Poisson Regression

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Previously….

Linear regression - not discussed, classed as basic regression. Model of a continuous dependent/outcome/response variable, that is normally distributed with a constant variance and has a mean linear function of the covariates

We have discussed 2 further types of regression

Logistic regression

Proportional Hazards

By the end of this session

You will:

- Know when Poisson Regression can be used
- Be able to identify count data
- Know how to use Poisson regression to adjust for basic time dependent variables
- Know what assumptions are made by the model
- Identify the strengths and weaknesses of Poisson regression
- Be able to identify extensions to the basic Poisson model and when these can be used
- Recognise Windows and menu functions in SPSS

Poisson Regression

1. Count data (ex. no. of surgical site infections)
2. Time-to-event data (ex. time-to-stroke with time dependent covar) as alternative to survival analysis
3. Binary data (ex. Received vaccine(yes/no) as alternative to logistic reg

The Poisson Distribution

Count data are observations that assume only non-negative integer values: 0, 1, 2, etc

Count data have a **Poisson distribution** if the frequencies of the values have the following features:

- Small-valued observations are quiet common
- Starting at some value, frequencies decrease very rapidly
- The average of observations is approximately equal to their variance

Count Data Violate OLS assumptions

Count variables can be modelled with OLS regression but:

- Linear models yield negative predicted values and counts are never negative

Similar to the problem of the Linear Probability Model

- Count variables are often highly skewed

  For example: # smoked this week many people are zero or very low; a few people are very high

Extreme skew violates the normality assumption of basic OLS regression.

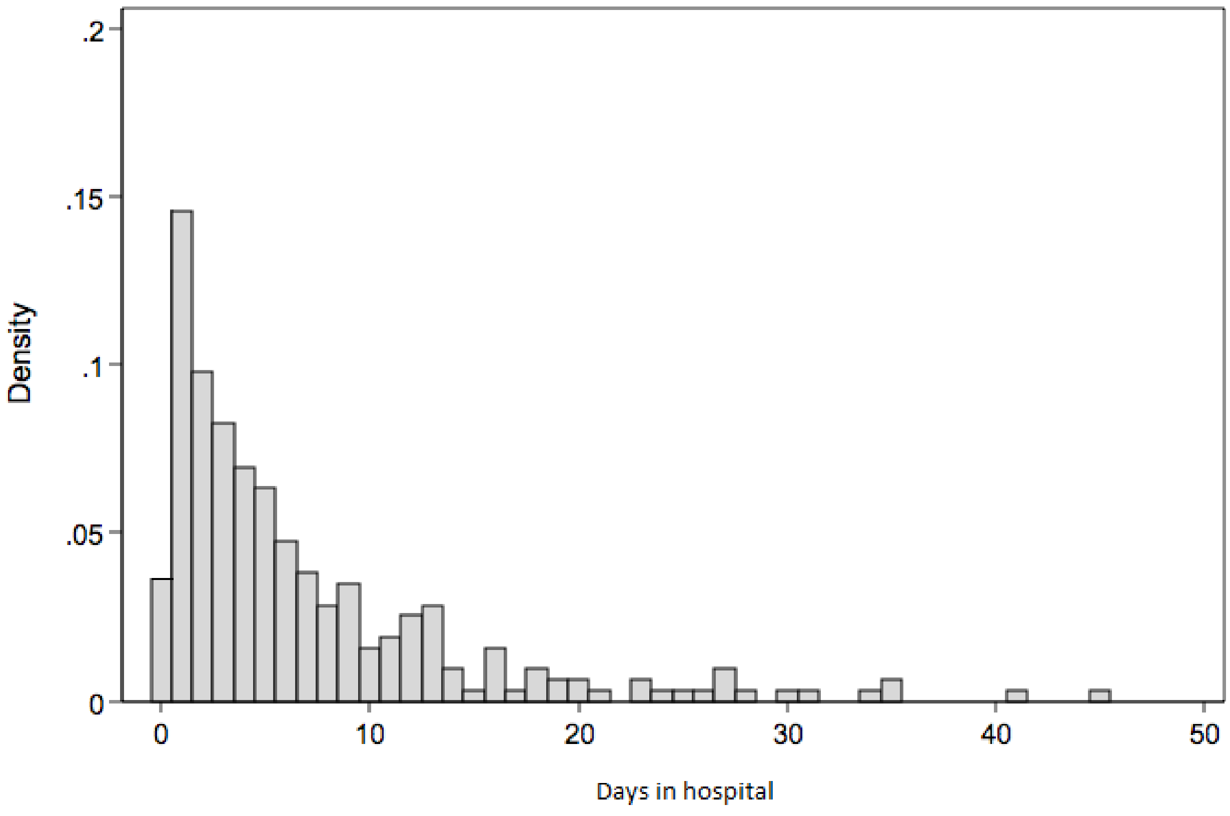
Count Data Examples

Many dependent variables are counts: Non-negative integers

- # hospitalisations a person has over a year
- # parity
- # lung opacities
- Any other examples?

Count data: Example

- Days in hospital for asthma exacerbations in the last year



Data with Poisson Distribution

One of the questions in a Health Sciences survey asked how many times a respondent visited a doctor in the past month. For a sample of 150 people, the frequencies of the responses were

Number of visits	0	1	2	3	4	5	6	7	8
Number of respondents	9	33	36	34	20	9	6	2	1

Note that

- 0 visits is quite a common response,
- 1, 2, or 3 visits are the most frequent observations,
- starting with 4 visits frequencies quickly decrease,
- The average is 2.60 visits and is nearly equal to the variance, which is 2.63 visits squared.

These are the features of a variable distributed according to a Poisson distribution.

Formula for Poisson Distribution

Poisson distributions are discrete with the **probability function** given by

$P(X = n) = \frac{\lambda^n e^{-\lambda}}{n!}$ where $n = 0, 1, 2, \ldots$, and $n! = (1)(2)(3) \ldots (n-1)(n)$

is called the **factorial** of n. By definition, $0! = 1$.

Here λ is both the mean and variance of X, and is termed **rate**.

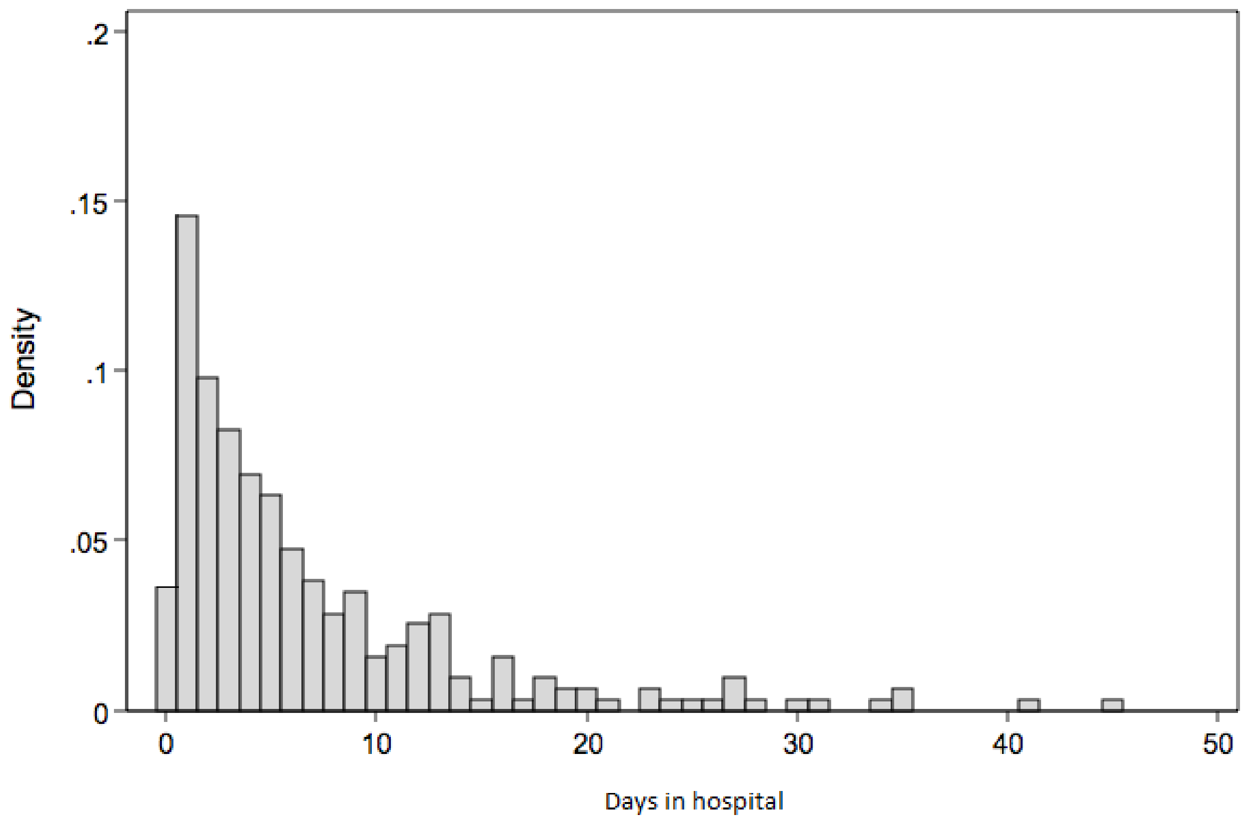
Note that the probabilities of small values are reasonably high, and for larger values, the probabilities decrease very fast:

$P(X = 0) = e^{-\lambda}$, $P(X = 1) = \lambda e^{-\lambda}$, $P(X = 2) = \frac{\lambda^2 e^{-\lambda}}{2}$, $P(X = 3) = \frac{\lambda^3 e^{-\lambda}}{6}$,

…, $P(X = 10) = \frac{\lambda^{10} e^{-\lambda}}{3{,}628{,}800}$, …

Count data: Example

- Days in hospital for asthma exacerbations in the last year



The Poisson Regression Model

The **Poisson regression model** specifies that the dependent variable *Y*, given independent variables $x_1, x_2, \ldots, x_k$, follows a Poisson distribution with the probability function

$$P\left(Y = y \middle| x_{1,}x_{2,\ldots,}x_k\right) = \frac{\lambda^y e^{-\lambda}}{y!}, y = 0, 1, 2, \ldots,$$

where the rate $\lambda = Exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)$,

or, equivalently,

$$ln\, \lambda = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k.$$

Example in SPSS

- SPSS Basic Syntax

```
GENLIN n_outcome var BY dependent var(ORDER=ASCENDING)
WITH covariates
        /MODEL var specifictaion INTERCEPT=YES
        DISTRIBUTION=POISSON LINK=LOG
        /PRINT FIT SUMMARY SOLUTION (EXPONENTIATED).
```

- SPSS Point-&-Click Instructions

Analyze → Generalized Linear Models → Generalized Linear Models → Poisson loglinear (fill in the bubble) → Response tab → Identify dependent variable → Predictors tab → Identify factors and covariates →Model tab →Identify the model →Statistics tab →Include exponential parameter estimates (check the box) → hit OK!

Interpretation of Coefficients

In Poisson Regression, Y is typically conceptualized as a rate

Positive coefficients indicate higher rate and negative lower

Like logit, Poisson models are non-linear so coefficients don’t have a simple linear interpretation. Unless we utilise the log form of the model; which exponentiates coefficients to aid interpretation giving incidence rate ratios

If x_1 is <u>continuous</u>, then the quantity $(Exp(\hat{\beta}_1)-1)\cdot 100\%$ represents the <u>estimated percent change in mean response</u> when X_1 is increased by one unit, and the other X variables are held fixed.

If x_1 is a <u>categorical</u> variable with several levels, then $Exp(\hat{\beta}_1)\cdot 100\%$ represents the <u>estimated percent ratio in mean response</u> for the level $x_1=1$ and that for the reference level, provided the other X variables are unchanged.

Example in SPSS

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-.672	.2612	-1.184	-.160	6.611	1	.010	.511	.306	.852
[health=1]	.588	.2511	.096	1.081	5.489	1	.019	1.801	1.101	2.946
[health=2]	.253	.2018	-.142	.649	1.576	1	.209	1.288	.867	1.913
[health=3]	.173	.1878	-.195	.541	.844	1	.358	1.188	.822	1.717
[health=4]	0[a]	.	.	.	.	.	.	1	.	.
age	.026	.0048	.017	.035	29.144	1	.000	1.026	1.017	1.036
(Scale)	1[b]									

Dependent Variable: n_visits

Model: (Intercept), health, age

a. Set to zero because this parameter is redundant.

b. Fixed at the displayed value.

Goodness-of-Fit Test

- A measure of **goodness of fit** of the Poisson regression model is obtained by computing the **deviance statistic** of a **base model** against the **full model**. A **base model** includes only the intercept, while the **full model** includes the intercept and all the x- variables. The **deviance** is defined as -2 multiplied by the log-likelihood ratio,

deviance = -2 (ln L(base model) - ln L(full model)).

- The deviance is used as a test statistic for testing H_0: the base model has a good fit against H_1: the full model has a good fit. Under H_0, the deviance has a chi-squared distribution with the degrees of freedom = number of x-variables in the full model.
- If the deviance is large (formally, p-value < 0.05), then H_0 is rejected and the conclusion is that the <u>full model has a good fit</u>.

Including an exposure variable

- Poisson outcome variables are typically conceptualized as **rates**
    - X hours per week
    - X in past year
- Cases may vary in **exposure** to “risk” of a given outcome
    - To properly model rates, we must account for the fact that some cases have greater exposure than others
    - Ex: # disease episodes in lifetime
        - Older people have greater opportunity to have higher counts
    - Alternately, exposure may vary due to research design
        - Ex: Some cases followed for longer time than others…

Including an exposure variable

Poisson (and other count models) can address varying exposure:

$$\mu_i t_i = e^{\sum_{j=1}^{K} \beta_j X_{ji} + \ln(t_i)}$$

- Where t_i = exposure time for case i

Easy to incorporate in SPSS:

- Ex: `poisson depisodes SES income, exposure(age)`

Poisson Model Assumptions

- Poisson regression makes a big assumption: That <u>variance of μ</u> = μ ("equidispersion")
    - In other words, the mean and variance are the same
    - This assumption is often **not met** in real data
    - Dispersion is often greater than μ: **overdispersion**
  - Consequence of overdispersion: Standard errors will be underestimated
    - Potential for overconfidence in results; rejecting H0 when you shouldn't!
    - Note: overdispersion doesn't necessarily affect predicted counts (compared to alternative models).

