SAS/STAT® 9.3 User’s Guide
The SURVEYLOGISTIC Procedure
(Chapter)
Chapter 87
The SURVEYLOGISTIC Procedure

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Overview: SURVEYLOGISTIC Procedure

Categorical responses arise extensively in sample survey. Common examples of responses include the following:

- binary: for example, attended graduate school or not
- ordinal: for example, mild, moderate, and severe pain
- nominal: for example, ABC, NBC, CBS, FOX TV network viewed at a certain hour

Logistic regression analysis is often used to investigate the relationship between such discrete responses and a set of explanatory variables. See Binder (1981, 1983); Roberts, Rao, and Kumar (1987); Skinner, Holt, and Smith (1989); Morel (1989); and Lehtonen and Pahkinen (1995) for description of logistic regression for sample survey data.

For binary response models, the response of a sampling unit can take a specified value or not (for example, attended graduate school or not). Suppose \( x \) is a row vector of explanatory variables and \( \pi \) is the response probability to be modeled. The linear logistic model has the form

\[
\logit(\pi) = \log \left( \frac{\pi}{1 - \pi} \right) = \alpha + x\beta
\]

where \( \alpha \) is the intercept parameter and \( \beta \) is the vector of slope parameters.

The logistic model shares a common feature with the more general class of generalized linear models—namely, that a function \( g = g(\mu) \) of the expected value, \( \mu \), of the response variable is assumed to be linearly related to the explanatory variables. Since \( \mu \) implicitly depends on the stochastic behavior of the
response, and since the explanatory variables are assumed to be fixed, the function $g$ provides the link between the random (stochastic) component and the systematic (deterministic) component of the response variable. For this reason, Nelder and Wedderburn (1972) refer to $g(\cdot)$ as a link function. One advantage of the logit function over other link functions is that differences on the logistic scale are interpretable regardless of whether the data are sampled prospectively or retrospectively (McCullagh and Nelder 1989, Chapter 4). Other link functions that are widely used in practice are the probit function and the complementary log-log function. The SURVEYLOGISTIC procedure enables you to choose one of these link functions, resulting in fitting a broad class of binary response models of the form

$$g(\pi) = \alpha + x\beta$$

For ordinal response models, the response $Y$ of an individual or an experimental unit might be restricted to one of a usually small number of ordinal values, denoted for convenience by $1, \ldots, D, D + 1$ ($D \geq 1$). For example, pain severity can be classified into three response categories as $1$=mild, $2$=moderate, and $3$=severe. The SURVEYLOGISTIC procedure fits a common slopes cumulative model, which is a parallel lines regression model based on the cumulative probabilities of the response categories rather than on their individual probabilities. The cumulative model has the form

$$g(\Pr(Y \leq d \mid x)) = \alpha_d + x\beta, \quad 1 \leq d \leq D$$

where $\alpha_1, \ldots, \alpha_k$ are $k$ intercept parameters and $\beta$ is the vector of slope parameters. This model has been considered by many researchers. Aitchison and Silvey (1957) and Ashford (1959) employ a probit scale and provide a maximum likelihood analysis; Walker and Duncan (1967) and Cox and Snell (1989) discuss the use of the log-odds scale. For the log-odds scale, the cumulative logit model is often referred to as the proportional odds model.

For nominal response logistic models, where the $D + 1$ possible responses have no natural ordering, the logit model can also be extended to a generalized logit model, which has the form

$$\log \left( \frac{\Pr(Y = i \mid x)}{\Pr(Y = D + 1 \mid x)} \right) = \alpha_i + x\beta_i, \quad i = 1, \ldots, D$$

where the $\alpha_1, \ldots, \alpha_D$ are $D$ intercept parameters and the $\beta_1, \ldots, \beta_D$ are $D$ vectors of parameters. These models were introduced by McFadden (1974) as the discrete choice model, and they are also known as multinomial models.

The SURVEYLOGISTIC procedure fits linear logistic regression models for discrete response survey data by the method of maximum likelihood. For statistical inferences, PROC SURVEYLOGISTIC incorporates complex survey sample designs, including designs with stratification, clustering, and unequal weighting.

The maximum likelihood estimation is carried out with either the Fisher scoring algorithm or the Newton-Raphson algorithm. You can specify starting values for the parameter estimates. The logit link function in the ordinal logistic regression models can be replaced by the probit function or the complementary log-log function.

Odds ratio estimates are displayed along with parameter estimates. You can also specify the change in the explanatory variables for which odds ratio estimates are desired.

Variances of the regression parameters and odds ratios are computed by using either the Taylor series (linearization) method or replication (resampling) methods to estimate sampling errors of estimators based on complex sample designs (Binder 1983; Särndal, Swensson, and Wretman 1992, Wolter 2007; Rao, Wu, and Yue 1992).
The SURVEYLOGISTIC procedure enables you to specify categorical variables (also known as CLASS variables) as explanatory variables. It also enables you to specify interaction terms in the same way as in the LOGISTIC procedure.

Like many procedures in SAS/STAT software that allow the specification of CLASS variables, the SURVEYLOGISTIC procedure provides a CONTRAST statement for specifying customized hypothesis tests concerning the model parameters. The CONTRAST statement also provides estimation of individual rows of contrasts, which is particularly useful for obtaining odds ratio estimates for various levels of the CLASS variables.

The SURVEYLOGISTIC procedure is similar to the LOGISTIC procedure and other regression procedures in the SAS System. See Chapter 53, “The LOGISTIC Procedure,” for general information about how to perform logistic regression by using SAS. PROC SURVEYLOGISTIC is designed to handle sample survey data, and thus it incorporates the sample design information into the analysis.

The following example illustrates how to use PROC SURVEYLOGISTIC to perform logistic regression for sample survey data.

In the customer satisfaction survey example in the section “Getting Started: SURVEYSELECT Procedure” on page 7590 of Chapter 91, “The SURVEYSELECT Procedure,” an Internet service provider conducts a customer satisfaction survey. The survey population consists of the company’s current subscribers from four states: Alabama (AL), Florida (FL), Georgia (GA), and South Carolina (SC). The company plans to select a sample of customers from this population, interview the selected customers and ask their opinions on customer service, and then make inferences about the entire population of subscribers from the sample data. A stratified sample is selected by using the probability proportional to size (PPS) method. The sample design divides the customers into strata depending on their types (‘Old’ or ‘New’) and their states (AL, FL, GA, SC). There are eight strata in all. Within each stratum, customers are selected and interviewed by using the PPS with replacement method, where the size variable is Usage. The stratified PPS sample contains 192 customers. The data are stored in the SAS data set SampleStrata. Figure 87.1 displays the first 10 observations of this data set.
Chapter 87: The SURVEYLOGISTIC Procedure

In the SAS data set SampleStrata, the variable CustomerID uniquely identifies each customer. The variable State contains the state of the customer’s address. The variable Type equals ‘Old’ if the customer has subscribed to the service for more than one year; otherwise, the variable Type equals ‘New’. The variable Usage contains the customer’s average monthly service usage, in hours. The variable Rating contains the customer’s responses to the survey. The sample design uses an unequal probability sampling method, with the sampling weights stored in the variable SamplingWeight.

The following SAS statements fit a cumulative logistic model between the satisfaction levels and the Internet usage by using the stratified PPS sample:

```
title 'Customer Satisfaction Survey';
proc surveylogistic data=SampleStrata;
   strata state type/list;
   model Rating (order=internal) = Usage;
   weight SamplingWeight;
run;
```

The PROC SURVEYLOGISTIC statement invokes the SURVEYLOGISTIC procedure. The STRATA statement specifies the stratification variables State and Type that are used in the sample design. The LIST option requests a summary of the stratification. In the MODEL statement, Rating is the response variable and Usage is the explanatory variable. The ORDER=internal is used for the response variable Rating to ask the procedure to order the response levels by using the internal numerical value (1–5) instead of the formatted character value. The WEIGHT statement specifies the variable SamplingWeight that contains the sampling weights.

The results of this analysis are shown in the following figures.
PROC SURVEYLOGISTIC first lists the following model fitting information and sample design information in Figure 87.2:

- The link function is the logit of the cumulative of the lower response categories.
- The Fisher scoring optimization technique is used to obtain the maximum likelihood estimates for the regression coefficients.
- The response variable is Rating, which has five response levels.
- The stratification variables are State and Type.
- There are eight strata in the sample.
- The weight variable is SamplingWeight.
- The variance adjustment method used for the regression coefficients is the default degrees of freedom adjustment.

Figure 87.3 lists the number of observations in the data set and the number of observations used in the analysis. Since there is no missing value in this example, observations in the entire data set are used in the analysis. The sums of weights are also reported in this table.
The “Response Profile” table in Figure 87.4 lists the five response levels, their ordered values, and their total frequencies and total weights for each category. Due to the ORDER=INTERNAL option for the response variable Rating, the category “Extremely Unsatisfied” has the Ordered Value 1, the category “Unsatisfied” has the Ordered Value 2, and so on.

Figure 87.4 Stratified PPS Sample, Response Profile

<table>
<thead>
<tr>
<th>Ordered Value</th>
<th>Rating</th>
<th>Total Frequency</th>
<th>Total Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Extremely Unsatisfied</td>
<td>52</td>
<td>2067.1092</td>
</tr>
<tr>
<td>2</td>
<td>Unsatisfied</td>
<td>47</td>
<td>2148.7127</td>
</tr>
<tr>
<td>3</td>
<td>Neutral</td>
<td>47</td>
<td>3649.4869</td>
</tr>
<tr>
<td>4</td>
<td>Satisfied</td>
<td>38</td>
<td>2533.5379</td>
</tr>
<tr>
<td>5</td>
<td>Extremely Satisfied</td>
<td>8</td>
<td>2863.8888</td>
</tr>
</tbody>
</table>

Probabilities modeled are cumulated over the lower Ordered Values.

Figure 87.5 displays the output of the stratification summary. There are a total of eight strata, and each stratum is defined by the customer types within each state. The table also shows the number of customers within each stratum.

Figure 87.5 Stratified PPS Sample, Stratification Summary

<table>
<thead>
<tr>
<th>Stratum Index</th>
<th>State</th>
<th>Type</th>
<th>N Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AL</td>
<td>New</td>
<td>22</td>
</tr>
<tr>
<td>2</td>
<td>AL</td>
<td>Old</td>
<td>24</td>
</tr>
<tr>
<td>3</td>
<td>FL</td>
<td>New</td>
<td>25</td>
</tr>
<tr>
<td>4</td>
<td>FL</td>
<td>Old</td>
<td>22</td>
</tr>
<tr>
<td>5</td>
<td>GA</td>
<td>New</td>
<td>25</td>
</tr>
<tr>
<td>6</td>
<td>GA</td>
<td>Old</td>
<td>25</td>
</tr>
<tr>
<td>7</td>
<td>SC</td>
<td>New</td>
<td>24</td>
</tr>
<tr>
<td>8</td>
<td>SC</td>
<td>Old</td>
<td>25</td>
</tr>
</tbody>
</table>

Figure 87.6 shows the chi-square test for testing the proportional odds assumption. The test is highly significant, which indicates that the cumulative logit model might not adequately fit the data.

Figure 87.6 Stratified PPS Sample, Testing the Proportional Odds Assumption

<table>
<thead>
<tr>
<th>Score Test for the Proportional Odds Assumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square</td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>911.1244</td>
</tr>
</tbody>
</table>
Figure 87.7 shows the iteration algorithm converged to obtain the MLE for this example. The “Model Fit Statistics” table contains the Akaike information criterion (AIC), the Schwarz criterion (SC), and the negative of twice the log likelihood (−2 log L) for the intercept-only model and the fitted model. AIC and SC can be used to compare different models, and the ones with smaller values are preferred.

**Figure 87.7** Stratified PPS Sample, Model Fitting Information

<table>
<thead>
<tr>
<th>Model Convergence Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convergence criterion (GCONV=1E-8) satisfied.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model Fit Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept and Criterion Only Covariates</td>
</tr>
<tr>
<td>Intercept Only Covariates</td>
</tr>
<tr>
<td>AIC</td>
</tr>
<tr>
<td>SC</td>
</tr>
<tr>
<td>−2 Log L</td>
</tr>
</tbody>
</table>

The table “Testing Global Null Hypothesis: BETA=0” in Figure 87.8 shows the likelihood ratio test, the efficient score test, and the Wald test for testing the significance of the explanatory variable (Usage). All tests are significant.

**Figure 87.8** Stratified PPS Sample

<table>
<thead>
<tr>
<th>Testing Global Null Hypothesis: BETA=0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test</td>
</tr>
<tr>
<td>Likelihood Ratio</td>
</tr>
<tr>
<td>Score</td>
</tr>
<tr>
<td>Wald</td>
</tr>
</tbody>
</table>

Figure 87.9 shows the parameter estimates of the logistic regression and their standard errors.

**Figure 87.9** Stratified PPS Sample, Parameter Estimates

<table>
<thead>
<tr>
<th>Analysis of Maximum Likelihood Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>Intercept Extremely Unsatisfied</td>
</tr>
<tr>
<td>Intercept Unsatisfied</td>
</tr>
<tr>
<td>Intercept Neutral</td>
</tr>
<tr>
<td>Intercept Satisfied</td>
</tr>
<tr>
<td>Usage</td>
</tr>
</tbody>
</table>
Figure 87.10 displays the odds ratio estimate and its confidence limits.

**Figure 87.10** Stratified PPS Sample, Odds Ratios

<table>
<thead>
<tr>
<th>Effect</th>
<th>Point Estimate</th>
<th>95% Wald Confidence Limits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Usage</td>
<td>1.038</td>
<td>1.003 - 1.075</td>
</tr>
</tbody>
</table>

### Syntax: SURVEYLOGISTIC Procedure

The following statements are available in PROC SURVEYLOGISTIC:

```plaintext
PROC SURVEYLOGISTIC <options>;
   BY variables ;
   CLASS variable <(v-options)> <variable <(v-options)> ...> </v-options> ;
   CLUSTER variables ;
   CONTRAST 'label' effect values <,...,effect values> </options> ;
   DOMAIN variables <variable+variable variable+variable+variable ...> ;
   EFFECT name = effect-type (variables </options>) ;
   ESTIMATE <'label'> estimate-specification </options> ;
   FREQ variable ;
   LSMEANS <model-effects> </options> ;
   LSMEANSTEST model-effect lsmeantest-specification </options> ;
   MODEL events/trials = <effects> <options> ;
   MODEL variable <(v-options)> = <effects> </options> ;
   OUTPUT <OUT=SAS-data-set> <options> </option> ;
   REPWEIGHTS variables </options> ;
   SLICE model-effect </options> ;
   STORE <OUT= item-store-name>/<LABEL='label'> ;
   STRATA variables </option> ;
   <'label'> TEST equation1 <,...,equationk> </options> ;
   UNITS independent1 = list1 <,...,independentk = listk> </option> ;
   WEIGHT variable ;
```

The PROC SURVEYLOGISTIC and MODEL statements are required.

The CLASS, CLUSTER, CONTRAST, EFFECT, ESTIMATE, LSMEANS, LSMEANSTEST, REPWEIGHTS, SLICE, STRATA, TEST statements can appear multiple times. You should use only one of each following statements: MODEL, WEIGHT, STORE, OUTPUT, and UNITS.

The CLASS statement (if used) must precede the MODEL statement, and the CONTRAST statement (if used) must follow the MODEL statement.

The rest of this section provides detailed syntax information for each of the preceding statements, except
the **EFFECT, ESTIMATE, LSMEANS, LSMESTIMATE, SLICE, STORE** statements. These statements are also available in many other procedures. Summary descriptions of functionality and syntax for these statements are shown in this chapter, and full documentation about them is available in Chapter 19, “Shared Concepts and Topics.”

The syntax descriptions begin with the PROC SURVEYLOGISTIC statement; the remaining statements are covered in alphabetical order.

---

**PROC SURVEYLOGISTIC Statement**

```latex
PROC SURVEYLOGISTIC <options> ;
```

The **PROC SURVEYLOGISTIC** statement invokes the SURVEYLOGISTIC procedure and optionally identifies input data sets, controls the ordering of the response levels, and specifies the variance estimation method. The **PROC SURVEYLOGISTIC** statement is required.

**ALPHA=** *value*

sets the confidence level for confidence limits. The value of the **ALPHA=** option must be between 0 and 1, and the default value is 0.05. A confidence level of $\alpha$ produces $100(1 - \alpha)\%$ confidence limits.

The default of **ALPHA=0.05** produces 95% confidence limits.

**DATA=** *SAS-data-set*

names the SAS data set containing the data to be analyzed. If you omit the **DATA=** option, the procedure uses the most recently created SAS data set.

**INEST=** *SAS-data-set*

names the SAS data set that contains initial estimates for all the parameters in the model. BY-group processing is allowed in setting up the **INEST=** data set. See the section “**INEST= Data Set**” on page 7316 for more information.

**MISSING**

 treats missing values as a valid (nonmissing) category for all categorical variables, which include **CLASS, STRATA, CLUSTER, and DOMAIN** variables.

By default, if you do not specify the **MISSING** option, an observation is excluded from the analysis if it has a missing value. For more information, see the section “**Missing Values**” on page 7305.

**NAMELEN=** *n*

specifies the length of effect names in tables and output data sets to be *n* characters, where *n* is a value between 20 and 200. The default length is 20 characters.

**NOMCAR**

requests that the procedure treat missing values in the variance computation as not missing completely at random (NOMCAR) for Taylor series variance estimation. When you specify the **NOMCAR** option, **PROC SURVEYLOGISTIC** computes variance estimates by analyzing the nonmissing values as a domain or subpopulation, where the entire population includes both nonmissing and missing domains. See the section “**Missing Values**” on page 7305 for more details.
By default, PROC SURVEYLOGISTIC completely excludes an observation from analysis if that observation has a missing value, unless you specify the MISSING option. Note that the NOMCAR option has no effect on a classification variable when you specify the MISSING option, which treats missing values as a valid nonmissing level.

The NOMCAR option applies only to Taylor series variance estimation. The replication methods, which you request with the VARMETHOD=BRR and VARMETHOD=JACKKNIFE options, do not use the NOMCAR option.

NOSORT
suppresses the internal sorting process to shorten the computation time if the data set is presorted by the STRATA and CLUSTER variables. By default, the procedure sorts the data by the STRATA variables if you use the STRATA statement; then the procedure sorts the data by the CLUSTER variables within strata. If your data are already stored by the order of STRATA and CLUSTER variables, then you can specify this option to omit this sorting process to reduce the usage of computing resources, especially when your data set is very large. However, if you specify this NOSORT option while your data are not presorted by STRATA and CLUSTER variables, then any changes in these variables creates a new stratum or cluster.

ORDER=DATA | FORMATTED | FREQ | INTERNAL
specifies the sorting order for the levels of the response variable. This option, except for ORDER=FREQ, also determines the sorting order for the levels of CLUSTER and DOMAIN variables and controls STRATA variable levels in the “Stratum Information” table. By default, ORDER=INTERNAL. However, if an ORDER= option is specified after the response variable, in the MODEL statement, it overrides this option for the response variable. This option does not affect the ordering of the CLASS variable levels; see the ORDER= option in the CLASS statement for more information.

RATE=value | SAS-data-set
R=value | SAS-data-set
specifies the sampling rate as a nonnegative value, or specifies an input data set that contains the stratum sampling rates. The procedure uses this information to compute a finite population correction for Taylor series variance estimation. The procedure does not use the RATE= option for BRR or jackknife variance estimation, which you request with the VARMETHOD=BRR or VARMETHOD=JACKKNIFE option.

If your sample design has multiple stages, you should specify the first-stage sampling rate, which is the ratio of the number of PSUs selected to the total number of PSUs in the population.

For a nonstratified sample design, or for a stratified sample design with the same sampling rate in all strata, you should specify a nonnegative value for the RATE= option. If your design is stratified with different sampling rates in the strata, then you should name a SAS data set that contains the stratification variables and the sampling rates. See the section “Specification of Population Totals and Sampling Rates” on page 7316 for more details.

The value in the RATE= option or the values of _RATE_ in the secondary data set must be nonnegative numbers. You can specify value as a number between 0 and 1. Or you can specify value in percentage form as a number between 1 and 100, and PROC SURVEYLOGISTIC converts that number to a proportion. The procedure treats the value 1 as 100% instead of 1%.
If you do not specify the TOTAL= or RATE= option, then the Taylor series variance estimation does not include a finite population correction. You cannot specify both the TOTAL= and RATE= options.

**TOTAL=**value | SAS-data-set

**N=**value | SAS-data-set

specifies the total number of primary sampling units in the study population as a positive value, or specifies an input data set that contains the stratum population totals. The procedure uses this information to compute a finite population correction for Taylor series variance estimation. The procedure does not use the TOTAL= option for BRR or jackknife variance estimation, which you request with the VARMETHOD=BRR or VARMETHOD=JACKKNIFE option.

For a nonstratified sample design, or for a stratified sample design with the same population total in all strata, you should specify a positive value for the TOTAL= option. If your sample design is stratified with different population totals in the strata, then you should name a SAS data set that contains the stratification variables and the population totals. See the section “Specification of Population Totals and Sampling Rates” on page 7316 for more details.

If you do not specify the TOTAL= or RATE= option, then the Taylor series variance estimation does not include a finite population correction. You cannot specify both the TOTAL= and RATE= options.

**VARMETHOD=**BRR < (method-options) >

**VARMETHOD=**JACKKNIFE | JK < (method-options) >

**VARMETHOD=**TAYLOR

specifies the variance estimation method. VARMETHOD=TAYLOR requests the Taylor series method, which is the default if you do not specify the VARMETHOD= option or the REPWEIGHTS statement. VARMETHOD=BRR requests variance estimation by balanced repeated replication (BRR), and VARMETHOD=JACKKNIFE requests variance estimation by the delete-1 jackknife method.

For VARMETHOD=BRR and VARMETHOD=JACKKNIFE you can specify method-options in parentheses. Table 87.1 summarizes the available method-options.

<table>
<thead>
<tr>
<th>VARMETHOD=</th>
<th>Variance Estimation Method</th>
<th>Method-Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRR</td>
<td>Balanced repeated replication</td>
<td>FAY=value, HADAMARD=SAS-data-set, OUTWEIGHTS=SAS-data-set, PRINTH, REPS=number</td>
</tr>
<tr>
<td>TAYLOR</td>
<td>Taylor series linearization</td>
<td>None</td>
</tr>
</tbody>
</table>

Method-options must be enclosed in parentheses following the method keyword. For example:

```
varmethod=BRR(reps=60 outweights=myReplicateWeights)
```
The following values are available for the VARMETHOD= option:

**BRR < (method-options) >** requests balanced repeated replication (BRR) variance estimation. The BRR method requires a stratified sample design with two primary sampling units (PSUs) per stratum. See the section “Balanced Repeated Replication (BRR) Method” on page 7323 for more information.

You can specify the following method-options in parentheses following VARMETHOD=BRR:

- **FAY < = value >** requests Fay’s method, a modification of the BRR method, for variance estimation. See the section “Fay’s BRR Method” on page 7324 for more information.

You can specify the value of the Fay coefficient, which is used in converting the original sampling weights to replicate weights. The Fay coefficient must be a nonnegative number less than 1. By default, the value of the Fay coefficient equals 0.5.

- **HADAMARD=SAS-data-set**
- **H=SAS-data-set**

names a SAS data set that contains the Hadamard matrix for BRR replicate construction. If you do not provide a Hadamard matrix with the HADAMARD= method-option, PROC SURVEYLOGISTIC generates an appropriate Hadamard matrix for replicate construction. See the sections “Balanced Repeated Replication (BRR) Method” on page 7323 and “Hadamard Matrix” on page 7326 for details.

If a Hadamard matrix of a given dimension exists, it is not necessarily unique. Therefore, if you want to use a specific Hadamard matrix, you must provide the matrix as a SAS data set in the HADAMARD= method-option.

In the HADAMARD= input data set, each variable corresponds to a column of the Hadamard matrix, and each observation corresponds to a row of the matrix. You can use any variable names in the HADAMARD= data set. All values in the data set must equal either 1 or -1. You must ensure that the matrix you provide is indeed a Hadamard matrix—that is, $A^T A = R I$, where $A$ is the Hadamard matrix of dimension $R$ and $I$ is an identity matrix. PROC SURVEYLOGISTIC does not check the validity of the Hadamard matrix that you provide.

The HADAMARD= input data set must contain at least $H$ variables, where $H$ denotes the number of first-stage strata in your design. If the data set contains more than $H$ variables, the procedure uses only the first $H$ variables. Similarly, the HADAMARD= input data set must contain at least $H$ observations.

If you do not specify the REPS= method-option, then the number of replicates is taken to be the number of observations in the HADAMARD= input data set. If you specify the number of replicates—for example,
PROC SURVEYLOGISTIC Statement ◆ 7277

REPS=number—then the first number observations in the HADAMARD= data set are used to construct the replicates.

You can specify the PRINTH option to display the Hadamard matrix that the procedure uses to construct replicates for BRR.

OUTWEIGHTS= SAS-data-set

names a SAS data set that contains replicate weights. See the section “Balanced Repeated Replication (BRR) Method” on page 7323 for information about replicate weights. See the section “Replicate Weights Output Data Set” on page 7334 for more details about the contents of the OUTWEIGHTS= data set.

