitting models based on user-specified criteria.

Statistics and Forecast Tables

Figure 3-2
Apply Time Series Models, Statistics tab



The Statistics tab provides options for displaying tables of model fit statistics, model parameters, autocorrelation functions, and forecasts. Unless model parameters are reestimated (Reestimate from data on the Models tab), displayed values of fit measures, Ljung-Box values, and model parameters are those from the model file and reflect the data used when each model was developed (or last updated). Outlier information is always taken from the model file.

Display fit measures, Ljung-Box statistic, and number of outliers by model. Select (check) this option to display a table containing selected fit measures, Ljung-Box value, and the number of outliers for each model.

Fit Measures. You can select one or more of the following for inclusion in the table containing fit measures for each model:

- Stationary *R*-square
- *R*-square
- Root mean square error
- Mean absolute percentage error
- Mean absolute error
- Maximum absolute percentage error
- Maximum absolute error
- Normalized BIC

For more information, see the topic Goodness-of-Fit Measures in Appendix A on p. 92.

Statistics for Comparing Models. This group of options controls the display of tables containing statistics across all models. Each option generates a separate table. You can select one or more of the following options:

- **Goodness of fit.** Table of summary statistics and percentiles for stationary *R*-square, *R*-square, root mean square error, mean absolute percentage error, mean absolute error, maximum absolute percentage error, maximum absolute error, and normalized Bayesian Information Criterion.
- **Residual autocorrelation function (ACF).** Table of summary statistics and percentiles for autocorrelations of the residuals across all estimated models. This table is only available if model parameters are reestimated (Reestimate from data on the Models tab).
- **Residual partial autocorrelation function (PACF).** Table of summary statistics and percentiles for partial autocorrelations of the residuals across all estimated models. This table is only available if model parameters are reestimated (Reestimate from data on the Models tab).

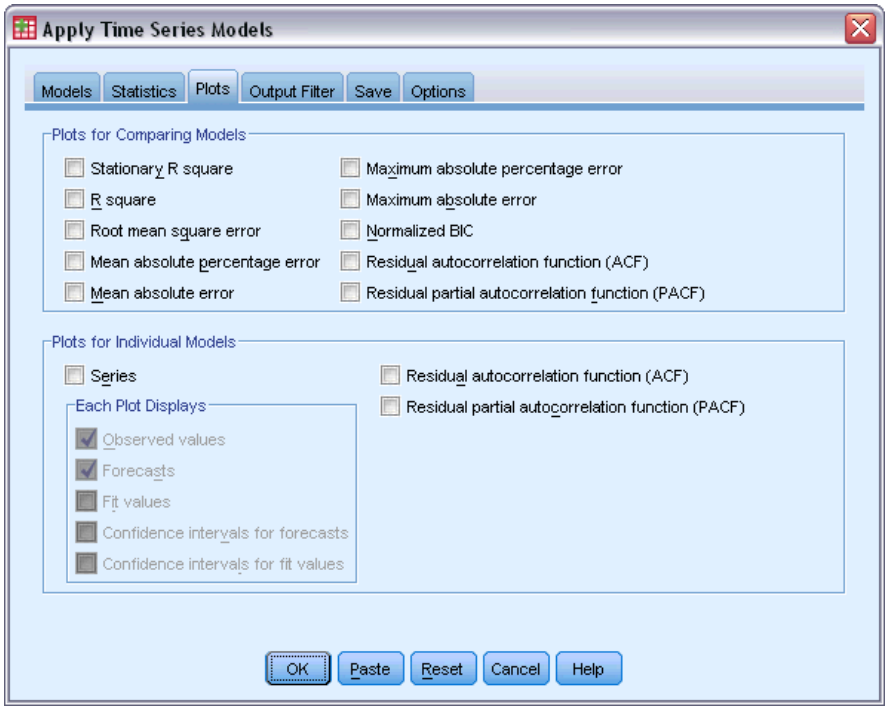
Statistics for Individual Models. This group of options controls display of tables containing detailed information for each model. Each option generates a separate table. You can select one or more of the following options:

- **Parameter estimates.** Displays a table of parameter estimates for each model. Separate tables are displayed for exponential smoothing and ARIMA models. If outliers exist, parameter estimates for them are also displayed in a separate table.
- **Residual autocorrelation function (ACF).** Displays a table of residual autocorrelations by lag for each estimated model. The table includes the confidence intervals for the autocorrelations. This table is only available if model parameters are reestimated (Reestimate from data on the Models tab).
- **Residual partial autocorrelation function (PACF).** Displays a table of residual partial autocorrelations by lag for each estimated model. The table includes the confidence intervals for the partial autocorrelations. This table is only available if model parameters are reestimated (Reestimate from data on the Models tab).

Display forecasts. Displays a table of model forecasts and confidence intervals for each model.

Plots

Figure 3-3
Apply Time Series Models, Plots tab



The Plots tab provides options for displaying plots of model fit statistics, autocorrelation functions, and series values (including forecasts).

Plots for Comparing Models

This group of options controls the display of plots containing statistics across all models. Unless model parameters are reestimated (Reestimate from data on the Models tab), displayed values are those from the model file and reflect the data used when each model was developed (or last updated). In addition, autocorrelation plots are only available if model parameters are reestimated. Each option generates a separate plot. You can select one or more of the following options:

- Stationary *R*-square
- *R*-square
- Root mean square error
- Mean absolute percentage error
- Mean absolute error
- Maximum absolute percentage error
- Maximum absolute error
- Normalized BIC

- Residual autocorrelation function (ACF)
- Residual partial autocorrelation function (PACF)

For more information, see the topic Goodness-of-Fit Measures in Appendix A on p. 92.

Plots for Individual Models

Series. Select (check) this option to obtain plots of the predicted values for each model. Observed values, fit values, confidence intervals for fit values, and autocorrelations are only available if model parameters are reestimated (Reestimate from data on the Models tab). You can select one or more of the following for inclusion in the plot:

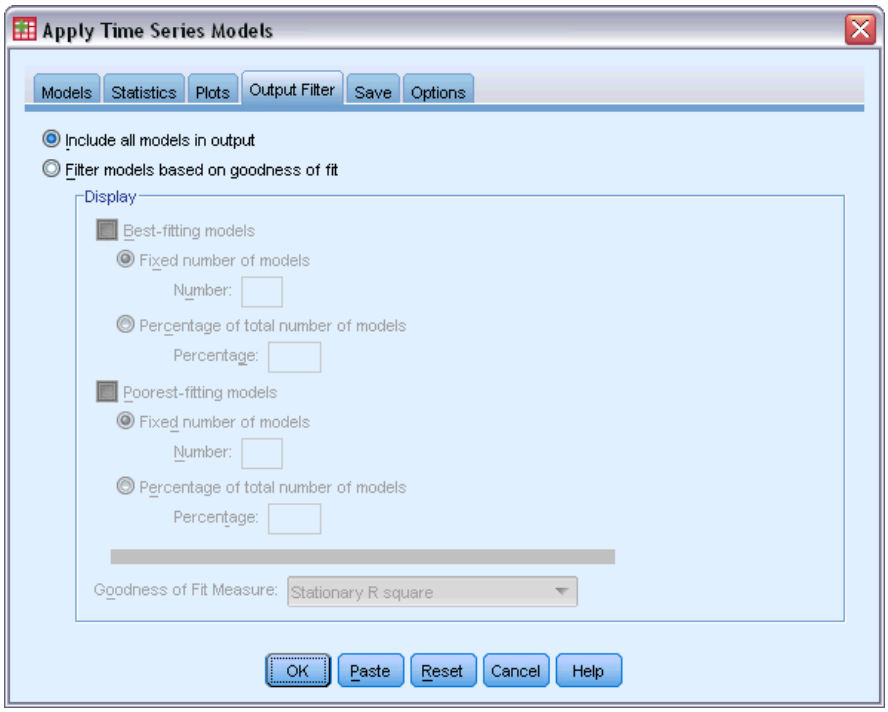
- **Observed values.** The observed values of the dependent series.
- **Forecasts.** The model predicted values for the forecast period.
- **Fit values.** The model predicted values for the estimation period.
- **Confidence intervals for forecasts.** The confidence intervals for the forecast period.
- **Confidence intervals for fit values.** The confidence intervals for the estimation period.

Residual autocorrelation function (ACF). Displays a plot of residual autocorrelations for each estimated model.

Residual partial autocorrelation function (PACF). Displays a plot of residual partial autocorrelations for each estimated model.

Limiting Output to the Best- or Poorest-Fitting Models

Figure 3-4
Apply Time Series Models, Output Filter tab



The Output Filter tab provides options for restricting both tabular and chart output to a subset of models. You can choose to limit output to the best-fitting and/or the poorest-fitting models according to fit criteria you provide. By default, all models are included in the output. Unless model parameters are reestimated (Reestimate from data on the Models tab), values of fit measures used for filtering models are those from the model file and reflect the data used when each model was developed (or last updated).

Best-fitting models. Select (check) this option to include the best-fitting models in the output. Select a goodness-of-fit measure and specify the number of models to include. Selecting this option does not preclude also selecting the poorest-fitting models. In that case, the output will consist of the poorest-fitting models as well as the best-fitting ones.

- **Fixed number of models.** Specifies that results are displayed for the *n* best-fitting models. If the number exceeds the total number of models, all models are displayed.
- **Percentage of total number of models.** Specifies that results are displayed for models with goodness-of-fit values in the top *n* percent across all models.

Poorest-fitting models. Select (check) this option to include the poorest-fitting models in the output. Select a goodness-of-fit measure and specify the number of models to include. Selecting this option does not preclude also selecting the best-fitting models. In that case, the output will consist of the best-fitting models as well as the poorest-fitting ones.

- **Fixed number of models.** Specifies that results are displayed for the *n* poorest-fitting models. If the number exceeds the total number of models, all models are displayed.
- **Percentage of total number of models.** Specifies that results are displayed for models with goodness-of-fit values in the bottom *n* percent across all models.

Goodness of Fit Measure. Select the goodness-of-fit measure to use for filtering models. The default is stationary *R*-square.

Saving Model Predictions and Model Specifications

The Save tab allows you to save model predictions as new variables in the active dataset and save model specifications to an external file in XML format.

Save Variables. You can save model predictions, confidence intervals, and residuals as new variables in the active dataset. Each model gives rise to its own set of new variables. New cases are added if the forecast period extends beyond the length of the dependent variable series associated with the model. Unless model parameters are reestimated (Reestimate from data on the Models tab), predicted values and confidence limits are only created for the forecast period. Choose to save new variables by selecting the associated Save check box for each. By default, no new variables are saved.

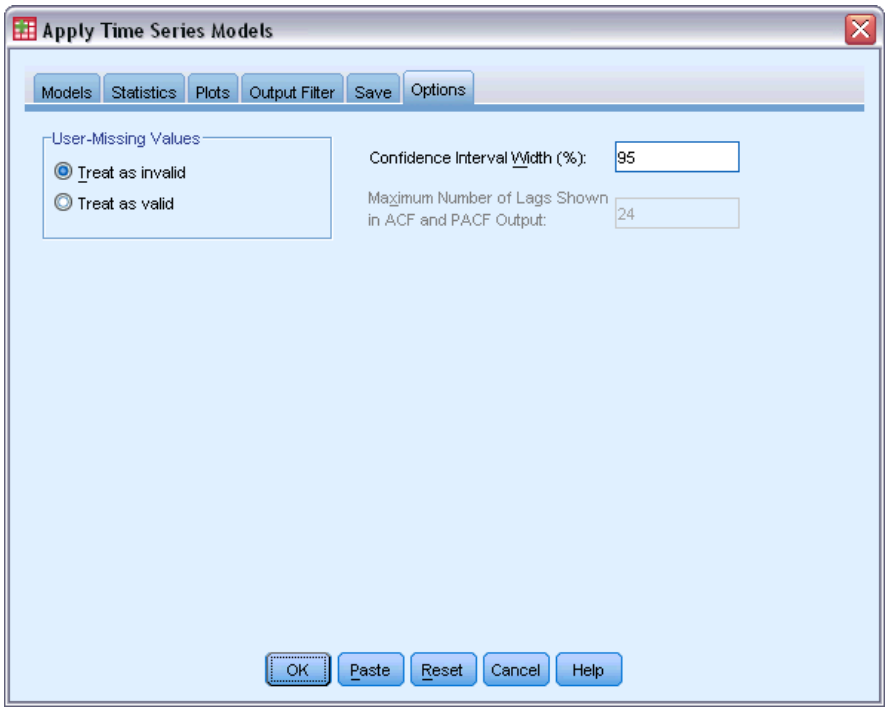
- **Predicted Values.** The model predicted values.
- **Lower Confidence Limits.** Lower confidence limits for the predicted values.
- **Upper Confidence Limits.** Upper confidence limits for the predicted values.
- **Noise Residuals.** The model residuals. When transformations of the dependent variable are performed (for example, natural log), these are the residuals for the transformed series. This choice is only available if model parameters are reestimated (Reestimate from data on the Models tab).
- **Variable Name Prefix.** Specify prefixes to be used for new variable names or leave the default prefixes. Variable names consist of the prefix, the name of the associated dependent variable, and a model identifier. The variable name is extended if necessary to avoid variable naming conflicts. The prefix must conform to the rules for valid variable names.

Export Model File Model specifications, containing reestimated parameters and fit statistics, are exported to the specified file in XML format. This option is only available if model parameters are reestimated (Reestimate from data on the Models tab).

- **XML File.** Model specifications are saved in an XML file that can be used with IBM SPSS applications.
- **PMML File.** Model specifications are saved in a PMML-compliant XML file that can be used with PMML-compliant applications, including IBM SPSS applications.

Options

Figure 3-5
Apply Time Series Models, Options tab



The Options tab allows you to specify the handling of missing values, set the confidence interval width, and set the number of lags shown for autocorrelations.

User-Missing Values. These options control the handling of user-missing values.

- **Treat as invalid.** User-missing values are treated like system-missing values.
- **Treat as valid.** User-missing values are treated as valid data.

Missing Value Policy. The following rules apply to the treatment of missing values (includes system-missing values and user-missing values treated as invalid):

- Cases with missing values of a dependent variable that occur within the estimation period are included in the model. The specific handling of the missing value depends on the estimation method.
- For ARIMA models, a warning is issued if a predictor has any missing values within the estimation period. Any models involving the predictor are not reestimated.
- If any independent variable has missing values within the forecast period, the procedure issues a warning and forecasts as far as it can.

Confidence Interval Width (%). Confidence intervals are computed for the model predictions and residual autocorrelations. You can specify any positive value less than 100. By default, a 95% confidence interval is used.

Maximum Number of Lags Shown in ACF and PACF Output. You can set the maximum number of lags shown in tables and plots of autocorrelations and partial autocorrelations. This option is only available if model parameters are reestimated (Reestimate from data on the Models tab).

TSAPPLY Command Additional Features

Additional features are available if you paste your selections into a syntax window and edit the resulting `TSAPPLY` command syntax. The command syntax language allows you to:

- Specify that only a subset of the models in a model file are to be applied to the active dataset (with the `DROP` and `KEEP` keywords on the `MODEL` subcommand).
- Apply models from two or more model files to your data (with the `MODEL` subcommand). For example, one model file might contain models for series that represent unit sales, and another might contain models for series that represent revenue.

See the *Command Syntax Reference* for complete syntax information.

Chapter
4

Seasonal Decomposition

The Seasonal Decomposition procedure decomposes a series into a seasonal component, a combined trend and cycle component, and an "error" component. The procedure is an implementation of the Census Method I, otherwise known as the ratio-to-moving-average method.

Example. A scientist is interested in analyzing monthly measurements of the ozone level at a particular weather station. The goal is to determine if there is any trend in the data. In order to uncover any real trend, the scientist first needs to account for the variation in readings due to seasonal effects. The Seasonal Decomposition procedure can be used to remove any systematic seasonal variations. The trend analysis is then performed on a seasonally adjusted series.

Statistics. The set of seasonal factors.

Data. The variables should be numeric.

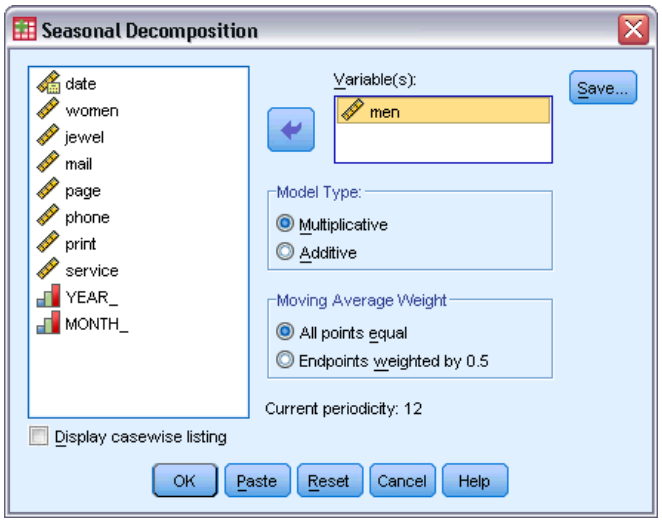
Assumptions. The variables should not contain any embedded missing data. At least one periodic date component must be defined.

Estimating Seasonal Factors

▶ From the menus choose:

Analyze > Forecasting > Seasonal Decomposition...

Figure 4-1
Seasonal Decomposition dialog box



▶ Select one or more variables from the available list and move them into the Variable(s) list. Note that the list includes only numeric variables.

Model Type. The Seasonal Decomposition procedure offers two different approaches for modeling the seasonal factors: multiplicative or additive.

- **Multiplicative.** The seasonal component is a factor by which the seasonally adjusted series is multiplied to yield the original series. In effect, seasonal components that are proportional to the overall level of the series. Observations without seasonal variation have a seasonal component of 1.
- **Additive.** The seasonal adjustments are added to the seasonally adjusted series to obtain the observed values. This adjustment attempts to remove the seasonal effect from a series in order to look at other characteristics of interest that may be "masked" by the seasonal component. In effect, seasonal components that do not depend on the overall level of the series. Observations without seasonal variation have a seasonal component of 0.

Moving Average Weight. The Moving Average Weight options allow you to specify how to treat the series when computing moving averages. These options are available only if the periodicity of the series is even. If the periodicity is odd, all points are weighted equally.

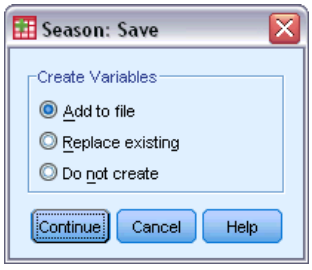
- **All points equal.** Moving averages are calculated with a span equal to the periodicity and with all points weighted equally. This method is always used if the periodicity is odd.
- **Endpoints weighted by .5.** Moving averages for series with even periodicity are calculated with a span equal to the periodicity plus 1 and with the endpoints of the span weighted by 0.5.

Optionally, you can:

- Click Save to specify how new variables should be saved.

Seasonal Decomposition Save

Figure 4-2
Season Save dialog box



Create Variables. Allows you to choose how to treat new variables.

- **Add to file.** The new series created by Seasonal Decomposition are saved as regular variables in your active dataset. Variable names are formed from a three-letter prefix, an underscore, and a number.
- **Replace existing.** The new series created by Seasonal Decomposition are saved as temporary variables in your active dataset. At the same time, any existing temporary variables created by the Forecasting procedures are dropped. Variable names are formed from a three-letter prefix, a pound sign (#), and a number.
- **Do not create.** The new series are not added to the active dataset.

New Variable Names

The Seasonal Decomposition procedure creates four new variables (series), with the following three-letter prefixes, for each series specified:

SAF. *Seasonal adjustment factors.* These values indicate the effect of each period on the level of the series.

SAS. *Seasonally adjusted series.* These are the values obtained after removing the seasonal variation of a series.

STC. *Smoothed trend-cycle components.* These values show the trend and cyclical behavior present in the series.

ERR. *Residual or "error" values.* The values that remain after the seasonal, trend, and cycle components have been removed from the series.

SEASON Command Additional Features

The command syntax language also allows you to:

- Specify any periodicity within the `SEASON` command rather than select one of the alternatives offered by the Define Dates procedure.

See the *Command Syntax Reference* for complete syntax information.

Chapter
5

Spectral Plots

The Spectral Plots procedure is used to identify periodic behavior in time series. Instead of analyzing the variation from one time point to the next, it analyzes the variation of the series as a whole into periodic components of different frequencies. Smooth series have stronger periodic components at low frequencies; random variation ("white noise") spreads the component strength over all frequencies.

Series that include missing data cannot be analyzed with this procedure.

Example. The rate at which new houses are constructed is an important barometer of the state of the economy. Data for housing starts typically exhibit a strong seasonal component. But are there longer cycles present in the data that analysts need to be aware of when evaluating current figures?

Statistics. Sine and cosine transforms, periodogram value, and spectral density estimate for each frequency or period component. When bivariate analysis is selected: real and imaginary parts of cross-periodogram, cospectral density, quadrature spectrum, gain, squared coherency, and phase spectrum for each frequency or period component.

Plots. For univariate and bivariate analyses: periodogram and spectral density. For bivariate analyses: squared coherency, quadrature spectrum, cross amplitude, cospectral density, phase spectrum, and gain.

Data. The variables should be numeric.

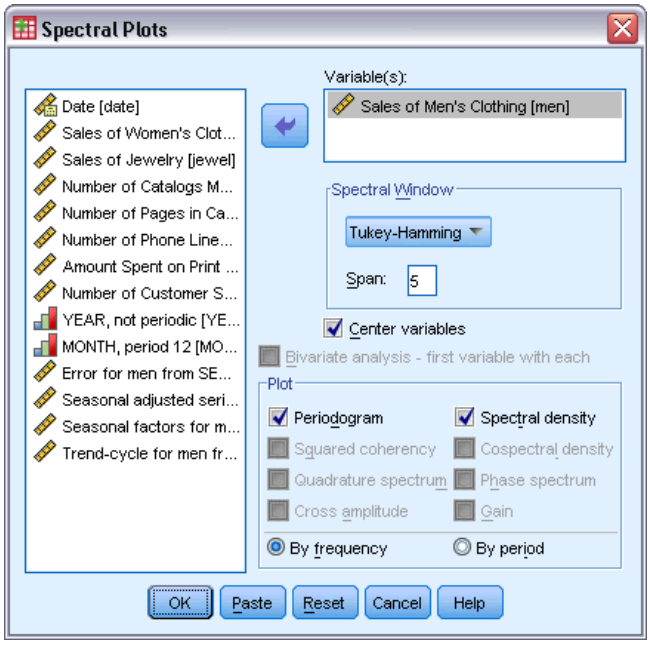
Assumptions. The variables should not contain any embedded missing data. The time series to be analyzed should be stationary and any non-zero mean should be subtracted out from the series.

- **Stationary.** A condition that must be met by the time series to which you fit an ARIMA model. Pure MA series will be stationary; however, AR and ARMA series might not be. A stationary series has a constant mean and a constant variance over time.

Obtaining a Spectral Analysis

▶ From the menus choose:
Analysis > Time Series > Spectral Analysis...