Poisson Model Assumptions

- Overdispersion is most often caused by highly skewed dependent variables
  - Often due to variables with high numbers of zeros
    - Ex: Number of traffic tickets per year
    - Most people have zero, some can have 50!
    - Mean of variable is low, but SD is high
  - Other examples of skewed outcomes
    - # of scholarly publications
    - # cigarettes smoked per day
    - # riots per year (for sample of cities in US).

Further Points

- Poisson & Negative binomial models suffer all the same basic issues as "normal" regression
    - Model specification / omitted variable bias
    - Multicollinearity
    - Outliers/influential cases
  - Also, it uses Maximum Likelihood
    - N > 500 = fine; N < 100 can be worrisome
      - Results aren't necessarily wrong if N<100;
      - But it is a possibility; and hard to know when problems crop up
    - Plus ~10 cases per independent variable.

Extensions to basic Poisson

Poisson for binary data

$$\ln\left(\frac{n}{t}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots$$

Model for logarithm of the no. of cases using poisson distribution and log link function
Yields prevalence ratios e
Watch out for estimates close to or out of bounds.
Intercept 0 included in the model
Not symmetric
Use robust variance estimation (available in SPSS) to obtain valid Cis
Sensitivity analysis necessary
Compare results across models
Be aware of the lack of symmetry
Can only be used for cohort analyses not cross-sectional

Poisson for binary data

```
GENLIN outcome var BY dependent var (ORDER=ASCENDING) WITH covariates
 /MODEL var specification INTERCEPT=YES
DISTRIBUTION=POISSON LINK=LOG
 /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=ROBUST MAXITERATIONS=100
MAXSTEPHALVING=5
PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012 ANALYSISTYPE=3(WALD) CILEVEL=95
CITYPE=WALD
LIKELIHOOD=FULL
/EMMEANS TABLES=smoking SCALE=ORIGINAL
/MISSING CLASSMISSING=EXCLUDE
/PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION (EXPONENTIATED).
```

SPSS Point-&-Click Instructions

Analyze → Generalized Linear Models → Generalized Linear Models → *Custom (fill in the bubble)* → on drop down distribution menu choose poisson → On drop down link function menu choose log → Response tab → Identify dependent variable → Choose binary reference category →Choose reference category first lowest value → Predictors tab → Identify factors and covariates → In options choose to exclude cases with missing data → In options choose → Model tab →Identify the model →Statistics tab →Include exponential parameter estimates (check the box) → hit OK!

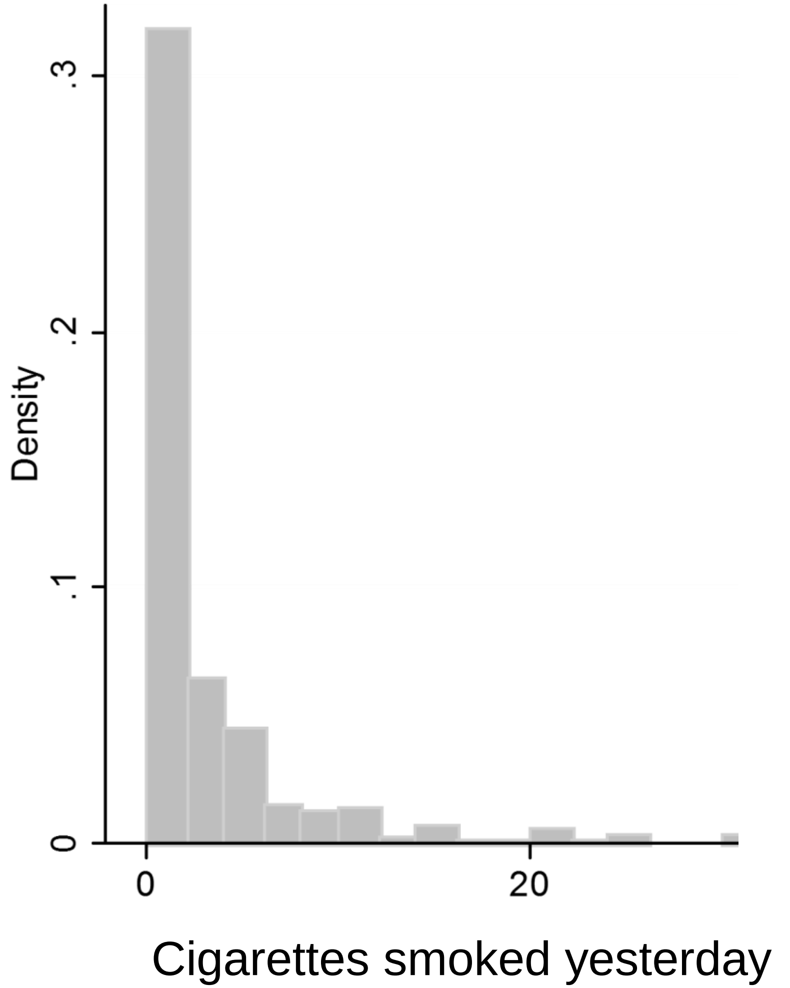
Zero-Inflated Poisson Regression

<u>Example</u>. If you randomly choose 100 students and ask them how many cigarettes they smoked yesterday. Some students will report that they smoked zero number of cigarettes. There are two possible reasons for that. Either they don't smoke at all, or they happened not to smoke a single cigarette that day.

<u>Definition</u>. A **structural zero** is recorded when the respondent's behavior is not in the behavioral repertoire under study (e.g., the person doesn't smoke).

<u>Definition</u>. A **chance zero** is recorded when the respondent's behavior is normally in the behavioral repertoire under study but just not during the studied time frame (e.g., just happened not to smoke yesterday).

Zero-Inflated Poisson Regression



Zero-Inflated Poisson Regression

The presence of structural zeros inflates the number of zeros in the Poisson model, which makes the model invalid. A **zero-inflated Poisson (ZIP) model** is used instead. In ZIP model, the response variable

$$Y = \begin{cases} 0, & \text{with probability } p, \\ \sim \text{Poisson}(\lambda), & \text{with probability } 1-p, \end{cases}$$

Zero-Inflated Poisson Regression

that is,

$$Y = \begin{cases} 0, & \text{with probability } p + (1-p)e^{-\lambda}, \\ y, & \text{with probability } (1-p)\dfrac{\lambda^y}{y!}e^{-\lambda}, y = 1, 2, \ldots. \end{cases}$$

Here $\log(\lambda) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k$ and $logit\ \mathrm{p} = \log\left(\dfrac{\mathrm{p}}{1-\mathrm{p}}\right) = \gamma_0 + \gamma_1 \mathrm{z}_1 + \ldots + \gamma_{\mathrm{m}} \mathrm{z}_{\mathrm{m}}$

where $x_1, \ldots, x_k$ are the predictors, $\beta_1, \ldots, \beta_k$ are the regression coefficients, $\mathrm{z}_1, \ldots, \mathrm{z}_{\mathrm{m}}$ are the zero-inflated predictors responsible for inflation of the number of zeros in the model, and $\gamma_1, \ldots, \gamma_{\mathrm{m}}$ are the zero-inflated coefficients.
The parameters of the model to be estimated from the data are $\beta_1, \ldots, \beta_k$ and $\gamma_1, \ldots, \gamma_{\mathrm{m}}$.

Overdispersion in Poisson Regression

- In Poisson regression, it is assumed that mean and variance of the response variable are approximately the same. It is rarely the case with real-life data.
- Often the variance is much larger than the mean. This situation is called **overdispersion**.
- There is a formal test for overdispersion. And the suggested remedy is to fit Negative Binomial regression model instead.

Negative Binomial Regression

Strategy: Modify the Poisson model to address overdispersion

- Add an "error" term to the basic model:

$$\mu = e^{\sum_{j=1}^{K} \beta_j X_{ji} + \varepsilon_i}$$

Coefficients interpreted same way as in poisson regression.

Additional model assumptions:

- Expected value of exponentiated error = 1 ($e^{e} = 1$)
- Exponentiated error is Gamma distributed
- Use if these assumptions are more plausible than the equidispersion assumption!

Poisson or Negative Binomial

It is often useful to try both Poisson and Negative Binomial models

- Allows you to test for overdispersion
- Use LRtest on alpha (a) to guide model choice

– If you don’t suspect dispersion and alpha appears to be zero, use Poission Regression

- It makes fewer assumptions
  - Such as gamma-distributed error.

Zero-truncated Poisson & NB reg

- Truncation – the absence of information about cases in some range of a variable
  - Example: Suppose we study income based on data from tax returns…
    - Cases with income below a certain value are not required to submit a tax return… so data is missing
  - Example: Data on # crimes committed, taken from legal records
    - Individuals with zero crimes are not evident in data
  - Example: An on-line survey of web use
    - Individuals with zero web use are not in data
- Zero-truncated Poisson & Zero-truncated NB reg: Poisson & NB have been adapted to address truncated data

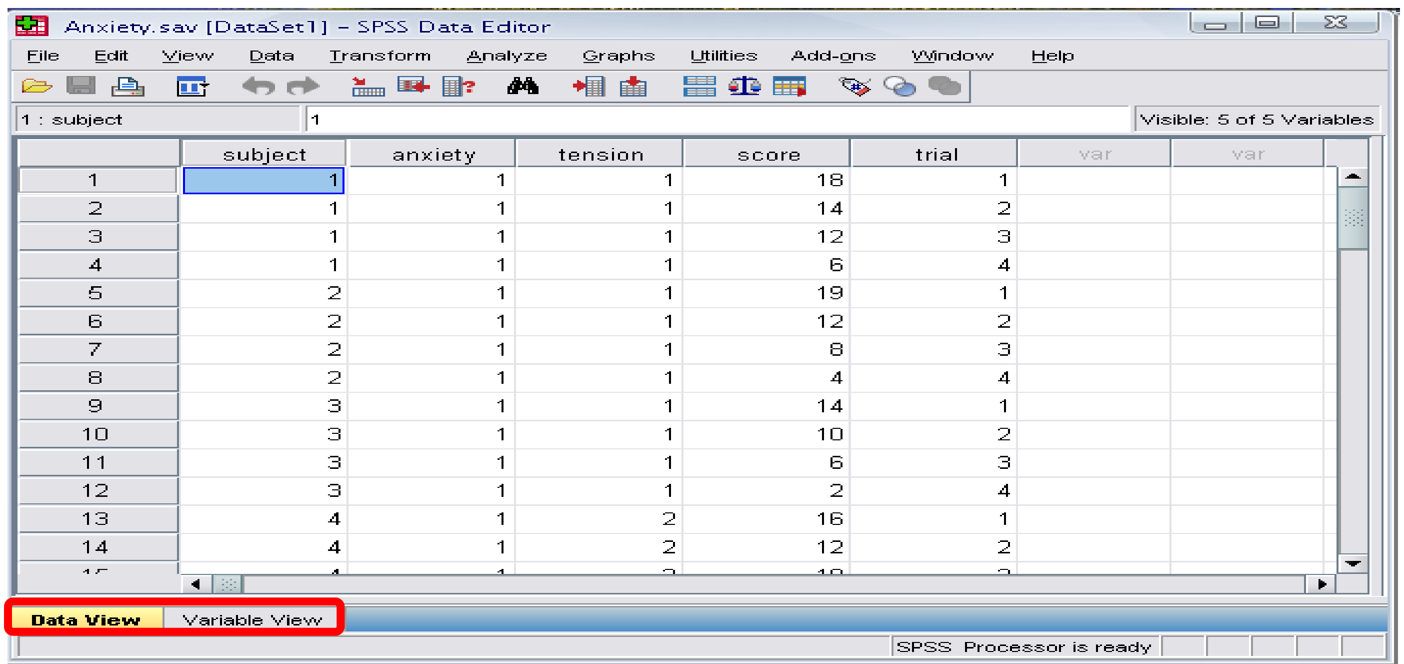
Poisson regression in SPSS

Statistical Product and Service Solutions

- A popular Windows based computerised statistics package
- Can handle large amounts pf complex data
- Can be used to perform data entry, manipulation and analysis and to produce tables and graphs using only basic input
- Can read open programming using BASIC
- For further info '*Discovering statistics using SPSS* by Andy Field, 2009'

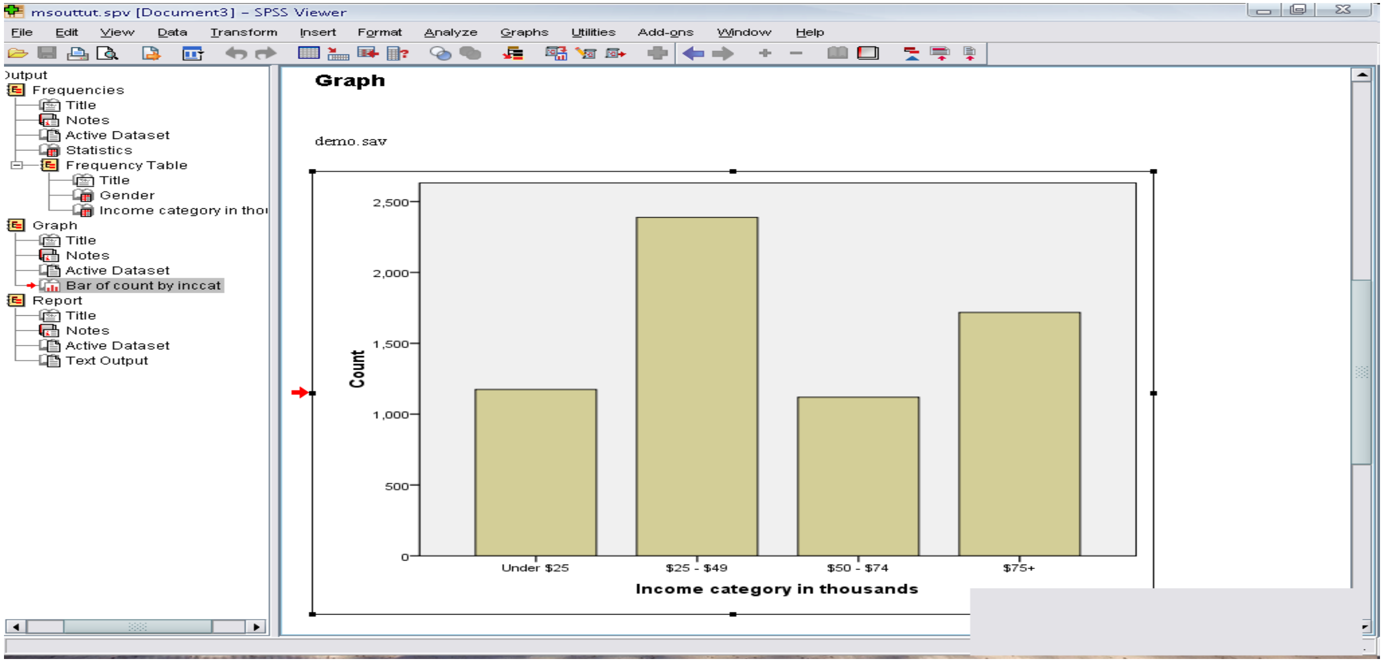
The Four Windows: Data Editor

- Spreadsheet-like system for defining, entering, editing, and displaying data.
- Two screen views Data View and Variable View
- All information can be saved as one data file.