The OUTWEIGHTS= method-option is not available when you provide replicate weights with the REPWEIGHTS statement.

PRINTH

displays the Hadamard matrix.

When you provide your own Hadamard matrix with the HADAMARD= method-option, only the rows and columns of the Hadamard matrix that are used by the procedure are displayed. See the sections “Balanced Repeated Replication (BRR) Method” on page 7323 and “Hadamard Matrix” on page 7326 for details.

The PRINTH method-option is not available when you provide replicate weights with the REPWEIGHTS statement because the procedure does not use a Hadamard matrix in this case.

REPS=number

specifies the number of replicates for BRR variance estimation. The value of number must be an integer greater than 1.

If you do not provide a Hadamard matrix with the HADAMARD= method-option, the number of replicates should be greater than the number of strata and should be a multiple of 4. See the section “Balanced Repeated Replication (BRR) Method” on page 7323 for more information. If a Hadamard matrix cannot be constructed for the REPS= value that you specify, the value is increased until a Hadamard matrix of that dimension can be constructed. Therefore, it is possible for the actual number of replicates used to be larger than the REPS= value that you specify.

If you provide a Hadamard matrix with the HADAMARD= method-option, the value of REPS= must not be less than the number of rows in the Hadamard matrix. If you provide a Hadamard matrix and do not specify the REPS= method-option, the number of replicates equals the number of rows in the Hadamard matrix.

If you do not specify the REPS= or HADAMARD= method-option and do not include a REPWEIGHTS statement, the number of replicates equals the smallest multiple of 4 that is greater than the number of strata.
If you provide replicate weights with the REPWEIGHTS statement, the procedure does not use the REPS= method-option. With a REPWEIGHTS statement, the number of replicates equals the number of REPWEIGHTS variables.

JACKKNIFE JK <(method-options)> requests variance estimation by the delete-1 jackknife method. See the section “Jackknife Method” on page 7325 for details. If you provide replicate weights with a REPWEIGHTS statement, VARMETHOD=JACKKNIFE is the default variance estimation method.

You can specify the following method-options in parentheses following VARMETHOD=JACKKNIFE:

OUTJKCOEFS=SAS-data-set

names a SAS data set that contains jackknife coefficients. See the section “Jackknife Method” on page 7325 for information about jackknife coefficients. See the section “Jackknife Coefficients Output Data Set” on page 7335 for more details about the contents of the OUTJKCOEFS= data set.

OUTWEIGHTS=SAS-data-set

names a SAS data set that contains replicate weights. See the section “Jackknife Method” on page 7325 for information about replicate weights. See the section “Replicate Weights Output Data Set” on page 7334 for more details about the contents of the OUTWEIGHTS= data set.

The OUTWEIGHTS= method-option is not available when you provide replicate weights with the REPWEIGHTS statement.

TAYLOR

requests Taylor series variance estimation. This is the default method if you do not specify the VARMETHOD= option or a REPWEIGHTS statement. See the section “Taylor Series (Linearization)” on page 7322 for more information.

**BY Statement**

BY variables ;

You can specify a BY statement with PROC SURVEYLOGISTIC to obtain separate analyses on 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 SURVEYLOGISTIC 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).

Note that using a BY statement provides completely separate analyses of the BY groups. It does not provide a statistically valid domain (subpopulation) analysis, where the total number of units in the subpopulation is not known with certainty. You should use the DOMAIN statement to obtain domain analysis. For more information about subpopulation analysis for sample survey data, see Cochran (1977).

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

The CLASS statement names the classification variables to be used in the analysis. The CLASS statement must precede the MODEL statement. You can specify various v-options for each variable by enclosing them in parentheses after the variable name. You can also specify global v-options for the CLASS statement by placing them after a slash (/). Global v-options are applied to all the variables specified in the CLASS statement. However, individual CLASS variable v-options override the global v-options.

CPREFIX= n
specifies that, at most, the first n characters of a CLASS variable name be used in creating names for the corresponding dummy variables. The default is 32 − min(32, max(2, f)), where f is the formatted length of the CLASS variable.

DESCENDING
DESC
reverses the sorting order of the classification variable.

LPREFIX= n
specifies that, at most, the first n characters of a CLASS variable label be used in creating labels for the corresponding dummy variables.

ORDER=DATA | FORMATTED | FREQ | INTERNAL
specifies the order in which to sort the levels of the classification variables.

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. With this option, 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>
</tbody>
</table>
Table 87.1  continued

<table>
<thead>
<tr>
<th>Value of ORDER=</th>
<th>Levels Sorted By</th>
</tr>
</thead>
<tbody>
<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 sorting 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.

**PARAM=**keyword

specifies the parameterization method for the classification variable or variables. Design matrix columns are created from CLASS variables according to the following coding schemes; the default is PARAM=EFFECT.

- **EFFECT** specifies effect coding
- **GLM** specifies less-than-full-rank, reference cell coding; this option can be used only as a global option
- **ORDINAL** specifies the cumulative parameterization for an ordinal CLASS variable
- **POLYNOMIAL | POLY** specifies polynomial coding
- **REFERENCE | REF** specifies reference cell coding
- **ORTHEFFECT** orthogonalizes PARAM=EFFECT
- **ORTHORDINAL | ORTHOTHERM** orthogonalizes PARAM=ORDINAL
- **ORTHPOLY** orthogonalizes PARAM=POLYNOMIAL
- **ORTHREF** orthogonalizes PARAM=REFERENCE

If PARAM=ORTHPOLY or PARAM=POLY, and the CLASS levels are numeric, then the ORDER= option in the CLASS statement is ignored, and the internal, unformatted values are used.

**EFFECT, POLYNOMIAL, REFERENCE, ORDINAL,** and their orthogonal parameterizations are full rank. The REF= option in the CLASS statement determines the reference level for EFFECT, REFERENCE, and their orthogonal parameterizations.

Parameter names for a CLASS predictor variable are constructed by concatenating the CLASS variable name with the CLASS levels. However, for the POLYNOMIAL and orthogonal parameterizations, parameter names are formed by concatenating the CLASS variable name and keywords that reflect the parameterization.
REFERENCE='level' | keyword

specifies the reference level for PARAM=EFFECT or PARAM=REFERENCE. For an individual (but not a global) variable REF= option, you can specify the level of the variable to use as the reference level. For a global or individual variable REF= option, you can use one of the following keywords. The default is REF=LAST.

FIRST designates the first ordered level as reference
LAST designates the last ordered level as reference

CLUSTER Statement

CLUSTER variables ;

The CLUSTER statement names variables that identify the clusters in a clustered sample design. The combinations of categories of CLUSTER variables define the clusters in the sample. If there is a STRATA statement, clusters are nested within strata.

If you provide replicate weights for BRR or jackknife variance estimation with the REPWEIGHTS statement, you do not need to specify a CLUSTER statement.

If your sample design has clustering at multiple stages, you should identify only the first-stage clusters (primary sampling units (PSUs)), in the CLUSTER statement. See the section “Primary Sampling Units (PSUs)” on page 7317 for more information.

The CLUSTER variables are one or more variables in the DATA= input data set. These variables can be either character or numeric. The formatted values of the CLUSTER variables determine the CLUSTER variable levels. Thus, you can use formats to group values into levels. See the FORMAT procedure in the Base SAS Procedures Guide and the FORMAT statement and SAS formats in SAS Formats and Informats: Reference for more information.

When determining levels of a CLUSTER variable, an observation with missing values for this CLUSTER variable is excluded, unless you specify the MISSING option. For more information, see the section “Missing Values” on page 7305.

You can use multiple CLUSTER statements to specify cluster variables. The procedure uses variables from all CLUSTER statements to create clusters.

CONTRAST Statement

CONTRAST 'label' row-description < , ... , row-description </ options> ;

where a row-description is defined as follows:

effect values < , . . . , effect values >
Chapter 87: The SURVEYLOGISTIC Procedure

The CONTRAST statement provides a mechanism for obtaining customized hypothesis tests. It is similar to the CONTRAST statement in PROC LOGISTIC and PROC GLM, depending on the coding schemes used with any classification variables involved.

The CONTRAST statement enables you to specify a matrix, \( L \), for testing the hypothesis \( L\theta = 0 \), where \( \theta \) is the parameter vector. You must be familiar with the details of the model parameterization that PROC SURVEYLOGISTIC uses (for more information, see the PARAM= option in the section “CLASS Statement” on page 7279). Optionally, the CONTRAST statement enables you to estimate each row, \( l_i \), of \( L\theta \) and test the hypothesis \( l_i \theta = 0 \). Computed statistics are based on the asymptotic chi-square distribution of the Wald statistic.

There is no limit to the number of CONTRAST statements that you can specify, but they must appear after the MODEL statement.

The following parameters can be specified in the CONTRAST statement:

- **label** identifies the contrast on the output. A label is required for every contrast specified, and it must be enclosed in quotes.
- **effect** identifies an effect that appears in the MODEL statement. The name INTERCEPT can be used as an effect when one or more intercepts are included in the model. You do not need to include all effects that are included in the MODEL statement.
- **values** are constants that are elements of the \( L \) matrix associated with the effect. To correctly specify your contrast, it is crucial to know the ordering of parameters within each effect and the variable levels associated with any parameter. The “Class Level Information” table shows the ordering of levels within variables. The E option, described later in this section, enables you to verify the proper correspondence of **values** to parameters.

The rows of \( L \) are specified in order and are separated by commas. Multiple degree-of-freedom hypotheses can be tested by specifying multiple row-descriptions. For any of the full-rank parameterizations, if an effect is not specified in the CONTRAST statement, all of its coefficients in the \( L \) matrix are set to 0. If too many values are specified for an effect, the extra ones are ignored. If too few values are specified, the remaining ones are set to 0.

When you use effect coding (by default or by specifying PARAM=EFFECT in the CLASS statement), all parameters are directly estimable (involve no other parameters).

For example, suppose an effect that is coded CLASS variable A has four levels. Then there are three parameters \((\alpha_1, \alpha_2, \alpha_3)\) that represent the first three levels, and the fourth parameter is represented by \(-\alpha_1 - \alpha_2 - \alpha_3\).

To test the first versus the fourth level of A, you would test

\[ \alpha_1 = -\alpha_1 - \alpha_2 - \alpha_3 \]

or, equivalently,

\[ 2\alpha_1 + \alpha_2 + \alpha_3 = 0 \]

which, in the form \( L\theta = 0 \), is

\[
\begin{bmatrix}
2 & 1 & 1
\end{bmatrix}
\begin{bmatrix}
\alpha_1 \\
\alpha_2 \\
\alpha_3
\end{bmatrix} = 0
\]
Therefore, you would use the following CONTRAST statement:

```
contrast '1 vs. 4' A 2 1 1;
```

To contrast the third level with the average of the first two levels, you would test

$$\frac{\alpha_1 + \alpha_2}{2} = \alpha_3$$

or, equivalently,

$$\alpha_1 + \alpha_2 - 2\alpha_3 = 0$$

Therefore, you would use the following CONTRAST statement:

```
contrast '1&2 vs. 3' A 1 1 -2;
```

Other CONTRAST statements are constructed similarly. For example:

```
contrast '1 vs. 2' A 1 -1 0;
contrast '1&2 vs. 4' A 3 3 2;
contrast '1&2 vs. 3&4' A 2 2 0;
contrast 'Main Effect' A 1 0 0,
                A 0 1 0,
                A 0 0 1;
```

When you use the less-than-full-rank parameterization (by specifying PARAM=GLM in the CLASS statement), each row is checked for estimability. If PROC SURVEYLOGISTIC finds a contrast to be nonestimable, it displays missing values in corresponding rows in the results. PROC SURVEYLOGISTIC handles missing level combinations of classification variables in the same manner as PROC LOGISTIC. Parameters corresponding to missing level combinations are not included in the model. This convention can affect the way in which you specify the \( L \) matrix in your CONTRAST statement. If the elements of \( L \) are not specified for an effect that contains a specified effect, then the elements of the specified effect are distributed over the levels of the higher-order effect just as the LOGISTIC procedure does for its CONTRAST and ESTIMATE statements. For example, suppose that the model contains effects A and B and their interaction A*B. If you specify a CONTRAST statement involving A alone, the \( L \) matrix contains nonzero terms for both A and A*B, since A*B contains A.

The degrees of freedom is the number of linearly independent constraints implied by the CONTRAST statement—that is, the rank of \( L \).

You can specify the following options after a slash (/):

**ALPHA=value**

sets the confidence level for confidence limits. The value of the ALPHA= option must be between 0 and 1, and the default value is 0.05. A confidence level of \( \alpha \) produces \( 100(1 - \alpha)\% \) confidence limits. The default of ALPHA=0.05 produces 95% confidence limits.

**E**

requests that the \( L \) matrix be displayed.

**ESTIMATE=keyword**

requests that each individual contrast (that is, each row, \( l_i \beta \), of \( L\beta \)) or exponentiated contrast (\( e^{l_i \beta} \))
be estimated and tested. PROC SURVEYLOGISTIC displays the point estimate, its standard error, a Wald confidence interval, and a Wald chi-square test for each contrast. The significance level of the confidence interval is controlled by the ALPHA= option. You can estimate the contrast or the exponentiated contrast \( e^{\hat{\beta}} \), or both, by specifying one of the following keywords:

- \texttt{PARM} specifies that the contrast itself be estimated
- \texttt{EXP} specifies that the exponentiated contrast be estimated
- \texttt{BOTH} specifies that both the contrast and the exponentiated contrast be estimated

\texttt{SINGULAR=value}

 tunes the estimability checking. If \( \mathbf{v} \) is a vector, define \( \text{ABS}(\mathbf{v}) \) to be the largest absolute value of the elements of \( \mathbf{v} \). For a row vector \( \mathbf{l} \) of the matrix \( \mathbf{L} \), define

\[
c = \begin{cases} 
\text{ABS}(\mathbf{l}) & \text{if } \text{ABS}(\mathbf{l}) > 0 \\
1 & \text{otherwise}
\end{cases}
\]

If \( \text{ABS}(\mathbf{l} - \mathbf{I}_H) \) is greater than \( c^* \text{value} \), then \( \mathbf{l} \hat{\beta} \) is declared nonestimable. The \( \mathbf{H} \) matrix is the Hermite form matrix \( \mathbf{I}_0^0 \mathbf{I}_0 \), where \( \mathbf{I}_0^0 \) represents a generalized inverse of the information matrix \( \mathbf{I}_0 \) of the null model. The \text{value} must be between 0 and 1; the default is 10\(^{-4}\).

**DOMAIN Statement**

\[
\text{DOMAIN variables < variable*variable variable*variable variable*variable ... > ;}
\]

The DOMAIN statement requests analysis for domains (subpopulations) in addition to analysis for the entire study population. The DOMAIN statement names the variables that identify domains, which are called domain variables.

It is common practice to compute statistics for domains. The formation of these domains might be unrelated to the sample design. Therefore, the sample sizes for the domains are random variables. Use a DOMAIN statement to incorporate this variability into the variance estimation.

Note that a DOMAIN statement is different from a BY statement. In a BY statement, you treat the sample sizes as fixed in each subpopulation, and you perform analysis within each BY group independently. See the section “Domain Analysis” on page 7327 for more details.

Use the DOMAIN statement on the entire data set to perform a domain analysis. Creating a new data set from a single domain and analyzing that with PROC SURVEYLOGISTIC yields inappropriate estimates of variance.

A domain variable can be either character or numeric. The procedure treats domain variables as categorical variables. If a variable appears by itself in a DOMAIN statement, each level of this variable determines a domain in the study population. If two or more variables are joined by asterisks (*), then every possible combination of levels of these variables determines a domain. The procedure performs a descriptive analysis within each domain that is defined by the domain variables.

When determining levels of a DOMAIN variable, an observation with missing values for this DOMAIN variable is excluded, unless you specify the \texttt{MISSING} option. For more information, see the section “Missing Values” on page 7305.
The formatted values of the domain variables determine the categorical variable levels. Thus, you can use formats to group values into levels. See the FORMAT procedure in the *Base SAS Procedures Guide* and the FORMAT statement and SAS formats in *SAS Formats and Informats: Reference* for more information.

**EFFECT Statement**

```
EFFECT name = effect-type ( variables < / options > ) ;
```

The 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 formed from continuous or classification variables, as discussed in the section “GLM Parameterization of Classification Variables and Effects” on page 394 of Chapter 19, “Shared Concepts and Topics.”

The following *effect-types* are available:

- **COLLECTION** is 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** is a classification effect in which the level that is used for a given period corresponds to the level in the preceding period.
  
  **Note:** The LAG *effect-type* is experimental in this release.
- **MULTIMEMBER | MM** is a multimember classification effect whose levels are determined by one or more variables that appear in a CLASS statement.
- **POLYNOMIAL | POLY** is a multivariate polynomial effect in the specified numeric variables.
- **SPLINE** is 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 87.2 summarizes important options for each type of EFFECT statement.

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Options for Collection Effects</strong></td>
<td></td>
</tr>
<tr>
<td>DETAILS</td>
<td>Displays the constituents of the collection effect</td>
</tr>
<tr>
<td><strong>Options for Lag Effects</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</td>
</tr>
</tbody>
</table>

Table 87.2 Important EFFECT Statement Options
Table 87.2 continued

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>WITHIN=</td>
<td>Names the variable or variables that define the group within which each period is defined</td>
</tr>
</tbody>
</table>

Options for Multimember Effects

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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>
</tbody>
</table>

Options for Polynomial Effects

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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>
</tbody>
</table>

Options for Spline Effects

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BASIS=</td>
<td>Specifies the type of basis (B-spline basis or truncated power function basis) for the spline expansion</td>
</tr>
<tr>
<td>DEGREE=</td>
<td>Specifies the degree of the spline transformation</td>
</tr>
<tr>
<td>KNOTMETHOD=</td>
<td>Specifies how to construct the knots for spline effects</td>
</tr>
</tbody>
</table>

For further details about the syntax of these effect-types and how columns of constructed effects are computed, see the section “EFFECT Statement” on page 403 of Chapter 19, “Shared Concepts and Topics.”

**ESTIMATE Statement**

```
ESTIMATE < 'label'> estimate-specification <(divisor=n)> <, . . . < 'label'> estimate-specification <(divisor=n)> > < / options > ;
```

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 87.3 summarizes important options in the ESTIMATE statement.
### Table 87.3 Important ESTIMATE Statement Options

<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>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>

For details about the syntax of the ESTIMATE statement, see the section “ESTIMATE Statement” on page 448 of Chapter 19, “Shared Concepts and Topics.”

---

### FREQ Statement

**FREQ** `variable`;  

The `variable` in the FREQ statement identifies a variable that contains the frequency of occurrence of each observation. PROC SURVEYLOGISTIC treats each observation as if it appears \(n\) times, where \(n\) is the
value of the FREQ variable for the observation. If it is not an integer, the frequency value is truncated to an integer. If the frequency value is less than 1 or missing, the observation is not used in the model fitting. When the FREQ statement is not specified, each observation is assigned a frequency of 1.

If you use the events/trials syntax in the MODEL statement, the FREQ statement is not allowed because the event and trial variables represent the frequencies in the data set.

---

**LSMEANS Statement**

```plaintext
LSMEANS <model-effects> </options>;
```

The LSMEANS statement computes and compares least squares means (LS-means) of fixed effects. LS-means are *predicted margins*—that is, they estimate the marginal means over a hypothetical balanced population.

Table 87.4 summarizes important options in the LSMEANS statement.

<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 - \alpha))</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 ODS statistical graphics 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>
Table 87.4  continued

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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>
<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 464 of Chapter 19, “Shared Concepts and Topics.”

---

**LSMESTEIMATE Statement**

\[
\text{LSMESTEIMATE} \ \text{model-effect} \ \langle \text{'label'} \rangle \ \text{values} \ \langle \text{divisor=n} \rangle \\
\langle, \ldots, \langle \text{'label'} \rangle \ \text{values} \ \langle \text{divisor=n} \rangle \rangle \\
\langle / \text{options} \rangle ;
\]

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

Table 87.5 summarizes important options in the LSMESTEIMATE statement.

Table 87.5  Important LSMESTEIMATE 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=( \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 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>
</tbody>
</table>
Table 87.5  continued

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Statistical Output</strong></td>
<td>Constructs confidence limits for means and mean differences</td>
</tr>
<tr>
<td>CL</td>
<td>Displays the correlation matrix of LS-means</td>
</tr>
<tr>
<td>CORR</td>
<td>Displays the covariance matrix of LS-means</td>
</tr>
<tr>
<td>COV</td>
<td>Prints the L matrix</td>
</tr>
<tr>
<td>E</td>
<td>Prints the K matrix</td>
</tr>
<tr>
<td>ELSM</td>
<td>Produces a joint F or chi-square test for the LS-means and LS-means differences</td>
</tr>
<tr>
<td>JOINT</td>
<td>Specifies the seed for computations that depend on random numbers</td>
</tr>
<tr>
<td>SEED=</td>
<td>Specifies how to construct estimable functions with multinomial data</td>
</tr>
<tr>
<td>EXP</td>
<td>Exponentiates and displays LS-means estimates</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>

For details about the syntax of the LSMESTIMATE statement, see the section “LSMESTIMATE Statement” on page 480 of Chapter 19, “Shared Concepts and Topics.”

**MODEL Statement**

```
MODEL events/trials = <effects < / options >> ;
MODEL variable < (v-options) > = <effects> < / options > ;
```

The MODEL statement names the response variable and the explanatory effects, including covariates, main effects, interactions, and nested effects; see the section “Specification of Effects” on page 3186 of Chapter 41, “The GLM Procedure,” for more information. If you omit the explanatory variables, the procedure fits an intercept-only model. Model options can be specified after a slash (/).

Two forms of the MODEL statement can be specified. The first form, referred to as single-trial syntax, is applicable to binary, ordinal, and nominal response data. The second form, referred to as events/trials syntax, is restricted to the case of binary response data. The single-trial syntax is used when each observation in the DATA= data set contains information about only a single trial, such as a single subject in an experiment. When each observation contains information about multiple binary-response trials, such as the counts of the number of subjects observed and the number responding, then events/trials syntax can be used.

In the events/trials syntax, you specify two variables that contain count data for a binomial experiment. These two variables are separated by a slash. The value of the first variable, events, is the number of positive
responses (or events), and it must be nonnegative. The value of the second variable, trials, is the number of trials, and it must not be less than the value of events.

In the single-trial syntax, you specify one variable (on the left side of the equal sign) as the response variable. This variable can be character or numeric. Options specific to the response variable can be specified immediately after the response variable with parentheses around them.

For both forms of the MODEL statement, explanatory effects follow the equal sign. Variables can be either continuous or classification variables. Classification variables can be character or numeric, and they must be declared in the CLASS statement. When an effect is a classification variable, the procedure enters a set of coded columns into the design matrix instead of directly entering a single column containing the values of the variable.

**Response Variable Options**

You specify the following options by enclosing them in parentheses after the response variable:

**DESCENDING**

reverses the order of response categories. If both the DESCENDING and the ORDER= options are specified, PROC SURVEYLOGISTIC orders the response categories according to the ORDER= option and then reverses that order. See the section “Response Level Ordering” on page 7306 for more detail.

**EVENT='category' | keyword**

specifies the event category for the binary response model. PROC SURVEYLOGISTIC models the probability of the event category. The EVENT= option has no effect when there are more than two response categories. You can specify the value (formatted if a format is applied) of the event category in quotes or you can specify one of the following keywords. The default is EVENT=FIRST.

FIRST designates the first ordered category as the event
LAST designates the last ordered category as the event

One of the most common sets of response levels is \{0,1\}, with 1 representing the event for which the probability is to be modeled. Consider the example where Y takes the values 1 and 0 for event and nonevent, respectively, and Exposure is the explanatory variable. To specify the value 1 as the event category, use the following MODEL statement:

```
model Y(event='1') = Exposure;
```

**ORDER=DATA | FORMATTED | FREQ | INTERNAL**

specifies the sorting order for the levels of the response variable. By default, ORDER=INTERNAL. For ORDER=FORMATTED and ORDER=INTERNAL, the sort order is machine-dependent.

When the default ORDER=FORMATTED is in effect for numeric variables for which you have supplied no explicit format,
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Value of ORDER= Levels Sorted By
---
DATA Order of appearance in the input data set
FORMATTED External formatted value, except for numeric variables with no explicit format, which are sorted by their unformatted (internal) value
FREQ Descending frequency count; levels with the most observations come first in the order
INTERNAL Unformatted value

For more information about sorting 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.

REFERENCE=’category’ | keyword
REF=’category’ | keyword
specifies the reference category for the generalized logit model and the binary response model. For the generalized logit model, each nonreference category is contrasted with the reference category. For the binary response model, specifying one response category as the reference is the same as specifying the other response category as the event category. You can specify the value (formatted if a format is applied) of the reference category in quotes or you can specify one of the following keywords. The default is REF=LAST.

FIRST designates the first ordered category as the reference
LAST designates the last ordered category as the reference

Model Options

Model options can be specified after a slash (/). Table 87.6 summarizes the options available in the MODEL statement.

