As mentioned before you need to build your own X matrix for performing regression. For example, to perform the regression in S-Plus/R with

```
lm(BTUIn ~ BTUOut * damper, data=furnace)
```

```
> summary(furnace.lm2)

Call:
lm(formula = BTUIn ~ BTUOut * Damper, data = furnace)

Residuals:
      Min        1Q    Median        3Q       Max
-3.089841 -0.219128  0.003471  0.303370  1.812594

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.16470    0.30425   0.541    0.590
BTUOut            0.92183    0.02755  33.458   <2e-16 ***
DamperTVD         0.01959    0.43054   0.045    0.964
BTUOut:DamperTVD -0.01717    0.03839  -0.447    0.656

Residual standard error: 0.5576 on 86 degrees of freedom
Multiple R-Squared: 0.9635,     Adjusted R-squared: 0.9622
F-statistic: 756.3 on 3 and 86 DF,  p-value: < 2.2e-16



> anova(furnace.lm2)
Analysis of Variance Table

Response: BTUIn
              Df Sum Sq Mean Sq   F value Pr(>F)
BTUOut         1 704.66  704.66 2266.7663 <2e-16 ***
Damper         1   0.61    0.61    1.9483 0.1664
BTUOut:Damper  1   0.06    0.06    0.2000 0.6559
Residuals     86  26.73    0.31
```

In Matlab you would need to do something like

```
>> xmat = [ones(size(damper)) BTUOut damper BTUOut.*damper];
>> [b, bint, r, rint, stats] = regress(BTUIn, xmat)
>> b

b =

    0.1647
    0.9218
    0.0196
   -0.0172

>> bint

bint =

   -0.4401    0.7695
    0.8671    0.9766
   -0.8363    0.8755
   -0.0935    0.0591

>> stats

stats =

    0.9635  756.3049         0
```

There is another function that makes doing regression a bit easier in that is will automate some of the setup. The function is `regstat`.

