Exponential Smoothing Models

Objectives

Learn how to apply exponential smoothing to time series data.

Data

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 10 regions over a four-year period (**starting January 2008**). In this lab, you will use the Expert Modeler to produce exponential smoothing model and forecasts for the next three months for each of the 10 local markets.

Recommended Approach to Modeling

The general approach when developing an exponential smoothing model is as follows:

- Define the time series dates using the define date procedure in SPSS
- Run a sequence chart for the variable which you wish to forecast, so that general trend and seasonal patterns can be identified
- Specify the appropriate trend and seasonal patterns for the exponential smoothing model or use the Expert Modeler
- Estimate the model parameters for the exponential smoothing model
- Test model performance
- Forecast (to be discussed in a later lab)

In this data set the time series dates have already been created.

Open the broadband.sav data file from Blackboard.

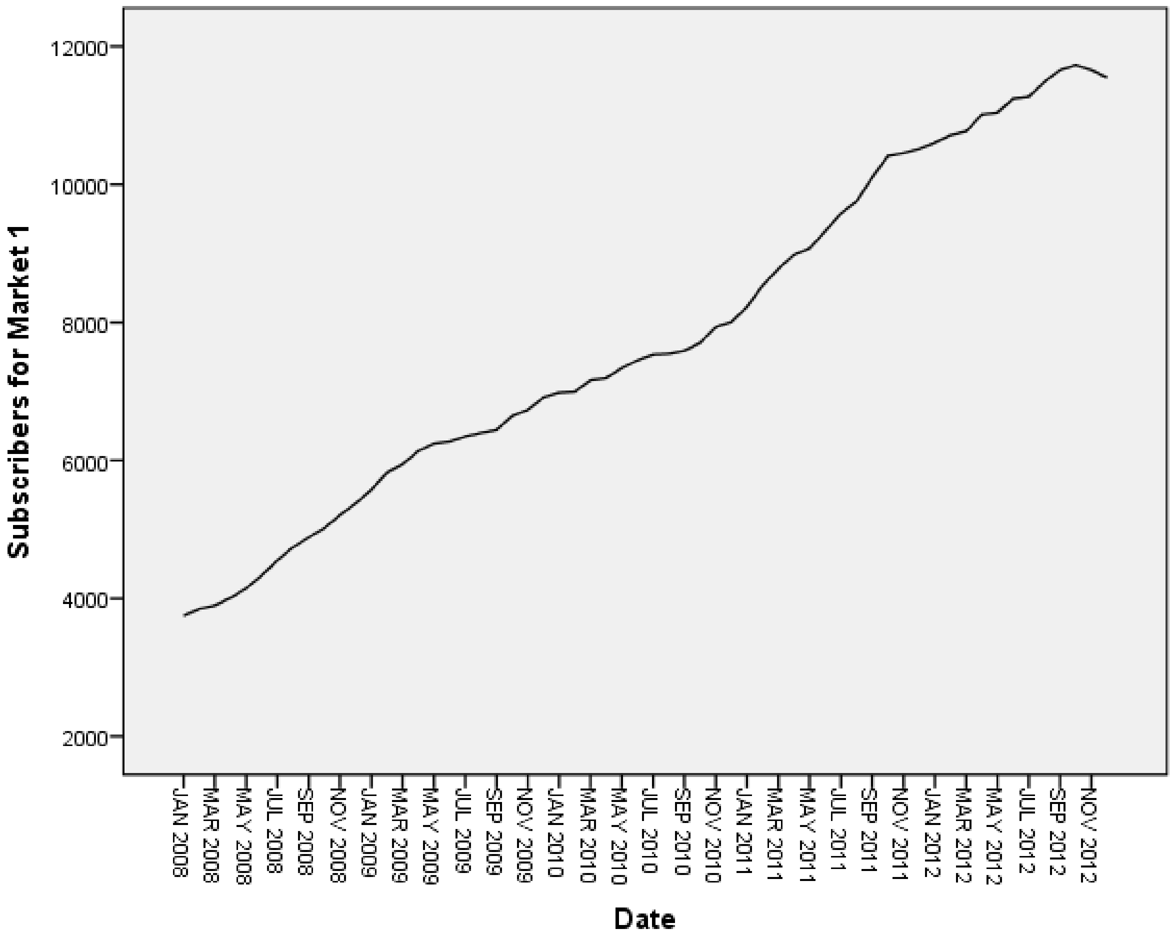
Assign the appropriate dates to each row in the data editor:

Click **Data...Define Date and time…**

Viewing the Series on a Sequence Chart

The next stage is to view how the series changes over time by looking at a sequence chart for Market 1.

Figure 4.1 Sequence Chart



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.

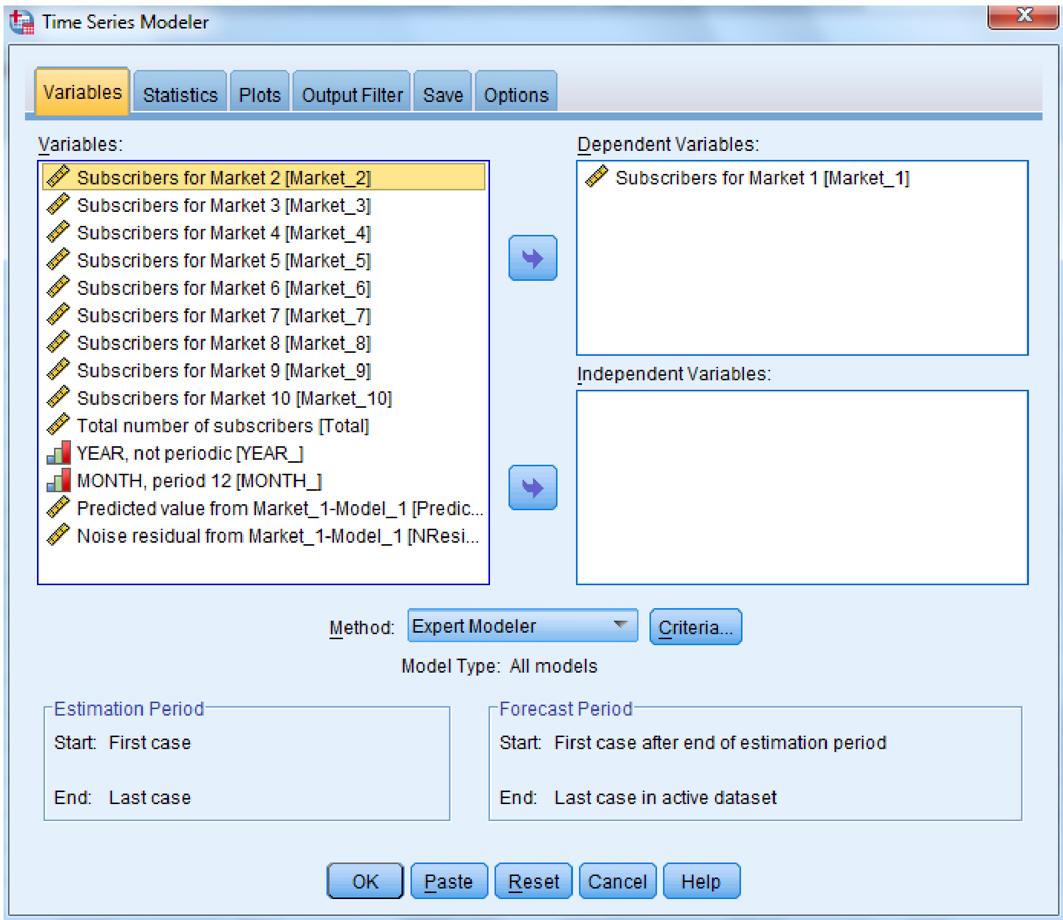
Next, we will first use the Expert Modeler to model the series.