Figure 5-1
Spectral Plots dialog box



- Select one or more variables from the available list and move them to the Variable(s) list. Note that the list includes only numeric variables.
- Select one of the Spectral Window options to choose how to smooth the periodogram in order to obtain a spectral density estimate. Available smoothing options are Tukey-Hamming, Tukey, Parzen, Bartlett, Daniell (Unit), and None.
  - **Tukey-Hamming.** The weights are Wk = .54Dp(2 pi fk) + .23Dp (2 pi fk + pi/p) + .23Dp (2 pi fk - pi/p), for k = 0, ..., p, where p is the integer part of half the span and Dp is the Dirichlet kernel of order p.
  - **Tukey.** The weights are Wk = 0.5Dp(2 pi fk) + 0.25Dp (2 pi fk + pi/p) + 0.25Dp(2 pi fk - pi/p), for k = 0, ..., p, where p is the integer part of half the span and Dp is the Dirichlet kernel of order p.
  - **Parzen.** The weights are Wk = 1/p(2 + cos(2 pi fk)) (F[p/2] (2 pi fk))**2, for k= 0, ... p, where p is the integer part of half the span and F[p/2] is the Fejer kernel of order p/2.
  - **Bartlett.** The shape of a spectral window for which the weights of the upper half of the window are computed as Wk = Fp (2*pi*fk), for k = 0, ... p, where p is the integer part of half the span and Fp is the Fejer kernel of order p. The lower half is symmetric with the upper half.
  - **Daniell (Unit).** The shape of a spectral window for which the weights are all equal to 1.
  - **None.** No smoothing. If this option is chosen, the spectral density estimate is the same as the periodogram.

  Span. The range of consecutive values across which the smoothing is carried out. Generally, an odd integer is used. Larger spans smooth the spectral density plot more than smaller spans.

  Center variables. Adjusts the series to have a mean of 0 before calculating the spectrum and to remove the large term that may be associated with the series mean.

Bivariate analysis—first variable with each. If you have selected two or more variables, you can select this option to request bivariate spectral analyses.

- The first variable in the Variable(s) list is treated as the independent variable, and all remaining variables are treated as dependent variables.
- Each series after the first is analyzed with the first series independently of other series named. Univariate analyses of each series are also performed.

Plot. Periodogram and spectral density are available for both univariate and bivariate analyses. All other choices are available only for bivariate analyses.

- **Periodogram.** Unsmoothed plot of spectral amplitude (plotted on a logarithmic scale) against either frequency or period. Low-frequency variation characterizes a smooth series. Variation spread evenly across all frequencies indicates "white noise."
- **Squared coherency.** The product of the gains of the two series.
- **Quadrature spectrum.** The imaginary part of the cross-periodogram, which is a measure of the correlation of the out-of-phase frequency components of two time series. The components are out of phase by pi/2 radians.
- **Cross amplitude.** The square root of the sum of the squared cospectral density and the squared quadrature spectrum.
- **Spectral density.** A periodogram that has been smoothed to remove irregular variation.
- **Cospectral density.** The real part of the cross-periodogram, which is a measure of the correlation of the in-phase frequency components of two time series.
- **Phase spectrum.** A measure of the extent to which each frequency component of one series leads or lags the other.
- **Gain.** The quotient of dividing the cross amplitude by the spectral density for one of the series. Each of the two series has its own gain value.

By frequency. All plots are produced by frequency, ranging from frequency 0 (the constant or mean term) to frequency 0.5 (the term for a cycle of two observations).

By period. All plots are produced by period, ranging from 2 (the term for a cycle of two observations) to a period equal to the number of observations (the constant or mean term). Period is displayed on a logarithmic scale.

SPECTRA Command Additional Features

The command syntax language also allows you to:

- Save computed spectral analysis variables to the active dataset for later use.
- Specify custom weights for the spectral window.
- Produce plots by both frequency and period.
- Print a complete listing of each value shown in the plot.

See the *Command Syntax Reference* for complete syntax information.

Part II: Examples

Chapter 6

Bulk Forecasting with the Expert Modeler

An analyst for a national broadband provider is required to produce forecasts of user subscriptions in order to predict utilization of bandwidth. Forecasts are needed for each of the 85 local markets that make up the national subscriber base. Monthly historical data is collected in *broadband_1.sav*. For more information, see the topic Sample Files in Appendix D on p. 98.

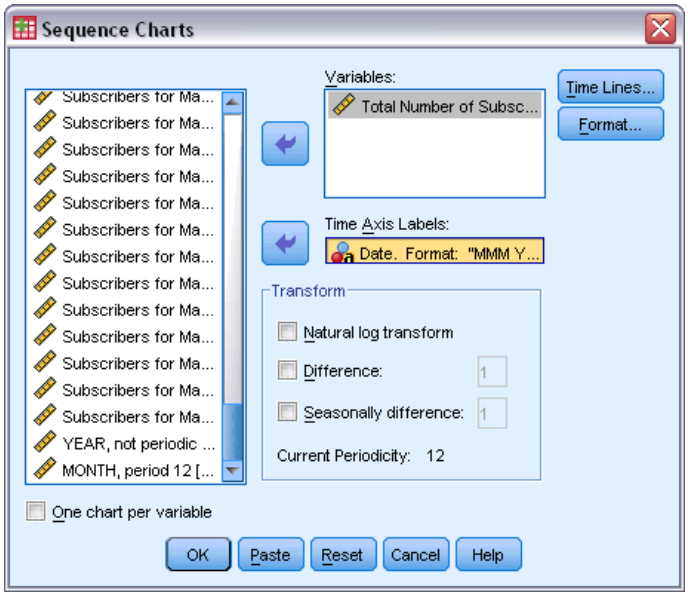
In this example, you will use the Expert Modeler to produce forecasts for the next three months for each of the 85 local markets, saving the generated models to an external XML file. Once you are finished, you might want to work through the next example, Bulk Reforecasting by Applying Saved Models in Chapter 7 on p. 53, which applies the saved models to an updated dataset in order to extend the forecasts by another three months without having to rebuild the models.

Examining Your Data

It is always a good idea to have a feel for the nature of your data before building a model. Does the data exhibit seasonal variations? Although the Expert Modeler will automatically find the best seasonal or non-seasonal model for each series, you can often obtain faster results by limiting the search to non-seasonal models when seasonality is not present in your data. Without examining the data for each of the 85 local markets, we can get a rough picture by plotting the total number of subscribers over all markets.

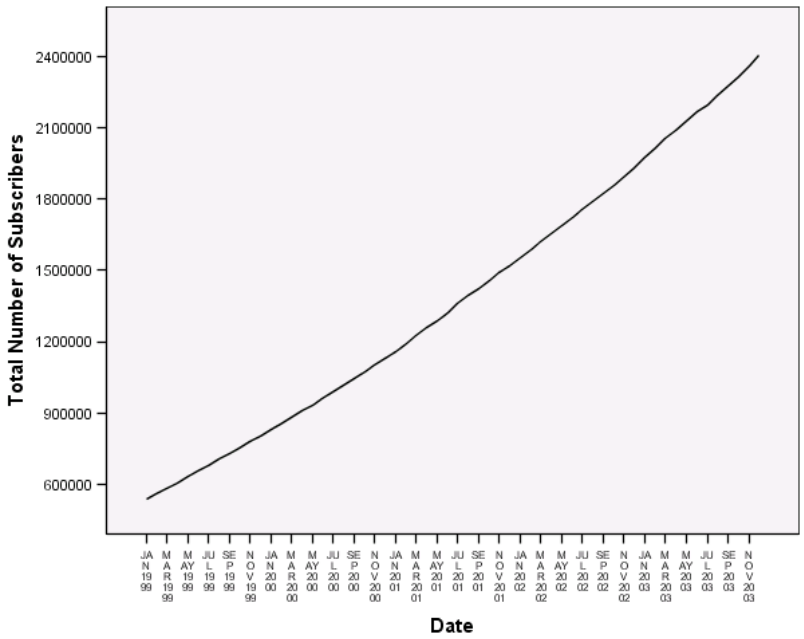
▶ From the menus choose:
Analyze > Forecasting > Sequence Charts...

Figure 6-1
Sequence Charts dialog box



- Select *Total Number of Subscribers* and move it into the Variables list.
- Select *Date* and move it into the Time Axis Labels box.
- Click OK.

Figure 6-2
Total number of broadband subscribers across all markets



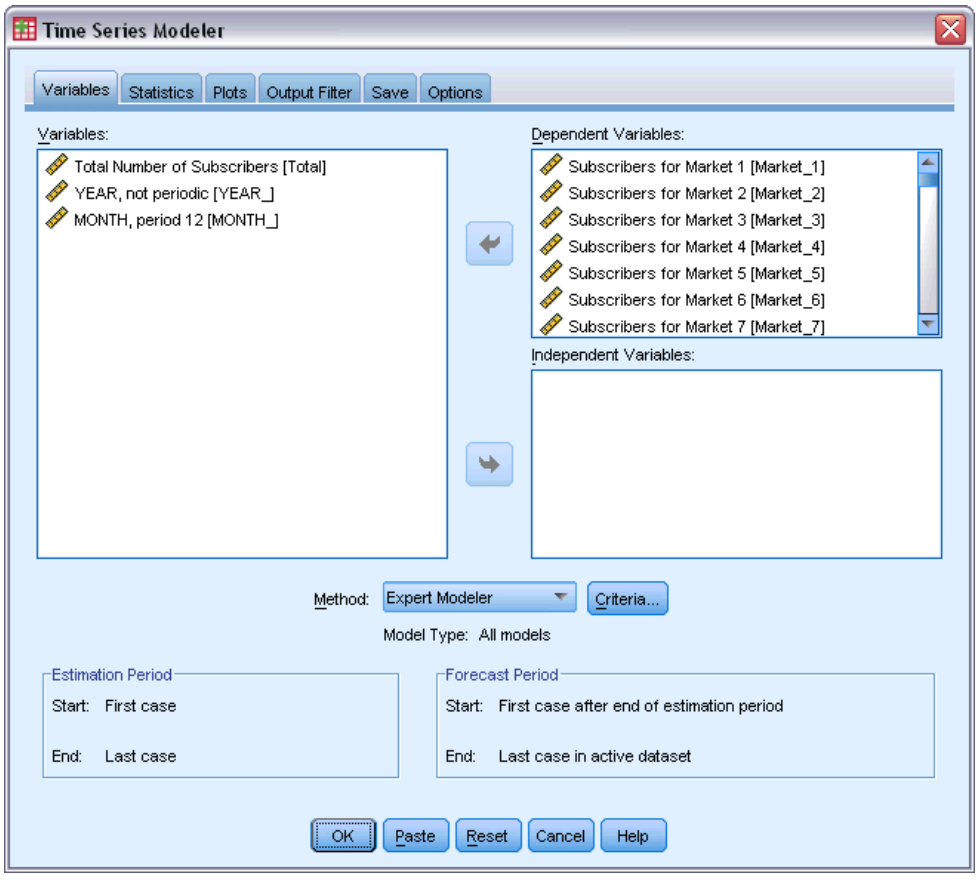
The series exhibits a very smooth upward trend with no hint of seasonal variations. There might be individual series with seasonality, but it appears that seasonality is not a prominent feature of the data in general. Of course you should inspect each of the series before ruling out seasonal models. You can then separate out series exhibiting seasonality and model them separately. In the present case, inspection of the 85 series would show that none exhibit seasonality.

Running the Analysis

To use the Expert Modeler:

- From the menus choose:
  Analyze > Forecasting > Create Models...

Figure 6-3
Time Series Modeler dialog box



- Select *Subscribers for Market 1* through *Subscribers for Market 85* for dependent variables.

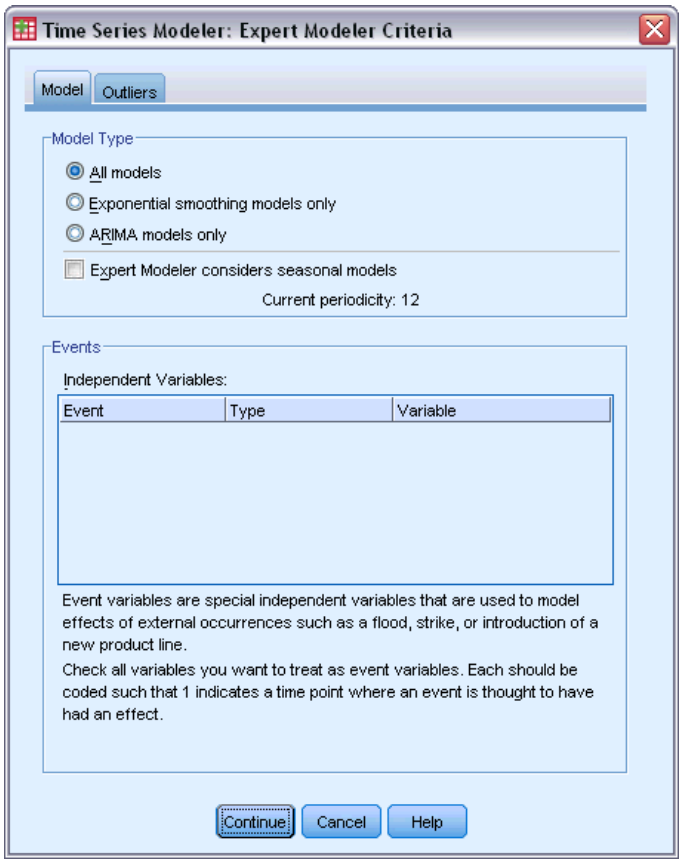
- Verify that Expert Modeler is selected in the Method drop-down list. The Expert Modeler will automatically find the best-fitting model for each of the dependent variable series.

The set of cases used to estimate the model is referred to as the **estimation period**. By default, it includes all of the cases in the active dataset. You can set the estimation period by selecting Based on time or case range in the Select Cases dialog box. For this example, we will stick with the default.

Notice also that the default forecast period starts after the end of the estimation period and goes through to the last case in the active dataset. If you are forecasting beyond the last case, you will need to extend the forecast period. This is done from the Options tab as you will see later on in this example.

▶ Click Criteria.

Figure 6-4
Expert Modeler Criteria dialog box, Model tab



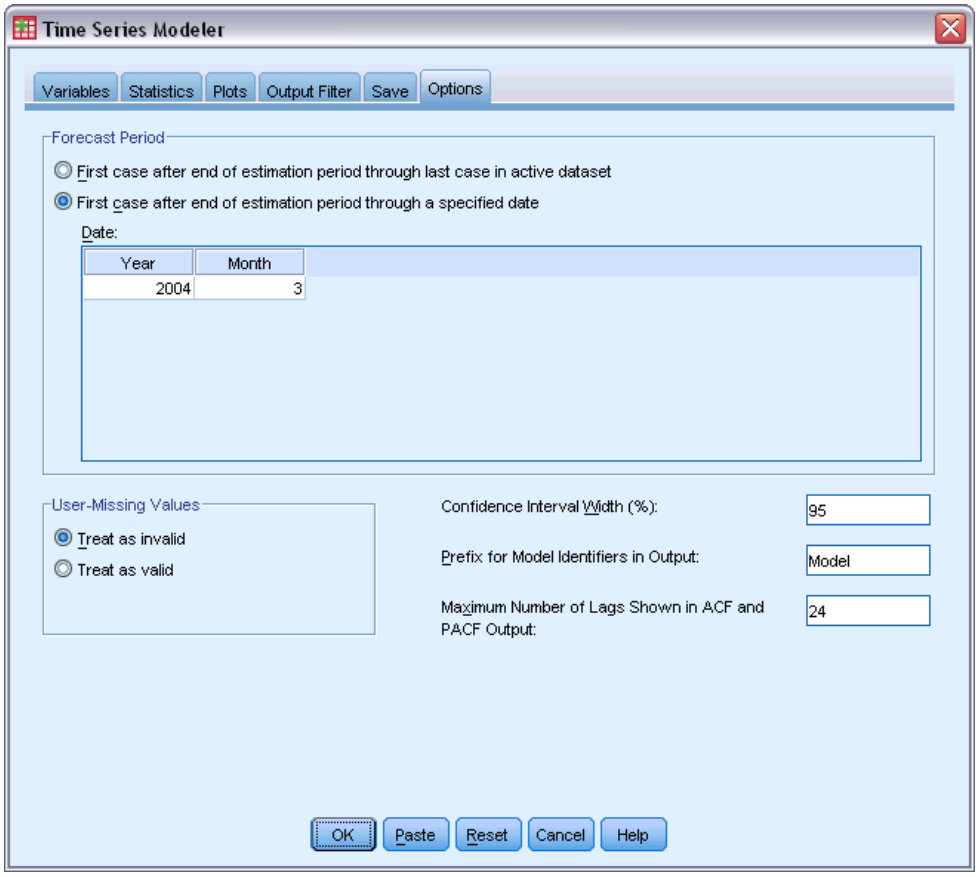
▶ Deselect Expert Modeler considers seasonal models in the Model Type group.

Although the data is monthly and the current periodicity is 12, we have seen that the data does not exhibit any seasonality, so there is no need to consider seasonal models. This reduces the space of models searched by the Expert Modeler and can significantly reduce computing time.

▶ Click Continue.

▶ Click the Options tab on the Time Series Modeler dialog box.

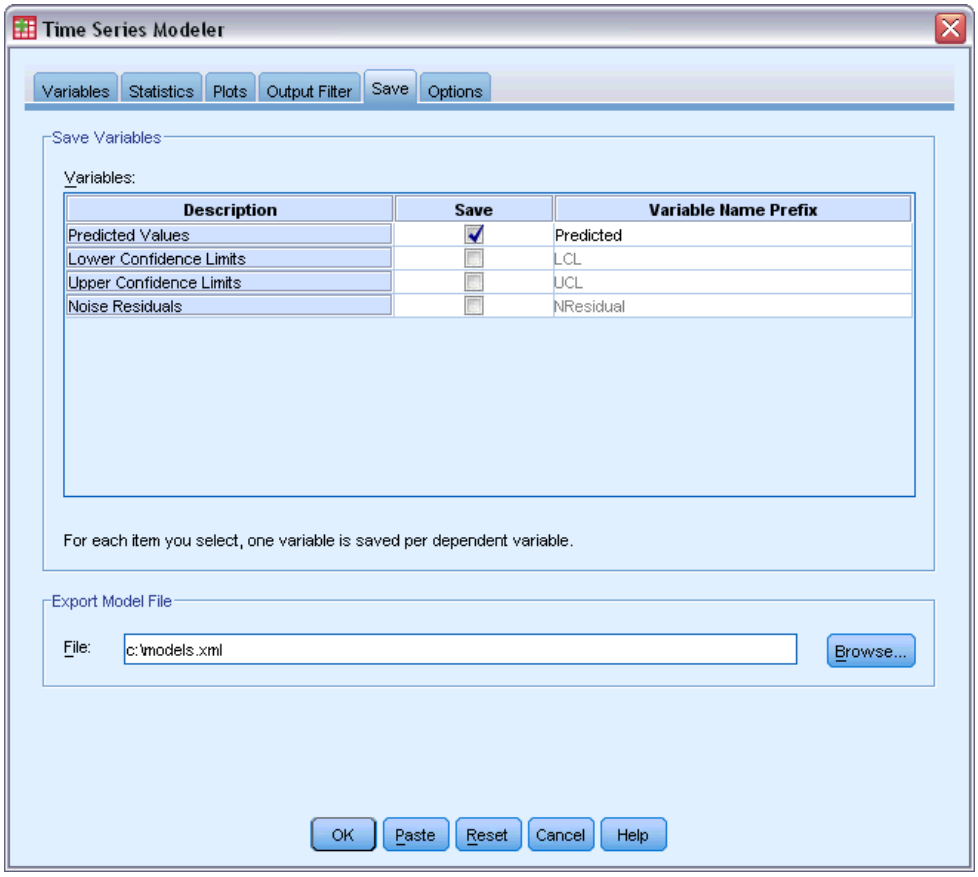
Figure 6-5
Time Series Modeler, Options tab



- Select First case after end of estimation period through a specified date in the Forecast Period group.
- In the Date grid, enter 2004 for the year and 3 for the month.

  The dataset contains data from January 1999 through December 2003. With the current settings, the forecast period will be January 2004 through March 2004.
- Click the Save tab.

Figure 6-6
Time Series Modeler, Save tab



- Select (check) the entry for Predicted Values in the *Save* column, and leave the default value *Predicted* as the Variable Name Prefix.

  The model predictions are saved as new variables in the active dataset, using the prefix *Predicted* for the variable names. You can also save the specifications for each of the models to an external XML file. This will allow you to reuse the models to extend your forecasts as new data becomes available.

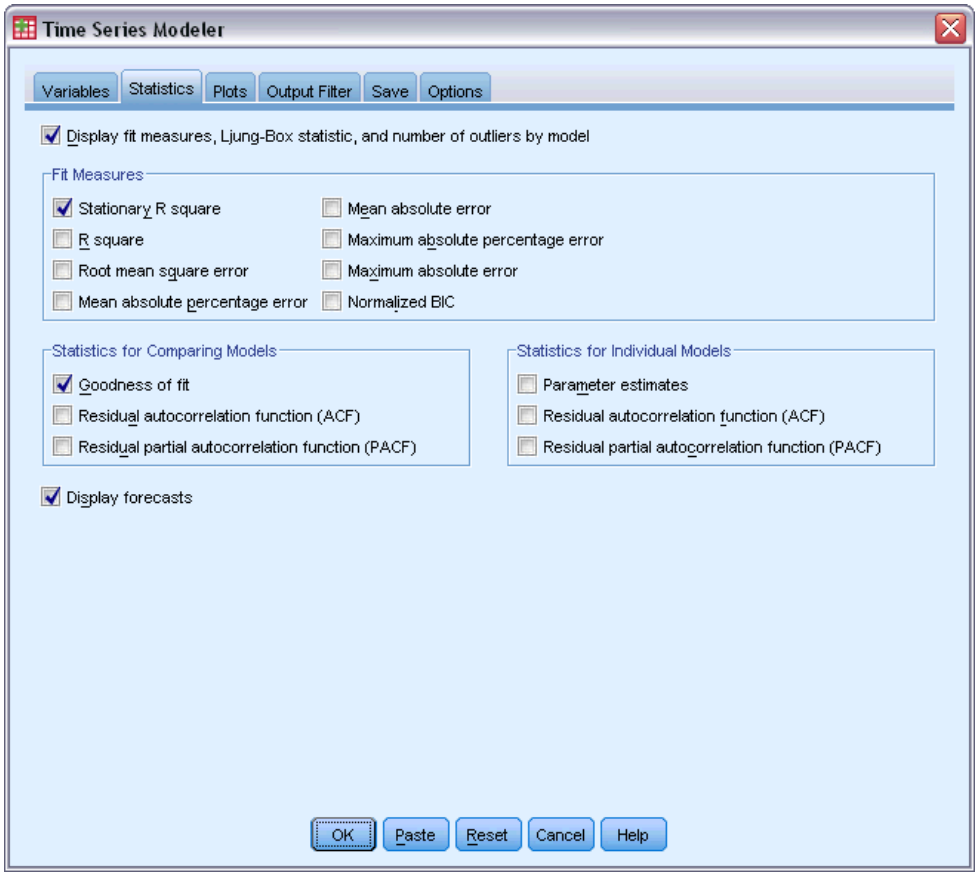
- Click the Browse button on the Save tab.

  This will take you to a standard dialog box for saving a file.

- Navigate to the folder where you would like to save the XML model file, enter a filename, and click Save.

- Click the Statistics tab.

