# Chapter 85
## The ORTHOREG Procedure

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</tr>
</tbody>
</table>
Overview: ORTHOREG Procedure

The ORTHOREG procedure fits general linear models by the method of least squares. Other SAS/STAT software procedures, such as the GLM and REG procedures, fit the same types of models, but PROC ORTHOREG can produce more accurate estimates than other regression procedures when your data are ill-conditioned. Instead of collecting crossproducts, PROC ORTHOREG uses Gentleman-Givens transformations to update and compute the upper triangular matrix $R$ of the QR decomposition of the data matrix, with special care for scaling (Gentleman 1972, 1973). This method has the advantage over other orthogonalization methods (for example, Householder transformations) of not requiring the data matrix to be stored in memory.

The standard SAS regression procedures (PROC REG and PROC GLM) are very accurate for most problems. However, if you have very ill-conditioned data, these procedures can produce estimates that yield an error sum of squares very close to the minimum but still different from the exact least squares estimates. Normally, this coincides with estimates that have very high standard errors. In other words, the numerical error is much smaller than the statistical standard error.

PROC ORTHOREG fits models by the method of linear least squares, minimizing the sum of the squared residuals for predicting the responses—that is, the distance between the regression line and the observed $Y$s. The “ORTHO” in the name of the procedure refers to the orthogonalization approach to solving the least squares equations. In particular, PROC ORTHOREG does not perform the modeling method known as “orthogonal regression,” which minimizes a different criterion (namely, the distance between the regression line and the X/Y points taken together.)

Getting Started: ORTHOREG Procedure

Longley Data

The labor statistics data set of Longley (1967) is noted for being ill-conditioned. Both the ORTHOREG and GLM procedures are applied for comparison (only portions of the PROC GLM results are shown).

**NOTE:** The results from this example vary from machine to machine, depending on floating-point configuration.

The following statements read the data into the SAS data set Longley:

```
title 'PROC ORTHOREG used with Longley data';
data Longley;
   input Employment Prices GNP Jobless Military PopSize Year;
datalines;
60323   83.0  234289  2356  1590  107608  1947
61122   88.5  259426  2325  1456  108632  1948
60171   88.2  258054  3682  1616  109773  1949
61187   89.5  284599  3351  1650  110929  1950
```
The data set contains one dependent variable, Employment (total derived employment), and six independent variables: Prices (GNP implicit price deflator normalized to the value 100 in 1954), GNP (gross national product), Jobless (unemployment), Military (size of armed forces), PopSize (noninstitutional population aged 14 and over), and Year (year).

The following statements use the ORTHOREG procedure to model the Longley data by using a quadratic model in each independent variable, without interaction:

```sas
proc orthoreg data=Longley;
  model Employment = Prices Prices*Prices
                   GNP GNP*GNP
                   Jobless Jobless*Jobless
                   Military Military*Military
                   PopSize PopSize*PopSize
                   Year Year*Year;
run;
```

Figure 85.1 shows the resulting analysis.

**Figure 85.1 PROC ORTHOREG Results**

**PROC ORTHOREG used with Longley data**

**The ORTHOREG Procedure**

**Dependent Variable: Employment**

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>12</td>
<td>184864508.5</td>
<td>15405375.709</td>
<td>320.24</td>
<td>0.0003</td>
</tr>
<tr>
<td>Error</td>
<td>3</td>
<td>144317.49568</td>
<td>48105.831895</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corrected Total</td>
<td>15</td>
<td>185008826</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Root MSE 219.33041717
R-Square 0.9992199426
The estimates in Figure 85.1 compare very well with the best estimates available; for additional information, see Longley (1967) and Beaton, Rubin, and Barone (1976).

The following statements request the same analysis from the GLM procedure:

```plaintext
proc glm data=Longley;
  model Employment = Prices Prices*Prices
                    GNP GNP*GNP
                    Jobless Jobless*Jobless
                    Military Military*Military
                    PopSize PopSize*PopSize
                    Year Year*Year;
  ods select OverallANOVA
       FitStatistics
       ParameterEstimates
       Notes;
run;
```

Figure 85.2 contains the overall ANOVA table and the parameter estimates produced by PROC GLM. Notice that the PROC ORTHOREG fit achieves a somewhat smaller root mean square error (RMSE) and also that the GLM procedure detects spurious singularities.
Figure 85.2 Partial PROC GLM Results

PROC ORTHOREG used with Longley data

The GLM Procedure

Dependent Variable: Employment

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>11</td>
<td>184791061.6</td>
<td>16799187.4</td>
<td>308.58</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Error</td>
<td>4</td>
<td>217764.4</td>
<td>54441.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corrected Total</td>
<td>15</td>
<td>18508826.0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

R-Square Coeff Var Root MSE Employment Mean
0.998823 0.357221 233.3262 65317.00

| Parameter          | Estimate | Standard Error | t Value | Pr > |t| |
|--------------------|----------|----------------|---------|------|------|
| Intercept          | -3598851.899 B | 1327335.652 | -2.71  | 0.0535 |
| Prices             | 523.802   | 688.979       | 0.76   | 0.4894 |
| Prices*Prices      | -2.326    | 3.507         | -0.66  | 0.5434 |
| GNP                | -0.138    | 0.078         | -1.76  | 0.1526 |
| GNP*GNP            | 0.000     | 0.000         | 0.24   | 0.8218 |
| Jobless            | -4.599    | 1.459         | -3.15  | 0.0344 |
| Jobless*Jobless    | 0.000     | 0.000         | 1.14   | 0.3183 |
| Military           | 4.994     | 1.942         | 2.57   | 0.0619 |
| Military*Military  | -0.001    | 0.000         | -3.15  | 0.0346 |
| PopSize            | -4.246    | 5.156         | -0.82  | 0.4565 |
| PopSize*PopSize    | 0.000     | 0.000         | 0.81   | 0.4655 |
| Year               | 0.000     | 0.000         |       |      |
| Year*Year          | 1.038     | 0.419         | 2.48   | 0.0683 |

Note: The X’X matrix has been found to be singular, and a generalized inverse was used to solve the normal equations. Terms whose estimates are followed by the letter ‘B’ are not uniquely estimable.
Chapter 85: The ORTHOREG Procedure

Syntax: ORTHOREG Procedure

The following statements are available in the ORTHOREG procedure:

```
PROC ORTHOREG <options> ;
  CLASS variables </option> ;
  MODEL dependent-variable = independent-effects </option> ;
  BY variables ;
  EFFECT name = effect-type (variables </options> ) ;
  EFFECTPLOT <plot-type <(plot-definition-options)> </options> ;
  ESTIMATE 'label' estimate-specification </options> ;
  LSMEANS <model-effects </options> ;
  LSMESTIMATE model-effect lsmestimate-specification </options> ;
  SLICE model-effect </options> ;
  STORE <OUT= >item-store-name </LABEL='label' > ;
  TEST <model-effects </options> ;
  WEIGHT variable ;
```

The BY, CLASS, MODEL, and WEIGHT statements are described in full after the PROC ORTHOREG statement in alphabetical order. The EFFECT, EFFECTPLOT, ESTIMATE, LSMEANS, LSMESTIMATE, SLICE, STORE, and TEST statements are common to many procedures. Summary descriptions of functionality and syntax for these statements are also given after the PROC ORTHOREG statement in alphabetical order, and full documentation about them is available in Chapter 19, “Shared Concepts and Topics.”