An Analysis with Expert Modeler

To start the analysis we need to:

Click **Analyze -> Forecasting -> Create Traditional Models**
Move **Starts** into the Dependent Variables box

Figure 4.2 Expert Modeler Main Dialog Box

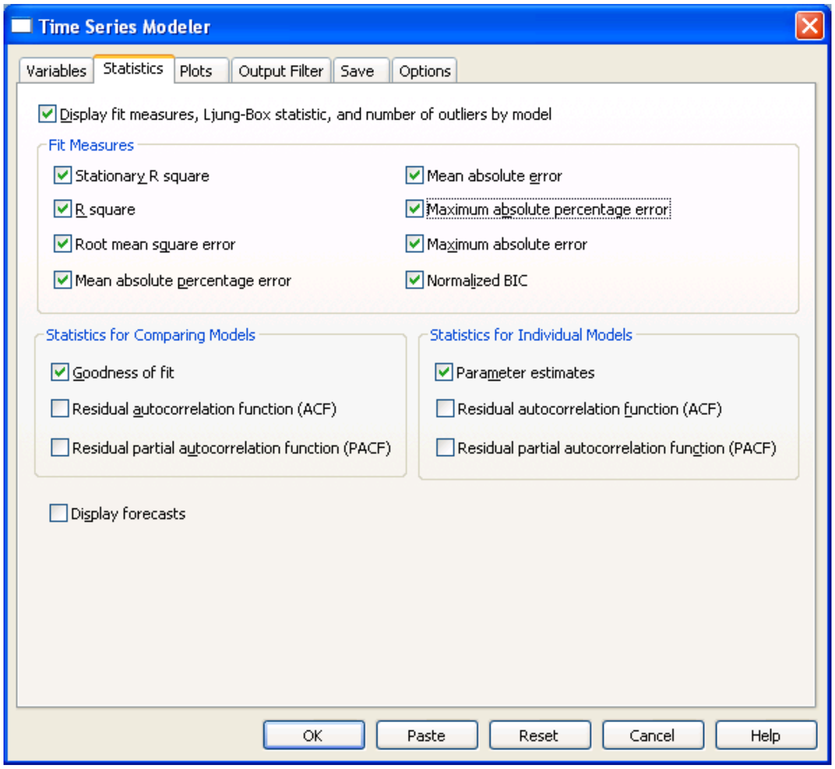


You might think that we should choose the Exponential Smoothing method from the dropdown list. However, if you do so, the Expert Modeler will not choose among the many available exponential smoothing models. Instead, you will be forced to choose *one* exponential smoothing model to estimate. We have selected a dataset where exponential smoothing is the preferred method for purposes of exposition.

Next we go to the Statistics tab.