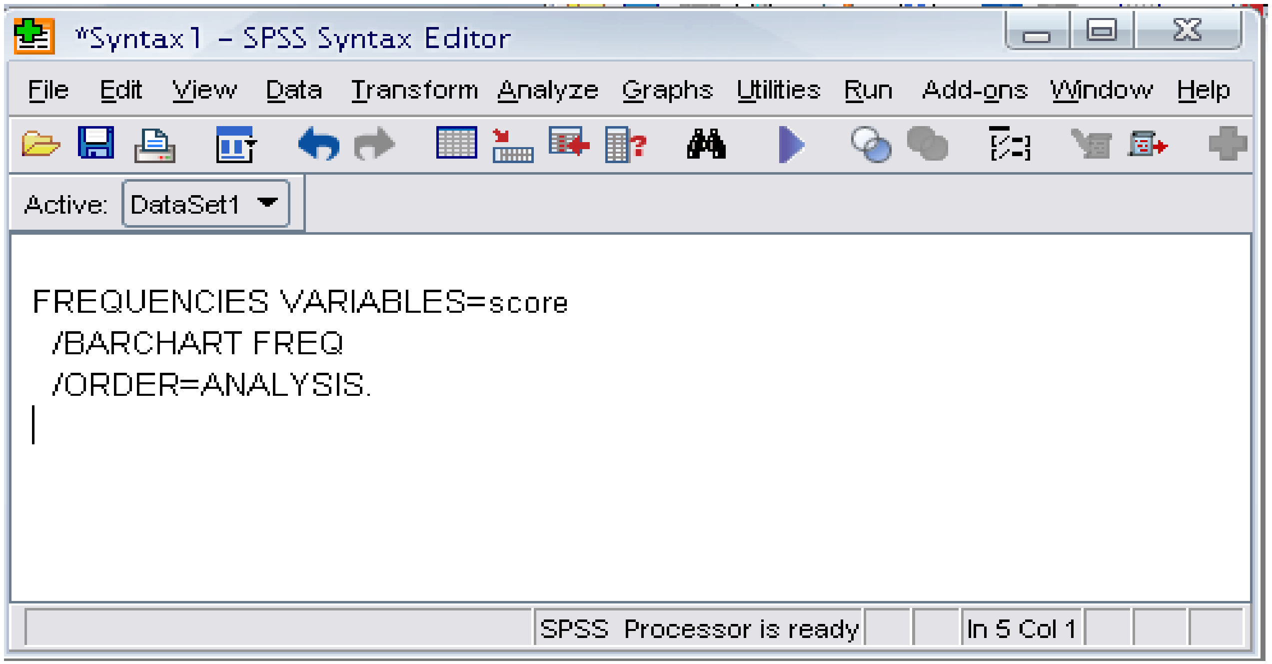
The Four Windows: Output Viewer

- Displays any outputs (eg. Tables, graphs) including any errors. Output can also be saved will be “spv.”



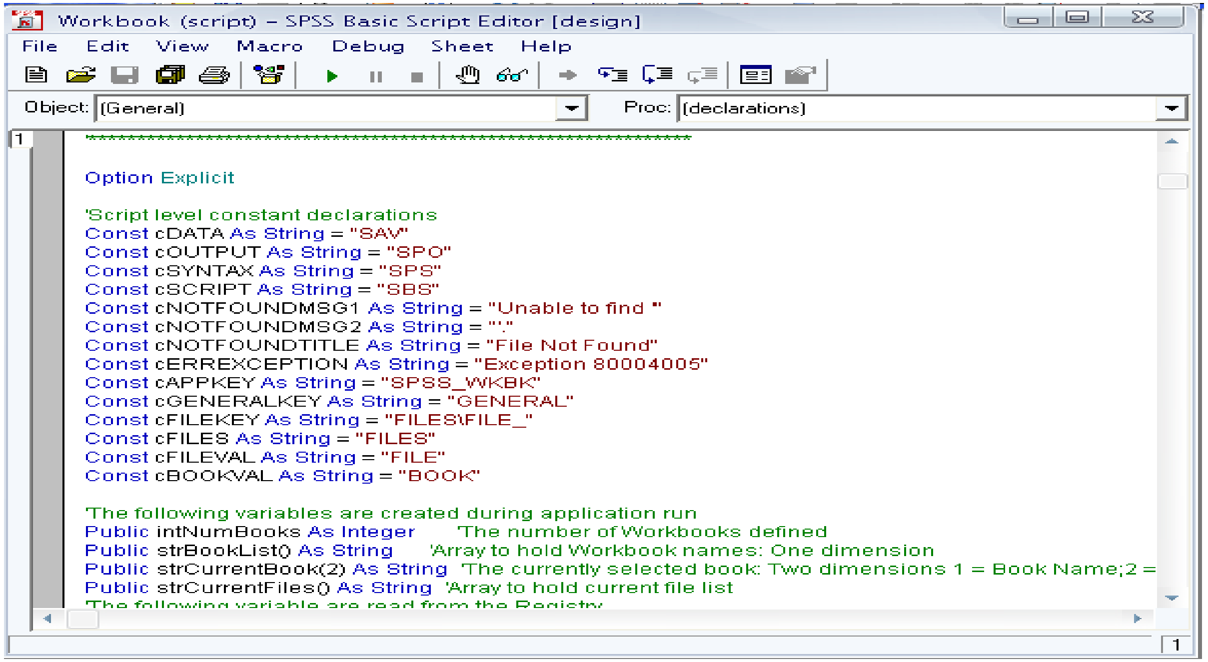
The Four Windows: Syntax editor

Text editor for syntax composition.

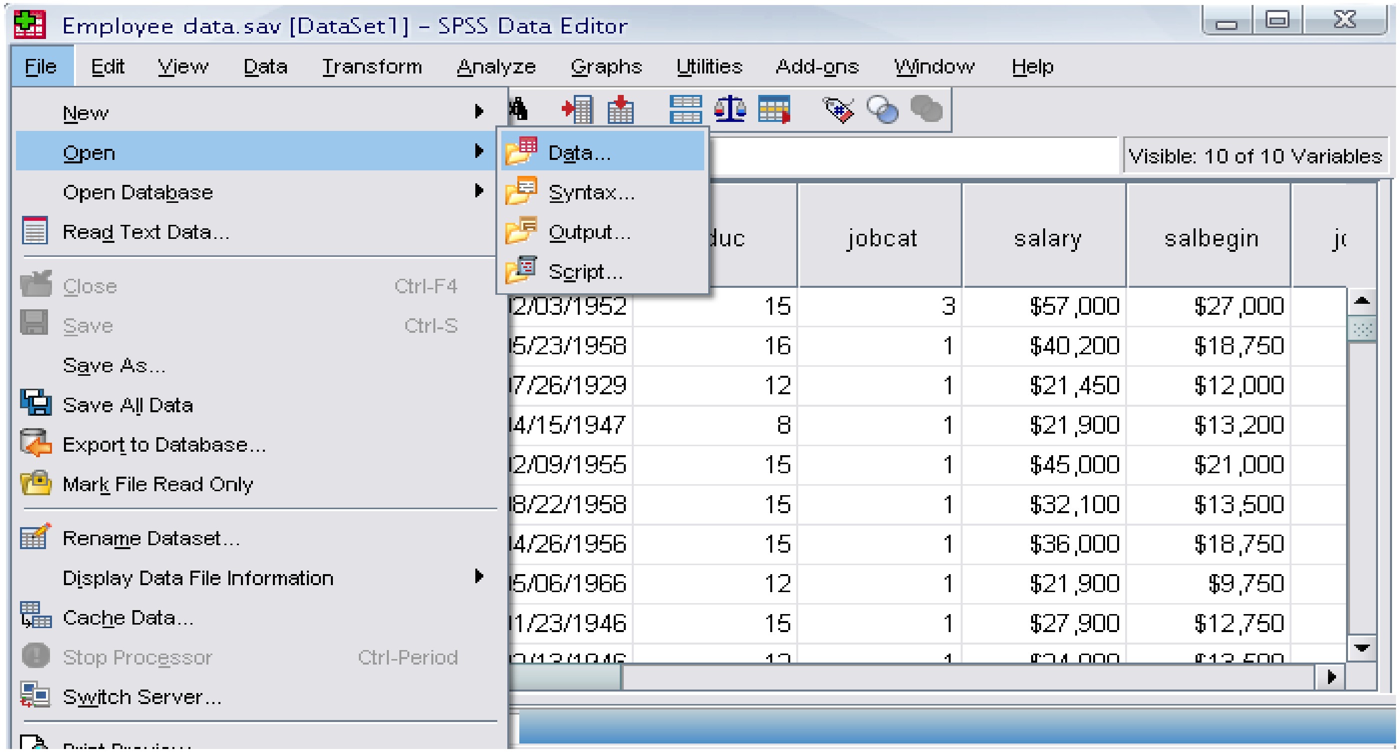


The Four Windows: Script Window

Further text editor for syntax composition. Provides the opportunity to write programs, in a BASIC-like language.