Figure 6-7
Time Series Modeler, Statistics tab



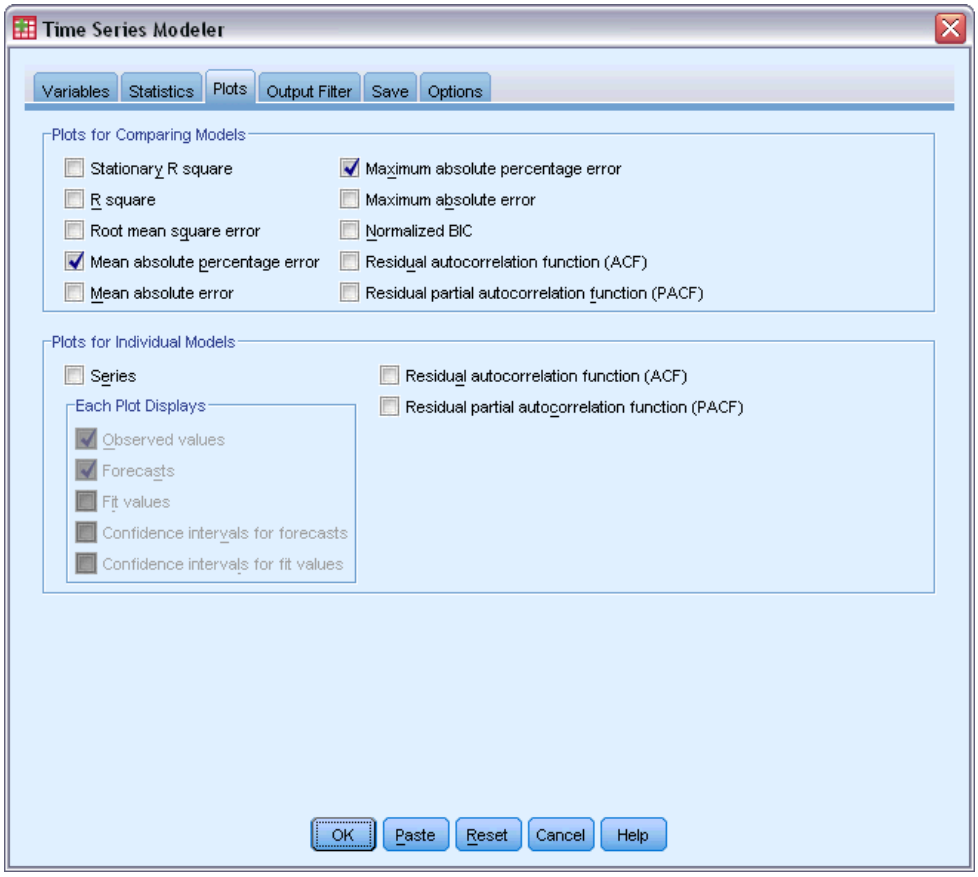
▶ Select Display forecasts.

This option produces a table of forecasted values for each dependent variable series and provides another option—other than saving the predictions as new variables—for obtaining these values.

The default selection of Goodness of fit (in the Statistics for Comparing Models group) produces a table with fit statistics—such as *R*-squared, mean absolute percentage error, and normalized BIC—calculated across all of the models. It provides a concise summary of how well the models fit the data.

▶ Click the Plots tab.

Figure 6-8
Time Series Modeler, Plots tab



▶ Deselect Series in the Plots for Individual Models group.

This suppresses the generation of series plots for each of the models. In this example, we are more interested in saving the forecasts as new variables than generating plots of the forecasts.

The Plots for Comparing Models group provides several plots (in the form of histograms) of fit statistics calculated across all models.

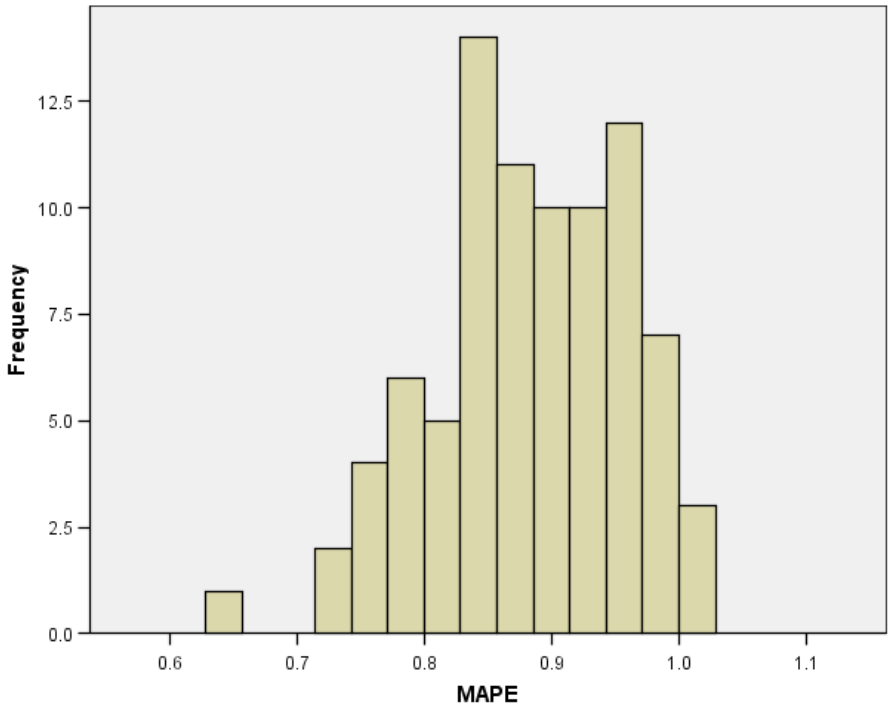
▶ Select Mean absolute percentage error and Maximum absolute percentage error in the Plots for Comparing Models group.

Absolute percentage error is a measure of how much a dependent series varies from its model-predicted level. By examining the mean and maximum across all models, you can get an indication of the uncertainty in your predictions. And looking at summary plots of percentage errors, rather than absolute errors, is advisable since the dependent series represent subscriber numbers for markets of varying sizes.

▶ Click OK in the Time Series Modeler dialog box.

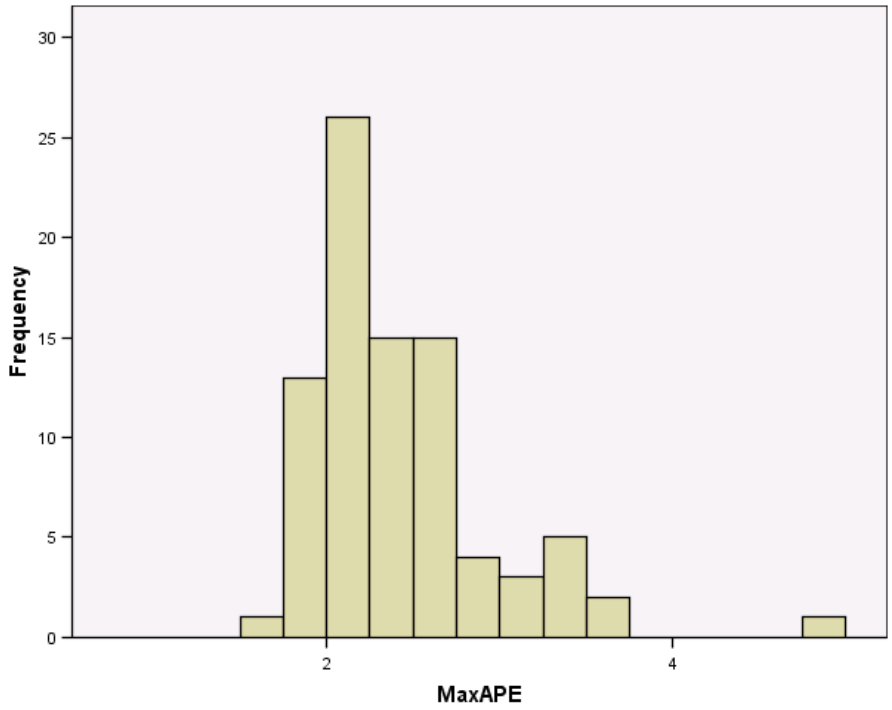
Model Summary Charts

Figure 6-9
Histogram of mean absolute percentage error



This histogram displays the mean absolute percentage error (MAPE) across all models. It shows that all models display a mean uncertainty of roughly 1%.

Figure 6-10
Histogram of maximum absolute percentage error



This histogram displays the maximum absolute percentage error (MaxAPE) across all models and is useful for imagining a worst-case scenario for your forecasts. It shows that the largest percentage error for each model falls in the range of 1 to 5%. Do these values represent an acceptable amount of uncertainty? This is a situation in which your business sense comes into play because acceptable risk will change from problem to problem.

Model Predictions

Figure 6-11
New variables containing model predictions

YEAR_	MONTH_	DATE_	Predicted_Market_1_Model_1	Predicted_Market_2_Model_2
2003	10	OCT 2003	11820	51084
2003	11	NOV 2003	11857	51273
2003	12	DEC 2003	11687	53082
2004	1	JAN 2004	11503	54893
2004	2	FEB 2004	11447	55856
2004	3	MAR 2004	11390	56704

The Data Editor shows the new variables containing the model predictions. Although only two are shown here, there are 85 new variables, one for each of the 85 dependent series. The variable names consist of the default prefix *Predicted*, followed by the name of the associated dependent variable (for example, *Market_1*), followed by a model identifier (for example, *Model_1*).

Three new cases, containing the forecasts for January 2004 through March 2004, have been added to the dataset, along with automatically generated date labels. Each of the new variables contains the model predictions for the estimation period (January 1999 through December 2003), allowing you to see how well the model fits the known values.

Figure 6-12
Forecast table

Model		JAN 2004	FEB 2004	MAR 2004
Subscribers for Market 1-Model_1	Forecast	11503	11447	11390
	UCL	11686	11767	11870
	LCL	11321	11126	10910
Subscribers for Market 2-Model_2	Forecast	54893	55856	56704
	UCL	55632	57195	58575
	LCL	54154	54518	54832
Subscribers for Market 3-Model_3	Forecast	59656	59305	58954
	UCL	60457	60753	61158
	LCL	58856	57857	56750
Subscribers for Market 4-Model_4	Forecast	18235	18424	18628
	UCL	18413	18731	19121
	LCL	18058	18116	18136

You also chose to create a table with the forecasted values. The table consists of the predicted values in the forecast period but—unlike the new variables containing the model predictions—does not include predicted values in the estimation period. The results are organized by model and identified by the model name, which consists of the name (or label) of the associated dependent variable followed by a model identifier—just like the names of the new variables containing the model predictions. The table also includes the upper confidence limits (UCL) and lower confidence limits (LCL) for the forecasted values (95% by default).

You have now seen two approaches for obtaining the forecasted values: saving the forecasts as new variables in the active dataset and creating a forecast table. With either approach, you will have a number of options available for exporting your forecasts (for example, into an Excel spreadsheet).

Summary

You have learned how to use the Expert Modeler to produce forecasts for multiple series, and you have saved the resulting models to an external XML file. In the next example, you will learn how to extend your forecasts as new data becomes available—without having to rebuild your models—by using the Apply Time Series Models procedure.

Chapter 7

Bulk Reforecasting by Applying Saved Models

You have used the Time Series Modeler to create models for your time series data and to produce initial forecasts based on available data. You plan to reuse these models to extend your forecasts as more current data becomes available, so you saved the models to an external file. You are now ready to apply the saved models.

This example is a natural extension of the previous one, Bulk Forecasting with the Expert Modeler in Chapter 6 on p. 42, but can also be used independently. In this scenario, you are an analyst for a national broadband provider who is required to produce monthly forecasts of user subscriptions for each of 85 local markets. You have already used the Expert Modeler to create models and to forecast three months into the future. Your data warehouse has been refreshed with actual data for the original forecast period, so you would like to use that data to extend the forecast horizon by another three months.

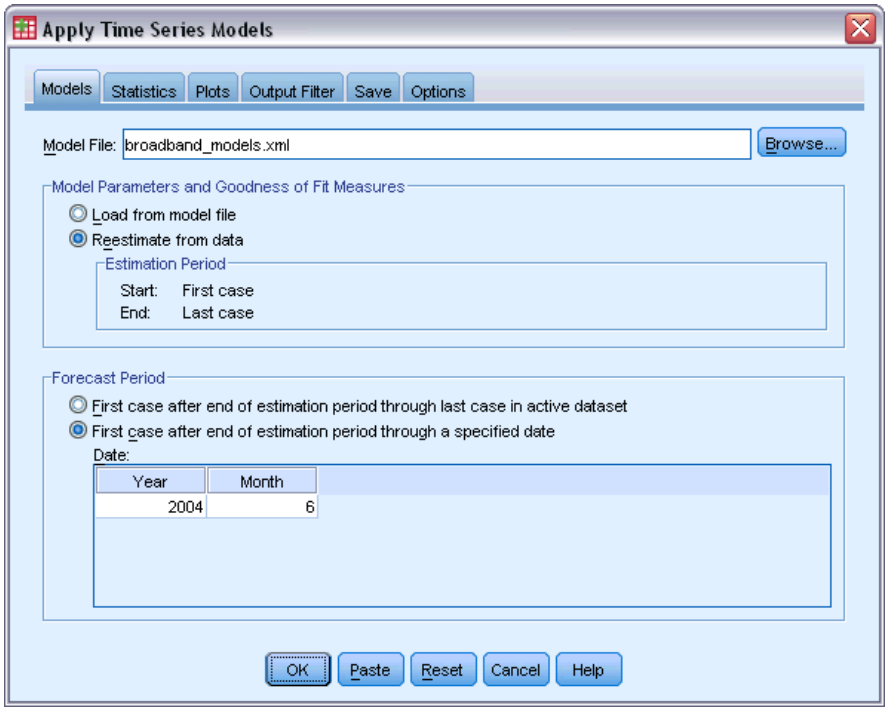
The updated monthly historical data is collected in *broadband_2.sav*, and the saved models are in *broadband_models.xml*. For more information, see the topic Sample Files in Appendix D on p. 98. Of course, if you worked through the previous example and saved your own model file, you can use that one instead of *broadband_models.xml*.

Running the Analysis

To apply models:

- From the menus choose:
  Analyze > Forecasting > Apply Models...

Figure 7-1
Apply Time Series Models dialog box



- Click Browse, then navigate to and select *broadband_models.xml* (or choose your own model file saved from the previous example). For more information, see the topic Sample Files in Appendix D on p. 98.

- Select Reestimate from data.

  To incorporate new values of your time series into forecasts, the Apply Time Series Models procedure will have to reestimate the model parameters. The structure of the models remains the same though, so the computing time to reestimate is much quicker than the original computing time to build the models.

  The set of cases used for reestimation needs to include the new data. This will be assured if you use the default estimation period of First Case to Last Case. If you ever need to set the estimation period to something other than the default, you can do so by selecting Based on time or case range in the Select Cases dialog box.

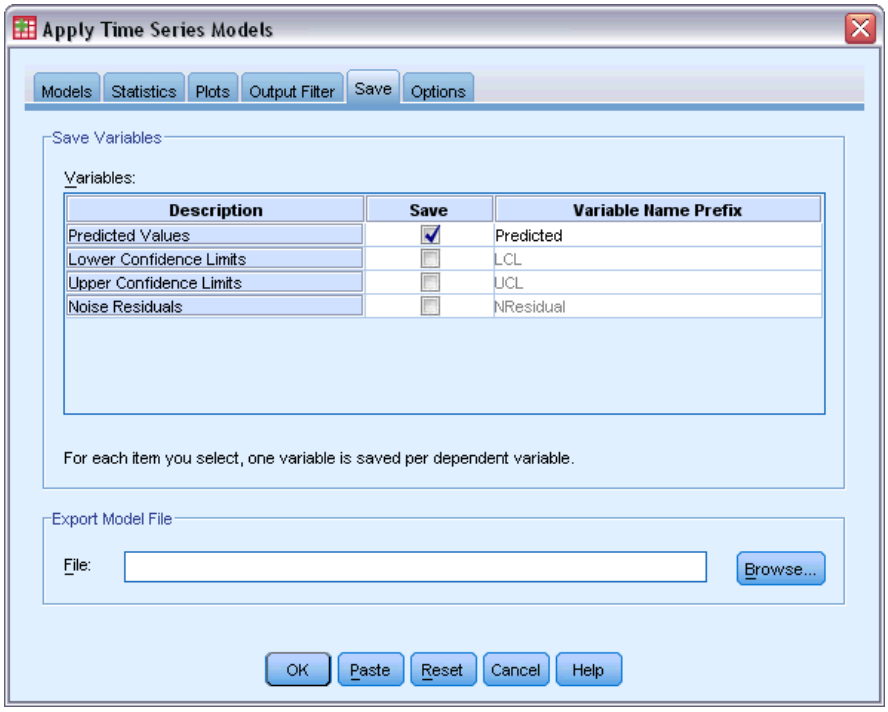
- Select First case after end of estimation period through a specified date in the Forecast Period group.

- In the Date grid, enter 2004 for the year and 6 for the month.

  The dataset contains data from January 1999 through March 2004. With the current settings, the forecast period will be April 2004 through June 2004.

- Click the Save tab.

Figure 7-2
Apply Time Series Models, Save tab

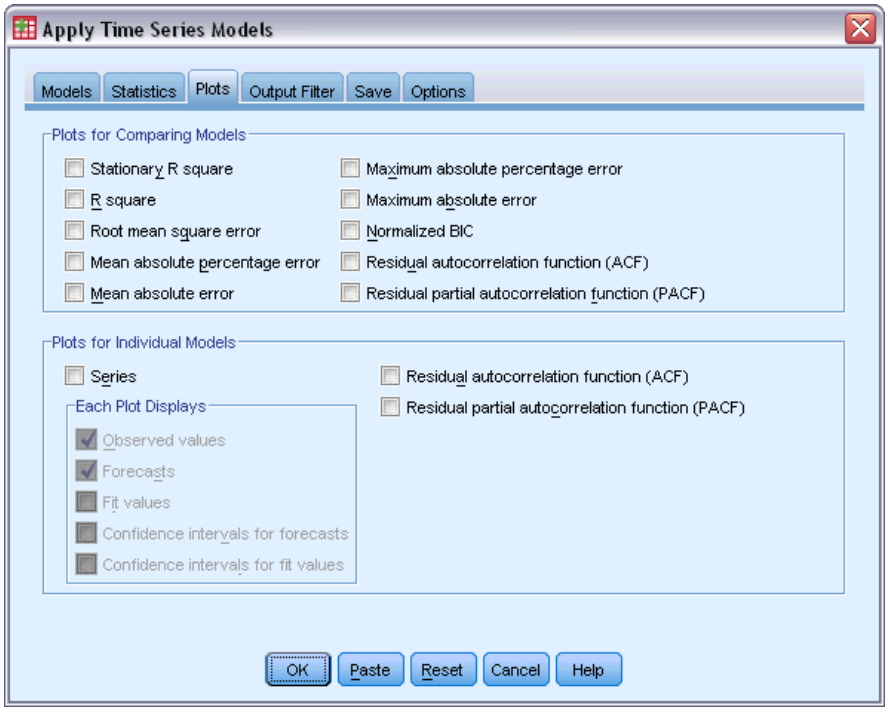


- Select (check) the entry for Predicted Values in the *Save* column and leave the default value *Predicted* as the Variable Name Prefix.

  The model predictions will be saved as new variables in the active dataset, using the prefix *Predicted* for the variable names.

- Click the Plots tab.

Figure 7-3
Apply Time Series Models, Plots tab



- Deselect Series in the Plots for Individual Models group.

  This suppresses the generation of series plots for each of the models. In this example, we are more interested in saving the forecasts as new variables than generating plots of the forecasts.

- Click OK in the Apply Time Series Models dialog box.

Model Fit Statistics

Figure 7-4
Model Fit table

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.181	.141	-4.34E-015	.609	-9.59E-016	1.22E-016	.070	.193	.252	.359	.453
R-squared	.999	.000	.998	1.000	.999	.999	.999	.999	.999	.999	1.000
RMSE	187.766	149.959	45.048	764.698	52.558	59.848	93.155	138.913	205.742	433.883	493.904
MAPE	.886	.074	.669	1.026	.754	.792	.832	.894	.948	.976	.996
MaxAPE	2.446	.512	1.742	4.373	1.840	1.952	2.103	2.321	2.663	3.313	3.676
MAE	146.373	113.749	35.573	612.989	41.209	48.742	73.553	111.569	162.306	331.207	364.582
MaxAE	499.714	434.112	116.966	2143.993	131.261	144.918	226.960	345.221	574.071	1165.207	1587.793
Normalized BIC	10.086	1.343	7.749	13.412	8.049	8.285	9.193	9.968	10.717	12.210	12.494

The Model Fit table provides fit statistics calculated across all of the models. It provides a concise summary of how well the models, with reestimated parameters, fit the data. For each statistic, the table provides the mean, standard error (SE), minimum, and maximum value across all models. It also contains percentile values that provide information on the distribution of the statistic across models. For each percentile, that percentage of models have a value of the fit statistic

below the stated value. For instance, 95% of the models have a value of MaxAPE (maximum absolute percentage error) that is less than 3.676.

While a number of statistics are reported, we will focus on two: MAPE (mean absolute percentage error) and MaxAPE (maximum absolute percentage error). Absolute percentage error is a measure of how much a dependent series varies from its model-predicted level and provides an indication of the uncertainty in your predictions. The mean absolute percentage error varies from a minimum of 0.669% to a maximum of 1.026% across all models. The maximum absolute percentage error varies from 1.742% to 4.373% across all models. So the mean uncertainty in each model's predictions is about 1% and the maximum uncertainty is around 2.5% (the mean value of MaxAPE), with a worst case scenario of about 4%. Whether these values represent an acceptable amount of uncertainty depends on the degree of risk you are willing to accept.

Model Predictions

Figure 7-5
New variables containing model predictions

YEAR_	MONTH_	DATE_	Predicted_Market_1_Model_1	Predicted_Market_2_Model_2
2004	1	JAN 2004	11513	54947
2004	2	FEB 2004	11806	56810
2004	3	MAR 2004	11950	57344
2004	4	APR 2004	12312	59631
2004	5	MAY 2004	12501	60717
2004	6	JUN 2004	12689	61659

The Data Editor shows the new variables containing the model predictions. Although only two are shown here, there are 85 new variables, one for each of the 85 dependent series. The variable names consist of the default prefix *Predicted*, followed by the name of the associated dependent variable (for example, *Market_1*), followed by a model identifier (for example, *Model_1*).

Three new cases, containing the forecasts for April 2004 through June 2004, have been added to the dataset, along with automatically generated date labels.

Summary

You have learned how to apply saved models to extend your previous forecasts when more current data becomes available. And you have done this without rebuilding your models. Of course, if there is reason to think that a model has changed, then you should rebuild it using the Time Series Modeler procedure.

Chapter 8

Using the Expert Modeler to Determine Significant Predictors

A catalog company, interested in developing a forecasting model, has collected data on monthly sales of men's clothing along with several series that might be used to explain some of the variation in sales. Possible predictors include the number of catalogs mailed, the number of pages in the catalog, the number of phone lines open for ordering, the amount spent on print advertising, and the number of customer service representatives. Are any of these predictors useful for forecasting?