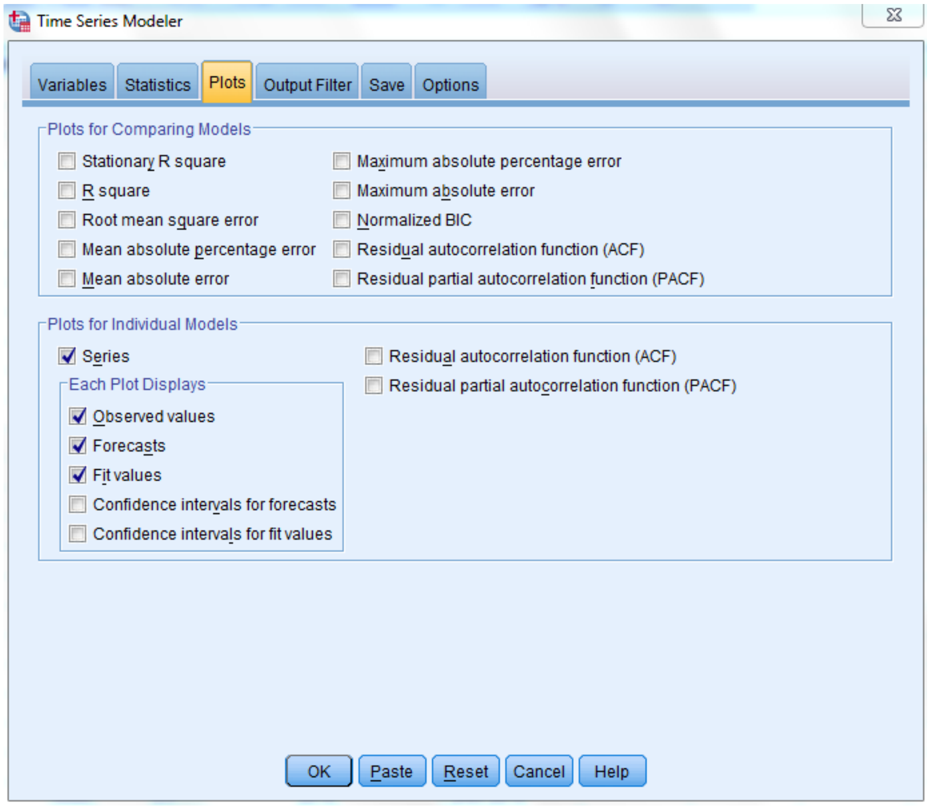
Click on the **Statistics tab**
Check <u>all</u> the boxes in the **Fit Measures** section
In **Statistics for individual Models** check the **Parameter estimates** check box

Figure 4.3 Statistics Tab



Click on the **Plots tab**
In the **Plots for Individual Models** section check the boxes for **Fit values**

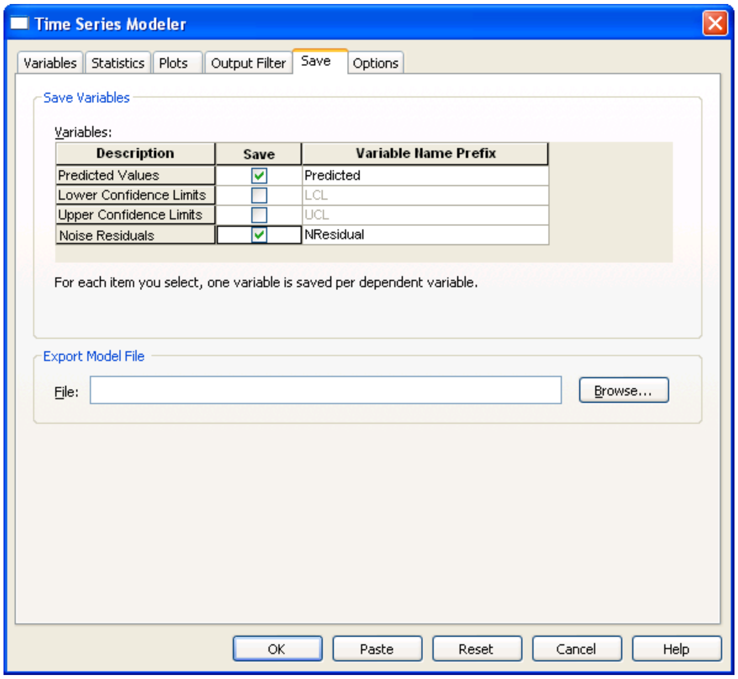
Figure 4.4 Plots tab



Now we will save the fit values and residuals in the Save tab.

Click **Save tab**
Check the **Predicted values** and **Noise Residuals** check boxes

Figure 4.5 Save Tab



Click **OK**

Examining the Results

We'll begin our examination of the results by seeing what type of exponential smoothing model was selected by the Expert Modeler and reviewing the model parameters.

The Model Description table tells us that a Simple Seasonal model was selected. As a reminder, a simple seasonal model allows for changing seasonal effects and local level shifts, but no trend. Since this model was selected, it means that there is no trend for the series to decrease over time.