PROC ORTHOREG Statement

```PROC ORTHOREG <options> ;
```

The PROC ORTHOREG statement invokes the ORTHOREG procedure. Table 85.1 summarizes the options available in the PROC ORTHOREG statement.

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DATA=</td>
<td>Specifies the input SAS data set</td>
</tr>
<tr>
<td>NOPRINT</td>
<td>Suppresses the normal display of results</td>
</tr>
<tr>
<td>ORDER=</td>
<td>Specifies the order in which to sort class levels</td>
</tr>
<tr>
<td>OUTTEST=</td>
<td>Produces an output data set</td>
</tr>
<tr>
<td>SINGULAR=</td>
<td>Specifies the singularity criterion</td>
</tr>
</tbody>
</table>

Table 85.1  PROC ORTHOREG Statement Options

The PROC ORTHOREG statement has the following options:

- **DATA=SAS-data-set**
  - specifies the input SAS data set to use. By default, the procedure uses the most recently created SAS data set. The data set specified cannot be a TYPE=CORR, TYPE=COV, or TYPE=SSCP data set.
NOPRINT suppresses the normal display of results. This option temporarily disables the Output Delivery System (ODS); for more information, see Chapter 20, “Using the Output Delivery System.”

ORDER=DATA | FORMATTED | FREQ | INTERNAL

specifies the sort order for the levels of the classification variables (which are specified in the CLASS statement).

This ordering determines which parameters in the model correspond to each level in the data, so the ORDER= option may be useful when you use ESTIMATE statement. This option applies to the levels for all classification variables, except when you use the (default) ORDER=FORMATTED option with numeric classification variables that have no explicit format. In that case, the levels of such variables are ordered by their internal value.

The ORDER= option can take the following values:

<table>
<thead>
<tr>
<th>Value of ORDER=</th>
<th>Levels Sorted By</th>
</tr>
</thead>
<tbody>
<tr>
<td>DATA</td>
<td>Order of appearance in the input data set</td>
</tr>
<tr>
<td>FORMATTED</td>
<td>External formatted value, except for numeric variables with no explicit format, which are sorted by their unformatted (internal) value</td>
</tr>
<tr>
<td>FREQ</td>
<td>Descending frequency count; levels with the most observations come first in the order</td>
</tr>
<tr>
<td>INTERNAL</td>
<td>Unformatted value</td>
</tr>
</tbody>
</table>

By default, ORDER=FORMATTED. For ORDER=FORMATTED and ORDER=INTERNAL, the sort order is machine-dependent.

For more information about sort order, see the chapter on the SORT procedure in the Base SAS Procedures Guide and the discussion of BY-group processing in SAS Language Reference: Concepts.

OUTEST=SAS-data-set produces an output data set that contains the parameter estimates, the BY variables, and the special variables _TYPE_ (value “PARMS”), _NAME_ (blank), and _RMSE_ (root mean squared error).

SINGULAR=s specifies a singularity criterion ($s \geq 0$) for the inversion of the triangular matrix $R$. By default, SINGULAR=1E-12.

BY Statement

BY variables ;

You can specify a BY statement with PROC ORTHOREG to obtain separate analyses of observations in groups that are defined by the BY variables. When a BY statement appears, the procedure expects the input
data set to be sorted in order of the BY variables. If you specify more than one BY statement, only the last one specified is used.

If your input data set is not sorted in ascending order, use one of the following alternatives:

- Sort the data by using the SORT procedure with a similar BY statement.
- Specify the NOTSORTED or DESCENDING option in the BY statement for the ORTHOREG procedure. The NOTSORTED option does not mean that the data are unsorted but rather that the data are arranged in groups (according to values of the BY variables) and that these groups are not necessarily in alphabetical or increasing numeric order.
- Create an index on the BY variables by using the DATASETS procedure (in Base SAS software).

For more information about BY-group processing, see the discussion in *SAS Language Reference: Concepts*. For more information about the DATASETS procedure, see the discussion in the *Base SAS Procedures Guide*.

---

**CLASS Statement**

```
CLASS variable <(REF= option)> . . . <variable <(REF= option) >> </global-options> ;
```

The CLASS statement names the classification variables to be used in the model. Typical classification variables are Treatment, Sex, Race, Group, and Replication. If you use the CLASS statement, it must appear before the MODEL statement.

Classification variables can be either character or numeric. By default, class levels are determined from the entire set of formatted values of the CLASS variables.

**NOTE:** Prior to SAS 9, class levels were determined by using no more than the first 16 characters of the formatted values. To revert to this previous behavior, you can use the TRUNCATE option in the CLASS statement.

In any case, you can use formats to group values into levels. See the discussion of the FORMAT procedure in the *Base SAS Procedures Guide* and the discussions of the FORMAT statement and SAS formats in *SAS Formats and Informats: Reference*. You can adjust the order of CLASS variable levels with the ORDER= option in the PROC ORTHOREG statement.

You can specify the following REF= option to indicate how the levels of an individual classification variable are to be ordered by enclosing it in parentheses after the variable name:

**REF= 'level' | FIRST | LAST**

specifies a level of the classification variable to be put at the end of the list of levels. This level thus corresponds to the reference level in the usual interpretation of the estimates with PROC ORTHOREG’s singular parameterization. You can specify the level of the variable to use as the reference level; specify a value that corresponds to the formatted value of the variable if a format is assigned. Alternatively, you can specify REF=FIRST to designate that the first ordered level serve as the reference, or REF=LAST to designate that the last ordered level serve as the reference. To specify that REF=FIRST or REF=LAST be used for all classification variables, use the REF= global-option after the slash (/) in the CLASS statement.

You can specify the following global-options in the CLASS statement after a slash (/):
**EFFECT** Statement

**EFFECT** statement enables you to construct special collections of columns for design matrices. These collections are referred to as *constructed effects* to distinguish them from the usual model effects that are formed from continuous or classification variables, as discussed in the section “GLM Parameterization of Classification Variables and Effects” on page 385 in Chapter 19, “Shared Concepts and Topics.”