In this example, you will use the Expert Modeler with all of the candidate predictors to find the best model. Since the Expert Modeler only selects those predictors that have a statistically significant relationship with the dependent series, you will know which predictors are useful, and you will have a model for forecasting with them. Once you are finished, you might want to work through the next example, Experimenting with Predictors by Applying Saved Models in Chapter 9 on p. 69, which investigates the effect on sales of different predictor scenarios using the model built in this example.

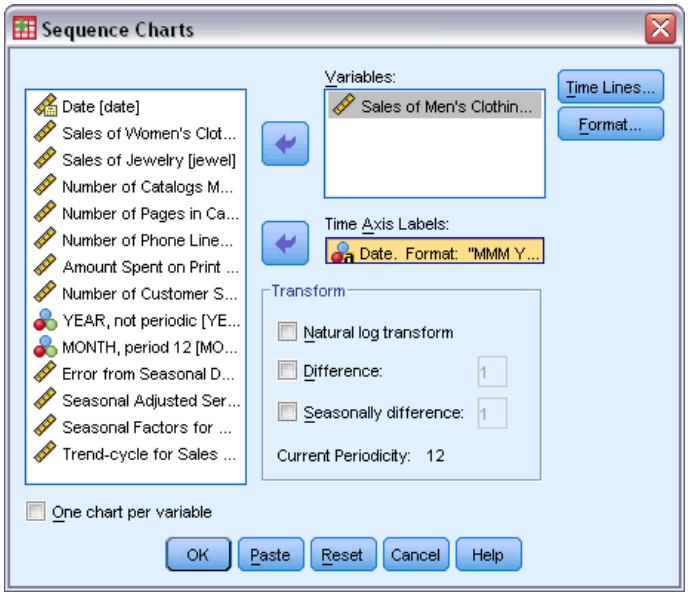
The data for the current example is collected in *catalog_seasfac.sav*. For more information, see the topic Sample Files in Appendix D on p. 98.

Plotting Your Data

It is always a good idea to plot your data, especially if you are only working with one series:

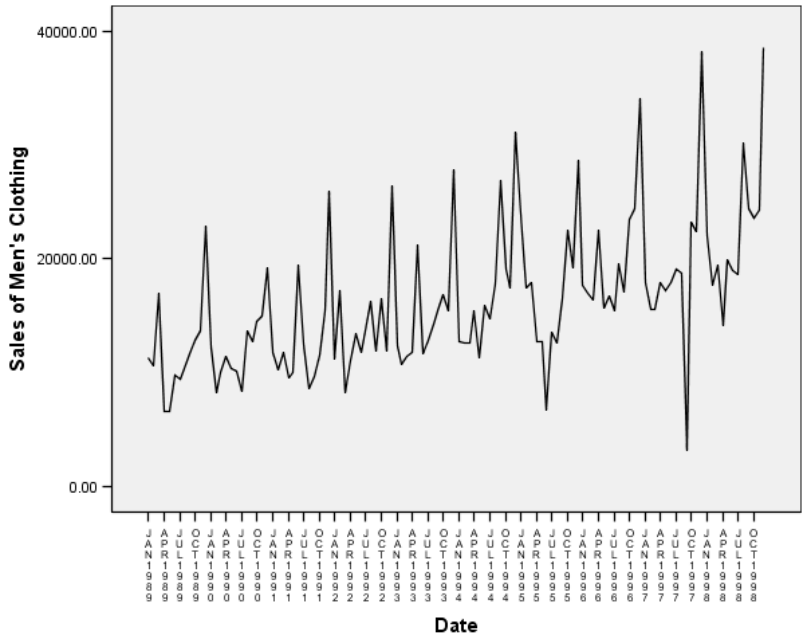
- From the menus choose:
  Analyze > Forecasting > Sequence Charts...

Figure 8-1
Sequence Charts dialog box



- Select *Sales of Men's Clothing* and move it into the Variables list.
- Select *Date* and move it into the Time Axis Labels box.
- Click OK.

Figure 8-2
Sales of men's clothing (in U.S. dollars)



The series exhibits numerous peaks, many of which appear to be equally spaced, as well as a clear upward trend. The equally spaced peaks suggests the presence of a periodic component to the time series. Given the seasonal nature of sales, with highs typically occurring during the holiday season, you should not be surprised to find an annual seasonal component to the data.

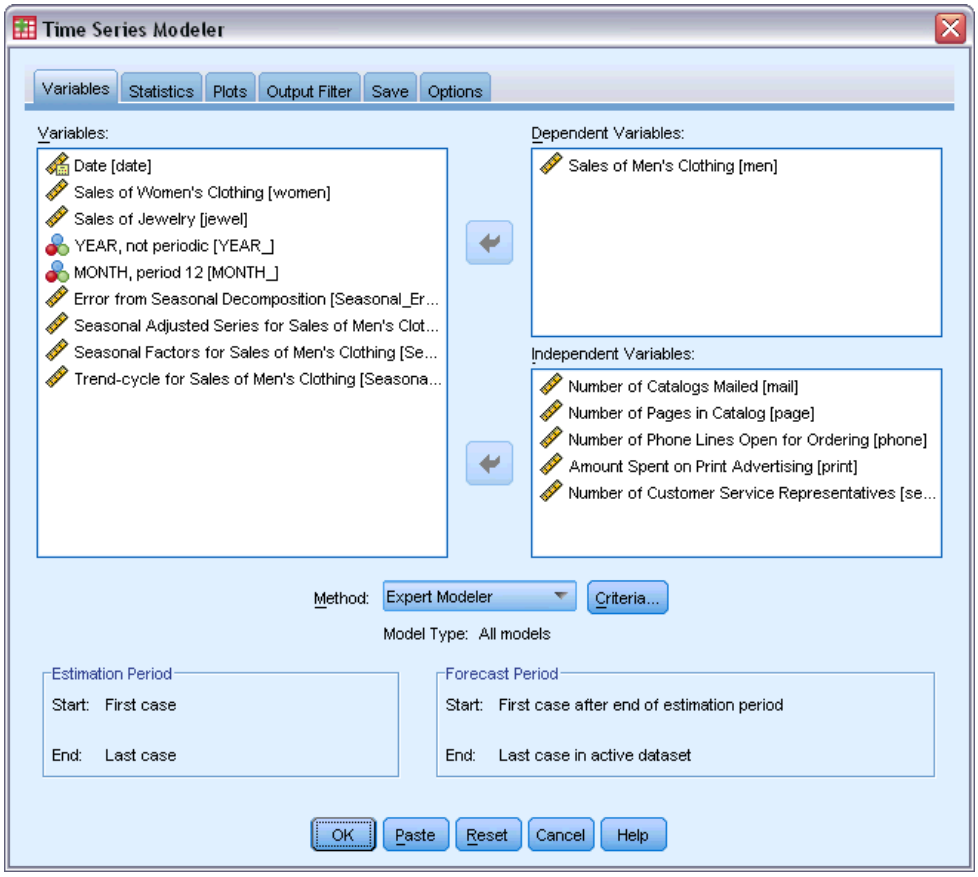
There are also peaks that do not appear to be part of the seasonal pattern and which represent significant deviations from the neighboring data points. These points may be outliers, which can and should be addressed by the Expert Modeler.

Running the Analysis

To use the Expert Modeler:

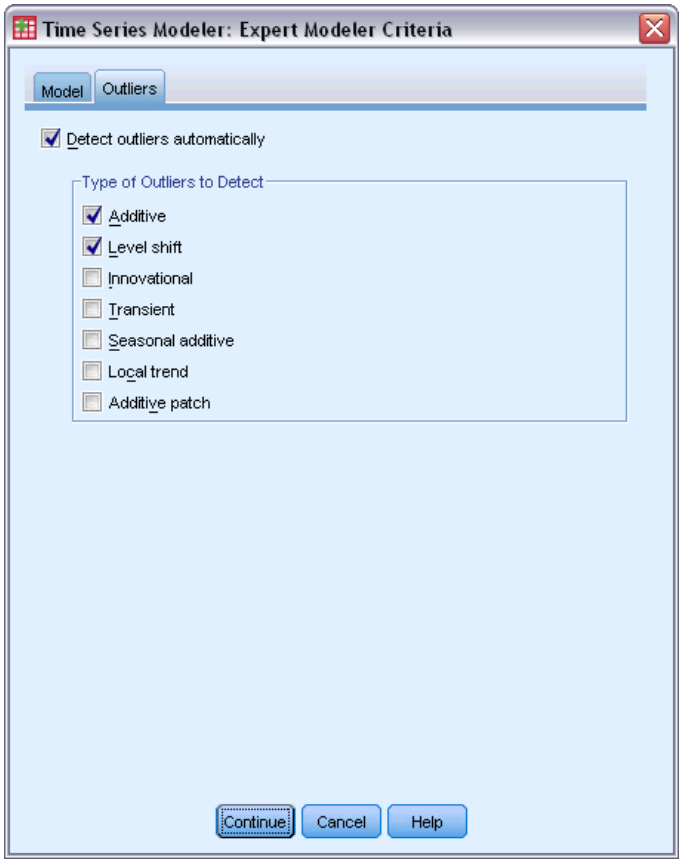
- From the menus choose:
  Analyze > Forecasting > Create Models...

Figure 8-3
Time Series Modeler dialog box



- Select *Sales of Men's Clothing* for the dependent variable.
- Select *Number of Catalogs Mailed* through *Number of Customer Service Representatives* for the independent variables.
- Verify that Expert Modeler is selected in the Method drop-down list. The Expert Modeler will automatically find the best-fitting seasonal or non-seasonal model for the dependent variable series.
- Click Criteria and then click the Outliers tab.

Figure 8-4
Expert Modeler Criteria dialog box, Outliers tab



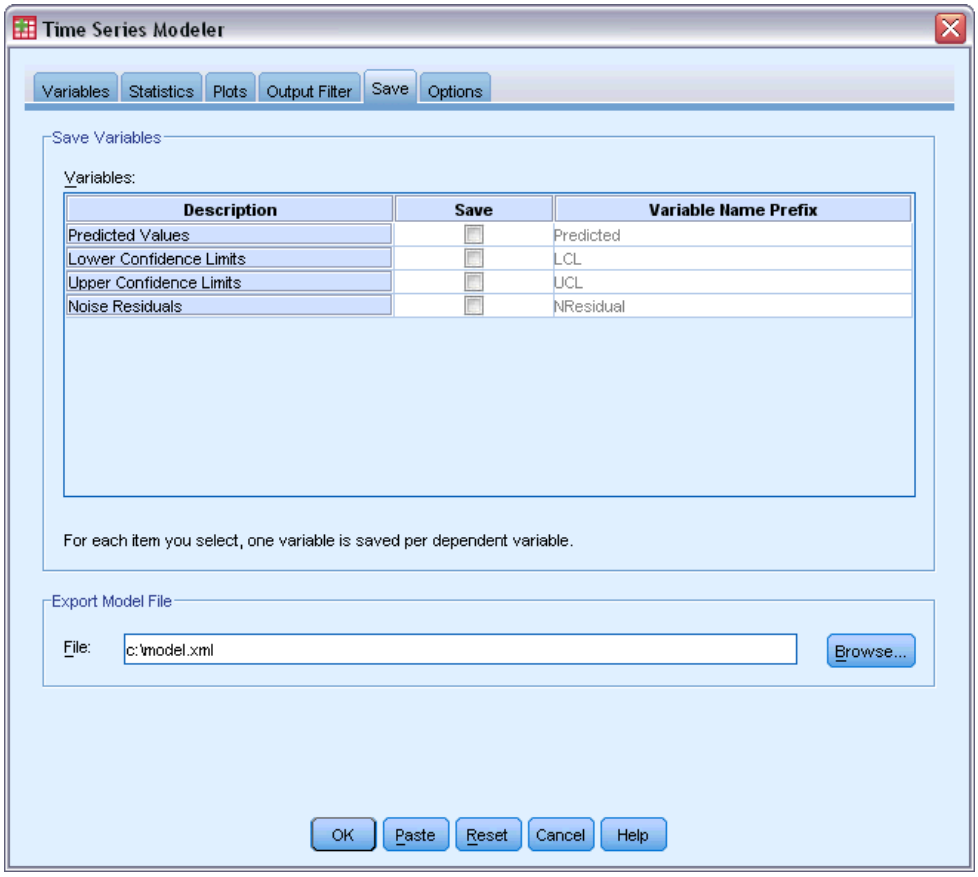
- Select Detect outliers automatically and leave the default selections for the types of outliers to detect.

  Our visual inspection of the data suggested that there may be outliers. With the current choices, the Expert Modeler will search for the most common outlier types and incorporate any outliers into the final model. Outlier detection can add significantly to the computing time needed by the Expert Modeler, so it is a feature that should be used with some discretion, particularly when modeling many series at once. By default, outliers are not detected.

- Click Continue.

- Click the Save tab on the Time Series Modeler dialog box.

Figure 8-5
Time Series Modeler, Save tab



You will want to save the estimated model to an external XML file so that you can experiment with different values of the predictors—using the Apply Time Series Models procedure—without having to rebuild the model.

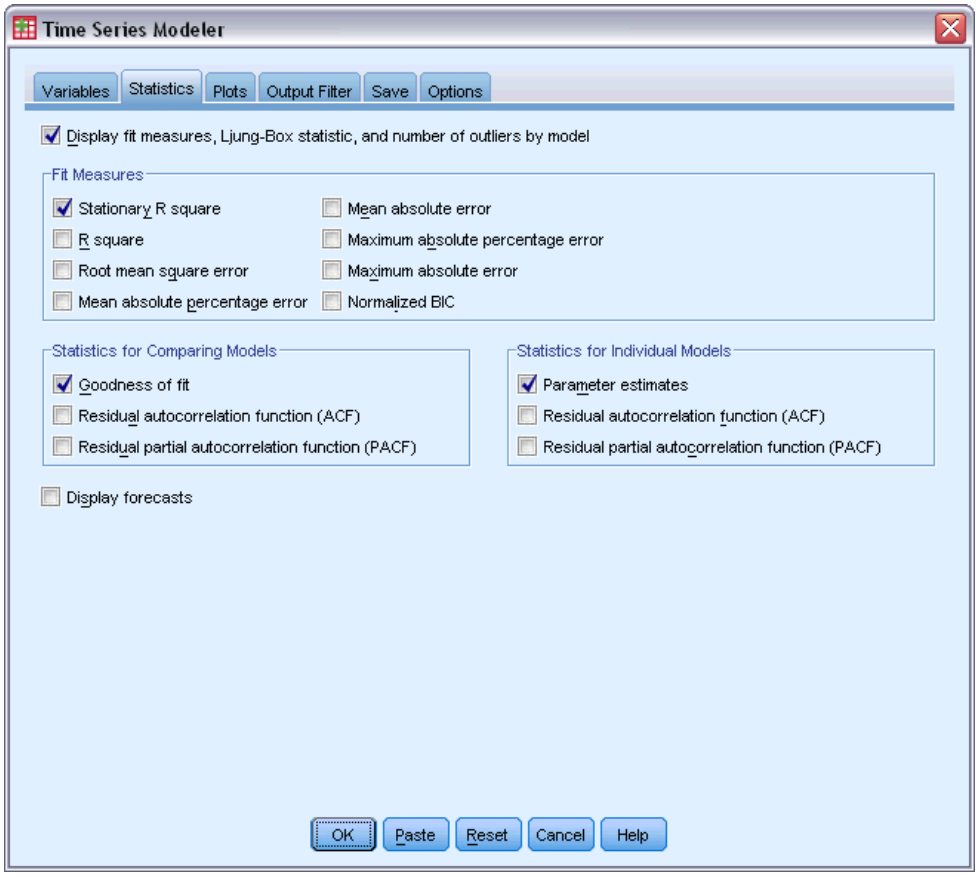
- Click the Browse button on the Save tab.

  This will take you to a standard dialog box for saving a file.

- Navigate to the folder where you would like to save the XML model file, enter a filename, and click Save.

- Click the Statistics tab.

Figure 8-6
Time Series Modeler, Statistics tab

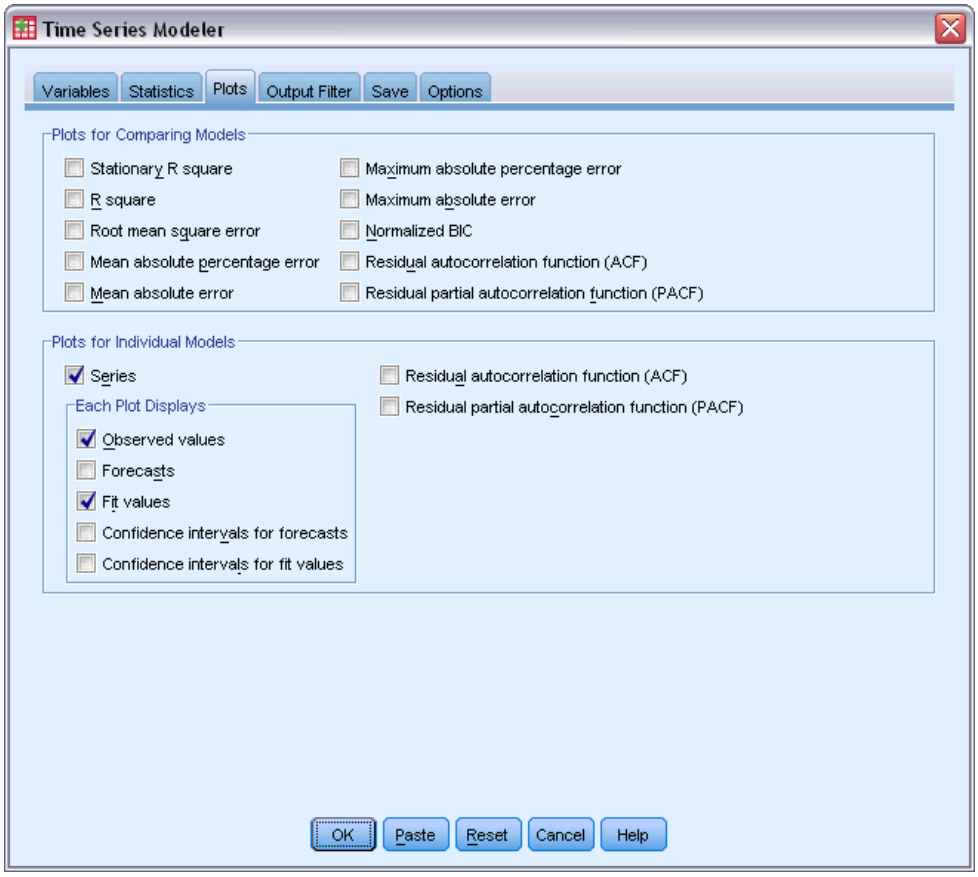


- Select Parameter estimates.

  This option produces a table displaying all of the parameters, including the significant predictors, for the model chosen by the Expert Modeler.

- Click the Plots tab.

Figure 8-7
Time Series Modeler, Plots tab



▶ Deselect Forecasts.

In the current example, we are only interested in determining the significant predictors and building a model. We will not be doing any forecasting.

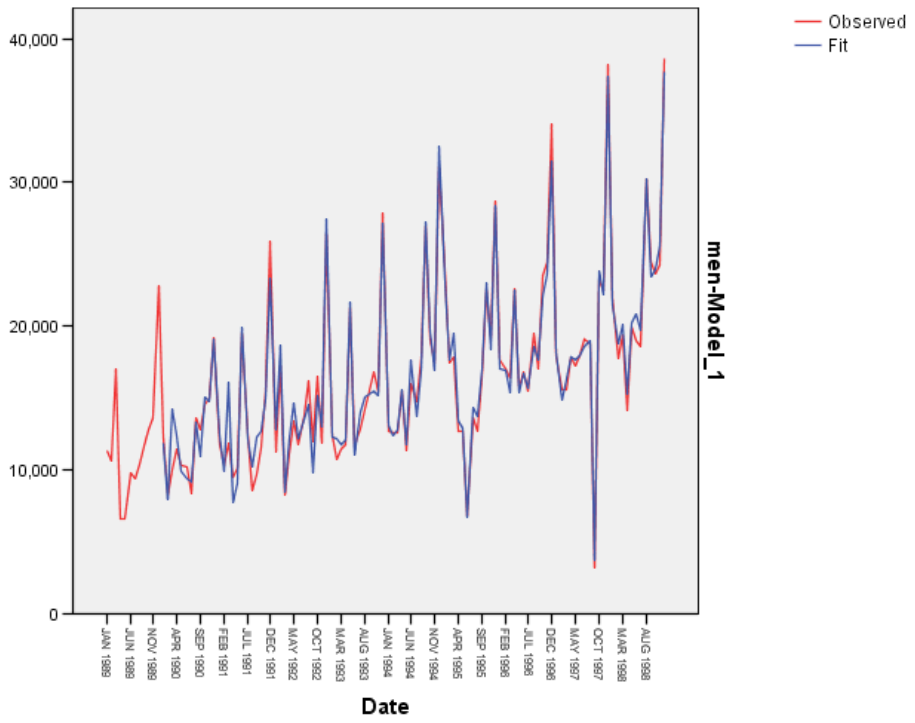
▶ Select Fit values.

This option displays the predicted values in the period used to estimate the model. This period is referred to as the **estimation period**, and it includes all cases in the active dataset for this example. These values provide an indication of how well the model fits the observed values, so they are referred to as **fit values**. The resulting plot will consist of both the observed values and the fit values.

▶ Click OK in the Time Series Modeler dialog box.

Series Plot

Figure 8-8
Predicted and observed values



The predicted values show good agreement with the observed values, indicating that the model has satisfactory predictive ability. Notice how well the model predicts the seasonal peaks. And it does a good job of capturing the upward trend of the data.

Model Description Table

Figure 8-9
Model Description table

			Model Type
Model ID	Sales of Men's Clothing	Model_1	ARIMA(0,0,0)(0,1,0)

The model description table contains an entry for each estimated model and includes both a model identifier and the model type. The model identifier consists of the name (or label) of the associated dependent variable and a system-assigned name. In the current example, the dependent variable is *Sales of Men's Clothing* and the system-assigned name is *Model_1*.

The Time Series Modeler supports both exponential smoothing and ARIMA models. Exponential smoothing model types are listed by their commonly used names such as Holt and Winters' Additive. ARIMA model types are listed using the standard notation of ARIMA(p,d,q)(P,D,Q), where p is the order of autoregression, d is the order of differencing (or integration), and q is the order of moving-average, and (P,D,Q) are their seasonal counterparts.

The Expert Modeler has determined that sales of men's clothing is best described by a seasonal ARIMA model with one order of differencing. The seasonal nature of the model accounts for the seasonal peaks that we saw in the series plot, and the single order of differencing reflects the upward trend that was evident in the data.

Model Statistics Table

Figure 8-10
Model Statistics table

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
Sales of Men's Clothing-Model_1	2	.948	7.589	18	.984	9

The model statistics table provides summary information and goodness-of-fit statistics for each estimated model. Results for each model are labeled with the model identifier provided in the model description table. First, notice that the model contains two predictors out of the five candidate predictors that you originally specified. So it appears that the Expert Modeler has identified two independent variables that may prove useful for forecasting.