The form of the function is

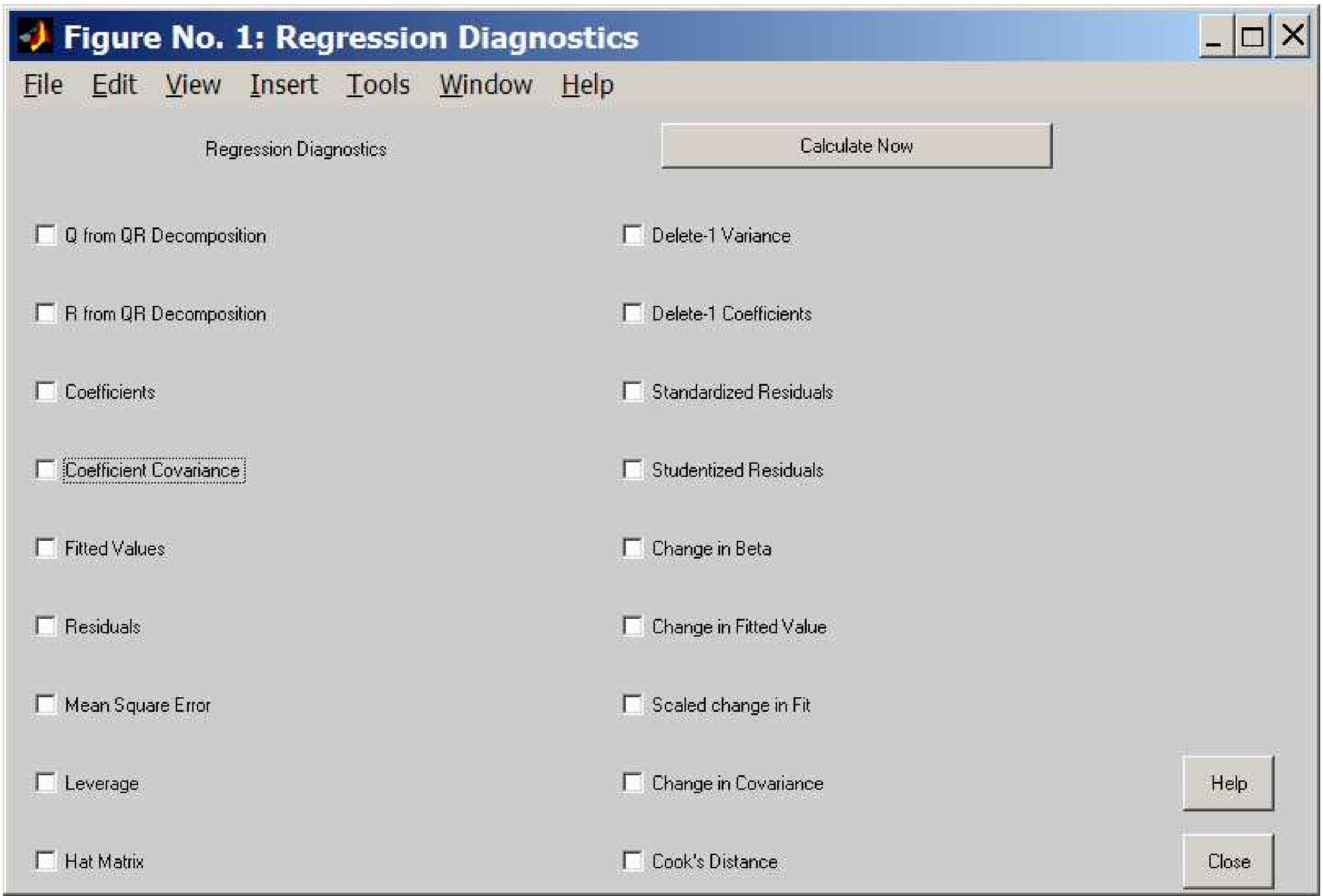
```
>> regstats(y ,data ,'model')
```

`data` is a matrix with each column corresponding to a different variable.

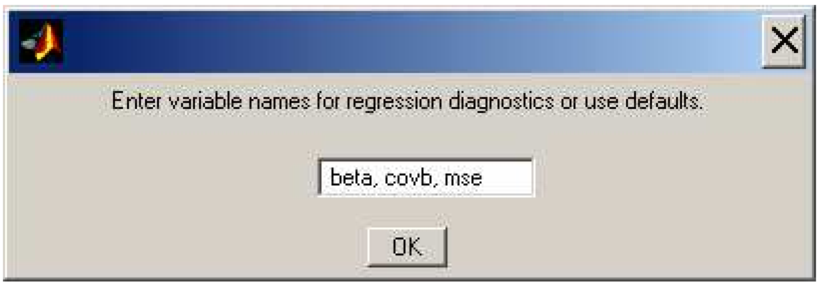
`'model'` can be one of the following strings

- `'linear'` Includes constant and linear terms (default).
- `'interaction'` Includes constant, linear, and cross product terms.
- `'quadratic'` Includes interactions and squared terms.
- `'purequadratic'` Includes constant, linear, and squared terms.

The basic form of the function will bring up a dialog box asking with values you want returned by the function.



One you checked off the variables you want returned, click Calculate Now and a second box will come up asking where you want to store them



```
>> regstats(BTUIn,[BTUOut damper],'interaction')
>> beta2

beta2 =

    0.1647
    0.9218
    0.0196
   -0.0172

>> sqrt(diag(covb2))

ans =

    0.3043
    0.0276
    0.4305
    0.0384
```

Note that the same values are being returned as R.

For programming purposes, there is a second form of the function call that skips the dialog boxes.

```
>> stattest = regstats(BTUIn,[BTUOut damper], 'interaction',
{'beta' 'covb' 'mse'})
```

To access a component of the output you need to give a command like

```
>> stattest.covb

ans =

    0.0926   -0.0080   -0.0926    0.0080
   -0.0080    0.0008    0.0080   -0.0008
   -0.0926    0.0080    0.1854   -0.0159
    0.0080   -0.0008   -0.0159    0.0015
```

To help construct dummy variables to include categorical factors into your linear model, there is the `dummyvar` function. It will take a matrix, where the columns correspond to the different factors, and create a set of dummy variables which could tend be used in a regression

```
>> group

group =

     1     1
     1     2
     1     3
     2     1
     2     2
     2     3

>> D = dummyvar(group)

D =

     1     0     1     0     0
     1     0     0     1     0
     1     0     0     0     1
     0     1     1     0     0
     0     1     0     1     0
     0     1     0     0     1
```

Analysis of Variance

There are 3 functions for peforming Analysis of Variance in Matlab.

anova1: Balanced 1-way ANOVA

anova2: Balanced 2-way ANOVA

anovan: Unbalanced and higher way ANOVA

In the first 2 functions there must be the same number of observations for each treatment combination. If this doesn't hold, you must use anovan.