You can specify the following **effect-types**:

- **COLLECTION** specifies a collection effect that defines one or more variables as a single effect with multiple degrees of freedom. The variables in a collection are considered as a unit for estimation and inference.

- **LAG** specifies a classification effect in which the level that is used for a particular period corresponds to the level in the preceding period.

- **MULTIMEMBER | MM** specifies a multimember classification effect whose levels are determined by one or more variables that appear in a CLASS statement.

- **POLYNOMIAL | POLY** specifies a multivariate polynomial effect in the specified numeric variables.

- **SPLINE** specifies a regression spline effect whose columns are univariate spline expansions of one or more variables. A spline expansion replaces the original variable with an expanded or larger set of new variables.

Table 85.2 summarizes the **options** available in the EFFECT statement.

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Collection Effects Options</strong></td>
<td></td>
</tr>
<tr>
<td>DETAILS</td>
<td>Displays the constituents of the collection effect</td>
</tr>
<tr>
<td>Option</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>-------------</td>
</tr>
<tr>
<td><strong>Lag Effects Options</strong></td>
<td></td>
</tr>
<tr>
<td>DESIGNROLE=</td>
<td>Names a variable that controls to which lag design an observation is assigned</td>
</tr>
<tr>
<td>DETAILS</td>
<td>Displays the lag design of the lag effect</td>
</tr>
<tr>
<td>NLAG=</td>
<td>Specifies the number of periods in the lag</td>
</tr>
<tr>
<td>PERIOD=</td>
<td>Names the variable that defines the period. This option is required.</td>
</tr>
<tr>
<td>WITHIN=</td>
<td>Names the variable or variables that define the group within which each period is defined. This option is required.</td>
</tr>
<tr>
<td><strong>Multimember Effects Options</strong></td>
<td></td>
</tr>
<tr>
<td>NOEFFECT</td>
<td>Specifies that observations with all missing levels for the multimember variables should have zero values in the corresponding design matrix columns</td>
</tr>
<tr>
<td>WEIGHT=</td>
<td>Specifies the weight variable for the contributions of each of the classification effects</td>
</tr>
<tr>
<td><strong>Polynomial Effects Options</strong></td>
<td></td>
</tr>
<tr>
<td>DEGREE=</td>
<td>Specifies the degree of the polynomial</td>
</tr>
<tr>
<td>MDEGREE=</td>
<td>Specifies the maximum degree of any variable in a term of the polynomial</td>
</tr>
<tr>
<td>STANDARDIZE=</td>
<td>Specifies centering and scaling suboptions for the variables that define the polynomial</td>
</tr>
<tr>
<td><strong>Spline Effects Options</strong></td>
<td></td>
</tr>
<tr>
<td>BASIS=</td>
<td>Specifies the type of basis (B-spline basis or truncated power function basis) for the spline effect</td>
</tr>
<tr>
<td>DEGREE=</td>
<td>Specifies the degree of the spline effect</td>
</tr>
<tr>
<td>KNOTMETHOD=</td>
<td>Specifies how to construct the knots for the spline effect</td>
</tr>
</tbody>
</table>

For more information about the syntax of these `effect-types` and how columns of constructed effects are computed, see the section “EFFECT Statement” on page 395 in Chapter 19, “Shared Concepts and Topics.”
EFFECTPLOT Statement

\texttt{EFFECTPLOT < \textit{plot-type} < (\textit{plot-definition-options}) > > < / \textit{options} > ;}

The EFFECTPLOT statement produces a display of the fitted model and provides options for changing and enhancing the displays. Table 85.3 describes the available \textit{plot-types} and their \textit{plot-definition-options}.

\begin{table}[h]
\centering
\begin{tabular}{|l|l|}
\hline
\textbf{Plot-Type and Description} & \textbf{Plot-Definition-Options} \\
\hline
\textbf{BOX} & \text{PLOTBY= variable or CLASS effect} \\
 & \text{X= CLASS variable or effect} \\
Displays a box plot of continuous response data at each level of a CLASS effect, with predicted values superimposed and connected by a line. This is an alternative to the INTERACTION \textit{plot-type}. & \\
\textbf{CONTOUR} & \text{PLOTBY= variable or CLASS effect} \\
 & \text{X= continuous variable} \\
 & \text{Y= continuous variable} \\
Displays a contour plot of predicted values against two continuous covariates. & \\
\textbf{FIT} & \text{PLOTBY= variable or CLASS effect} \\
 & \text{X= continuous variable} \\
Displays a curve of predicted values versus a continuous variable. & \\
\textbf{INTERACTION} & \text{PLOTBY= variable or CLASS effect} \\
 & \text{SLICEBY= variable or CLASS effect} \\
 & \text{X= CLASS variable or effect} \\
Displays a plot of predicted values (possibly with error bars) versus the levels of a CLASS effect. The predicted values are connected with lines and can be grouped by the levels of another CLASS effect. & \\
\textbf{MOSAIC} & \text{PLOTBY= variable or CLASS effect} \\
 & \text{X= CLASS effects} \\
Displays a mosaic plot of predicted values using up to three CLASS effects. & \\
\textbf{SLICEFIT} & \text{PLOTBY= variable or CLASS effect} \\
 & \text{SLICEBY= variable or CLASS effect} \\
 & \text{X= continuous variable} \\
Displays a curve of predicted values versus a continuous variable grouped by the levels of a CLASS effect. & \\
\hline
\end{tabular}
\end{table}

For full details about the syntax and options of the EFFECTPLOT statement, see the section “EFFECTPLOT Statement” on page 414 in Chapter 19, “Shared Concepts and Topics.”
The ESTIMATE statement provides a mechanism for obtaining custom hypothesis tests. Estimates are formed as linear estimable functions of the form $L\hat{\beta}$. You can perform hypothesis tests for the estimable functions, construct confidence limits, and obtain specific nonlinear transformations.

Table 85.4 summarizes the options available in the ESTIMATE statement.