Although the Time Series Modeler offers a number of different goodness-of-fit statistics, we opted only for the stationary *R*-squared value. This statistic provides an estimate of the proportion of the total variation in the series that is explained by the model and is preferable to ordinary *R*-squared when there is a trend or seasonal pattern, as is the case here. Larger values of stationary *R*-squared (up to a maximum value of 1) indicate better fit. A value of 0.948 means that the model does an excellent job of explaining the observed variation in the series.

The Ljung-Box statistic, also known as the modified Box-Pierce statistic, provides an indication of whether the model is correctly specified. A significance value less than 0.05 implies that there is structure in the observed series which is not accounted for by the model. The value of 0.984 shown here is not significant, so we can be confident that the model is correctly specified.

The Expert Modeler detected nine points that were considered to be outliers. Each of these points has been modeled appropriately, so there is no need for you to remove them from the series.

ARIMA Model Parameters Table

Figure 8-11
ARIMA Model Parameters table

					Estimate	SE	t	Sig.
Sales of Men's Clothing-Model_1	Sales of Men's Clothing	No Transformation	Seasonal Difference		1			
	Number of Catalogs Mailed	No Transformation	Numerator	Lag 0	1.549	.071	21.943	.000
			Seasonal Difference		1			
	Number of Phone Lines Open for Ordering	No Transformation	Numerator	Lag 0	315.262	15.298	20.607	.000
			Seasonal Difference		1			

The ARIMA model parameters table displays values for all of the parameters in the model, with an entry for each estimated model labeled by the model identifier. For our purposes, it will list all of the variables in the model, including the dependent variable and any independent variables that the Expert Modeler determined were significant. We already know from the model statistics table

that there are two significant predictors. The model parameters table shows us that they are the *Number of Catalogs Mailed* and the *Number of Phone Lines Open for Ordering*.

Summary

You have learned how to use the Expert Modeler to build a model and identify significant predictors, and you have saved the resulting model to an external file. You are now in a position to use the Apply Time Series Models procedure to experiment with alternative scenarios for the predictor series and see how the alternatives affect the sales forecasts.

Chapter 9

Experimenting with Predictors by Applying Saved Models

You've used the Time Series Modeler to create a model for your data and to identify which predictors may prove useful for forecasting. The predictors represent factors that are within your control, so you'd like to experiment with their values in the forecast period to see how forecasts of the dependent variable are affected. This task is easily accomplished with the Apply Time Series Models procedure, using the model file that is created with the Time Series Modeler procedure.

This example is a natural extension of the previous example, Using the Expert Modeler to Determine Significant Predictors in Chapter 8 on p. 58, but this example can also be used independently. The scenario involves a catalog company that has collected data about monthly sales of men's clothing from January 1989 through December 1998, along with several series that are thought to be potentially useful as predictors of future sales. The Expert Modeler has determined that only two of the five candidate predictors are significant: the number of catalogs mailed and the number of phone lines open for ordering.

When planning your sales strategy for the next year, you have limited resources to print catalogs and keep phone lines open for ordering. Your budget for the first three months of 1999 allows for either 2000 additional catalogs or 5 additional phone lines over your initial projections. Which choice will generate more sales revenue for this three-month period?

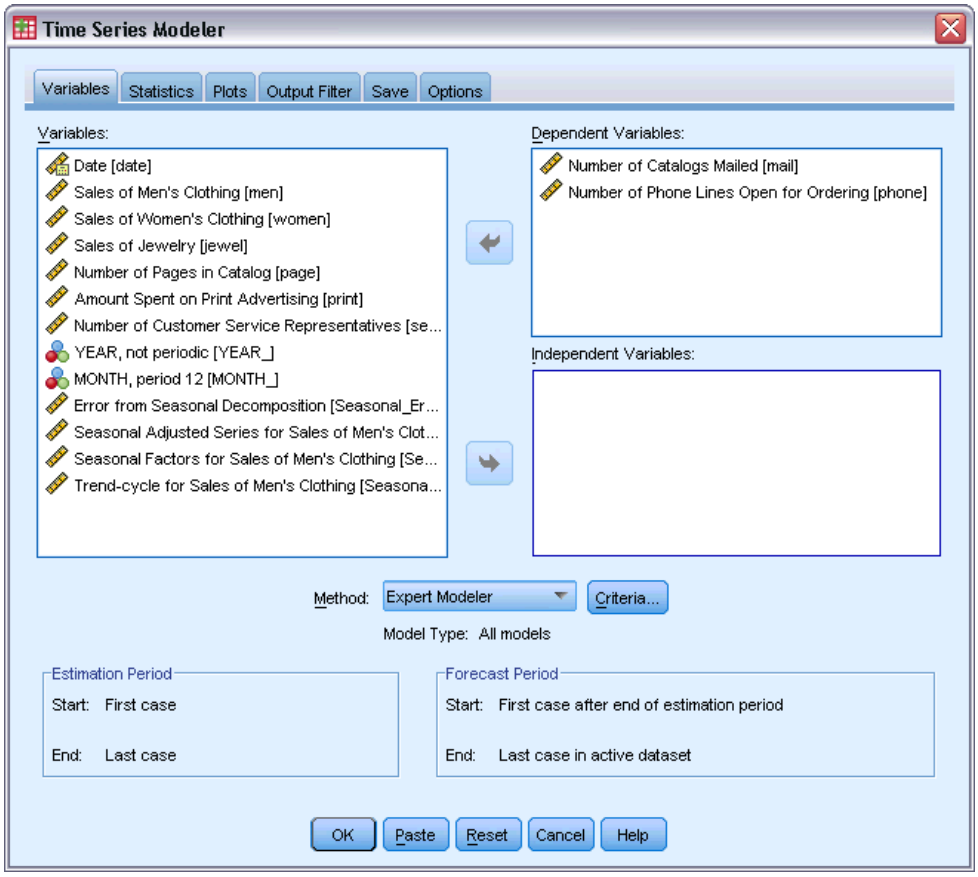
The data for this example are collected in *catalog_seasfac.sav*, and *catalog_model.xml* contains the model of monthly sales that is built with the Expert Modeler. For more information, see the topic Sample Files in Appendix D on p. 98. Of course, if you worked through the previous example and saved your own model file, you can use that file instead of *catalog_model.xml*.

Extending the Predictor Series

When you're creating forecasts for dependent series with predictors, each predictor series needs to be extended through the forecast period. Unless you know precisely what the future values of the predictors will be, you'll need to estimate them. You can then modify the estimates to test different predictor scenarios. The initial projections are easily created by using the Expert Modeler.

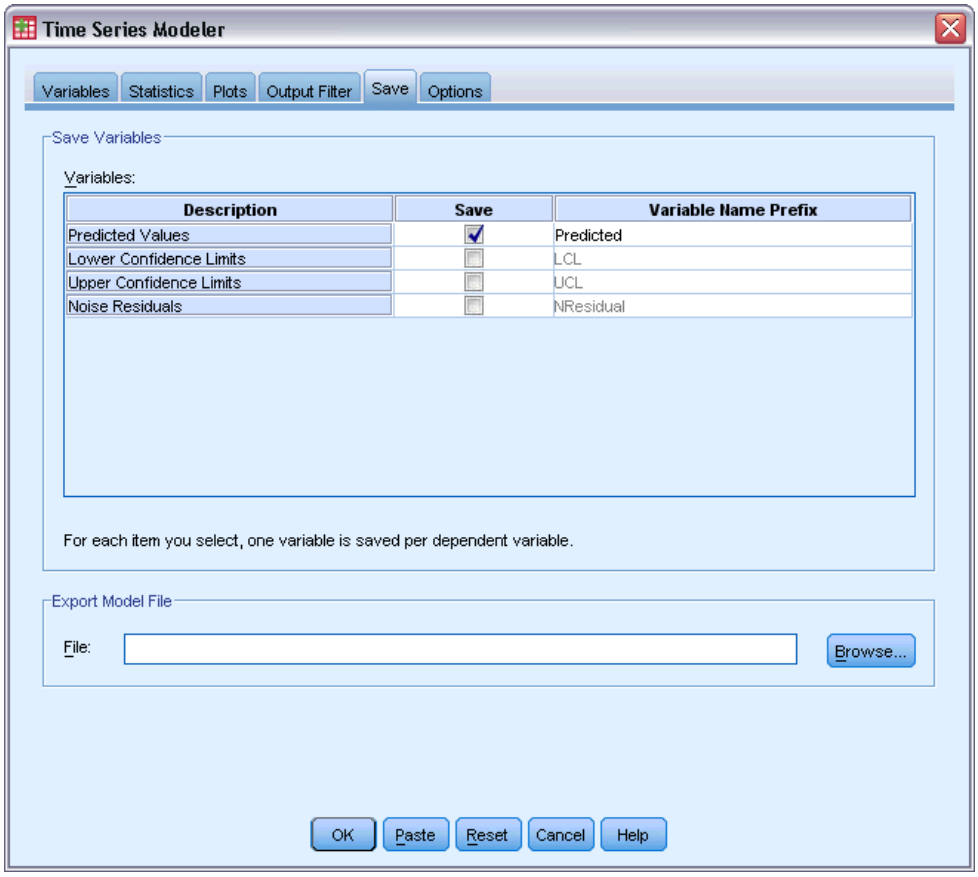
▶ From the menus choose:
Analyze > Forecasting > Create Models...

Figure 9-1
Time Series Modeler dialog box



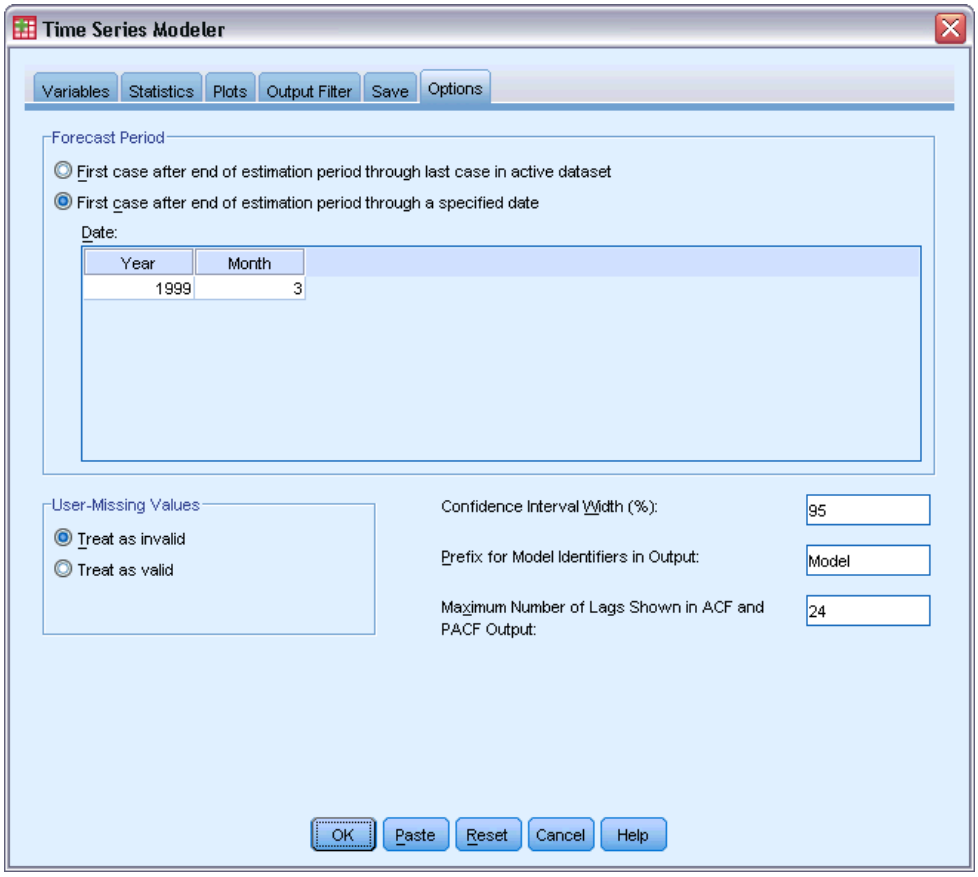
- Select *Number of Catalogs Mailed* and *Number of Phone Lines Open for Ordering* for the dependent variables.
- Click the Save tab.

Figure 9-2
Time Series Modeler, Save tab



- In the *Save* column, select (check) the entry for Predicted Values, and leave the default value *Predicted* for the Variable Name Prefix.
- Click the Options tab.

Figure 9-3
Time Series Modeler, Options tab



- In the Forecast Period group, select First case after end of estimation period through a specified date.
- In the Date grid, enter 1999 for the year and 3 for the month.

  The data set contains data from January 1989 through December 1998, so with the current settings, the forecast period will be January 1999 through March 1999.
- Click OK.

Figure 9-4
New variables containing forecasts for predictor series

	Predicted_mail_Model_1	Predicted_phone_Model_2
121	11742	51
122	11853	45
123	11965	45

Data View | Variable View

The Data Editor shows the new variables *Predicted_mail_Model_1* and *Predicted_phone_Model_2*, containing the model predicted values for the number of catalogs mailed and the number of phone lines. To extend our predictor series, we only need the values for January 1999 through March 1999, which amounts to cases 121 through 123.

- Copy the values of these three cases from *Predicted_mail_Model_1* and append them to the variable *mail*.
- Repeat this process for *Predicted_phone_Model_2*, copying the last three cases and appending them to the variable *phone*.

Figure 9-5
Predictor series extended through the forecast period

	mail	page	phone	print	service	YEAR_	MONTH_	DATE_
121	11742	.	51	.	.	1999	1	JAN 1999
122	11853	.	45	.	.	1999	2	FEB 1999
123	11965	.	45	.	.	1999	3	MAR 1999

Data View | Variable View

The predictors have now been extended through the forecast period.

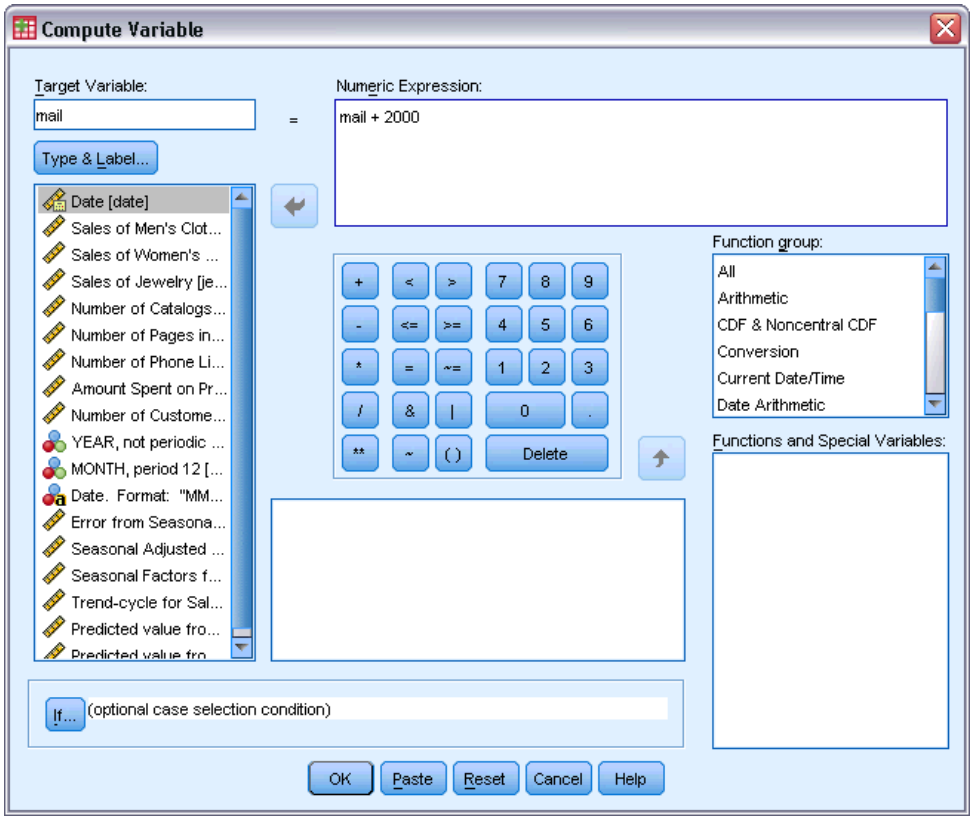
Modifying Predictor Values in the Forecast Period

Testing the two scenarios of mailing more catalogs or providing more phone lines requires modifying the estimates for the predictors *mail* or *phone*, respectively. Because we're only modifying the predictor values for three cases (months), it would be easy to enter the new values directly into the appropriate cells of the Data Editor. For instructional purposes, we'll use the Compute Variable dialog box. When you have more than a few values to modify, you'll probably find the Compute Variable dialog box more convenient.

- From the menus choose:

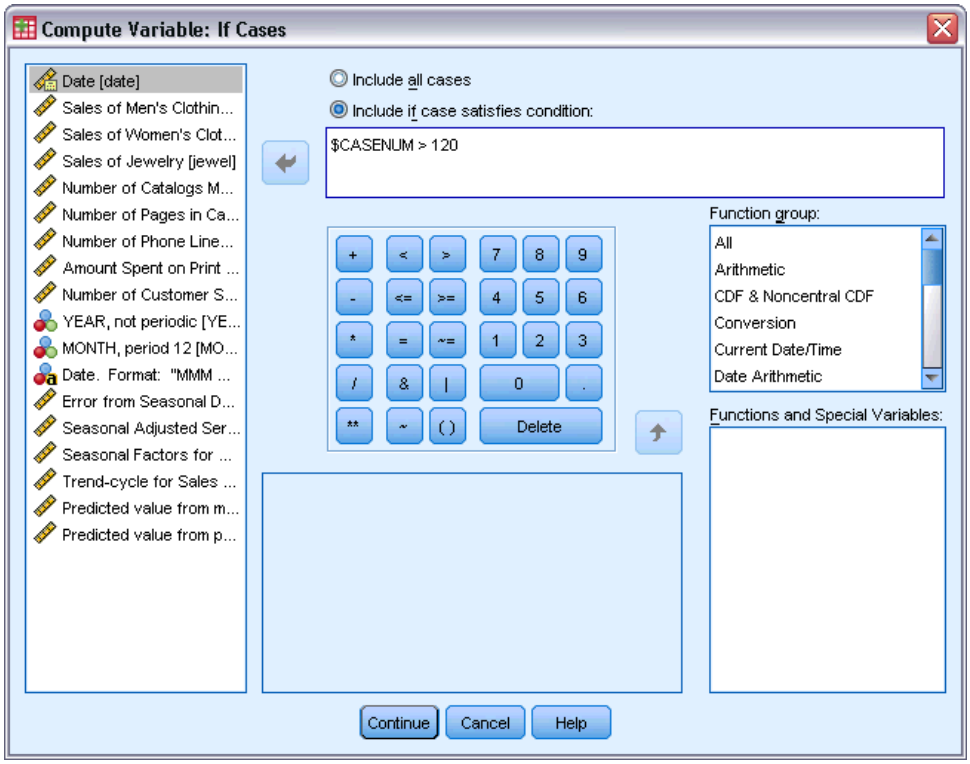
  Transform > Compute Variable...

Figure 9-6
Compute Variable dialog box



- Enter mail for the target variable.
- In the Numeric Expression text box, enter mail + 2000.
- Click If.

Figure 9-7
Compute Variable If Cases dialog box



- Select Include if case satisfies condition.
- In the text box, enter $CASENUM > 120.

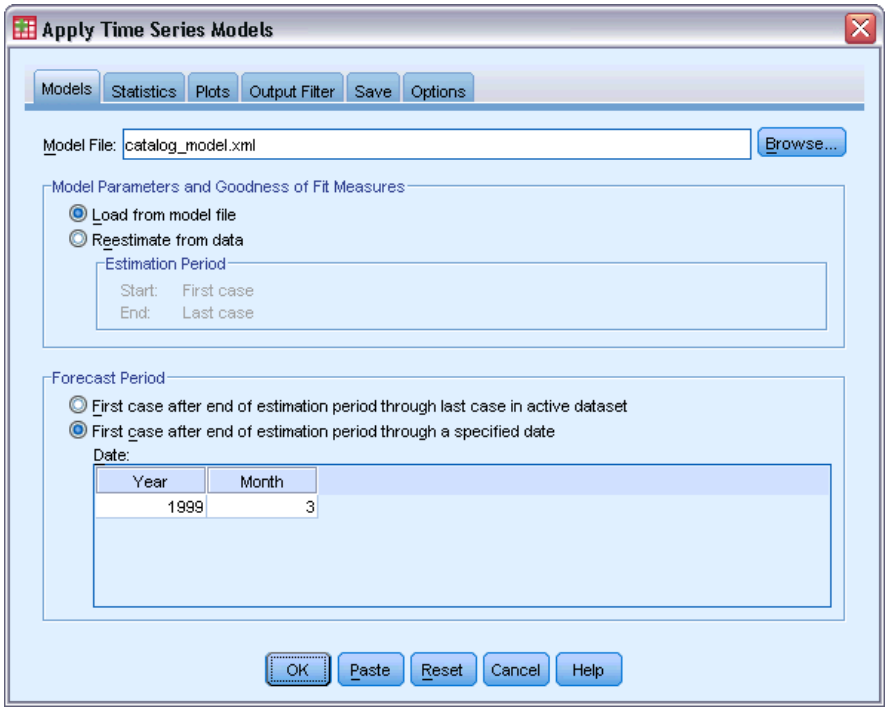
  This will limit changes to the variable *mail* to the cases in the forecast period.
- Click Continue.
- Click OK in the Compute Variable dialog box, and click OK when asked whether you want to change the existing variable.

  This results in increasing the values for *mail*—the number of catalogs mailed—by 2000 for each of the three months in the forecast period. You've now prepared the data to test the first scenario, and you are ready to run the analysis.

Running the Analysis

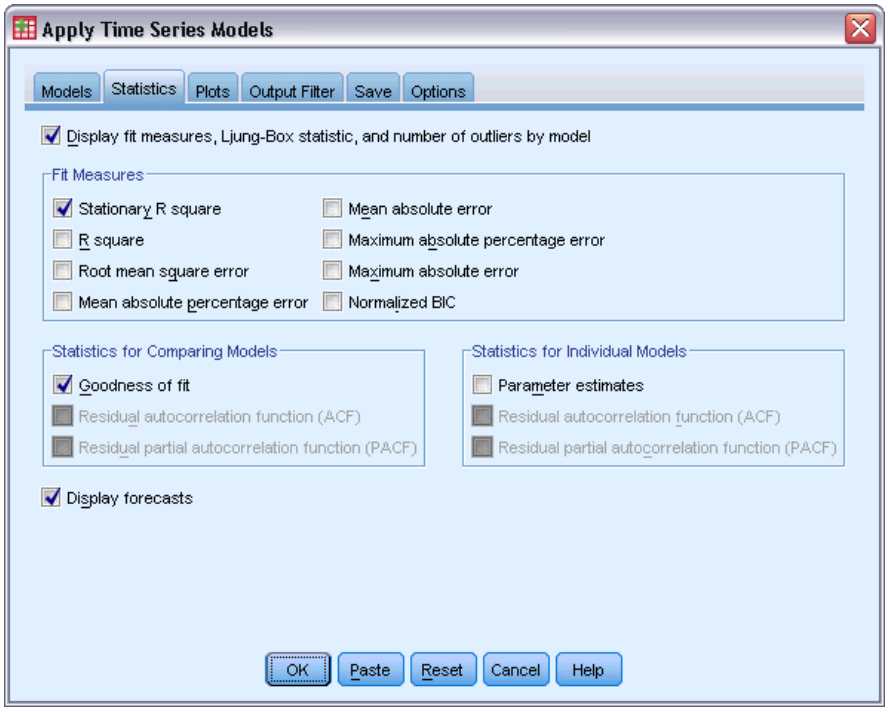
- From the menus choose:
  Analyze > Forecasting > Apply Models...