The following example is taken from a study by Hogg and Ledolter (1987) of bacteria counts in shipments of milk.

```
>> hogg

hogg =

    24    14    11     7    19
    15     7     9     7    24
    21    12     7     4    19
    27    17    13     7    15
    33    14    12    12    10
    23    16    18    18    20
```

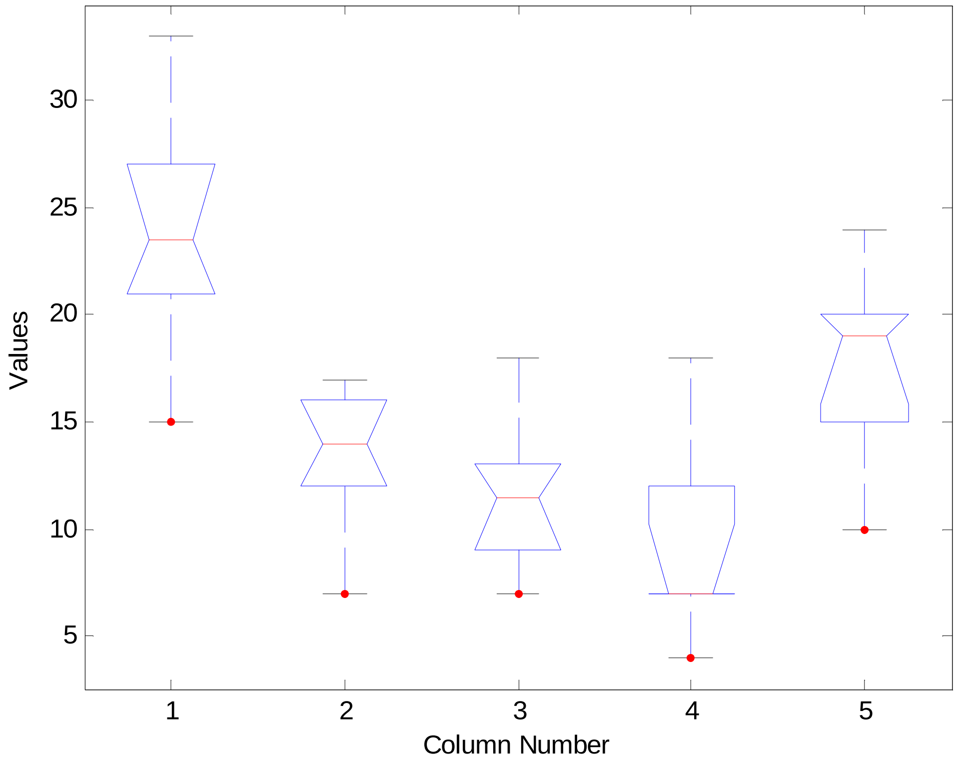
The desired form for the data is for each column to correspond to a different factor levels. To for this example, column 1 is 6 observations from shipment 1, column 2 is shipment 2, etc.

```
>> [pa1,tbla1,statsa1] = anova1(hogg)

pa1 =

  1.1971e-004    % p-value from F test


tbla1 =          % ANOVA table

    'Source'     'SS'               'df'    'MS'          'F'          'Prob>F'
    'Columns'    [   803.0000]      [ 4]    [200.7500]    [9.0076]     [1.1971e-004]
    'Error'      [   557.1667]      [25]    [ 22.2867]          []                []
    'Total'      [1.3602e+003]      [29]            []          []                []


statsa1 =        % ANOVA study information

    gnames: [5x1 char]
         n: [6 6 6 6 6]
    source: 'anova1'
     means: [23.8333 13.3333 11.6667 9.1667 17.8333]
        df: 25
         s: 4.7209
```