Table 87.6 MODEL Statement Options

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Specification Options</td>
<td></td>
</tr>
<tr>
<td>LINK=</td>
<td>Specifies link function</td>
</tr>
<tr>
<td>NOINT</td>
<td>Suppresses intercept(s)</td>
</tr>
<tr>
<td>OFFSET=</td>
<td>Specifies offset variable</td>
</tr>
<tr>
<td>Convergence Criterion Options</td>
<td></td>
</tr>
<tr>
<td>ABSFCONV=</td>
<td>Specifies absolute function convergence criterion</td>
</tr>
<tr>
<td>FCONV=</td>
<td>Specifies relative function convergence criterion</td>
</tr>
<tr>
<td>GCONV=</td>
<td>Specifies relative gradient convergence criterion</td>
</tr>
<tr>
<td>XCONV=</td>
<td>Specifies relative parameter convergence criterion</td>
</tr>
<tr>
<td>MAXITER=</td>
<td>Specifies maximum number of iterations</td>
</tr>
<tr>
<td>NOCHECK</td>
<td>Suppresses checking for infinite parameters</td>
</tr>
<tr>
<td>RIDGING=</td>
<td>Specifies technique used to improve the log-likelihood function when its value is worse than that of the previous step</td>
</tr>
</tbody>
</table>
Table 87.6  (continued)

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SINGULAR=</td>
<td>Specifies tolerance for testing singularity</td>
</tr>
<tr>
<td>TECHNIQUE=</td>
<td>Specifies iterative algorithm for maximization</td>
</tr>
</tbody>
</table>

**Options for Adjustment to Variance Estimation**

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>VADJUST=</td>
<td>Chooses variance estimation adjustment method</td>
</tr>
</tbody>
</table>

**Options for Confidence Intervals**

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALPHA=</td>
<td>Specifies $\alpha$ for the $100(1 - \alpha)%$ confidence intervals</td>
</tr>
<tr>
<td>CLPARM</td>
<td>Computes confidence intervals for parameters</td>
</tr>
<tr>
<td>CLODDS</td>
<td>Computes confidence intervals for odds ratios</td>
</tr>
</tbody>
</table>

**Options for Display of Details**

<table>
<thead>
<tr>
<th>Option</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CORRB</td>
<td>Displays correlation matrix</td>
</tr>
<tr>
<td>COVB</td>
<td>Displays covariance matrix</td>
</tr>
<tr>
<td>EXPB</td>
<td>Displays exponentiated values of estimates</td>
</tr>
<tr>
<td>ITPRINT</td>
<td>Displays iteration history</td>
</tr>
<tr>
<td>NODUMMYPRINT</td>
<td>Suppresses “Class Level Information” table</td>
</tr>
<tr>
<td>PARMLABEL</td>
<td>Displays parameter labels</td>
</tr>
<tr>
<td>RSQUARE</td>
<td>Displays generalized $R^2$</td>
</tr>
<tr>
<td>STB</td>
<td>Displays standardized estimates</td>
</tr>
</tbody>
</table>

The following list describes these options:

**ABSFCONV=value**

specifies the absolute function convergence criterion. Convergence requires a small change in the log-likelihood function in subsequent iterations:

$$|l^{(i)} - l^{(i-1)}| < value$$

where $l^{(i)}$ is the value of the log-likelihood function at iteration $i$. See the section “Convergence Criteria” on page 7313.

**ALPHA=value**

sets the level of significance $\alpha$ for $100(1 - \alpha)\%$ confidence intervals for regression parameters or odds ratios. The value $\alpha$ must be between 0 and 1. By default, $\alpha$ is equal to the value of the ALPHA= option in the PROC SURVEYLOGISTIC statement, or $\alpha = 0.05$ if the ALPHA= option is not specified. This option has no effect unless confidence limits for the parameters or odds ratios are requested.

**CLODDS**

requests confidence intervals for the odds ratios. Computation of these confidence intervals is based on individual Wald tests. The confidence coefficient can be specified with the ALPHA= option.

See the section “Wald Confidence Intervals for Parameters” on page 7328 for more information.

**CLPARM**

requests confidence intervals for the parameters. Computation of these confidence intervals is based on the individual Wald tests. The confidence coefficient can be specified with the ALPHA= option.

See the section “Wald Confidence Intervals for Parameters” on page 7328 for more information.
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CORRB

displays the correlation matrix of the parameter estimates.

COVB

displays the covariance matrix of the parameter estimates.

EXPB

EXPEST

displays the exponentiated values ($e^{\hat{\theta}_i}$) of the parameter estimates $\hat{\theta}_i$ in the “Analysis of Maximum Likelihood Estimates” table for the logit model. These exponentiated values are the estimated odds ratios for the parameters corresponding to the continuous explanatory variables.

FCONV=value

specifies the relative function convergence criterion. Convergence requires a small relative change in the log-likelihood function in subsequent iterations:

$$\frac{|f(i) - f(i-1)|}{|f(i-1)| + 1E-6} < value$$

where $f(i)$ is the value of the log likelihood at iteration $i$. See the section “Convergence Criteria” on page 7313 for details.

GCONV=value

specifies the relative gradient convergence criterion. Convergence requires that the normalized prediction function reduction is small:

$$\frac{g(i)'F(i)g(i)}{|f(i)| + 1E-6} < value$$

where $f(i)$ is the value of the log-likelihood function, $g(i)$ is the gradient vector, and $F(i)$ the (expected) information matrix. All of these functions are evaluated at iteration $i$. This is the default convergence criterion, and the default value is 1E–8. See the section “Convergence Criteria” on page 7313 for details.

ITPRINT

displays the iteration history of the maximum-likelihood model fitting. The ITPRINT option also displays the last evaluation of the gradient vector and the final change in the $-2 \log L$.

LINK=keyword

L=keyword

specifies the link function that links the response probabilities to the linear predictors. You can specify one of the following keywords. The default is LINK=LOGIT.

CLOGLOG

specifies the complementary log-log function. PROC SURVEYLOGISTIC fits the binary complementary log-log model for binary response and fits the cumulative complementary log-log model when there are more than two response categories. Aliases: CCLOGLOG, CCLL, CUMCLOGLOG.

GLOGIT

specifies the generalized logit function. PROC SURVEYLOGISTIC fits the generalized logit model where each nonreference category is contrasted with the reference category. You can use the response variable option REF= to specify the reference category.
LOGIT specifies the cumulative logit function. PROC SURVEYLOGISTIC fits the binary logit model when there are two response categories and fits the cumulative logit model when there are more than two response categories. Aliases: CLOGIT, CUMLOGIT.

PROBIT specifies the inverse standard normal distribution function. PROC SURVEYLOGISTIC fits the binary probit model when there are two response categories and fits the cumulative probit model when there are more than two response categories. Aliases: NORMIT, CPROBIT, CUMPROBIT.

See the section “Link Functions and the Corresponding Distributions” on page 7310 for details.

MAXITER=n specifies the maximum number of iterations to perform. By default, MAXITER=25. If convergence is not attained in n iterations, the displayed output created by the procedure contains results that are based on the last maximum likelihood iteration.

NOCHECK disables the checking process to determine whether maximum likelihood estimates of the regression parameters exist. If you are sure that the estimates are finite, this option can reduce the execution time when the estimation takes more than eight iterations. For more information, see the section “Existence of Maximum Likelihood Estimates” on page 7313.

NODUMMYPRINT suppresses the “Class Level Information” table, which shows how the design matrix columns for the CLASS variables are coded.

NOINT suppresses the intercept for the binary response model or the first intercept for the ordinal response model.

OFFSET=name names the offset variable. The regression coefficient for this variable is fixed at 1.

PARMLABEL displays the labels of the parameters in the “Analysis of Maximum Likelihood Estimates” table.

RIDGING=ABSOLUTE | RELATIVE | NONE specifies the technique used to improve the log-likelihood function when its value in the current iteration is less than that in the previous iteration. If you specify the RIDGING=ABSOLUTE option, the diagonal elements of the negative (expected) Hessian are inflated by adding the ridge value. If you specify the RIDGING=RELATIVE option, the diagonal elements are inflated by a factor of 1 plus the ridge value. If you specify the RIDGING=NONE option, the crude line search method of taking half a step is used instead of ridging. By default, RIDGING=RELATIVE.

RSQUARE requests a generalized $R^2$ measure for the fitted model.

For more information, see the section “Generalized Coefficient of Determination” on page 7315.
SINGULAR=value
specifies the tolerance for testing the singularity of the Hessian matrix (Newton-Raphson algorithm) or the expected value of the Hessian matrix (Fisher scoring algorithm). The Hessian matrix is the matrix of second partial derivatives of the log likelihood. The test requires that a pivot for sweeping this matrix be at least this value times a norm of the matrix. Values of the SINGULAR= option must be numeric. By default, SINGULAR=10^{-12}.

STB
displays the standardized estimates for the parameters for the continuous explanatory variables in the “Analysis of Maximum Likelihood Estimates” table. The standardized estimate of \( \theta_i \) is given by \( \hat{\theta}_i / (s_i) \), where \( s_i \) is the total sample standard deviation for the \( i \)th explanatory variable and

\[
s = \begin{cases} 
\pi / \sqrt{3} & \text{Logistic} \\
1 & \text{Normal} \\
\pi / \sqrt{6} & \text{Extreme-value}
\end{cases}
\]

For the intercept parameters and parameters associated with a CLASS variable, the standardized estimates are set to missing.

TECHNIQUE=FISHER | NEWTON
TECH=FISHER | NEWTON
specifies the optimization technique for estimating the regression parameters. NEWTON (or NR) is the Newton-Raphson algorithm and FISHER (or FS) is the Fisher scoring algorithm. Both techniques yield the same estimates, but the estimated covariance matrices are slightly different except for the case where the LOGIT link is specified for binary response data. The default is TECHNIQUE=FISHER. If the LINK=GLOGIT option is specified, then Newton-Raphson is the default and only available method. See the section “Iterative Algorithms for Model Fitting” on page 7312 for details.

VADJUST=DF
VADJUST=MOREL < (Morel-options) >
VADJUST=NONE
specifies an adjustment to the variance estimation for the regression coefficients.

By default, PROC SURVEYLOGISTIC uses the degrees of freedom adjustment VADJUST=DF.

If you do not want to use any variance adjustment, you can specify the VADJUST=NONE option. You can specify the VADJUST=MOREL option for the variance adjustment proposed by Morel (1989).

You can specify the following Morel-options within parentheses after the VADJUST=MOREL option:

ADJBOUND=\phi
sets the upper bound coefficient \( \phi \) in the variance adjustment. This upper bound must be positive. By default, the procedure uses \( \phi = 0.5 \). See the section “Adjustments to the Variance Estimation” on page 7322 for more details on how this upper bound is used in the variance estimation.

DEFFBOUND=\delta
sets the lower bound of the estimated design effect in the variance adjustment. This lower bound must be positive. By default, the procedure uses \( \delta = 1 \). See the section “Adjustments to the
Variance Estimation” on page 7322 for more details about how this lower bound is used in the variance estimation.

\[ \text{XCONV} = \text{value} \]

specifies the relative parameter convergence criterion. Convergence requires a small relative parameter change in subsequent iterations:

\[ \max_j |\delta_j^{(i)}| < \text{value} \]

where

\[ \delta_j^{(i)} = \begin{cases} \frac{\theta_j^{(i)} - \theta_j^{(i-1)}}{\theta_j^{(i-1)}} & |\theta_j^{(i-1)}| < 0.01 \\ \frac{\theta_j^{(i)} - \theta_j^{(i-1)}}{\theta_j^{(i-1)}} & \text{otherwise} \end{cases} \]

and \( \theta_j^{(i)} \) is the estimate of the \( j \)th parameter at iteration \( i \). See the section “Convergence Criteria” on page 7313 for details.

---

**OUTPUT Statement**

\[
\text{OUTPUT}\ <\ \text{OUT=}\text{SAS-data-set}>\ <\text{options}>\ <\ /\ \text{option}>\ ;
\]

The OUTPUT statement creates a new SAS data set that contains all the variables in the input data set and, optionally, the estimated linear predictors and their standard error estimates, the estimates of the cumulative or individual response probabilities, and the confidence limits for the cumulative probabilities. Formulas for the statistics are given in the section “Linear Predictor, Predicted Probability, and Confidence Limits” on page 7332.

If you use the single-trial syntax, the data set also contains a variable named _LEVEL_, which indicates the level of the response that the given row of output is referring to. For example, the value of the cumulative probability variable is the probability that the response variable is as large as the corresponding value of _LEVEL_. For details, see the section “OUT= Data Set in the OUTPUT Statement” on page 7333.

The estimated linear predictor, its standard error estimate, all predicted probabilities, and the confidence limits for the cumulative probabilities are computed for all observations in which the explanatory variables have no missing values, even if the response is missing. By adding observations with missing response values to the input data set, you can compute these statistics for new observations, or for settings of the explanatory variables not present in the data, without affecting the model fit.

You can specify the following options in the OUTPUT statement:

\[
\text{LOWER} | \quad \text{L=}\text{name}
\]

names the variable that contains the lower confidence limits for \( \pi \), where \( \pi \) is the probability of the event response if events/trials syntax or the single-trial syntax with binary response is specified; \( \pi \) is cumulative probability (that is, the probability that the response is less than or equal to the value of _LEVEL_) for a cumulative model; and \( \pi \) is the individual probability (that is, the probability that the response category is represented by the value of _LEVEL_) for the generalized logit model. See the ALPHA= option for information about setting the confidence level.
OUT=SAS-data-set
names the output data set. If you omit the OUT= option, the output data set is created and given a
default name by using the DATA_ convention.

The statistic options in the OUTPUT statement specify the statistics to be included in the output data
set and name the new variables that contain the statistics.

PREDICTED | P=name
names the variable that contains the predicted probabilities. For the events/trials syntax or the single-
trial syntax with binary response, it is the predicted event probability. For a cumulative model, it is
the predicted cumulative probability (that is, the probability that the response variable is less than or
equal to the value of _LEVEL_); and for the generalized logit model, it is the predicted individual
probability (that is, the probability of the response category represented by the value of _LEVEL_).

PREDPROBS=(keywords)
requests individual, cumulative, or cross validated predicted probabilities. Descriptions of the key-
words are as follows.

INDIVIDUAL | I requests the predicted probability of each response level. For a response variable
Y with three levels, 1, 2, and 3, the individual probabilities are Pr(Y=1), Pr(Y=2), and Pr(Y=3).

CUMULATIVE | C requests the cumulative predicted probability of each response level. For a re-
sponse variable Y with three levels, 1, 2, and 3, the cumulative probabilities are
Pr(Y≤1), Pr(Y≤2), and Pr(Y≤3). The cumulative probability for the last response
level always has the constant value of 1. For generalized logit models, the cumu-
lative predicted probabilities are not computed and are set to missing.

CROSSVALIDATE | XVALIDATE | X requests the cross validated individual predicted probabil-
ity of each response level. These probabilities are derived from the leave-one-out
principle; that is, dropping the data of one subject and reestimating the parameter
estimates. PROC SURVEYLOGISTIC uses a less expensive one-step approxi-
mation to compute the parameter estimates. This option is valid only for binary
response models; for nominal and ordinal models, the cross validated probabilities
are not computed and are set to missing.

See the section “Details of the PREDPROBS= Option” on page 7299 at the end of this section for
further details.

STDXBETA=name
names the variable that contains the standard error estimates of XBETA (the definition of which
follows).

UPPER | U=name
names the variable that contains the upper confidence limits for π, where π is the probability of the
event response if events/trials syntax or single-trial syntax with binary response is specified; π is
cumulative probability (that is, the probability that the response is less than or equal to the value of
_LEVEL_) for a cumulative model; and π is the individual probability (that is, the probability that the
response category is represented by the value of _LEVEL_) for the generalized logit model. See the
ALPHA= option for information about setting the confidence level.
XBETA=name

names the variable that contains the estimates of the linear predictor \( \alpha_i + \mathbf{x}\beta \), where \( i \) is the corresponding ordered value of _LEVEL_.

You can specify the following option in the OUTPUT statement after a slash (/):

ALPHA=value

sets the level of significance \( \alpha \) for 100(1 - \( \alpha \))% confidence limits for the appropriate response probabilities. The value \( \alpha \) must be between 0 and 1. By default, \( \alpha \) is equal to the value of the ALPHA= option in the PROC SURVEYLOGISTIC statement, or 0.05 if the ALPHA= option is not specified.

Details of the PREDPROBS= Option

You can request any of the three given types of predicted probabilities. For example, you can request both the individual predicted probabilities and the cross validated probabilities by specifying PREDPROBS=(I X).

When you specify the PREDPROBS= option, two automatic variables _FROM_ and _INTO_ are included for the single-trial syntax and only one variable, _INTO_, is included for the events/trials syntax. The _FROM_ variable contains the formatted value of the observed response. The variable _INTO_ contains the formatted value of the response level with the largest individual predicted probability.

If you specify PREDPROBS=INDIVIDUAL, the OUTPUT data set contains \( k \) additional variables representing the individual probabilities, one for each response level, where \( k \) is the maximum number of response levels across all BY groups. The names of these variables have the form IP_xxx, where xxx represents the particular level. The representation depends on the following situations:

- If you specify the events/trials syntax, xxx is either Event or Nonevent. Thus, the variable that contains the event probabilities is named IP_Event and the variable containing the nonevent probabilities is named IP_Nonevent.

- If you specify the single-trial syntax with more than one BY group, xxx is 1 for the first ordered level of the response, 2 for the second ordered level of the response, and so forth, as given in the “Response Profile” table. The variable that contains the predicted probabilities \( \Pr(Y=1) \) is named IP_1, where \( Y \) is the response variable. Similarly, IP_2 is the name of the variable containing the predicted probabilities \( \Pr(Y=2) \), and so on.

- If you specify the single-trial syntax with no BY-group processing, xxx is the left-justified formatted value of the response level (the value can be truncated so that IP_xxx does not exceed 32 characters). For example, if \( Y \) is the response variable with response levels ‘None,’ ‘Mild,’ and ‘Severe,’ the variables representing individual probabilities \( \Pr(Y=’None’) \), \( \Pr(Y=’Mild’) \), and \( \Pr(Y=’Severe’) \) are named IP_None, IP_Mild, and IP_Severe, respectively.

If you specify PREDPROBS=CUMULATIVE, the OUTPUT data set contains \( k \) additional variables that represent the cumulative probabilities, one for each response level, where \( k \) is the maximum number of response levels across all BY groups. The names of these variables have the form CP_xxx, where xxx represents the particular response level. The naming convention is similar to that given by PREDPROBS=INDIVIDUAL. The PREDPROBS=CUMULATIVE values are the same as those output by the
PREDICT=keyword, but they are arranged in variables in each output observation rather than in multiple output observations.

If you specify PREDPROBS=CROSSVALIDATE, the OUTPUT data set contains $k$ additional variables representing the cross validated predicted probabilities of the $k$ response levels, where $k$ is the maximum number of response levels across all BY groups. The names of these variables have the form $XP_{xxx}$, where $xxx$ represents the particular level. The representation is the same as that given by PREDPROBS=INDIVIDUAL, except that for the events/trials syntax there are four variables for the cross validated predicted probabilities instead of two:

- $XP_{EVENT_R1E}$ is the cross validated predicted probability of an event when a current event trial is removed.
- $XP_{NONEVENT_R1E}$ is the cross validated predicted probability of a nonevent when a current event trial is removed.
- $XP_{EVENT_R1N}$ is the cross validated predicted probability of an event when a current nonevent trial is removed.
- $XP_{NONEVENT_R1N}$ is the cross validated predicted probability of a nonevent when a current nonevent trial is removed.

**REPWEIGHTS Statement**

```
REPWEIGHTS variables < / options> ;
```

The REPWEIGHTS statement names variables that provide replicate weights for BRR or jackknife variance estimation, which you request with the VARMETHOD=BRR or VARMETHOD=JACKKNIFE option in the PROC SURVEYLOGISTIC statement. If you do not provide replicate weights for these methods by using a REPWEIGHTS statement, then the procedure constructs replicate weights for the analysis. See the sections “Balanced Repeated Replication (BRR) Method” on page 7323 and “Jackknife Method” on page 7325 for information about replicate weights.

Each REPWEIGHTS variable should contain the weights for a single replicate, and the number of replicates equals the number of REPWEIGHTS variables. The REPWEIGHTS variables must be numeric, and the variable values must be nonnegative numbers.

If you provide replicate weights with a REPWEIGHTS statement, you do not need to specify a CLUSTER or STRATA statement. If you use a REPWEIGHTS statement and do not specify the VARMETHOD= option in the PROC SURVEYLOGISTIC statement, the procedure uses VARMETHOD=JACKKNIFE by default.

If you specify a REPWEIGHTS statement but do not include a WEIGHT statement, the procedure uses the average of replicate weights of each observation as the observation’s weight.

You can specify the following options in the REPWEIGHTS statement after a slash (/):

- **DF=df** specifies the degrees of freedom for the analysis. The value of $df$ must be a positive number. By default, the degrees of freedom equals the number of REPWEIGHTS variables.
**JKCOEFS=**

Specifies a jackknife coefficient for VARMETHOD=JACKKNIFE. The coefficient value must be a nonnegative number. See the section “Jackknife Method” on page 7325 for details about jackknife coefficients.

You can use this option to specify a single value of the jackknife coefficient, which the procedure uses for all replicates. To specify different coefficients for different replicates, use the JKCOEFS=values or JKCOEFS=SAS-data-set option.

**JKCOEFS=values**

Specifies jackknife coefficients for VARMETHOD=JACKKNIFE, where each coefficient corresponds to an individual replicate that is identified by a REPWEIGHTS variable. You can separate values with blanks or commas. The coefficient values must be nonnegative numbers. The number of values must equal the number of replicate weight variables named in the REPWEIGHTS statement. List these values in the same order in which you list the corresponding replicate weight variables in the REPWEIGHTS statement.

See the section “Jackknife Method” on page 7325 for details about jackknife coefficients.

To specify different coefficients for different replicates, you can also use the JKCOEFS=SAS-data-set option. To specify a single jackknife coefficient for all replicates, use the JKCOEFS=value option.

**JKCOEFS=SAS-data-set**

Names a SAS data set that contains the jackknife coefficients for VARMETHOD=JACKKNIFE. You provide the jackknife coefficients in the JKCOEFS= data set variable JKCoefficient. Each coefficient value must be a nonnegative number. The observations in the JKCOEFS= data set should correspond to the replicates that are identified by the REPWEIGHTS variables. Arrange the coefficients or observations in the JKCOEFS= data set in the same order in which you list the corresponding replicate weight variables in the REPWEIGHTS statement. The number of observations in the JKCOEFS= data set must not be less than the number of REPWEIGHTS variables.

See the section “Jackknife Method” on page 7325 for details about jackknife coefficients.

To specify different coefficients for different replicates, you can also use the JKCOEFS=values option. To specify a single jackknife coefficient for all replicates, use the JKCOEFS=value option.

---

**SLICE Statement**

```
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 19.19. For details about the syntax of the SLICE statement, see the section “SLICE Statement” on page 510 of Chapter 19, “Shared Concepts and Topics.”
**STORE Statement**

```
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 is 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 513 of Chapter 19, “Shared Concepts and Topics.”

**STRATA Statement**

```
STRATA variables < / option> ;
```

The STRATA statement specifies variables that form the strata in a stratified sample design. The combinations of categories of STRATA variables define the strata in the sample.

If your sample design has stratification at multiple stages, you should identify only the first-stage strata in the STRATA statement. See the section “Specification of Population Totals and Sampling Rates” on page 7316 for more information.

If you provide replicate weights for BRR or jackknife variance estimation with the REPWEIGHTS statement, you do not need to specify a STRATA statement.

The STRATA variables are one or more variables in the DATA= input data set. These variables can be either character or numeric. The formatted values of the STRATA variables determine the levels. Thus, you can use formats to group values into levels. See the FORMAT procedure in the Base SAS Procedures Guide and the FORMAT statement and SAS formats in SAS Formats and Informats: Reference for more information.

When determining levels of a STRATA variable, an observation with missing values for this STRATA variable is excluded, unless you specify the MISSING option. For more information, see the section “Missing Values” on page 7305.

You can use multiple STRATA statements to specify stratum variables.