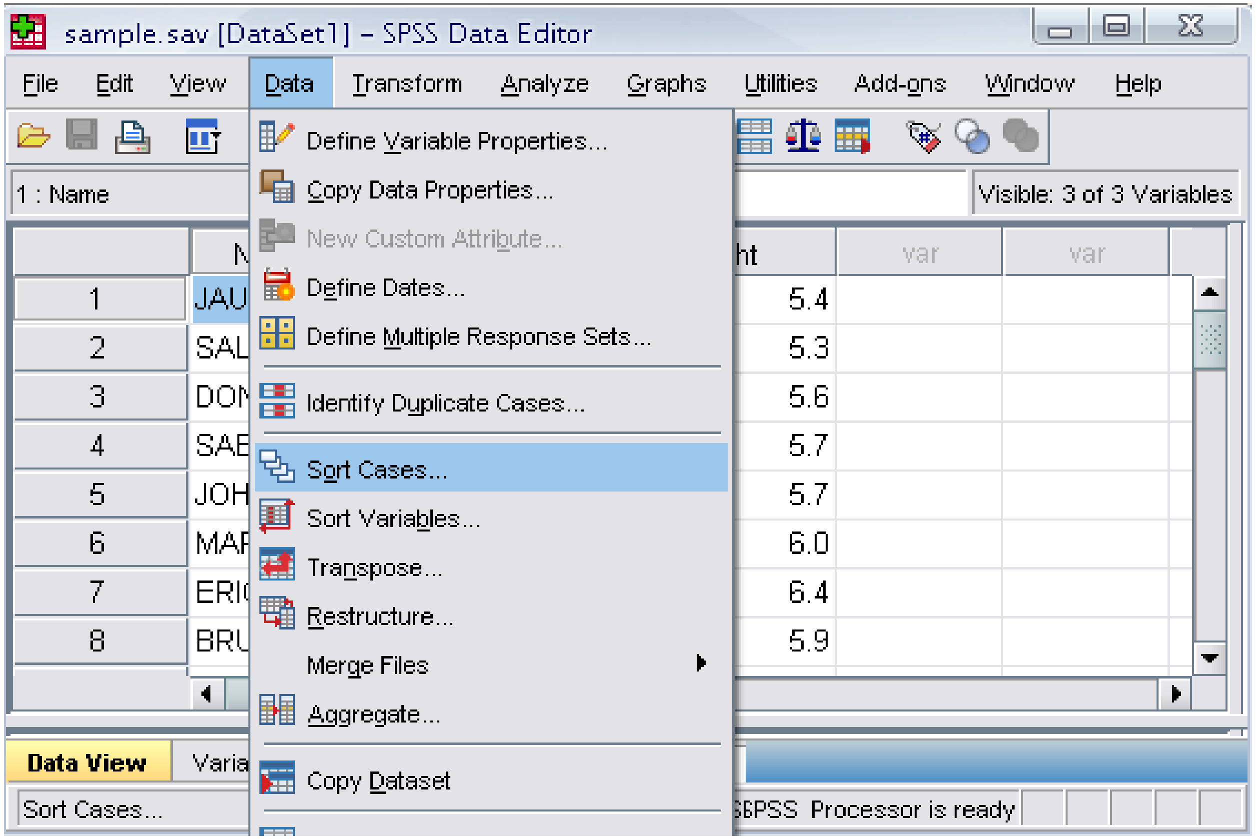


File menu

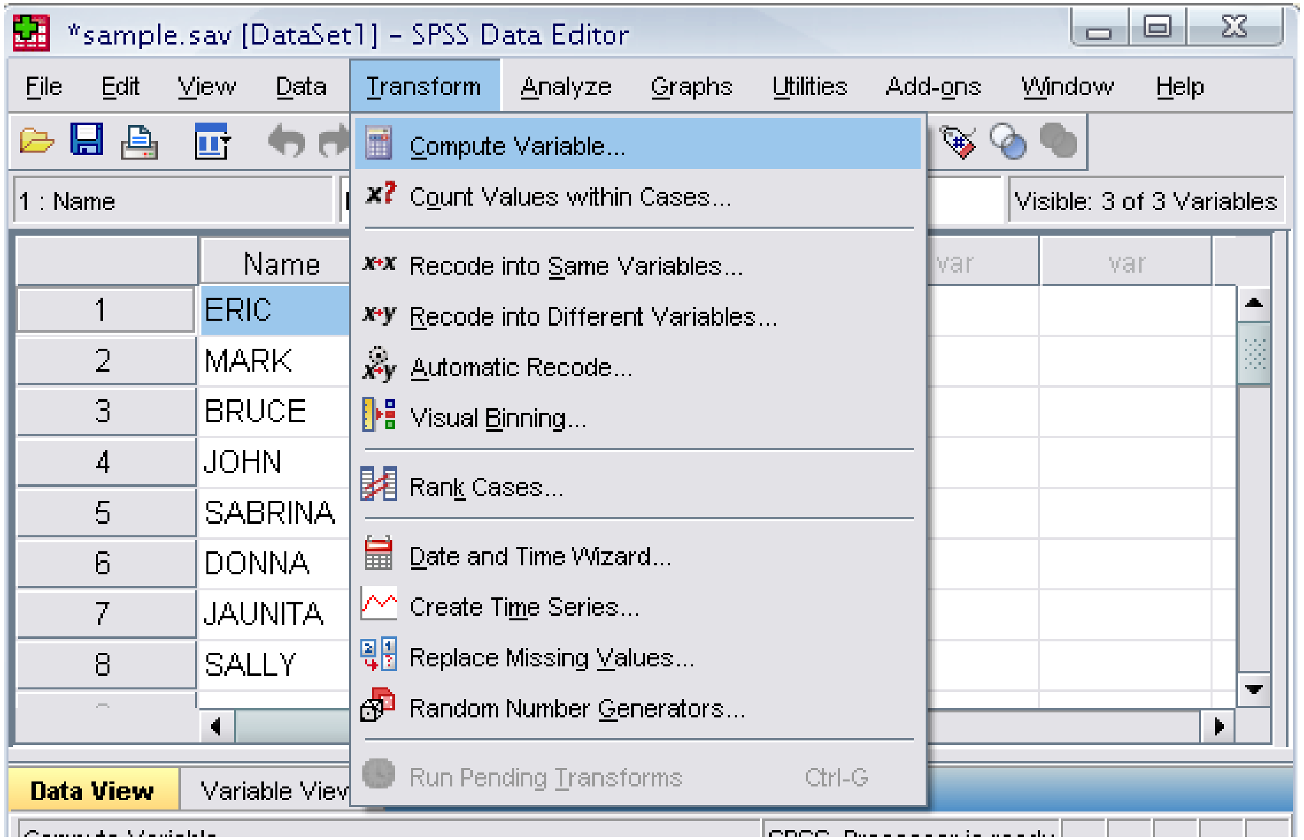


Employee data.sav [DataSet1] - SPSS Data Editor
File
Edit
View
Data
Transform
Analyze
Graphs
Utilities
Add-ons
Window
Help
New
Open
Open Database
Read Text Data...
Close Ctrl-F4
Save Ctrl-S
Save As...
Save All Data
Export to Database...
Mark File Read Only
Rename Dataset...
Display Data File Information
Cache Data...
Stop Processor Ctrl-Period
Switch Server...
Data...
Syntax...
Output...
Script...
Visible: 10 of 10 Variables
jobcat
salary
salbegin

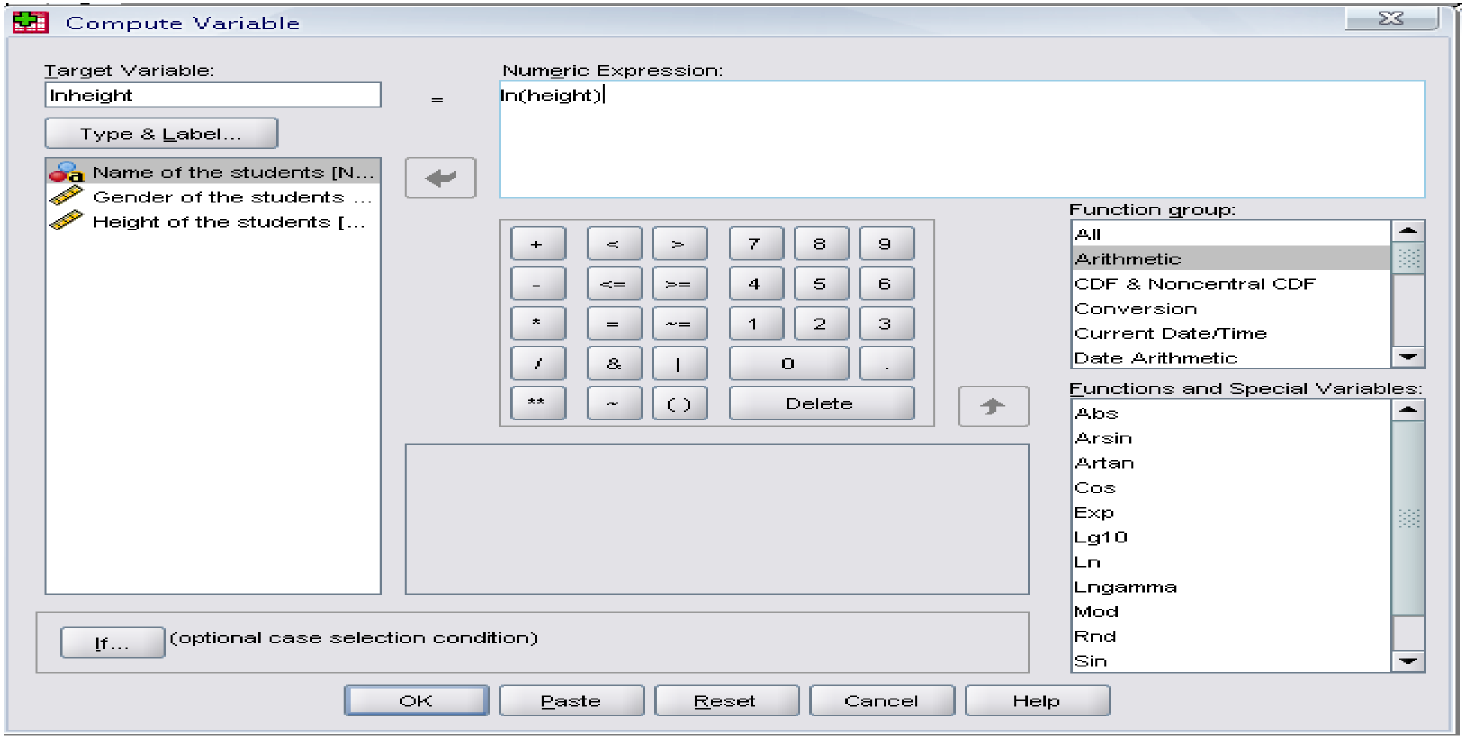
Data menu


sample.sav [DataSet1] - SPSS Data Editor
File
Edit
View
Data
Transform
Analyze
Graphs
Utilities
Add-ons
Window
Help
1 : Name
Visible: 3 of 3 Variables
Define Variable Properties...
Copy Data Properties...
New Custom Attribute...
Define Dates...
Define Multiple Response Sets...
Identify Duplicate Cases...
Sort Cases...
Sort Variables...
Transpose...
Restructure...
Merge Files
Aggregate...
Copy Dataset
var
var
5.4
5.3
5.6
5.7
5.7
6.0
6.4
5.9
Data View
Sort Cases...
SPSS Processor is ready

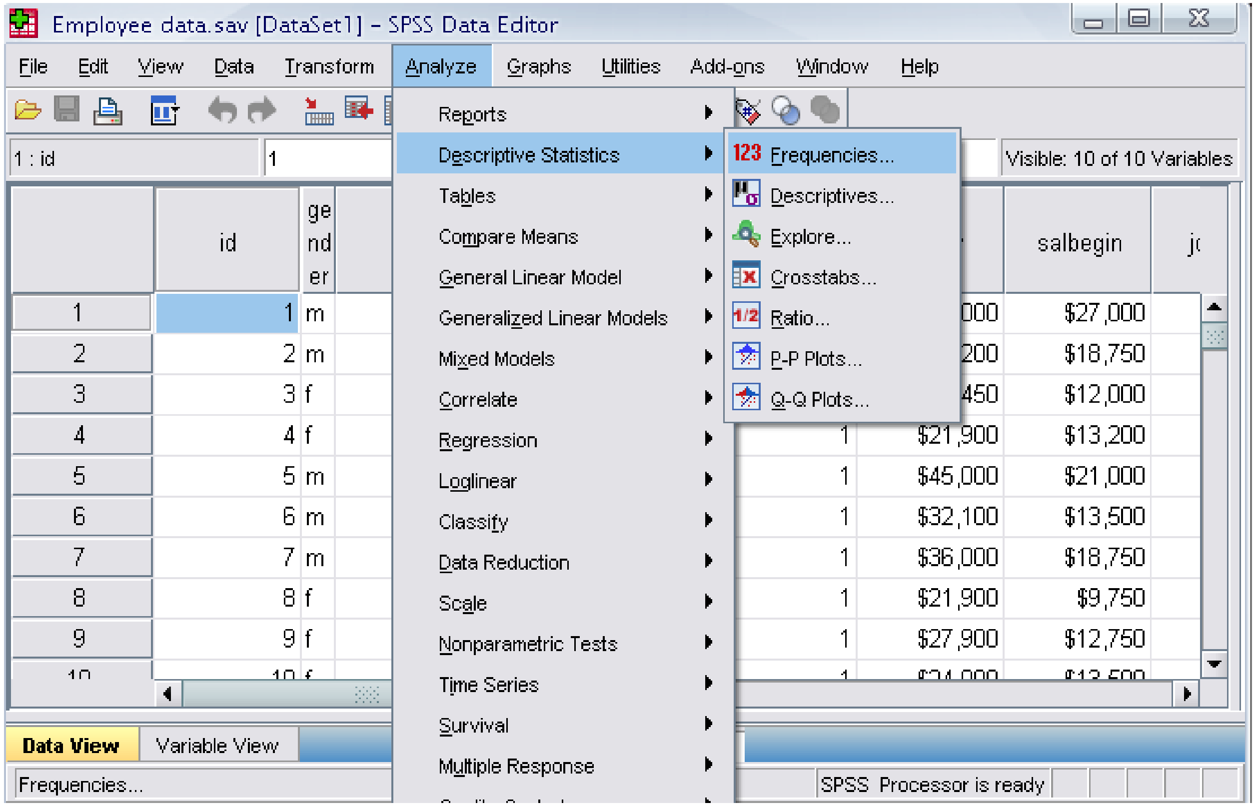
Transform menu



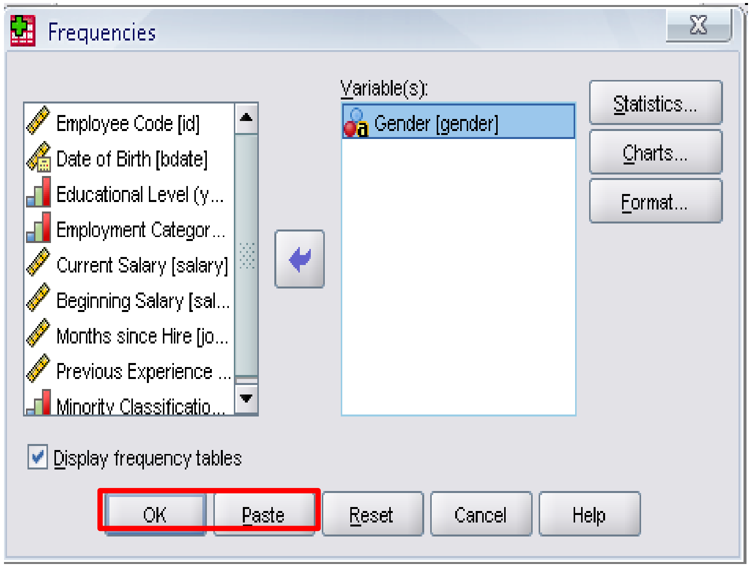
Sub-menus

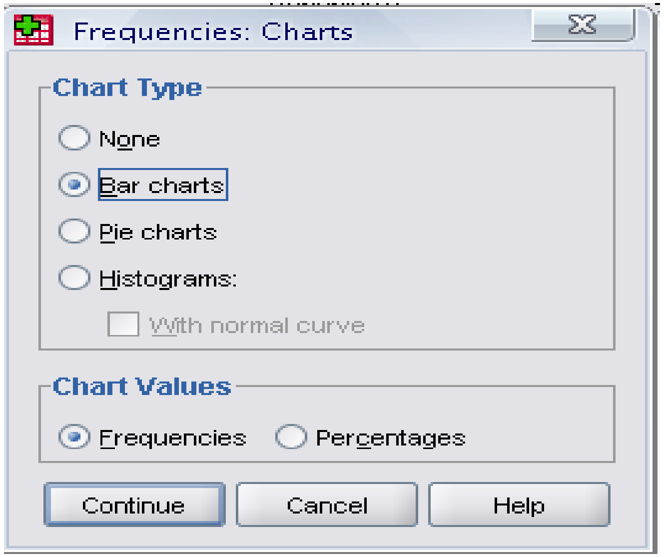

Compute Variable
Target Variable:
lnheight
Type & Label...
Name of the students [N...
Gender of the students ...
Height of the students [...
Numeric Expression:
ln(height)
Function group:
All
Arithmetic
CDF & Noncentral CDF
Conversion
Current Date/Time
Date Arithmetic
Functions and Special Variables:
Abs
Arsin
Artan
Cos
Exp
Lg10
Ln
Lngamma
Mod
Rnd
Sin
Delete
If...
(optional case selection condition)
OK
Paste
Reset
Cancel
Help

Analyze menu

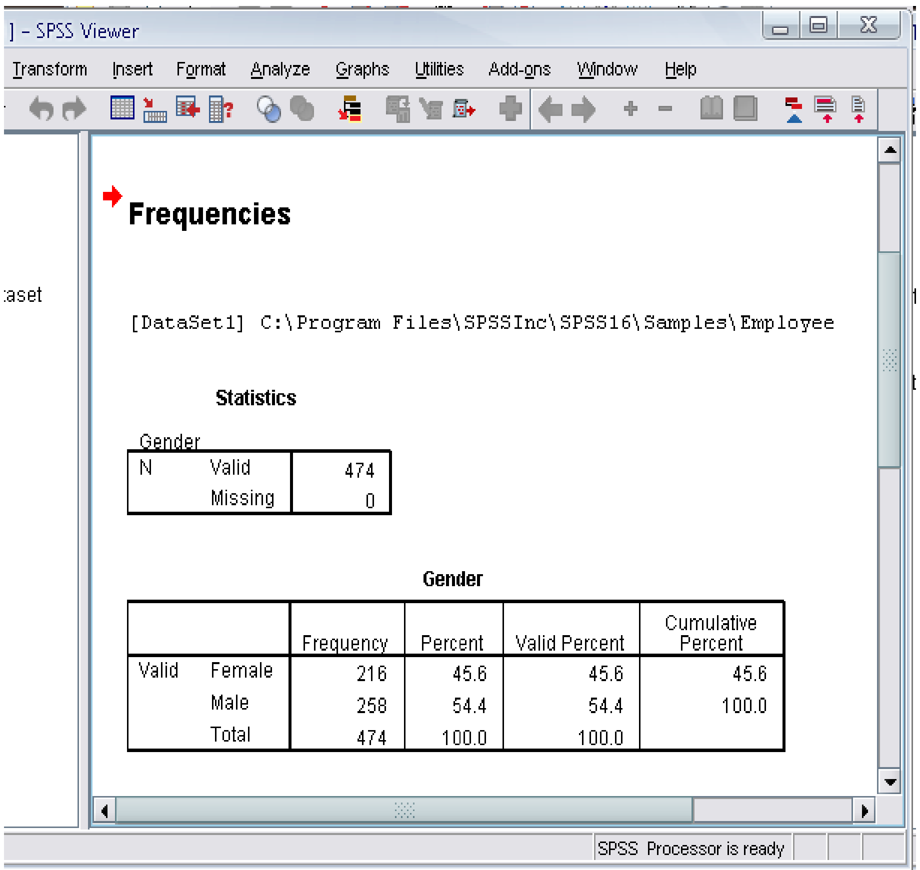


Sub-menus


Frequencies
Employee Code [id]
Date of Birth [bdate]
Educational Level (y...
Employment Categor...
Current Salary [salary]
Beginning Salary [sal...
Months since Hire [jo...
Previous Experience ...
Minority Classificatio...
Variable(s):
Gender [gender]
Statistics...
Charts...
Format...
Display frequency tables
OK
Paste
Reset
Cancel
Help