In addition to the saved output, anova1 generates two figures, one with the ANOVA table and the other with boxplots of the observations

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	803	4	200.75	9.01	0.0001
Error	557.17	25	22.287		
Total	1360.17	29			



Given the highly significant *F* test, it would be nice to figure which shipments are different. This can be done with the multcompare function. This function takes the ANOVA study information from the anova functions and compares the different groups, taking account of the different number of tests involved.

```
>> [ca1,ma1] = multcompare(statsa1)

ca1 =

    1.0000    2.0000    2.4953   10.5000   18.5047
    1.0000    3.0000    4.1619   12.1667   20.1714
    1.0000    4.0000    6.6619   14.6667   22.6714
    1.0000    5.0000   -2.0047    6.0000   14.0047
    2.0000    3.0000   -6.3381    1.6667    9.6714
    2.0000    4.0000   -3.8381    4.1667   12.1714
    2.0000    5.0000  -12.5047   -4.5000    3.5047
    3.0000    4.0000   -5.5047    2.5000   10.5047
    3.0000    5.0000  -14.1714   -6.1667    1.8381
    4.0000    5.0000  -16.6714   -8.6667   -0.6619


ma1 =

   23.8333    1.9273
   13.3333    1.9273
   11.6667    1.9273
    9.1667    1.9273
   17.8333    1.9273
```

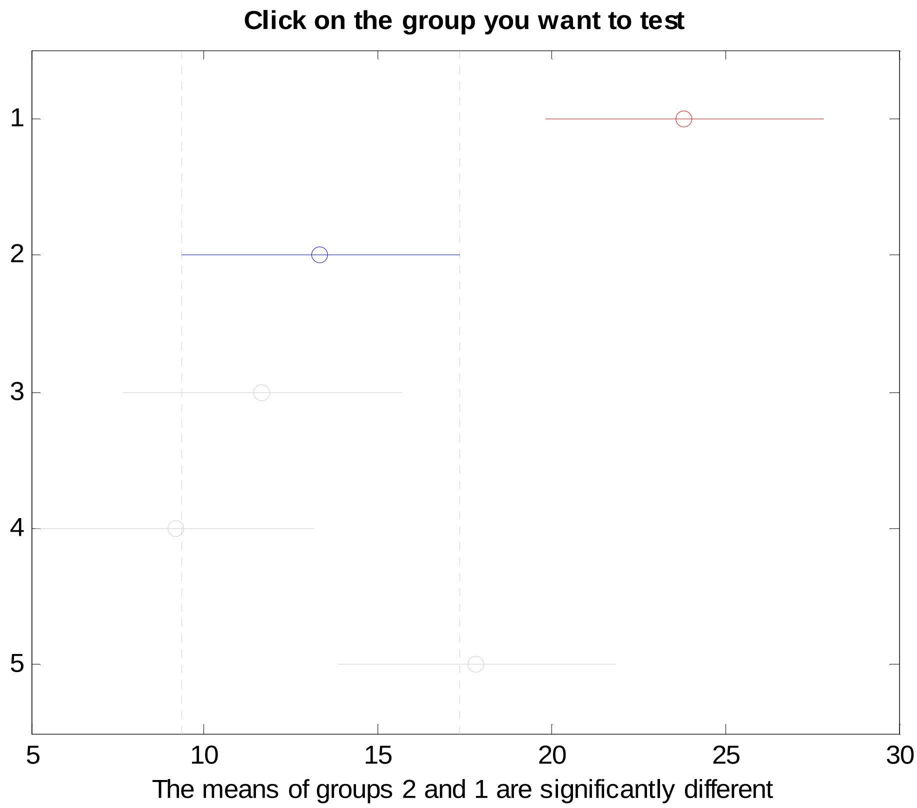
The first variable output given confidence intervals for the difference in means for each treatment comparison

```
    2.0000    4.0000   -3.8381    4.1667   12.1714

    Level 1   Level 2   Lower CI    Est      Upper CI
```

The estimate of the difference is the first level minus the second level.

The second variable output gives the estimated treatment effects with their standard errors.

In addition the function gives a graphical summary indicating which groups are significantly different. This summary gives a graphical summary of the CI's for each treatment. Clicking on a interval will show which treatment are different than the one of interest.