You can specify the following option in the STRATA statement after a slash (/):

**LIST**

- displays a “Stratum Information” table, which includes values of the STRATA variables and the number of observations, number of clusters, population total, and sampling rate for each stratum. See the section “Stratum Information” on page 7338 for more details.
**TEST Statement**

```< label: > TEST equation1 <, equation2, ...> </ option> ;```

The TEST statement tests linear hypotheses about the regression coefficients. The Wald test is used to jointly test the null hypotheses \( H_0: \mathbf{L}\theta = \mathbf{c} \) specified in a single TEST statement. When \( \mathbf{c} = \mathbf{0} \) you should specify a CONTRAST statement instead.

Each *equation* specifies a linear hypothesis (a row of the \( \mathbf{L} \) matrix and the corresponding element of the \( \mathbf{c} \) vector); multiple *equations* are separated by commas. The label, which must be a valid SAS name, is used to identify the resulting output and should always be included. You can submit multiple TEST statements.

The form of an *equation* is as follows:

```term < ± term ... > = ± term < ± term ... >```

where *term* is a parameter of the model, or a constant, or a constant times a parameter. For a binary response model, the intercept parameter is named INTERCEPT; for an ordinal response model, the intercept parameters are named INTERCEPT, INTERCEPT2, INTERCEPT3, and so on. When no equal sign appears, the expression is set to 0. The following illustrates possible uses of the TEST statement:

```proc surveylogistic;```
```  model y= a1 a2 a3 a4;```
```  test1: test intercept + .5 * a2 = 0;```
```  test2: test intercept + .5 * a2;```
```  test3: test a1=a2=a3;```
```  test4: test a1=a2, a2=a3;```
```run;```

Note that the first and second TEST statements are equivalent, as are the third and fourth TEST statements.

You can specify the following option in the TEST statement after a slash (/):

**PRINT**

`PRINT` displays intermediate calculations in the testing of the null hypothesis \( H_0: \mathbf{L}\theta = \mathbf{c} \). This includes \( \mathbf{L}\hat{\mathbf{V}}(\hat{\theta})\mathbf{L}' \) bordered by \( (\mathbf{L}\hat{\theta} - \mathbf{c}) \) and \( [\mathbf{L}\hat{\mathbf{V}}(\hat{\theta})\mathbf{L}']^{-1} \) bordered by \( [\mathbf{L}\hat{\mathbf{V}}(\hat{\theta})\mathbf{L}']^{-1}(\mathbf{L}\hat{\theta} - \mathbf{c}) \), where \( \hat{\theta} \) is the pseudo-estimator of \( \theta \) and \( \hat{\mathbf{V}}(\hat{\theta}) \) is the estimated covariance matrix of \( \hat{\theta} \).

For more information, see the section “Testing Linear Hypotheses about the Regression Coefficients” on page 7328.

**UNITS Statement**

```UNITS independent1 = list1 < ... independentk = listk>/ option> ;```

The UNITS statement enables you to specify units of change for the continuous explanatory variables so that customized odds ratios can be estimated. An estimate of the corresponding odds ratio is produced for each unit of change specified for an explanatory variable. The UNITS statement is ignored for CLASS variables.
If the `CLODDS` option is specified in the `MODEL` statement, the corresponding confidence limits for the odds ratios are also displayed.

The term `independent` is the name of an explanatory variable, and `list` represents a list of units of change, separated by spaces, that are of interest for that variable. Each unit of change in a list has one of the following forms:

- `number`
- `SD` or `–SD`
- `number * SD`

where `number` is any nonzero number and `SD` is the sample standard deviation of the corresponding independent variable. For example, `X = –2` requests an odds ratio that represents the change in the odds when the variable `X` is decreased by two units. `X = 2*SD` requests an estimate of the change in the odds when `X` is increased by two sample standard deviations.

You can specify the following option in the `UNITS` statement after a slash (/):

```
DEFAULT=list
```

gives a list of units of change for all explanatory variables that are not specified in the `UNITS` statement. Each unit of change can be in any of the forms described previously. If the `DEFAULT=` option is not specified, PROC SURVEYLOGISTIC does not produce customized odds ratio estimates for any explanatory variable that is not listed in the `UNITS` statement.

For more information, see the section “Odds Ratio Estimation” on page 7328.

---

**WEIGHT Statement**

```
WEIGHT variable ;
```

The WEIGHT statement names the variable that contains the sampling weights. This variable must be numeric, and the sampling weights must be positive numbers. If an observation has a weight that is nonpositive or missing, then the procedure omits that observation from the analysis. See the section “Missing Values” on page 7305 for more information. If you specify more than one WEIGHT statement, the procedure uses only the first WEIGHT statement and ignores the rest.

If you do not specify a WEIGHT statement but provide replicate weights with a `REPWEIGHTS` statement, PROC SURVEYLOGISTIC uses the average of replicate weights of each observation as the observation’s weight.

If you do not specify a WEIGHT statement or a `REPWEIGHTS` statement, PROC SURVEYLOGISTIC assigns all observations a weight of one.
Details: SURVEYLOGISTIC Procedure

Missing Values

If you have missing values in your survey data for any reason, such as nonresponse, this can compromise the quality of your survey results. If the respondents are different from the nonrespondents with regard to a survey effect or outcome, then survey estimates might be biased and cannot accurately represent the survey population. There are a variety of techniques in sample design and survey operations that can reduce nonresponse. After data collection is complete, you can use imputation to replace missing values with acceptable values, and/or you can use sampling weight adjustments to compensate for nonresponse. You should complete this data preparation and adjustment before you analyze your data with PROC SURVEYLOGISTIC. See Cochran (1977), Kalton and Kaspyzyk (1986), and Brick and Kalton (1996) for more information.

If an observation has a missing value or a nonpositive value for the WEIGHT or FREQ variable, then that observation is excluded from the analysis.

An observation is also excluded if it has a missing value for any design (STRATA, CLUSTER, or DOMAIN) variable, unless you specify the MISSING option in the PROC SURVEYLOGISTIC statement. If you specify the MISSING option, the procedure treats missing values as a valid (nonmissing) category for all categorical variables.

By default, if an observation contains missing values for the response, offset, or any explanatory variables used in the independent effects, the observation is excluded from the analysis. This treatment is based on the assumption that the missing values are missing completely at random (MCAR). However, this assumption is not true sometimes. For example, evidence from other surveys might suggest that observations with missing values are systematically different from observations without missing values. If you believe that missing values are not missing completely at random, then you can specify the NOMCAR option to include these observations with missing values in the dependent variable and the independent variables in the variance estimation.

Whether or not the NOMCAR option is used, observations with missing or invalid values for WEIGHT, FREQ, STRATA, CLUSTER, or DOMAIN variables are always excluded, unless the MISSING option is also specified.

When you specify the NOMCAR option, the procedure treats observations with and without missing values for variables in the regression model as two different domains, and it performs a domain analysis in the domain of nonmissing observations.

If you use a REPWEIGHTS statement, all REPWEIGHTS variables must contain nonmissing values.
Model Specification

Response Level Ordering

Response level ordering is important because, by default, PROC SURVEYLOGISTIC models the probabilities of response levels with lower Ordered Values. Ordered Values, displayed in the “Response Profile” table, are assigned to response levels in ascending sorted order. That is, the lowest response level is assigned Ordered Value 1, the next lowest is assigned Ordered Value 2, and so on. For example, if your response variable $Y$ takes values in $\{1, \ldots, D + 1\}$, then the functions of the response probabilities modeled with the cumulative model are

$$\text{logit}(\Pr(Y \leq i | x)), \quad i = 1, \ldots, D$$

and for the generalized logit model they are

$$\log \left( \frac{\Pr(Y = i | x)}{\Pr(Y = D + 1 | x)} \right), \quad i = 1, \ldots, D$$

where the highest Ordered Value $Y = D + 1$ is the reference level. You can change these default functions by specifying the EVENT=, REF=, DESCENDING, or ORDER= response variable options in the MODEL statement.

For binary response data with event and nonevent categories, the procedure models the function

$$\text{logit}(p) = \log \left( \frac{p}{1 - p} \right)$$

where $p$ is the probability of the response level assigned to Ordered Value 1 in the “Response Profiles” table. Since

$$\text{logit}(p) = -\text{logit}(1 - p)$$

the effect of reversing the order of the two response levels is to change the signs of $\alpha$ and $\beta$ in the model $\text{logit}(p) = \alpha + x\beta$.

If your event category has a higher Ordered Value than the nonevent category, the procedure models the nonevent probability. You can use response variable options to model the event probability. For example, suppose the binary response variable $Y$ takes the values 1 and 0 for event and nonevent, respectively, and Exposure is the explanatory variable. By default, the procedure assigns Ordered Value 1 to response level $Y=0$, and Ordered Value 2 to response level $Y=1$. Therefore, the procedure models the probability of the nonevent (Ordered Value=1) category. To model the event probability, you can do the following:

- Explicitly state which response level is to be modeled by using the response variable option EVENT= in the MODEL statement:

  $$\text{model } Y(\text{event}='1') = \text{Exposure;}$$
• Specify the response variable option `DESCENDING` in the MODEL statement:

```
model Y(descending)=Exposure;
```

• Specify the response variable option `REF=` in the MODEL statement as the nonevent category for the response variable. This option is most useful when you are fitting a generalized logit model.

```
model Y(ref='0') = Exposure;
```

• Assign a format to `Y` such that the first formatted value (when the formatted values are put in sorted order) corresponds to the event. For this example, `Y=1` is assigned formatted value ‘event’ and `Y=0` is assigned formatted value ‘nonevent.’ Since `ORDER= FORMATTED` by default, Ordered Value 1 is assigned to response level `Y=1` so the procedure models the event.

```
proc format;
  value Disease 1='event' 0='nonevent';
run;

proc surveylogistic;
  format Y Disease.;
  model Y=Exposure;
run;
```

**CLASS Variable Parameterization**

Consider a model with one CLASS variable `A` with four levels: 1, 2, 5, and 7. Details of the possible choices for the `PARAM=` option follow.

**EFFECT**

Three columns are created to indicate group membership of the nonreference levels. For the reference level, all three dummy variables have a value of −1. For instance, if the reference level is 7 (REF=7), the design matrix columns for `A` are as follows.

<table>
<thead>
<tr>
<th>Design Matrix</th>
<th>A</th>
<th>A1</th>
<th>A2</th>
<th>A5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>−1</td>
<td>−1</td>
<td>−1</td>
<td>−1</td>
</tr>
</tbody>
</table>

For CLASS main effects that use the EFFECT coding scheme, individual parameters correspond to the difference between the effect of each nonreference level and the average over all four levels.

**GLM**

As in PROC GLM, four columns are created to indicate group membership. The design matrix columns for `A` are as follows.
For CLASS main effects that use the GLM coding scheme, individual parameters correspond to the difference between the effect of each level and the last level.

**ORDINAL** Three columns are created to indicate group membership of the higher levels of the effect. For the first level of the effect (which for $A$ is 1), all three dummy variables have a value of 0. The design matrix columns for $A$ are as follows.

<table>
<thead>
<tr>
<th></th>
<th>$A$</th>
<th>$A2$</th>
<th>$A5$</th>
<th>$A7$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

The first level of the effect is a control or baseline level.

For CLASS main effects that use the ORDINAL coding scheme, the first level of the effect is a control or baseline level; individual parameters correspond to the difference between effects of the current level and the preceding level. When the parameters for an ordinal main effect have the same sign, the response effect is monotonic across the levels.

**POLYNOMIAL**

**POLY** Three columns are created. The first represents the linear term ($x$), the second represents the quadratic term ($x^2$), and the third represents the cubic term ($x^3$), where $x$ is the level value. If the CLASS levels are not numeric, they are translated into 1, 2, 3, ... according to their sorting order. The design matrix columns for $A$ are as follows.

<table>
<thead>
<tr>
<th></th>
<th>$A$</th>
<th>APOLY1</th>
<th>APOLY2</th>
<th>APOLY3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>25</td>
<td>125</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>7</td>
<td>49</td>
<td>343</td>
<td></td>
</tr>
</tbody>
</table>

**REFERENCE**

**REF** Three columns are created to indicate group membership of the nonreference levels. For the reference level, all three dummy variables have a value of 0. For instance, if the reference level is 7 (REF=7), the design matrix columns for $A$ are as follows.
For CLASS main effects that use the REFERENCE coding scheme, individual parameters correspond to the difference between the effect of each nonreference level and the reference level.

**ORTH**

The columns are obtained by applying the Gram-Schmidt orthogonalization to the columns for PARAM=EFFECT. The design matrix columns for A are as follows.

<table>
<thead>
<tr>
<th>Design Matrix</th>
<th>A</th>
<th>A1</th>
<th>A2</th>
<th>A5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**ORTHORDINAL**

The columns are obtained by applying the Gram-Schmidt orthogonalization to the columns for PARAM=ORDINAL. The design matrix columns for A are as follows.

<table>
<thead>
<tr>
<th>Design Matrix</th>
<th>A</th>
<th>AOORD1</th>
<th>AOORD2</th>
<th>AOORD3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-7.3205</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.57735</td>
<td>-1.63299</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.57735</td>
<td>0.81650</td>
<td>-1.41421</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.57735</td>
<td>0.81650</td>
<td>1.41421</td>
<td></td>
</tr>
</tbody>
</table>

**ORTHOTHERM**

The columns are obtained by applying the Gram-Schmidt orthogonalization to the columns for PARAM=POLY. The design matrix columns for A are as follows.

<table>
<thead>
<tr>
<th>Design Matrix</th>
<th>A</th>
<th>AOPOLY1</th>
<th>AOPOLY2</th>
<th>AOPOLY5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1.153</td>
<td>0.907</td>
<td>-0.921</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.734</td>
<td>-0.540</td>
<td>1.473</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.524</td>
<td>-1.370</td>
<td>-0.921</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1.363</td>
<td>1.004</td>
<td>0.368</td>
<td></td>
</tr>
</tbody>
</table>

**ORTHREF**

The columns are obtained by applying the Gram-Schmidt orthogonalization to the columns for PARAM=REFERENCE. The design matrix columns for A are as follows.
### Link Functions and the Corresponding Distributions

Four link functions are available in the SURVEYLOGISTIC procedure. The logit function is the default. To specify a different link function, use the LINK= option in the MODEL statement. The link functions and the corresponding distributions are as follows:

- **The logit function**
  
  \[ g(p) = \log \left( \frac{p}{1 - p} \right) \]

  is the inverse of the cumulative logistic distribution function, which is

  \[ F(x) = \frac{1}{1 + e^{-x}} \]

- **The probit (or normit) function**

  \[ g(p) = \Phi^{-1}(p) \]

  is the inverse of the cumulative standard normal distribution function, which is

  \[ F(x) = \Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{1}{2}z^2} dz \]

  Traditionally, the probit function includes an additive constant 5, but throughout PROC SURVEYLOGISTIC, the terms probit and normit are used interchangeably, previously defined as \( g(p) \).

- **The complementary log-log function**

  \[ g(p) = \log(-\log(1 - p)) \]

  is the inverse of the cumulative extreme-value function (also called the Gompertz distribution), which is

  \[ F(x) = 1 - e^{-e^x} \]

- **The generalized logit function** extends the binary logit link to a vector of levels \((\pi_1, \ldots, \pi_{k+1})\) by contrasting each level with a fixed level

  \[ g(\pi_i) = \log \left( \frac{\pi_i}{\pi_{k+1}} \right) \quad i = 1, \ldots, k \]
The variances of the normal, logistic, and extreme-value distributions are not the same. Their respective means and variances are

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Mean</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Logistic</td>
<td>0</td>
<td>$\frac{\pi^2}{3}$</td>
</tr>
<tr>
<td>Extreme-value</td>
<td>$-\gamma$</td>
<td>$\frac{\pi^2}{6}$</td>
</tr>
</tbody>
</table>

where $\gamma$ is the Euler constant. In comparing parameter estimates that use different link functions, you need to take into account the different scalings of the corresponding distributions and, for the complementary log-log function, a possible shift in location. For example, if the fitted probabilities are in the neighborhood of 0.1 to 0.9, then the parameter estimates from using the logit link function should be about $\pi/\sqrt{3} \approx 1.8$ larger than the estimates from the probit link function.

**Model Fitting**

**Determining Observations for Likelihood Contributions**

If you use the events/trials syntax, each observation is split into two observations. One has the response value 1 with a frequency equal to the value of the *events* variable. The other observation has the response value 2 and a frequency equal to the value of (*trials* − *events*). These two observations have the same explanatory variable values and the same WEIGHT values as the original observation.

For either the single-trial or the events/trials syntax, let $j$ index all observations. In other words, for the single-trial syntax, $j$ indexes the actual observations. And, for the events/trials syntax, $j$ indexes the observations after splitting (as described previously). If your data set has 30 observations and you use the single-trial syntax, $j$ has values from 1 to 30; if you use the events/trials syntax, $j$ has values from 1 to 60.

Suppose the response variable in a cumulative response model can take on the ordered values $1, \ldots, k, k+1$, where $k$ is an integer $\geq 1$. The likelihood for the $j$th observation with ordered response value $y_j$ and explanatory variables vector (row vectors) $x_j$ is given by

$$L_j = \begin{cases} 
F(\alpha_1 + x_j \beta) & y_j = 1 \\
F(\alpha_i + x_j \beta) - F(\alpha_{i-1} + x_j \beta) & 1 < y_j = i \leq k \\
1 - F(\alpha_k + x_j \beta) & y_j = k + 1 
\end{cases}$$

where $F(.)$ is the logistic, normal, or extreme-value distribution function; $\alpha_1, \ldots, \alpha_k$ are ordered intercept parameters; and $\beta$ is the slope parameter vector.

For the generalized logit model, letting the $k + 1$st level be the reference level, the intercepts $\alpha_1, \ldots, \alpha_k$ are unordered and the slope vector $\beta_i$ varies with each logit. The likelihood for the $j$th observation with
Chapter 87: The SURVEYLOGISTIC Procedure

ordered response value $y_j$ and explanatory variables vector $x_j$ (row vectors) is given by

$$L_j = \Pr(Y = y_j | x_j) = \begin{cases} 
  e^{\alpha_i + x_j \beta_i} & 1 \leq y_j = i \leq k \\
  1 + \sum_{i=1}^{k} e^{\alpha_i + x_j \beta_i} & y_j = k + 1
\end{cases}$$

Iterative Algorithms for Model Fitting

Two iterative maximum likelihood algorithms are available in PROC SURVEYLOGISTIC to obtain the pseudo-estimate $\hat{\theta}$ of the model parameter $\theta$. The default is the Fisher scoring method, which is equivalent to fitting by iteratively reweighted least squares. The alternative algorithm is the Newton-Raphson method. Both algorithms give the same parameter estimates; the covariance matrix of $\hat{\theta}$ is estimated in the section “Variance Estimation” on page 7321. For a generalized logit model, only the Newton-Raphson technique is available. You can use the TECHNIQUE= option in the MODEL statement to select a fitting algorithm.

Iteratively Reweighted Least Squares Algorithm (Fisher Scoring)

Let $Y$ be the response variable that takes values $1, \ldots, k, k+1 (k \geq 1)$. Let $j$ index all observations and $Y_j$ be the value of response for the $j$th observation. Consider the multinomial variable $Z_j = (Z_{1j}, \ldots, Z_{kj})'$ such that

$$Z_{ij} = \begin{cases} 
  1 & \text{if } Y_j = i \\
  0 & \text{otherwise}
\end{cases}$$

and $Z_{(k+1)j} = 1 - \sum_{i=1}^{k} Z_{ij}$. With $\pi_{ij}$ denoting the probability that the $j$th observation has response value $i$, the expected value of $Z_j$ is $\pi_j = (\pi_{1j}, \ldots, \pi_{kj})'$, and $\pi_{(k+1)j} = 1 - \sum_{i=1}^{k} \pi_{ij}$. The covariance matrix of $Z_j$ is $V_j$, which is the covariance matrix of a multinomial random variable for one trial with parameter vector $\pi_j$. Let $\theta$ be the vector of regression parameters—for example, $\theta = (\alpha_1, \ldots, \alpha_k, \beta')'$ for cumulative logit model. Let $D_j$ be the matrix of partial derivatives of $\pi_j$ with respect to $\theta$. The estimating equation for the regression parameters is

$$\sum_j D_j' W_j (Z_j - \pi_j) = 0$$

where $W_j = w_j f_j V_j^{-1}$, and $w_j$ and $f_j$ are the WEIGHT and FREQ values of the $j$th observation.

With a starting value of $\theta^{(0)}$, the pseudo-estimate of $\theta$ is obtained iteratively as

$$\theta^{(i+1)} = \theta^{(i)} + (\sum_j D_j' W_j D_j)^{-1} \sum_j D_j' W_j (Z_j - \pi_j)$$
where \(D_j, W_j, \text{ and } \pi_j\) are evaluated at the \(i\)th iteration \(\theta^{(i)}\). The expression after the plus sign is the step size. If the log likelihood evaluated at \(\theta^{(i+1)}\) is less than that evaluated at \(\theta^{(i)}\), then \(\theta^{(i+1)}\) is recomputed by step-halving or ridging. The iterative scheme continues until convergence is obtained—that is, until \(\theta^{(i+1)}\) is sufficiently close to \(\theta^{(i)}\). Then the maximum likelihood estimate of \(\theta\) is \(\hat{\theta} = \theta^{(i+1)}\).

By default, starting values are zero for the slope parameters, and starting values are the observed cumulative logits (that is, logits of the observed cumulative proportions of response) for the intercept parameters. Alternatively, the starting values can be specified with the INEST= option in the PROC SURVEYLOGISTIC statement.

**Newton-Raphson Algorithm**

Let

\[
\begin{align*}
g & = \sum_j w_j f_j \frac{\partial l_j}{\partial \theta} \\
H & = \sum_j -w_j f_j \frac{\partial^2 l_j}{\partial \theta^2}
\end{align*}
\]

be the gradient vector and the Hessian matrix, where \(l_j = \log L_j\) is the log likelihood for the \(j\)th observation. With a starting value of \(\theta^{(0)}\), the pseudo-estimate \(\hat{\theta}\) of \(\theta\) is obtained iteratively until convergence is obtained:

\[
\theta^{(i+1)} = \theta^{(i)} + H^{-1}g
\]

where \(H\) and \(g\) are evaluated at the \(i\)th iteration \(\theta^{(i)}\). If the log likelihood evaluated at \(\theta^{(i+1)}\) is less than that evaluated at \(\theta^{(i)}\), then \(\theta^{(i+1)}\) is recomputed by step-halving or ridging. The iterative scheme continues until convergence is obtained—that is, until \(\theta^{(i+1)}\) is sufficiently close to \(\theta^{(i)}\). Then the maximum likelihood estimate of \(\theta\) is \(\hat{\theta} = \theta^{(i+1)}\).

**Convergence Criteria**

Four convergence criteria are allowed: ABSFCONV=, FCONV=, GCONV=, and XCONV=. If you specify more than one convergence criterion, the optimization is terminated as soon as one of the criteria is satisfied. If none of the criteria is specified, the default is GCONV=1E−8.

**Existence of Maximum Likelihood Estimates**

The likelihood equation for a logistic regression model does not always have a finite solution. Sometimes there is a nonunique maximum on the boundary of the parameter space, at infinity. The existence, finiteness, and uniqueness of pseudo-estimates for the logistic regression model depend on the patterns of data points in the observation space (Albert and Anderson 1984; Santner and Duffy 1986).

Consider a binary response model. Let \(Y_j\) be the response of the \(i\)th subject, and let \(x_j\) be the row vector of explanatory variables (including the constant 1 associated with the intercept). There are three mutually
exclusive and exhaustive types of data configurations: complete separation, quasi-complete separation, and overlap.

**Complete separation**
There is a complete separation of data points if there exists a vector \( \mathbf{b} \) that correctly allocates all observations to their response groups; that is,

\[
\begin{align*}
& x_j \mathbf{b} > 0 & Y_j = 1 \\
& x_j \mathbf{b} < 0 & Y_j = 2
\end{align*}
\]

This configuration gives nonunique infinite estimates. If the iterative process of maximizing the likelihood function is allowed to continue, the log likelihood diminishes to zero, and the dispersion matrix becomes unbounded.

**Quasi-complete separation**
The data are not completely separable, but there is a vector \( \mathbf{b} \) such that

\[
\begin{align*}
& x_j \mathbf{b} \geq 0 & Y_j = 1 \\
& x_j \mathbf{b} \leq 0 & Y_j = 2
\end{align*}
\]

and equality holds for at least one subject in each response group. This configuration also yields nonunique infinite estimates. If the iterative process of maximizing the likelihood function is allowed to continue, the dispersion matrix becomes unbounded and the log likelihood diminishes to a nonzero constant.

**Overlap**
If neither complete nor quasi-complete separation exists in the sample points, there is an overlap of sample points. In this configuration, the pseudo-estimates exist and are unique.

Complete separation and quasi-complete separation are problems typically encountered with small data sets. Although complete separation can occur with any type of data, quasi-complete separation is not likely with truly continuous explanatory variables.

The SURVEYLOGISTIC procedure uses a simple empirical approach to recognize the data configurations that lead to infinite parameter estimates. The basis of this approach is that any convergence method of maximizing the log likelihood must yield a solution that gives complete separation, if such a solution exists. In maximizing the log likelihood, there is no checking for complete or quasi-complete separation if convergence is attained in eight or fewer iterations. Subsequent to the eighth iteration, the probability of the observed response is computed for each observation. If the probability of the observed response is one for all observations, there is a complete separation of data points and the iteration process is stopped. If the complete separation of data has not been determined and an observation is identified to have an extremely large probability (≥0.95) of the observed response, there are two possible situations. First, there is overlap in the data set, and the observation is an atypical observation of its own group. The iterative process, if allowed to continue, stops when a maximum is reached. Second, there is quasi-complete separation in the data set, and the asymptotic dispersion matrix is unbounded. If any of the diagonal elements of the dispersion matrix for the standardized observations vectors (all explanatory variables standardized to zero mean and unit variance) exceeds 5,000, quasi-complete separation is declared and the iterative process is stopped. If either complete separation or quasi-complete separation is detected, a warning message is displayed in the procedure output.