Frequencies: Charts
Chart Type
None
Bar charts
Pie charts
Histograms:
With normal curve
Chart Values
Frequencies
Percentages
Continue
Cancel
Help

Output



Frequencies

[DataSet1] C:\Program Files\SPSSInc\SPSS16\Samples\Employee

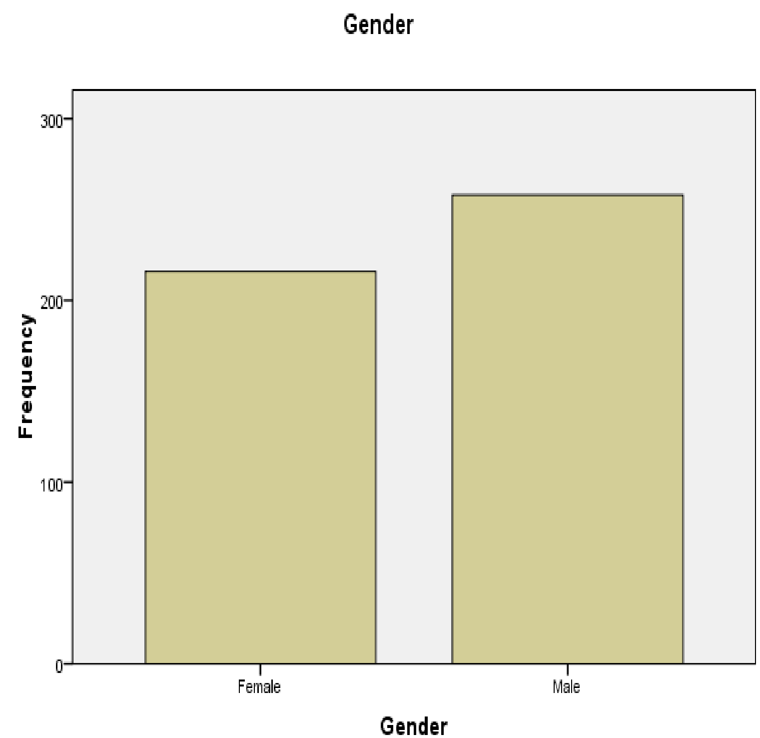
Statistics

Gender

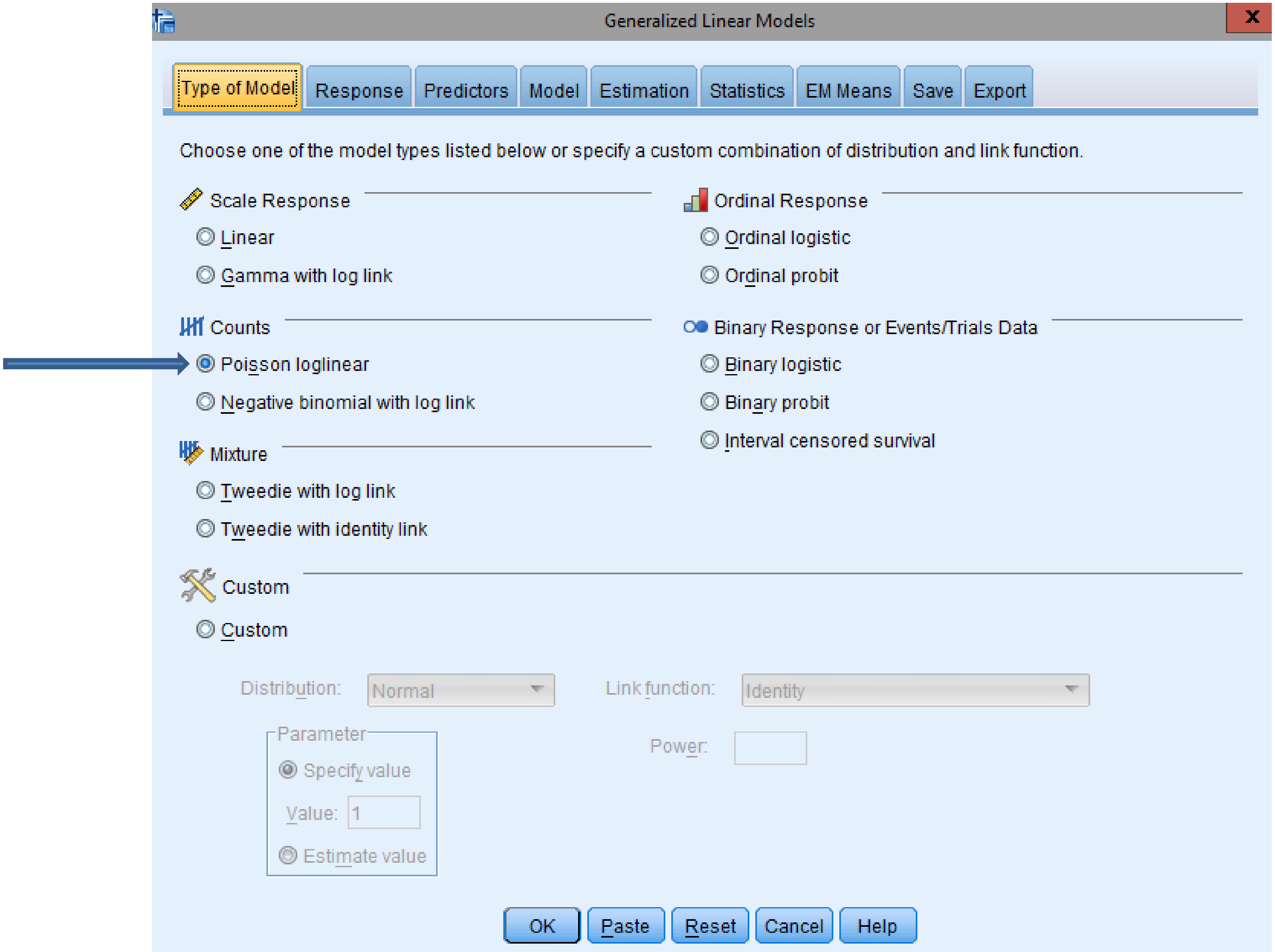
N	Valid	474
	Missing	0

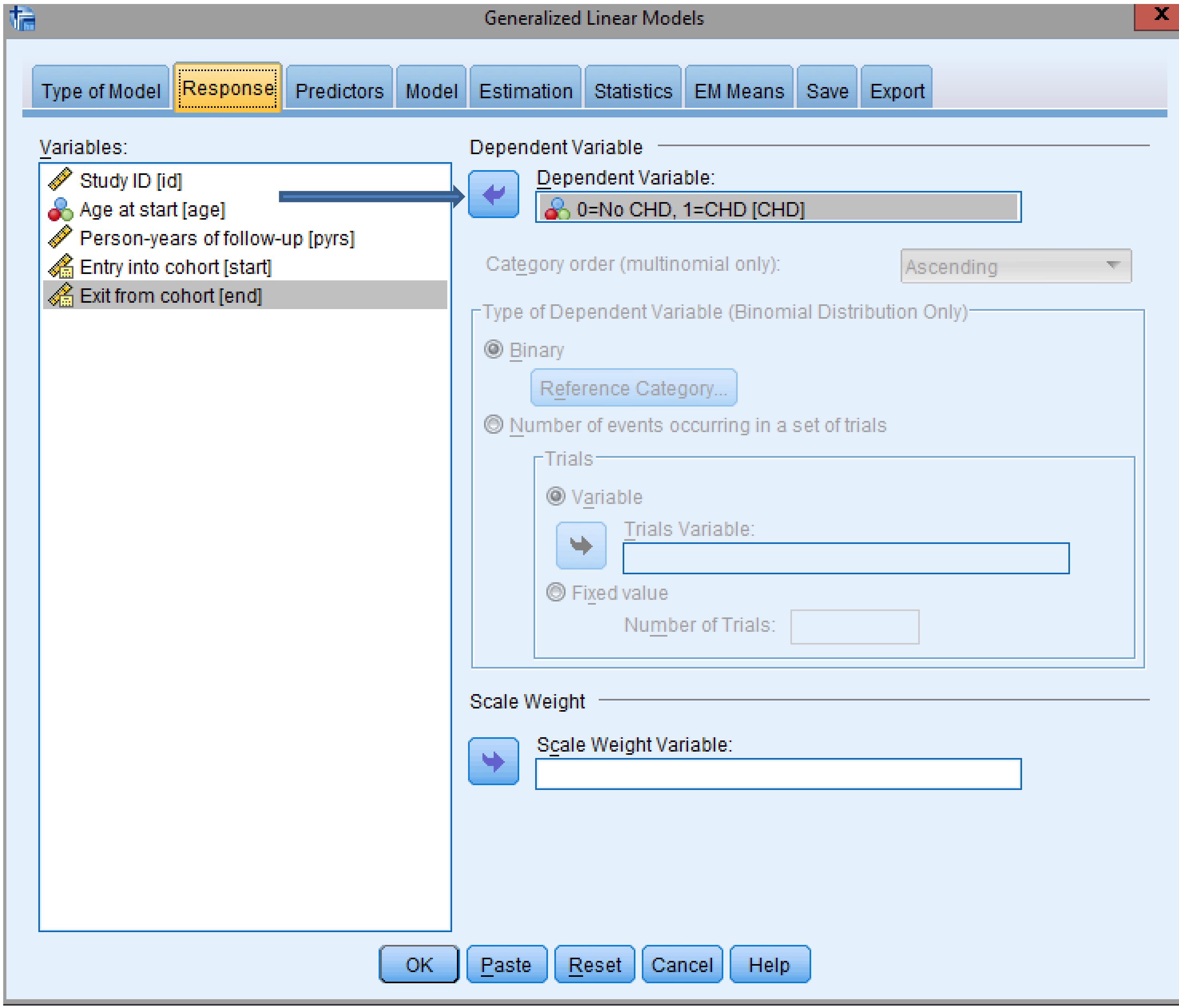
Gender

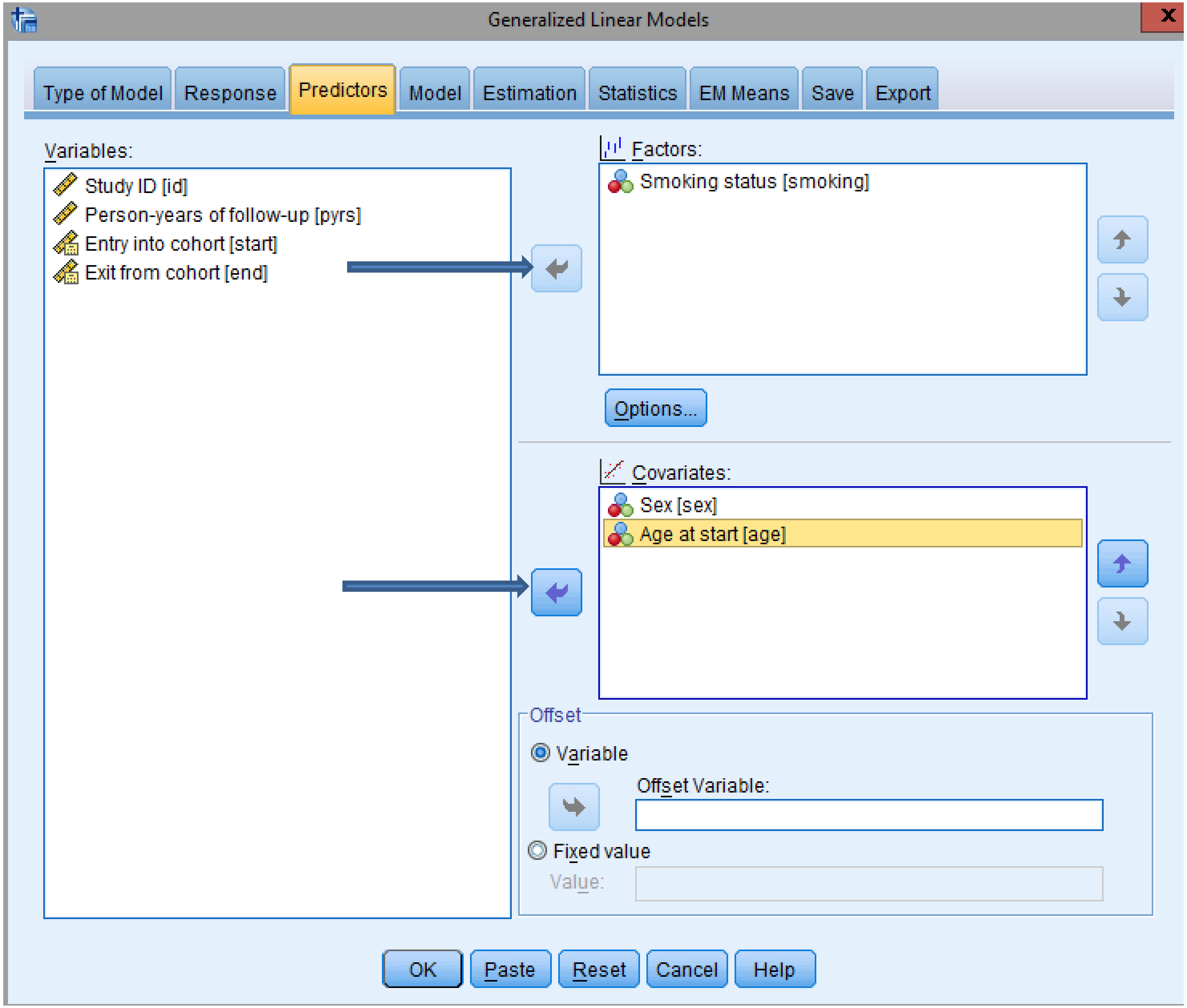
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	216	45.6	45.6	45.6
	Male	258	54.4	54.4	100.0
	Total	474	100.0	100.0	



