## Multiple Linear Regression

## Example: Blood Viscosity and Packed Cell Volume

The following blood viscosity data studied earlier are a good example of where multiple regression could be used. Recall that the data blood viscosity in samples taken from 32 hospital patients. We wish to model viscosity ( $y$ ) as a function three covariates

- Packed Cell Volume (PCV), $x_{1}$.
- Plasma Fibrinogen, $x_{2}$.
- Plasma Protein, $x_{3}$.

| Unit | Viscosity <br> $y$ | PCV <br> $x_{1}$ | Plasma Fib. <br> $x_{2}$ | Plasma Pro. <br> $x_{3}$ |
| ---: | :---: | :---: | :---: | :---: |
| 1 | 3.71 | 40.00 | 344 | 6.27 |
| 2 | 3.78 | 40.00 | 330 | 4.86 |
| 3 | 3.85 | 42.50 | 280 | 5.09 |
| 4 | 3.88 | 42.00 | 418 | 6.79 |
| 5 | 3.98 | 45.00 | 774 | 6.40 |
| 6 | 4.03 | 42.00 | 388 | 5.48 |
| 7 | 4.05 | 42.50 | 336 | 6.27 |
| 8 | 4.14 | 47.00 | 431 | 6.89 |
| 9 | 4.14 | 46.75 | 276 | 5.18 |
| 10 | 4.20 | 48.00 | 422 | 5.73 |
| 11 | 4.20 | 46.00 | 280 | 5.89 |
| 12 | 4.27 | 47.00 | 460 | 6.58 |
| 13 | 4.27 | 43.25 | 412 | 5.67 |
| 14 | 4.37 | 45.00 | 320 | 6.23 |
| 15 | 4.41 | 50.00 | 502 | 4.99 |
| 16 | 4.64 | 45.00 | 550 | 6.37 |
| 17 | 4.68 | 51.25 | 414 | 6.40 |
| 18 | 4.73 | 50.25 | 304 | 6.00 |
| 19 | 4.87 | 49.00 | 472 | 5.94 |
| 20 | 4.94 | 50.00 | 728 | 5.16 |
| 21 | 4.95 | 50.00 | 716 | 6.29 |
| 22 | 4.96 | 49.00 | 400 | 5.96 |
| 23 | 5.02 | 50.50 | 576 | 5.90 |
| 24 | 5.02 | 51.25 | 354 | 5.81 |
| 25 | 5.12 | 49.50 | 392 | 5.49 |
| 26 | 5.15 | 56.00 | 352 | 5.41 |
| 27 | 5.17 | 50.00 | 572 | 6.24 |
| 28 | 5.18 | 47.00 | 634 | 6.50 |
| 29 | 5.38 | 53.25 | 458 | 6.60 |
| 30 | 5.77 | 57.00 | 1070 | 4.82 |
| 31 | 5.90 | 54.00 | 488 | 5.70 |
| 32 | 5.90 | 54.00 | 488 | 5.70 |
|  |  |  |  |  |

We consider four analyses:

```
Multiple regression : \(y=\beta_{0}+\beta_{1} x_{1}+\beta_{2} x_{2}+\beta_{3} x_{3}+\epsilon\)
    Regression on \(\boldsymbol{x}_{\mathbf{1}}: \quad y=\beta_{0}+\beta_{1} x_{1}+\epsilon\)
    Regression on \(\boldsymbol{x}_{\mathbf{2}}: \quad y=\beta_{0}+\beta_{2} x_{2}+\epsilon\)
    Regression on \(\boldsymbol{x}_{3}: \quad y=\beta_{0}+\beta_{3} x_{3}+\epsilon\)
```


## Multiple Regression

## Model Summary ${ }^{\text {b }}$

| Model | R | R Square | Adjusted <br> R Square | Std. Error of <br> the Estimate |
| :--- | ---: | ---: | ---: | ---: |
| 1 | $.885^{\mathrm{a}}$ | .784 | .761 | .30370 |

a. Predictors: (Constant), Plasma Protein (g/100ml), Plasma Fibrinogen ( $\mathrm{mg} / 100 \mathrm{ml}$ ), Packed Cell Volume (\%)