Checking for quasi-complete separation is less foolproof than checking for complete separation. The NOCHECK option in the MODEL statement turns off the process of checking for infinite parameter esti-
mates. In cases of complete or quasi-complete separation, turning off the checking process typically results in the procedure failing to converge.

**Model Fitting Statistics**

Suppose the model contains \( s \) explanatory effects. For the \( j \)th observation, let \( \hat{\pi}_j \) be the estimated probability of the observed response. The three criteria displayed by the SURVEYLOGISTIC procedure are calculated as follows:

- **−2 log likelihood:**
  \[
  -2 \log L = -2 \sum_j w_j f_j \log(\hat{\pi}_j)
  \]
  where \( w_j \) and \( f_j \) are the weight and frequency values, respectively, of the \( j \)th observation. For binary response models that use the events/trials syntax, this is equivalent to
  \[
  -2 \log L = -2 \sum_j w_j f_j \{r_j \log(\hat{\pi}_j) + (n_j - r_j) \log(1 - \hat{\pi}_j)\}
  \]
  where \( r_j \) is the number of events, \( n_j \) is the number of trials, and \( \hat{\pi}_j \) is the estimated event probability.

- **Akaike information criterion:**
  \[
  \text{AIC} = -2 \log L + 2p
  \]
  where \( p \) is the number of parameters in the model. For cumulative response models, \( p = k + s \), where \( k \) is the total number of response levels minus one, and \( s \) is the number of explanatory effects. For the generalized logit model, \( p = k(s + 1) \).

- **Schwarz criterion:**
  \[
  \text{SC} = -2 \log L + p \log\left( \sum_j f_j \right)
  \]
  where \( p \) is the number of parameters in the model. For cumulative response models, \( p = k + s \), where \( k \) is the total number of response levels minus one, and \( s \) is the number of explanatory effects. For the generalized logit model, \( p = k(s + 1) \).

The \( -2 \) log likelihood statistic has a chi-square distribution under the null hypothesis (that all the explanatory effects in the model are zero), and the procedure produces a \( p \)-value for this statistic. The AIC and SC statistics give two different ways of adjusting the \( -2 \) log likelihood statistic for the number of terms in the model and the number of observations used.

**Generalized Coefficient of Determination**

Cox and Snell (1989, pp. 208–209) propose the following generalization of the coefficient of determination to a more general linear model:

\[
R^2 = 1 - \left\{ \frac{L(\mathbf{0})}{L(\hat{\theta})} \right\}^{\frac{2}{\hat{\pi}}}
\]
where $L(0)$ is the likelihood of the intercept-only model, $L(\hat{\theta})$ is the likelihood of the specified model, and $n$ is the sample size. The quantity $R^2$ achieves a maximum of less than 1 for discrete models, where the maximum is given by

$$R_{\text{max}}^2 = 1 - \frac{L(0)}{n}$$

Nagelkerke (1991) proposes the following adjusted coefficient, which can achieve a maximum value of 1:

$$\hat{R}^2 = \frac{R^2}{R_{\text{max}}^2}$$

Properties and interpretation of $R^2$ and $\hat{R}^2$ are provided in Nagelkerke (1991). In the “Testing Global Null Hypothesis: BETA=0” table, $R^2$ is labeled as “RSquare” and $\hat{R}^2$ is labeled as “Max-rescaled RSquare.” Use the RSQUARE option to request $R^2$ and $\hat{R}^2$.

**INEST= Data Set**

You can specify starting values for the iterative algorithm in the INEST= data set.

The INEST= data set contains one observation for each BY group. The INEST= data set must contain the intercept variables (named Intercept for binary response models and Intercept, Intercept2, Intercept3, and so forth, for ordinal response models) and all explanatory variables in the MODEL statement. If BY processing is used, the INEST= data set should also include the BY variables, and there must be one observation for each BY group. If the INEST= data set also contains the _TYPE_ variable, only observations with _TYPE_ value ‘PARMS’ are used as starting values.

**Survey Design Information**

**Specification of Population Totals and Sampling Rates**

To include a finite population correction ($fpc$) in Taylor series variance estimation, you can input either the sampling rate or the population total by using the RATE= or TOTAL= option in the PROC SURVEYLOGISTIC statement. (You cannot specify both of these options in the same PROC SURVEYLOGISTIC statement.) The RATE= and TOTAL= options apply only to Taylor series variance estimation. The procedure does not use a finite population correction for BRR or jackknife variance estimation.

If you do not specify the RATE= or TOTAL= option, the Taylor series variance estimation does not include a finite population correction. For fairly small sampling fractions, it is appropriate to ignore this correction. See Cochran (1977) and Kish (1965) for more information.

If your design has multiple stages of selection and you are specifying the RATE= option, you should input the first-stage sampling rate, which is the ratio of the number of PSUs in the sample to the total number of PSUs in the study population. If you are specifying the TOTAL= option for a multistage design, you should input the total number of PSUs in the study population. See the section “Primary Sampling Units (PSUs)” on page 7317 for more details.
For a nonstratified sample design, or for a stratified sample design with the same sampling rate or the same population total in all strata, you can use the RATE=value or TOTAL=value option. If your sample design is stratified with different sampling rates or population totals in different strata, use the RATE=SAS-data-set or TOTAL=SAS-data-set option to name a SAS data set that contains the stratum sampling rates or totals. This data set is called a secondary data set, as opposed to the primary data set that you specify with the DATA= option.

The secondary data set must contain all the stratification variables listed in the STRATA statement and all the variables in the BY statement. If there are formats associated with the STRATA variables and the BY variables, then the formats must be consistent in the primary and the secondary data sets. If you specify the TOTAL=SAS-data-set option, the secondary data set must have a variable named _TOTAL_ that contains the stratum population totals. Or if you specify the RATE=SAS-data-set option, the secondary data set must have a variable named _RATE_ that contains the stratum sampling rates. If the secondary data set contains more than one observation for any one stratum, then the procedure uses the first value of _TOTAL_ or _RATE_ for that stratum and ignores the rest.

The value in the RATE= option or the values of _RATE_ in the secondary data set must be nonnegative numbers. You can specify value as a number between 0 and 1. Or you can specify value in percentage form as a number between 1 and 100, and PROC SURVEYLOGISTIC converts that number to a proportion. The procedure treats the value 1 as 100% instead of 1%.

If you specify the TOTAL=value option, value must not be less than the sample size. If you provide stratum population totals in a secondary data set, these values must not be less than the corresponding stratum sample sizes.

**Primary Sampling Units (PSUs)**

When you have clusters, or primary sampling units (PSUs), in your sample design, the procedure estimates variance from the variation among PSUs when the Taylor series variance method is used. See the section “Taylor Series (Linearization)” on page 7322 for more information.

BRR or jackknife variance estimation methods draw multiple replicates (or subsamples) from the full sample by following a specific resampling scheme. These subsamples are constructed by deleting PSUs from the full sample.

If you use a REPWEIGHTS statement to provide replicate weights for BRR or jackknife variance estimation, you do not need to specify a CLUSTER statement. Otherwise, you should specify a CLUSTER statement whenever your design includes clustering at the first stage of sampling. If you do not specify a CLUSTER statement, then PROC SURVEYLOGISTIC treats each observation as a PSU.

**Logistic Regression Models and Parameters**

The SURVEYLOGISTIC procedure fits a logistic regression model and estimates the corresponding regression parameters. Each model uses the link function you specified in the LINK= option in the MODEL statement. There are four types of model you can use with the procedure: cumulative logit model, complementary log-log model, probit model, and generalized logit model.
Notation

Let $Y$ be the response variable with categories $1, 2, \ldots, D, D + 1$. The $p$ covariates are denoted by a $p$-dimension row vector $\mathbf{x}$.

For a stratified clustered sample design, each observation is represented by a row vector, $(w_{hij}, y_{hij}, y_{hij(D+1)}, x_{hij})$, where

- $h = 1, 2, \ldots, H$ is the stratum index
- $i = 1, 2, \ldots, n_h$ is the cluster index within stratum $h$
- $j = 1, 2, \ldots, m_{hi}$ is the unit index within cluster $i$ of stratum $h$
- $w_{hij}$ denotes the sampling weight
- $y_{hij}$ is a $D$-dimensional column vector whose elements are indicator variables for the first $D$ categories for variable $Y$. If the response of the $j$th unit of the $i$th cluster in stratum $h$ falls in category $d$, the $d$th element of the vector is one, and the remaining elements of the vector are zero, where $d = 1, 2, \ldots, D$.
- $y_{hij(D+1)}$ is the indicator variable for the $(D + 1)$ category of variable $Y$
- $x_{hij}$ denotes the $k$-dimensional row vector of explanatory variables for the $j$th unit of the $i$th cluster in stratum $h$. If there is an intercept, then $x_{hij1} \equiv 1$.
- $n = \sum_{h=1}^{H} \sum_{i=1}^{n_h} m_{hi}$ is the total sample size

The following notations are also used:

- $f_h$ denotes the sampling rate for stratum $h$
- $\mathbf{\pi}_{hij}$ is the expected vector of the response variable:

  $$
  \mathbf{\pi}_{hij} = E(y_{hij} | x_{hij})
  = (\pi_{hij1}, \pi_{hij2}, \ldots, \pi_{hijD})'
  \pi_{hij(D+1)} = E(y_{hij(D+1)} | x_{hij})
  $$

  Note that $\pi_{hij(D+1)} = 1 - \mathbf{1}' \pi_{hij}$, where $\mathbf{1}$ is a $D$-dimensional column vector whose elements are 1.

Logistic Regression Models

If the response categories of the response variable $Y$ can be restricted to a number of ordinal values, you can fit cumulative probabilities of the response categories with a cumulative logit model, a complementary log-log model, or a probit model. Details of cumulative logit models (or proportional odds models) can be found in McCullagh and Nelder (1989). If the response categories of $Y$ are nominal responses without
natural ordering, you can fit the response probabilities with a generalized logit model. Formulation of the
generalized logit models for nominal response variables can be found in Agresti (2002). For each model,
the procedure estimates the model parameter $\theta$ by using a pseudo-log-likelihood function. The procedure
obtains the pseudo-maximum likelihood estimator $\hat{\theta}$ by using iterations described in the section “Iterative
Algorithms for Model Fitting” on page 7312 and estimates its variance described in the section “Variance
Estimation” on page 7321.

**Cumulative Logit Model**

A cumulative logit model uses the logit function

$$g(t) = \log \left( \frac{t}{1-t} \right)$$

as the link function.

Denote the cumulative sum of the expected proportions for the first $d$ categories of variable $Y$ by

$$F_{hijd} = \sum_{r=1}^{d} \pi_{hijr}$$

for $d = 1, 2, \ldots, D$. Then the cumulative logit model can be written as

$$\log \left( \frac{F_{hijd}}{1-F_{hijd}} \right) = \alpha_d + x_{hij} \beta$$

with the model parameters

$$\beta = (\beta_1, \beta_2, \ldots, \beta_k)'$$
$$\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_D)', \quad \alpha_1 < \alpha_2 < \cdots < \alpha_D$$
$$\theta = (\alpha', \beta')'$$

**Complementary Log-Log Model**

A complementary log-log model uses the complementary log-log function

$$g(t) = \log(-\log(1-t))$$

as the link function. Denote the cumulative sum of the expected proportions for the first $d$ categories of
variable $Y$ by

$$F_{hijd} = \sum_{r=1}^{d} \pi_{hijr}$$

for $d = 1, 2, \ldots, D$. Then the complementary log-log model can be written as

$$\log(-\log(1-F_{hijd})) = \alpha_d + x_{hij} \beta$$

with the model parameters

$$\beta = (\beta_1, \beta_2, \ldots, \beta_k)'$$
$$\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_D)', \quad \alpha_1 < \alpha_2 < \cdots < \alpha_D$$
$$\theta = (\alpha', \beta')'$$
**Probit Model**

A probit model uses the probit (or normit) function, which is the inverse of the cumulative standard normal distribution function,

\[ g(t) = \Phi^{-1}(t) \]

as the link function, where

\[ \Phi(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{t} e^{-\frac{1}{2}z^2} dz \]

Denote the cumulative sum of the expected proportions for the first \( d \) categories of variable \( Y \) by

\[ F_{hijd} = \sum_{r=1}^{d} \pi_{hijr} \]

for \( d = 1, 2, \ldots, D \). Then the probit model can be written as

\[ F_{hijd} = \Phi(\alpha_d + x_{hij} \beta) \]

with the model parameters

\[ \beta = (\beta_1, \beta_2, \ldots, \beta_k)' \]

\[ \alpha = (\alpha_1, \alpha_2, \ldots, \alpha_D)', \quad \alpha_1 < \alpha_2 < \cdots < \alpha_D \]

\[ \theta = (\alpha', \beta')' \]

**Generalized Logit Model**

For nominal response, a generalized logit model is to fit the ratio of the expected proportion for each response category over the expected proportion of a reference category with a logit link function.

Without loss of generality, let category \( D + 1 \) be the reference category for the response variable \( Y \). Denote the expected proportion for the \( d \)th category by \( \pi_{hijd} \) as in the section “Notation” on page 7318. Then the generalized logit model can be written as

\[ \log \left( \frac{\pi_{hijd}}{\pi_{hij(D+1)}} \right) = x_{hij} \beta_d \]

for \( d = 1, 2, \ldots, D \), with the model parameters

\[ \beta_d = (\beta_{d1}, \beta_{d2}, \ldots, \beta_{dk})' \]

\[ \theta = (\beta_1', \beta_2', \ldots, \beta_D')' \]
Likelihood Function

Let \( g(\cdot) \) be a link function such that

\[
\pi = g(x, \theta)
\]

where \( \theta \) is a column vector for regression coefficients. The pseudo-log likelihood is

\[
l(\theta) = \sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} w_{hij} \left( \log(\pi_{hij}) y_{hij} + \log(\pi_{hij}(D+1)) y_{hij}(D+1) \right)
\]

Denote the pseudo-estimator as \( \hat{\theta} \), which is a solution to the estimating equations:

\[
\sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} w_{hij} D_{hij} \left( \text{diag}(\pi_{hij}) - \pi_{hij} \pi_{hij}' \right)^{-1} (y_{hij} - \pi_{hij}) = 0
\]

where \( D_{hij} \) is the matrix of partial derivatives of the link function \( g \) with respect to \( \theta \).

To obtain the pseudo-estimator \( \hat{\theta} \), the procedure uses iterations with a starting value \( \theta^{(0)} \) for \( \theta \). See the section “Iterative Algorithms for Model Fitting” on page 7312 for more details.

Variance Estimation

Due to the variability of characteristics among items in the population, researchers apply scientific sample designs in the sample selection process to reduce the risk of a distorted view of the population, and they make inferences about the population based on the information from the sample survey data. In order to make statistically valid inferences for the population, they must incorporate the sample design in the data analysis.

The SURVEYLOGISTIC procedure fits linear logistic regression models for discrete response survey data by using the maximum likelihood method. In the variance estimation, the procedure uses the Taylor series (linearization) method or replication (resampling) methods to estimate sampling errors of estimators based on complex sample designs, including designs with stratification, clustering, and unequal weighting (Binder (1981, 1983); Roberts, Rao, and Kumar (1987); Skinner, Holt, and Smith (1989); Binder and Roberts (2003); Morel (1989); Lehtonen and Pahkinen (1995); Woodruff (1971); Fuller (1975); Särndal, Swensson, and Wretman (1992); Wolter (2007); Rust (1985); Dippo, Fay, and Morganstein (1984); Rao and Shao (1999); Rao, Wu, and Yue (1992); and Rao and Shao (1996)).

You can use the VARMETHOD= option to specify a variance estimation method to use. By default, the Taylor series method is used. However, replication methods have recently gained popularity for estimating variances in complex survey data analysis. One reason for this popularity is the relative simplicity of replication-based estimates, especially for nonlinear estimators; another is that modern computational capacity has made replication methods feasible for practical survey analysis.

Replication methods draw multiple replicates (also called subsamples) from a full sample according to a specific resampling scheme. The most commonly used resampling schemes are the balanced repeated
replication (BRR) method and the jackknife method. For each replicate, the original weights are modified for the PSUs in the replicates to create replicate weights. The parameters of interest are estimated by using the replicate weights for each replicate. Then the variances of parameters of interest are estimated by the variability among the estimates derived from these replicates. You can use the REPWEIGHTS statement to provide your own replicate weights for variance estimation.

The following sections provide details about how the variance-covariance matrix of the estimated regression coefficients is estimated for each variance estimation method.

**Taylor Series (Linearization)**

The Taylor series (linearization) method is the most commonly used method to estimate the covariance matrix of the regression coefficients for complex survey data. It is the default variance estimation method used by PROC SURVEYLOGISTIC.

Using the notation described in the section “Notation” on page 7318, the estimated covariance matrix of model parameters \( \hat{\theta} \) by the Taylor series method is

\[
\hat{V}(\hat{\theta}) = \hat{Q}^{-1} \hat{G} \hat{Q}^{-1}
\]

where

\[
\hat{Q} = \sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} w_{hij} \hat{D}_{hij} \left( \text{diag}(\hat{\pi}_{hij}) - \hat{\pi}_{hij} \hat{\pi}_{hij}' \right)^{-1} \hat{D}_{hij}'
\]

\[
\hat{G} = \frac{n - 1}{n - p} \sum_{h=1}^{H} \frac{n_h}{n_h - 1} \sum_{i=1}^{n_h} (\hat{e}_{hi} - \bar{\hat{e}}_{hi})(\hat{e}_{hi} - \bar{\hat{e}}_{hi})'
\]

\[
\hat{e}_{hi} = \sum_{j=1}^{m_{hi}} w_{hij} \hat{D}_{hij} \left( \text{diag}(\hat{\pi}_{hij}) - \hat{\pi}_{hij} \hat{\pi}_{hij}' \right)^{-1} (\hat{y}_{hij} - \hat{\pi}_{hij})
\]

and \( D_{hij} \) is the matrix of partial derivatives of the link function \( g \) with respect to \( \theta \) and \( \hat{D}_{hij} \) and the response probabilities \( \hat{\pi}_{hij} \) are evaluated at \( \hat{\theta} \).

If you specify the TECHNIQUE=NEWTON option in the MODEL statement to request the Newton-Raphson algorithm, the matrix \( \hat{Q} \) is replaced by the negative (expected) Hessian matrix when the estimated covariance matrix \( \hat{V}(\hat{\theta}) \) is computed.

**Adjustments to the Variance Estimation**

The factor \((n - 1)/(n - p)\) in the computation of the matrix \( \hat{G} \) reduces the small sample bias associated with using the estimated function to calculate deviations (Morel 1989; Hidiroglou, Fuller, and Hickman 1980). For simple random sampling, this factor contributes to the degrees-of-freedom correction applied to the residual mean square for ordinary least squares in which \( p \) parameters are estimated. By default,
the procedure uses this adjustment in Taylor series variance estimation. It is equivalent to specifying the VADJUST=DF option in the MODEL statement. If you do not want to use this multiplier in the variance estimation, you can specify the VADJUST=None option in the MODEL statement to suppress this factor.

In addition, you can specify the VADJUST=MOREL option to request an adjustment to the variance estimator for the model parameters \( \hat{\theta} \), introduced by Morel (1989):

\[
\hat{\mathbf{V}}(\hat{\theta}) = \hat{\mathbf{Q}}^{-1}\hat{\mathbf{G}}\hat{\mathbf{Q}}^{-1} + \kappa \lambda \hat{\mathbf{Q}}^{-1}
\]

where for given nonnegative constants \( \delta \) and \( \phi \),

\[
\kappa = \max \left( \delta, \frac{1}{p} \text{tr} \left( \hat{\mathbf{Q}}^{-1}\hat{\mathbf{G}} \right) \right)
\]
\[
\lambda = \min \left( \phi, 1 - \frac{p}{n - p} \right)
\]

The adjustment \( \kappa \lambda \hat{\mathbf{Q}}^{-1} \) does the following:

- reduces the small sample bias reflected in inflated Type I error rates
- guarantees a positive-definite estimated covariance matrix provided that \( \hat{\mathbf{Q}}^{-1} \) exists
- is close to zero when the sample size becomes large

In this adjustment, \( \kappa \) is an estimate of the design effect, which has been bounded below by the positive constant \( \delta \). You can use DEFFBOUND=\( \delta \) in the VADJUST=MOREL option in the MODEL statement to specify this lower bound; by default, the procedure uses \( \delta = 1 \). The factor \( \lambda \) converges to zero when the sample size becomes large, and \( \lambda \) has an upper bound \( \phi \). You can use ADJBOUND=\( \phi \) in the VADJUST=MOREL option in the MODEL statement to specify this upper bound; by default, the procedure uses \( \phi = 0.5 \).

Balanced Repeated Replication (BRR) Method

The balanced repeated replication (BRR) method requires that the full sample be drawn by using a stratified sample design with two primary sampling units (PSUs) per stratum. Let \( H \) be the total number of strata. The total number of replicates \( R \) is the smallest multiple of 4 that is greater than \( H \). However, if you prefer a larger number of replicates, you can specify the REPS=number option. If a number \( \times \) number Hadamard matrix cannot be constructed, the number of replicates is increased until a Hadamard matrix becomes available.

Each replicate is obtained by deleting one PSU per stratum according to the corresponding Hadamard matrix and adjusting the original weights for the remaining PSUs. The new weights are called replicate weights.

Replicates are constructed by using the first \( H \) columns of the \( R \times R \) Hadamard matrix. The \( r \)-th \(( r = 1, 2, \ldots, R )\) replicate is drawn from the full sample according to the \( r \)-th row of the Hadamard matrix as follows:
- If the \((r, h)\)th element of the Hadamard matrix is 1, then the first PSU of stratum \(h\) is included in the \(r\)th replicate and the second PSU of stratum \(h\) is excluded.

- If the \((r, h)\)th element of the Hadamard matrix is \(-1\), then the second PSU of stratum \(h\) is included in the \(r\)th replicate and the first PSU of stratum \(h\) is excluded.

Note that the “first” and “second” PSUs are determined by data order in the input data set. Thus, if you reorder the data set and perform the same analysis by using BRR method, you might get slightly different results, because the contents in each replicate sample might change.

The replicate weights of the remaining PSUs in each half-sample are then doubled to their original weights. For more details about the BRR method, see Wolter (2007) and Lohr (2009).

By default, an appropriate Hadamard matrix is generated automatically to create the replicates. You can request that the Hadamard matrix be displayed by specifying the \texttt{VARMETHOD=BRR(PRINTH)} method-option. If you provide a Hadamard matrix by specifying the \texttt{VARMETHOD=BRR(HADAMARD=)} method-option, then the replicates are generated according to the provided Hadamard matrix.

You can use the \texttt{VARMETHOD=BRR(OUTWEIGHTS=)} method-option to save the replicate weights into a SAS data set.

Let \(\hat{\theta}\) be the estimated regression coefficients from the full sample for \(\theta\), and let \(\hat{\theta}_r\) be the estimated regression coefficient from the \(r\)th replicate by using replicate weights. PROC SURVEYLOGISTIC estimates the covariance matrix of \(\hat{\theta}\) by

\[
\hat{\Sigma}(\hat{\theta}) = \frac{1}{R} \sum_{r=1}^{R} \left( \hat{\theta}_r - \hat{\theta} \right) \left( \hat{\theta}_r - \hat{\theta} \right)'
\]

with \(H\) degrees of freedom, where \(H\) is the number of strata.

### Fay’s BRR Method

Fay’s method is a modification of the BRR method, and it requires a stratified sample design with two primary sampling units (PSUs) per stratum. The total number of replicates \(R\) is the smallest multiple of 4 that is greater than the total number of strata \(H\). However, if you prefer a larger number of replicates, you can specify the \texttt{REPS=} method-option.

For each replicate, Fay’s method uses a Fay coefficient \(0 \leq \epsilon < 1\) to impose a perturbation of the original weights in the full sample that is gentler than using only half-samples, as in the traditional BRR method. The Fay coefficient \(0 \leq \epsilon < 1\) can be set by specifying the \texttt{FAY = \epsilon} method-option. By default, \(\epsilon = 0.5\) if the \texttt{FAY} method-option is specified without providing a value for \(\epsilon\) (Judkins 1990; Rao and Shao 1999).

When \(\epsilon = 0\), Fay’s method becomes the traditional BRR method. For more details, see Dippo, Fay, and Morganstein (1984), Fay (1984), Fay (1989), and Judkins (1990).

Let \(H\) be the number of strata. Replicates are constructed by using the first \(H\) columns of the \(R \times R\) Hadamard matrix, where \(R\) is the number of replicates, \(R > H\). The \(r\)th \((r = 1, 2, ..., R)\) replicate is created from the full sample according to the \(r\)th row of the Hadamard matrix as follows:
If the \((r, h)\)th element of the Hadamard matrix is 1, then the full sample weight of the first PSU in stratum \(h\) is multiplied by \(\epsilon\) and the full sample weight of the second PSU is multiplied by \(2 - \epsilon\) to obtain the \(r\)th replicate weights.