There are many different multiple comparison procedures built into this function. Which one you use depends on the sort of comparisons you are interested.

The default is Tukey's HSD (honestly significant difference), which is optimal for balanced designed where all pairwise comparisons are being made.

Also available are `lsd`, `bonferoni`, `dunn-sidak`, and `scheffe`. These may be more appropriate. For example, if there are other treatment contrasts of interest, `scheffe` may be more appropriate as it provides a simultaneous confidence level for all possible treatment contrasts.

Not surprisingly, you can set the significance level for the `multcompare`. The default level is 0.05.

anovan:

This can be used to fit more complicated ANOVA designs involving more that 2 factors and with unbalanced data.

The structure of the functions call is

```
[p, table, stats, terms] = anovan(y, {fac1
fac2 … facn}, model, sstype, 'varlabels')
```

`y`:	response variable
`faci`:	factor levels
`model`:	model to be fit
`sstype`:	sum of squares type (1, 2, 3)
`varlabels`:	factor variable names

`p:`	p-values form each *F* test
`table:`	ANOVA table as a cell array
`stats:`	ANOVA summary output (not particularly readable
`terms:`	model fit

The model can be specified in many ways. Possibilities are

`'linear'`	main effects only
`'interaction'`	main and two way interactions
`'full'`	all interactions up to order n

A single number indicates the maximum order of interactions to be fit. So 1 is equivalent to `'linear'`, 2 with `'interaction'`, and *n* with `'full'`. A choice of 3 would fit the model with all main effects, all 2 and 3 factor interactions. It is also possible to fit more complicated models, such as A + B*C using S notation. However is a bit kludgy as it is based on the base 2 reprentations of the numbers.

Let 1 represent fac1

Let 2 represent fac2

Let 4 represent fac3

Let 2^k represent fack

To include an effect in the model, you need to add the numbers corresponding to the factors in the effect

For example, for the furnace data set

type: 1

chshape: 2

chliner: 4

So to fit the model type * chshape * chliner (= type + chshape + chliner + type:chshape) you would need the terms 1, 2, 4 plus (3 = 1 + 2).

The call would be

```
>> [pn, tablen, statsn, termsn] = anovan(BTUIn,{type chshape
chliner},[1 2 4 3],1,varnames)
```

Note that the model indicated by `[1 2 4 3]` is not the same as `[3 4]` as this would not included the main effects for factors 1 and 2.

In addition to the output variables, anovan also returns the ANOVA table as a figure

Analysis of Variance

Source	Sum Sq.	d.f.	Mean Sq.	F	Prob>F
Type	8.351	2	4.1757	0.54	0.5863
ChimShape	50.271	2	25.1357	3.24	0.0446
ChinLiner	8.088	2	4.0442	0.52	0.5962
Type*ChimShape	32.155	4	8.0387	1.03	0.3946
Error	605.832	78	7.7671		
Total	704.698	88			

Sequential (Type I) Sums of Squares

This model was fit using Sequential (Type I) sums of squares. The default choice is Type III. For balanced designs, it doesn't matter which you use. However for unbalanced designs, it does.

Analysis of Variance

Source	Sum Sq.	d.f.	Mean Sq.	F	Prob>F
Type	14.011	2	7.0055	0.9	0.41
ChimShape	5.743	2	2.87153	0.37	0.6921
ChinLiner	5.977	2	2.98836	0.38	0.6819
Type*ChimShape	32.155	4	8.0387	1.03	0.3946
Error	605.832	78	7.76707		
Total	704.698	88			

Contained (Type III) Sums of Squares

In unbalanced designs, the *F* tests reported in the table, are different for the different sums of squares types.

Analysis of Covariance

The function aoctool is useful examining models involving 1 continuous predictor and 1 categorical predictor.

It allows for all possible models involving these two predictors to be examined in an interactive format.

The function starts off by fitting the full interactions model (`y ~ A * B`), but you can fit the models (`y ~ 1, y ~ A, y ~ B, y ~ A + B`) as well.