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Construction and Computation of Estimable Functions</strong></td>
<td></td>
</tr>
<tr>
<td>DIVISOR=</td>
<td>Specifies a list of values to divide the coefficients</td>
</tr>
<tr>
<td>NOFILL</td>
<td>Suppresses the automatic fill-in of coefficients for higher-order effects</td>
</tr>
<tr>
<td>SINGULAR=</td>
<td>Tunes the estimability checking difference</td>
</tr>
<tr>
<td><strong>Degrees of Freedom and $p$-values</strong></td>
<td></td>
</tr>
<tr>
<td>ADJUST=</td>
<td>Determines the method for multiple comparison adjustment of estimates</td>
</tr>
<tr>
<td>ALPHA=$\alpha$</td>
<td>Determines the confidence level $(1 - \alpha)$</td>
</tr>
<tr>
<td>LOWER</td>
<td>Performs one-sided, lower-tailed inference</td>
</tr>
<tr>
<td>STEPDOWN</td>
<td>Adjusts multiplicity-corrected $p$-values further in a step-down fashion</td>
</tr>
<tr>
<td>TESTVALUE=</td>
<td>Specifies values under the null hypothesis for tests</td>
</tr>
<tr>
<td>UPPER</td>
<td>Performs one-sided, upper-tailed inference</td>
</tr>
<tr>
<td><strong>Statistical Output</strong></td>
<td></td>
</tr>
<tr>
<td>CL</td>
<td>Constructs confidence limits</td>
</tr>
<tr>
<td>CORR</td>
<td>Displays the correlation matrix of estimates</td>
</tr>
<tr>
<td>COV</td>
<td>Displays the covariance matrix of estimates</td>
</tr>
<tr>
<td>E</td>
<td>Prints the $L$ matrix</td>
</tr>
<tr>
<td>JOINT</td>
<td>Produces a joint $F$ or chi-square test for the estimable functions</td>
</tr>
<tr>
<td>PLOTS=</td>
<td>Requests ODS statistical graphics if the analysis is sampling-based</td>
</tr>
<tr>
<td>SEED=</td>
<td>Specifies the seed for computations that depend on random numbers</td>
</tr>
<tr>
<td><strong>Generalized Linear Modeling</strong></td>
<td></td>
</tr>
<tr>
<td>CATEGORY=</td>
<td>Specifies how to construct estimable functions with multinomial data</td>
</tr>
<tr>
<td>EXP</td>
<td>Exponentiates and displays estimates</td>
</tr>
<tr>
<td>ILINK</td>
<td>Computes and displays estimates and standard errors on the inverse linked scale</td>
</tr>
</tbody>
</table>
LSMEANS Statement

The LSMEANS statement computes and compares least squares means (LS-means) of fixed effects. LS-means are predicted population margins—that is, they estimate the marginal means over a balanced population. In a sense, LS-means are to unbalanced designs as class and subclass arithmetic means are to balanced designs.

Table 85.5 summarizes the options available in the LSMEANS statement.

Table 85.5  LSMEANS Statement Options

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Construction and Computation of LS-Means</strong></td>
<td></td>
</tr>
<tr>
<td>AT</td>
<td>Modifies the covariate value in computing LS-means</td>
</tr>
<tr>
<td>BYLEVEL</td>
<td>Computes separate margins</td>
</tr>
<tr>
<td>DIFF</td>
<td>Requests differences of LS-means</td>
</tr>
<tr>
<td>OM=</td>
<td>Specifies the weighting scheme for LS-means computation as determined by the input data set</td>
</tr>
<tr>
<td>SINGULAR=</td>
<td>Tunes estimability checking</td>
</tr>
<tr>
<td><strong>Degrees of Freedom and p-values</strong></td>
<td></td>
</tr>
<tr>
<td>ADJUST=</td>
<td>Determines the method for multiple-comparison adjustment of LS-means differences</td>
</tr>
<tr>
<td>ALPHA=α</td>
<td>Determines the confidence level (1 − α)</td>
</tr>
<tr>
<td>STEPDOWN</td>
<td>Adjusts multiple-comparison p-values further in a step-down fashion</td>
</tr>
<tr>
<td><strong>Statistical Output</strong></td>
<td></td>
</tr>
<tr>
<td>CL</td>
<td>Constructs confidence limits for means and mean differences</td>
</tr>
<tr>
<td>CORR</td>
<td>Displays the correlation matrix of LS-means</td>
</tr>
<tr>
<td>COV</td>
<td>Displays the covariance matrix of LS-means</td>
</tr>
<tr>
<td>E</td>
<td>Prints the L matrix</td>
</tr>
<tr>
<td>LINES</td>
<td>Produces a “Lines” display for pairwise LS-means differences</td>
</tr>
<tr>
<td>MEANS</td>
<td>Prints the LS-means</td>
</tr>
<tr>
<td>PLOTS=</td>
<td>Requests graphs of means and mean comparisons</td>
</tr>
<tr>
<td>SEED=</td>
<td>Specifies the seed for computations that depend on random numbers</td>
</tr>
<tr>
<td><strong>Generalized Linear Modeling</strong></td>
<td></td>
</tr>
<tr>
<td>EXP</td>
<td>Exponentiates and displays estimates of LS-means or LS-means differences</td>
</tr>
<tr>
<td>ILINK</td>
<td>Computes and displays estimates and standard errors of LS-means (but not differences) on the inverse linked scale</td>
</tr>
</tbody>
</table>
Table 85.5 continued

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ODDSRATIO</td>
<td>Reports (simple) differences of least squares means in terms of odds ratios if permitted by the link function</td>
</tr>
</tbody>
</table>

For details about the syntax of the LSMEANS statement, see the section “LSMEANS Statement” on page 458 in Chapter 19, “Shared Concepts and Topics.”

**LSMESTIMATE Statement**

```
LSMESTIMATE model-effect < 'label' > values < divisor=n >
<, . . .< 'label' > values < divisor=n >>
</options> ;
```

The LSMESTIMATE statement provides a mechanism for obtaining custom hypothesis tests among least squares means.

Table 85.6 summarizes the options available in the LSMESTIMATE statement.

**Table 85.6 LSMESTIMATE Statement Options**

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Construction and Computation of LS-Means</strong></td>
<td></td>
</tr>
<tr>
<td>AT</td>
<td>Modifies covariate values in computing LS-means</td>
</tr>
<tr>
<td>BYLEVEL</td>
<td>Computes separate margins</td>
</tr>
<tr>
<td>DIVISOR=</td>
<td>Specifies a list of values to divide the coefficients</td>
</tr>
<tr>
<td>OM=</td>
<td>Specifies the weighting scheme for LS-means computation as determined by a data set</td>
</tr>
<tr>
<td>SINGULAR=</td>
<td>Tunes estimability checking</td>
</tr>
<tr>
<td><strong>Degrees of Freedom and p-values</strong></td>
<td></td>
</tr>
<tr>
<td>ADJUST=</td>
<td>Determines the method for multiple-comparison adjustment of LS-means differences</td>
</tr>
<tr>
<td>ALPHA=α</td>
<td>Determines the confidence level ((1 - α))</td>
</tr>
<tr>
<td>LOWER</td>
<td>Performs one-sided, lower-tailed inference</td>
</tr>
<tr>
<td>STEPDOWN</td>
<td>Adjusts multiple-comparison (p)-values further in a step-down fashion</td>
</tr>
<tr>
<td>TESTVALUE=</td>
<td>Specifies values under the null hypothesis for tests</td>
</tr>
<tr>
<td>UPPER</td>
<td>Performs one-sided, upper-tailed inference</td>
</tr>
<tr>
<td><strong>Statistical Output</strong></td>
<td></td>
</tr>
<tr>
<td>CL</td>
<td>Constructs confidence limits for means and mean differences</td>
</tr>
<tr>
<td>CORR</td>
<td>Displays the correlation matrix of LS-means</td>
</tr>
<tr>
<td>COV</td>
<td>Displays the covariance matrix of LS-means</td>
</tr>
</tbody>
</table>
### Table 85.6  continued