Figure 9-8
Apply Time Series Models dialog box



- Click Browse, then navigate to and select *catalog_model.xml*, or choose your own model file (saved from the previous example). For more information, see the topic Sample Files in Appendix D on p. 98.
- In the Forecast Period group, select First case after end of estimation period through a specified date.
- In the Date grid, enter 1999 for the year and 3 for the month.
- Click the Statistics tab.

Figure 9-9
Apply Time Series Models, Statistics tab



▶ Select Display forecasts.

This results in a table of forecasted values for the dependent variable.

▶ Click OK in the Apply Time Series Models dialog box.

Figure 9-10
Forecast table

Model		JAN 1999	FEB 1999	MAR 1999
Sales of Men's Clothing-Model_1	Forecast	25279.91	22064.72	21580.96
	UCL	27591.62	24376.42	23892.66
	LCL	22968.21	19753.02	19269.25

The forecast table contains the predicted values of the dependent series, taking into account the values of the two predictors *mail* and *phone* in the forecast period. The table also includes the upper confidence limit (UCL) and lower confidence limit (LCL) for the predictions.

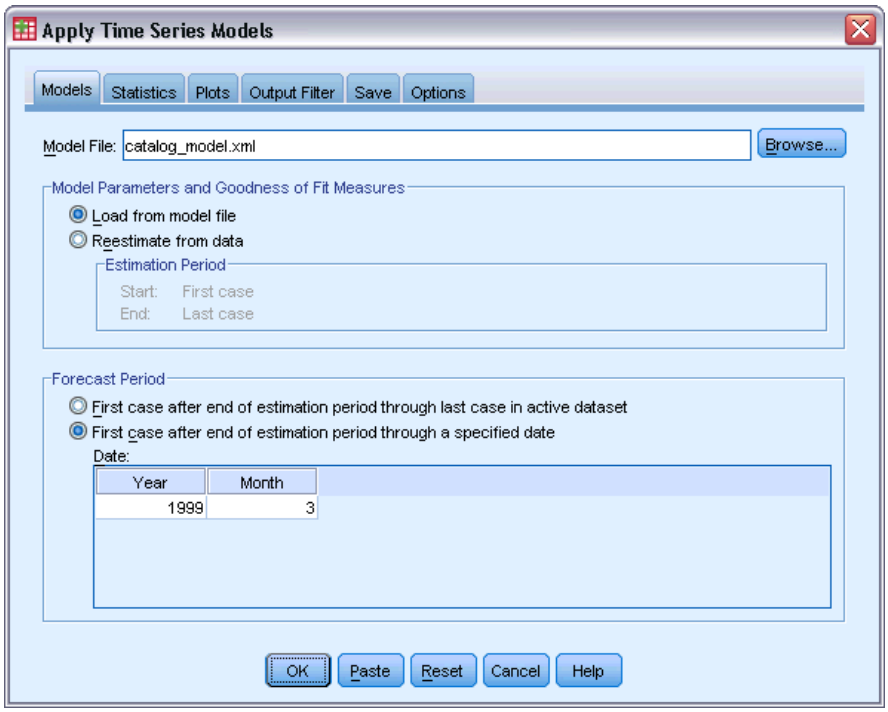
You've produced the sales forecast for the scenario of mailing 2000 more catalogs each month. You'll now want to prepare the data for the scenario of increasing the number of phone lines, which means resetting the variable *mail* to the original values and increasing the variable *phone* by 5. You can reset *mail* by copying the values of *Predicted_mail_Model_1* in the forecast period and pasting them over the current values of *mail* in the forecast period. And you can increase the number of phone lines—by 5 for each month in the forecast period—either directly in the data editor or using the Compute Variable dialog box, like we did for the number of catalogs.

To run the analysis, reopen the Apply Time Series Models dialog box as follows:

▶ Click the Dialog Recall toolbar button.

▶ Choose Apply Time Series Models.

Figure 9-11
Apply Time Series Models dialog box



▶ Click OK in the Apply Time Series Models dialog box.

Figure 9-12
Forecast tables for the two scenarios

Forecast with more catalogs

Model		JAN 1999	FEB 1999	MAR 1999
Sales of Men's Clothing-Model_1	Forecast	25279.91	22064.72	21580.96
	UCL	27591.62	24376.42	23892.66
	LCL	22968.21	19753.02	19269.25

Forecast with more phone lines

Model		JAN 1999	FEB 1999	MAR 1999
Sales of Men's Clothing-Model_1	Forecast	23757.25	20542.06	20058.29
	UCL	26068.95	22853.76	22370.00
	LCL	21445.55	18230.35	17746.59

Displaying the forecast tables for both scenarios shows that, in each of the three forecasted months, increasing the number of mailed catalogs is expected to generate approximately $1500 more in sales than increasing the number of phone lines that are open for ordering. Based on the analysis, it seems wise to allocate resources to the mailing of 2000 additional catalogs.

Chapter
10

Seasonal Decomposition

Removing Seasonality from Sales Data

A catalog company is interested in modeling the upward trend of sales of its men's clothing line on a set of predictor variables (such as the number of catalogs mailed and the number of phone lines open for ordering). To this end, the company collected monthly sales of men's clothing for a 10-year period. This information is collected in *catalog.sav*. For more information, see the topic Sample Files in Appendix D on p. 98.

To perform a trend analysis, you must remove any seasonal variations present in the data. This task is easily accomplished with the Seasonal Decomposition procedure.

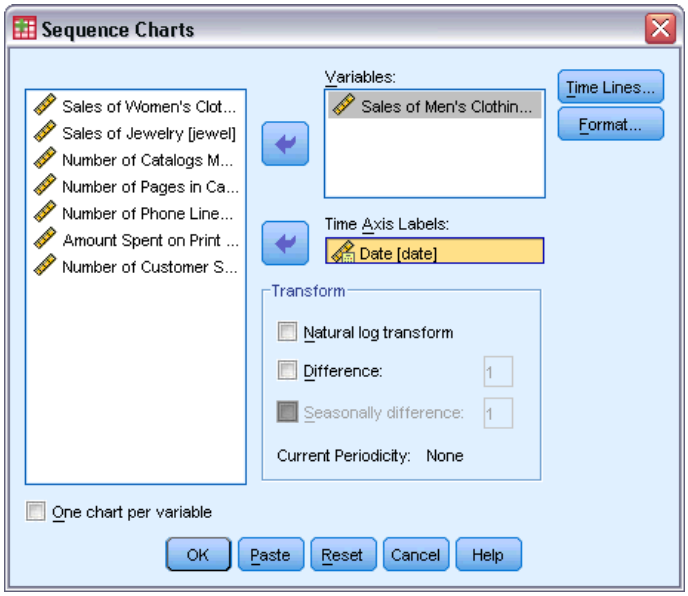
Determining and Setting the Periodicity

The Seasonal Decomposition procedure requires the presence of a periodic date component in the active dataset—for example, a yearly periodicity of 12 (months), a weekly periodicity of 7 (days), and so on. It's a good idea to plot your time series first, because viewing a time series plot often leads to a reasonable guess about the underlying periodicity.

To obtain a plot of men's clothing sales over time:

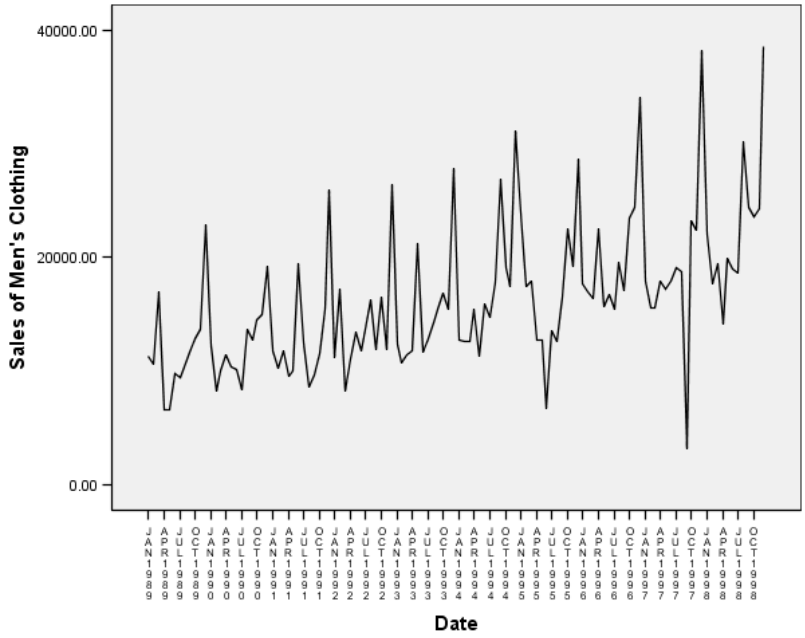
- From the menus choose:
  Analyze > Forecasting > Sequence Charts...

Figure 10-1
Sequence Charts dialog box



- Select *Sales of Men's Clothing* and move it into the Variables list.
- Select *Date* and move it into the Time Axis Labels list.
- Click OK.

Figure 10-2
Sales of men's clothing (in U.S. dollars)

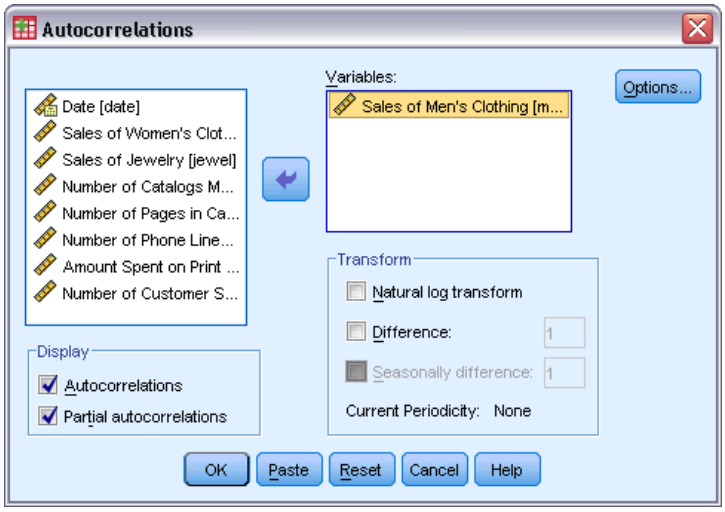


The series exhibits a number of peaks, but they do not appear to be equally spaced. This output suggests that if the series has a periodic component, it also has fluctuations that are not periodic—the typical case for real-time series. Aside from the small-scale fluctuations, the significant peaks appear to be separated by more than a few months. Given the seasonal nature of sales, with typical highs during the December holiday season, the time series probably has an annual periodicity. Also notice that the seasonal variations appear to grow with the upward series trend, suggesting that the seasonal variations may be proportional to the level of the series, which implies a multiplicative model rather than an additive model.

Examining the autocorrelations and partial autocorrelations of a time series provides a more quantitative conclusion about the underlying periodicity.

▶ From the menus choose:
Analyze > Forecasting > Autocorrelations...

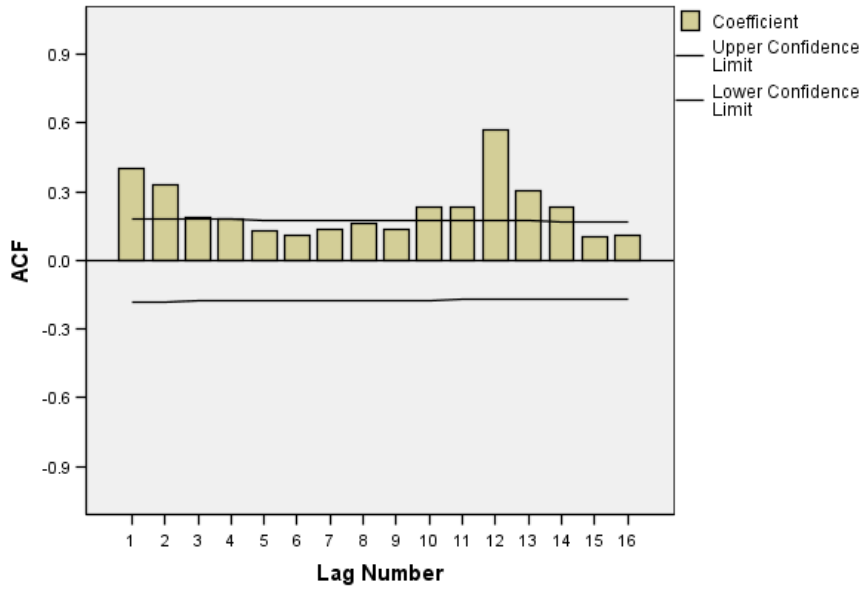
Figure 10-3
Autocorrelations dialog box



▶ Select *Sales of Men's Clothing* and move it into the Variables list.

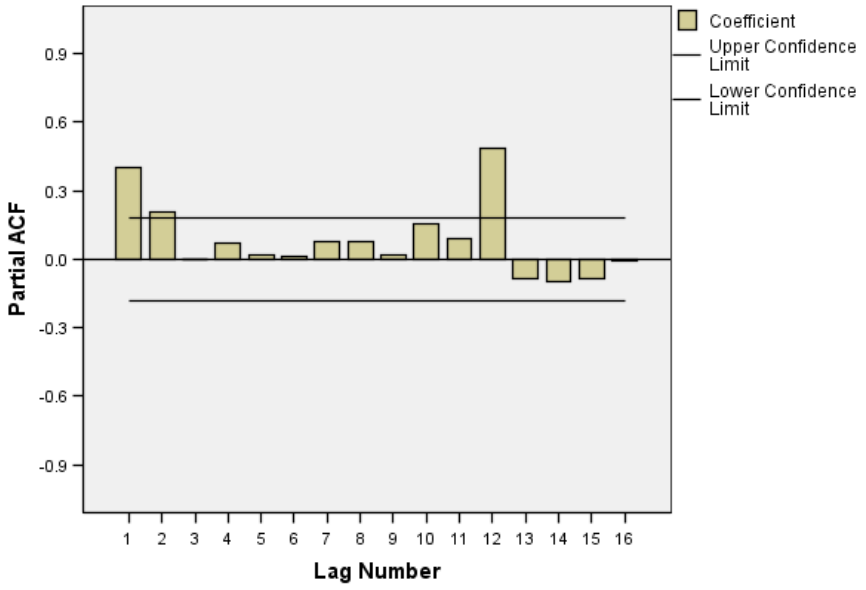
▶ Click OK.

Figure 10-4
Autocorrelation plot for men



The autocorrelation function shows a significant peak at a lag of 1 with a long exponential tail—a typical pattern for time series. The significant peak at a lag of 12 suggests the presence of an annual seasonal component in the data. Examination of the partial autocorrelation function will allow a more definitive conclusion.

Figure 10-5
Partial autocorrelation plot for men

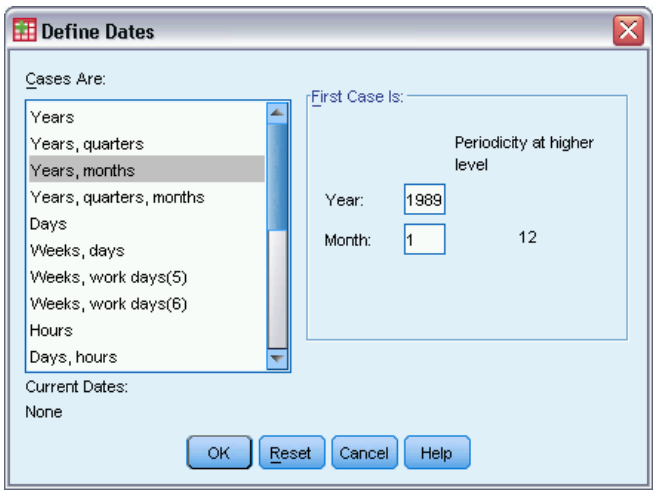


The significant peak at a lag of 12 in the partial autocorrelation function confirms the presence of an annual seasonal component in the data.

To set an annual periodicity:

- From the menus choose:
  Data > Define Dates...

Figure 10-6
Define Dates dialog box



- Select Years, months in the Cases Are list.
- Enter 1989 for the year and 1 for the month.
- Click OK.

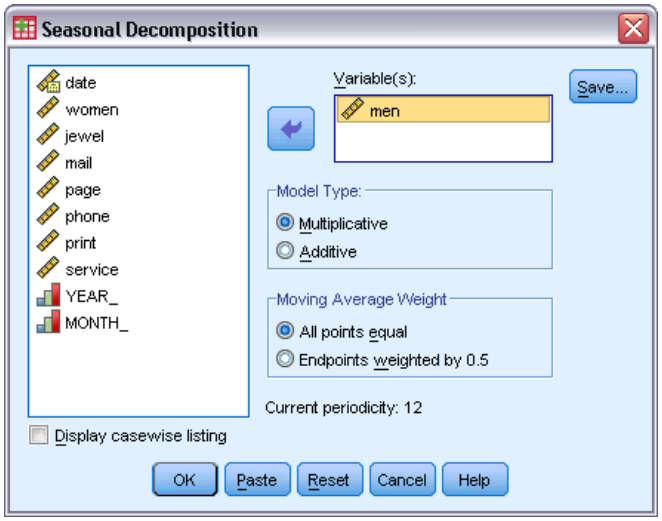
  This sets the periodicity to 12 and creates a set of date variables that are designed to work with Forecasting procedures.

Running the Analysis

To run the Seasonal Decomposition procedure:

- From the menus choose:
  Analyze > Forecasting > Seasonal Decomposition...

Figure 10-7
Seasonal Decomposition dialog box



- Right click anywhere in the source variable list and from the context menu select Display Variable Names.
- Select *men* and move it into the Variables list.
- Select Multiplicative in the Model Type group.
- Click OK.

Understanding the Output

The Seasonal Decomposition procedure creates four new variables for each of the original variables analyzed by the procedure. By default, the new variables are added to the active data set. The new series have names beginning with the following prefixes:

SAF. Seasonal adjustment factors, representing seasonal variation. For the multiplicative model, the value 1 represents the absence of seasonal variation; for the additive model, the value 0 represents the absence of seasonal variation.

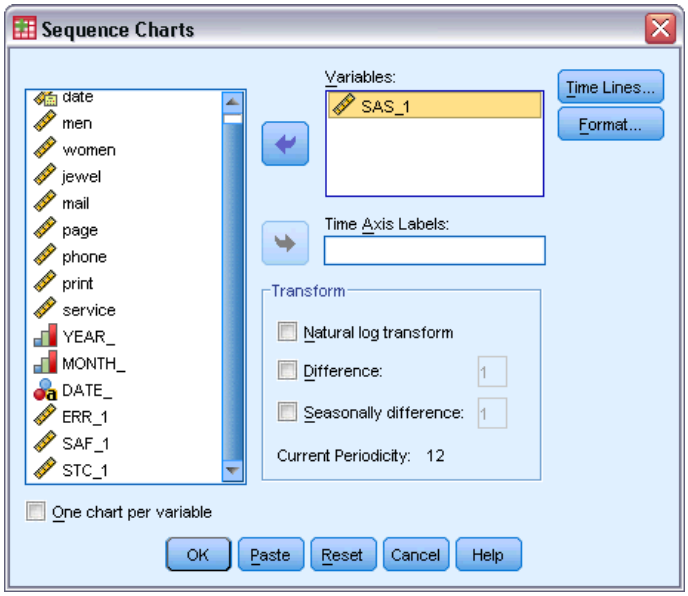
SAS. Seasonally adjusted series, representing the original series with seasonal variations removed. Working with a seasonally adjusted series, for example, allows a trend component to be isolated and analyzed independent of any seasonal component.

STC. Smoothed trend-cycle component, which is a smoothed version of the seasonally adjusted series that shows both trend and cyclic components.

ERR. The residual component of the series for a particular observation.

For the present case, the seasonally adjusted series is the most appropriate, because it represents the original series with the seasonal variations removed.

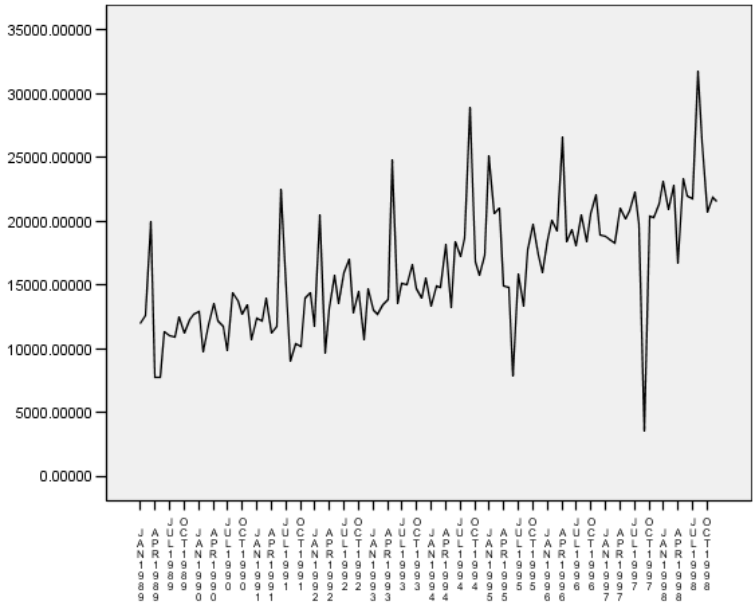
Figure 10-8
Sequence Charts dialog box



To plot the seasonally adjusted series:

- Open the Sequence Charts dialog box.
- Click Reset to clear any previous selections.
- Right click anywhere in the source variable list, and from the context menu select Display Variable Names.
- Select *SAS_1* and move it into the Variables list.
- Click OK.

Figure 10-9
Seasonally adjusted series



The seasonally adjusted series shows a clear upward trend. A number of peaks are evident, but they appear at random intervals, showing no evidence of an annual pattern.

Summary

Using the Seasonal Decomposition procedure, you have removed the seasonal component of a periodic time series to produce a series that is more suitable for trend analysis. Examination of the autocorrelations and partial autocorrelations of the time series was useful in determining the underlying periodicity—in this case, annual.

Related Procedures

The Seasonal Decomposition procedure is useful for removing a single seasonal component from a periodic time series.

- To perform a more in-depth analysis of the periodicity of a time series than is provided by the partial correlation function, use the Spectral Plots procedure. For more information, see Chapter 11.

Chapter
11

Spectral Plots

Using Spectral Plots to Verify Expectations about Periodicity

Time series representing retail sales typically have an underlying annual periodicity, due to the usual peak in sales during the holiday season. Producing sales projections means building a model of the time series, which means identifying any periodic components. A plot of the time series may not always uncover the annual periodicity because time series contain random fluctuations that often mask the underlying structure.