The form of the function call is

```
aoctool(y, cont_pred, cat_pred)
```

```
>> aoctool(BTUOut,BTUIn,damper)
```

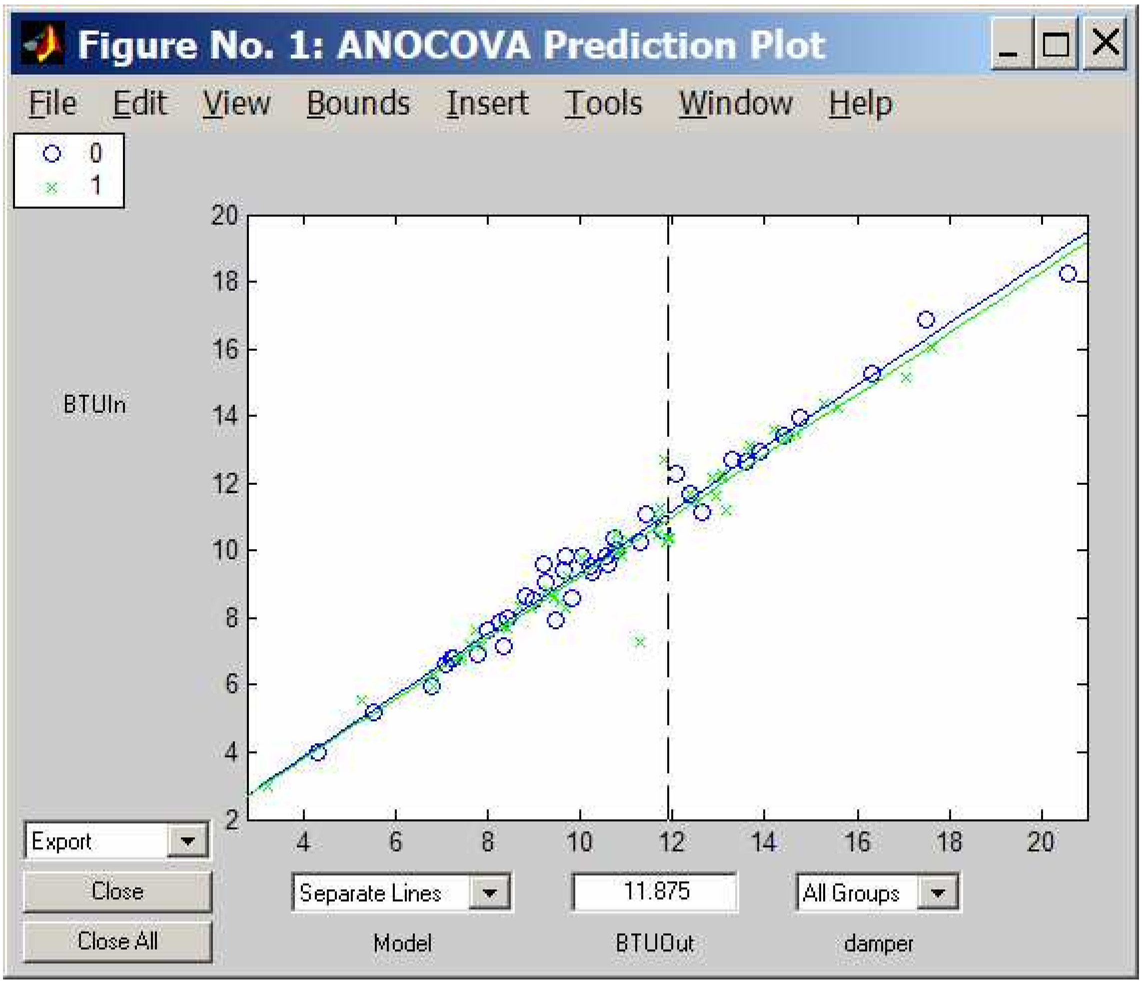


Figure No. 2: ANOCOVA Test Results

File Edit View Insert Tools Window Help

ANOVA Table

Source	d.f.	Sum Sq	Mean Sq	F	Prob>F
damper	1	0.606	0.606	1.95	0.1664
BTUOut	1	704.031	704.031	2264.76	0
damper*BTUOut	1	0.062	0.062	0.2	0.6559
Error	86	26.734	0.311		