If the \((r, h)\)th element of the Hadamard matrix is \(-1\), then the full sample weight of the first PSU in stratum \(h\) is multiplied by \(2 - \epsilon\) and the full sample weight of the second PSU is multiplied by \(\epsilon\) to obtain the \(r\)th replicate weights.

You can use the `VARMETHOD=BRR(OUTWEIGHTS=)` method-option to save the replicate weights into a SAS data set.

By default, an appropriate Hadamard matrix is generated automatically to create the replicates. You can request that the Hadamard matrix be displayed by specifying the `VARMETHOD=BRR(PRINTH)` method-option. If you provide a Hadamard matrix by specifying the `VARMETHOD=BRR(HADAMARD=)` method-option, then the replicates are generated according to the provided Hadamard matrix.

Let \(\hat{\theta}\) be the estimated regression coefficients from the full sample for \(\theta\). Let \(\hat{\theta}_r\) be the estimated regression coefficient obtained from the \(r\)th replicate by using replicate weights. PROC SURVEYLOGISTIC estimates the covariance matrix of \(\hat{\theta}\) by

\[
\hat{\Sigma}(\hat{\theta}) = \frac{1}{R(1 - \epsilon)^2} \sum_{r=1}^{R} (\hat{\theta}_r - \hat{\theta})(\hat{\theta}_r - \hat{\theta})'
\]

with \(H\) degrees of freedom, where \(H\) is the number of strata.

**Jackknife Method**

The jackknife method of variance estimation deletes one PSU at a time from the full sample to create replicates. The total number of replicates \(R\) is the same as the total number of PSUs. In each replicate, the sample weights of the remaining PSUs are modified by the jackknife coefficient \(\alpha_r\). The modified weights are called replicate weights.

The jackknife coefficient and replicate weights are described as follows.

**Without Stratification** If there is no stratification in the sample design (no `STRATA` statement), the jackknife coefficients \(\alpha_r\) are the same for all replicates:

\[
\alpha_r = \frac{R - 1}{R} \quad \text{where} \quad r = 1, 2, \ldots, R
\]

Denote the original weight in the full sample for the \(j\)th member of the \(i\)th PSU as \(w_{ij}\). If the \(i\)th PSU is included in the \(r\)th replicate \((r = 1, 2, \ldots, R)\), then the corresponding replicate weight for the \(j\)th member of the \(i\)th PSU is defined as

\[
w_{ij}^{(r)} = w_{ij}/\alpha_r
\]
With Stratification  If the sample design involves stratification, each stratum must have at least two PSUs to use the jackknife method.

Let stratum \( \tilde{h}_r \) be the stratum from which a PSU is deleted for the \( r \)th replicate. Stratum \( \tilde{h}_r \) is called the *donor stratum*. Let \( n_{\tilde{h}_r} \) be the total number of PSUs in the donor stratum \( \tilde{h}_r \). The jackknife coefficients are defined as

\[
\alpha_r = \frac{n_{\tilde{h}_r} - 1}{n_{\tilde{h}_r}} \quad \text{where} \quad r = 1, 2, \ldots, R
\]

Denote the original weight in the full sample for the \( j \)th member of the \( i \)th PSU as \( w_{ij} \). If the \( i \)th PSU is included in the \( r \)th replicate \((r = 1, 2, \ldots, R)\), then the corresponding replicate weight for the \( j \)th member of the \( i \)th PSU is defined as

\[
w^{(r)}_{ij} = \begin{cases} w_{ij} & \text{if } i \text{th PSU is not in the donor stratum } \tilde{h}_r \\ w_{ij}/\alpha_r & \text{if } i \text{th PSU is in the donor stratum } \tilde{h}_r \end{cases}
\]

You can use the `VARMETHOD=JACKKNIFE(OUTJKCOEFS=)` method-option to save the jackknife coefficients into a SAS data set and use the `VARMETHOD=JACKKNIFE(OUTWEIGHTS=)` method-option to save the replicate weights into a SAS data set.

If you provide your own replicate weights with a `REPWEIGHTS` statement, then you can also provide corresponding jackknife coefficients with the `JKCOEFS=` option.

Let \( \hat{\theta} \) be the estimated regression coefficients from the full sample for \( \theta \). Let \( \hat{\theta}_r \) be the estimated regression coefficient obtained from the \( r \)th replicate by using replicate weights. PROC SURVEYLOGISTIC estimates the covariance matrix of \( \hat{\theta} \) by

\[
\hat{V}(\hat{\theta}) = \sum_{r=1}^{R} \alpha_r \left( \hat{\theta}_r - \hat{\theta} \right) \left( \hat{\theta}_r - \hat{\theta} \right)'
\]

with \( R - H \) degrees of freedom, where \( R \) is the number of replicates and \( H \) is the number of strata, or \( R - 1 \) when there is no stratification.

Hadamard Matrix

A Hadamard matrix \( H \) is a square matrix whose elements are either 1 or −1 such that

\[
HH' = kI
\]

where \( k \) is the dimension of \( H \) and \( I \) is the identity matrix of order \( k \). The order \( k \) is necessarily 1, 2, or a positive integer that is a multiple of 4.

For example, the following matrix is a Hadamard matrix of dimension \( k = 8 \):

\[
\begin{bmatrix}
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\
1 & 1 & -1 & -1 & 1 & 1 & -1 & -1 \\
1 & -1 & -1 & 1 & 1 & -1 & -1 & 1 \\
1 & 1 & 1 & -1 & -1 & -1 & -1 & 1 \\
1 & -1 & 1 & -1 & -1 & 1 & -1 & 1 \\
1 & 1 & -1 & -1 & -1 & 1 & 1 & -1 \\
1 & -1 & -1 & 1 & 1 & 1 & 1 & 1
\end{bmatrix}
\]
Domain Analysis

A DOMAIN statement requests that the procedure perform logistic regression analysis for each domain.

For a domain \( \Omega \), let \( I_\Omega \) be the corresponding indicator variable:

\[
I_\Omega (h, i, j) = \begin{cases} 
1 & \text{if observation } (h, i, j) \text{ belongs to } \Omega \\
0 & \text{otherwise}
\end{cases}
\]

Let

\[
v_{hij} = w_{hij} I_\Omega (h, i, j) = \begin{cases} 
w_{hij} & \text{if observation } (h, i, j) \text{ belongs to } \Omega \\
0 & \text{otherwise}
\end{cases}
\]

The regression in domain \( \Omega \) uses \( v \) as the weight variable.

Hypothesis Testing and Estimation

Score Statistics and Tests

To understand the general form of the score statistics, let \( g(\theta) \) be the vector of first partial derivatives of the log likelihood with respect to the parameter vector \( \theta \), and let \( H(\theta) \) be the matrix of second partial derivatives of the log likelihood with respect to \( \theta \). That is, \( g(\theta) \) is the gradient vector, and \( H(\theta) \) is the Hessian matrix. Let \( I(\theta) \) be either \( -H(\theta) \) or the expected value of \( -H(\theta) \). Consider a null hypothesis \( H_0 \). Let \( \hat{\theta} \) be the MLE of \( \theta \) under \( H_0 \). The chi-square score statistic for testing \( H_0 \) is defined by

\[
g(\hat{\theta}) I^{-1}(\hat{\theta}) g(\hat{\theta})
\]

It has an asymptotic \( \chi^2 \) distribution with \( r \) degrees of freedom under \( H_0 \), where \( r \) is the number of restrictions imposed on \( \theta \) by \( H_0 \).

Testing the Parallel Lines Assumption

For an ordinal response, PROC SURVEYLOGISTIC performs a test of the parallel lines assumption. In the displayed output, this test is labeled “Score Test for the Equal Slopes Assumption” when the LINK= option is NORMIT or CLOGLOG. When LINK=LOGIT, the test is labeled as “Score Test for the Proportional Odds Assumption” in the output. This section describes the methods used to calculate the test.

For this test, the number of response levels, \( D + 1 \), is assumed to be strictly greater than 2. Let \( Y \) be the response variable taking values \( 1, \ldots, D, D + 1 \). Suppose there are \( k \) explanatory variables. Consider the general cumulative model without making the parallel lines assumption:

\[
g(\Pr(Y \leq d \mid x)) = (1, x) \theta_d, \quad 1 \leq d \leq D
\]
where \( g(\cdot) \) is the link function, and \( \theta_d = (\alpha_d, \beta_{d1}, \ldots, \beta_{dk})' \) is a vector of unknown parameters consisting of an intercept \( \alpha_d \) and \( k \) slope parameters \( \beta_{k1}, \ldots, \beta_{kd} \). The parameter vector for this general cumulative model is

\[
\theta = (\theta_1', \ldots, \theta_D')'
\]

Under the null hypothesis of parallelism \( H_0: \beta_{1i} = \beta_{2i} = \cdots = \beta_{Di}, 1 \leq i \leq k \), there is a single common slope parameter for each of the \( s \) explanatory variables. Let \( \hat{\alpha}_1, \ldots, \hat{\alpha}_D \) and \( \hat{\beta}_1, \ldots, \hat{\beta}_D \) be the MLEs of the intercept parameters and the common slope parameters. Then, under \( H_0 \), the MLE of \( \theta \) is

\[
\hat{\theta} = (\hat{\theta}_1', \ldots, \hat{\theta}_D')' \quad \text{with} \quad \hat{\theta}_d = (\hat{\alpha}_d, \hat{\beta}_1, \ldots, \hat{\beta}_k)', \quad 1 \leq d \leq D
\]

and the chi-squared score statistic \( g'(\hat{\theta}) \hat{V}^{-1}(\hat{\theta}) g(\hat{\theta}) \) has an asymptotic chi-square distribution with \( k(D - 1) \) degrees of freedom. This tests the parallel lines assumption by testing the equality of separate slope parameters simultaneously for all explanatory variables.

### Wald Confidence Intervals for Parameters

Wald confidence intervals are sometimes called normal confidence intervals. They are based on the asymptotic normality of the parameter estimators. The \( 100(1 - \alpha)\% \) Wald confidence interval for \( \theta_j \) is given by

\[
\hat{\theta}_j \pm z_{1-\alpha/2} \hat{\sigma}_j
\]

where \( z_{1-\alpha/2} \) is the \( 100(1 - \alpha/2) \)th percentile of the standard normal distribution, \( \hat{\theta}_j \) is the pseudo-estimate of \( \theta_j \), and \( \hat{\sigma}_j \) is the standard error estimate of \( \hat{\theta}_j \) in the section “Variance Estimation” on page 7321.

### Testing Linear Hypotheses about the Regression Coefficients

Linear hypotheses for \( \theta \) are expressed in matrix form as

\[
H_0: L\theta = c
\]

where \( L \) is a matrix of coefficients for the linear hypotheses and \( c \) is a vector of constants. The vector of regression coefficients \( \theta \) includes slope parameters as well as intercept parameters. The Wald chi-square statistic for testing \( H_0 \) is computed as

\[
\chi^2_W = (L\hat{\theta} - c)'[L\hat{V}(\hat{\theta})L']^{-1}(L\hat{\theta} - c)
\]

where \( \hat{V}(\hat{\theta}) \) is the estimated covariance matrix in the section “Variance Estimation” on page 7321. Under \( H_0 \), \( \chi^2_W \) has an asymptotic chi-square distribution with \( r \) degrees of freedom, where \( r \) is the rank of \( L \).

### Odds Ratio Estimation

Consider a dichotomous response variable with outcomes event and nonevent. Let a dichotomous risk factor variable \( X \) take the value 1 if the risk factor is present and 0 if the risk factor is absent. According to the
logistic model, the log odds function, \( g(X) \), is given by
\[
g(X) = \log \left( \frac{\Pr(\text{event} \mid X)}{\Pr(\text{nonevent} \mid X)} \right) = \beta_0 + \beta_1 X
\]

The odds ratio \( \psi \) is defined as the ratio of the odds for those with the risk factor \( (X = 1) \) to the odds for those without the risk factor \( (X = 0) \). The log of the odds ratio is given by
\[
\log(\psi) = \log(\psi(X = 1, X = 0)) = g(X = 1) - g(X = 0) = \beta_1
\]

The parameter, \( \beta_1 \), associated with \( X \) represents the change in the log odds from \( X = 0 \) to \( X = 1 \). So the odds ratio is obtained by simply exponentiating the value of the parameter associated with the risk factor.

The parameter, \( \beta_1 \), associated with \( X \) represents the change in the log odds from \( X = 0 \) to \( X = 1 \). So the odds ratio is obtained by simply exponentiating the value of the parameter associated with the risk factor.

For a polytomous risk factor, the computation of odds ratios depends on how the risk factor is parameterized. For illustration, suppose that \( \text{Race} \) is a risk factor with four categories: White, Black, Hispanic, and Other.

For the effect parameterization scheme (PARAM=EFFECT) with White as the reference group, the design variables for \( \text{Race} \) are as follows.

<table>
<thead>
<tr>
<th>Race</th>
<th>( X_1 )</th>
<th>( X_2 )</th>
<th>( X_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Other</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>White</td>
<td>(-1)</td>
<td>(-1)</td>
<td>(-1)</td>
</tr>
</tbody>
</table>

The log odds for Black is
\[
g(\text{Black}) = \beta_0 + \beta_1(X_1 = 1) + \beta_2(X_2 = 0) + \beta_3(X_3 = 0)
\]
\[
= \beta_0 + \beta_1
\]

The log odds for White is
\[
g(\text{White}) = \beta_0 + \beta_1(X_1 = -1) + \beta_2(X_2 = -1) + \beta_3(X_3 = -1))
\]
\[
= \beta_0 - \beta_1 - \beta_2 - \beta_3
\]
Therefore, the log odds ratio of Black versus White becomes

\[
\log(\psi(\text{Black, White})) = g(\text{Black}) - g(\text{White}) \\
= 2\beta_1 + \beta_2 + \beta_3
\]

For the reference cell parameterization scheme (PARAM=REF) with White as the reference cell, the design variables for race are as follows.

<table>
<thead>
<tr>
<th>Race</th>
<th>Design Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>1 0 0</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0 1 0</td>
</tr>
<tr>
<td>Other</td>
<td>0 0 1</td>
</tr>
<tr>
<td>White</td>
<td>0 0 0</td>
</tr>
</tbody>
</table>

The log odds ratio of Black versus White is given by

\[
\log(\psi(\text{Black, White})) = g(\text{Black}) - g(\text{White}) \\
= (\beta_0 + \beta_1(X_1 = 1) + \beta_2(X_2 = 0)) + \beta_3(X_3 = 0)) - \\
(\beta_0 + \beta_1(X_1 = 0) + \beta_2(X_2 = 0) + \beta_3(X_3 = 0)) \\
= \beta_1
\]

For the GLM parameterization scheme (PARAM=GLM), the design variables are as follows.

<table>
<thead>
<tr>
<th>Race</th>
<th>Design Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>1 0 0 0</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0 1 0 0</td>
</tr>
<tr>
<td>Other</td>
<td>0 0 1 0</td>
</tr>
<tr>
<td>White</td>
<td>0 0 0 1</td>
</tr>
</tbody>
</table>

The log odds ratio of Black versus White is

\[
\log(\psi(\text{Black, White})) = g(\text{Black}) - g(\text{White}) \\
= (\beta_0 + \beta_1(X_1 = 1) + \beta_2(X_2 = 0) + \beta_3(X_3 = 0) + \beta_4(X_4 = 0)) - \\
(\beta_0 + \beta_1(X_1 = 0) + \beta_2(X_2 = 0) + \beta_3(X_3 = 0) + \beta_4(X_4 = 1)) \\
= \beta_1 - \beta_4
\]

Consider the hypothetical example of heart disease among race in Hosmer and Lemeshow (2000, p. 51). The entries in the following contingency table represent counts.
The computation of odds ratio of Black versus White for various parameterization schemes is shown in Table 87.7.

### Table 87.7

<table>
<thead>
<tr>
<th>Disease Status</th>
<th>White</th>
<th>Black</th>
<th>Hispanic</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Present</td>
<td>5</td>
<td>20</td>
<td>15</td>
<td>10</td>
</tr>
<tr>
<td>Absent</td>
<td>20</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
</tbody>
</table>

Since the log odds ratio ($\log(\psi)$) is a linear function of the parameters, the Wald confidence interval for $\log(\psi)$ can be derived from the parameter estimates and the estimated covariance matrix. Confidence intervals for the odds ratios are obtained by exponentiating the corresponding confidence intervals for the log odd ratios. In the displayed output of PROC SURVEYLOGISTIC, the “Odds Ratio Estimates” table contains the odds ratio estimates and the corresponding 95% Wald confidence intervals computed by using the covariance matrix in the section “Variance Estimation” on page 7321. For continuous explanatory variables, these odds ratios correspond to a unit increase in the risk factors.

To customize odds ratios for specific units of change for a continuous risk factor, you can use the UNITS statement to specify a list of relevant units for each explanatory variable in the model. Estimates of these customized odds ratios are given in a separate table. Let $(L_j, U_j)$ be a confidence interval for $\log(\psi)$. The corresponding lower and upper confidence limits for the customized odds ratio $\exp(c \beta_j)$ are $\exp(c L_j)$ and $\exp(c U_j)$, respectively, (for $c > 0$); or $\exp(c U_j)$ and $\exp(c L_j)$, respectively, (for $c < 0$). You use the CLODDS option in the MODEL statement to request confidence intervals for the odds ratios.

For a generalized logit model, odds ratios are computed similarly, except $D$ odds ratios are computed for each effect, corresponding to the $D$ logits in the model.

### Rank Correlation of Observed Responses and Predicted Probabilities

The predicted mean score of an observation is the sum of the Ordered Values (shown in the “Response Profile” table) minus one, weighted by the corresponding predicted probabilities for that observation; that is, the predicted means score is $\sum_{d=1}^{D+1} (d-1) \tilde{\pi}_d$, where $D + 1$ is the number of response levels and $\tilde{\pi}_d$ is the predicted probability of the $d$th (ordered) response.

A pair of observations with different observed responses is said to be concordant if the observation with the lower ordered response value has a lower predicted mean score than the observation with the higher ordered response value. If the observation with the lower ordered response value has a higher predicted mean score than the observation with the higher ordered response value, then the pair is discordant. If the pair is neither concordant nor discordant, it is a tie. Enumeration of the total numbers of concordant and discordant pairs...
is carried out by categorizing the predicted mean score into intervals of length \( D/500 \) and accumulating the corresponding frequencies of observations.

Let \( N \) be the sum of observation frequencies in the data. Suppose there are a total of \( t \) pairs with different responses, \( n_c \) of them are concordant, \( n_d \) of them are discordant, and \( t - n_c - n_d \) of them are tied. PROC SURVEYLOGISTIC computes the following four indices of rank correlation for assessing the predictive ability of a model:

\[
\begin{align*}
    c &= (n_c + 0.5(t - n_c - n_d))/t \\
    \text{Somers’ } D &= (n_c - n_d)/t \\
    \text{Goodman-Kruskal Gamma} &= (n_c - n_d)/(n_c + n_d) \\
    \text{Kendall’s Tau-}a &= (n_c - n_d)/(0.5N(N - 1))
\end{align*}
\]

Note that \( c \) also gives an estimate of the area under the receiver operating characteristic (ROC) curve when the response is binary (Hanley and McNeil 1982).

For binary responses, the predicted mean score is equal to the predicted probability for Ordered Value 2. As such, the preceding definition of concordance is consistent with the definition used in previous releases for the binary response model.

---

**Linear Predictor, Predicted Probability, and Confidence Limits**

This section describes how predicted probabilities and confidence limits are calculated by using the pseudo-estimates (MLEs) obtained from PROC SURVEYLOGISTIC. For a specific example, see the section “Getting Started: SURVEYLOGISTIC Procedure” on page 7267. Predicted probabilities and confidence limits can be output to a data set with the OUTPUT statement.

**Cumulative Response Models**

For a row vector of explanatory variables \( \mathbf{x} \), the linear predictor

\[
\eta_i = g(\Pr(Y \leq i \mid \mathbf{x})) = \alpha_i + \mathbf{x} \beta.
\]

is estimated by

\[
\hat{\eta}_i = \hat{\alpha}_i + \mathbf{x} \hat{\beta}
\]

where \( \hat{\alpha}_i \) and \( \hat{\beta} \) are the MLEs of \( \alpha_i \) and \( \beta \). The estimated standard error of \( \eta_i \) is \( \hat{\sigma}(\hat{\eta}_i) \), which can be computed as the square root of the quadratic form \( (1, \mathbf{x}') \hat{\mathbf{V}}_b (1, \mathbf{x})' \), where \( \hat{\mathbf{V}}_b \) is the estimated covariance matrix of the parameter estimates. The asymptotic 100(1 - \( \alpha \))% confidence interval for \( \eta_i \) is given by

\[
\hat{\eta}_i \pm z_{\alpha/2} \hat{\sigma}(\hat{\eta}_i)
\]

where \( z_{\alpha/2} \) is the 100(1 - \( \alpha/2 \)) percentile point of a standard normal distribution.

The predicted value and the 100(1 - \( \alpha \))% confidence limits for \( \Pr(Y \leq i \mid \mathbf{x}) \) are obtained by backtransferring the corresponding measures for the linear predictor.
Output Data Sets

<table>
<thead>
<tr>
<th>Link</th>
<th>Predicted Probability</th>
<th>100(1 − α) Confidence Limits</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOGIT</td>
<td>(1/(1 + e^{-\hat{\eta}_i}))</td>
<td>(1/(1 + e^{-\hat{\eta}<em>i} \pm z</em>{\alpha/2} \hat{\sigma}(\hat{\eta}_i)))</td>
</tr>
<tr>
<td>PROBIT</td>
<td>(\Phi(\hat{\eta}_i))</td>
<td>(\Phi(\hat{\eta}<em>i \pm z</em>{\alpha/2} \hat{\sigma}(\hat{\eta}_i)))</td>
</tr>
<tr>
<td>CLOGLOG</td>
<td>(1 - e^{-e^{\hat{\eta}_i}})</td>
<td>(1 - e^{\hat{\eta}<em>i \pm z</em>{\alpha/2} \hat{\sigma}(\hat{\eta}_i)})</td>
</tr>
</tbody>
</table>

**Generalized Logit Model**

For a vector of explanatory variables \(x\), let \(\pi_i\) denote the probability of obtaining the response value \(i\):

\[
\pi_i = \begin{cases} 
\pi_{k+1} e^{\alpha_i + x\beta_i} & 1 \leq i \leq k \\
1 & i = k + 1 
\end{cases}
\]

By the delta method,

\[
\sigma^2(\pi_i) = \left( \frac{\partial \pi_i}{\partial \theta} \right)' V(\theta) \frac{\partial \pi_i}{\partial \theta}
\]

A 100(1 − α)% confidence level for \(\pi_i\) is given by

\[
\hat{\pi}_i \pm z_{\alpha/2} \hat{\sigma}(\hat{\pi}_i)
\]

where \(\hat{\pi}_i\) is the estimated expected probability of response \(i\) and \(\hat{\sigma}(\hat{\pi}_i)\) is obtained by evaluating \(\sigma(\pi_i)\) at \(\theta = \hat{\theta}\).

**Output Data Sets**

You can use the Output Delivery System (ODS) to create a SAS data set from any piece of PROC SURVEYLOGISTIC output. See the section “ODS Table Names” on page 7341 for more information. For a more detailed description of using ODS, see Chapter 20, “Using the Output Delivery System.”

PROC SURVEYLOGISTIC also provides an OUTPUT statement to create a data set that contains estimated linear predictors, the estimates of the cumulative or individual response probabilities, and their confidence limits.

If you use BRR or jackknife variance estimation, PROC SURVEYLOGISTIC provides an output data set that stores the replicate weights and an output data set that stores the jackknife coefficients for jackknife variance estimation.

**OUT= Data Set in the OUTPUT Statement**

The OUT= data set in the OUTPUT statement contains all the variables in the input data set along with statistics you request by using keyword=name options or the PREDPROBS= option in the OUTPUT statement. In addition, if you use the single-trial syntax and you request any of the XBETA=, STDERRBETA=,
PREDICTED=, LCL=, and UCL= options, the OUT= data set contains the automatic variable _LEVEL_. The value of _LEVEL_ identifies the response category upon which the computed values of XBETA=, STDERRXBETA=, PREDICTED=, LCL=, and UCL= are based.

When there are more than two response levels, only variables named by the XBETA=, STDERRXBETA=, PREDICTED=, LOWER=, and UPPER= options and the variables given by PREDPROBS=(INDIVIDUAL CUMULATIVE) have their values computed; the other variables have missing values. If you fit a generalized logit model, the cumulative predicted probabilities are not computed.

When there are only two response categories, each input observation produces one observation in the OUT= data set.

If there are more than two response categories and you specify only the PREDPROBS= option, then each input observation produces one observation in the OUT= data set. However, if you fit an ordinal (cumulative) model and specify options other than the PREDPROBS= options, each input observation generates as many output observations as one fewer than the number of response levels, and the predicted probabilities and their confidence limits correspond to the cumulative predicted probabilities. If you fit a generalized logit model and specify options other than the PREDPROBS= options, each input observation generates as many output observations as the number of response categories; the predicted probabilities and their confidence limits correspond to the probabilities of individual response categories.