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>Prints the L matrix</td>
</tr>
<tr>
<td>ELSM</td>
<td>Prints the K matrix</td>
</tr>
<tr>
<td>JOINT</td>
<td>Produces a joint F or chi-square test for the LS-means and LS-means differences</td>
</tr>
<tr>
<td>PLOTS=</td>
<td>Requests graphs of means and mean comparisons</td>
</tr>
<tr>
<td>SEED=</td>
<td>Specifies the seed for computations that depend on random numbers</td>
</tr>
</tbody>
</table>

#### Generalized Linear Modeling
- **CATEGORY=** Specifies how to construct estimable functions with multinomial data
- **EXP** Exponentiates and displays LS-means estimates
- **ILINK** Computes and displays estimates and standard errors of LS-means (but not differences) on the inverse linked scale

For details about the syntax of the LSMESTIMATE statement, see the section “LSMESTIMATE Statement” on page 477 in Chapter 19, “Shared Concepts and Topics.”

### MODEL Statement

**MODEL**  
`MODEL dependent-variable = independent-effects < / option> ;`

The MODEL statement names the dependent variable and the independent effects. Only one MODEL statement is allowed. The specification of effects and the parameterization of the linear model are the same as in the GLM procedure; for more information, see Chapter 47, “The GLM Procedure.”

The following **option** can be used in the MODEL statement:

- **NOINT** omits the intercept term from the model. Often, this omission also changes the total sum of squares in the ANOVA and the value of R square to forms of these statistics that are not corrected for the mean. However, if the model is determined to contain an implicit intercept, in the sense that the all-ones intercept vector is in the column space of the design, then the usual mean-corrected forms of these statistics are used.

### SLICE Statement

**SLICE**  
`SLICE model-effect < / options> ;`

The SLICE statement provides a general mechanism for performing a partitioned analysis of the LS-means for an interaction. This analysis is also known as an analysis of simple effects.
The SLICE statement uses the same options as the LSMEANS statement, which are summarized in Table 19.21. For details about the syntax of the SLICE statement, see the section “SLICE Statement” on page 506 in Chapter 19, “Shared Concepts and Topics.”

---

**STORE Statement**

```julia
STORE <OUT=>item-store-name < / LABEL='label' > ;
```

The STORE statement requests that the procedure save the context and results of the statistical analysis. The resulting item store has a binary file format that cannot be modified. The contents of the item store can be processed with the PLM procedure. For details about the syntax of the STORE statement, see the section “STORE Statement” on page 509 in Chapter 19, “Shared Concepts and Topics.”

---

**TEST Statement**

```julia
TEST <model-effects> < / options > ;
```

The TEST statement enables you to perform F tests for model effects that test Type I, Type II, or Type III hypotheses. See Chapter 15, “The Four Types of Estimable Functions,” for details about the construction of Type I, II, and III estimable functions.

Table 85.7 summarizes the options available in the TEST statement.

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CHISQ</td>
<td>Requests chi-square tests</td>
</tr>
<tr>
<td>DDF=</td>
<td>Specifies denominator degrees of freedom for fixed effects</td>
</tr>
<tr>
<td>E</td>
<td>Requests Type I, Type II, and Type III coefficients</td>
</tr>
<tr>
<td>E1</td>
<td>Requests Type I coefficients</td>
</tr>
<tr>
<td>E2</td>
<td>Requests Type II coefficients</td>
</tr>
<tr>
<td>E3</td>
<td>Requests Type III coefficients</td>
</tr>
<tr>
<td>HTYPE=</td>
<td>Indicates the type of hypothesis test to perform</td>
</tr>
<tr>
<td>INTERCEPT</td>
<td>Adds a row that corresponds to the overall intercept</td>
</tr>
</tbody>
</table>

For details about the syntax of the TEST statement, see the section “TEST Statement” on page 510 in Chapter 19, “Shared Concepts and Topics.”

---

**WEIGHT Statement**

```julia
WEIGHT variable ;
```

A WEIGHT statement names a variable in the input data set whose values are relative weights for a weighted least squares regression. If the weight value is proportional to the reciprocal of the variance for each observation, the weighted estimates are the best linear unbiased estimates (BLUE). For a more complete
description of the WEIGHT statement, see the section “WEIGHT Statement” on page 3669 in Chapter 47, “The GLM Procedure.”

**Details: ORTHOREG Procedure**

**Missing Values**

If there is a missing value for any model variable in an observation, the entire observation is dropped from the analysis.

**Output Data Set**

The OUTEST= option produces a TYPE=EST output SAS data set that contains the BY variables, parameter estimates, and four special variables. For each new value of the BY variables, PROC ORTHOREG outputs an observation to the OUTEST= data set. The variables in the data set are as follows:

- parameter estimates for all variables listed in the MODEL statement
- BY variables
- _TYPE_, which is a character variable with the value PARMS for every observation
- _NAME_, which is a character variable left blank for every observation
- _RMSE_, which is the root mean square error (the estimate of the standard deviation of the true errors)
- Intercept, which is the estimated intercept. This variable does not exist in the OUTEST= data set if the NOINT option is specified.

**Displayed Output**

PROC ORTHOREG displays the parameter estimates and associated statistics. These include the following:

- overall model analysis of variance, including the error mean square, which is an estimate of $\sigma^2$ (the variance of the true errors), and the overall $F$ test for a model effect.
- root mean square error, which is an estimate of the standard deviation of the true errors. It is calculated as the square root of the mean squared error.
- R square ($R^2$) measures how much variation in the dependent variable can be accounted for by the model. R square, which can range from 0 to 1, is the ratio of the sum of squares for the model to the corrected total sum of squares. In general, the larger the value of R square, the better the model’s fit.
- estimates for the parameters in the linear model
The table of parameter estimates consists of the following:

- the terms used as regressors, including the intercept.
- degrees of freedom (DF) for the variable. There is one degree of freedom for each parameter being estimated unless the model is not full rank.
- estimated linear coefficients.
- estimates of the standard errors of the parameter estimates.
- the critical $t$ values for testing whether the parameters are 0.
- the two-sided $p$-value for the $t$ test, which is the probability that a $t$ statistic would obtain a greater absolute value than that observed given that the true parameter is zero.