ANOVA ${ }^{b}$

| Model |  | Sum of <br> Squares | df | Mean Square | F | Sig. |
| :--- | :--- | ---: | ---: | ---: | ---: | ---: |
| 1 | Regression | 9.368 | 3 | 3.123 | 33.856 | $.000^{\mathrm{a}}$ |
|  | Residual | 2.582 | 28 | .092 |  |  |
|  | Total | 11.950 | 31 |  |  |  |

a. Predictors: (Constant), Plasma Protein (g/100ml), Plasma Fibrinogen (mg/100ml), Packed Cell Volume (\%)
b. Dependent Variable: Blood Viscosity (cP)

## Multiple Regression: Parameter Estimates



## Regression on Packed Cell Volume only

Model Summary

| Model | R | R Square | Adjusted <br> R Square | Std. Error of <br> the Estimate |
| :--- | ---: | ---: | ---: | ---: |
| 1 | $.879^{\mathrm{a}}$ | .772 | .765 | .30116 |

a. Predictors: (Constant), Packed Cell Volume (\%)

ANOVA ${ }^{\text {b }}$

| Model |  | Sum of <br> Squares | df | Mean Square | F | Sig. |
| :--- | :--- | ---: | ---: | ---: | ---: | ---: |
| 1 | Regression | 9.230 | 1 | 9.230 | 101.764 | $.000^{\mathrm{a}}$ |
|  | Residual | 2.721 | 30 | .091 |  |  |
|  | Total | 11.950 | 31 |  |  |  |

a. Predictors: (Constant), Packed Cell Volume (\%)
b. Dependent Variable: Blood Viscosity (cP)

Coefficients ${ }^{a}$

| Model | Unstandardized Coefficients |  | Standardized Coefficients Beta | t | Sig. | 95\% Confidence Interval for B |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | B | Std. Error |  |  |  | Lower Bound | Upper Bound |
| 1 (Constant) | -1.223 | . 584 |  | -2.094 | . 045 | -2.416 | -. 030 |
| Packed Cell Volume (\%) | . 122 | . 012 | . 879 | 10.088 | . 000 | . 098 | . 147 |
| a. Dependent Variable: Blood Viscosity (cP) |  |  |  |  |  |  |  |
|  |  |  |  |  |  | PCV is a significant term in the model ( p < 0.001) |  |

## Regression on Plasma Protein only

Model Summary

| Model | R | R Square | Adjusted <br> R Square | Std. Error of <br> the Estimate |
| :--- | ---: | ---: | ---: | ---: |
| 1 | $.457^{\mathrm{a}}$ | .209 | .183 | .56129 |

a. Predictors: (Constant), Plasma Fibrinogen (mg/100ml)

ANOVA ${ }^{b}$

| Model |  | Sum of <br> Squares | df | Mean Square | F | Sig. |
| :--- | :--- | ---: | ---: | ---: | ---: | ---: |
| 1 | Regression | 2.499 | 1 | 2.499 | 7.932 | $.009^{\text {a }}$ |
|  | Residual | 9.451 | 30 | .315 |  |  |
|  | Total | 11.950 | 31 |  |  |  |

a. Predictors: (Constant), Plasma Fibrinogen (mg/100ml)
b. Dependent Variable: Blood Viscosity (cP)

Coefficients ${ }^{\text {a }}$

| Model |  | Unstandardized Coefficients |  | Standardized Coefficients | t | Sig. | 95\% Confidence Interval for B |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | B | Std. Error | Beta |  |  | Lower Bound | Upper Bound |
| 1 | (Constant) | 3.871 | . 292 |  | 13.236 | . 000 | 3.274 | 4.468 |
|  | Plasma Fibrinogen ( $\mathrm{mg} / 100 \mathrm{ml}$ ) | . 002 | . 001 | . 457 | 2.816 | . 009 | . 000 | . 003 |

a. Dependent Variable: Blood Viscosity (cP)

## Regression on Plasma Fibrinogen only

Model Summary

| Model | R | R Square | Adjusted <br> R Square | Std. Error of <br> the Estimate |
| :--- | ---: | ---: | ---: | ---: |
| 1 | $.101^{\mathrm{a}}$ | .010 | -.023 | .62791 |

a. Predictors: (Constant), Plasma Protein (g/100ml)