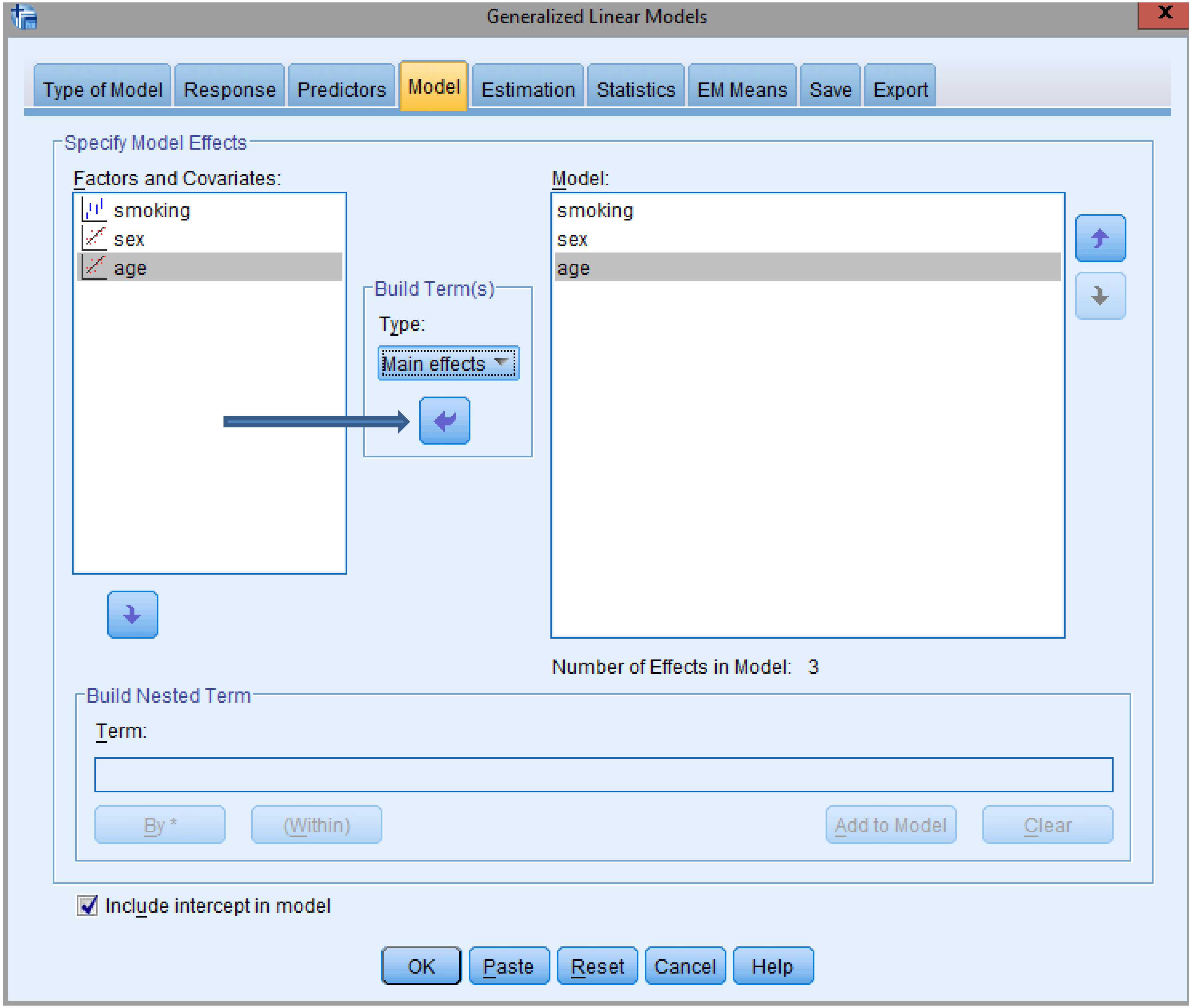
Poisson for count data

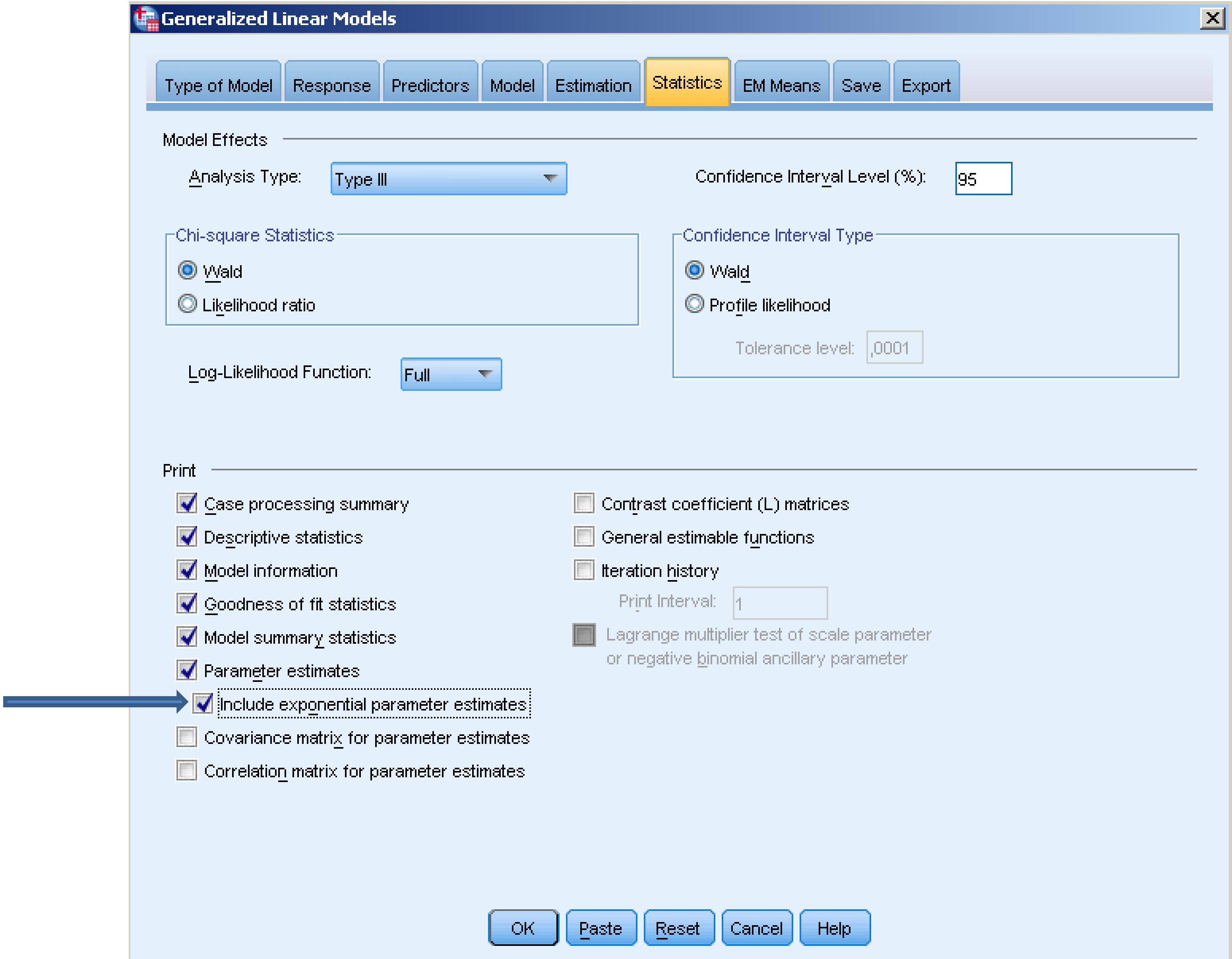



Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Variables:
Study ID [id]
Age at start [age]
Person-years of follow-up [pyrs]
Entry into cohort [start]
Exit from cohort [end]
Dependent Variable
Dependent Variable:
0=No CHD, 1=CHD [CHD]
Category order (multinomial only):
Ascending
Type of Dependent Variable (Binomial Distribution Only)
Binary
Reference Category...
Number of events occurring in a set of trials
Trials
Variable
Trials Variable:
Fixed value
Number of Trials:
Scale Weight
Scale Weight Variable:
OK
Paste
Reset
Cancel
Help

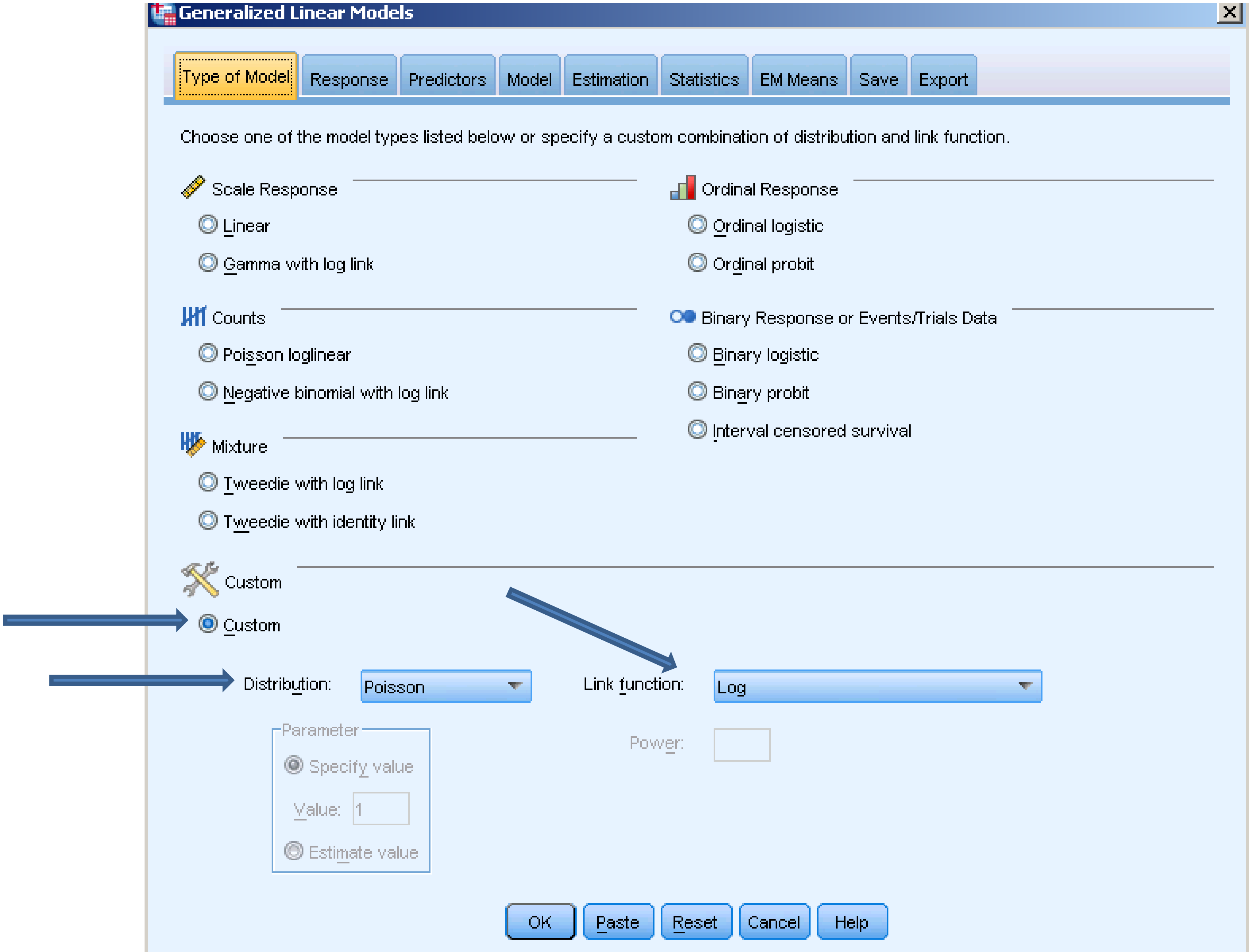


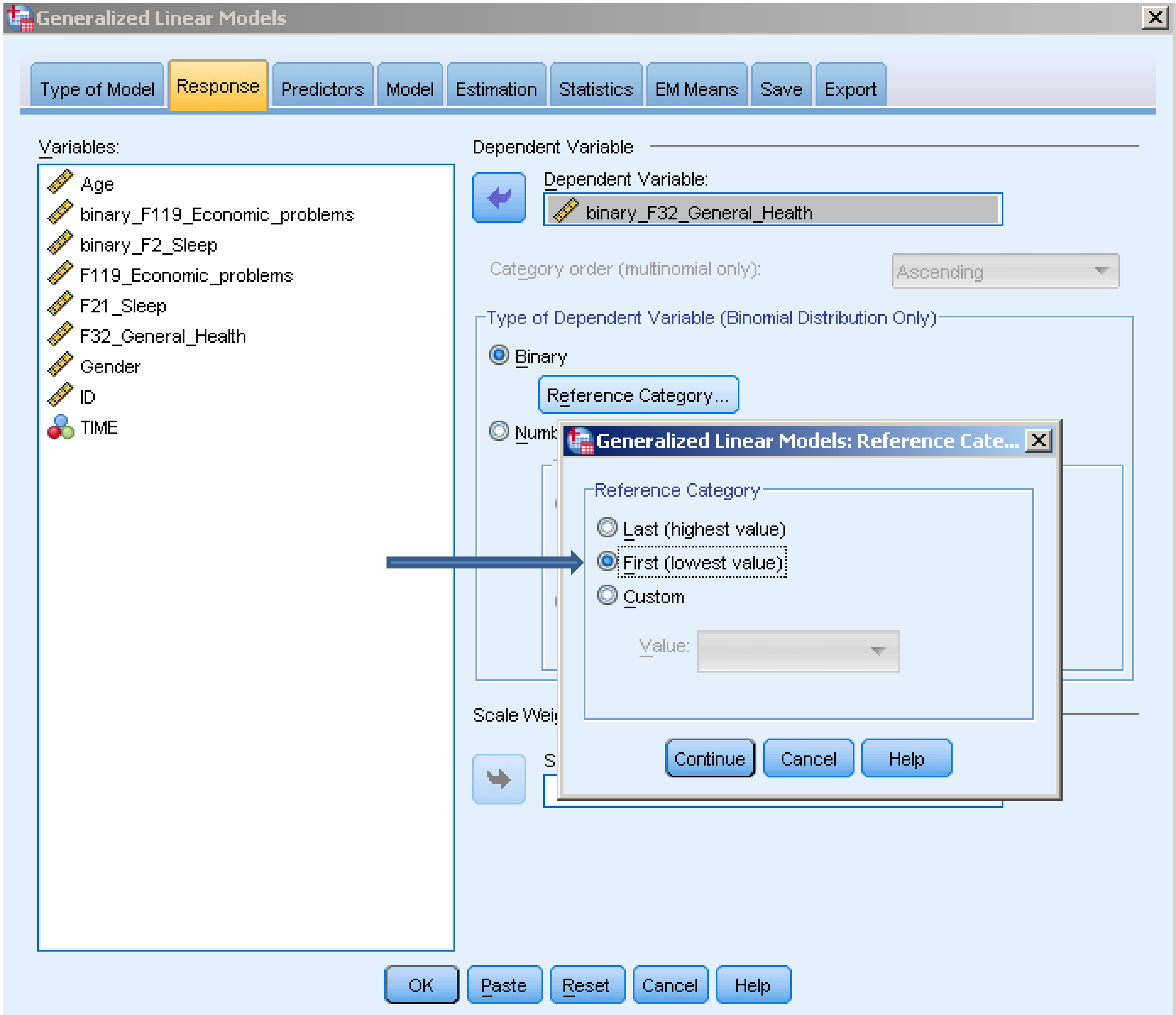
Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Variables:
Study ID [id]
Person-years of follow-up [pyrs]
Entry into cohort [start]
Exit from cohort [end]
Factors:
Smoking status [smoking]
Options...
Covariates:
Sex [sex]
Age at start [age]
Offset
Variable
Offset Variable:
Fixed value
Value:
OK
Paste
Reset
Cancel
Help