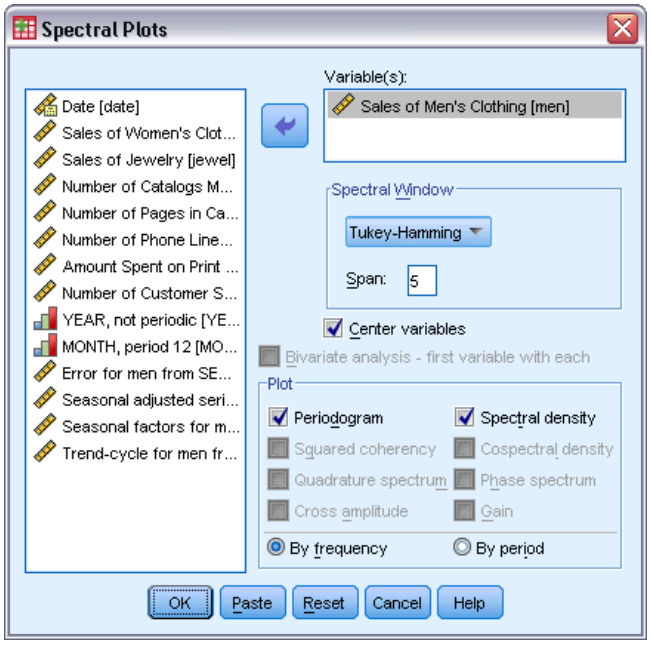
Monthly sales data for a catalog company are stored in *catalog.sav*. For more information, see the topic Sample Files in Appendix D on p. 98. Before proceeding with sales projections, you want to confirm that the sales data exhibits an annual periodicity. A plot of the time series shows many peaks with an irregular spacing, so any underlying periodicity is not evident. Use the Spectral Plots procedure to identify any periodicity in the sales data.

Running the Analysis

To run the Spectral Plots procedure:

- From the menus choose:
  Analyze > Forecasting > Spectral Analysis...

Figure 11-1
Spectral Plots dialog box



- Select *Sales of Men's Clothing* and move it into the Variables list.
- Select Spectral density in the Plot group.
- Click OK.

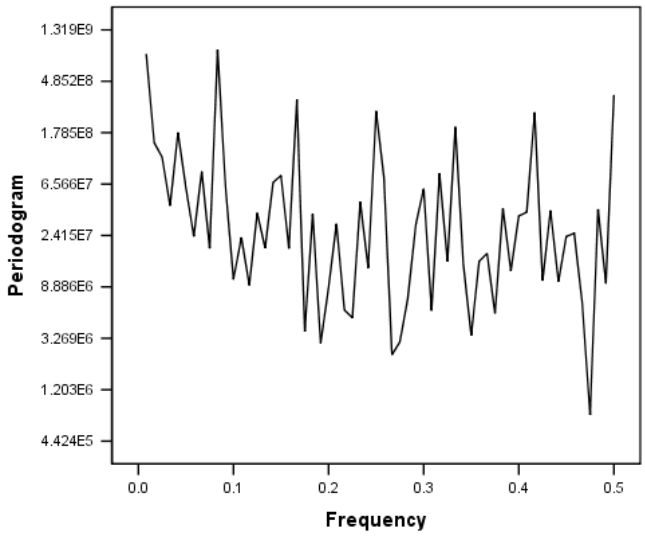
These selections generate the following command syntax:

```
* Spectral Analysis.
TSET  PRINT=DEFAULT.
SPECTRA
  /VARIABLES=men
  /WINDOW=HAMMING(5)
  /CENTER
  /PLOT=P S BY FREQUENCY.
```

Note that in order to obtain the univariate statistics table in the output, the `TSET` command needs to be changed to read `TSET PRINT=DETAILED.`

Understanding the Periodogram and Spectral Density

Figure 11-2
Periodogram



The plot of the periodogram shows a sequence of peaks that stand out from the background noise, with the lowest frequency peak at a frequency of just less than 0.1. You suspect that the data contain an annual periodic component, so consider the contribution that an annual component would make to the periodogram. Each of the data points in the time series represents a month, so an annual periodicity corresponds to a period of 12 in the current data set. Because period and frequency are reciprocals of each other, a period of 12 corresponds to a frequency of 1/12 (or 0.083). So an annual component implies a peak in the periodogram at 0.083, which seems consistent with the presence of the peak just below a frequency of 0.1.

Figure 11-3
Univariate statistics table

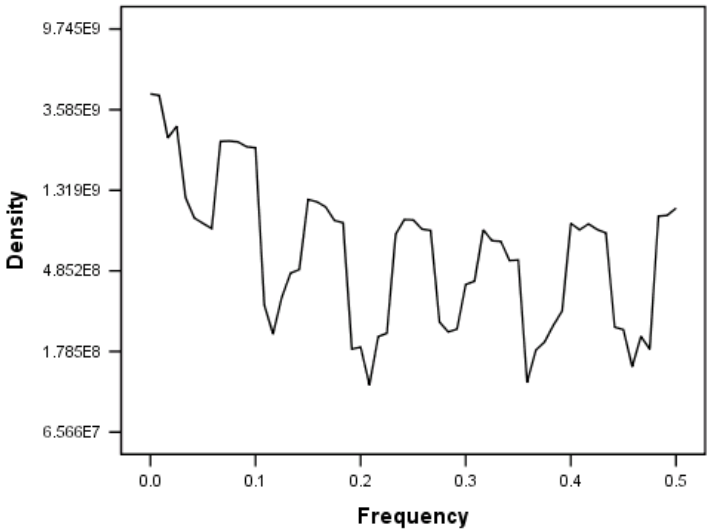
Series Name: men

	Frequency	Sine Transform	Cosine Transform	Periodogram	Spectral Density Estimate
1	.00000	.000	16242.813	.000	4.361E+09
2	.00833	-3696.643	370.153	828131182	4.278E+09
3	.01667	-1496.277	454.831	146743038	2.526E+09
4	.02500	-1336.400	252.087	110970821	2.921E+09
5	.03333	-662.146	529.734	43143315.6	1.210E+09
6	.04167	-1654.614	501.571	179359225	935924937
7	.05000	-784.814	-636.729	61281367.3	875492029
8	.05833	-335.646	532.062	23744855.0	820375352
9	.06667	-1094.178	-451.489	84064108.9	2.420E+09
10	.07500	264.554	492.876	18774933.5	2.429E+09
11	.08333	-3053.934	2370.483	896742149	2.401E+09
12	.09167	-978.882	-287.035	62435897.6	2.263E+09
13	.10000	-403.128	93.036	10270064.4	2.235E+09

The univariate statistics table contains the data points that are used to plot the periodogram. Notice that, for frequencies of less than 0.1, the largest value in the *Periodogram* column occurs at a frequency of 0.08333—precisely what you expect to find if there is an annual periodic component.

This information confirms the identification of the lowest frequency peak with an annual periodic component. But what about the other peaks at higher frequencies?

Figure 11-4
Spectral density



The remaining peaks are best analyzed with the spectral density function, which is simply a smoothed version of the periodogram. Smoothing provides a means of eliminating the background noise from a periodogram, allowing the underlying structure to be more clearly isolated.

The spectral density consists of five distinct peaks that appear to be equally spaced. The lowest frequency peak simply represents the smoothed version of the peak at 0.08333. To understand the significance of the four higher frequency peaks, remember that the periodogram is calculated by modeling the time series as the sum of cosine and sine functions. Periodic components that have the shape of a sine or cosine function (sinusoidal) show up in the periodogram as single peaks. Periodic components that are not sinusoidal show up as a series of equally spaced peaks of different heights, with the lowest frequency peak in the series occurring at the frequency of the periodic component. So the four higher frequency peaks in the spectral density simply indicate that the annual periodic component is not sinusoidal.

You have now accounted for all of the discernible structure in the spectral density plot and conclude that the data contain a single periodic component with a period of 12 months.

Summary

Using the Spectral Plots procedure, you have confirmed the existence of an annual periodic component of a time series, and you have verified that no other significant periodicities are present. The spectral density was seen to be more useful than the periodogram for uncovering the underlying structure, because the spectral density smoothes out the fluctuations that are caused by the nonperiodic component of the data.

Related Procedures

The Spectral Plots procedure is useful for identifying the periodic components of a time series.

- To remove a periodic component from a time series—for instance, to perform a trend analysis—use the Seasonal Decomposition procedure. See Chapter 10 for details.

Appendix

A

Goodness-of-Fit Measures

This section provides definitions of the goodness-of-fit measures used in time series modeling.

- **Stationary R-squared.** A measure that compares the stationary part of the model to a simple mean model. This measure is preferable to ordinary R-squared when there is a trend or seasonal pattern. Stationary R-squared can be negative with a range of negative infinity to 1. Negative values mean that the model under consideration is worse than the baseline model. Positive values mean that the model under consideration is better than the baseline model.
- **R-squared.** An estimate of the proportion of the total variation in the series that is explained by the model. This measure is most useful when the series is stationary. R-squared can be negative with a range of negative infinity to 1. Negative values mean that the model under consideration is worse than the baseline model. Positive values mean that the model under consideration is better than the baseline model.
- **RMSE.** Root Mean Square Error. The square root of mean square error. A measure of how much a dependent series varies from its model-predicted level, expressed in the same units as the dependent series.
- **MAPE.** Mean Absolute Percentage Error. A measure of how much a dependent series varies from its model-predicted level. It is independent of the units used and can therefore be used to compare series with different units.
- **MAE.** Mean absolute error. Measures how much the series varies from its model-predicted level. MAE is reported in the original series units.
- **MaxAPE.** Maximum Absolute Percentage Error. The largest forecasted error, expressed as a percentage. This measure is useful for imagining a worst-case scenario for your forecasts.
- **MaxAE.** Maximum Absolute Error. The largest forecasted error, expressed in the same units as the dependent series. Like MaxAPE, it is useful for imagining the worst-case scenario for your forecasts. Maximum absolute error and maximum absolute percentage error may occur at different series points–for example, when the absolute error for a large series value is slightly larger than the absolute error for a small series value. In that case, the maximum absolute error will occur at the larger series value and the maximum absolute percentage error will occur at the smaller series value.
- **Normalized BIC.** Normalized Bayesian Information Criterion. A general measure of the overall fit of a model that attempts to account for model complexity. It is a score based upon the mean square error and includes a penalty for the number of parameters in the model and the length of the series. The penalty removes the advantage of models with more parameters, making the statistic easy to compare across different models for the same series.

Appendix

B

Outlier Types

This section provides definitions of the outlier types used in time series modeling.

- **Additive.** An outlier that affects a single observation. For example, a data coding error might be identified as an additive outlier.
- **Level shift.** An outlier that shifts all observations by a constant, starting at a particular series point. A level shift could result from a change in policy.
- **Innovational.** An outlier that acts as an addition to the noise term at a particular series point. For stationary series, an innovational outlier affects several observations. For nonstationary series, it may affect every observation starting at a particular series point.
- **Transient.** An outlier whose impact decays exponentially to 0.
- **Seasonal additive.** An outlier that affects a particular observation and all subsequent observations separated from it by one or more seasonal periods. All such observations are affected equally. A seasonal additive outlier might occur if, beginning in a certain year, sales are higher every January.
- **Local trend.** An outlier that starts a local trend at a particular series point.
- **Additive patch.** A group of two or more consecutive additive outliers. Selecting this outlier type results in the detection of individual additive outliers in addition to patches of them.

Appendix

C

Guide to ACF/PACF Plots

The plots shown here are those of pure or theoretical ARIMA processes. Here are some general guidelines for identifying the process:

- Nonstationary series have an ACF that remains significant for half a dozen or more lags, rather than quickly declining to 0. You must difference such a series until it is stationary before you can identify the process.
- Autoregressive processes have an exponentially declining ACF and spikes in the first one or more lags of the PACF. The number of spikes indicates the order of the autoregression.
- Moving average processes have spikes in the first one or more lags of the ACF and an exponentially declining PACF. The number of spikes indicates the order of the moving average.
- Mixed (ARMA) processes typically show exponential declines in both the ACF and the PACF.

At the identification stage, you do not need to worry about the sign of the ACF or PACF, or about the speed with which an exponentially declining ACF or PACF approaches 0. These depend upon the sign and actual value of the AR and MA coefficients. In some instances, an exponentially declining ACF alternates between positive and negative values.

ACF and PACF plots from real data are never as clean as the plots shown here. You must learn to pick out what is essential in any given plot. Always check the ACF and PACF of the residuals, in case your identification is wrong. Bear in mind that:

- Seasonal processes show these patterns at the seasonal lags (the multiples of the seasonal period).
- You are entitled to treat nonsignificant values as 0. That is, you can ignore values that lie within the confidence intervals on the plots. You do not have to ignore them, however, particularly if they continue the pattern of the statistically significant values.
- An occasional autocorrelation will be statistically significant by chance alone. You can ignore a statistically significant autocorrelation if it is isolated, preferably at a high lag, and if it does not occur at a seasonal lag.

Consult any text on ARIMA analysis for a more complete discussion of ACF and PACF plots.

Table C-1
ARIMA(0,0,1), q>0

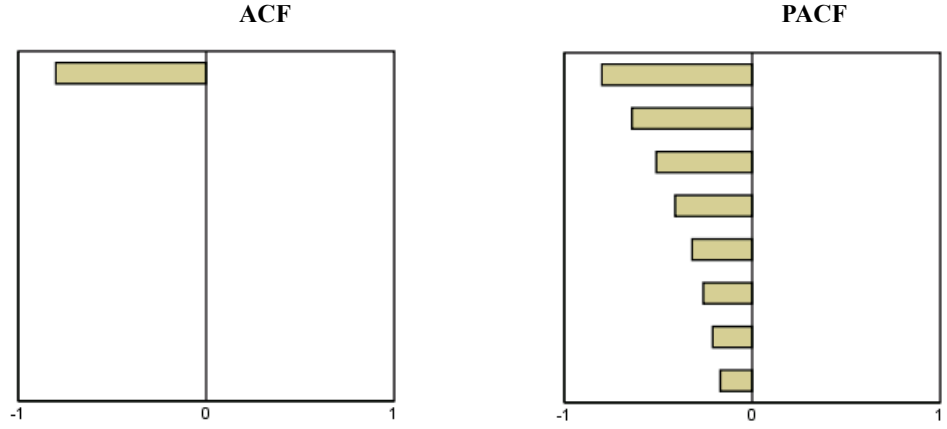
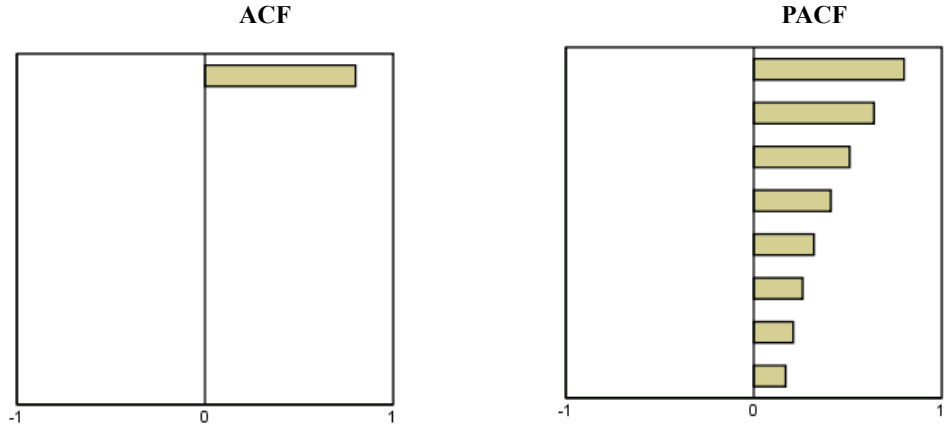


Table C-2
ARIMA(0,0,1), q<0



ARIMA(0,0,2), $\theta_1\theta_2>0$

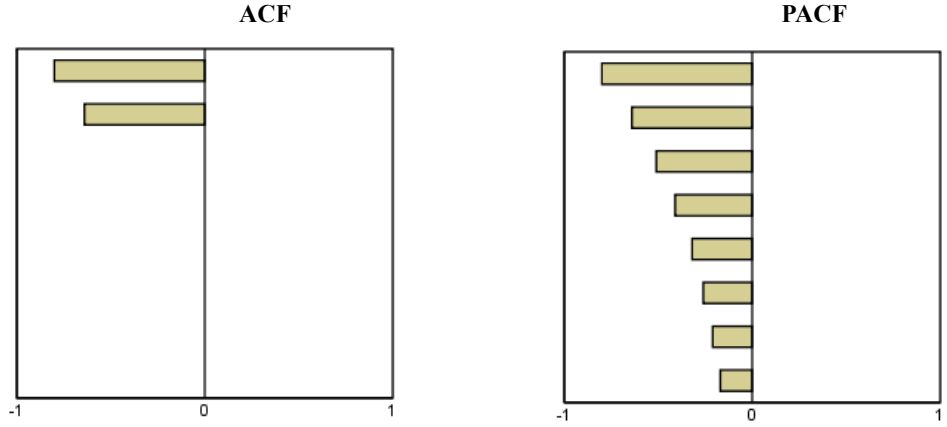


Table C-3
ARIMA(1,0,0), f>0

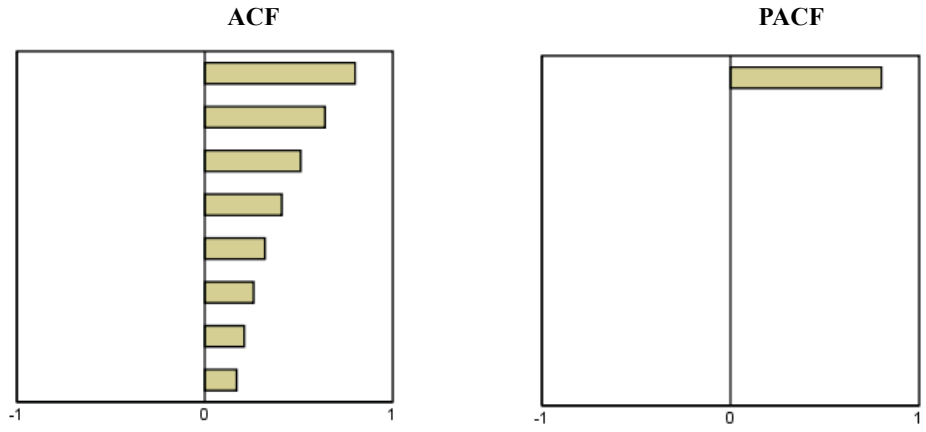
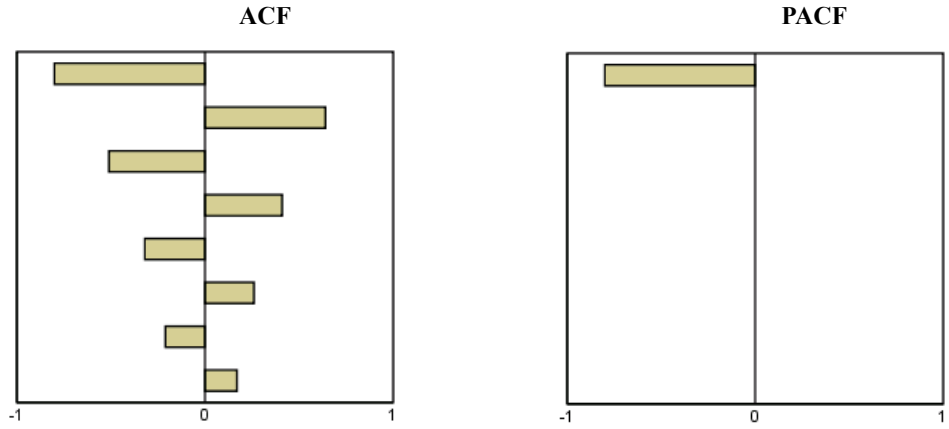
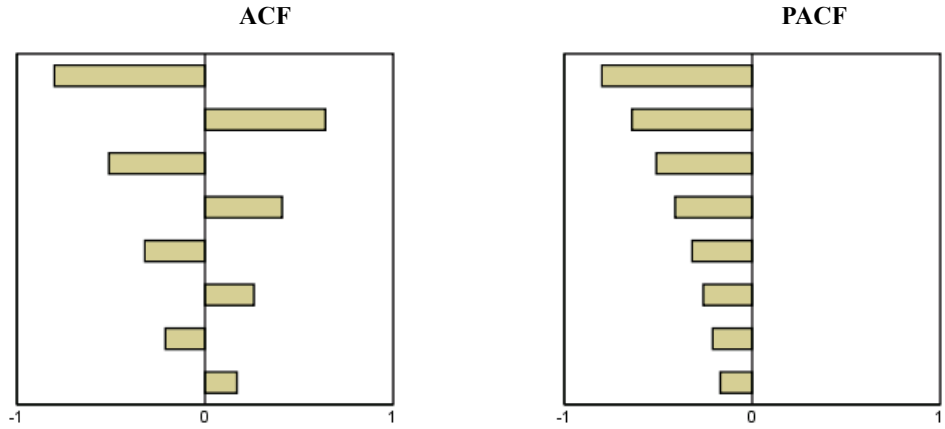


Table C-4
ARIMA(1,0,0), f<0



ARIMA(1,0,1), $\phi<0$, $\theta>0$



ARIMA(2,0,0), $\phi_1\phi_2>0$

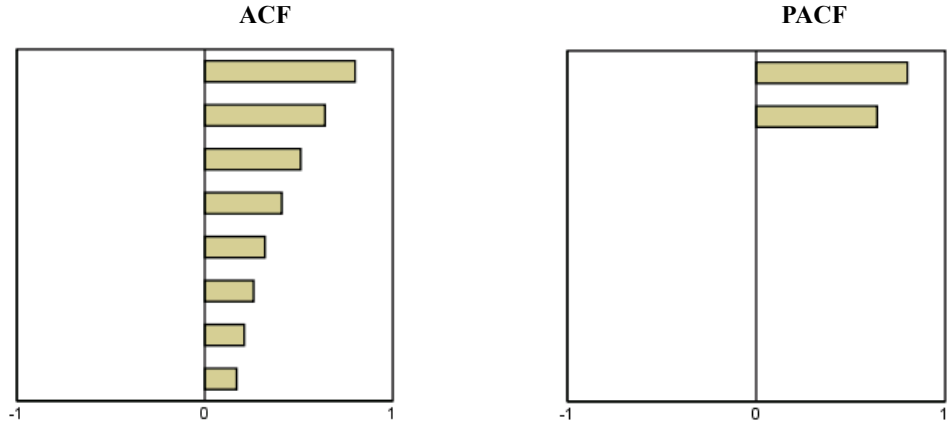
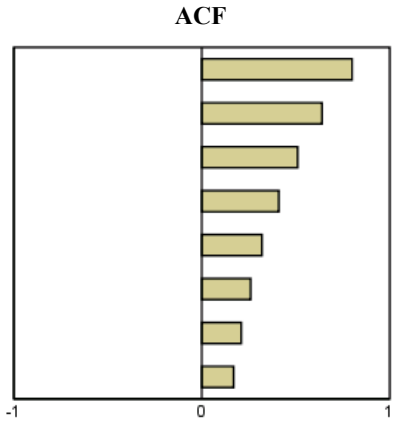


Table C-5
ARIMA(0,1,0) (integrated series)



Appendix

D

Sample Files

The sample files installed with the product can be found in the *Samples* subdirectory of the installation directory. There is a separate folder within the Samples subdirectory for each of the following languages: English, French, German, Italian, Japanese, Korean, Polish, Russian, Simplified Chinese, Spanish, and Traditional Chinese.