**ODS Table Names**

PROC ORTHOREG assigns a name to each table it creates. You can use these names to reference the table when you use the Output Delivery System (ODS) to select tables and create output data sets. These names are listed in Table 85.8. For more information about ODS, see Chapter 20, “Using the Output Delivery System.”

Each of the EFFECT, ESTIMATE, LSMEANS, LSMESTIMATE, and SLICE statements also creates tables, which are not listed in Table 85.8. For information about these tables, see the corresponding sections of Chapter 19, “Shared Concepts and Topics.”

<table>
<thead>
<tr>
<th>ODS Table Name</th>
<th>Description</th>
<th>Statement</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANOVA</td>
<td>Analysis of variance</td>
<td>Default</td>
</tr>
<tr>
<td>FitStatistics</td>
<td>Overall statistics for fit</td>
<td>Default</td>
</tr>
<tr>
<td>Levels</td>
<td>Table of class levels</td>
<td>CLASS</td>
</tr>
<tr>
<td>ParameterEstimates</td>
<td>Parameter estimates</td>
<td>Default</td>
</tr>
</tbody>
</table>

**ODS Graphics**

Statistical procedures use ODS Graphics to create graphs as part of their output. ODS Graphics is described in detail in Chapter 21, “Statistical Graphics Using ODS.”

Before you create graphs, ODS Graphics must be enabled (for example, by specifying the ODS GRAPHICS ON statement). For more information about enabling and disabling ODS Graphics, see the section “Enabling and Disabling ODS Graphics” on page 607 in Chapter 21, “Statistical Graphics Using ODS.”

The overall appearance of graphs is controlled by ODS styles. Styles and other aspects of using ODS Graphics are discussed in the section “A Primer on ODS Statistical Graphics” on page 606 in Chapter 21, “Statistical Graphics Using ODS.”
When ODS Graphics is enabled, then each of the EFFECT, ESTIMATE, LSMEANS, LSMESTIMATE, and SLICE statements can produce plots associated with their analyses. For information about these plots, see the corresponding sections of Chapter 19, “Shared Concepts and Topics.”

Example 85.1: Precise Analysis of Variance

The data for the following example are from Powell, Murphy, and Gramlich (1982). In order to calibrate an instrument for measuring atomic weight, 24 replicate measurements of the atomic weight of silver (chemical symbol Ag) are made with the new instrument and with a reference instrument.

Note: The results from this example vary from machine to machine, depending on floating-point configuration.

The following statements read the measurements for the two instruments into the SAS data set AgWeight:

```sas
/* Atomic Weight of Silver by Two Different Instruments */
data AgWeight;
  input Instrument AgWeight @@;
datalines;
1 107.8681568 1 107.8681465 1 107.8681572 1 107.8681785
1 107.8681446 1 107.8681903 1 107.8681526 1 107.8681494
1 107.8681616 1 107.8681587 1 107.8681519 1 107.8681486
1 107.8681419 1 107.8681569 1 107.8681508 1 107.8681672
1 107.8681385 1 107.8681518 1 107.8681662 1 107.8681424
1 107.8681360 1 107.8681333 1 107.8681610 1 107.8681477
2 107.8681079 2 107.8681344 2 107.8681513 2 107.8681197
2 107.8681604 2 107.8681385 2 107.8681642 2 107.8681365
2 107.8681151 2 107.8681082 2 107.8681517 2 107.8681448
2 107.8681198 2 107.8681482 2 107.8681334 2 107.8681609
2 107.8681101 2 107.8681512 2 107.8681469 2 107.8681360
2 107.8681254 2 107.8681261 2 107.8681450 2 107.8681368
;```

Notice that the variation in the atomic weight measurements is several orders of magnitude less than their mean. This is a situation that can be difficult for standard, regression-based analysis-of-variance procedures to handle correctly.

The following statements invoke the ORTHOREG procedure to perform a simple one-way analysis of variance, testing for differences between the two instruments:

```sas
proc orthoreg data=AgWeight;
  class Instrument;
  model AgWeight = Instrument;
run;
```

Output 85.1.1 shows the resulting analysis.
The mean difference between instruments is about $1.74 \times 10^{-5}$ (the value of the $(\text{Instrument}='1')$ parameter in the parameter estimates table), whereas the level of background variation in the measurements is about $1.51 \times 10^{-5}$ (the value of the root mean square error). At this level of error, the difference is significant, with a $p$-value of 0.0002.

The National Institute of Standards and Technology (1998) has provided certified ANOVA values for this data set. The following statements use ODS to examine the ANOVA values produced by ORTHOREG more precisely, for comparison with the NIST-certified values:

```plaintext
ods listing close;
proc orthoreg data=AgWeight;
  class Instrument;
  model AgWeight = Instrument;
  ods output ANOVA = OrthoregANOVA
                   FitStatistics = OrthoregFitStat;
run;
ods listing;
```
data _null_;  
set OrthoregANOVA (in=inANOVA)  
 OrthoregFitStat(in=inFitStat);  
if (inANOVA) then do;  
if (Source = 'Model') then put "Model SS: " ss e20.;  
if (Source = 'Error') then put "Error SS: " ss e20.;  
end;  
if (inFitStat) then do;  
if (Statistic = 'Root MSE') then  
 put "Root MSE: " nValue1 e20.;  
if (Statistic = 'R-Square') then  
 put "R-Square: " nValue1 best20.;  
end;  
run;  

Table 85.9 and Table 85.10 compare the ANOVA values certified by NIST with those produced by ORTHOREG. As you can see, the agreement is quite good.

Table 85.9  Accuracy Comparison for Sums of Squares

<table>
<thead>
<tr>
<th>Values</th>
<th>Model SS</th>
<th>Error SS</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIST-certified</td>
<td>3.6383418750000E–09</td>
<td>1.0495172916667E–08</td>
</tr>
<tr>
<td>ORTHOREG</td>
<td>3.6383418747907E–09</td>
<td>1.0495172916797E–08</td>
</tr>
</tbody>
</table>

Table 85.10  Accuracy Comparison for Fit Statistics

<table>
<thead>
<tr>
<th>Values</th>
<th>Root MSE</th>
<th>R Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIST-certified</td>
<td>1.5104831444641E–05</td>
<td>0.25742654453832</td>
</tr>
<tr>
<td>ORTHOREG</td>
<td>1.5104831444735E–05</td>
<td>0.25742654452494</td>
</tr>
</tbody>
</table>

Example 85.2: Wampler Data

This example applies the ORTHOREG procedure to a collection of data sets noted for being ill-conditioned. The OUTEST= data set is used to collect the results for comparison with values certified to be correct by the National Institute of Standards and Technology (1998).

NOTE: The results from this example vary from machine to machine, depending on floating-point configuration.
The data are from Wampler (1970). The independent variates for all five data sets are \( x^i, i = 1, \ldots, 5 \), for \( x = 0, 1, \ldots, 20 \). Two of the five dependent variables are exact linear functions of the independent terms:

\[
\begin{align*}
y_1 &= 1 + x + x^2 + x^3 + x^4 + x^5 \\
y_2 &= 1 + 0.1x + 0.01x^2 + 0.001x^3 + 0.0001x^4 + 0.00001x^5
\end{align*}
\]

The other three dependent variables have the same mean value as \( y_1 \), but with nonzero errors:

\[
\begin{align*}
y_3 &= y_1 + e \\
y_4 &= y_1 + 100e \\
y_5 &= y_1 + 10000e
\end{align*}
\]

where \( e \) is a vector of values with standard deviation ~2044, chosen to be orthogonal to the mean model for \( y_1 \).

The following statements create a SAS data set Wampler that contains the Wampler data, run a SAS macro program that uses PROC ORTHOREG to fit a fifth-order polynomial in \( x \) to each of the Wampler dependent variables, and collect the results in a data set named ParmEst:

```sas
data Wampler;
  do x=0 to 20;
    input e @@;
    y1 = 1 + x + x**2 + x**3 + x**4 + x**5;
    y2 = 1 + .1 *x + .01 *x**2 + .001*x**3 + .0001*x**4 + .00001*x**5;
    y3 = y1 + e;
    y4 = y1 + 100*e;
    y5 = y1 + 10000*e;
    output;
  end;
datalines;
759 -2048 2048 -2048 2523 -2048 2048 -2048 1838 -2048 2048 -2048 2048 -2048 1838 -2048 2048 -2048 2523 -2048 2048 -2048 759
;
%macro WTest;
  data ParmEst; if (0); run;
  %do i = 1 %to 5;
    proc orthoreg data=Wampler outest=ParmEst&i noprint;
      model y&i = x x*x x*x*x x*x*x*x x*x*x*x*x;
      data ParmEst&i; set ParmEst&i; Dep = "y&i";
      data ParmEst; set ParmEst ParmEst&i;
      label Col1='x' Col2='x**2' Col3='x**3' Col4='x**4' Col5='x**5';
    run;
  %end;
%mend;
%WTest;
```
Instead of displaying the raw values of the RMSE and parameter estimates, use an additional DATA step as follows to compute the deviations from the values certified to be correct by the National Institute of Standards and Technology (1998):

```sas
data ParmEst; set ParmEst;
  if (Dep = 'y1') then
    _RMSE_ = _RMSE_ - 0.00000000000000000000;
  else if (Dep = 'y2') then
    _RMSE_ = _RMSE_ - 0.00000000000000000000;
  else if (Dep = 'y3') then
    _RMSE_ = _RMSE_ - 2360.14502379268;
  else if (Dep = 'y4') then
    _RMSE_ = _RMSE_ - 236014.502379268;
  else if (Dep = 'y5') then
    _RMSE_ = _RMSE_ - 23601450.2379268;
  if (Dep ^= 'y2') then do;
    Intercept = Intercept - 1.00000000000000000000;
    Col1 = Col1 - 1.00000000000000000000;
    Col2 = Col2 - 1.00000000000000000000;
    Col3 = Col3 - 1.00000000000000000000;
    Col4 = Col4 - 1.00000000000000000000;
    Col5 = Col5 - 1.00000000000000000000;
  end;
  else do;
    Intercept = Intercept - 1.00000000000000000000;
    Col1 = Col1 - 0.10000000000000000000;
    Col2 = Col2 - 0.10000000000000000000e-1;
    Col3 = Col3 - 0.10000000000000000000e-2;
    Col4 = Col4 - 0.10000000000000000000e-3;
    Col5 = Col5 - 0.10000000000000000000e-4;
  end;
run;
```

```sas
proc print data=ParmEst label noobs;
  title 'Wampler data: Deviations from Certified Values';
  format _RMSE_ Intercept Col1-Col5 e9.;
  var Dep _RMSE_ Intercept Col1-Col5;
run;
```

The results, shown in Output 85.2.1, indicate that the values computed by PROC ORTHOREG are quite close to the NIST-certified values.

**Output 85.2.1**  Wampler Data: Deviations from Certified Values

<table>
<thead>
<tr>
<th>Dep</th>
<th><em>RMSE</em></th>
<th>Intercept</th>
<th>x</th>
<th>x*2</th>
<th>x*3</th>
<th>x*4</th>
<th>x*5</th>
</tr>
</thead>
<tbody>
<tr>
<td>y1</td>
<td>0.00E+00</td>
<td>5.46E-12</td>
<td>-9.82E-11</td>
<td>1.55E-11</td>
<td>-5.68E-13</td>
<td>3.55E-14</td>
<td>-6.66E-16</td>
</tr>
<tr>
<td>y2</td>
<td>0.00E+00</td>
<td>8.88E-16</td>
<td>-3.19E-15</td>
<td>1.24E-15</td>
<td>-1.88E-16</td>
<td>1.20E-17</td>
<td>-2.57E-19</td>
</tr>
<tr>
<td>y3</td>
<td>-2.09E-11</td>
<td>-7.73E-11</td>
<td>1.46E-11</td>
<td>-2.09E-11</td>
<td>2.50E-12</td>
<td>-1.28E-13</td>
<td>2.66E-15</td>
</tr>
<tr>
<td>y4</td>
<td>-4.07E-10</td>
<td>-5.38E-10</td>
<td>8.99E-10</td>
<td>-3.29E-10</td>
<td>4.23E-11</td>
<td>-2.27E-12</td>
<td>4.35E-14</td>
</tr>
<tr>
<td>y5</td>
<td>-3.35E-08</td>
<td>-4.10E-08</td>
<td>8.07E-08</td>
<td>-2.77E-08</td>
<td>3.54E-09</td>
<td>-1.90E-10</td>
<td>3.64E-12</td>
</tr>
</tbody>
</table>
Example 85.3: Fitting Polynomials

The extra accuracy of the regression algorithm used by PROC ORTHOREG is most useful when the model contains near-singularities that you want to be able to distinguish from true singularities. This example demonstrates this usefulness in the context of fitting polynomials of high degree.

**NOTE:** The results from this example vary from machine to machine, depending on floating-point configuration.

The following DATA step computes a response \( y \) as an exact ninth-degree polynomial function of a predictor \( x \) evaluated at 0, 0.01, 0.02, \ldots, 1.

```plaintext
title 'Polynomial Data';
data Polynomial;
  do i = 1 to 101;
    x = (i-1)/(101-1);
    y = 10**(9/2);
    do j = 0 to 8;
      y = y * (x - j/8);
    end;
    output;
  end;
run;
```

The polynomial is constructed in such a way that its zeros lie at \( x = i/8 \) for \( i = 0, \ldots, 8 \). The following statements use the EFFECT statement to fit a ninth-degree polynomial to this data with PROC ORTHOREG. The EFFECT statement makes it easy to specify complicated polynomial models.