Figure 4.6 Exponential Smoothing Model

Model Description

			Model Type
Model ID	Subscribers for Market 1	Model_1	Holt

Next we review the Model Statistics (the table was edited to fit on the page).

Figure 4.7 Model Statistics

Fit Statistic	Mean
Stationary R-squared	.262
R-squared	.999
RMSE	90.490
MAPE	.939
MaxAPE	2.141
MAE	73.765
MaxAE	223.839
Normalized BIC	9.147

The stationary R Square is 0.262, which is fairly low, although hardly perfect prediction. Whether this is adequate will have to be judged along with other measures. The mean absolute percentage error (MAPE) is 0.939. Normally errors should be under 10% for satisfactory models, so this is reassuring. The maximum absolute percentage error (MaxAPE) is 2.141, which is a worst case scenario for the model.

The mean absolute error (MAE) is 73.765, in the original units of subscribers. The maximum absolute error (MaxAE) of prediction is 223.839. This is a worst case scenario for model performance.

The Normalized BIC value is not meaningful until we have another model to compare to this one

Overall, so far the model appears to be quite acceptable.

Now we turn to the model parameters for the simple seasonal model.

Figure 4.8 Model Parameters

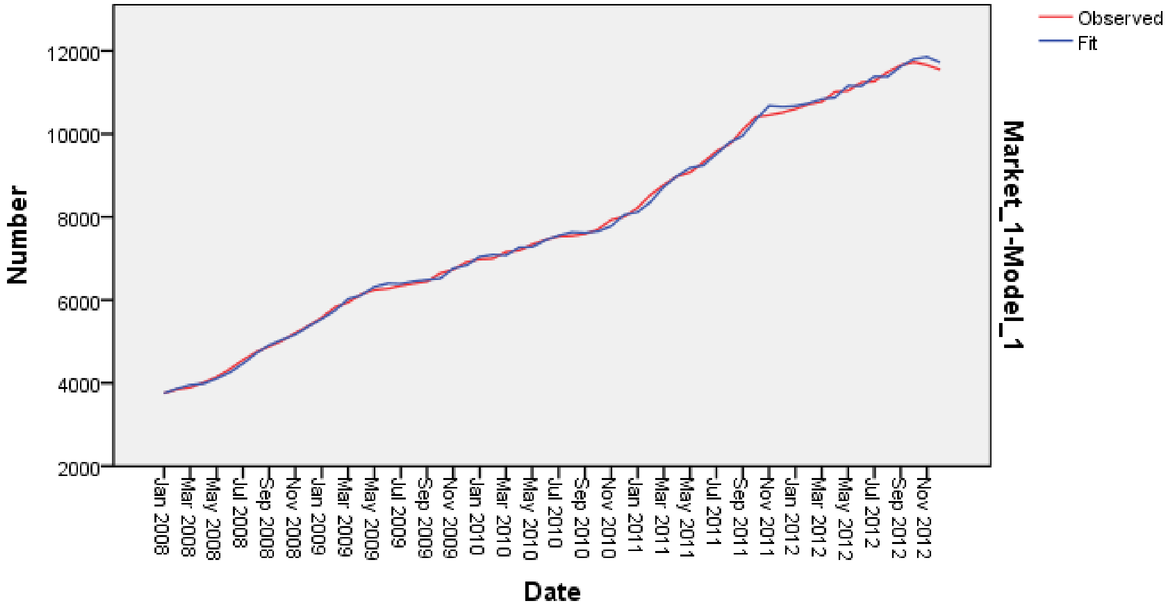
Exponential Smoothing Model Parameters

Model			Estimate	SE	t	Sig.
Subscribers for Market 1-Model_1	No Transformation	Alpha (Level)	1.000	.138	7.239	.000
		Gamma (Trend)	.300	.135	2.223	.030

In this model the gamma coefficient for measuring the change in trend is significant while the coefficient for level (alpha) is also significant with an alpha of 1. Since gamma is significant, this means that trend changes over time. This appeared to be true from the sequence chart.