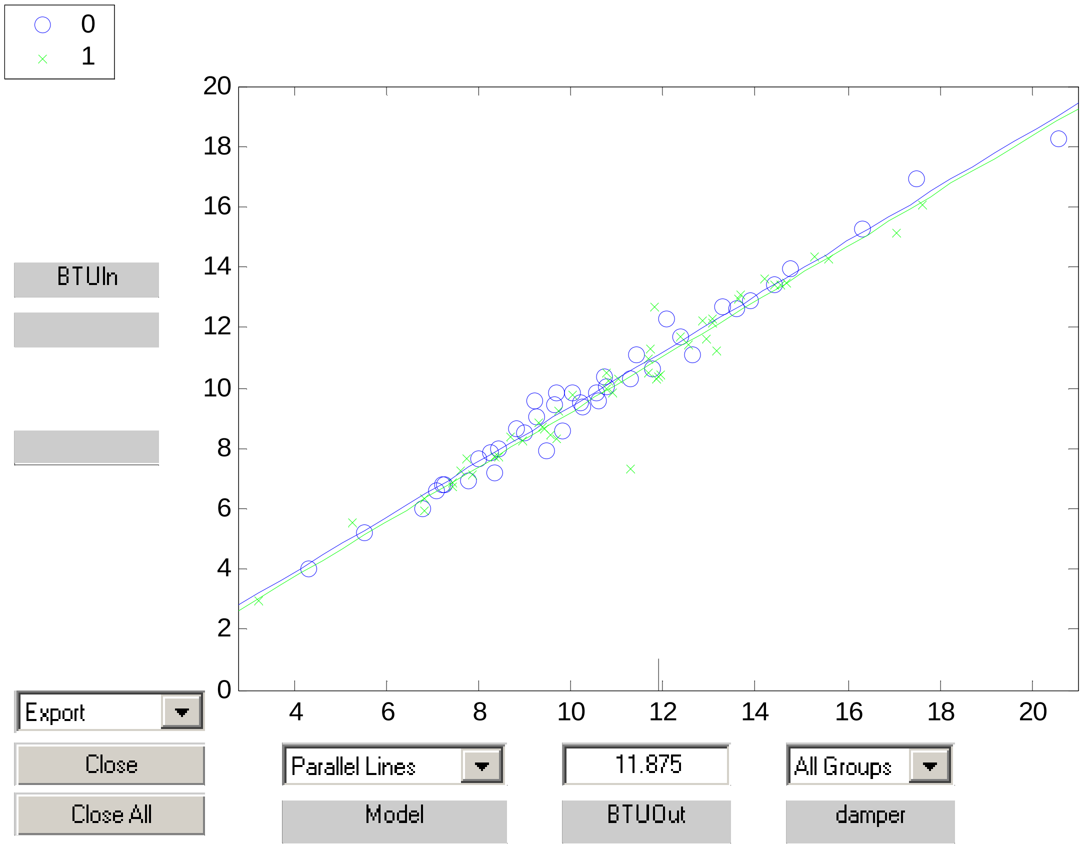
Figure No. 3: ANOCOVA Coefficients

File Edit View Insert Tools Window Help

Coefficient Estimates

Term	Estimate	Std. Err.	T	Prob>|T|
Intercept	0.1745	0.21527	0.81	0.4199
0	-0.0098	0.21527	-0.05	0.9638
1	0.0098	0.21527	0.05	0.9638
Slope	0.9132	0.01919	47.58	0
0	0.0086	0.01919	0.45	0.6559
1	-0.0086	0.01919	-0.45	0.6559

When a different model is request by changing the model menu, all figures update automatically.



ANOVA Table

Source	d.f.	Sum Sq	Mean Sq	F	Prob>F
damper	1	0.606	0.606	1.97	0.1644
BTUOut	1	704.031	704.031	2285.78	0
Error	87	26.796	0.308		

Coefficient Estimates

Term	Estimate	Std. Err.	T	Prob>|T|
Intercept	0.1754	0.21427	0.82	0.4152
0	0.0828	0.05901	1.4	0.1644
1	-0.0828	0.05901	-1.4	0.1644
Slope	0.913	0.0191	47.81	0

It is possible to focus on an individual groups and predictions for given level of the continuous predictor.