For observations in which only the response variable is missing, values of the XBETA=, STDERRXBETA=, PREDICTED=, UPPER=, LOWER=, and PREDPROBS= options are computed even though these observations do not affect the model fit. This enables, for instance, predicted probabilities to be computed for new observations.

Replicate Weights Output Data Set

If you specify the OUTWEIGHTS= method-option for VARMETHOD=BRR or VARMETHOD=JACKKNIFE, PROC SURVEYLOGISTIC stores the replicate weights in an output data set. The OUTWEIGHTS= output data set contains all observations from the DATA= input data set that are valid (used in the analysis). (A valid observation is an observation that has a positive value of the WEIGHT variable. Valid observations must also have nonmissing values of the STRATA and CLUSTER variables, unless you specify the MISSING option.)

The OUTWEIGHTS= data set contains the following variables:

- all variables in the DATA= input data set
- RepWt_1, RepWt_2, . . ., RepWt_n, which are the replicate weight variables

where n is the total number of replicates in the analysis. Each replicate weight variable contains the replicate weights for the corresponding replicate. Replicate weights equal zero for those observations not included in the replicate.

After the procedure creates replicate weights for a particular input data set and survey design, you can use the OUTWEIGHTS= method-option to store these replicate weights and then use them again in subsequent analyses, either in PROC SURVEYLOGISTIC or in the other survey procedures. You can use the REPEIGHTS statement to provide replicate weights for the procedure.
Jackknife Coefficients Output Data Set

If you specify the OUTJKCOEFS= method-option for VARMETHOD=JACKKNIFE, PROC SURVEYLOGISTIC stores the jackknife coefficients in an output data set. The OUTJKCOEFS= output data set contains one observation for each replicate. The OUTJKCOEFS= data set contains the following variables:

- **Replicate**, which is the replicate number for the jackknife coefficient
- **JKCoefficient**, which is the jackknife coefficient
- **DonorStratum**, which is the stratum of the PSU that was deleted to construct the replicate, if you specify a STRATA statement

After the procedure creates jackknife coefficients for a particular input data set and survey design, you can use the OUTJKCOEFS= method-option to store these coefficients and then use them again in subsequent analyses, either in PROC SURVEYLOGISTIC or in the other survey procedures. You can use the JKCOEFS= option in the REPWEIGHTS statement to provide jackknife coefficients for the procedure.

---

Displayed Output

The SURVEYLOGISTIC procedure produces output that is described in the following sections.

Output that is generated by the EFFECT, ESTIMATE, LSMEANS, LSMESTIMATE, and SLICE statements are not listed below. For information about the output that is generated by these statements, see the corresponding sections of Chapter 19, “Shared Concepts and Topics.”

Model Information

By default, PROC SURVEYLOGISTIC displays the following information in the “Model Information” table:

- name of the input Data Set
- name and label of the Response Variable if the single-trial syntax is used
- number of Response Levels
- name of the Events Variable if the events/trials syntax is used
- name of the Trials Variable if the events/trials syntax is used
- name of the Offset Variable if the OFFSET= option is specified
- name of the Frequency Variable if the FREQ statement is specified
- name(s) of the Stratum Variable(s) if the STRATA statement is specified
• total Number of Strata if the STRATA statement is specified
• name(s) of the Cluster Variable(s) if the CLUSTER statement is specified
• total Number of Clusters if the CLUSTER statement is specified
• name of the Weight Variable if the WEIGHT statement is specified
• Variance Adjustment method
• Upper Bound ADJBOUND parameter used in the VADJUST=MOREL(ADJBOUND= ) option
• Lower Bound DEFFBOUND parameter used in the VADJUST=MOREL(DEFFBOUND= ) option
• whether FPC (finite population correction) is used

Variance Estimation

By default, PROC SURVEYLOGISTIC displays the following variance estimation information in the “Variance Estimation” table:

• Method, which is the variance estimation method
• Variance Adjustment method
• Upper Bound ADJBOUND parameter specified in the VADJUST=MOREL(ADJBOUND= ) option
• Lower Bound DEFFBOUND parameter specified in the VADJUST=MOREL(DEFFBOUND= ) option
• whether FPC (finite population correction) is used
• Number of Replicates, if you specify the VARMETHOD=BRR or VARMETHOD=JACKKNIFE option
• Number of Replicates Used, if you specify the VARMETHOD=BRR or VARMETHOD=JACKKNIFE option and some of the replicates are excluded due to unattained convergence
• Hadamard Data Set name, if you specify the VARMETHOD=BRR(HADAMARD=) method-option
• Fay Coefficient, if you specify the VARMETHOD=BRR(FAY) method-option
• Replicate Weights input data set name, if you use a REPWEIGHTS statement
• whether Missing Levels are created for categorical variables by the MISSING option
• whether observations with Missing Values are included in the analysis by the NOMCAR option
Data Summary

By default, PROC SURVEYLOGISTIC displays the following information for the entire data set:

- Number of Observations read from the input data set
- Number of Observations used in the analysis

If there is a DOMAIN statement, PROC SURVEYLOGISTIC also displays the following:

- Number of Observations in the current domain
- Number of Observations not in the current domain

If there is a FREQ statement, PROC SURVEYLOGISTIC also displays the following:

- Sum of Frequencies of all the observations read from the input data set
- Sum of Frequencies of all the observations used in the analysis

If there is a WEIGHT statement, PROC SURVEYLOGISTIC also displays the following:

- Sum of Weights of all the observations read from the input data set
- Sum of Weights of all the observations used in the analysis
- Sum of Weights of all the observations in the current domain, if DOMAIN statement is also specified.

Response Profile

By default, PROC SURVEYLOGISTIC displays a “Response Profile” table, which gives, for each response level, the ordered value (an integer between one and the number of response levels, inclusive); the value of the response variable if the single-trial syntax is used or the values “EVENT” and “NO EVENT” if the events/trials syntax is used; the count or frequency; and the sum of weights if the WEIGHT statement is specified.

Class Level Information

If you use a CLASS statement to name classification variables, PROC SURVEYLOGISTIC displays a "Class Level Information" table. This table contains the following information for each classification variable:

- Class, which lists each CLASS variable name
• Value, which lists the values of the classification variable. The values are separated by a white space character; therefore, to avoid confusion, you should not include a white space character within a classification variable value.

• Design Variables, which lists the parameterization used for the classification variables

**Stratum Information**

When you specify the LIST option in the STRATA statement, PROC SURVEYLOGISTIC displays a "Stratum Information" table, which provides the following information for each stratum:

• Stratum Index, which is a sequential stratum identification number

• STRATA variable(s), which lists the levels of STRATA variables for the stratum

• Population Total, if you specify the TOTAL= option

• Sampling Rate, if you specify the TOTAL= or RATE= option. If you specify the TOTAL= option, the sampling rate is based on the number of nonmissing observations in the stratum.

• N Obs, which is the number of observations

• number of Clusters, if you specify a CLUSTER statement

**Maximum Likelihood Iteration History**

The “Maximum Likelihood Iterative Phase” table gives the iteration number, the step size (in the scale of 1.0, 0.5, 0.25, and so on) or the ridge value, \(-2\log\text{likelihood}\), and parameter estimates for each iteration. Also displayed are the last evaluation of the gradient vector and the last change in the \(-2\log\text{likelihood}\). You need to use the ITPRINT option in the MODEL statement to obtain this table.

**Score Test**

The “Score Test” table displays the score test result for testing the parallel lines assumption, if an ordinal response model is fitted. If LINK=CLOGLOG or LINK=PROBIT, this test is labeled “Score Test for the Parallel Slopes Assumption.” The proportion odds assumption is a special case of the parallel lines assumption when LINK=LOGIT. In this case, the test is labeled “Score Test for the Proportional Odds Assumption.”

**Model Fit Statistics**

By default, PROC SURVEYLOGISTIC displays the following information in the “Model Fit Statistics” table:
• “Model Fit Statistics” and “Testing Global Null Hypothesis: BETA=0” tables, which give the various criteria (−2 Log L, AIC, SC) based on the likelihood for fitting a model with intercepts only and for fitting a model with intercepts and explanatory variables. If you specify the NOINT option, these statistics are calculated without considering the intercept parameters. The third column of the table gives the chi-square statistics and p-values for the −2 Log L statistic and for the Score statistic. These test the joint effect of the explanatory variables included in the model. The Score criterion is always missing for the models identified by the first two columns of the table. Note also that the first two rows of the Chi-Square column are always missing, since tests cannot be performed for AIC and SC.

• generalized $R^2$ measures for the fitted model if you specify the RSQUARE option in the MODEL statement

Type III Analysis of Effects

PROC SURVEYLOGISTIC displays the “Type III Analysis of Effects” table if the model contains an effect involving a CLASS variable. This table gives the degrees of freedom, the Wald Chi-square statistic, and the p-value for each effect in the model.

Analysis of Maximum Likelihood Estimates

By default, PROC SURVEYLOGISTIC displays the following information in the “Analysis of Maximum Likelihood Estimates” table:

• the degrees of freedom for Wald chi-square test

• maximum likelihood estimate of the parameter

• estimated standard error of the parameter estimate, computed as the square root of the corresponding diagonal element of the estimated covariance matrix

• Wald chi-square statistic, computed by squaring the ratio of the parameter estimate divided by its standard error estimate

• p-value of the Wald chi-square statistic with respect to a chi-square distribution with one degree of freedom

• standardized estimate for the slope parameter, given by $\hat{\beta}_i/(s/s_i)$, where $s_i$ is the total sample standard deviation for the $i$th explanatory variable and

\[
s = \begin{cases} 
\pi / \sqrt{3} & \text{logistic} \\
1 & \text{normal} \\
\pi / \sqrt{6} & \text{extreme-value}
\end{cases}
\]

You need to specify the STB option in the MODEL statement to obtain these estimates. Standardized estimates of the intercept parameters are set to missing.

• value of $(e^{\hat{\beta}_i})$ for each slope parameter $\hat{\beta}_i$ if you specify the EXPB option in the MODEL statement. For continuous variables, this is equivalent to the estimated odds ratio for a one-unit change.
label of the variable (if space permits) if you specify the PARMLABEL option in the MODEL statement. Due to constraints on the line size, the variable label might be suppressed in order to display the table in one panel. Use the SAS system option LINESIZE= to specify a larger line size to accommodate variable labels. A shorter line size can break the table into two panels, allowing labels to be displayed.

Odds Ratio Estimates

The “Odds Ratio Estimates” table displays the odds ratio estimates and the corresponding 95% Wald confidence intervals. For continuous explanatory variables, these odds ratios correspond to a unit increase in the risk factors.

Association of Predicted Probabilities and Observed Responses

The “Association of Predicted Probabilities and Observed Responses” table displays measures of association between predicted probabilities and observed responses, which include a breakdown of the number of pairs with different responses, and four rank correlation indexes: Somers’ D, Goodman-Kruskal Gamma, and Kendall’s Tau-a, and c.

Wald Confidence Interval for Parameters

The “Wald Confidence Interval for Parameters” table displays confidence intervals for all the parameters if you use the CLPARM option in the MODEL statement.

Wald Confidence Interval for Odds Ratios

The “Wald Confidence Interval for Odds Ratios” table displays confidence intervals for all the odds ratios if you use the CLODDS option in the MODEL statement.

Estimated Covariance Matrix

PROC SURVEYLOGISTIC displays the following information in the “Estimated Covariance Matrix” table:

- estimated covariance matrix of the parameter estimates if you use the COVB option in the MODEL statement
- estimated correlation matrix of the parameter estimates if you use the CORRB option in the MODEL statement
**Linear Hypotheses Testing Results**

The “Linear Hypothesis Testing” table gives the result of the Wald test for each TEST statement (if specified).

**Hadamard Matrix**

If you specify the `VARMETHOD=BRR(PRINTH)` method-option in the PROC SURVEYLOGISTIC statement, the procedure displays the Hadamard matrix.

When you provide a Hadamard matrix with the `VARMETHOD=BRR(HADAMARD=)` method-option, the procedure displays only used rows and columns of the Hadamard matrix.

---

**ODS Table Names**

PROC SURVEYLOGISTIC assigns a name to each table it creates; these names are listed in Table 87.8. You can use these names to refer the table when using the Output Delivery System (ODS) to select tables and create output data sets. The EFFECT, ESTIMATE, LSMEANS, LSMESTIMATE, and SLICE statements also create tables, which are not listed in Table 87.8. For information about these tables, see the corresponding sections of Chapter 19, “Shared Concepts and Topics.”

For more information about ODS, see Chapter 20, “Using the Output Delivery System.”

**Table 87.8** ODS Tables Produced by PROC SURVEYLOGISTIC

<table>
<thead>
<tr>
<th>ODS Table Name</th>
<th>Description</th>
<th>Statement</th>
<th>Option</th>
</tr>
</thead>
<tbody>
<tr>
<td>Association</td>
<td>Association of predicted probabilities and observed responses</td>
<td>MODEL</td>
<td>Default</td>
</tr>
<tr>
<td>ClassLevelInfo</td>
<td>Class variable levels and design variables</td>
<td>MODEL</td>
<td>Default (with CLASS vars)</td>
</tr>
<tr>
<td>CLOddsWald</td>
<td>Wald’s confidence limits for odds ratios</td>
<td>MODEL</td>
<td>CLODDS</td>
</tr>
<tr>
<td>CLparmWald</td>
<td>Wald’s confidence limits for parameters</td>
<td>MODEL</td>
<td>CLPARM</td>
</tr>
<tr>
<td>ContrastCoeff</td>
<td>L matrix from CONTRAST</td>
<td>CONTRAST</td>
<td>E</td>
</tr>
<tr>
<td>ContrastEstimate</td>
<td>Estimates from CONTRAST</td>
<td>CONTRAST</td>
<td>ESTIMATE=</td>
</tr>
<tr>
<td>ContrastTest</td>
<td>Wald test for CONTRAST</td>
<td>CONTRAST</td>
<td>Default</td>
</tr>
<tr>
<td>ConvergenceStatus</td>
<td>Convergence status</td>
<td>MODEL</td>
<td>Default</td>
</tr>
<tr>
<td>CorrB</td>
<td>Estimated correlation matrix of parameter estimators</td>
<td>MODEL</td>
<td>CORRB</td>
</tr>
<tr>
<td>CovB</td>
<td>Estimated covariance matrix of parameter estimators</td>
<td>MODEL</td>
<td>COVB</td>
</tr>
<tr>
<td>CumulativeModelTest</td>
<td>Test of the cumulative model assumption</td>
<td>MODEL</td>
<td>(Ordinal response)</td>
</tr>
</tbody>
</table>
Table 87.8 continued

<table>
<thead>
<tr>
<th>ODS Table Name</th>
<th>Description</th>
<th>Statement</th>
<th>Option</th>
</tr>
</thead>
<tbody>
<tr>
<td>DomainSummary</td>
<td>Domain summary</td>
<td>DOMAIN</td>
<td>Default</td>
</tr>
<tr>
<td>FitStatistics</td>
<td>Model fit statistics</td>
<td>MODEL</td>
<td>Default</td>
</tr>
<tr>
<td>GlobalTests</td>
<td>Test for global null hypothesis</td>
<td>MODEL</td>
<td>Default</td>
</tr>
<tr>
<td>HadamardMatrix</td>
<td>Hadamard matrix</td>
<td>PROC</td>
<td>PRINTH</td>
</tr>
<tr>
<td>IterHistory</td>
<td>Iteration history</td>
<td>MODEL</td>
<td>ITPRINT</td>
</tr>
<tr>
<td>LastGradient</td>
<td>Last evaluation of gradient</td>
<td>MODEL</td>
<td>ITPRINT</td>
</tr>
<tr>
<td>Linear</td>
<td>Linear combination</td>
<td>PROC</td>
<td>Default</td>
</tr>
<tr>
<td>LogLikeChange</td>
<td>Final change in the log likelihood</td>
<td>MODEL</td>
<td>ITPRINT</td>
</tr>
<tr>
<td>ModelInfo</td>
<td>Model information</td>
<td>PROC</td>
<td>Default</td>
</tr>
<tr>
<td>NObs</td>
<td>Number of observations</td>
<td>PROC</td>
<td>Default</td>
</tr>
<tr>
<td>OddsEst</td>
<td>Adjusted odds ratios</td>
<td>UNITS</td>
<td>Default</td>
</tr>
<tr>
<td>OddsRatios</td>
<td>Odds ratios</td>
<td>MODEL</td>
<td>Default</td>
</tr>
<tr>
<td>ParameterEstimates</td>
<td>Maximum likelihood estimates of model parameters</td>
<td>MODEL</td>
<td>Default</td>
</tr>
<tr>
<td>RSquare</td>
<td>R-square</td>
<td>MODEL</td>
<td>RSQUARE</td>
</tr>
<tr>
<td>ResponseProfile</td>
<td>Response profile</td>
<td>PROC</td>
<td>Default</td>
</tr>
<tr>
<td>StrataInfo</td>
<td>Stratum information</td>
<td>STRATA</td>
<td>LIST</td>
</tr>
<tr>
<td>TestPrint1</td>
<td>$L[cov(b)]L'$ and $Lb - c$</td>
<td>TEST</td>
<td>PRINT</td>
</tr>
<tr>
<td>TestPrint2</td>
<td>$Ginv(L[cov(b)]L')$ and $Ginv(L[cov(b)]L')(Lb - c)$</td>
<td>TEST</td>
<td>PRINT</td>
</tr>
<tr>
<td>TestStmts</td>
<td>Linear hypotheses testing results</td>
<td>TEST</td>
<td>Default</td>
</tr>
<tr>
<td>Type3</td>
<td>Type III tests of effects</td>
<td>MODEL</td>
<td>Default</td>
</tr>
<tr>
<td></td>
<td>(with CLASS variables)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VarianceEstimation</td>
<td>Variance estimation</td>
<td>PROC</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, with the ODS GRAPHICS ON statement). For more information about enabling and disabling ODS Graphics, see the section “Enabling and Disabling ODS Graphics” on page 609 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 608 in Chapter 21, “Statistical Graphics Using ODS.”

When ODS Graphics is enabled, then the ESTIMATE, LSMEANS, LSMESTIMATE, and SLICE state-
ments can produce plots that are associated with their analyses. For information about these plots, see the corresponding sections of Chapter 19, “Shared Concepts and Topics.”

---

**Examples: SURVEYLOGISTIC Procedure**

---

**Example 87.1: Stratified Cluster Sampling**

A market research firm conducts a survey among undergraduate students at a certain university to evaluate three new Web designs for a commercial Web site targeting undergraduate students at the university.

The sample design is a stratified sample where the strata are students’ classes. Within each class, 300 students are randomly selected by using simple random sampling without replacement. The total number of students in each class in the fall semester of 2001 is shown in the following table:

<table>
<thead>
<tr>
<th>Class</th>
<th>Enrollment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - Freshman</td>
<td>3,734</td>
</tr>
<tr>
<td>2 - Sophomore</td>
<td>3,565</td>
</tr>
<tr>
<td>3 - Junior</td>
<td>3,903</td>
</tr>
<tr>
<td>4 - Senior</td>
<td>4,196</td>
</tr>
</tbody>
</table>

This total enrollment information is saved in the SAS data set *Enrollment* by using the following SAS statements:

```sas
proc format ;
  value Class
    1='Freshman' 2='Sophomore'
    3='Junior'   4='Senior';
run;

data Enrollment;
  format Class Class.;
  input Class _TOTAL_;
datalines;
1 3734
2 3565
3 3903
4 4196
;
```

In the data set *Enrollment*, the variable `_TOTAL_` contains the enrollment figures for all classes. They are also the population size for each stratum in this example.

Each student selected in the sample evaluates one randomly selected Web design by using the following scale:
The survey results are collected and shown in the following table, with the three different Web designs coded as A, B, and C.

<table>
<thead>
<tr>
<th>Strata</th>
<th>Design</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freshman</td>
<td>A</td>
<td>10</td>
<td>34</td>
<td>35</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>5</td>
<td>6</td>
<td>24</td>
<td>30</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>11</td>
<td>14</td>
<td>20</td>
<td>34</td>
<td>21</td>
</tr>
<tr>
<td>Sophomore</td>
<td>A</td>
<td>19</td>
<td>12</td>
<td>26</td>
<td>18</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>10</td>
<td>18</td>
<td>32</td>
<td>23</td>
<td>26</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>15</td>
<td>22</td>
<td>34</td>
<td>9</td>
<td>20</td>
</tr>
<tr>
<td>Junior</td>
<td>A</td>
<td>8</td>
<td>21</td>
<td>23</td>
<td>26</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>1</td>
<td>4</td>
<td>15</td>
<td>33</td>
<td>47</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>16</td>
<td>19</td>
<td>30</td>
<td>23</td>
<td>12</td>
</tr>
<tr>
<td>Senior</td>
<td>A</td>
<td>11</td>
<td>14</td>
<td>24</td>
<td>33</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>8</td>
<td>15</td>
<td>25</td>
<td>30</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>2</td>
<td>34</td>
<td>30</td>
<td>18</td>
<td>16</td>
</tr>
</tbody>
</table>

The survey results are stored in a SAS data set `WebSurvey` by using the following SAS statements:

```sas
proc format;
  value Design 1='A' 2='B' 3='C';
  value Rating
    1='dislike very much'
    2='dislike'
    3='neutral'
    4='like'
    5='like very much';
run;

data WebSurvey;
  format Class Class. Design Design. Rating Rating. ;
  do Class=1 to 4;
    do Design=1 to 3;
      do Rating=1 to 5;
        input Count @@;
        output;
      end;
    end;
  end;
end;
```
Example 87.1: Stratified Cluster Sampling

```sas
datalines;
  10 34 35 16 15 8 21 23 26 22 5 10 24 30 21
  1 14 25 23 37 11 14 20 34 21 16 19 30 23 12
  19 12 26 18 25 11 14 24 33 18 10 18 32 23 17
  8 15 35 30 12 15 22 34 9 20 2 34 30 18 16
;

data WebSurvey; set WebSurvey;
  if Class=1 then Weight=3734/300;
  if Class=2 then Weight=3565/300;
  if Class=3 then Weight=3903/300;
  if Class=4 then Weight=4196/300;
run;

The data set WebSurvey contains the variables Class, Design, Rating, Count, and Weight. The variable Class is the stratum variable, with four strata: freshman, sophomore, junior, and senior. The variable Design specifies the three new Web designs: A, B, and C. The variable Rating contains students' evaluations of the new Web designs. The variable Count gives the frequency with which each Web design received each rating within each stratum. The variable weight contains the sampling weights, which are the reciprocals of selection probabilities in this example.

Output 87.1.1 shows the first 20 observations of the data set.

Output 87.1.1 Web Design Survey Sample (First 20 Observations)

<table>
<thead>
<tr>
<th>Obs</th>
<th>Class</th>
<th>Design</th>
<th>Rating</th>
<th>Count</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Freshman</td>
<td>A</td>
<td>dislike very much</td>
<td>10</td>
<td>12.4467</td>
</tr>
<tr>
<td>2</td>
<td>Freshman</td>
<td>A</td>
<td>dislike</td>
<td>34</td>
<td>12.4467</td>
</tr>
<tr>
<td>3</td>
<td>Freshman</td>
<td>A</td>
<td>neutral</td>
<td>35</td>
<td>12.4467</td>
</tr>
<tr>
<td>4</td>
<td>Freshman</td>
<td>A</td>
<td>like</td>
<td>16</td>
<td>12.4467</td>
</tr>
<tr>
<td>5</td>
<td>Freshman</td>
<td>A</td>
<td>like very much</td>
<td>15</td>
<td>12.4467</td>
</tr>
<tr>
<td>6</td>
<td>Freshman</td>
<td>B</td>
<td>dislike very much</td>
<td>8</td>
<td>12.4467</td>
</tr>
<tr>
<td>7</td>
<td>Freshman</td>
<td>B</td>
<td>dislike</td>
<td>21</td>
<td>12.4467</td>
</tr>
<tr>
<td>8</td>
<td>Freshman</td>
<td>B</td>
<td>neutral</td>
<td>23</td>
<td>12.4467</td>
</tr>
<tr>
<td>9</td>
<td>Freshman</td>
<td>B</td>
<td>like</td>
<td>26</td>
<td>12.4467</td>
</tr>
<tr>
<td>10</td>
<td>Freshman</td>
<td>B</td>
<td>like very much</td>
<td>22</td>
<td>12.4467</td>
</tr>
<tr>
<td>11</td>
<td>Freshman</td>
<td>C</td>
<td>dislike very much</td>
<td>5</td>
<td>12.4467</td>
</tr>
<tr>
<td>12</td>
<td>Freshman</td>
<td>C</td>
<td>dislike</td>
<td>10</td>
<td>12.4467</td>
</tr>
<tr>
<td>13</td>
<td>Freshman</td>
<td>C</td>
<td>neutral</td>
<td>24</td>
<td>12.4467</td>
</tr>
<tr>
<td>14</td>
<td>Freshman</td>
<td>C</td>
<td>like</td>
<td>30</td>
<td>12.4467</td>
</tr>
<tr>
<td>15</td>
<td>Freshman</td>
<td>C</td>
<td>like very much</td>
<td>21</td>
<td>12.4467</td>
</tr>
<tr>
<td>16</td>
<td>Sophomore</td>
<td>A</td>
<td>dislike very much</td>
<td>1</td>
<td>11.8833</td>
</tr>
<tr>
<td>17</td>
<td>Sophomore</td>
<td>A</td>
<td>dislike</td>
<td>14</td>
<td>11.8833</td>
</tr>
<tr>
<td>18</td>
<td>Sophomore</td>
<td>A</td>
<td>neutral</td>
<td>25</td>
<td>11.8833</td>
</tr>
<tr>
<td>19</td>
<td>Sophomore</td>
<td>A</td>
<td>like</td>
<td>23</td>
<td>11.8833</td>
</tr>
<tr>
<td>20</td>
<td>Sophomore</td>
<td>A</td>
<td>like very much</td>
<td>37</td>
<td>11.8833</td>
</tr>
</tbody>
</table>
```

The following SAS statements perform the logistic regression:

```sas
proc surveylogistic data=WebSurvey total=Enrollment;
  stratum Class;
  freq Count;
  class Design;
```
model Rating (order=internal) = design;
weight Weight;
run;

The PROC SURVEYLOGISTIC statement invokes the procedure. The TOTAL= option specifies the data set Enrollment, which contains the population totals in the strata. The population totals are used to calculate the finite population correction factor in the variance estimates. The response variable Rating is in the ordinal scale. A cumulative logit model is used to investigate the responses to the Web designs. In the MODEL statement, rating is the response variable, and Design is the effect in the regression model. The ORDER=INTERNAL option is used for the response variable Rating to sort the ordinal response levels of Rating by its internal (numerical) values rather than by the formatted values (for example, ‘like very much’). Because the sample design involves stratified simple random sampling, the STRATA statement is used to specify the stratification variable Class. The WEIGHT statement specifies the variable Weight for sampling weights.