ANOVA ${ }^{\text {b }}$

| Model |  | Sum of <br> Squares | df | Mean Square | F | Sig. |
| :--- | :--- | ---: | ---: | ---: | ---: | ---: |
| 1 | Regression | .122 | 1 | .122 | .310 | $.582^{\mathrm{a}}$ |
|  | Residual | 11.828 | 30 | .394 |  |  |
|  | Total | 11.950 | 31 |  |  |  |

a. Predictors: (Constant), Plasma Protein (g/100ml)
b. Dependent Variable: Blood Viscosity (cP)

Coefficients ${ }^{\text {a }}$

| Model |  | Unstandardized Coefficients |  | Standardized Coefficients Beta | t | Sig. | 95\% Confidence Interval for B |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | B | Std. Error |  |  |  | Lower Bound | Upper Bound |
| 1 | (Constant) | 5.296 | 1.174 |  | 4.510 | . 000 | 2.898 | 7.694 |
|  | Plasma Protein (g/100ml) | -. 110 | . 198 | -. 101 | -. 556 | . 582 | -. 515 | . 295 |

a. Dependent Variable: Blood Viscosity (cP)


Use the Analyze, Regression, Linear pulldown selections


Select the Dependent variable (viscosity) and the three independent variables ${ }^{3}$ (pcv, plasfib and plaspro)


Click the Statistics button: on the Statistics dialog, select Estimates, Confidence ${ }^{4}$ Intervals and Model fit. Click Continue.


Click the Plots button


Select *ZRESID for the $Y$ variable and *ZPRED for the $X$ variable.
Then click Next.


Select *ZRESID for the $Y$ variable and *ZPRED for the $X$ variable.
Then click Produce all partial Plots. Then Continue.


Click the Save button, to compute and store the residuals etc.

Select the quantities to store as new variables in the data set.
Click Continue.


Click OK and the output is generated.


## New variables have been computed.



Full information on the new variables is available.


## Results: Model Summary


a. Predictors: (Constant), Plasma Protein (g/100ml), Plasma Fibrinogen ( $\mathrm{mg} / 100 \mathrm{ml}$ ), Packed Cell Volume (\%)
b. Dependent Variable: Blood Viscosity (cP)

Results: ANOVA

| ANOVA ${ }^{\text {b }}$ |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Model |  | Sum of Squares | df | Mean Square | F | Sig. |
| 1 | Regression | 9.368 | 3 | 3.123 | 33.856 | . $000{ }^{\text {a }}$ |
|  | Residual | 2.582 | 28 | . 092 |  |  |
|  | Total | 11.950 | 31 |  |  |  |

a. Predictors: (Constant), Plasma Protein (g/100ml), Plasma Fibrinogen (mg/100ml), Packed Cell Volume (\%)
b. Dependent Variable: Blood Viscosity (cP)

```
The ANOVA for the multiple regression has a highly significant F value, with a p-value < 0.001. Here
H0: E[Y] = beta.0
H1 : E[Y] = beta. 0 + beta. 1 x1 + beta. 2 x2 + beta. }3\times
This result implies that the multiple regression(Ha) fits significantly better than the model with no dependence on any of the
predictors (H0).
```

Results: Parameter Estimates

Coefficients ${ }^{\text {a }}$


Results: Scatterplot of Standardized Residual vs Predicted Value

Scatterplot

Dependent Variable: Blood Viscosity (cP)


Obtaining: Plots of Residuals vs Covariates


Use the Matrix Scatter option, and click Define


Select the standardized residuals, and the three covariates for the

## Matrix Variables. Click OK.

Results: Scatterplot Matrix


Null Model


Main Effect Model: Significant Factor Effect
(different intercept in both groups, slope=0)


## Main Effect Model: Significant Covariate Effect

(intercept, slope same in both groups)


## Main Effect Model: Significant Covariate and Factor Effect

 (intercept different, slope same in the two groups)

Interaction Model: Covariate, Factor and Interaction Effect (different intercept and slope in the two groups)


Original Data


Log-scale Data


Log-scale Data


Subgroups


Group 1


Group 2



Fits to the three subgroups


Projection back to the axis


## Factor Predictor Regression

We need to take some care when combining factor predictors and covariates in the regression model. Suppose that we have only two predictors

- A covariate, $x_{1}$
- A factor predictor, $x_{2}$, now taking $L$ levels, with the levels being indexed by $l=1,2, \ldots, L$.