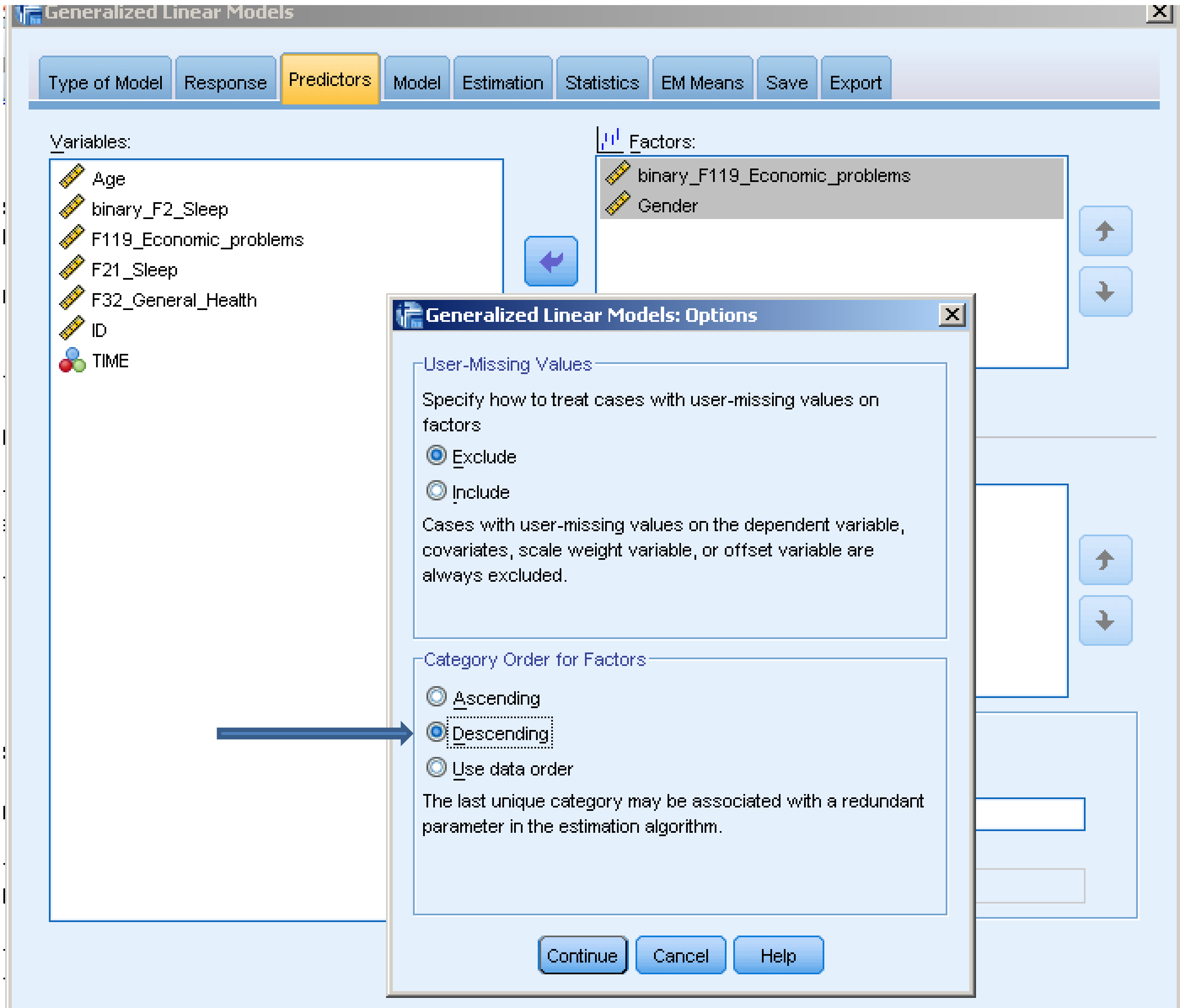

Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Specify Model Effects
Factors and Covariates:
smoking
sex
age
Build Term(s)
Type:
Main effects
Model:
smoking
sex
age
Number of Effects in Model: 3
Build Nested Term
Term:
By *
(Within)
Add to Model
Clear
Include intercept in model
OK
Paste
Reset
Cancel
Help

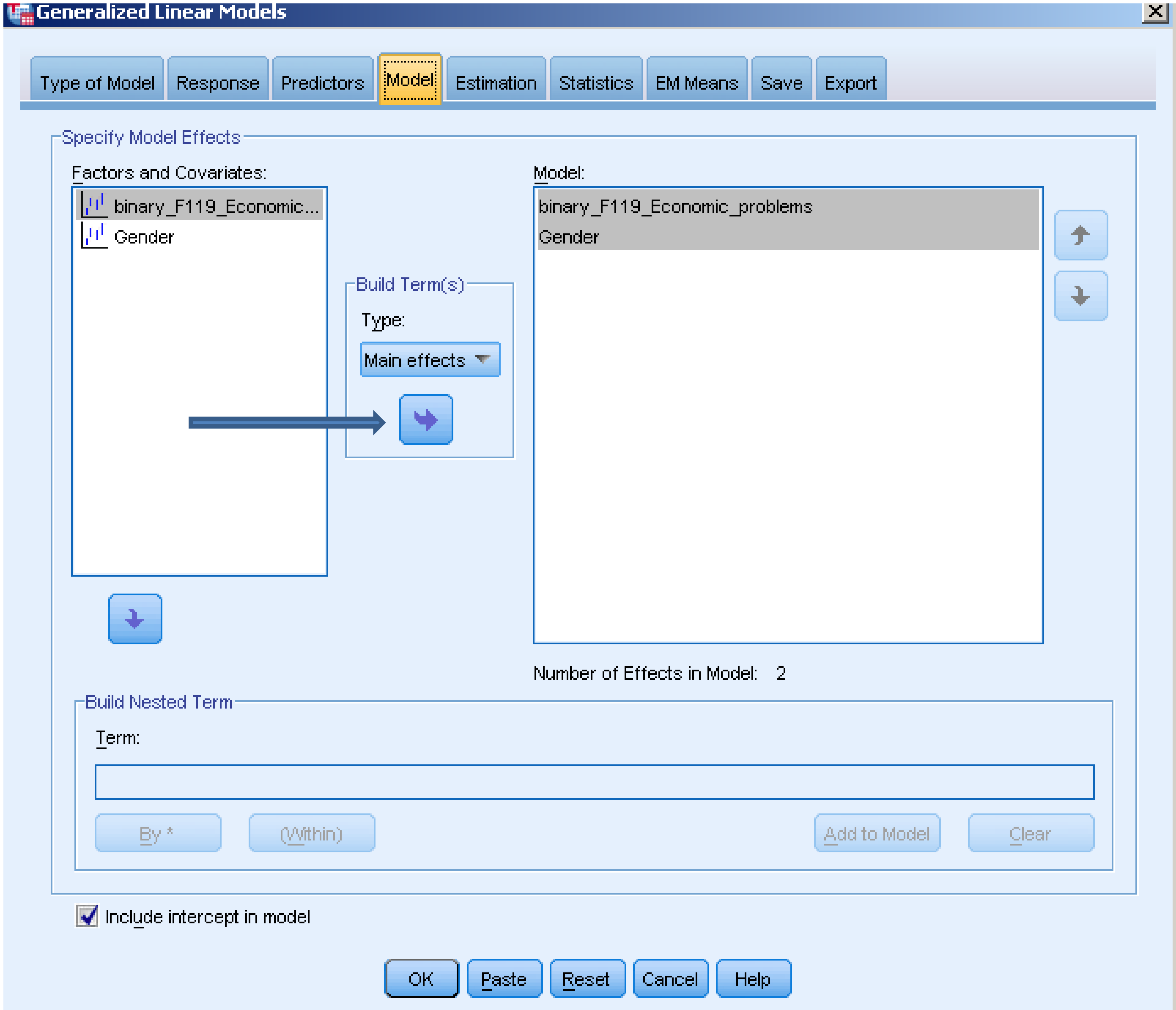

Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Model Effects
Analysis Type:
Type III
Confidence Interval Level (%):
95
Chi-square Statistics
Wald
Likelihood ratio
Confidence Interval Type
Wald
Profile likelihood
Tolerance level:
,0001
Log-Likelihood Function:
Full
Print
Case processing summary
Descriptive statistics
Model information
Goodness of fit statistics
Model summary statistics
Parameter estimates
Include exponential parameter estimates
Covariance matrix for parameter estimates
Correlation matrix for parameter estimates
Contrast coefficient (L) matrices
General estimable functions
Iteration history
Print Interval:
1
Lagrange multiplier test of scale parameter
or negative binomial ancillary parameter
OK
Paste
Reset
Cancel
Help