The alpha parameter of 1 indicates that there is a level shift incorporated into the model and indicates that the recent observations have an influence on the current series value.

Figure 4.9 Sequence Chart of Observed and Fit Values



The model fits the data quite well, and this was also evident.

The model saved two new variables per our request, the fit and residuals.

Switch to the **Data Editor** window and scroll to the far right

Figure 4.10 Data Editor Window Showing New Variables

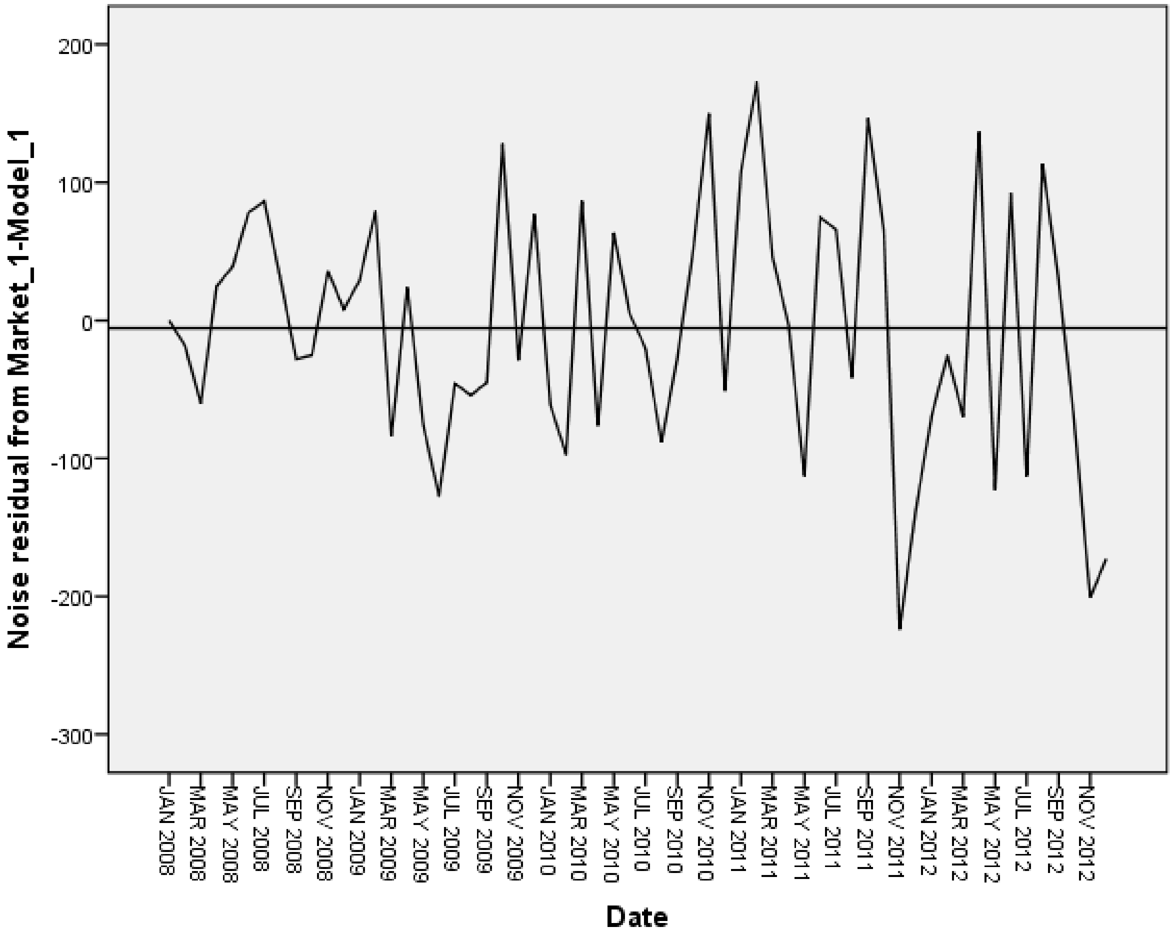
DATE_	Predicted_Market_1_Model_1	NResidual_Market_1_Model_1
JAN 2008	3750	0
FEB 2008	3864	-18
MAR 2008	3955	-60
APR 2008	3985	25
MAY 2008	4108	39
JUN 2008	4256	78
JUL 2008	4468	86
AUG 2008	4713	31
SEP 2008	4913	-28
OCT 2008	5045	-25
NOV 2008	5172	36
DEC 2008	5371	8
JAN 2009	5545	29
FEB 2009	5748	79
MAR 2009	6026	-84
APR 2009	6115	24
MAY 2009	6319	-75