We want to build a model that takes into account both $x_{1}$ and $x_{2}$.

Example : Binary Factor $L=2$
Suppose that factor predictor $x_{2}$ takes two levels, labelled 0 and 1 , that identify two data subgroups. Five models can be considered, that correspond to different straight-line models

- MODEL 0 : Same intercept, slope zero, in the two subgroups
- MODEL 1 : Different intercept, slope zero, in the two subgroups
- MODEL 2: Same intercept, same non-zero slope, in the two subgroups
- MODEL 3 : Different intercept, same non-zero slope, in the two subgroups
- MODEL 4 : Different intercept, different non-zero slopes, in the two subgroups

We can write out the models in terms of the usual slope and intercept parameters. The general model can be written

$$
y=\left\{\begin{array}{lll}
\beta_{00}+\beta_{01} x_{1}+\epsilon & \text { GROUP } 0 & (l=0) \\
\beta_{10}+\beta_{11} x_{1}+\epsilon & \text { GROUP } 1 & (l=1)
\end{array}\right.
$$

- MODEL 0 :

$$
\beta_{00}=\beta_{10}=\beta_{0}, \beta_{01}=\beta_{11}=0
$$

- MODEL $1: \quad \beta_{00} \neq \beta_{10}, \beta_{01}=\beta_{11}=0$
- MODEL 2: $\quad \beta_{00}=\beta_{10}=\beta_{0}, \beta_{01}=\beta_{11}=\beta_{1} \neq 0$
- MODEL $3: \quad \beta_{00} \neq \beta_{10}, \beta_{01}=\beta_{11}=\beta_{1} \neq 0$
- MODEL 4: $\quad \beta_{00} \neq \beta_{10}, \beta_{01} \neq \beta_{11}$

The numbers of parameters, $p$, in each model are as follows:
MODEL $0 \quad: \quad p=1 \quad \beta_{0}$
MODEL $1: p=2 \quad \beta_{00}, \beta_{10}$
MODEL $2: p=2 \quad \beta_{0}, \beta_{1}$
MODEL $3: p=3 \quad \beta_{00}, \beta_{10}, \beta_{1}$
MODEL $4: \quad p=4 \quad \beta_{00}, \beta_{10}, \beta_{10}, \beta_{11}$

SPSS Parameterization: The default parameterization used by SPSS is different from the one described above. SPSS takes a baseline group, and looks for differences in the parameters compared to the baseline group. The baseline group is taken to be the last listed subgroup for the factor predictor; in the binary example above, the baseline group would be Group 1.

The interaction model is therefore written

$$
y=\left[\beta_{0}+\left(1-x_{2}\right) \delta_{00}\right]+\left[\left(\beta_{1}+\left(1-x_{2}\right) \delta_{01}\right) x_{1}\right]+\epsilon
$$

- $\delta_{00}$ is the change in intercept from Group 1 to Group 0
- $\delta_{01}$ is the change in slope from Group 1 to Group 0


## Example: Diabetes Data Set

The data in the data set DIABETES.SAV contain information on 68 diabetes patients falling into two clinically different categories (overt and chemical diabetics) and 76 normal controls. Measurements of plasma glucose in blood samples when fasting and in a dietary test are recorded.

The objective is to predict the the test glucose levels from the fasting glucose levels in the three subgroups, and to find out if there is any significant difference between the subgroups.