The sample and analysis summary is shown in Output 87.1.2. There are five response levels for the Rating, with ‘dislike very much’ as the lowest ordered value. The regression model is modeling lower cumulative probabilities by using logit as the link function. Because the TOTAL= option is used, the finite population correction is included in the variance estimation. The sampling weight is also used in the analysis.

Output 87.1.2  Web Design Survey, Model Information

<table>
<thead>
<tr>
<th>Response Profile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ordered Value</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>

Probabilities modeled are cumulated over the lower Ordered Values.

In Output 87.1.3, the score chi-square for testing the proportional odds assumption is 98.1957, which is highly significant. This indicates that the cumulative logit model might not adequately fit the data.
An alternative model is to use the generalized logit model with the LINK=GLOGIT option, as shown in the following SAS statements:

```sas
proc surveylogistic data=WebSurvey total=Enrollment;
    stratum Class;
    freq Count;
    class Design;
    model Rating (ref='neutral') = Design /link=glogit;
    weight Weight;
run;
```

The REF='neutral' option is used for the response variable Rating to indicate that all other response levels are referenced to the level ‘neutral.’ The option LINK=GLOGIT option requests that the procedure fit a generalized logit model.

The summary of the analysis is shown in Output 87.1.4, which indicates that the generalized logit model is used in the analysis.

```
Output 87.1.3 Web Design Survey, Testing the Proportional Odds Assumption

<table>
<thead>
<tr>
<th>Score Test for the Proportional Odds Assumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square</td>
</tr>
<tr>
<td>-------------</td>
</tr>
<tr>
<td>98.1957</td>
</tr>
</tbody>
</table>
```

```
Output 87.1.4 Web Design Survey, Model Information

The SUMMARYLOGISTIC Procedure

Model Information

<table>
<thead>
<tr>
<th>Data Set</th>
<th>WORK.WEBSURVEY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response Variable</td>
<td>Rating</td>
</tr>
<tr>
<td>Number of Response Levels</td>
<td>5</td>
</tr>
<tr>
<td>Frequency Variable</td>
<td>Count</td>
</tr>
<tr>
<td>Stratum Variable</td>
<td>Class</td>
</tr>
<tr>
<td>Number of Strata</td>
<td>4</td>
</tr>
<tr>
<td>Weight Variable</td>
<td>Weight</td>
</tr>
<tr>
<td>Model</td>
<td>Generalized Logit</td>
</tr>
<tr>
<td>Optimization Technique</td>
<td>Newton-Raphson</td>
</tr>
<tr>
<td>Variance Adjustment</td>
<td>Degrees of Freedom (DF)</td>
</tr>
<tr>
<td>Finite Population Correction</td>
<td>Used</td>
</tr>
</tbody>
</table>
```
Output 87.1.4 continued

<table>
<thead>
<tr>
<th>Ordered Value</th>
<th>Rating</th>
<th>Total Frequency</th>
<th>Total Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>dislike</td>
<td>227</td>
<td>2933.0433</td>
</tr>
<tr>
<td>2</td>
<td>dislike very much</td>
<td>116</td>
<td>1489.0733</td>
</tr>
<tr>
<td>3</td>
<td>like</td>
<td>283</td>
<td>3606.8067</td>
</tr>
<tr>
<td>4</td>
<td>like very much</td>
<td>236</td>
<td>3005.7000</td>
</tr>
<tr>
<td>5</td>
<td>neutral</td>
<td>338</td>
<td>4363.3767</td>
</tr>
</tbody>
</table>

Logits modeled use Rating='neutral' as the reference category.

Output 87.1.5 shows the parameterization for the main effect Design.

Output 87.1.5 Web Design Survey, Class Level Information

<table>
<thead>
<tr>
<th>Class Variable</th>
<th>Design A</th>
<th>Design B</th>
<th>Design C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design</td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>Value</td>
<td>1</td>
<td>0</td>
<td>-1</td>
</tr>
</tbody>
</table>

The parameter and odds ratio estimates are shown in Output 87.1.6. For each odds ratio estimate, the 95% confidence limits shown in the table contain the value 1.0. Therefore, no conclusion about which Web design is preferred can be made based on this survey.

Output 87.1.6 Web Design Survey, Parameter and Odds Ratio Estimates

<table>
<thead>
<tr>
<th>Parameter Rating</th>
<th>DF</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Wald Chi-Square</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept dislike</td>
<td>1</td>
<td>-0.3964</td>
<td>0.0832</td>
<td>22.7100</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Intercept dislike very much</td>
<td>1</td>
<td>-1.0826</td>
<td>0.1045</td>
<td>107.3889</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Intercept like</td>
<td>1</td>
<td>-0.1892</td>
<td>0.0780</td>
<td>5.8888</td>
<td>0.0152</td>
</tr>
<tr>
<td>Intercept like very much</td>
<td>1</td>
<td>-0.3767</td>
<td>0.0824</td>
<td>20.9223</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Design A dislike</td>
<td>1</td>
<td>-0.0942</td>
<td>0.1166</td>
<td>0.6518</td>
<td>0.4195</td>
</tr>
<tr>
<td>Design A dislike very much</td>
<td>1</td>
<td>-0.0647</td>
<td>0.1469</td>
<td>0.1940</td>
<td>0.6596</td>
</tr>
<tr>
<td>Design A like</td>
<td>1</td>
<td>-0.1370</td>
<td>0.1104</td>
<td>1.5400</td>
<td>0.2146</td>
</tr>
<tr>
<td>Design A like very much</td>
<td>1</td>
<td>0.0446</td>
<td>0.1130</td>
<td>0.1555</td>
<td>0.6933</td>
</tr>
<tr>
<td>Design B dislike</td>
<td>1</td>
<td>0.0391</td>
<td>0.1201</td>
<td>0.1057</td>
<td>0.7451</td>
</tr>
<tr>
<td>Design B dislike very much</td>
<td>1</td>
<td>0.2721</td>
<td>0.1448</td>
<td>3.5294</td>
<td>0.0603</td>
</tr>
<tr>
<td>Design B like</td>
<td>1</td>
<td>0.1669</td>
<td>0.1102</td>
<td>2.2954</td>
<td>0.1298</td>
</tr>
<tr>
<td>Design B like very much</td>
<td>1</td>
<td>0.1420</td>
<td>0.1174</td>
<td>1.4641</td>
<td>0.2263</td>
</tr>
</tbody>
</table>
Example 87.2: The Medical Expenditure Panel Survey (MEPS)

The U.S. Department of Health and Human Services conducts the Medical Expenditure Panel Survey (MEPS) to produce national and regional estimates of various aspects of health care. The MEPS has a complex sample design that includes both stratification and clustering. The sampling weights are adjusted for nonresponse and raked with respect to population control totals from the Current Population Survey. See the MEPS Survey Background (2006) and Machlin, Yu, and Zodet (2005) for details.

In this example, the 1999 full-year consolidated data file HC-038 (MEPS HC-038, 2002) from the MEPS is used to investigate the relationship between medical insurance coverage and the demographic variables. The data can be downloaded directly from the Agency for Healthcare Research and Quality (AHRQ) Web site at http://www.meps.ahrq.gov/mepsweb/data_stats/download_data_files_detail.jsp?cboPufNumber=HC-038 in either ASCII format or SAS transport format. The Web site includes a detailed description of the data as well as the SAS program used to access and format it.

For this example, the SAS transport format data file for HC-038 is downloaded to ‘C:H38.ssp’ on a Windows-based PC. The instructions on the Web site lead to the following SAS statements for creating a SAS data set MEPS, which contains only the sample design variables and other variables necessary for this analysis.

```sas
proc format;
  value racex
    -9 = 'NOT ASCERTAINED'
    -8 = 'DK'
    -7 = 'REFUSED'
    -1 = 'INAPPLICABLE'
    1 = 'AMERICAN INDIAN'
    2 = 'ALEUT, ESKIMO'
    3 = 'ASIAN OR PACIFIC ISLANDER'
    4 = 'BLACK'
    5 = 'WHITE'
    91 = 'OTHER'
    ;
```

---

**Output 87.1.6 continued**

<table>
<thead>
<tr>
<th>Effect</th>
<th>Rating</th>
<th>Point Estimate</th>
<th>95% Wald Confidence Limits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design A vs C</td>
<td>dislike</td>
<td>0.861</td>
<td>0.583</td>
</tr>
<tr>
<td>Design A vs C</td>
<td>dislike very much</td>
<td>1.153</td>
<td>0.692</td>
</tr>
<tr>
<td>Design A vs C</td>
<td>like</td>
<td>0.899</td>
<td>0.618</td>
</tr>
<tr>
<td>Design A vs C</td>
<td>like very much</td>
<td>1.260</td>
<td>0.851</td>
</tr>
<tr>
<td>Design B vs C</td>
<td>dislike</td>
<td>0.984</td>
<td>0.659</td>
</tr>
<tr>
<td>Design B vs C</td>
<td>dislike very much</td>
<td>1.615</td>
<td>0.975</td>
</tr>
<tr>
<td>Design B vs C</td>
<td>like</td>
<td>1.218</td>
<td>0.838</td>
</tr>
<tr>
<td>Design B vs C</td>
<td>like very much</td>
<td>1.389</td>
<td>0.925</td>
</tr>
</tbody>
</table>
value sex
  -9 = 'NOT ASCERTAINED'
  -8 = 'DK'
  -7 = 'REFUSED'
  -1 = 'INAPPLICABLE'
  1 = 'MALE'
  2 = 'FEMALE'
;
value povcat9h
  1 = 'NEGATIVE OR POOR'
  2 = 'NEAR POOR'
  3 = 'LOW INCOME'
  4 = 'MIDDLE INCOME'
  5 = 'HIGH INCOME'
;
value inscov9f
  1 = 'ANY PRIVATE'
  2 = 'PUBLIC ONLY'
  3 = 'UNINSURED'
;
run;

libname mylib '';
filename in1 'H38.SSP';
proc xcopy in=in1 out=mylib import;
run;

data meps;
  set mylib.H38;
  label racex= sex= inscov99= povcat99= varstr99= varpsu99= perwt99f= totexp99=;
  format racex racex. sex sex. povcat99 povcat9h. inscov99 inscov9f. ;
  keep inscov99 sex racex povcat99 varstr99 varpsu99 perwt99f totexp99;
run;

There are a total of 24,618 observations in this SAS data set. Each observation corresponds to a person in the survey. The stratification variable is VARSTR99, which identifies the 143 strata in the sample. The variable VARPSU99 identifies the 460 PSUs in the sample. The sampling weights are stored in the variable PERWT99F. The response variable is the health insurance coverage indicator variable, INSCOV99, which has three values:

1. The person had any private insurance coverage any time during 1999
2. The person had only public insurance coverage during 1999
3. The person was uninsured during all of 1999

The demographic variables include gender (SEX), race (RACEX), and family income level as a percent of the poverty line (POVCAT99). The variable RACEX has five categories:
The variable \texttt{POVCAT99} is constructed by dividing family income by the applicable poverty line (based on family size and composition), with the resulting percentages grouped into five categories:

1. Negative or poor (less than 100%)
2. Near poor (100% to less than 125%)
3. Low income (125% to less than 200%)
4. Middle income (200% to less than 400%)
5. High income (greater than or equal to 400%)

The data set also contains the total health care expenditure in 1999, \texttt{TOTEXP99}, which is used as a covariate in the analysis.

\textbf{Output 87.2.1} displays the first 30 observations of this data set.
The following SAS statements fit a generalized logit model for the 1999 full-year consolidated MEPS data:

```sas
proc surveylogistic data=meps;
  stratum VARSTR99;
  cluster VARPSU99;
  weight PERWT99F;
  class SEX RACEX POVCAT99;
  model INSCOV99 = TOTEXP99 SEX RACEX POVCAT99 / link=glogit;
run;
```

The STRATUM statement specifies the stratification variable VARSTR99. The CLUSTER statement specifies the PSU variable VARPSU99. The WEIGHT statement specifies the sample weight variable PERWT99F. The demographic variables SEX, RACEX, and POVCAT99 are listed in the CLASS state-
Example 87.2: The Medical Expenditure Panel Survey (MEPS)

In the MODEL statement, the response variable is INSCOV99, and the independent variables are TOTEXP99 along with the selected demographic variables. The LINK= option requests that the procedure fit the generalized logit model because the response variable INSCOV99 has nominal responses.

The results of this analysis are shown in the following outputs.

PROC SURVEYLOGISTIC lists the model fitting information and sample design information in Output 87.2.2.

Output 87.2.2 MEPS, Model Information

<table>
<thead>
<tr>
<th>The SURVEYLOGISTIC Procedure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Information</td>
</tr>
<tr>
<td>Data Set</td>
</tr>
<tr>
<td>Response Variable</td>
</tr>
<tr>
<td>Number of Response Levels</td>
</tr>
<tr>
<td>Stratum Variable</td>
</tr>
<tr>
<td>Number of Strata</td>
</tr>
<tr>
<td>Cluster Variable</td>
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<tr>
<td>Number of Clusters</td>
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<tr>
<td>Weight Variable</td>
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<tr>
<td>Model</td>
</tr>
<tr>
<td>Optimization Technique</td>
</tr>
<tr>
<td>Variance Adjustment</td>
</tr>
</tbody>
</table>

Output 87.2.3 displays the number of observations and the total of sampling weights both in the data set and used in the analysis. Only the observations with positive person-level weight are used in the analysis. Therefore, 1,053 observations with zero person-level weights were deleted.

Output 87.2.3 MEPS, Number of Observations

| Number of Observations Read  | 24618       |
| Number of Observations Used  | 23565       |
| Sum of Weights Read          | 2.7641E8    |
| Sum of Weights Used          | 2.7641E8    |

Output 87.2.4 lists the three insurance coverage levels for the response variable INSCOV99. The “UNINSURED” category is used as the reference category in the model.
Output 87.2.4 MEPS, Response Profile

<table>
<thead>
<tr>
<th>Ordered Value</th>
<th>INSCOV99</th>
<th>Total Frequency</th>
<th>Total Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ANY PRIVATE</td>
<td>16130</td>
<td>204403997</td>
<td></td>
</tr>
<tr>
<td>2 PUBLIC ONLY</td>
<td>4241</td>
<td>41809572</td>
<td></td>
</tr>
<tr>
<td>3 UNINSURED</td>
<td>3194</td>
<td>30197198</td>
<td></td>
</tr>
</tbody>
</table>

Logits modeled use INSCOV99='UNINSURED' as the reference category.

Output 87.2.5 shows the parameterization in the regression model for each categorical independent variable.

Output 87.2.5 MEPS, Classification Levels

<table>
<thead>
<tr>
<th>Class</th>
<th>Value</th>
<th>Design Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEX</td>
<td>FEMALE 1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MALE -1</td>
<td></td>
</tr>
<tr>
<td>RACEX</td>
<td>ALEUT, ESKIMO 1 0 0 0 0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>AMERICAN INDIAN 0 1 0 0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ASIAN OR PACIFIC ISLANDER 0 0 1 0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>BLACK 0 0 0 1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WHITE -1 -1 -1 -1</td>
<td></td>
</tr>
<tr>
<td>POVCAT99</td>
<td>HIGH INCOME 1 0 0 0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LOW INCOME 0 1 0 0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MIDDLE INCOME 0 0 1 0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>NEAR POOR 0 0 0 1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>NEGATIVE OR POOR -1 -1 -1 -1</td>
<td></td>
</tr>
</tbody>
</table>

Output 87.2.6 displays the parameter estimates and their standard errors.

Output 87.2.7 displays the odds ratio estimates and their standard errors.

For example, after adjusting for the effects of sex, race, and total health care expenditures, a person with high income is estimated to be 11.595 times more likely than a poor person to choose private health care insurance over no insurance, but only 0.274 times as likely to choose public health insurance over no insurance.
Output 87.2.6 MEPS, Parameter Estimates

Analysis of Maximum Likelihood Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>INSCOV99</th>
<th>DF</th>
<th>Estimate</th>
<th>Error</th>
<th>Chi-Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
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<td>2.7703</td>
<td>0.1906</td>
<td>211.3648</td>
</tr>
<tr>
<td>Intercept</td>
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<td>1.9216</td>
<td>0.1561</td>
<td>151.4590</td>
</tr>
<tr>
<td>TOTEXP99</td>
<td>ANY PRIVATE</td>
<td>1</td>
<td>0.000215</td>
<td>0.000071</td>
<td>9.1895</td>
</tr>
<tr>
<td>TOTEXP99</td>
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<td>1</td>
<td>0.000241</td>
<td>0.000072</td>
<td>11.1509</td>
</tr>
<tr>
<td>SEX</td>
<td>FEMALE</td>
<td>ANY PRIVATE</td>
<td>1</td>
<td>0.1208</td>
<td>0.0248</td>
</tr>
<tr>
<td>SEX</td>
<td>FEMALE</td>
<td>PUBLIC ONLY</td>
<td>1</td>
<td>0.1741</td>
<td>0.0308</td>
</tr>
<tr>
<td>RACEX</td>
<td>ALEUT, ESKIMO</td>
<td>ANY PRIVATE</td>
<td>1</td>
<td>7.1457</td>
<td>0.6976</td>
</tr>
<tr>
<td>RACEX</td>
<td>ALEUT, ESKIMO</td>
<td>PUBLIC ONLY</td>
<td>1</td>
<td>7.6303</td>
<td>0.5022</td>
</tr>
<tr>
<td>RACEX</td>
<td>AMERICAN INDIAN</td>
<td>ANY PRIVATE</td>
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<td>0.2615</td>
</tr>
<tr>
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</tr>
<tr>
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<td>ANY PRIVATE</td>
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<td>-1.8055</td>
<td>0.2299</td>
</tr>
<tr>
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<td>PUBLIC ONLY</td>
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<td>-1.9914</td>
<td>0.2285</td>
</tr>
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<td>-1.7517</td>
<td>0.1983</td>
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<td>0.0685</td>
</tr>
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<tr>
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<td>0.0666</td>
</tr>
<tr>
<td>POVCAT99</td>
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<tr>
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<td>0.6467</td>
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<td>0.0807</td>
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<td>0.0952</td>
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Analysis of Maximum Likelihood Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>INSCOV99</th>
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<tbody>
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<tr>
<td>Intercept</td>
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<td>&lt;.0001</td>
</tr>
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<td>0.0024</td>
</tr>
<tr>
<td>TOTEXP99</td>
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</tr>
<tr>
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<td>FEMALE</td>
<td>ANY PRIVATE</td>
</tr>
<tr>
<td>SEX</td>
<td>FEMALE</td>
<td>PUBLIC ONLY</td>
</tr>
<tr>
<td>RACEX</td>
<td>ALEUT, ESKIMO</td>
<td>ANY PRIVATE</td>
</tr>
<tr>
<td>RACEX</td>
<td>ALEUT, ESKIMO</td>
<td>PUBLIC ONLY</td>
</tr>
<tr>
<td>RACEX</td>
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<td>PUBLIC ONLY</td>
</tr>
<tr>
<td>RACEX</td>
<td>ASIAN OR PACIFIC ISLANDER</td>
<td>ANY PRIVATE</td>
</tr>
<tr>
<td>RACEX</td>
<td>ASIAN OR PACIFIC ISLANDER</td>
<td>PUBLIC ONLY</td>
</tr>
<tr>
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<td>BLACK</td>
<td>ANY PRIVATE</td>
</tr>
<tr>
<td>RACEX</td>
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</tr>
<tr>
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</tr>
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<tr>
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<td>ANY PRIVATE</td>
</tr>
<tr>
<td>POVCAT99</td>
<td>MIDDLE INCOME</td>
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</tr>
<tr>
<td>POVCAT99</td>
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</tr>
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<td>POVCAT99</td>
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</table>
Output 87.2.7  MEPS, Odds Ratios

<table>
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<tr>
<th>Effect</th>
<th>INSCOV99</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOTEXP99 ANY PRIVATE</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>TOTEXP99 PUBLIC ONLY</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>SEX FEMALE vs MALE ANY PRIVATE</td>
<td>1.273</td>
<td></td>
</tr>
<tr>
<td>SEX FEMALE vs MALE PUBLIC ONLY</td>
<td>1.417</td>
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</tr>
<tr>
<td>RACEX ALEUT, ESKIMO vs WHITE</td>
<td>&gt;999.999</td>
<td></td>
</tr>
<tr>
<td>RACEX ALEUT, ESKIMO PUBLIC ONLY</td>
<td>&gt;999.999</td>
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</tr>
<tr>
<td>RACEX AMERICAN INDIAN vs WHITE</td>
<td>0.553</td>
<td></td>
</tr>
<tr>
<td>RACEX AMERICAN INDIAN PUBLIC ONLY</td>
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<tr>
<td>RACEX ASIAN OR PACIFIC ISLANDER vs WHITE ANY PRIVATE</td>
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<td></td>
</tr>
<tr>
<td>RACEX ASIAN OR PACIFIC ISLANDER vs WHITE PUBLIC ONLY</td>
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<td></td>
</tr>
<tr>
<td>RACEX BLACK vs WHITE ANY PRIVATE</td>
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<td></td>
</tr>
<tr>
<td>RACEX BLACK vs WHITE PUBLIC ONLY</td>
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</tr>
<tr>
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<td></td>
</tr>
<tr>
<td>POVCAT99 HIGH INCOME vs NEGATIVE OR POOR PUBLIC ONLY</td>
<td>0.274</td>
<td></td>
</tr>
<tr>
<td>POVCAT99 LOW INCOME vs NEGATIVE OR POOR ANY PRIVATE</td>
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<td></td>
</tr>
<tr>
<td>POVCAT99 LOW INCOME vs NEGATIVE OR POOR PUBLIC ONLY</td>
<td>0.492</td>
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</tr>
<tr>
<td>POVCAT99 MIDDLE INCOME vs NEGATIVE OR POOR ANY PRIVATE</td>
<td>5.162</td>
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</tr>
<tr>
<td>POVCAT99 MIDDLE INCOME vs NEGATIVE OR POOR PUBLIC ONLY</td>
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<td></td>
</tr>
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Odds Ratio Estimates

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<th>Estimate</th>
</tr>
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<td>SEX FEMALE vs MALE ANY PRIVATE</td>
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<td>1.417</td>
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</tr>
<tr>
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<td></td>
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<tr>
<td>RACEX ALEUT, ESKIMO PUBLIC ONLY</td>
<td>&gt;999.999</td>
<td></td>
</tr>
<tr>
<td>RACEX AMERICAN INDIAN vs WHITE</td>
<td>0.553</td>
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</tr>
<tr>
<td>RACEX AMERICAN INDIAN PUBLIC ONLY</td>
<td>1.146</td>
<td></td>
</tr>
<tr>
<td>RACEX ASIAN OR PACIFIC ISLANDER vs WHITE ANY PRIVATE</td>
<td>0.735</td>
<td></td>
</tr>
<tr>
<td>RACEX ASIAN OR PACIFIC ISLANDER vs WHITE PUBLIC ONLY</td>
<td>1.045</td>
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<tr>
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<td>0.776</td>
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<td>POVCAT99 HIGH INCOME vs NEGATIVE OR POOR PUBLIC ONLY</td>
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<tr>
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<tr>
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95% Wald Confidence Limits

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<th>Estimate</th>
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<tr>
<td>1.000</td>
<td>1.000</td>
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<tr>
<td>1.155</td>
<td>1.403</td>
</tr>
<tr>
<td>1.255</td>
<td>1.598</td>
</tr>
<tr>
<td>&gt;999.999</td>
<td>&gt;999.999</td>
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