It is good practice to look at a sequence plot of the errors.

Click **Analyze...Forecasting…Sequence charts**
Remove **Market_1** and add **NResidual_Market_1_Model_1** to the Variables box (not shown)
Click **Format**
Click **Reference line at mean of series** check box
Click **Continue**, and then click **OK**

The plot looks random. However, the errors appear to be getting larger with time.

Figure 4.11 Sequence Plot of Residuals

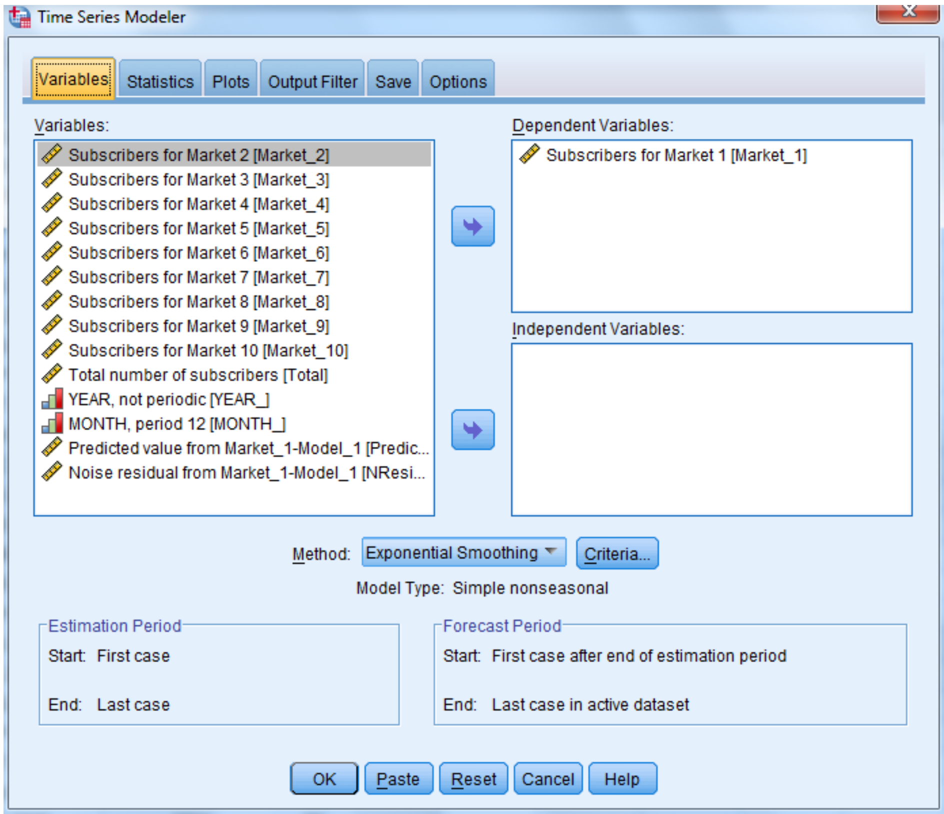


Creating a Custom Model

At times you may wish to specify a particular model with the Expert Modeler. In this section, we will ask the In this case we will rerun the analysis with a different model, and review the options available for exponential smoothing.