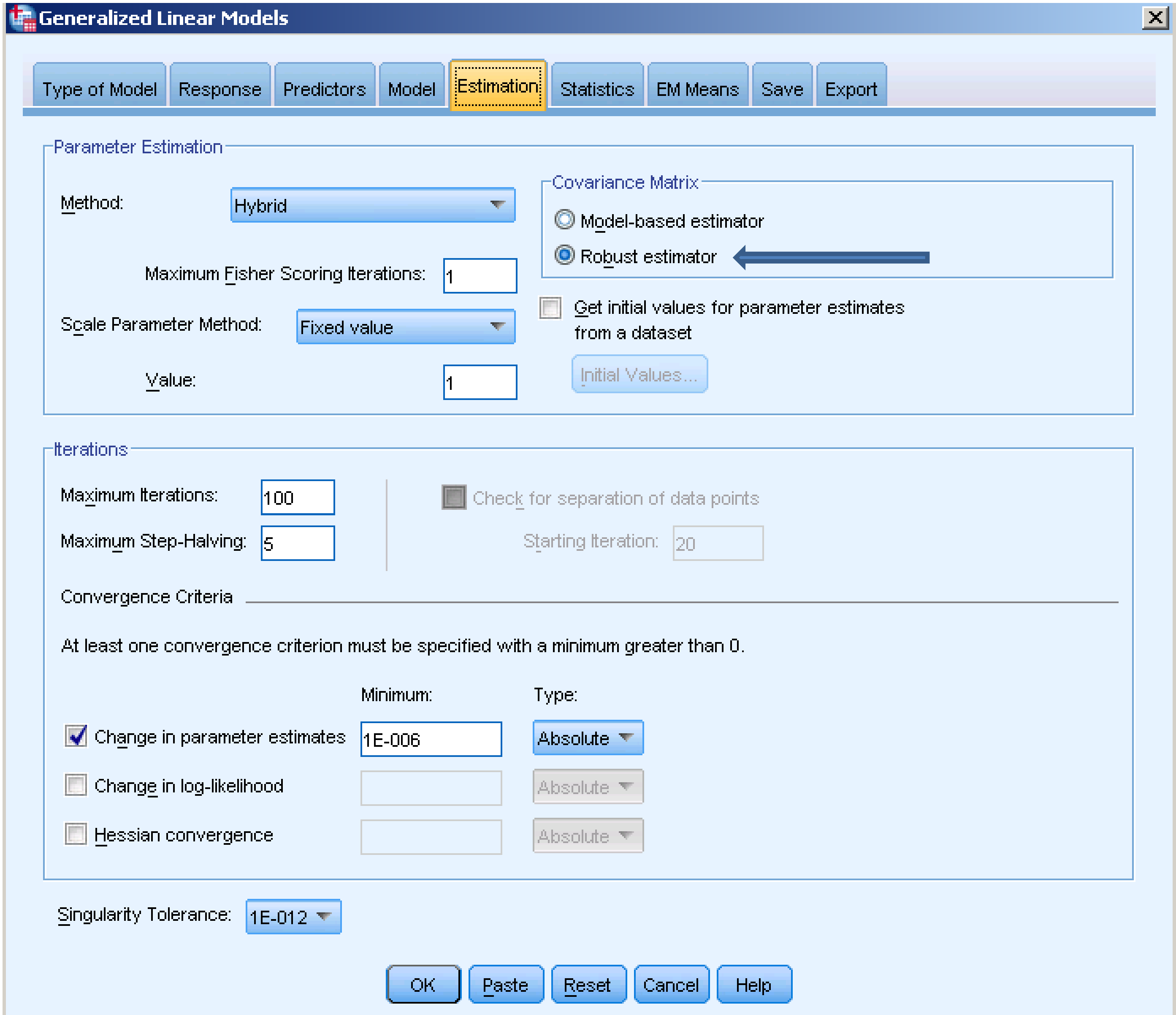
Poisson for binary data

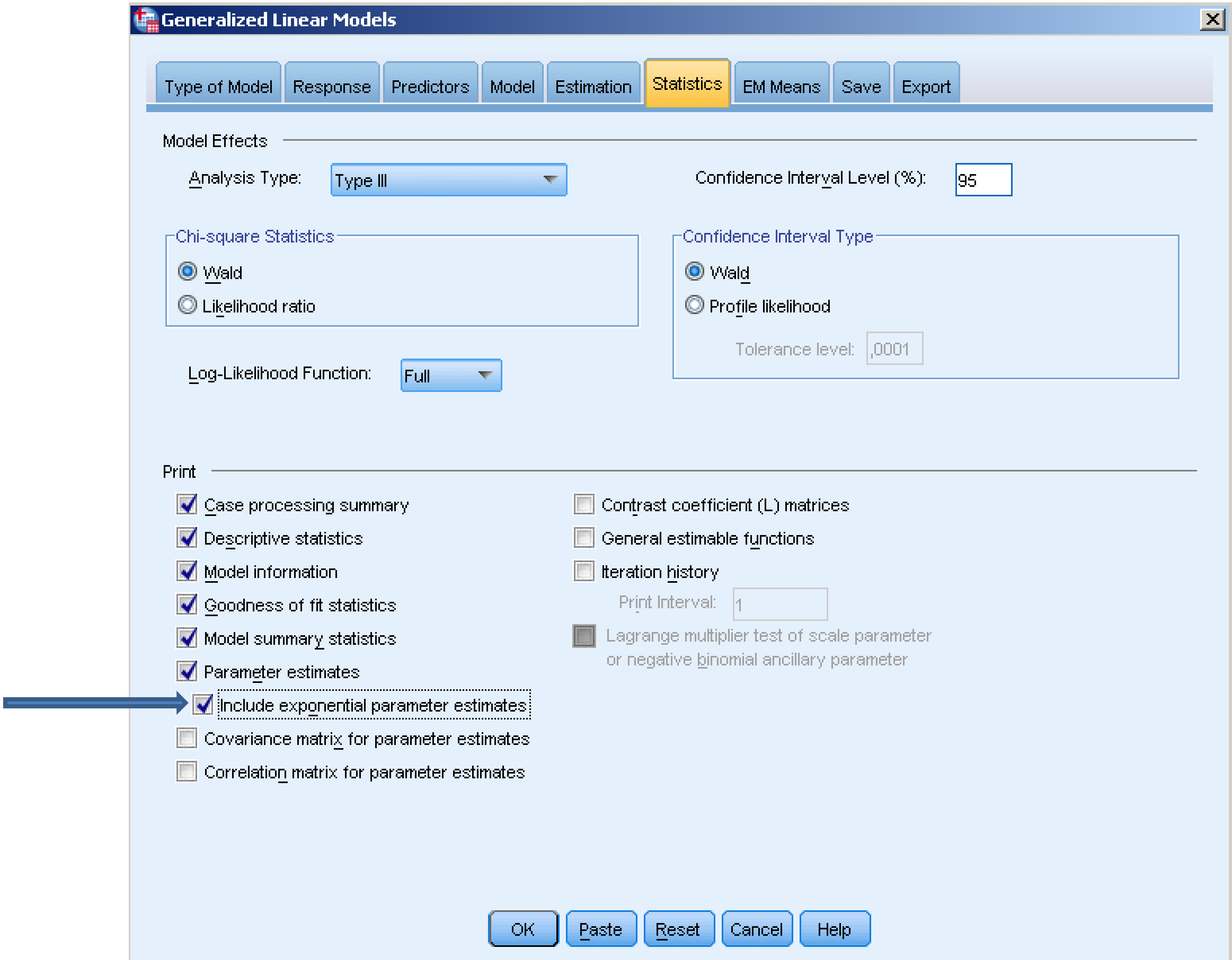


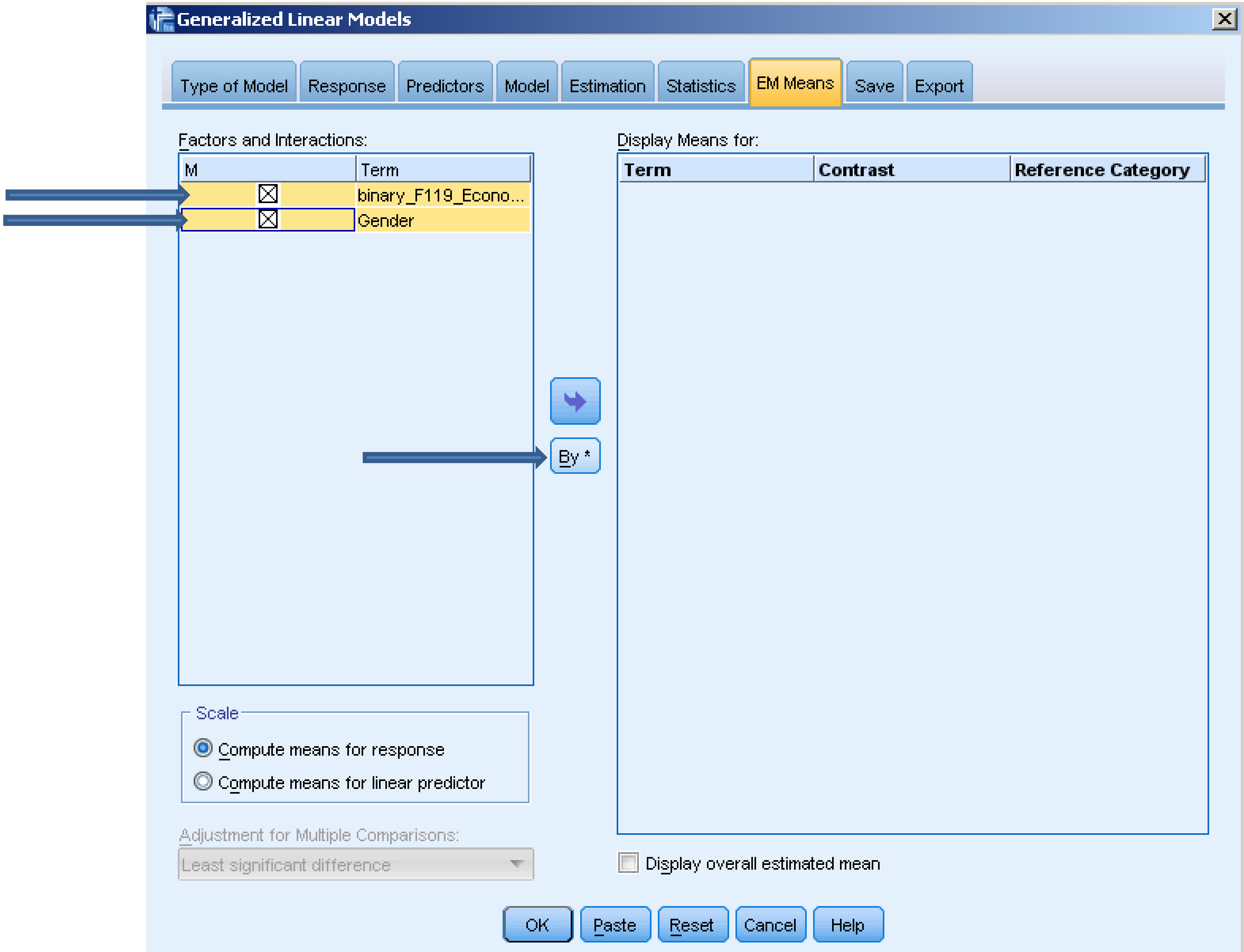

Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Variables:
Age
binary_F119_Economic_problems
binary_F2_Sleep
F119_Economic_problems
F21_Sleep
F32_General_Health
Gender
ID
TIME
Dependent Variable
Dependent Variable:
binary_F32_General_Health
Category order (multinomial only):
Ascending
Type of Dependent Variable (Binomial Distribution Only)
Binary
Reference Category...
Generalized Linear Models: Reference Cate...
Reference Category
Last (highest value)
First (lowest value)
Custom
Value:
Continue
Cancel
Help
OK
Paste
Reset
Cancel
Help


Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Variables:
Age
binary_F2_Sleep
F119_Economic_problems
F21_Sleep
F32_General_Health
ID
TIME
Factors:
binary_F119_Economic_problems
Gender
Generalized Linear Models: Options
User-Missing Values
Specify how to treat cases with user-missing values on factors
Exclude
Include
Cases with user-missing values on the dependent variable, covariates, scale weight variable, or offset variable are always excluded.
Category Order for Factors
Ascending
Descending
Use data order
The last unique category may be associated with a redundant parameter in the estimation algorithm.
Continue
Cancel
Help

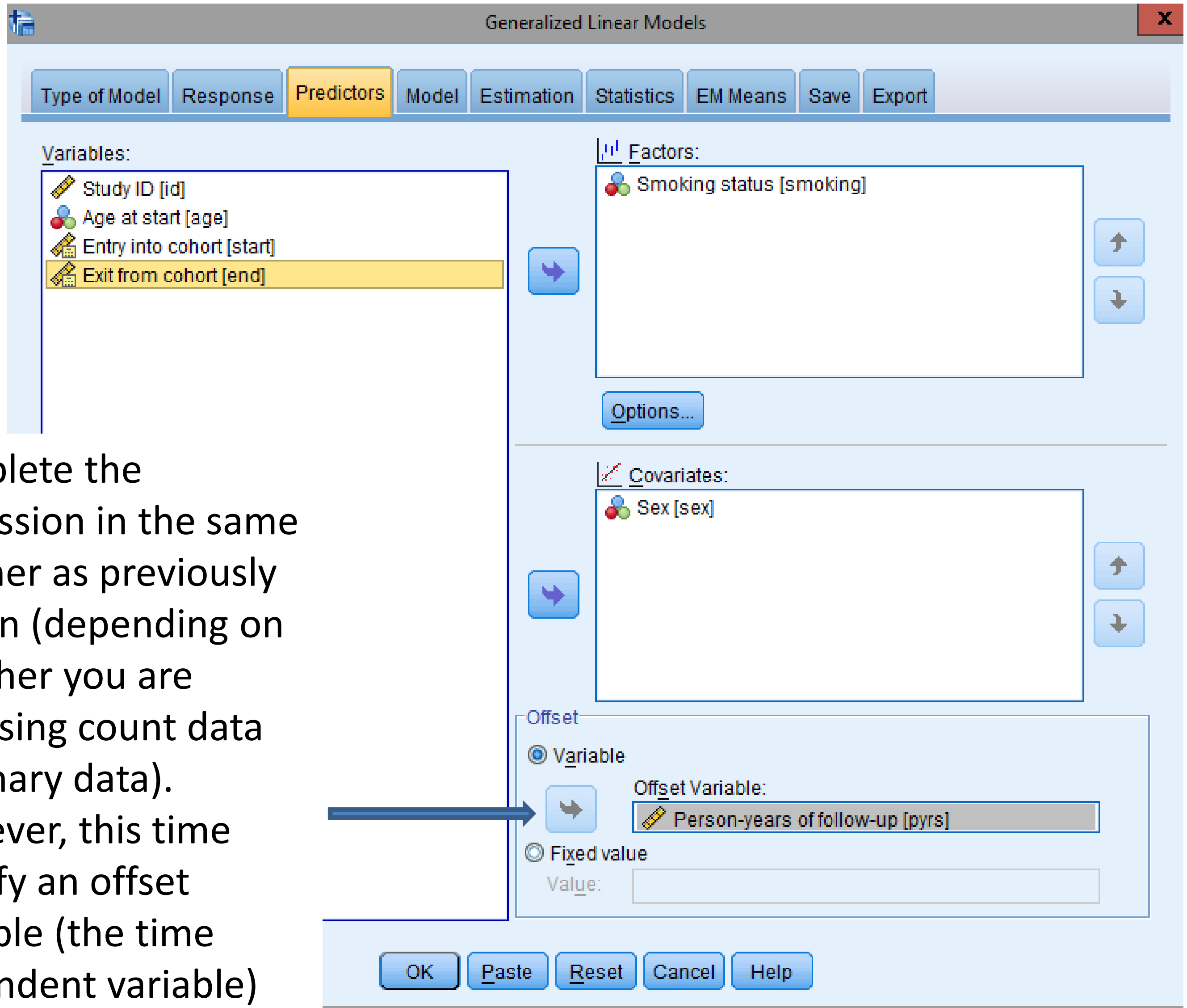

Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Specify Model Effects
Factors and Covariates:
binary_F119_Economic...
Gender
Model:
binary_F119_Economic_problems
Gender
Build Term(s)
Type:
Main effects
Number of Effects in Model: 2
Build Nested Term
Term:
By *
(Within)
Add to Model
Clear
Include intercept in model
OK
Paste
Reset
Cancel
Help


Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Parameter Estimation
Method:
Hybrid
Maximum Fisher Scoring Iterations:
1
Scale Parameter Method:
Fixed value
Value:
1
Covariance Matrix
Model-based estimator
Robust estimator
Get initial values for parameter estimates from a dataset
Initial Values...
Iterations
Maximum Iterations:
100
Maximum Step-Halving:
5
Check for separation of data points
Starting Iteration:
20
Convergence Criteria
At least one convergence criterion must be specified with a minimum greater than 0.
Minimum:
Type:
Change in parameter estimates
1E-006
Absolute
Change in log-likelihood
Absolute
Hessian convergence
Absolute
Singularity Tolerance:
1E-012
OK
Paste
Reset
Cancel
Help


Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Model Effects
Analysis Type:
Type III
Confidence Interval Level (%):
95
Chi-square Statistics
Wald
Likelihood ratio
Confidence Interval Type
Wald
Profile likelihood
Tolerance level:
,0001
Log-Likelihood Function:
Full
Print
Case processing summary
Descriptive statistics
Model information
Goodness of fit statistics
Model summary statistics
Parameter estimates
Include exponential parameter estimates
Covariance matrix for parameter estimates
Correlation matrix for parameter estimates
Contrast coefficient (L) matrices
General estimable functions
Iteration history
Print Interval:
1
Lagrange multiplier test of scale parameter
or negative binomial ancillary parameter
OK
Paste
Reset
Cancel
Help


Generalized Linear Models
Type of Model
Response
Predictors
Model
Estimation
Statistics
EM Means
Save
Export
Factors and Interactions:
M
Term
binary_F119_Econo...
Gender
By *
Display Means for:
Term
Contrast
Reference Category
Scale
Compute means for response
Compute means for linear predictor
Adjustment for Multiple Comparisons:
Least significant difference
Display overall estimated mean
OK
Paste
Reset
Cancel
Help

Poisson adding an exposure variable



Complete the regression in the same manner as previously shown (depending on whether you are analysing count data or binary data). However, this time specify an offset variable (the time dependent variable) on the predictors tab.