```plaintext
ods graphics on;
proc orthoreg data=Polynomial;
  effect xMod = polynomial(x / degree=9);
  model y = xMod;
  effectplot fit / obs;
  store OStore;
run;
ods graphics off;
```

The effect xMod defined by the EFFECT statement refers to all nine degrees of freedom in the ninth-degree polynomial (excluding the intercept term). The resulting output is shown in Output 85.3.1. Note that the R square for the fit is 1, indicating that the ninth-degree polynomial has been correctly fit.
Output 85.3.1 PROC ORTHOREG Results for Ninth-Degree Polynomial

Polynomial Data

The ORTHOREG Procedure

Dependent Variable: y

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>9</td>
<td>15.527180055</td>
<td>1.7252422284</td>
<td>1.65E22</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Error</td>
<td>91</td>
<td>9.496616E-21</td>
<td>1.043584E-22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corrected Total</td>
<td>100</td>
<td>15.527180055</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Root MSE 1.02156E-11
R-Square 1

| Parameter | DF | Parameter Estimate | Standard Error | t Value | Pr > |t| |
|-----------|----|--------------------|----------------|---------|------|---|
| Intercept | 1  | -3.24572035915E-11 | 8.114115E-12  | -4.00   | 0.0001 |
| x         | 1  | 75.9977312440678  | 4.898326E-10  | 1.55E11 | <.0001 |
| x^2       | 1  | -1652.40781362191 | 9.5027919E-9  | -174E9  | <.0001 |
| x^3       | 1  | 14249.4539769783  | 8.3110512E-8  | 1.71E11 | <.0001 |
| x^4       | 1  | -64932.461575205  | 3.8997072E-7  | -167E9  | <.0001 |
| x^5       | 1  | 173315.359360779  | 1.066611E-6   | 1.62E11 | <.0001 |
| x^6       | 1  | -280158.03646002  | 1.7523078E-6  | -16E10  | <.0001 |
| x^7       | 1  | 269781.812887653  | 1.7021134E-6  | 1.58E11 | <.0001 |
| x^8       | 1  | -142302.494710055 | 9.0027891E-7  | -158E9  | <.0001 |
| x^9       | 1  | 31622.7766022468  | 1.997493E-7   | 1.58E11 | <.0001 |

The fit plot produced by the EFFECTPLOT statement, Output 85.3.2, also demonstrates the perfect fit.
Finally, you can use the PLM procedure with the fit model saved by the STORE statement in the item store OStore to check the predicted values for the known zeros of the polynomial, as shown in the following statements:

```
data Zeros(keep=x);
  do j = 0 to 8;
    x = j/8;
    output;
  end;
run;

proc plm restore=OStore noprint;
  score data=Zeros out=OZeros pred=OPred;
run;

proc print noobs;
run;
```

The predicted values of the zeros, shown in Output 85.3.3, are again all minuscule.
Example 85.3: Fitting Polynomials

Output 85.3.3 Predicted Zeros for Ninth-Degree Polynomial

Polynomial Data

<table>
<thead>
<tr>
<th>x</th>
<th>OPred</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.000</td>
<td>-3.2457E-11</td>
</tr>
<tr>
<td>0.125</td>
<td>-2.1262E-11</td>
</tr>
<tr>
<td>0.250</td>
<td>-9.5867E-12</td>
</tr>
<tr>
<td>0.375</td>
<td>-2.2895E-11</td>
</tr>
<tr>
<td>0.500</td>
<td>-5.2154E-11</td>
</tr>
<tr>
<td>0.625</td>
<td>-1.2329E-10</td>
</tr>
<tr>
<td>0.750</td>
<td>-2.5329E-10</td>
</tr>
<tr>
<td>0.875</td>
<td>-3.9836E-10</td>
</tr>
<tr>
<td>1.000</td>
<td>-5.9663E-10</td>
</tr>
</tbody>
</table>

To compare these results with those from a least squares fit produced by an alternative algorithm, consider fitting a polynomial to this data using the GLM procedure. PROC GLM does not have an EFFECT statement, but the familiar bar notation can still be used to specify a ninth-degree polynomial fairly succinctly, as shown in the following statements:

```plaintext
proc glm data=Polynomial;
  model y = x|x|x|x|x|x|x|x|x;
  store GStore;
run;
```

Partial results are shown in Output 85.3.4. In this case, the R square for the fit is only about 0.83, indicating that the full ninth-degree polynomial was not correctly fit.

Output 85.3.4 PROC GLM for Ninth-Degree Polynomial

Polynomial Data

The GLM Procedure

Dependent Variable: y

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>8</td>
<td>12.91166643</td>
<td>1.61395830</td>
<td>56.77</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Error</td>
<td>92</td>
<td>2.61551363</td>
<td>0.02842950</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corrected Total</td>
<td>100</td>
<td>15.52718006</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

R-Square Coeff Var Root MSE y Mean
0.831553 -6.6691E17 0.168610 -0.000000

The following statements, which use the PLM procedure to compute predictions based on the GLM fit at the true zeros of the polynomial, also confirm that PROC GLM is not able to correctly fit a polynomial of this degree, as shown in Output 85.3.5.
proc plm restore=GStore noprint;
    score data=Zeros out=GZeros pred=GPred;
run;

data Zeros;
    merge OZeros GZeros;
run;

proc print noobs;
run;

**Output 85.3.5** Predicted Zeros for Ninth-Degree Polynomial

<table>
<thead>
<tr>
<th>x</th>
<th>OPred</th>
<th>GPred</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.000</td>
<td>-3.2457E-11</td>
<td>0.44896</td>
</tr>
<tr>
<td>0.125</td>
<td>-2.1262E-11</td>
<td>0.22087</td>
</tr>
<tr>
<td>0.250</td>
<td>-9.5867E-12</td>
<td>-0.19037</td>
</tr>
<tr>
<td>0.375</td>
<td>-2.2895E-11</td>
<td>0.12710</td>
</tr>
<tr>
<td>0.500</td>
<td>-5.2154E-11</td>
<td>0.00000</td>
</tr>
<tr>
<td>0.625</td>
<td>-1.2329E-10</td>
<td>-0.12710</td>
</tr>
<tr>
<td>0.750</td>
<td>-2.5329E-10</td>
<td>0.19037</td>
</tr>
<tr>
<td>0.875</td>
<td>-3.9836E-10</td>
<td>-0.22087</td>
</tr>
<tr>
<td>1.000</td>
<td>-5.9663E-10</td>
<td>-0.44896</td>
</tr>
</tbody>
</table>

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