> Click **Analyze…Forecasting…Create Traditional Models**
> In the Variables tab, select **Exponential Smoothing** on the Method dropdown

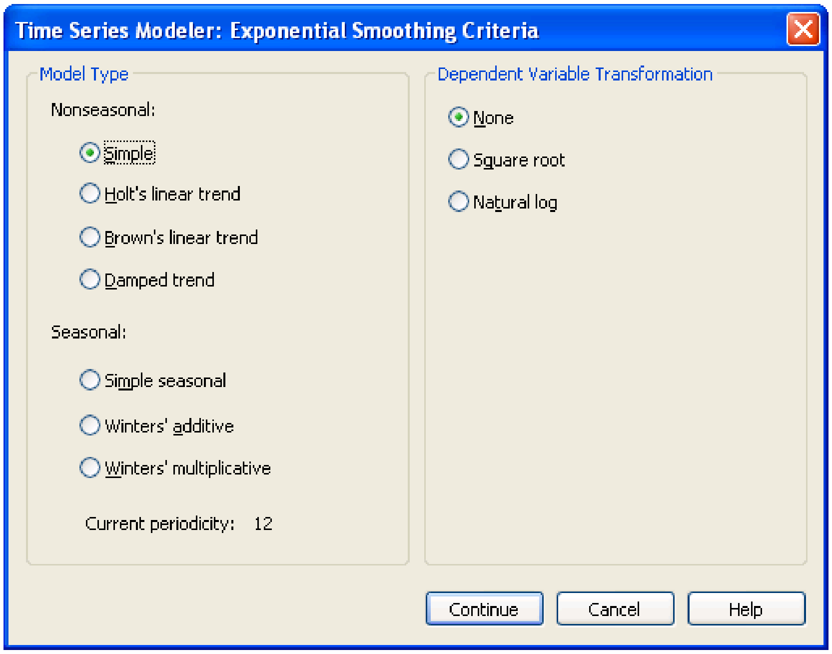
Figure 4.12 Main Dialog Box with Exponential Smoothing Selected



Click **Criteria** button

All seven of the exponential smoothing methods we reviewed earlier are listed. You can select one to estimate in each execution of the Expert Modeler.

Figure 4.13 Criteria Dialog Box



When we reviewed the sequence plot for *Market_1*, it appeared that there was a rate of change was decreasing over time. Let's see what happens if we include a model with a damped trend.

Select **Damped trend** option button

All our other selections can remain as is.

Click on **Continue**
Click on **OK**

The Model Description table confirms that a Damped trend model has been estimated.

Figure 4.14 Model Description Table

Model Description

			Model Type
Model ID	Subscribers for Market 1	Model_1	Damped Trend

Did we make the correct decision? For that we need to review the Model Parameters table.

Figure 4.15 Model Parameters

Exponential Smoothing Model Parameters

Model			Estimate	SE	t	Sig.
Subscribers for Market 1-Model_1	No Transformation	Alpha (Level)	.999	.146	6.838	.000
		Gamma (Trend)	.324	.163	1.985	.052
		Phi (Trend damping factor)	.973	.031	31.335	.000

The trend parameter (gamma) is nonsignificant.

The level coefficient is about the same, .999 (as compared to 1 in the previous model).

The model fit statistics are, on the whole, slightly worse than Holt's model. The stationary R square is lower, MAPE and MAE are worse (higher). Although these differences are small, you should normally choose the better-fitting model, all things being equal.

Figure 4.16 Statistics for Damped Model

Fit Statistic	Mean
Stationary R-squared	.067
R-squared	.999
RMSE	90.500
MAPE	.929
MaxAPE	2.101
MAE	72.685
MaxAE	209.633
Normalized BIC	9.215

We don't need to review the graphical output, given our findings.