Not all sample files are available in all languages. If a sample file is not available in a language, that language folder contains an English version of the sample file.

Descriptions

Following are brief descriptions of the sample files used in various examples throughout the documentation.

- **accidents.sav.** This is a hypothetical data file that concerns an insurance company that is studying age and gender risk factors for automobile accidents in a given region. Each case corresponds to a cross-classification of age category and gender.
- **adl.sav.** This is a hypothetical data file that concerns efforts to determine the benefits of a proposed type of therapy for stroke patients. Physicians randomly assigned female stroke patients to one of two groups. The first received the standard physical therapy, and the second received an additional emotional therapy. Three months following the treatments, each patient's abilities to perform common activities of daily life were scored as ordinal variables.
- **advert.sav.** This is a hypothetical data file that concerns a retailer's efforts to examine the relationship between money spent on advertising and the resulting sales. To this end, they have collected past sales figures and the associated advertising costs..
- **aflatoxin.sav.** This is a hypothetical data file that concerns the testing of corn crops for aflatoxin, a poison whose concentration varies widely between and within crop yields. A grain processor has received 16 samples from each of 8 crop yields and measured the alfatoxin levels in parts per billion (PPB).
- **anorectic.sav.** While working toward a standardized symptomatology of anorectic/bulimic behavior, researchers (Van der Ham, Meulman, Van Strien, and Van Engeland, 1997) made a study of 55 adolescents with known eating disorders. Each patient was seen four times over four years, for a total of 220 observations. At each observation, the patients were scored for each of 16 symptoms. Symptom scores are missing for patient 71 at time 2, patient 76 at time 2, and patient 47 at time 3, leaving 217 valid observations.
- **bankloan.sav.** This is a hypothetical data file that concerns a bank's efforts to reduce the rate of loan defaults. The file contains financial and demographic information on 850 past and prospective customers. The first 700 cases are customers who were previously given loans. The last 150 cases are prospective customers that the bank needs to classify as good or bad credit risks.
- **bankloan_binning.sav.** This is a hypothetical data file containing financial and demographic information on 5,000 past customers.

- **behavior.sav.** In a classic example (Price and Bouffard, 1974), 52 students were asked to rate the combinations of 15 situations and 15 behaviors on a 10-point scale ranging from 0="extremely appropriate" to 9="extremely inappropriate." Averaged over individuals, the values are taken as dissimilarities.
- **behavior_ini.sav.** This data file contains an initial configuration for a two-dimensional solution for *behavior.sav*.
- **brakes.sav.** This is a hypothetical data file that concerns quality control at a factory that produces disc brakes for high-performance automobiles. The data file contains diameter measurements of 16 discs from each of 8 production machines. The target diameter for the brakes is 322 millimeters.
- **breakfast.sav.** In a classic study (Green and Rao, 1972), 21 Wharton School MBA students and their spouses were asked to rank 15 breakfast items in order of preference with 1="most preferred" to 15="least preferred." Their preferences were recorded under six different scenarios, from "Overall preference" to "Snack, with beverage only."
- **breakfast-overall.sav.** This data file contains the breakfast item preferences for the first scenario, "Overall preference," only.
- **broadband_1.sav.** This is a hypothetical data file containing the number of subscribers, by region, to a national broadband service. The data file contains monthly subscriber numbers for 85 regions over a four-year period.
- **broadband_2.sav.** This data file is identical to *broadband_1.sav* but contains data for three additional months.
- **car_insurance_claims.sav.** A dataset presented and analyzed elsewhere (McCullagh and Nelder, 1989) concerns damage claims for cars. The average claim amount can be modeled as having a gamma distribution, using an inverse link function to relate the mean of the dependent variable to a linear combination of the policyholder age, vehicle type, and vehicle age. The number of claims filed can be used as a scaling weight.
- **car_sales.sav.** This data file contains hypothetical sales estimates, list prices, and physical specifications for various makes and models of vehicles. The list prices and physical specifications were obtained alternately from *edmunds.com* and manufacturer sites.
- **car_sales_uprepared.sav.** This is a modified version of *car_sales.sav* that does not include any transformed versions of the fields.
- **carpet.sav.** In a popular example (Green and Wind, 1973), a company interested in marketing a new carpet cleaner wants to examine the influence of five factors on consumer preference—package design, brand name, price, a *Good Housekeeping* seal, and a money-back guarantee. There are three factor levels for package design, each one differing in the location of the applicator brush; three brand names (*K2R*, *Glory*, and *Bissell*); three price levels; and two levels (either no or yes) for each of the last two factors. Ten consumers rank 22 profiles defined by these factors. The variable *Preference* contains the rank of the average rankings for each profile. Low rankings correspond to high preference. This variable reflects an overall measure of preference for each profile.
- **carpet_prefs.sav.** This data file is based on the same example as described for *carpet.sav*, but it contains the actual rankings collected from each of the 10 consumers. The consumers were asked to rank the 22 product profiles from the most to the least preferred. The variables *PREF1* through *PREF22* contain the identifiers of the associated profiles, as defined in *carpet_plan.sav*.

- **catalog.sav.** This data file contains hypothetical monthly sales figures for three products sold by a catalog company. Data for five possible predictor variables are also included.
- **catalog_seasfac.sav.** This data file is the same as *catalog.sav* except for the addition of a set of seasonal factors calculated from the Seasonal Decomposition procedure along with the accompanying date variables.
- **cellular.sav.** This is a hypothetical data file that concerns a cellular phone company's efforts to reduce churn. Churn propensity scores are applied to accounts, ranging from 0 to 100. Accounts scoring 50 or above may be looking to change providers.
- **ceramics.sav.** This is a hypothetical data file that concerns a manufacturer's efforts to determine whether a new premium alloy has a greater heat resistance than a standard alloy. Each case represents a separate test of one of the alloys; the heat at which the bearing failed is recorded.
- **cereal.sav.** This is a hypothetical data file that concerns a poll of 880 people about their breakfast preferences, also noting their age, gender, marital status, and whether or not they have an active lifestyle (based on whether they exercise at least twice a week). Each case represents a separate respondent.
- **clothing_defects.sav.** This is a hypothetical data file that concerns the quality control process at a clothing factory. From each lot produced at the factory, the inspectors take a sample of clothes and count the number of clothes that are unacceptable.
- **coffee.sav.** This data file pertains to perceived images of six iced-coffee brands (Kennedy, Riquier, and Sharp, 1996) . For each of 23 iced-coffee image attributes, people selected all brands that were described by the attribute. The six brands are denoted AA, BB, CC, DD, EE, and FF to preserve confidentiality.
- **contacts.sav.** This is a hypothetical data file that concerns the contact lists for a group of corporate computer sales representatives. Each contact is categorized by the department of the company in which they work and their company ranks. Also recorded are the amount of the last sale made, the time since the last sale, and the size of the contact's company.
- **creditpromo.sav.** This is a hypothetical data file that concerns a department store's efforts to evaluate the effectiveness of a recent credit card promotion. To this end, 500 cardholders were randomly selected. Half received an ad promoting a reduced interest rate on purchases made over the next three months. Half received a standard seasonal ad.
- **customer_dbase.sav.** This is a hypothetical data file that concerns a company's efforts to use the information in its data warehouse to make special offers to customers who are most likely to reply. A subset of the customer base was selected at random and given the special offers, and their responses were recorded.
- **customer_information.sav.** A hypothetical data file containing customer mailing information, such as name and address.
- **customer_subset.sav.** A subset of 80 cases from *customer_dbase.sav*.
- **debate.sav.** This is a hypothetical data file that concerns paired responses to a survey from attendees of a political debate before and after the debate. Each case corresponds to a separate respondent.
- **debate_aggregate.sav.** This is a hypothetical data file that aggregates the responses in *debate.sav*. Each case corresponds to a cross-classification of preference before and after the debate.

- **demo.sav.** This is a hypothetical data file that concerns a purchased customer database, for the purpose of mailing monthly offers. Whether or not the customer responded to the offer is recorded, along with various demographic information.
- **demo_cs_1.sav.** This is a hypothetical data file that concerns the first step of a company's efforts to compile a database of survey information. Each case corresponds to a different city, and the region, province, district, and city identification are recorded.
- **demo_cs_2.sav.** This is a hypothetical data file that concerns the second step of a company's efforts to compile a database of survey information. Each case corresponds to a different household unit from cities selected in the first step, and the region, province, district, city, subdivision, and unit identification are recorded. The sampling information from the first two stages of the design is also included.
- **demo_cs.sav.** This is a hypothetical data file that contains survey information collected using a complex sampling design. Each case corresponds to a different household unit, and various demographic and sampling information is recorded.
- **dmdata.sav.** This is a hypothetical data file that contains demographic and purchasing information for a direct marketing company. *dmdata2.sav* contains information for a subset of contacts that received a test mailing, and *dmdata3.sav* contains information on the remaining contacts who did not receive the test mailing.
- **dietstudy.sav.** This hypothetical data file contains the results of a study of the "Stillman diet" (Rickman, Mitchell, Dingman, and Dalen, 1974). Each case corresponds to a separate subject and records his or her pre- and post-diet weights in pounds and triglyceride levels in mg/100 ml.
- **dvdplayer.sav.** This is a hypothetical data file that concerns the development of a new DVD player. Using a prototype, the marketing team has collected focus group data. Each case corresponds to a separate surveyed user and records some demographic information about them and their responses to questions about the prototype.
- **german_credit.sav.** This data file is taken from the "German credit" dataset in the Repository of Machine Learning Databases (Blake and Merz, 1998) at the University of California, Irvine.
- **grocery_1month.sav.** This hypothetical data file is the *grocery_coupons.sav* data file with the weekly purchases "rolled-up" so that each case corresponds to a separate customer. Some of the variables that changed weekly disappear as a result, and the amount spent recorded is now the sum of the amounts spent during the four weeks of the study.
- **grocery_coupons.sav.** This is a hypothetical data file that contains survey data collected by a grocery store chain interested in the purchasing habits of their customers. Each customer is followed for four weeks, and each case corresponds to a separate customer-week and records information about where and how the customer shops, including how much was spent on groceries during that week.
- **guttman.sav.** Bell (Bell, 1961) presented a table to illustrate possible social groups. Guttman (Guttman, 1968) used a portion of this table, in which five variables describing such things as social interaction, feelings of belonging to a group, physical proximity of members, and formality of the relationship were crossed with seven theoretical social groups, including crowds (for example, people at a football game), audiences (for example, people at a theater or classroom lecture), public (for example, newspaper or television audiences), mobs (like a crowd but with much more intense interaction), primary groups (intimate), secondary groups

(voluntary), and the modern community (loose confederation resulting from close physical proximity and a need for specialized services).

- **health_funding.sav.** This is a hypothetical data file that contains data on health care funding (amount per 100 population), disease rates (rate per 10,000 population), and visits to health care providers (rate per 10,000 population). Each case represents a different city.
- **hivassay.sav.** This is a hypothetical data file that concerns the efforts of a pharmaceutical lab to develop a rapid assay for detecting HIV infection. The results of the assay are eight deepening shades of red, with deeper shades indicating greater likelihood of infection. A laboratory trial was conducted on 2,000 blood samples, half of which were infected with HIV and half of which were clean.
- **hourlywagedata.sav.** This is a hypothetical data file that concerns the hourly wages of nurses from office and hospital positions and with varying levels of experience.
- **insurance_claims.sav.** This is a hypothetical data file that concerns an insurance company that wants to build a model for flagging suspicious, potentially fraudulent claims. Each case represents a separate claim.
- **insure.sav.** This is a hypothetical data file that concerns an insurance company that is studying the risk factors that indicate whether a client will have to make a claim on a 10-year term life insurance contract. Each case in the data file represents a pair of contracts, one of which recorded a claim and the other didn't, matched on age and gender.
- **judges.sav.** This is a hypothetical data file that concerns the scores given by trained judges (plus one enthusiast) to 300 gymnastics performances. Each row represents a separate performance; the judges viewed the same performances.
- **kinship_dat.sav.** Rosenberg and Kim (Rosenberg and Kim, 1975) set out to analyze 15 kinship terms (aunt, brother, cousin, daughter, father, granddaughter, grandfather, grandmother, grandson, mother, nephew, niece, sister, son, uncle). They asked four groups of college students (two female, two male) to sort these terms on the basis of similarities. Two groups (one female, one male) were asked to sort twice, with the second sorting based on a different criterion from the first sort. Thus, a total of six "sources" were obtained. Each source corresponds to a 15×15 proximity matrix, whose cells are equal to the number of people in a source minus the number of times the objects were partitioned together in that source.
- **kinship_ini.sav.** This data file contains an initial configuration for a three-dimensional solution for *kinship_dat.sav*.
- **kinship_var.sav.** This data file contains independent variables *gender*, *gener*(ation), and *degree* (of separation) that can be used to interpret the dimensions of a solution for *kinship_dat.sav*. Specifically, they can be used to restrict the space of the solution to a linear combination of these variables.
- **marketvalues.sav.** This data file concerns home sales in a new housing development in Algonquin, Ill., during the years from 1999–2000. These sales are a matter of public record.
- **nhis2000_subset.sav.** The National Health Interview Survey (NHIS) is a large, population-based survey of the U.S. civilian population. Interviews are carried out face-to-face in a nationally representative sample of households. Demographic information and observations about health behaviors and status are obtained for members of each household. This data file contains a subset of information from the 2000 survey. National Center for Health Statistics. National Health Interview Survey, 2000. Public-use data file and documentation. *ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/NHIS/2000/*. Accessed 2003.

- **ozone.sav.** The data include 330 observations on six meteorological variables for predicting ozone concentration from the remaining variables. Previous researchers (Breiman and Friedman, 1985), (Hastie and Tibshirani, 1990), among others found nonlinearities among these variables, which hinder standard regression approaches.
- **pain_medication.sav.** This hypothetical data file contains the results of a clinical trial for anti-inflammatory medication for treating chronic arthritic pain. Of particular interest is the time it takes for the drug to take effect and how it compares to an existing medication.
- **patient_los.sav.** This hypothetical data file contains the treatment records of patients who were admitted to the hospital for suspected myocardial infarction (MI, or "heart attack"). Each case corresponds to a separate patient and records many variables related to their hospital stay.
- **patlos_sample.sav.** This hypothetical data file contains the treatment records of a sample of patients who received thrombolytics during treatment for myocardial infarction (MI, or "heart attack"). Each case corresponds to a separate patient and records many variables related to their hospital stay.
- **poll_cs.sav.** This is a hypothetical data file that concerns pollsters' efforts to determine the level of public support for a bill before the legislature. The cases correspond to registered voters. Each case records the county, township, and neighborhood in which the voter lives.
- **poll_cs_sample.sav.** This hypothetical data file contains a sample of the voters listed in *poll_cs.sav*. The sample was taken according to the design specified in the *poll.csplan* plan file, and this data file records the inclusion probabilities and sample weights. Note, however, that because the sampling plan makes use of a probability-proportional-to-size (PPS) method, there is also a file containing the joint selection probabilities (*poll_jointprob.sav*). The additional variables corresponding to voter demographics and their opinion on the proposed bill were collected and added the data file after the sample as taken.
- **property_assess.sav.** This is a hypothetical data file that concerns a county assessor's efforts to keep property value assessments up to date on limited resources. The cases correspond to properties sold in the county in the past year. Each case in the data file records the township in which the property lies, the assessor who last visited the property, the time since that assessment, the valuation made at that time, and the sale value of the property.
- **property_assess_cs.sav.** This is a hypothetical data file that concerns a state assessor's efforts to keep property value assessments up to date on limited resources. The cases correspond to properties in the state. Each case in the data file records the county, township, and neighborhood in which the property lies, the time since the last assessment, and the valuation made at that time.
- **property_assess_cs_sample.sav.** This hypothetical data file contains a sample of the properties listed in *property_assess_cs.sav*. The sample was taken according to the design specified in the *property_assess.csplan* plan file, and this data file records the inclusion probabilities and sample weights. The additional variable *Current value* was collected and added to the data file after the sample was taken.
- **recidivism.sav.** This is a hypothetical data file that concerns a government law enforcement agency's efforts to understand recidivism rates in their area of jurisdiction. Each case corresponds to a previous offender and records their demographic information, some details of their first crime, and then the time until their second arrest, if it occurred within two years of the first arrest.

- **recidivism_cs_sample.sav.** This is a hypothetical data file that concerns a government law enforcement agency's efforts to understand recidivism rates in their area of jurisdiction. Each case corresponds to a previous offender, released from their first arrest during the month of June, 2003, and records their demographic information, some details of their first crime, and the data of their second arrest, if it occurred by the end of June, 2006. Offenders were selected from sampled departments according to the sampling plan specified in *recidivism_cs.csplan*; because it makes use of a probability-proportional-to-size (PPS) method, there is also a file containing the joint selection probabilities (*recidivism_cs_jointprob.sav*).
- **rfm_transactions.sav.** A hypothetical data file containing purchase transaction data, including date of purchase, item(s) purchased, and monetary amount of each transaction.
- **salesperformance.sav.** This is a hypothetical data file that concerns the evaluation of two new sales training courses. Sixty employees, divided into three groups, all receive standard training. In addition, group 2 gets technical training; group 3, a hands-on tutorial. Each employee was tested at the end of the training course and their score recorded. Each case in the data file represents a separate trainee and records the group to which they were assigned and the score they received on the exam.
- **satisf.sav.** This is a hypothetical data file that concerns a satisfaction survey conducted by a retail company at 4 store locations. 582 customers were surveyed in all, and each case represents the responses from a single customer.
- **screws.sav.** This data file contains information on the characteristics of screws, bolts, nuts, and tacks (Hartigan, 1975).
- **shampoo_ph.sav.** This is a hypothetical data file that concerns the quality control at a factory for hair products. At regular time intervals, six separate output batches are measured and their pH recorded. The target range is 4.5–5.5.
- **ships.sav.** A dataset presented and analyzed elsewhere (McCullagh et al., 1989) that concerns damage to cargo ships caused by waves. The incident counts can be modeled as occurring at a Poisson rate given the ship type, construction period, and service period. The aggregate months of service for each cell of the table formed by the cross-classification of factors provides values for the exposure to risk.
- **site.sav.** This is a hypothetical data file that concerns a company's efforts to choose new sites for their expanding business. They have hired two consultants to separately evaluate the sites, who, in addition to an extended report, summarized each site as a "good," "fair," or "poor" prospect.
- **smokers.sav.** This data file is abstracted from the 1998 National Household Survey of Drug Abuse and is a probability sample of American households. (*http://dx.doi.org/10.3886/ICPSR02934*) Thus, the first step in an analysis of this data file should be to weight the data to reflect population trends.
- **stocks.sav** This hypothetical data file contains stocks prices and volume for one year.
- **stroke_clean.sav.** This hypothetical data file contains the state of a medical database after it has been cleaned using procedures in the Data Preparation option.
- **stroke_invalid.sav.** This hypothetical data file contains the initial state of a medical database and contains several data entry errors.

- **stroke_survival.** This hypothetical data file concerns survival times for patients exiting a rehabilitation program post-ischemic stroke face a number of challenges. Post-stroke, the occurrence of myocardial infarction, ischemic stroke, or hemorrhagic stroke is noted and the time of the event recorded. The sample is left-truncated because it only includes patients who survived through the end of the rehabilitation program administered post-stroke.
- **stroke_valid.sav.** This hypothetical data file contains the state of a medical database after the values have been checked using the Validate Data procedure. It still contains potentially anomalous cases.
- **survey_sample.sav.** This data file contains survey data, including demographic data and various attitude measures. It is based on a subset of variables from the 1998 NORC General Social Survey, although some data values have been modified and additional fictitious variables have been added for demonstration purposes.
- **telco.sav.** This is a hypothetical data file that concerns a telecommunications company's efforts to reduce churn in their customer base. Each case corresponds to a separate customer and records various demographic and service usage information.
- **telco_extra.sav.** This data file is similar to the *telco.sav* data file, but the "tenure" and log-transformed customer spending variables have been removed and replaced by standardized log-transformed customer spending variables.
- **telco_missing.sav.** This data file is a subset of the *telco.sav* data file, but some of the demographic data values have been replaced with missing values.
- **testmarket.sav.** This hypothetical data file concerns a fast food chain's plans to add a new item to its menu. There are three possible campaigns for promoting the new product, so the new item is introduced at locations in several randomly selected markets. A different promotion is used at each location, and the weekly sales of the new item are recorded for the first four weeks. Each case corresponds to a separate location-week.
- **testmarket_1month.sav.** This hypothetical data file is the *testmarket.sav* data file with the weekly sales "rolled-up" so that each case corresponds to a separate location. Some of the variables that changed weekly disappear as a result, and the sales recorded is now the sum of the sales during the four weeks of the study.
- **tree_car.sav.** This is a hypothetical data file containing demographic and vehicle purchase price data.
- **tree_credit.sav.** This is a hypothetical data file containing demographic and bank loan history data.
- **tree_missing_data.sav** This is a hypothetical data file containing demographic and bank loan history data with a large number of missing values.
- **tree_score_car.sav.** This is a hypothetical data file containing demographic and vehicle purchase price data.
- **tree_textdata.sav.** A simple data file with only two variables intended primarily to show the default state of variables prior to assignment of measurement level and value labels.
- **tv-survey.sav.** This is a hypothetical data file that concerns a survey conducted by a TV studio that is considering whether to extend the run of a successful program. 906 respondents were asked whether they would watch the program under various conditions. Each row represents a separate respondent; each column is a separate condition.

- **ulcer_recurrence.sav.** This file contains partial information from a study designed to compare the efficacy of two therapies for preventing the recurrence of ulcers. It provides a good example of interval-censored data and has been presented and analyzed elsewhere (Collett, 2003).
- **ulcer_recurrence_recoded.sav.** This file reorganizes the information in *ulcer_recurrence.sav* to allow you model the event probability for each interval of the study rather than simply the end-of-study event probability. It has been presented and analyzed elsewhere (Collett et al., 2003).
- **verd1985.sav.** This data file concerns a survey (Verdegaal, 1985). The responses of 15 subjects to 8 variables were recorded. The variables of interest are divided into three sets. Set 1 includes *age* and *marital*, set 2 includes *pet* and *news*, and set 3 includes *music* and *live*. *Pet* is scaled as multiple nominal and *age* is scaled as ordinal; all of the other variables are scaled as single nominal.
- **virus.sav.** This is a hypothetical data file that concerns the efforts of an Internet service provider (ISP) to determine the effects of a virus on its networks. They have tracked the (approximate) percentage of infected e-mail traffic on its networks over time, from the moment of discovery until the threat was contained.
- **wheeze_steubenville.sav.** This is a subset from a longitudinal study of the health effects of air pollution on children (Ware, Dockery, Spiro III, Speizer, and Ferris Jr., 1984). The data contain repeated binary measures of the wheezing status for children from Steubenville, Ohio, at ages 7, 8, 9 and 10 years, along with a fixed recording of whether or not the mother was a smoker during the first year of the study.
- **workprog.sav.** This is a hypothetical data file that concerns a government works program that tries to place disadvantaged people into better jobs. A sample of potential program participants were followed, some of whom were randomly selected for enrollment in the program, while others were not. Each case represents a separate program participant.
- **worldsales.sav** This hypothetical data file contains sales revenue by continent and product.

Appendix

E

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