In this analysis, there is a single response variable, one covariate and one factor predictor:

- $y$ : glutest, the test glucose level
- $x_{1}$ : covariate glufast, the fasting glucose level
- $x_{2}$ : factor predictor group, the diabetes group
- GROUP 1: Overt Diabetic
- GROUP 2: Chemical Diabetic
- GROUP 3: Normal Patients

Tests of Between-Subjects Effects
Dependent Variable: Log(GluTest)

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Gorreeted Model | $27.187^{1}$ | 5 | 5.407 | 569.463 | . 000 |
| Intereept | . 973 | 1 | . 073 | 101.006 | . 000 |
| group | . 104 | 2 | . 052 | 5.447 | . 005 |
| loggluf | . 675 | 1 | . 675 | 70.702 | . 000 |
| group * loggluf | . 155 | 2 | . 077 | 8.099 | . 000 |
| Error | 1.318 | 138 | . 010 |  |  |
| Fotal | 5500.040 | 144 |  |  |  |
| Corrected Total | 28.504 | 143 |  |  |  |

a. R Squared $=.954$ (Adjusted R Squared $=.952$ )

## Parameter Estimates

Dependent Variable: Log(GluTest)

| Parameter | B | Std. Error | t | Sig. | 95\% Confidence Interval |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  | Lower Bound | Upper Bound |
| Intercept | 4.504 | . 559 | 8.060 | . 000 | 3.399 | 5.608 |
| [group=1] | -2.037 | . 619 | -3.289 | . 001 | -3.262 | -. 813 |
| [group=2] | -1.436 | . 958 | -1.499 | . 136 | -3.330 | . 458 |
| [group=3] | $0^{\text {a }}$ |  |  |  |  |  |
| loggluf | . 299 | . 124 | 2.414 | . 017 | . 054 | . 544 |
| [group=1] * loggluf | . 535 | . 134 | 4.001 | . 000 | . 270 | . 799 |
| [group=2] * loggluf | . 382 | . 210 | 1.820 | . 071 | -. 033 | . 797 |
| [group=3] * loggluf | $0^{\text {a }}$ |  |  |  |  |  |

a. This parameter is set to zero because it is redundant.

The first ANOVA table demonstrates that there is a significant interaction between the covariate and the factor predictor $(F=8.099$, $p$-value $<0.001$ ). This means that there is a significantly different slope in at least two of the three subgroups.

The second table gives the slope and intercept parameters in the three groups. The SPSS parameterization is not directly in terms of the slopes and intercepts, but looks at differences from baseline subgroup, Group 3. For example, the Group 1 intercept and slope are, respectively, INTERCEPT $: 4.504+(-2.037)=2.467 \quad$ SLOPE $: 0.299+0.535=0.834$.

Diabetes Data Set


Create two new variables loggluf and logglut for the logged variables

| \％${ }^{\text {P Dia }}$ | betes．s． | ［Da | $1]$ | SS Data | ditor |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
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| $\square$ | 通 区 | not ${ }^{\text {mim }}$ |  | 回违 | ． |  |  |  |  |  |
|  | Name | Type | Wisth | Decimals | Label | Values | Mising | Colums | Align | Measure |
| 1 | id | Numeric |  |  | Patient I0 | None | None |  |  |  |
| 2 | remm | Numeric | 11 | 2 | Relative Weight | None | None |  |  |  |
| 3 | gluast | Numenic | 11 | 0 | Fasting Plasma Glucose |  | None | 8 | Right | Scale |
| 4 | gluest | Numenic | 11 | 0 | Test Plasma Gluose | None | None | 8 | Right | Scale |
|  |  |  | 11 |  | sma Insulin duing T |  |  |  |  |  |
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|  |  | Numenic | 8 |  | （iulest） | None | None |  |  |  |
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|  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |
| 7 |  |  |  |  |  |  |  |  |  |  |
| ${ }^{18}$ |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |
| ${ }_{21}^{21}$ |  |  |  |  |  |  |  |  |  |  |
| 2 |  |  |  |  |  |  |  |  |  |  |
| ${ }^{24}$ |  |  |  |  |  |  |  |  |  |  |
| ${ }_{-}^{25}$ |  |  |  |  |  |  |  |  |  |  |
| $\stackrel{27}{27}$ |  |  |  |  |  |  |  |  |  |  |
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| －30 |  |  |  |  |  |  |  |  |  |  |
| 32 |  |  |  |  |  |  |  |  |  |  |
| －${ }^{33} \times 14$ |  |  |  |  |  |  |  |  |  |  |
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| －${ }^{37}$ |  |  |  |  |  |  |  |  |  |  |
| －${ }_{-}{ }^{39}$ |  |  |  |  |  |  |  |  |  |  |
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| 41 <br>  |  |  |  |  |  |  |  |  |  |  |
| -4 <br> -45 |  |  |  |  |  |  |  |  |  |  |
| $\square$ |  |  |  |  |  |  |  |  |  |  |
| － 48 |  |  |  |  |  |  |  |  |  |  |
| $\bigcirc$ |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |

## Use the Compute pulldown menu to compute the log transform



In Target Variable insert loggluf, and in Numeric Expression type
Ln(glufast), and click OK

Click OK when the confirmation screen appears


The log transformed variable loggluf is computed.


The same procedure computes the log transformed variable logglut; we log transform the glutest variable using the Compute pulldown


## We now perform the linear regression using the General Linear Model pulldown. ${ }^{8}$



Select the Dependent Variable (logglut), the Fixed Factor (group) and the Covariate (loggluf).

To specify the model, click the Model button to get the Model Dialog.
We wish to specify a Custom main effects plus interaction model.


## We select the factor and covariate as main effects.




Select Interaction from the Build Terms pulldown.
困Diabetes.sav [DataSet1] - SPSS Data Editor



Highlight the two variables，and click the Build Terms arrow．


The Custom model has been built. Click Continue.


The model is now built. On the General Linear Model dialog, click Options.
Select Parameter Estimates and Residual plot
畇Diabetes.sav [DataSeti] - SPSS Data Editor



The output is generated.


The ANOVA table describes the results. It can be read in the same way as an ${ }^{17}$ ordinary ANOVA table. We note significant main effects and interaction.

Tests of Between-Subjects Effects
Dependent Variable: Log(GluTest)

|  | Type III Sum <br> of Squares | df | Mean Square | F | Sig. |
| :--- | ---: | ---: | ---: | ---: | ---: |
| Source | $27.1077^{2}$ | 5 | 5.437 | 509.403 | .000 |
| Corrected M4odel | .973 | 1 | .973 | 101.906 | .000 |
| notereept | .104 | 2 | .052 | 5.447 | .005 |
| group | .675 | 1 | .675 | 70.702 | .000 |
| loggluf | .155 | 2 | .077 | 8.099 | .000 |
| group * loggluf | 1.318 | 138 | .010 |  |  |
| Error | 5509.040 | 144 |  |  |  |
| fotal | 28.504 | 143 |  |  |  |
| Corrected Total |  |  |  |  |  |

a. R Squared $=.954$ (Adjusted R Squared $=.952$ )

The high R squared value means that the model fit is quite
good overall.

The parameter estimates/standard errors are also computed.
The SPSS parameterization of the model is used.

Parameter Estimates
Dependent Variable: Log(GluTest)

| Parameter | B | Std. Error | t | Sig. | 95\% Confidence Interval |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  | Lower Bound | Upper Bound |
| Intercept | 4.504 | . 559 | 8.060 | . 000 | 3.399 | 5.608 |
| [group=1] | -2.037 | . 619 | -3.289 | . 001 | -3.262 | -. 813 |
| [group=2] | -1.436 | . 958 | -1.499 | . 136 | -3.330 | . 458 |
| [group=3] | $0^{\text {a }}$ |  |  |  |  |  |
| loggluf | . 299 | . 124 | 2.414 | . 017 | . 054 | . 544 |
| [group=1] * loggluf | . 535 | . 134 | 4.001 | . 000 | . 270 | . 799 |
| [group=2] * loggluf | . 382 | . 210 | 1.820 | . 071 | -. 033 | . 797 |
| [group=3] * loggluf | $0^{\text {a }}$ |  |  |  |  |  |

a. This parameter is set to zero because it is redundant.

In the main effects plus interaction model, there are six parameters; we are fitting three separate straight lines to the three subgroups, and there are two parameters in each straight line.

The residual plots demonstrate no significant pattern.

Dependent Variable: Log(GluTest)


